Investigate_a_Dataset

November 4, 2018

1 Project: US Gun Permit Analysis

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Introduction

The purpose of this analysis is to know the relation between the gun permits on US and parameters as the states, health insurance, educational level or wealth level. Does the application for weapons permits depend on the educational or wealth level? Witch state has the highest number of gun owners? Witch the lowest? What differences are ther between this two states?

```
In [77]: # Use this cell to set up import statements for all of the packages that you
         #   plan to use.

         # Remember to include a 'magic word' so that your visualizations are plotted
         #   inline with the notebook. See this page for more:
         #   http://ipython.readthedocs.io/en/stable/interactive/magics.html
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         %matplotlib inline
```

Data Wrangling

1.1.1 General Properties

We load the information of American census with the properties that interest us (Population, Graduate(%), Degree(%), No Insurance(%), Incomes($), Poverty(%))

```
In [78]: df_census = pd.read_csv("U.S. Census Data.csv")
         df_census.columns.str.strip()
```

```
        #Get population
        population = df_census.iloc[0]
        #Get high school graduate or higher, percent
        graduatePercent = df_census.iloc[34]
        #Get bachelor's degree or higher, percent
        degreePercent = df_census.iloc[35]
        #Get persons without health insurance, percent
        noInsurancePercent = df_census.iloc[37]
        #Get per capita incomes
        incomes = df_census.iloc[48]
        #Get persons in poverty, percent
        povertyPercent = df_census.iloc[49]

        df_custom_census = pd.concat([population, graduatePercent, degreePercent, noInsurancePe
                                      , keys=['Population','Graduate(%)','Degree(%)','No Insuran
                                      , axis=1)
        df_custom_census.drop(['Fact','Fact Note'], inplace=True)
        df_custom_census.index.name = 'State'
```

In [79]:
```
df_custom_census.head()
```

Out[79]:

State	Population	Graduate(%)	Degree(%)	No Insurance(%)	Incomes($)	\
Alabama	4,863,300	84.30%	23.50%	10.70%	$24,091	
Alaska	741,894	92.10%	28.00%	15.50%	$33,413	
Arizona	6,931,071	86.00%	27.50%	11.90%	$25,848	
Arkansas	2,988,248	84.80%	21.10%	9.30%	$22,798	
California	39,250,017	81.80%	31.40%	8.30%	$30,318	

State	Poverty(%)
Alabama	17.10%
Alaska	9.90%
Arizona	16.40%
Arkansas	17.20%
California	14.30%

In [80]:
```
df_custom_census.shape
```

Out[80]: (50, 6)

In [81]:
```
df_custom_census.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 50 entries, Alabama to Wyoming
Data columns (total 6 columns):
Population          50 non-null object
Graduate(%)         50 non-null object
Degree(%)           50 non-null object
```

```
No Insurance(%)    50 non-null object
Incomes($)         50 non-null object
Poverty(%)         50 non-null object
dtypes: object(6)
memory usage: 2.7+ KB
```

We load the information of Gun Data of the last year with the properties that interest us (state and handgun)

```
In [82]: df_gunData = pd.read_excel("gun_data.xlsx")
         df_gunData.columns.str.strip()

         #Filter per month, state and permit
         df_gunData = df_gunData[['month','state','handgun']]

         #Filter data for last 1 year (column month). From 2016,10 to 2017,09
         #Grouped by "state" performing the average of rest of columns
         df_gunData_grouped = df_gunData[df_gunData['month'] > '2016-10'].groupby(['state']).mea
         df_gunData_grouped.index.name = 'State'
         df_gunData_grouped.columns = ['Handgun']

In [83]: df_gunData_grouped.head()

Out[83]:                  Handgun
         State
         Alabama      8430.181818
         Alaska       2916.272727
         Arizona     13132.090909
         Arkansas     6134.090909
         California  45531.272727

In [84]: df_gunData_grouped.shape

Out[84]: (55, 1)

In [85]: df_gunData_grouped.info()

<class 'pandas.core.frame.DataFrame'>
Index: 55 entries, Alabama to Wyoming
Data columns (total 1 columns):
Handgun    55 non-null float64
dtypes: float64(1)
memory usage: 880.0+ bytes
```

Concatenate the two dataSet

```
In [86]: df = pd.concat([df_custom_census, df_gunData_grouped], join='inner', axis=1)
```

```
In [87]: df.head()
```

```
Out[87]:             Population Graduate(%) Degree(%) No Insurance(%) Incomes($)  \
         State
         Alabama      4,863,300      84.30%    23.50%          10.70%   $24,091
         Alaska         741,894      92.10%    28.00%          15.50%   $33,413
         Arizona      6,931,071      86.00%    27.50%          11.90%   $25,848
         Arkansas     2,988,248      84.80%    21.10%           9.30%   $22,798
         California  39,250,017      81.80%    31.40%           8.30%   $30,318

                    Poverty(%)       Handgun
         State
         Alabama        17.10%   8430.181818
         Alaska          9.90%   2916.272727
         Arizona        16.40%  13132.090909
         Arkansas       17.20%   6134.090909
         California     14.30%  45531.272727
```

```
In [88]: df.shape
```

```
Out[88]: (50, 7)
```

```
In [89]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 50 entries, Alabama to Wyoming
Data columns (total 7 columns):
Population         50 non-null object
Graduate(%)        50 non-null object
Degree(%)          50 non-null object
No Insurance(%)    50 non-null object
Incomes($)         50 non-null object
Poverty(%)         50 non-null object
Handgun            50 non-null float64
dtypes: float64(1), object(6)
memory usage: 3.1+ KB
```

1.1.2 Data Cleaning

We review the data by formatting them to numerals It is necessary that we remove characters such as ($,%), homogenize some percentages (relative to 1 instead of 100) and eliminate values out of 25-75% on handgun values that may be poorly acquired.

```
In [90]: #Check the data
         df
```

```
Out[90]:                Population Graduate(%) Degree(%) No Insurance(%) Incomes($)  \
         State
```

Alabama	4,863,300	84.30%	23.50%	10.70%	$24,091
Alaska	741,894	92.10%	28.00%	15.50%	$33,413
Arizona	6,931,071	86.00%	27.50%	11.90%	$25,848
Arkansas	2,988,248	84.80%	21.10%	9.30%	$22,798
California	39,250,017	81.80%	31.40%	8.30%	$30,318
Colorado	5,540,545	90.70%	38.10%	8.60%	$32,217
Connecticut	3,576,452	89.90%	37.60%	5.70%	$38,803
Delaware	952,065	88.40%	30.00%	6.60%	$30,554
Florida	20,612,439	86.90%	27.30%	15.30%	$26,829
Georgia	10,310,371	85.40%	28.80%	14.80%	$25,737
Hawaii	1,428,557	91.00%	30.80%	4.20%	$29,822
Idaho	1,683,140	89.50%	25.90%	11.80%	$23,399
Illinois	12,801,539	87.90%	32.30%	7.40%	$30,494
Indiana	6,633,053	87.80%	24.10%	9.40%	$25,346
Iowa	3,134,693	91.50%	26.70%	5.00%	$27,950
Kansas	2,907,289	90.20%	31.00%	10.10%	$27,706
Kentucky	4,436,974	84.20%	22.30%	6.00%	$24,063
Louisiana	4,681,666	83.40%	22.50%	11.90%	$24,981
Maine	1,331,479	91.60%	29.00%	9.90%	$27,655
Maryland	6,016,447	89.40%	37.90%	7.00%	$36,897
Massachusetts	6,811,779	89.80%	40.50%	2.90%	$36,895
Michigan	9,928,300	89.60%	26.90%	6.30%	$26,607
Minnesota	5,519,952	92.40%	33.70%	4.80%	$32,157
Mississippi	2,988,726	82.30%	20.70%	13.90%	$21,057
Missouri	6,093,000	88.40%	27.10%	10.50%	$26,259
Montana	1,042,520	92.80%	29.50%	9.80%	$26,381
Nebraska	1,907,116	90.70%	29.30%	9.90%	$27,882
Nevada	2,940,058	85.10%	23.00%	13.10%	$26,541
New Hampshire	1,334,795	92.30%	34.90%	7.10%	$34,362
New Jersey	8,944,469	88.60%	36.80%	9.20%	$36,582
New Mexico	2081015	0.842	0.263	0.108	24012
New York	19745289	0.856	0.342	0.07	33236
North Carolina	10146788	0.858	0.284	0.122	25920
North Dakota	757952	0.917	0.277	0.081	32035
Ohio	11614373	0.891	0.261	0.066	26953
Oklahoma	3923561	0.869	0.241	0.161	25032
Oregon	4093465	0.898	0.308	0.073	27684
Pennsylvania	12784227	0.892	0.286	0.067	29291
Rhode Island	1056426	0.862	0.319	0.051	31118
South Carolina	4961119	0.856	0.258	0.119	24604
South Dakota	865454	0.909	0.27	0.103	26747
Tennessee	6651194	0.855	0.249	0.106	25227
Texas	27,862,596	81.90%	27.60%	18.60%	$26,999
Utah	3,051,217	91.20%	31.10%	9.70%	$24,686
Vermont	624,594	91.80%	36.00%	4.50%	$29,894
Virginia	8,411,808	88.30%	36.30%	10.10%	$34,152
Washington	7,288,000	90.40%	32.90%	6.90%	$31,762
West Virginia	1,831,102	85.00%	19.20%	6.50%	$23,450

Wisconsin	5,778,708	91.00%	27.80%	6.20%	$28,340
Wyoming	585,501	92.30%	25.70%	13.40%	$29,803

State	Poverty(%)	Handgun
Alabama	17.10%	8430.181818
Alaska	9.90%	2916.272727
Arizona	16.40%	13132.090909
Arkansas	17.20%	6134.090909
California	14.30%	45531.272727
Colorado	11.00%	19281.454545
Connecticut	9.80%	6309.454545
Delaware	11.70%	1980.727273
Florida	14.70%	53799.454545
Georgia	16.00%	14998.818182
Hawaii	9.30%	0.000000
Idaho	14.40%	3754.272727
Illinois	13.00%	24201.545455
Indiana	14.10%	21761.636364
Iowa	11.80%	229.909091
Kansas	12.10%	6266.272727
Kentucky	18.50%	10849.545455
Louisiana	20.20%	12102.181818
Maine	12.50%	3549.272727
Maryland	9.70%	4432.545455
Massachusetts	10.40%	5867.090909
Michigan	15.00%	12217.909091
Minnesota	9.90%	9361.000000
Mississippi	20.80%	8767.909091
Missouri	14.00%	21504.818182
Montana	13.30%	2859.636364
Nebraska	11.40%	147.454545
Nevada	13.80%	4972.545455
New Hampshire	7.30%	5410.909091
New Jersey	10.40%	5288.454545
New Mexico	0.198	5760.545455
New York	0.147	10876.000000
North Carolina	0.154	1447.909091
North Dakota	0.107	1637.181818
Ohio	0.146	29363.545455
Oklahoma	0.163	12465.727273
Oregon	0.133	14375.363636
Pennsylvania	0.129	49092.000000
Rhode Island	0.128	1120.454545
South Carolina	0.153	10649.454545
South Dakota	0.133	2708.181818
Tennessee	0.158	25349.090909
Texas	15.60%	48451.909091

```
Utah                10.20%   3825.727273
Vermont             11.90%   1496.909091
Virginia            11.00%  25141.090909
Washington          11.30%  16883.454545
West Virginia       17.90%   6844.909091
Wisconsin           11.80%  14899.545455
Wyoming             11.30%   1685.727273
```

We can see some issues on the format of the data - Percentage field without % shall be multiplied by 100 - Population. Comma shall be removed - The incomes without $ look like fine - Hawaii has 0 handgun. It look like an error on the data

In [91]:
```
#Remove %, $ y ',
removeComma = lambda x: x.replace(',','')
removePer = lambda x: float(x)*100 if not '%' in x else x.replace('%','')
removeDollar = lambda x: x.replace('$','')

df['Population'] = df['Population'].apply(removeComma)
df['Graduate(%)'] = df['Graduate(%)'].apply(removePer)
df['Degree(%)'] = df['Degree(%)'].apply(removePer)
df['No Insurance(%)'] = df['No Insurance(%)'].apply(removePer)
df['Incomes($)'] = df['Incomes($)'].apply(removeDollar).apply(removeComma)
df['Poverty(%)'] = df['Poverty(%)'].apply(removePer)

df.drop('Hawaii', inplace=True)

df = df.apply(pd.to_numeric)
```

In [92]:
```
#Add column Handgun/Population
df['Handgun Density'] = df['Handgun']/df['Population']
df['Handgun Density'].describe()
```

Out[92]:
```
count    49.000000
mean      0.002211
std       0.001060
min       0.000073
25%       0.001691
50%       0.002231
75%       0.002934
max       0.004054
Name: Handgun Density, dtype: float64
```

In [93]:
```
#Clean <25% or >75% Handgun data
filtered_df=df[df['Handgun Density'] >= 0.001691]
filtered_df=filtered_df[filtered_df['Handgun Density'] <= 0.004054]
filtered_df.head()
```

Out[93]:
```
           Population  Graduate(%)  Degree(%)  No Insurance(%)  Incomes($)  \
State
```

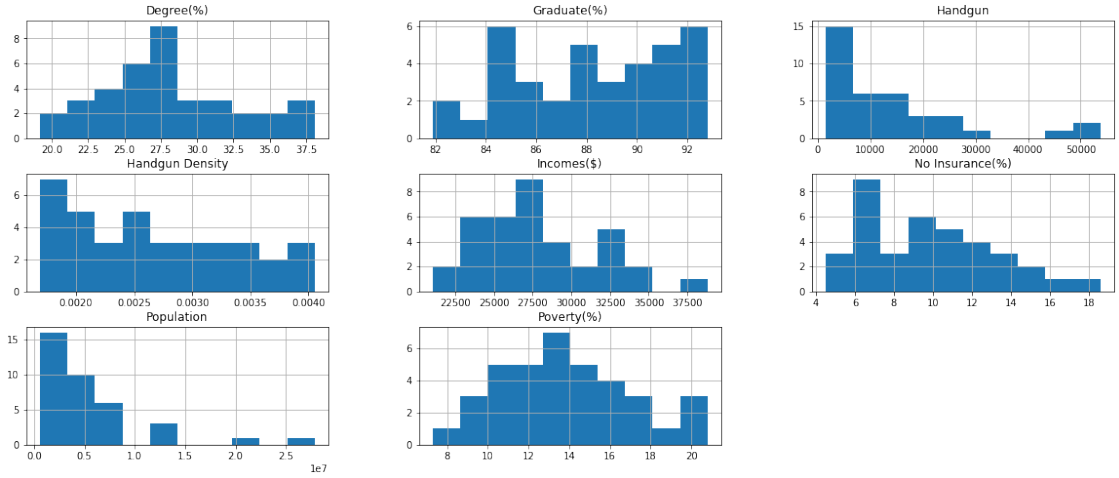
```
Alabama      4863300         84.3       23.5             10.7       24091
Alaska        741894         92.1       28.0             15.5       33413
Arizona      6931071         86.0       27.5             11.9       25848
Arkansas     2988248         84.8       21.1              9.3       22798
Colorado     5540545         90.7       38.1              8.6       32217

          Poverty(%)       Handgun  Handgun Density
State
Alabama         17.1   8430.181818         0.001733
Alaska           9.9   2916.272727         0.003931
Arizona         16.4  13132.090909         0.001895
Arkansas        17.2   6134.090909         0.002053
Colorado        11.0  19281.454545         0.003480
```

```
In [94]: print (filtered_df['Handgun Density'].describe())
         print ("STD/MEAN: {0}".format(filtered_df['Handgun Density'].std()/filtered_df['Handgun
```

```
count    37.000000
mean      0.002680
std       0.000711
min       0.001691
25%       0.002147
50%       0.002585
75%       0.003177
max       0.004054
Name: Handgun Density, dtype: float64
STD/MEAN: 0.265157208028867
```

```
In [95]: filtered_df.hist(figsize=(20,8))
```

```
Out[95]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f58a49272e8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f58a50bb208>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f58a4e0dda0>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x7f58a011e4e0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f58a443e400>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f58a443e208>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x7f58a20185f8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f58a20a6710>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f58a4cd2cc0>]], dtype=objec
```

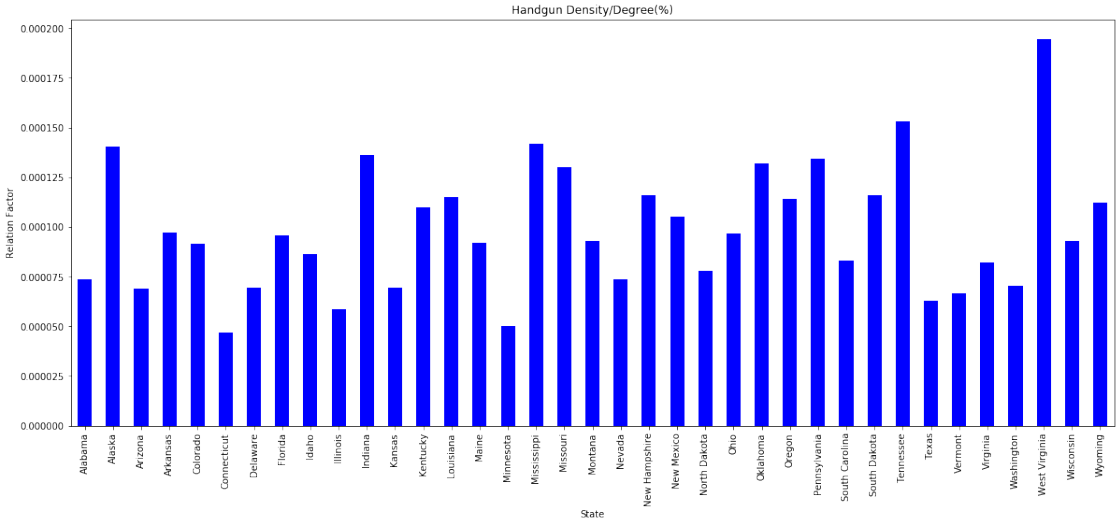


Exploratory Data Analysis

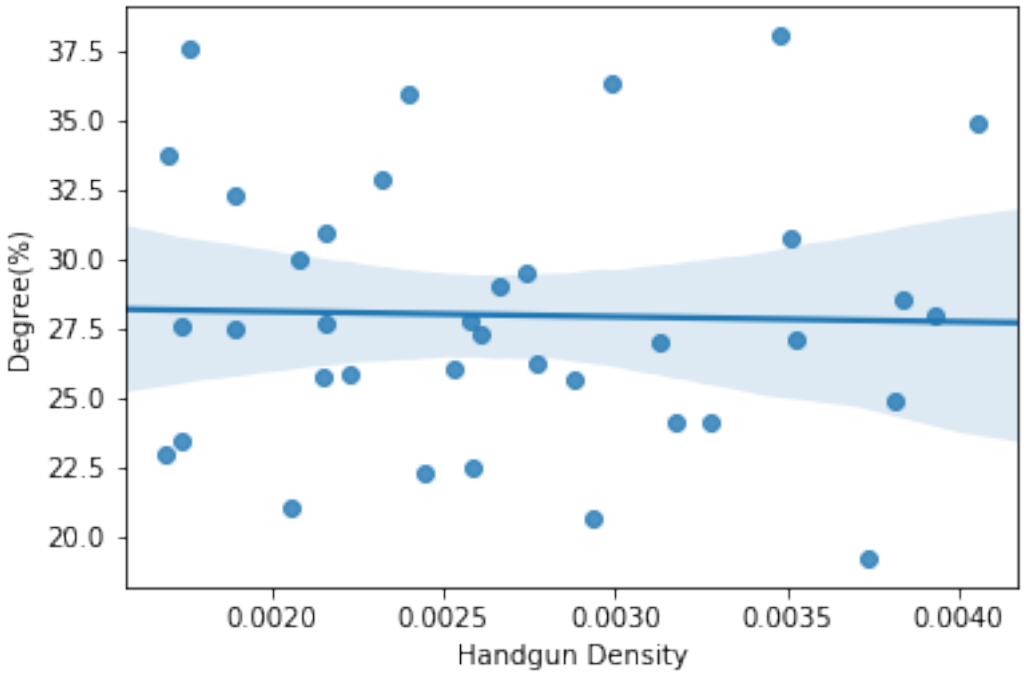
1.1.3 Is there a relationship between the density of small arms and poverty, education or sanitary security?

```
In [96]: result = filtered_df['Handgun Density']/filtered_df['Degree(%)']
         print (result.describe())
         print ("STD/MEAN: {0}".format(result.std()/result.mean()))
         result.plot(kind='bar',figsize=(20,8),color='blue',title='Handgun Density/Degree(%)')
         plt.ylabel("Relation Factor")
         plt.show()
         sns.regplot(x=filtered_df['Handgun Density'], y=filtered_df['Degree(%)'])
```

```
count    37.000000
mean      0.000099
std       0.000032
min       0.000047
25%       0.000074
50%       0.000093
75%       0.000116
max       0.000195
dtype: float64
STD/MEAN: 0.32428872053145963
```



Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x7f589aee8e10>

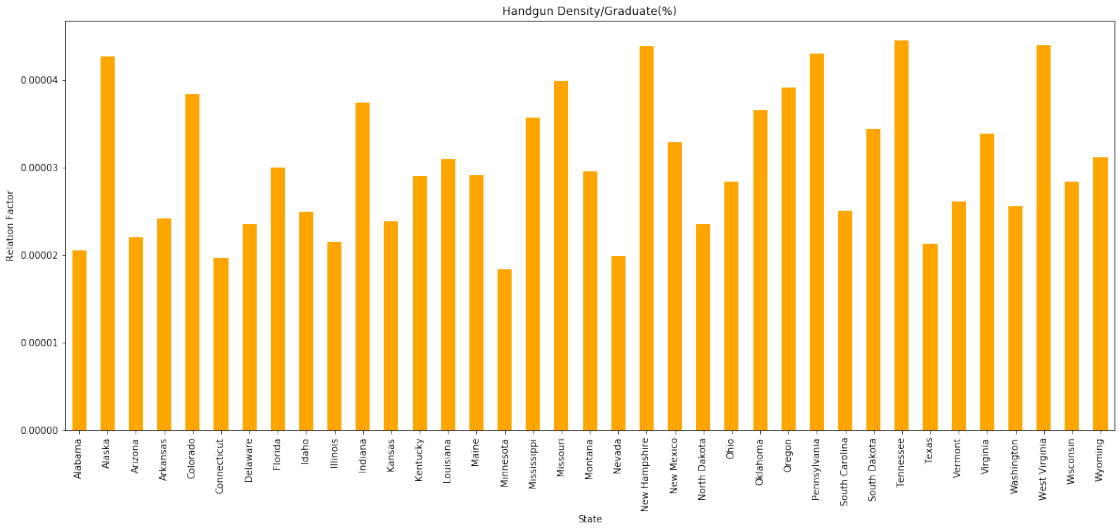


It seems that a university degree does not affect to the handgun density

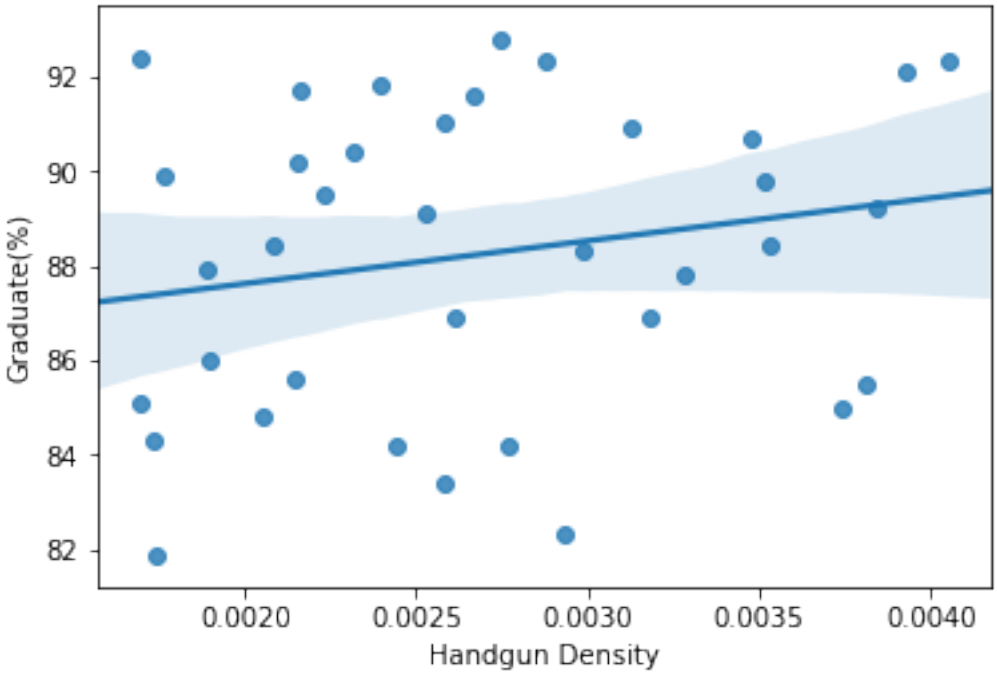
```
In [97]: result = filtered_df['Handgun Density']/filtered_df['Graduate(%)']
         print (result.describe())
```

```
        print ("STD/MEAN: {0}".format(result.std()/result.mean()))
        result.plot(kind='bar',figsize=(20,8),color='orange',title='Handgun Density/Graduate(%)
        plt.ylabel("Relation Factor")
        plt.show()
        sns.regplot(x=filtered_df['Handgun Density'], y=filtered_df['Graduate(%)'])
```

```
count    37.000000
mean      0.000030
std       0.000008
min       0.000018
25%       0.000024
50%       0.000029
75%       0.000037
max       0.000045
dtype: float64
STD/MEAN: 0.2602836996354789
```



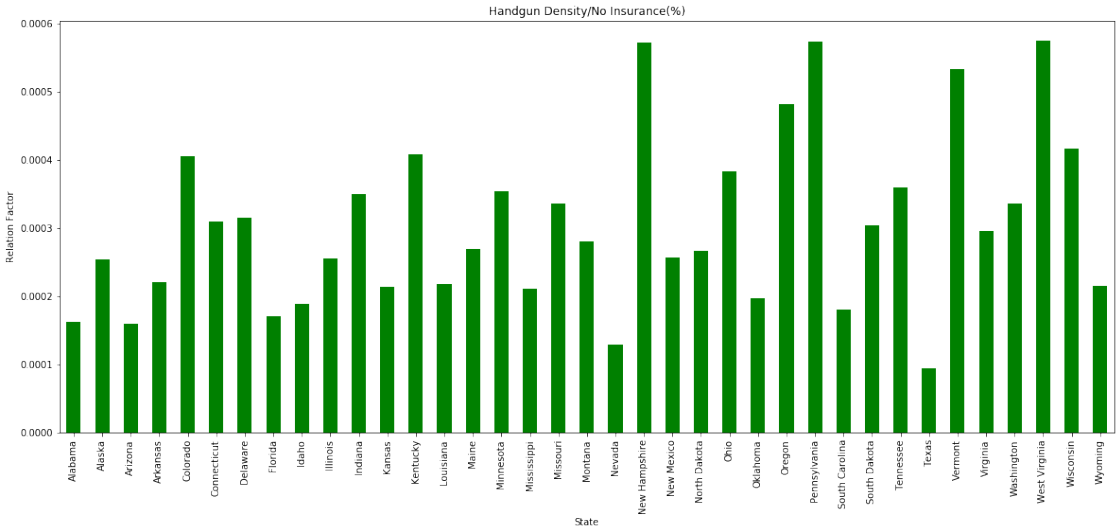
Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x7f589ad15668>



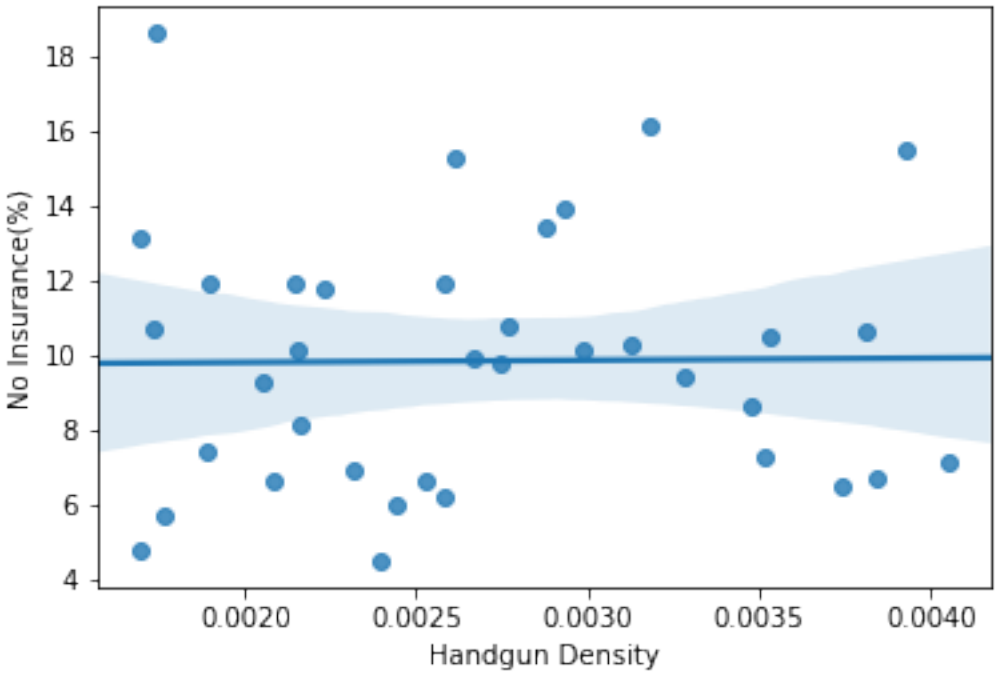
It seems that there is a slight correlation and the density of handgun increases with the increase in the number of high school graduates. Although we could hope otherwise.

```
In [98]: result = filtered_df['Handgun Density']/filtered_df['No Insurance(%)']
         print (result.describe())
         print ("STD/MEAN: {0}".format(result.std()/result.mean()))
         result.plot(kind='bar',figsize=(20,8),color='green',title='Handgun Density/No Insurance
         plt.ylabel("Relation Factor")
         plt.show()
         sns.regplot(x=filtered_df['Handgun Density'], y=filtered_df['No Insurance(%)'])
```

```
count    37.000000
mean      0.000304
std       0.000126
min       0.000093
25%       0.000213
50%       0.000280
75%       0.000360
max       0.000575
dtype: float64
STD/MEAN: 0.4154225964301723
```



Out[98]: <matplotlib.axes._subplots.AxesSubplot at 0x7f589ac1fc50>

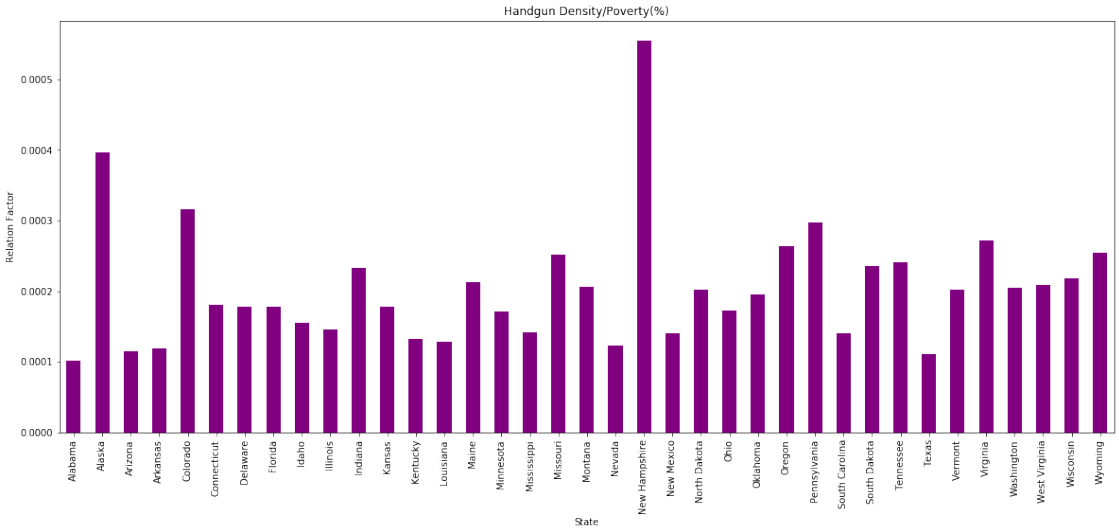


It seems that the percentage of population with health insurance does not affect to the handgun density

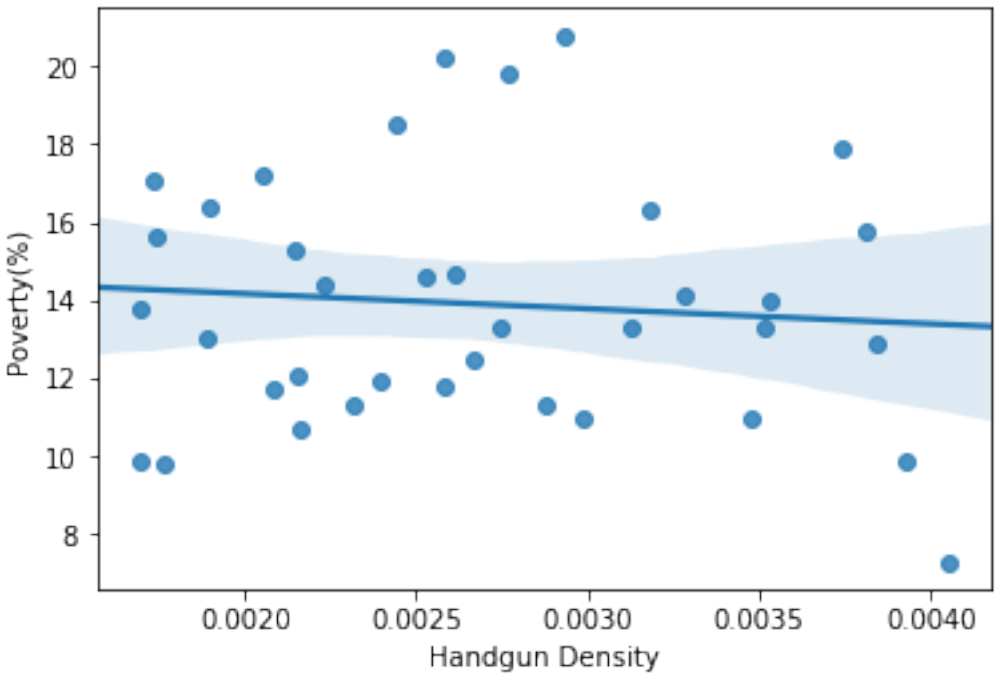
```
In [99]: result = filtered_df['Handgun Density']/filtered_df['Poverty(%)']
         print (result.describe())
```

```
        print ("STD/MEAN: {0}".format(result.std()/result.mean()))
        result.plot(kind='bar',figsize=(20,8),color='purple',title='Handgun Density/Poverty(%)'
        plt.ylabel("Relation Factor")
        plt.show()
        sns.regplot(x=filtered_df['Handgun Density'], y=filtered_df['Poverty(%)'])
```

```
count    37.000000
mean      0.000205
std       0.000087
min       0.000101
25%       0.000141
50%       0.000195
75%       0.000235
max       0.000555
dtype: float64
STD/MEAN: 0.42521397120159865
```




```
Out[99]: <matplotlib.axes._subplots.AxesSubplot at 0x7f589ade6588>
```



It seems that there is a slight correlation and the handgun density increases slightly with the decrease in poverty. Although we could also expect the opposite

It can be seen that none of the variables significantly affects the density of small arms. Although there is a small relationship between the level of studies and wealth. Affecting the increase of both to a slight increase in the density of the number of weapons

1.1.4 What variable of the above affects more the density of small handgun?

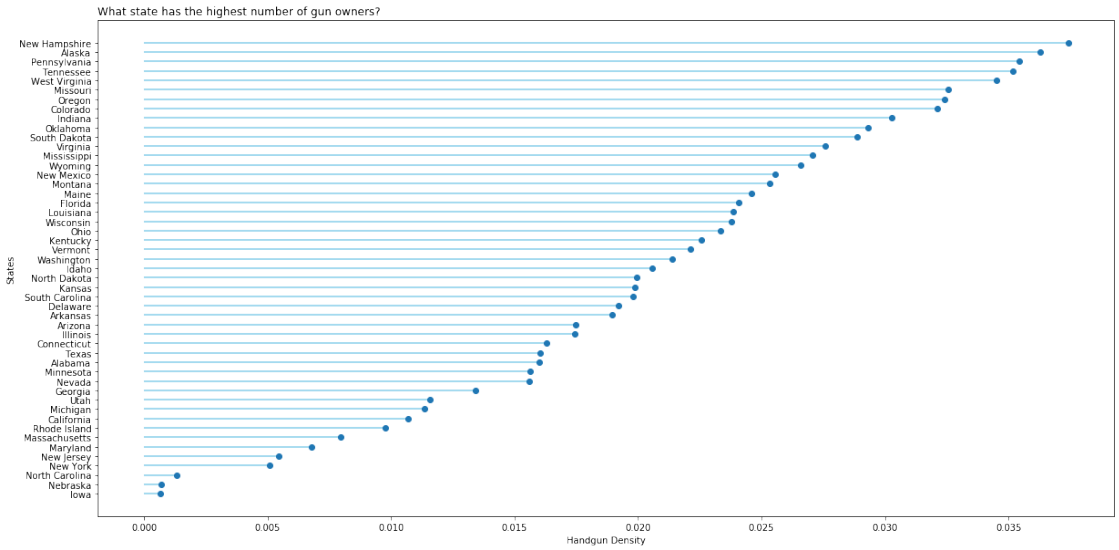
The STD/MEAN for the density of short weapons is 0.265 The only variable that reduces (0.260) the previous value is education (Graduate on High School)

1.1.5 Witch state has the highest number of gun owners? Witch the lowest? What differences are ther between this two states?

```
In [102]: df_hd_sum = df['Handgun Density'].sum()
          df_hd_per = (df['Handgun Density']/df_hd_sum).sort_values()
          #df_hd_per.sort_values().plot(kind='Pie', figsize=(25,25))

          my_range=range(1,len(df_hd_per.index)+1)

          # The vertival plot is made using the hline function
          # I load the seaborn library only to benefit the nice looking feature
          plt.hlines(y=my_range, xmin=0, xmax=df_hd_per.values, color='skyblue')
          plt.plot(df_hd_per.values, my_range, "o")
```

```
        # Add title and exis names
        plt.yticks(my_range, df_hd_per.index)
        plt.title("What state has the highest number of gun owners?", loc='left')
        plt.xlabel('Handgun Density')
        plt.ylabel('States')
```

Out[102]: Text(0,0.5,'States')

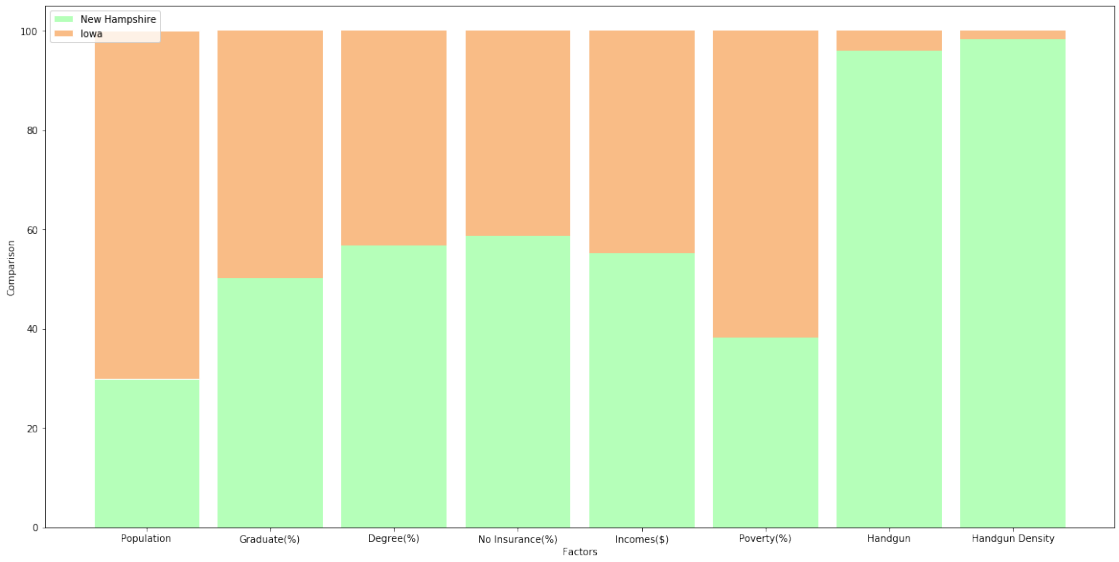


The state with highest handgun density is New Hampshire

The state with lowest handgun density is Iowa

```
In [103]: # Data
          r = [0,1,2,3,4,5,6,7]
          raw_data = {'New Hampshire': df.loc['New Hampshire'].values, 'Iowa': df.loc['Iowa'].va

          # From raw value to percentage
          totals = [i+j for i,j in zip(df.loc['New Hampshire'], df.loc['Iowa'])]
          greenBars = [i / j * 100 for i,j in zip(df.loc['New Hampshire'], totals)]
          orangeBars = [i / j * 100 for i,j in zip(df.loc['Iowa'], totals)]

          # plot
          barWidth = 0.85
          names = df.columns.values

          # Create green Bars
          plt.bar(r, greenBars, color='#b5ffb9', edgecolor='white', width=barWidth, label='New H
          # Create orange Bars
```

```
plt.bar(r, orangeBars, bottom=greenBars, color='#f9bc86', edgecolor='white', width=bar

# Custom x axis
plt.xticks(r, names)
plt.xlabel("Factors")
plt.ylabel("Comparison")

# Show graphic
plt.rcParams["figure.figsize"] = [20,10]
plt.legend()
plt.show()
```



The differences between the two extreme states regarding the density of handgun are not very large in percentage. There is a slight better education and wealth level in 'New Hampshire' (the state with more weapons) aligned with previous observations

Conclusions

As a final conclusion, there is no clear relationship in the chosen data (although it could initially appear) Education and wealth influences but very little significantly, slightly homogenizing the differences between states

This findings are tentative and you can not establish a clear causality without a deeper study

It is necessary to perform more complex analyzes to give answers to the questions raised at the beginning of this analysis. Analyze, for example, how the policy or the violence index might be interesting

Data Reference: The data comes from the FBI's National Instant Criminal Background Check System. The NICS is used by to determine whether a prospective buyer is eligible to buy firearms or explosives. Gun shops call into this system to ensure that each customer does not have a criminal record or isn't otherwise ineligible to make a purchase. The data has been supplemented with state level data from census.gov.

```
In [104]: from subprocess import call
          call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[104]: 0
```