# How Do the Factors of Number of Police, Average Income, Unemployment and School Rating Impact the Safety of a City?


The June-ypers

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Not to be mistaken with the June-pyters

# Question to Answer

- **Our original question was: Can we use crime statistics to better a community?**
  - The thought process behind this was can we could use a crime statistics data API to show where the most prevalent amount of crime happens in a **city**, and then distribute the officers in that area, according to the type/count of crime(s)?
  - We ran into the issue of insufficient data. The crime data API we found, did not have zip codes for the crimes themselves.
  - We have crime data, but it was based on the arresting police department.
- **A new question formed: Which cities are safest, and why?**
- Sample Size: State capitals and their respective police departments.
- Crime Variables: Rape, Simple Assaults, and Stolen Property
- How do these variables affect crime?.
  - Number of police officers
  - School Ratings
  - Avg. Unemployment Rate
  - Avg Income

# Issues with data, and made assumptions

- **We could not find an API to get police department codes**
  - The API source we used is an FBI data source. In order to get our specific crime numbers for capital cities, we needed police department codes, the ORI. Unfortunately there was no quick way to find them all, as there were 50+ in some locations, and they are broken out by county.
  - This will cause the numbers to be skewed, mainly a rather low amount of police officers.
    - Source: https://crime-data-explorer.fr.cloud.gov/api
- **School Ratings**
  - The school ratings are based on an anonymous user rating system. Basically anyone can go in and rate the schools.
    - Statistically, you are far more likely to rate/take time to comment only if you had a bad experience.
      - *https://www.fastcompany.com/90425093/why-your-brains-so-bad-at-letting-go-of-negative-comments*
    - Schools can also be rated by someone who has no affiliation towards the school.
    - Rankings out of 10
    - Includes Public and Private schools
- **Unemployment Rating**
  - Unemployment ratings were taken from the census, based on the state. This one was added late in our data collection, and we didn't have enough time to lookup the rate for each city.
    - *Script used from in-class instructor demo, and modified to suit just the unemployment and income ratings*
- **Avg. Income**
  - Same as above
  - Using Household Income

# Getting Data-1

Example: Alabama Capital City, Montgomery Police Department

```
response = requests.get(f"https://api.usa.gov/crime/fbi/sapi/api/police-employment/agencies/AL0030100/2018/2018?API_
pprint(response)
```

```
{'pagination': {'count': 1, 'page': 0, 'pages': 1, 'per_page': 0},
 'results': [{'agency_name_edit': 'MONTGOMERY PD',
              'agency_type_name': 'City',
              'civilian_ct': 92,
              'csv_header': 'data_year,ori,state_abbr,agency_name_edit,agency_type_name,ncic_agency_name,civilian_c
t,female_civilian_ct,female_officer_ct,female_total_ct,male_civilian_ct,male_officer_ct,male_total_ct,population,po
lice_emp_per_1000,total_pe_ct',
              'data_year': 2018,
              'female_civilian_ct': 70,
              'female_officer_ct': 94,
              'female_total_ct': 164,
              'male_civilian_ct': 22,
              'male_officer_ct': 380,
              'male_total_ct': 402,
              'ncic_agency_name': 'MONTGOMERY PD',
              'ori': 'AL0030100',
              'pe_ct_per_1000': 2.85,
              'population': 198662,
              'state_abbr': 'AL',
              'total_pe_ct': 566}]}
```

# Getting Data-2

```
# Getting data from 2018
ori_list =["AL0030100",
           "AK0010300",
           "AZ0072300",
           "AR0600200",
           "CA0340400",
           "CODPD0000",
           "CT0006400",
           "DE0010100",
           "FL0370300",
           "GAAPD0000"
           ]
female =[]
male =[]

begin_year = 2018
end_year = 2018

print("Beginning Data Retrieval")
print("------------------------")

for ori in range(len(ori_list)):
    response = requests.get(f"https://api.usa.gov/crime/fbi/sapi/api/police-employment/agencies/{ori_list[ori]}/{beg
    #print(response)
    try:
        print(f"Processing record {ori + 1}")
        female.append(response["results"][0]["female_officer_ct"])
        male.append(response["results"][0]["male_officer_ct"])
    except:
        print("Not found")
        pass
print("------------------------")
print("Data Retrieval Complete")
print("------------------------")
```

```
Beginning Data Retrieval
------------------------
Processing record 1
Processing record 2
Processing record 3
Processing record 4
```

# Getting Data-3

Example: Dataframe of 10 States

```
officer_2018_df = pd.DataFrame({"Male Officers": male, "Female Officers" : female})
officer_2018_df
```

| | Male Officers | Female Officers |
|---|---|---|
| 0 | 380 | 94 |
| 1 | 42 | 5 |
| 2 | 2524 | 395 |
| 3 | 475 | 100 |
| 4 | 549 | 102 |
| 5 | 1309 | 208 |
| 6 | 346 | 48 |
| 7 | 95 | 6 |
| 8 | 309 | 68 |
| 9 | 1283 | 252 |

```
officer_2018_df["Total Number"]=officer_2018_df["Male Officers"]+officer_2018_df["Female Officers"]
officer_2018_df
```

| | Male Officers | Female Officers | Total Number |
|---|---|---|---|
| 0 | 380 | 94 | 474 |
| 1 | 42 | 5 | 47 |
| 2 | 2524 | 395 | 2919 |
| 3 | 475 | 100 | 575 |
| 4 | 549 | 102 | 651 |
| 5 | 1309 | 208 | 1517 |
| 6 | 346 | 48 | 394 |
| 7 | 95 | 6 | 101 |
| 8 | 309 | 68 | 377 |
| 9 | 1283 | 252 | 1535 |

# Getting Data-4

Example: Alabama Capital City, Montgomery Police Department

```
# Look up dataset
response = requests.get(f"https://api.usa.gov/crime/fbi/sapi/api/data/arrest/agencies/offense/AL0030100/all/2018/201
pprint(response)
```

```
{'pagination': {'count': 1, 'page': 0, 'pages': 1, 'per_page': 0},
 'results': [{'aggravated_assault': 38,
              'all_other_offenses': 28,
              'arson': 0,
              'burglary': 58,
              'csv_header': None,
              'curfew': 0,
              'data_year': 2018,
              'disorderly': 0,
              'driving': 2,
              'drug_abuse_gt': 32,
              'drug_poss_m': 1,
              'drug_poss_opium': 6,
              'drug_poss_other': 23,
              'drug_poss_subtotal': 32,
              'drug_poss_synthetic': 2,
              'drug_sales_m': 0,
              'drug_sales_opium': 0,
              'drug_sales_other': 0,
              'drug_sales_subtotal': 0,
              'drug_sales_synthetic': 0,
              'drunkness': 0,
              'embezzlement': 2,
              'forgery': 6,
              'fraud': 8,
              'g_all': 0,
              'g_b': 0,
              'g_n': 0,
              'g_t': 0,
              'ht_c_s_a': 0,
              'ht_i_s': 0,
              'larceny': 116,
              'liquor': 0,
              'manslaughter': 0,
              'murder': 5,
              'mvt': 42,
              'offense_family': 0,
              'prostitution': 0,
              'prostitution_a_p_p': 0,
              'prostitution_p': 0,
              'prostitution_p_p': 0,
              'rape': 3,
              'robbery': 43,
              'sex_offense': 3,
              'simple_assault': 102,
              'stolen_property': 13,
              'suspicion': 0,
              'vagrancy': 0,
              'vandalism': 3,
              'weapons': 17}]}
```

# Getting Data-5

```
# Getting 2018 data
simple_assault_cases = []
stolen_property_cases = []
rape_cases = []

begin_year = 2018
end_year = 2018

ori_list = ori

print("Beginning Data Retrieval")
print("------------------------")

for ori in range(len(ori_list)):
    response = requests.get(f"https://api.usa.gov/crime/fbi/sapi/api/data/arrest/agencies/offense/{ori_list[ori]}/al
    try:
        print(f"Processing record {ori + 1}")
        simple_assault_cases.append(response["results"][0]["simple_assault"])
        stolen_property_cases.append(response["results"][0]["stolen_property"])
        rape_cases.append(response["results"][0]["rape"])
    except:
        print("Not found")
        pass
print("------------------------")
print("Data Retrieval Complete")
print("------------------------")
```

```
Beginning Data Retrieval
------------------------
Processing record 1
Processing record 2
Processing record 3
Processing record 4
Processing record 5
Processing record 6
Processing record 7
```

# Getting Data-6

Example: Dataframe of 10 States

```
df_2018 = pd.DataFrame(list(zip(ori_list, simple_assault_cases, stolen_property_cases, rape_cases)),
                       columns = ['Police Department', "Simple Assault Cases", "Stolen Property Cases", "Rape Cases"])
df_2018
```

| | Police Department | Simple Assault Cases | Stolen Property Cases | Rape Cases |
|---|---|---|---|---|
| **0** | AL0030100 | 102 | 13 | 3 |
| **1** | AK0010300 | 291 | 4 | 5 |
| **2** | AZ0072300 | 5726 | 364 | 103 |
| **3** | AR0600200 | 947 | 291 | 28 |
| **4** | CA0340400 | 1309 | 281 | 30 |
| **5** | CODPD0000 | 3435 | 132 | 143 |
| **6** | CT0006400 | 1780 | 9 | 17 |
| **7** | DE0010100 | 512 | 26 | 5 |

# Getting Data-7

Example: Dataframe of 10 States

Coding reference: Python-APIs 09-Stu_Census_API_Gmap

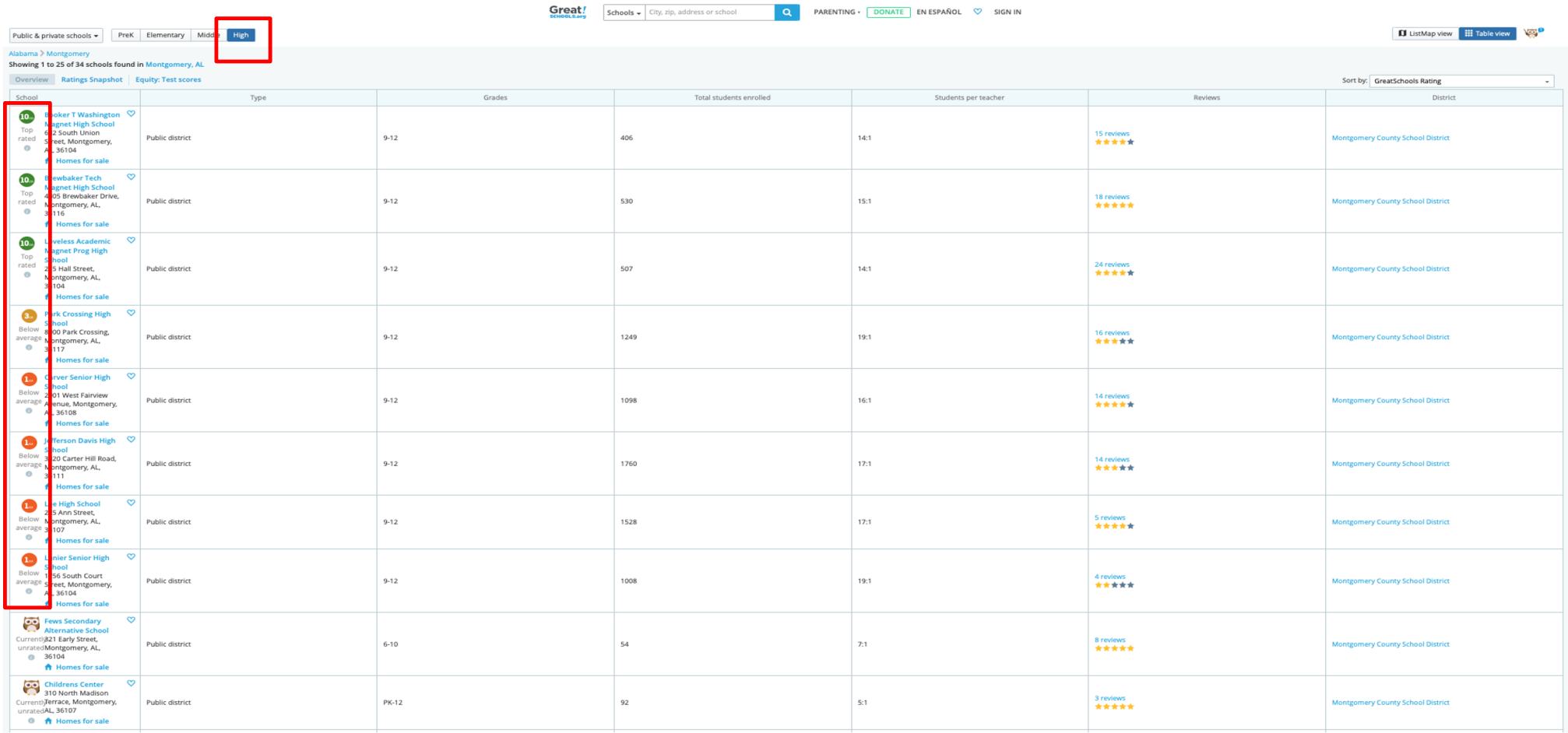
```
# Final DataFrame
census_pd = census_pd[["State", "Name","Household Income", "Unemployment Rate"]]
census_pd.head(10)
```

| | State | Name | Household Income | Unemployment Rate |
|---|---|---|---|---|
| **0** | 27 | Minnesota | 68411.0 | 2.156871 |
| **1** | 28 | Mississippi | 43567.0 | 3.681658 |
| **2** | 29 | Missouri | 53560.0 | 2.560861 |
| **3** | 30 | Montana | 52559.0 | 2.153433 |
| **4** | 31 | Nebraska | 59116.0 | 1.918614 |
| **5** | 32 | Nevada | 57598.0 | 3.481124 |
| **6** | 33 | New Hampshire | 74057.0 | 2.261946 |
| **7** | 34 | New Jersey | 79363.0 | 3.209739 |
| **8** | 35 | New Mexico | 48059.0 | 3.267487 |
| **9** | 36 | New York | 65323.0 | 3.071781 |

# Getting Data-8

Example for School Rating: Alabama Capital City, Montgomery

https://www.greatschools.org



Great! SCHOOLS.org | Schools | City, zip, address or school | PARENTING | DONATE | EN ESPAÑOL | SIGN IN

Public & private schools | PreK | Elementary | Middle | High | ListMap view | Table view

Alabama > Montgomery

Showing 1 to 25 of 34 schools found in Montgomery, AL

Overview | Ratings Snapshot | Equity: Test scores | Sort by: GreatSchools Rating

| School | Type | Grades | Total students enrolled | Students per teacher | Reviews | District |
|---|---|---|---|---|---|---|
| 10 Top rated — Booker T Washington Magnet High School, 612 South Union Street, Montgomery, AL 36104 — Homes for sale | Public district | 9-12 | 406 | 14:1 | 15 reviews | Montgomery County School District |
| 10 Top rated — Brewbaker Tech Magnet High School, 4405 Brewbaker Drive, Montgomery, AL, 36116 — Homes for sale | Public district | 9-12 | 530 | 15:1 | 18 reviews | Montgomery County School District |
| 10 Top rated — Loveless Academic Magnet Prog High School, 215 Hall Street, Montgomery, AL, 36104 — Homes for sale | Public district | 9-12 | 507 | 14:1 | 24 reviews | Montgomery County School District |
| 3 Below average — Park Crossing High School, 3300 Park Crossing, Montgomery, AL, 36117 — Homes for sale | Public district | 9-12 | 1249 | 19:1 | 16 reviews | Montgomery County School District |
| 1 Below average — Carver Senior High School, 2301 West Fairview Avenue, Montgomery, AL 36108 — Homes for sale | Public district | 9-12 | 1098 | 16:1 | 14 reviews | Montgomery County School District |
| 1 Below average — Jefferson Davis High School, 3220 Carter Hill Road, Montgomery, AL, 36111 — Homes for sale | Public district | 9-12 | 1760 | 17:1 | 14 reviews | Montgomery County School District |
| 1 Below average — Lee High School, 215 Ann Street, Montgomery, AL, 36107 — Homes for sale | Public district | 9-12 | 1528 | 17:1 | 5 reviews | Montgomery County School District |
| 1 Below average — Lanier Senior High School, 1256 South Court Street, Montgomery, AL 36104 — Homes for sale | Public district | 9-12 | 1008 | 19:1 | 4 reviews | Montgomery County School District |
| Currently unrated — Fews Secondary Alternative School, 821 Early Street, Montgomery, AL, 36104 — Homes for sale | Public district | 6-10 | 54 | 7:1 | 8 reviews | Montgomery County School District |
| Currently unrated — Childrens Center, 310 North Madison Terrace, Montgomery, AL, 36107 — Homes for sale | Public district | PK-12 | 92 | 5:1 | 3 reviews | Montgomery County School District |

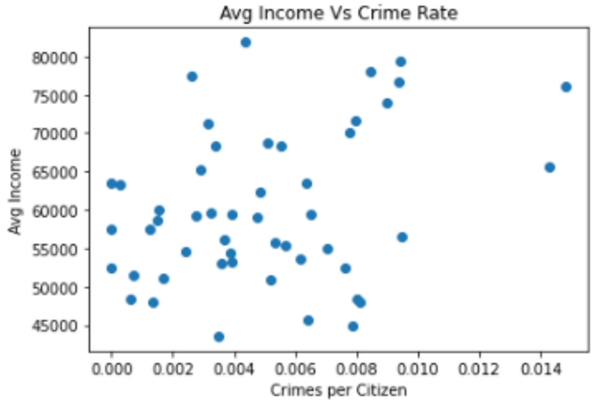
# Table of Stats

| State | State Ab. | State Capital | Population | ORI Code | No. of Officers | Year of Data | No. of Rapes | No. of Simple Assaults | No. of Stolen Property Cases | Total Crimes | School Ratings | Unemployment Rate | Avg. Income | Crimes(R,SA,SP) Per Citizen |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ALABAMA | AL | Montgome | 198,525 | AL0030100 | 474 | 2018 | 3 | 102 | 13 | 118 | 4.35 | 3.04 | $ 48,486.00 | 0.000594 |
| ALASKA | AK | Juneau | 32,113 | AK0010300 | 47 | 2018 | 5 | 291 | 4 | 300 | 6.50 | 3.8 | $ 76,715.00 | 0.009342 |
| ARIZONA | AZ | Phoenix | 1,680,992 | AZ0072300 | 2919 | 2018 | 103 | 5726 | 364 | 6193 | 4.72 | 3.03 | $ 56,213.00 | 0.003684 |
| ARKANSAS | AR | Little Rock | 197,312 | AR0600200 | 575 | 2018 | 28 | 947 | 291 | 1266 | 3.64 | 2.53 | $ 45,726.00 | 0.006416 |
| CALIFORNIA | CA | Sacramento | 513,624 | CA0340400 | 651 | 2018 | 30 | 1309 | 281 | 1620 | 4.63 | 3.38 | $ 71,228.00 | 0.003154 |
| COLORADO | CO | Denver | 727,211 | CODPD0000 | 1517 | 2018 | 143 | 3435 | 132 | 3710 | 3.75 | 2.52 | $ 68,811.00 | 0.005102 |
| CONNECTICUT | CT | Hartford | 122,105 | CT0006400 | 394 | 2018 | 17 | 1780 | 9 | 1806 | 2.80 | 3.52 | $ 76,106.00 | 0.014791 |
| DELAWARE | DE | Dover | 38,079 | DE0010100 | 101 | 2018 | 5 | 512 | 26 | 543 | n/a | 3 | $ 65,627.00 | 0.014260 |
| FLORIDA | FL | Tallahassee | 194,500 | FL0370300 | 377 | 2017 | 45 | 713 | 8 | 766 | 5.00 | 3.02 | $ 53,267.00 | 0.003938 |
| GEORGIA | GA | Atlanta | 506,811 | GAAPD0000 | 1535 | 2017 | 45 | 2144 | 511 | 2700 | 3.85 | 3.14 | $ 55,679.00 | 0.005327 |
| HAWAII | HI | Honolulu | 345,064 | HI0020000 | 1942 | 2018 | 51 | 2407 | 449 | 2907 | 6.33 | 2.25 | $ 78,084.00 | 0.008425 |
| IDAHO | ID | Boise | 228,959 | ID0010100 | 292 | 2018 | 54 | 741 | 21 | 816 | 4.11 | 2.23 | $ 53,089.00 | 0.003564 |
| ILLINOIS | IL | Springfield | 114,230 | IL0840200 | 239 | 2018 | 0 | 0 | 0 | 0 | 3.84 | 3.41 | $ 63,575.00 | 0.000000 |
| INDIANA | IN | Indianapoli | 876,384 | INIPD0000 | 2080 | 2018 | 81 | 3206 | 124 | 3411 | 2.78 | 2.73 | $ 54,325.00 | 0.003892 |
| IOWA | IA | Des Moines | 214,237 | IA0770300 | 0 | 2018 | 12 | 299 | 7 | 318 | 1.14 | 2.08 | $ 58,580.00 | 0.001484 |
| KANSAS | KS | Topeka | 125,310 | KS0890100 | 267 | 2018 | 0 | 0 | 0 | 0 | 3.57 | 2.24 | $ 57,422.00 | 0.000000 |
| KENTUCKY | KY | Frankfort | 27,679 | KY0370100 | 57 | 2018 | 0 | 190 | 32 | 222 | 6.00 | 2.89 | $ 48,392.00 | 0.008021 |
| LOUISIANA | LA | Baton Roug | 220,236 | LA0170200 | 631 | 2018 | 34 | 1467 | 281 | 1782 | 3.38 | 3.21 | $ 47,942.00 | 0.008091 |
| MAINE | ME | Augusta | 18,681 | ME0060100 | 45 | 2018 | 0 | 104 | 2 | 106 | 3.83 | 2.42 | $ 55,425.00 | 0.005674 |
| MARYLAND | MD | Annapolis | 39,174 | MD0020100 | 119 | 2018 | 5 | 162 | 3 | 170 | 3.67 | 3.02 | $ 81,868.00 | 0.004340 |
| MASSACHUSETTS | MA | Boston | 692,600 | MA0130100 | 2122 | 2018 | 43 | 1612 | 169 | 1824 | 2.97 | 2.98 | $ 77,378.00 | 0.002634 |
| MICHIGAN | MI | Lansing | 118,210 | MI3351900 | 188 | 2018 | 17 | 791 | 22 | 830 | 3.34 | 3.22 | $ 54,938.00 | 0.007021 |
| MINNESOTA | MN | Saint Paul | 308,096 | MN0620900 | 631 | 2018 | 16 | 984 | 43 | 1043 | 3.69 | 2.16 | $ 68,411.00 | 0.003385 |
| MISSISSIPPI | MS | Jackson | 160,628 | MS0250100 | 0 | 2018 | 8 | 445 | 106 | 559 | 2.00 | 3.68 | $ 43,567.00 | 0.003480 |
| MISSOURI | MO | Jefferson C | 42,838 | MO0260100 | 88 | 2018 | 3 | 260 | 0 | 263 | 5.50 | 2.56 | $ 53,560.00 | 0.006139 |
| MONTANA | MT | Helena | 32,315 | MT0250100 | 52 | 2018 | 5 | 239 | 2 | 246 | 5.50 | 2.15 | $ 52,559.00 | 0.007613 |
| NEBRASKA | NE | Lincoln | 289,102 | NB0550100 | 344 | 2018 | 19 | 1301 | 55 | 1375 | 2.50 | 1.92 | $ 59,116.00 | 0.004756 |
| NEVADA | NV | Carson City | 55,916 | NV0130000 | 95 | 2018 | 6 | 46 | 17 | 69 | 3.00 | 3.48 | $ 57,598.00 | 0.001234 |
| NEW HAMPSHIRE | NH | Concord | 43,627 | NH0071600 | 82 | 2018 | 1 | 340 | 51 | 392 | 3.00 | 2.26 | $ 74,057.00 | 0.008985 |
| NEW JERSEY | NJ | Trenton | 83,203 | NJ0111100 | 287 | 2018 | 6 | 652 | 125 | 783 | 2.97 | 3.2 | $ 79,363.00 | 0.009411 |
| NEW MEXICO | NM | Santa Fe | 84,683 | NM0260100 | 150 | 2018 | 3 | 66 | 43 | 112 | 5.35 | 3.27 | $ 48,059.00 | 0.001323 |
| NEW YORK | NY | Albany | 96,460 | NY0010100 | 316 | 2018 | 9 | 234 | 35 | 278 | 4.74 | 3.07 | $ 65,323.00 | 0.002882 |
| NORTH CAROLINA | NC | Raleigh | 474,069 | NC0920100 | 732 | 2018 | 0 | 0 | 0 | 0 | 6.13 | 3.08 | $ 52,413.00 | 0.000000 |
| NORTH DAKOTA | ND | Bismarck | 73,529 | ND0080100 | 127 | 2018 | 7 | 406 | 53 | 466 | 6.50 | 1.55 | $ 63,473.00 | 0.006338 |
| OHIO | OH | Columbus | 898,553 | OHCOP0000 | 1870 | 2018 | 53 | 1966 | 139 | 2158 | 3.33 | 2.95 | $ 54,533.00 | 0.002402 |
| OKLAHOMA | OK | Oklahoma | 655,057 | OK0550400 | 96 | 2018 | 3 | 417 | 34 | 454 | 4.48 | 2.53 | $ 51,424.00 | 0.000693 |

# Scatter Plots

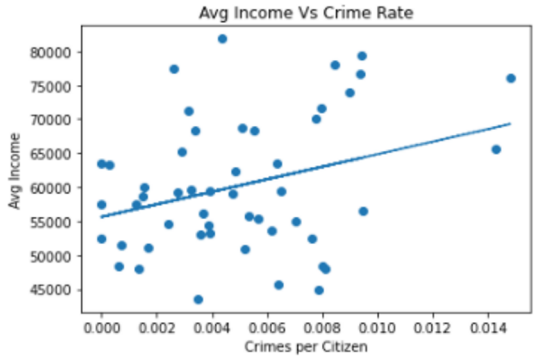
## We started with our original Plots

```
1  avg_income_ratings = file_df.iloc[:,13]
2  crime_rate = file_df.iloc[:,14]
3  plt.scatter(crime_rate, avg_income_ratings)
4  plt.ylabel('Avg Income')
5  plt.xlabel('Crimes per Citizen')
6  plt.title('Avg Income Vs Crime Rate')
7  plt.show()
```




## Then we added our linear regression script

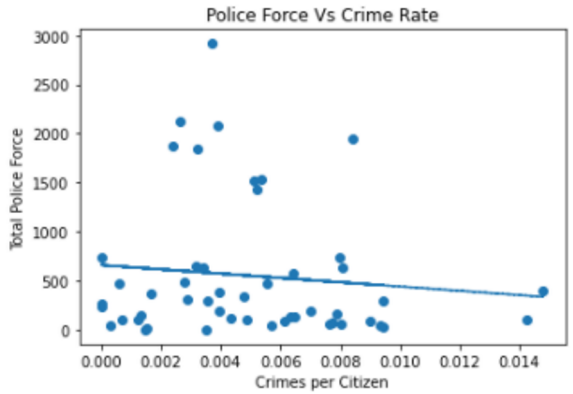
```
1  avg_income_ratings = file_df.iloc[:,13]
2  crime_rate = file_df.iloc[:,14]
3  ai_slope, ai_int, ai_r, ai_p, ai_std_err = stats.linregress(crime_rate, avg_income_ratings)
4  ai_fit = ai_slope * crime_rate + ai_int
5  plt.scatter(crime_rate,avg_income_ratings)
6  plt.plot(crime_rate,cr_fit,"--")
7  plt.ylabel('Avg Income')
8  plt.xlabel('Crimes per Citizen')
9  plt.title('Avg Income Vs Crime Rate')
10 plt.show()
```



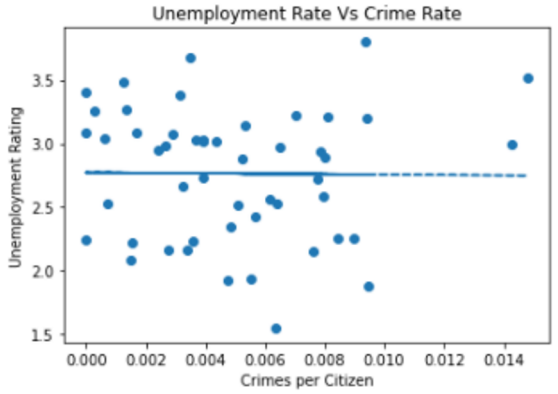

**The line shows us the relationship between the two factors.**

# Linear Regression Plots Cont.

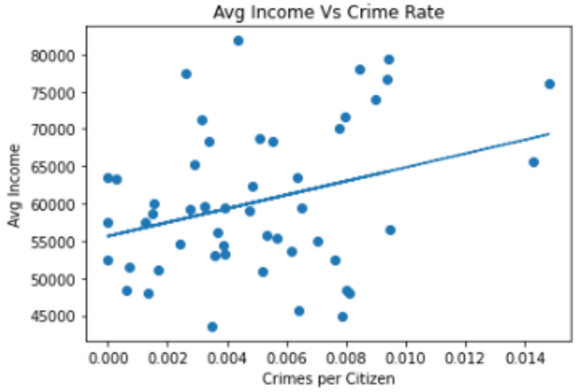
## Number of Police Officers v Crime Rate



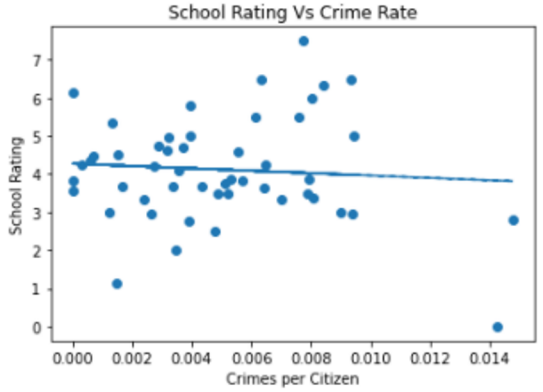

## Unemployment Rate v Crime Rate




## Avg Income Rate v Crime Rate




## School Ratings v Crime Rate



# R values & Correlations

## R Value table for reference

| Absolute Value of r | Strength of Correlation |
|---|---|
| $r < 0.3$ | None or very weak |
| $0.3 \leq r < 0.5$ | Weak |
| $0.5 \leq r < 0.7$ | Moderate |
| $r \geq 0.7$ | Strong |

## R Values for our factors

```
school_ratings = file_df.iloc[:,11]
unemployment_ratings = file_df.iloc[:,12]
avg_income_ratings = file_df.iloc[:,13]
total_police = file_df.iloc[:,5]
crime_rate = file_df.iloc[:,14]
correlation_sr = stats.pearsonr(school_ratings,crime_rate)
correlation_ur = stats.pearsonr(unemployment_ratings,crime_rate)
correlation_pf = stats.pearsonr(total_police,crime_rate)
correlation_ai = stats.pearsonr(avg_income_ratings,crime_rate)
print(f" The correlation between School Ratings & Crime Rate is {round(correlation_sr[0],2)}")
print(f" The correlation between Unemployment Rate & Crime Rate is {round(correlation_ur[0],2)}")
print(f" The correlation between Police Force & Crime Rate is {round(correlation_pf[0],2)}")
print(f" The correlation between Avg. Incomes & Crime Rate is {round(correlation_ai[0],2)}")
```

```
The correlation between School Ratings & Crime Rate is -0.08
The correlation between Unemployment Rate & Crime Rate is -0.01
The correlation between Police Force & Crime Rate is -0.11
The correlation between Avg. Incomes & Crime Rate is 0.32
```

# Conclusion

- What makes a city safe?
  - How does number of police, average income, unemployment, and school rating affect crime rates?
- Minimal correlation between test variables and crime rate.
  - Fail to reject the null hypothesis
- Improvements?
  - Larger sample size with more crime variables
  - Find a full collection of police data from the city rather than one station
  - Using more relevant cities and ORIs

# **Adding later**Crime Rate (R,SA,SP) per Citizen