A comparison of NYC's education levels and crime

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Introduction

In this project, we were interested in examining how education levels and crime rates have evolved over time at a narrow geographic level (a commute zone) within the United States – more specifically across New York City boroughs. Essentially, the project aims to investigate the main question:

What is the relationship between education levels and crime rates across NYC boroughs, and across time?

Using Python and its extensive libraries, we processed and visualized the data to highlight insightgul trends about how education and crime are more closely linked.

Table of Contents

1. About the Data

The data has been obtained from New York Police Department and the NYC Department of Education.

NYPD Historical Crime Data compiles reported crime and offense data from 2000 - 2017, categorized by police precinct. The data is separated into the following subsets:

1. Seven Major Felonies
2. Other Felony Crimes
3. Misdemeanors
4. Violations

NYC Department of Education compiles graduation outcomes data from the Cohort of 2001-2013 (Class of 2005-2017). The cohort consists of all students who first entered ninth grade in a given school year (e.g., the Cohort of 2001 entered 9th grade in the 2001-2002 school year). Graduates are defined as those students earning either a Local or Regents diploma and exclude those earning either a special education (IEP) diploma or GED. We will use the datasets disaggregated by Borough and District.

1.1 Data Sources

Website: New York Police Department, NYC Department of Education

Historical Data Span: 2005-2017

Data Sources URLs:

- Graduation levels across boroughs and districts: http://schools.nyc.gov/Accountability/data/GraduationDropoutRep (http://schools.nyc.gov/Accountability/data/GraduationDropoutRep
- NYC crime rates http://www1.nyc.gov/site/nypd/stats/crime-statistics/historical.page (http://www1.nyc.gov/site/nypd/stats/crime-statistics/historical.page)

2. Data Fetching, Cleaning, and Processing

2.1 Importing necessary libraries.

In [344]:

```
from IPython.display import display, Image
import pandas as pd
import matplotlib.pyplot as plt
from pylab import *
import numpy as np
import bs4 as bs

import os
import requests, io
import zipfile as zf
import shutil

import fiona
import geopandas as gpd
from shapely.geometry import Point, Polygon

from mpl_toolkits.axes_grid1.inset_locator import z
oomed_inset_axes
from mpl_toolkits.axes_grid1.inset_locator import m
ark_inset
```

2.2 Obtaining Data

Preparing the geopandas mapping data.

In [345]:

```
cwd = os.getcwd()
nyc_map = gpd.read_file(cwd) #mapping data
```

Importing Crime and Education Data.

In [346]:

```
seven_major = pd.read_excel("seven-major-felony-off
enses-by-precinct-2000-2017.xls", skip_footer=20, s
kiprows=2, usecols=[0,1, *range(7,20)])
nonseven_major = pd.read_excel("non-seven-major-fel
ony-offenses-by-precinct-2000-2017.xls", skip_foote
r=33, skiprows=2,usecols=[0,1, *range(7,20)])
misdemeanors = pd.read_excel("misdemeanor-offenses-
by-precinct-2000-2017.xls", skip_footer=41, skiprow
s=2,usecols=[0,1, *range(7,20)])
violations = pd.read_excel("violation-offenses-by-p
recinct-2000-2017.xls", skip_footer=19, skiprows=2,
usecols=[0,1, *range(7,20)])
grad_rate = pd.read_excel("2017Graduation_Rates_Pub
lic_Borough.xlsx") #graduation rates by borough
grad_rate_district = pd.read_excel("2017-Graduation
-Rates-Public-District.xlsx") #graduation rate by s
chool district
```

2.3 Cleaning Imported Data

Cleaning Education Data.

In [347]:

```
grad_rate_district = grad_rate_district.groupby("Di
strict") #grouping by school district
grad_rate_district.groups;
```

Cleaning Crime Data: Filling in NaN values under Precinct Column (PCT).

In [348]:

```
count=0
for var in seven_major["PCT"]:
    while count < len(seven_major["PCT"]):
        seven_major["PCT"][count:count+8] = seven_m
ajor["PCT"][count]
        count += 8

count=0
for var in nonseven_major["PCT"]:
    while count < len(nonseven_major["PCT"]):
        nonseven_major["PCT"][count:count+9] = nons
even_major["PCT"][count]
        count += 9

count=0
for var in misdemeanors["PCT"]:
    while count < len(misdemeanors["PCT"]):
        misdemeanors["PCT"][count:count+18] = misde
meanors["PCT"][count]
        count += 18

count=0
for var in violations["PCT"]:
    while count < len(violations["PCT"]):
        violations["PCT"][count:count+3] = violatio
ns["PCT"][count]
        count += 3
```

```
/anaconda3/lib/python3.6/site-packages/i
pykernel_launcher.py:4: SettingWithCopyW
arning:
A value is trying to be set on a copy of
a slice from a DataFrame

See the caveats in the documentation: ht
tp://pandas.pydata.org/pandas-docs/stabl
e/indexing.html#indexing-view-versus-cop
y
  after removing the cwd from sys.path.
/anaconda3/lib/python3.6/site-packages/i
pykernel_launcher.py:10: SettingWithCopy
Warning:
A value is trying to be set on a copy of
a slice from a DataFrame

See the caveats in the documentation: ht
tp://pandas.pydata.org/pandas-docs/stabl
e/indexing.html#indexing-view-versus-cop
y
  # Remove the CWD from sys.path while w
e load stuff.
/anaconda3/lib/python3.6/site-packages/i
pykernel_launcher.py:16: SettingWithCopy
Warning:
A value is trying to be set on a copy of
a slice from a DataFrame

See the caveats in the documentation: ht
tp://pandas.pydata.org/pandas-docs/stabl
e/indexing.html#indexing-view-versus-cop
y
  app.launch_new_instance()
/anaconda3/lib/python3.6/site-packages/i
pykernel_launcher.py:22: SettingWithCopy
Warning:
A value is trying to be set on a copy of
a slice from a DataFrame
```

```
See the caveats in the documentation: ht
tp://pandas.pydata.org/pandas-docs/stabl
e/indexing.html#indexing-view-versus-cop
y
```

Adding a column to distinguish category of crime.

In [349]:

```
violations["Crime Type"] = "Violation"
misdemeanors["Crime Type"] = "Misdemeanor"
seven_major["Crime Type"] = "Major Felony"
nonseven_major["Crime Type"] = "Non-Major Felony"
```

2.4 Merge

Now we can finally merge the two data sets, nyc_map and crime.

2.4.1 Combining crime data into one dataframe.

In [350]:

```
crime = seven_major.append([nonseven_major, misdeme
anors, violations], ignore_index=True)
crime = crime.sort_values(["PCT", "Crime Type"])
#crime = crime.set_index(["PCT", "Crime Type"])
crime.columns = [str(var) for var in crime.columns]
```

2.4.2 Scraper

We need to merge the nyc_amp data with the crime data, but there are no matching columns. To solve this we will scrape the nyc website to match the Police Precincts with Zip Codes.

In [351]:

```
#scraping nypd site for precinct zip codes
url = "http://www1.nyc.gov/site/nypd/bureaus/patro
l/precincts-landing.page"
sauce = requests.get(url).content
soup = bs.BeautifulSoup(sauce, 'lxml')
```

In [352]:

```
table = soup.table  #finds first table
table_all = soup.find_all('table') # find all table
s

table_rows = table.find_all('tr')  #finds all <tr>
 from first table

p_numbers = []

for tr in table_rows:   # for each <tr> in first <t
able>, print text from <td>
    anchors = tr.find_all('a')  #finds all <td>
    row = [i for i in anchors]  #gets text from <td
>
    row = str(row).split(sep="\"")
    trow = row.pop().split(sep="<")
    trow = trow[0].split(sep=">")
    hrow = trow.pop()
    hrow = hrow.replace("P", "p")
    hrow = hrow.replace(" ", "-")
    p_numbers += [hrow] #taking precinct numbers


p_numbers = [var for var in p_numbers if var != "
[]"] #removing empty lists
p_numbers;
```

In [353]:

```
p_zip = []
for var in p_numbers:
    url = "http://www1.nyc.gov/site/nypd/bureaus/pa
trol/precincts/" + var + ".page" #uses previous scr
aper data to find URL's we are actually interested
 in
    sauce = requests.get(url).content
    soup = bs.BeautifulSoup(sauce, 'lxml')
    para = (soup.find_all('p')[1]).text.split(sep=
', ').pop()
    p_zip+=[para[0:5]] #list of zip codes

p_zip[7] = "10001"
p_zip[9] = "10019"
p_zip[12] = "10024"
p_zip[57] = "11693"

p_zip;

p_zip_codes = []
for var in p_zip:
    p_zip_codes += [var]*38
```

Adding Zipcode column to crime data.

In [354]:

```
crime["ZIPCODE"] = p_zip_codes
```

Here is where we finally merge the nyc_map data with the crime data.

In [355]:

```
nyc_crime = pd.merge(nyc_map, crime, on="ZIPCODE",
how="outer", indicator = True)

#Remove extraneous columns
nyc_crime.columns = [str(var) for var in nyc_crime.
columns]
nyc_crime = nyc_crime.drop(["BLDGZIP", "PO_NAME","S
TATE","COUNTY","URL","CTY_FIPS","ST_FIPS", "SHAPE_L
EN","SHAPE_AREA", ], axis=1)
nyc_crime.set_index("ZIPCODE")
```

Out[355]:

	POPULATION	AREA	
ZIPCODE			
11436	18681.0	2.269930e+07	POLYGON ((1038098. 188138.38
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43

	POPULATION	AREA	
ZIPCODE			
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43

	POPULATION	AREA	
ZIPCODE			
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43

	POPULATION	AREA	
ZIPCODE			
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
11213	62426.0	2.963100e+07	POLYGON ((1001613. 186926.43
...	...	...	...
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57

	POPULATION	AREA	
ZIPCODE			
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57

	POPULATION	AREA	
ZIPCODE			
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57

	POPULATION	AREA	
ZIPCODE			
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
11361	28496.0	5.016352e+07	POLYGON ((1048944. 222063.57
10036	23543.0	1.139511e+07	POLYGON ((989419.2 215672.08

	POPULATION	AREA	
ZIPCODE			
11414	26148.0	6.392882e+07	POLYGON ((1025670. 184011.38
10310	25003.0	5.346328e+07	POLYGON ((950767.5 172848.96
11249	28481.0	1.777221e+07	POLYGON ((995877.3 203206.07
10162	0.0	2.103489e+04	POLYGON ((997731.7 219560.92
10119	0.0	1.263930e+05	POLYGON ((986038.6 213051.06

3338 rows × 20 columns

2.5 Cleaning Merged Data

Creating new column variables.

- Avg_Crime is the average crime occurances over 13 years.
- Avg_Crime_Person is average crime over 13 years standardized by population.
- ACP_Scaled just scales Crime per person to make the color differences more pronounced on the map.

In [356]:

```
#Add other columns
nyc_crime["Avg_Crime"] = (nyc_crime["2005"] + nyc_crime["2006"] + nyc_crime["2007"] + nyc_crime["2008"] + nyc_crime["2009"]+nyc_crime["2010"] + nyc_crime["2011"] + nyc_crime["2012"] + nyc_crime["2013"] + nyc_crime["2014"] + nyc_crime["2015"] + nyc_crime["2016"] + nyc_crime["2017"])/13
nyc_crime["Avg_Crime_Person"] = nyc_crime["Avg_Crime"]/nyc_crime["POPULATION"]
nyc_crime["ACP_Scaled"] = nyc_crime["Avg_Crime_Person"] * 10000000
```

Adding a Borough Column to dataframe.

In [357]:

```
borough = {'Brooklyn': ['11213', '11212', '11225',
'11218', '11226', '11219', '11210', '11230', '1120
4', '11222', '11237','11206','11251','11201', '1120
5','11208', '11207','11217', '11238','11231','1121
5', '11232','11203', '11239', '11236', '11220','112
34','11209','11228','11229', '11214','11223','1123
5','11224','11221'],
             'Bronx': ['10460', '10457', '10461','10
465', '10453', '10471', '10470', '10466', '10467',
'10463', '10475', '10464', '10469', '10468', '1045
8','10452', '10456', '10472', '10459', '10451', '10
473', '10474', '10455', '10454'],
             'Manhattan': ['00083','10034', '10033',
 '10462', '10040','10032','10031', '10039','10030',
 '10027', '10037', '10024', '10026','10035', '1004
8', '10025','10029','10128', '10023', '10028','1002
1','10044','10018', '10020','10017', '10001', '1001
1', '10016','10010','10003','10014', '10002','1000
9', '10012','10013', '10007', '10038','10006','1000
5', '10004','10280','10055', '10019', '10111', '101
53', '10154', '10152', '10115', '10022', '10065',
'10075', '10069', '10281', '10282',  '10279', '1016
5', '10168',  '10105', '10118', '10176', '10170',
'10112', '10122', '10107', '10103', '10174', '1016
6', '10169', '10167', '10177', '10172', '10171', '1
0270', '10104', '10271', '10110', '10175', '10151',
 '10173', '10178', '10121', '10123', '10106', '1015
8', '10041', '10120', '10278', '10155', '10043', '1
0081', '10096', '10097', '10196', '10275','10265',
'10045', '10047', '10080', '10203', '10259', '1026
0', '10285', '10286', '11371', '11361', '10036','10
162', '10119'],
             'Queens': ["11385",'11378','11436','113
57', '11356', '11359', '11360', '11105','11363','11
354','11102', '11370','11358', '11362','11369', '11
103', '11106', '11368', '11377', '11355', '11101',
'11364','11005', '11104', '11109','11367','11412',
 '11411',   '11413', '11422', '11420', '11417',  '1
```

```
1430','11693', '11096',   '11691',  '11692', '1030
6', '11694',  '10308', '11697', '10312', '11372',
'11004', '11040', '11426', '11365', '11001', '1137
5', '11427', '11374', '11366', '11423', '11428', '1
1432', '11379', '11429', '11435', '11415', '11418',
 '11433', '11451','11421', '11419', '11434','11216'
,'11233','11211', '11373','11416','11414','11249'],
            'Staten Island': ['10301', '10303', '10
302',  '10304', '10314','10305','10309', '10307','1
0310']
           } #dictionary mapping Borough to Zip Cod
es


borough_list = [] #list to contain boroughs from zi
p codes

key_list = list(borough.keys()) #list of boroughs
value_list = list(borough.values()) #list of zip co
des


for var in nyc_crime["ZIPCODE"]: #each zip code in
 column
    for i in range(0,len(value_list)): #sets range
        if var in value_list[i]: #compares zip code
 to value_list
            borough_list += [key_list[i]]


nyc_crime["Borough"] = borough_list
```

Separating Data

Here we will use the groupby() method to separate the data into crime, cross-sectioned by borough and year.

In [366]:

```
nyc_crime2 = pd.DataFrame(nyc_crime)
nyc_crime2 = nyc_crime.groupby("Borough") #creating
 a dummy variable

bronx_crime = pd.DataFrame(nyc_crime2.get_group("Br
onx"))
manhattan_crime = pd.DataFrame(nyc_crime2.get_group
("Manhattan"))
staten_island_crime = pd.DataFrame(nyc_crime2.get_g
roup("Staten Island"))
brooklyn_crime = pd.DataFrame(nyc_crime2.get_group(
"Brooklyn"))
queens_crime = pd.DataFrame(nyc_crime2.get_group("Q
ueens")) #separate dataframes for each borough

total_crime = pd.DataFrame({"Queens":(queens_crime)
.sum(),
                            "Brooklyn": brooklyn_cr
ime.sum(),
                            "Manhattan": manhattan_
crime.sum(),
                            "Staten Island": staten
_island_crime.sum(),
                            "Bronx": bronx_crime.su
m()
})

total_crime = total_crime.drop(["AREA","ZIPCODE","P
CT","POPULATION","_merge","Avg_Crime", "Avg_Crime_P
erson", "ACP_Scaled","Borough","2017","2016","2015"
,"2014"])
total_crime
```

Out[366]:

	Bronx	Brooklyn	Manhattan	Queens	State Islar
2005	287148	351514	340550	311080	3424
2006	286352	346276	333634	314774	3761
2007	298432	344016	342534	315874	3592
2008	293030	337212	338990	315440	3828
2009	295794	335048	329496	302406	3506
2010	291636	336738	326150	301530	3552
2011	279790	335030	314836	301086	3443
2012	273016	336538	322698	296990	3363
2013	261500	319790	318450	295098	3569

Similarly, we now separate education by borough and year.

In [359]:

```
grad_rate = grad_rate.groupby("Borough") #grouping
 by borough
bronx_edu = pd.DataFrame(grad_rate_gb.get_group("Br
onx")).set_index("Cohort Year")
manhattan_edu = pd.DataFrame(grad_rate_gb.get_group
("Manhattan")).set_index("Cohort Year")
staten_island_edu = pd.DataFrame(grad_rate_gb.get_g
roup("Staten Island")).set_index("Cohort Year")
brooklyn_edu = pd.DataFrame(grad_rate_gb.get_group(
"Brooklyn")).set_index("Cohort Year")
queens_edu = pd.DataFrame(grad_rate_gb.get_group("Q
ueens")).set_index("Cohort Year")
total_edu = pd.DataFrame({"Queens":queens_edu["% of
 cohort"],
                            "Brooklyn": brooklyn_ed
u["% of cohort"],
                            "Manhattan": manhattan_
edu["% of cohort"],
                            "Staten Island": staten
_island_edu["% of cohort"],
                            "Bronx": bronx_edu["% o
f cohort"]
})
total_edu = total_edu.drop([2001,2002,2003,2004])
total_edu
```

Out[359]:

	Bronx	Brooklyn	Manhattan	Queens
Cohort Year				
2013	62.91332	70.68073	71.96335	74.84678
2012	62.01040	69.18311	71.91213	73.20342
2011	58.29948	66.98756	69.23177	70.51550
2010	54.68409	63.80621	66.62219	66.52633
2009	52.34668	60.98572	63.35399	63.93174
2008	50.71478	60.14401	62.77248	63.58567
2007	52.67404	59.50431	62.65588	64.96090
2006	54.71468	58.79965	63.41983	63.73351
2005	54.22734	56.43723	61.95796	60.80159

3. Visualizing Data

3.1 Education Data

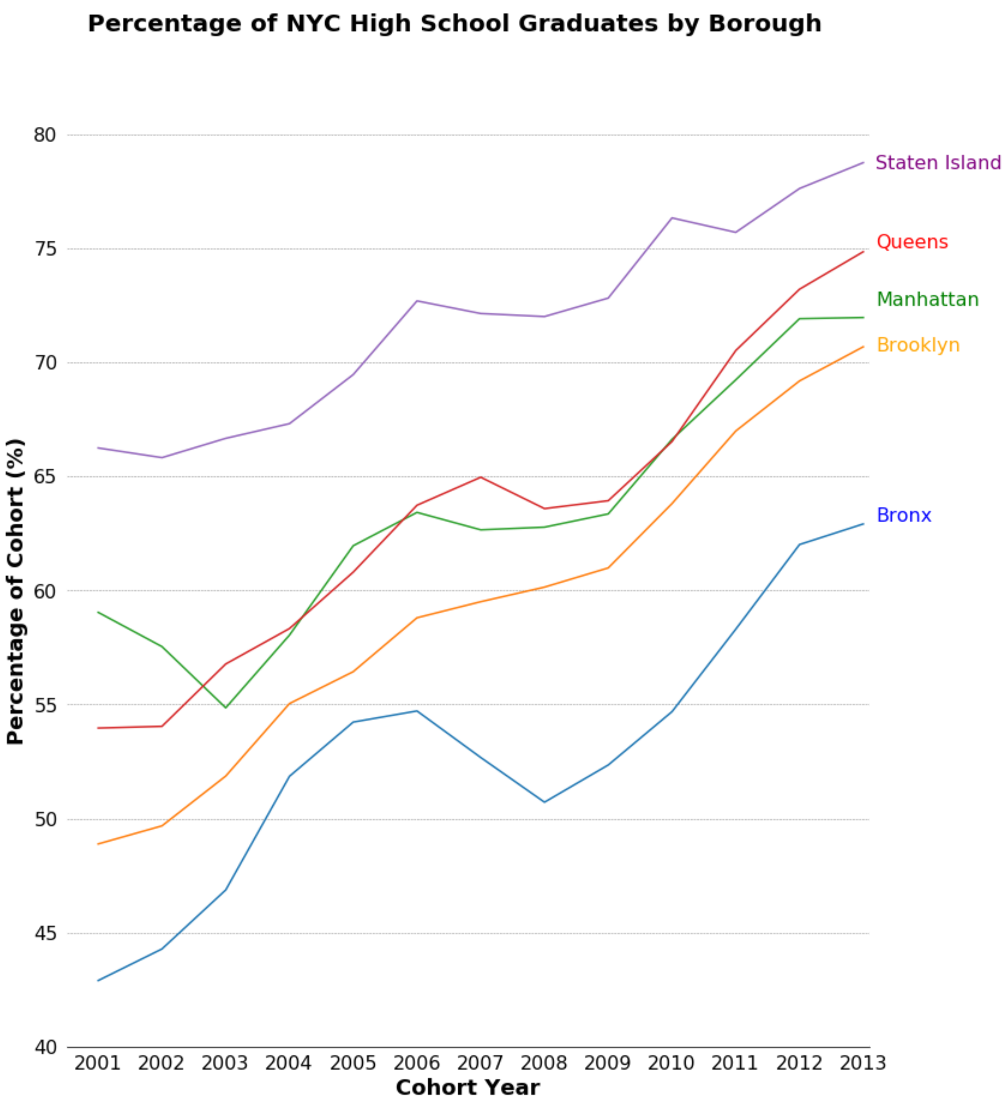
We will now plot our data, starting by plotting Percentage of Class Cohorts that Graduated over 12 years, separated by Borough.

3.1.1 Graphing Percentage of Graduates over time by Borough

In [360]:

```
# Here we include a graph that maps the percentage
 of students enrolled
# in "4 Year June" high school programs that gradua
ted, with data
# available for Cohort Years from 2001-2013 (Class
 of 2005-2017).

fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(1
2,14))

# We plot the 5 boroughs of Cohort Year against % o
f Cohort who graduated.
ax.plot(grad_rate.get_group("Bronx")["Cohort Year"
],grad_rate.get_group("Bronx")["% of cohort"])
ax.plot(grad_rate.get_group("Brooklyn")["Cohort Yea
r"],grad_rate.get_group("Brooklyn")["% of cohort"])
ax.plot(grad_rate.get_group("Manhattan")["Cohort Ye
ar"],grad_rate.get_group("Manhattan")["% of cohort"
])
ax.plot(grad_rate.get_group("Queens")["Cohort Year"
],grad_rate.get_group("Queens")["% of cohort"])
ax.plot(grad_rate.get_group("Staten Island")["Cohor
t Year"],grad_rate.get_group("Staten Island")["% of
 cohort"])

# We remove the top, right and left frame lines.
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_visible(False)

#Limit the range of the plot to only where the data
 is.
ax.set_xlim(2000.5, 2013.1)
ax.set_ylim(40, 80)

#Set axis ticks, showing Cohort Year and % of cohor
ts.
plt.xticks(range(2001, 2014, 1), fontsize=16)
```

```
plt.yticks(range(40, 85, 5), fontsize=16)

#Insert y gridlines for easier reading of the grap
h.
ax.grid(True, axis ='y', ls='--', lw=.5, c='k', alp
ha=.5)

ax.tick_params(axis='both', which='both', bottom='o
ff', top='off',
                labelbottom='on', left='off', right
='off', labelleft='on')

#Set x and y axis labels.
ax.set_ylabel("Percentage of Cohort (%)", fontsize
= 18, fontweight="bold")
ax.set_xlabel("Cohort Year", fontsize = 18, fontwei
ght="bold")

#Insert in-graph labels of the different boroughs.
ax.text(2013.2, 78.5, "Staten Island", fontsize=16,
 color = "purple")
ax.text(2013.2, 75, "Queens", fontsize=16, color =
"red")
ax.text(2013.2, 72.5, "Manhattan", fontsize=16, col
or = "green")
ax.text(2013.2, 70.5, "Brooklyn", fontsize=16, colo
r = "orange")
ax.text(2013.2, 63, "Bronx", fontsize=16, color =
"blue")

#Graph title
fig.suptitle('Percentage of NYC High School Graduat
es by Borough', fontsize=20, fontweight='bold', ha=
'center')

plt.show()
```



From this graph, we can see the relative standing of each borough with respect to graduation rates, With Staten Island being the highest and the Bronx being the lowest. Since it is measuring the percentage of cohort graduating, it is not affected by a population confounding variable (i.e. larger boroughs would have larger amounts of graduates). This is interesting because the top three boroughs with the most education also have the lowest three amounts of crime.

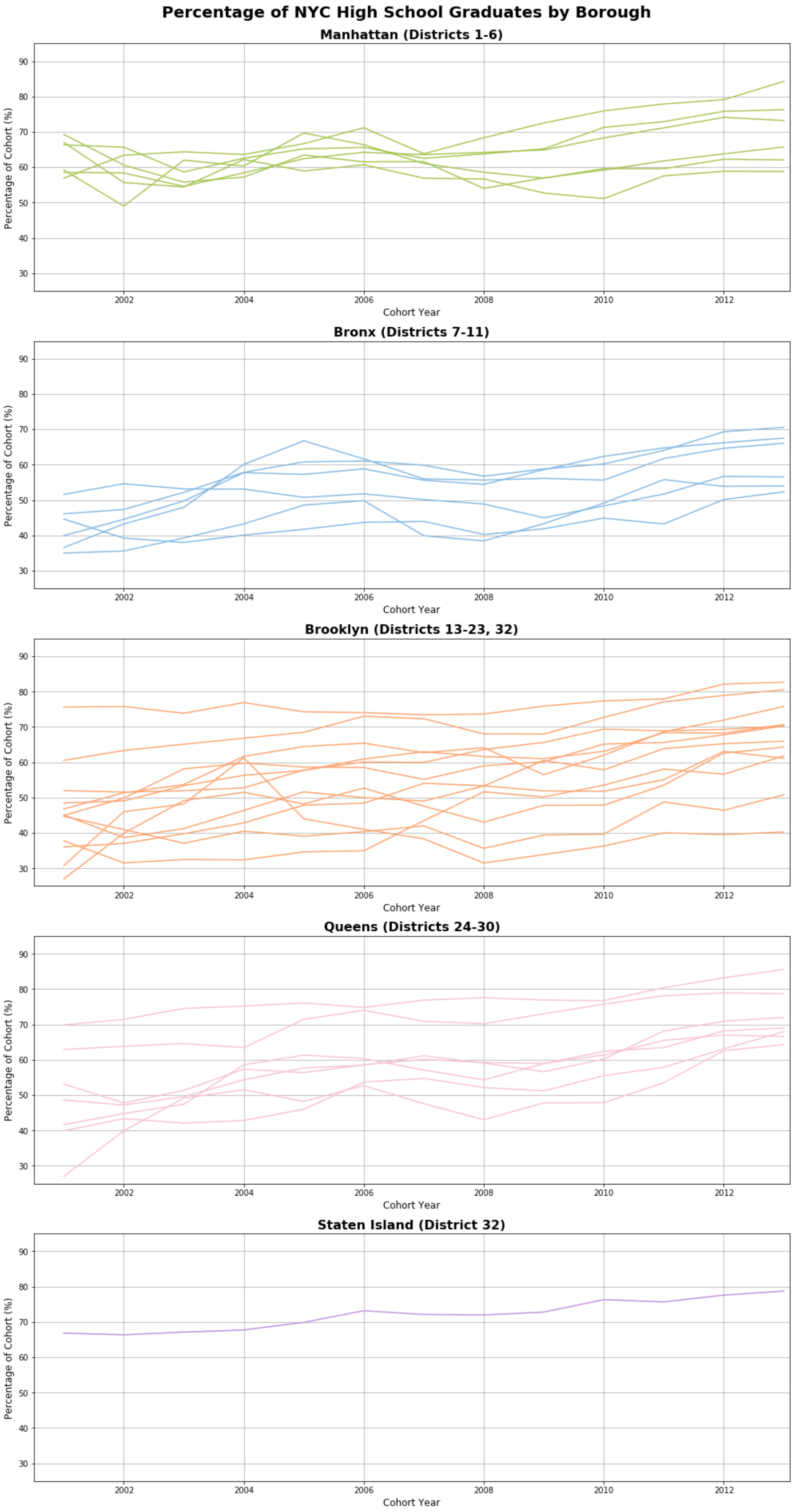
3.1.2 Graphing Graduation Rates over time by School District

In [361]:

```
fix, ax = plt.subplots(nrows=5, figsize = (14,26),
sharey=True, sharex=True)
fig = gcf()
fig.suptitle('Percentage of NYC High School Graduat
es by Borough', x=.51, y = 1.01, fontsize=20, fontw
eight='bold', ha='center')

#Plotting Manhattan districts
for var in range(1,6):
    ax[0].plot(grad_rate_district.get_group(var)["C
ohort Year"],grad_rate_district.get_group(var)["% o
f cohort"],
           color = '#a5c34f')
ax[0].plot(grad_rate_district.get_group(6)["Cohort
 Year"],grad_rate_district.get_group(6)["% of cohor
t"],
       color = '#a5c34f',
       label = "Manhattan")
ax[0].set_title("Manhattan (Districts 1-6)",fontsiz
e=16, fontweight="bold")



#Plotting Bronx districts
for var in range(7,12):
    ax[1].plot(grad_rate_district.get_group(var)["C
ohort Year"],grad_rate_district.get_group(var)["% o
f cohort"],
           color = '#82b7e3',)
ax[1].plot(grad_rate_district.get_group(12)["Cohort
 Year"],grad_rate_district.get_group(12)["% of coho
rt"],
       color = '#82b7e3',
       label = "Bronx")
ax[1].set_title("Bronx (Districts 7-11)",fontsize=1
6, fontweight="bold")



#Plotting Brooklyn districts
```

```
for var in range(13,24):
    ax[2].plot(grad_rate_district.get_group(var)["C
ohort Year"],grad_rate_district.get_group(var)["% o
f cohort"],
           color = '#fda26d',
           label = "Brooklyn")
ax[2].plot(grad_rate_district.get_group(32)["Cohort
 Year"],grad_rate_district.get_group(32)["% of coho
rt"],
       color = '#fda26d',
       label = "Brooklyn")
ax[2].set_title("Brooklyn (Districts 13-23, 32)", f
ontsize=16, fontweight="bold")

#Plotting Queens districts
for var in range(24,30):
    ax[3].plot(grad_rate_district.get_group(var)["C
ohort Year"],grad_rate_district.get_group(var)["% o
f cohort"],
           color = '#f7c3d2',)
ax[3].plot(grad_rate_district.get_group(30)["Cohort
 Year"],grad_rate_district.get_group(32)["% of coho
rt"],
       color = '#f7c3d2',
       label = "Queens")
ax[3].set_title("Queens (Districts 24-30)", fontsiz
e=16, fontweight="bold")

#Plotting Staten Island districts
ax[4].plot(grad_rate_district.get_group(31)["Cohort
 Year"],grad_rate_district.get_group(31)["% of coho
rt"],
       color = '#be8fe2',
       label = 'Staten Island')
ax[4].set_title("Staten Island (District 32)",fonts
ize=16, fontweight="bold")



for xxx in ax:
    xxx.set_ylabel("Percentage of Cohort (%)", font
```

```
size = 12)
    xxx.set_xlabel("Cohort Year", fontsize = 12)
    xxx.grid()
#     xxx.spines['top'].set_visible(False)
#     xxx.spines['right'].set_visible(False)
#     xxx.spines['left'].set_visible(False)

    xxx.get_xaxis().tick_bottom()
    xxx.get_yaxis().tick_left()
    xxx.set_xlim(2000.5, 2013.1)
    xxx.set_ylim(25, 95)




# plt.xticks(range(2001, 2014, 1), fontsize=12)
# plt.yticks(range(25, 95, 5), fontsize=12)
# plt.grid(True, axis ='y', ls='--', lw=.5, c='k',
 alpha=.5)
# plt.tick_params(axis='both', which='both', bottom
='off', top='off', labelbottom='on', left='off', ri
ght='off', labelleft='on')
# plt.legend(loc = "upper left")

plt.tight_layout()
plt.show()
```

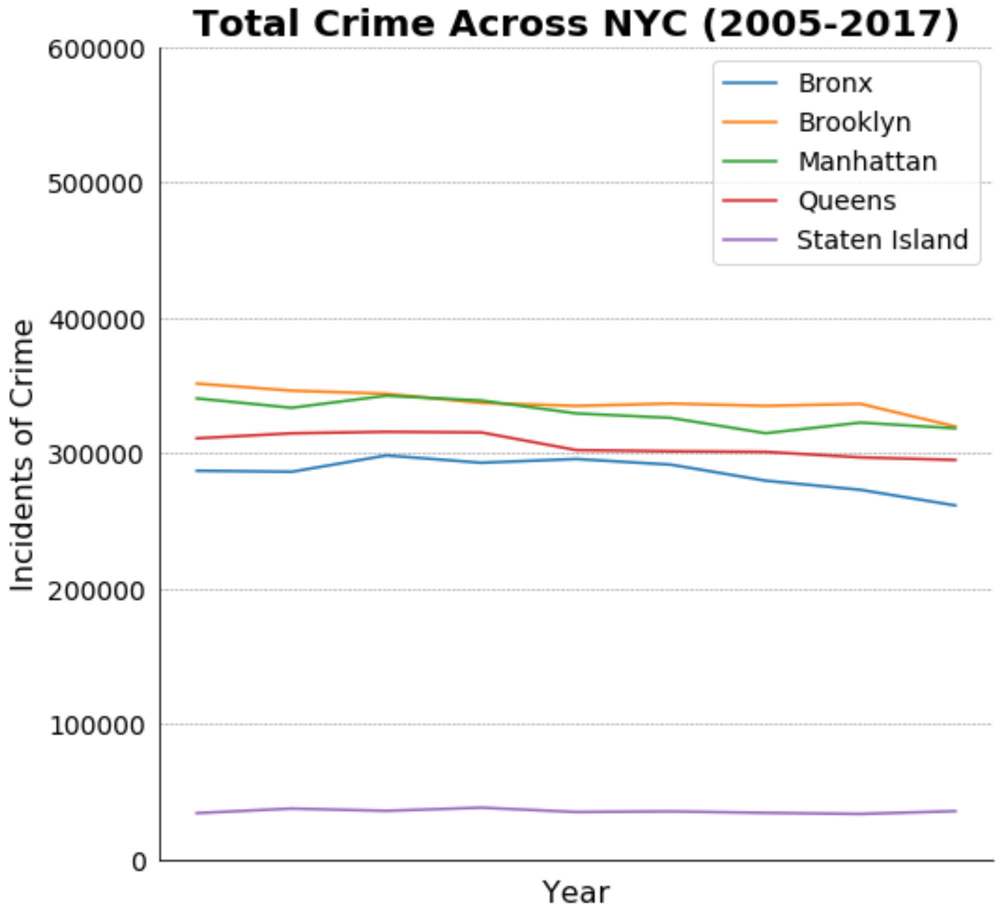

Percentage of NYC High School Graduates by Borough
Manhattan (Districts 1-6)
Bronx (Districts 7-11)
Brooklyn (Districts 13-23, 32)
Queens (Districts 24-30)
Staten Island (District 32)
Percentage of Cohort (%)
Cohort Year
90
80
70
60
50
40
30
2002
2004
2006
2008
2010
2012

3.2 Crime Data

3.2.1 Plot of Crime Data

In [362]:

```
ax = total_crime.plot(figsize=(8,8))

ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)



plt.yticks(range(0, 700000, 100000), fontsize=14)
plt.xticks(fontsize = 14, rotation = 0)

plt.grid(True, axis ='y', ls='--', lw=.5, c='k', al
pha=.5)

plt.tick_params(axis='both', which='both', bottom=
'off', top='off',
                labelbottom='on', left='off', right
='off', labelleft='on')

ax.set_ylabel("Incidents of Crime", fontsize = 16)
ax.set_xlabel("Year", fontsize = 16)

plt.title("Total Crime Across NYC (2005-2017)", fon
tsize = 20, fontweight = "bold")

plt.legend(loc = "upper right", fontsize = 14)
plt.tight_layout
plt.show()
```



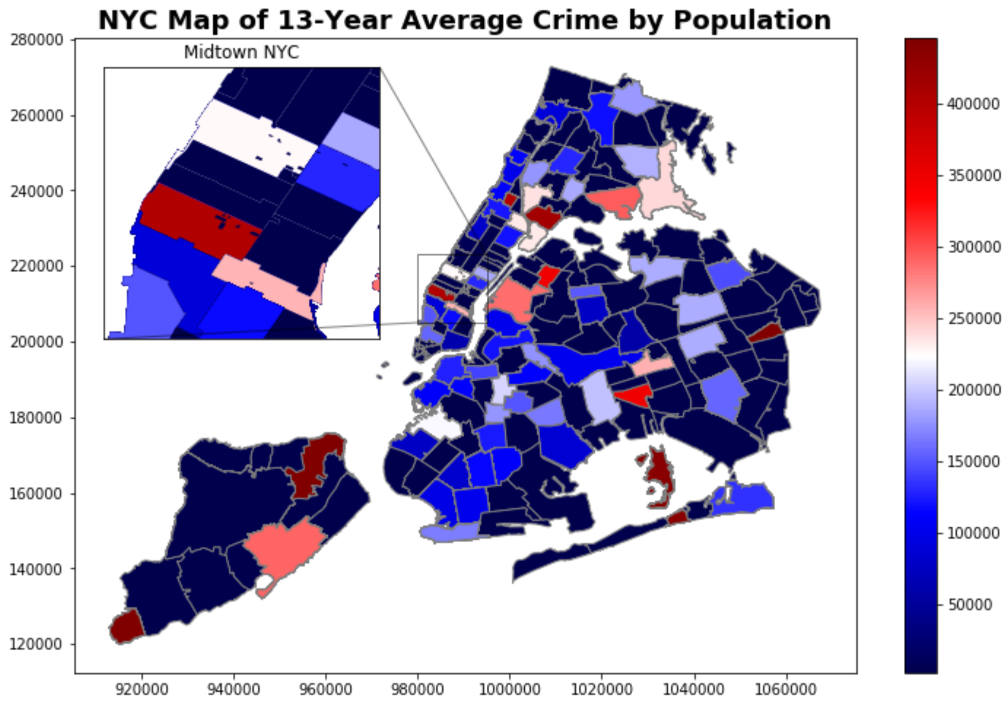
3.2.2 Mapping of Crime Across NYC

We will now create a mapping of crime across the city.

In [363]:

```
fig , ax = plt.subplots(nrows=1, ncols= 1, figsize
= (12,8))
nyc_crime.set_index("ACP_Scaled")
nyc_crime.plot(ax=ax, edgecolor="tab:grey", column=
"ACP_Scaled", cmap="seismic", vmin=2000, vmax=44622
7, alpha=1, legend=True)
#nyc_crime.plot(ax=ax, edgecolor="tab:grey", column
="POPULATION", cmap="OrRd", vmin=2000, vmax=446227,
 alpha=1, legend=True)



ax.set_title("NYC Map of 13-Year Average Crime by P
opulation", fontsize=18, fontweight="bold")
# ax.get_xaxis().set_visible(False)
# ax.get_yaxis().set_visible(False)






axins = zoomed_inset_axes(ax, 4, loc=2, borderpad=2
)
nyc_crime.plot(ax = axins, column='ACP_Scaled', cma
p='seismic',vmin=2000, vmax=446227, alpha=1)



x1, x2, y1, y2 = 980000, 995000, 205000, 223000
axins.set_xlim(x1, x2)
axins.set_ylim(y1, y2)

axins.set_title("Midtown NYC")
mark_inset(ax, axins, loc1=3, loc2=1, fc="none", al
pha = .5)
axins.get_xaxis().set_visible(False)
axins.get_yaxis().set_visible(False)

plt.show()
```

```
/anaconda3/lib/python3.6/site-packages/m
atplotlib/colors.py:489: RuntimeWarning:
invalid value encountered in less
  np.copyto(xa, -1, where=xa < 0.0)
```



This map of Average Crime Per Year for 13 years, standardized for population, gives another way to view crime spread across the city. The legend is based off the median average crime level; white areas are median crime level, red levels are above median, and blue levels are below median.

3.3 Analyzing Data

In [364]:

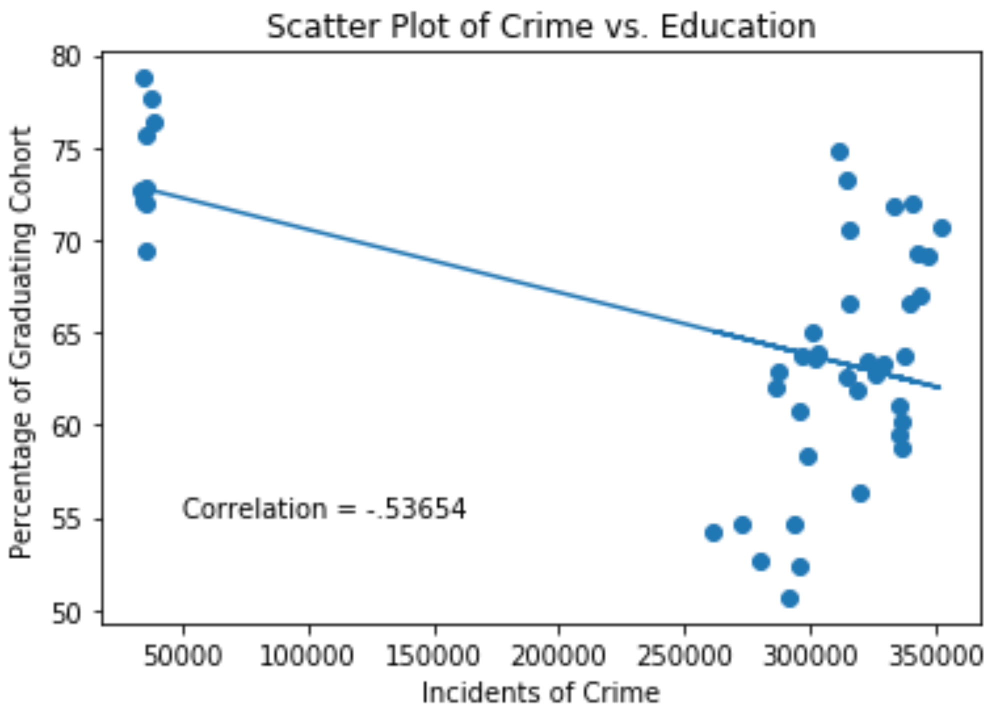
```
scatter = []
scatterx = []
scattery=[]
for var in total_crime.columns:
    for x in total_crime[var]:
        scatterx += [x]
    for y in total_edu[var]:
        scattery += [y]
        for y in total_edu[var]:
            scatter += [x] + [y]

correlation_matrix = pd.DataFrame({"x":scatterx,
"y":scattery})
cor = correlation_matrix.corr()
cor
```

Out[364]:

	x	y
x	1.00000	-0.53654
y	-0.53654	1.00000

In [365]:

```
plt.scatter(scatterx, scattery)

m,b = np.polyfit(scatterx, scattery, 1)
plt.plot(scatterx, np.array(scatterx)*m + b)
#plt.plot(sort(scatterx), sort(scatterx)*[-.53654])
plt.text(50000, 55, "Correlation = -.53654")
plt.title("Scatter Plot of Crime vs. Education")
plt.xlabel("Incidents of Crime")
plt.ylabel("Percentage of Graduating Cohort")
plt.show()
```



The scatter plot shows a negative correlation between crime and educartion, implying that as crime increases, education decreases. However, the data seems to show evidence of heteroskedasticity, which implies that a simple linear regression may not be an apporpriate fit for the data.

4. Conclusion

Conclusion

After analyzing the earlier visualizations of crime and education, we observe that between 2005 and 2017, New York City has experienced an increase in high school graduation levels (as a % of cohort) and a decrease in incidents of crime.

When we look deeper and disaggregate the education and crime data by boroughs, we make the following key observations:

- Staten Island has the highest graduation levels (as % of cohort) and the lowest incidents of crime across the 5 boroughs.
- The Bronx has the lowest graduation levels (as % of cohort), yet it does not have highest incidents of crime.

When examining crime rates geospatially, zipcode areas (shown by red areas) with relatively high incidents of crime do not necessarily correspond with total crime rates by borough. For example, 2 of the 7 zipcode areas with higher crime rates are in Staten Island, which has the lowest incidents of crime. From this, we can also see that the majority of NYC zipcode areas have relatively low incidents of crime compared to the median.

From the scatter plot, we can establish that there is a negative correlation (r = -0.53654) between graduation levels and incidents of crime. While we cannot conclusively establish the causal nature of these two variables, we can conclude that in New York City, as graduation levels increase, incidents of crime tend to decrease