> **Tip**: Welcome to the Investigate a Dataset project! You will find tips in quoted sections like this to help organize your approach to your investigation. Before submitting your project, it will be a good idea to go back through your report and remove these sections to make the presentation of your work as tidy as possible. First things first, you might want to double-click this Markdown cell and change the title so that it reflects your dataset and investigation.

Project: FBI Gun Data Exploration and Analysis

Table of Contents ¶

Introduction

> **Tip**: In this section of the report, provide a brief introduction to the dataset you've selected for analysis. At the end of this section, describe the questions that you plan on exploring over the course of the report. Try to build your report around the analysis of at least one dependent variable and three independent variables. If you're not sure what questions to ask, then make sure you familiarize yourself with the dataset, its variables and the dataset context for ideas of what to explore.
>
> If you haven't yet selected and downloaded your data, make sure you do that first before coming back here. In order to work with the data in this workspace, you also need to upload it to the workspace. To do so, click on the jupyter icon in the upper left to be taken back to the workspace directory. There should be an 'Upload' button in the upper right that will let you add your data file(s) to the workspace. You can then click on the .ipynb file name to come back here.
>
> **Notes**: The source of the data is NICS (FBI-National Instant Criminal Background Check System). This procedure is used to determine if a potential buyer is eligible to buy firearms and explosives. The NCIS data is found in the excel sheet. It has the data of number of firearms type, state and month. The data spreads across from Nov-1998 till Sept-2017. The United States Census data is available in a csv file. The data contains variables at state level.
>
> **Questions**: (what are the questions we wish to answer using the data.
>
> ```
> - Which state has the highest total purchases in April 2010 and A
> pril 2015?
> - What is per capita firearm sales for all states in April 2010 v
> s July 2016?
> ```

In [239]:
```
# Use this cell to set up import statements for all of the packages that
you
#   plan to use.

import pandas as pd
import numpy as np
from statistics import mode
import datetime
from IPython.display import display

%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
%config InlineBackend.figure_format = 'retina'
sns.set_style('darkgrid')

df_cesus = pd.read_excel('U.S. Census Data.xlsx')
df_gun = pd.read_excel('gun_data.xlsx')


# Remember to include a 'magic word' so that your visualizations are plo
tted
#   inline with the notebook. See this page for more:
#   http://ipython.readthedocs.io/en/stable/interactive/magics.html
```

Data Wrangling

> **Tip**: In this section of the report, you will load in the data, check for cleanliness, and then trim and clean your dataset for analysis. Make sure that you document your steps carefully and justify your cleaning decisions.

General Properties

In [240]:
```
# Load your data and print out a few lines. Perform operations to inspec
t data
#   types and look for instances of missing or possibly errant data.

#df_cesus.reset_index(drop=True, inplace=True)

display(df_cesus.head())
display(df_gun.head())
```

	State	Population estimates, July 1, 2016, (V2016)	Population estimates base, April 1, 2010, (V2016)	Population, percent change - April 1, 2010 (estimates base) to July 1, 2016, (V2016)	Population, Census, April 1, 2010	Persons under 5 years, percent, July 1, 2016, (V2016)	Persons under 5 years, percent, April 1, 2010	Persons under 18 years, percent, July 1, 2016, (V2016)	Persoı und . year percer April 20
0	Alabama	4863300	4780131	0.017	4779736	0.060	0.064	0.226	0.2
1	Alaska	741894	710249	0.045	710231	0.073	0.076	0.252	0.2
2	Arizona	6931071	6392301	0.084	6392017	0.063	0.071	0.235	0.2
3	Arkansas	2988248	2916025	0.025	2915918	0.064	0.068	0.236	0.2
4	California	39250017	37254522	0.054	37253956	0.063	0.068	0.232	0.2

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple	admin	prepa
0	2017-09	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0	
1	2017-09	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0	
2	2017-09	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0	
3	2017-09	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.0	
4	2017-09	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0	

In [243]:
```
df_cesus.set_index('State', inplace=True)
df_cesus
```

Out[243]:

State	Population estimates, July 1, 2016, (V2016)	Population estimates base, April 1, 2010, (V2016)	Population, percent change - April 1, 2010 (estimates base) to July 1, 2016, (V2016)	Population, Census, April 1, 2010	Persons under 5 years, percent, July 1, 2016, (V2016)	Persons under 5 years, percent, April 1, 2010	Persons under 18 years, percent, July 1, 2016, (V2016)	Per u y per Ap
Alabama	4863300	4780131	0.017	4779736	0.060	0.064	0.226	(
Alaska	741894	710249	0.045	710231	0.073	0.076	0.252	(
Arizona	6931071	6392301	0.084	6392017	0.063	0.071	0.235	(
Arkansas	2988248	2916025	0.025	2915918	0.064	0.068	0.236	(
California	39250017	37254522	0.054	37253956	0.063	0.068	0.232	(
Colorado	5540545	5029324	0.102	5029196	0.061	0.068	0.228	(
Connecticut	3576452	3574114	0.001	3574097	0.052	0.057	0.211	(
Delaware	952065	897936	0.060	897934	0.058	0.062	0.215	(
Florida	20612439	18804592	0.096	18801310	0.055	0.057	0.201	(
Georgia	10310371	9688680	0.064	9687653	0.064	0.071	0.244	(
Hawaii	1428557	1360301	0.050	1360301	0.064	0.064	0.216	(
Idaho	1683140	1567650	0.074	1567582	0.068	0.078	0.260	(
Illinois	12801539	12831574	-0.002	12830632	0.060	0.065	0.229	(
Indiana	6633053	6484136	0.023	6483802	0.064	0.067	0.238	(
Iowa	3134693	3046869	0.029	3046355	0.064	0.066	0.233	(
Kansas	2907289	2853129	0.019	2853118	0.067	0.072	0.246	(
Kentucky	4436974	4339344	0.022	4339367	0.062	0.065	0.228	(
Louisiana	4681666	4533479	0.033	4533372	0.066	0.069	0.238	(
Maine	1331479	1328364	0.002	1328361	0.049	0.052	0.191	(
Maryland	6016447	5773786	0.042	5773552	0.061	0.063	0.224	(
Massachusetts	6811779	6547813	0.040	6547629	0.053	0.056	0.202	(
Michigan	9928300	9884129	0.004	9883640	0.058	0.060	0.221	(
Minnesota	5519952	5303924	0.041	5303925	0.064	0.067	0.233	(
Mississippi	2988726	2968103	0.007	2967297	0.063	0.071	0.241	(
Missouri	6093000	5988928	0.017	5988927	0.061	0.065	0.228	(
Montana	1042520	989414	0.054	989415	0.060	0.063	0.218	(

State	Population estimates, July 1, 2016, (V2016)	Population estimates base, April 1, 2010, (V2016)	Population, percent change - April 1, 2010 (estimates base) to July 1, 2016, (V2016)	Population, Census, April 1, 2010	Persons under 5 years, percent, July 1, 2016, (V2016)	Persons under 5 years, percent, April 1, 2010	Persons under 18 years, percent, July 1, 2016, (V2016)	Per u y per Ap
Nebraska	1907116	1826334	0.044	1826341	0.070	0.072	0.248	(
Nevada	2940058	2700691	0.089	2700551	0.063	0.069	0.230	(
New Hampshire	1334795	1316461	0.014	1316470	0.048	0.053	0.195	(
New Jersey	8944469	8791953	0.017	8791894	0.058	0.062	0.222	(
New Mexico	2081015	2059198	0.011	2059179	0.062	0.070	0.236	(
New York	19745289	19378110	0.019	19378102	0.059	0.060	0.212	(
North Carolina	10146788	9535688	0.064	9535483	0.060	0.066	0.227	(
North Dakota	757952	672591	0.127	672591	0.073	0.066	0.233	(
Ohio	11614373	11536727	0.007	11536504	0.060	0.062	0.225	(
Oklahoma	3923561	3751615	0.046	3751351	0.068	0.070	0.245	(
Oregon	4093465	3831072	0.068	3831074	0.058	0.062	0.212	(
Pennsylvania	12784227	12702857	0.006	12702379	0.056	0.057	0.209	(
Rhode Island	1056426	1052940	0.003	1052567	0.052	0.055	0.197	(
South Carolina	4961119	4625410	0.073	4625364	0.059	0.065	0.221	(
South Dakota	865454	814195	0.063	814180	0.071	0.073	0.246	(
Tennessee	6651194	6346298	0.048	6346105	0.061	0.064	0.226	(
Texas	27862596	25146100	0.108	25145561	0.072	0.077	0.262	(
Utah	3051217	2763888	0.104	2763885	0.083	0.095	0.302	(
Vermont	624594	625741	-0.002	625741	0.049	0.051	0.190	(
Virginia	8411808	8001041	0.051	8001024	0.061	0.064	0.222	(
Washington	7288000	6724545	0.084	6724540	0.062	0.065	0.224	(
West Virginia	1831102	1853011	-0.012	1852994	0.055	0.056	0.205	(
Wisconsin	5778708	5687289	0.016	5686986	0.058	0.063	0.223	(
Wyoming	585501	563767	0.039	563626	0.065	0.071	0.237	(

In [244]:
```python
# lets try and get the idea about dimension of the dataframes.

print('Census shape: '+ str(df_cesus.shape))
print('Gun shape: ' + str(df_gun.shape))
```

```
Census shape: (50, 65)
Gun shape: (12485, 27)
```

In [245]:
```
# lets get the information on data types of each of the columns using in
fo()

df_cesus.info();
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 50 entries, Alabama to Wyoming
Data columns (total 65 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Population estimates, July 1, 2016,  (V2016)
50 non-null     int64
 1   Population estimates base, April 1, 2010,  (V2016)
50 non-null     int64
 2   Population, percent change - April 1, 2010 (estimates base) to Jul
y 1, 2016,  (V2016)   50 non-null     float64
 3   Population, Census, April 1, 2010
50 non-null     int64
 4   Persons under 5 years, percent, July 1, 2016,  (V2016)
50 non-null     float64
 5   Persons under 5 years, percent, April 1, 2010
50 non-null     float64
 6   Persons under 18 years, percent, July 1, 2016,  (V2016)
50 non-null     float64
 7   Persons under 18 years, percent, April 1, 2010
50 non-null     float64
 8   Persons 65 years and over, percent,  July 1, 2016,  (V2016)
50 non-null     float64
 9   Persons 65 years and over, percent, April 1, 2010
50 non-null     float64
 10  Female persons, percent,  July 1, 2016,  (V2016)
50 non-null     float64
 11  Female persons, percent, April 1, 2010
50 non-null     float64
 12  White alone, percent, July 1, 2016,  (V2016)
50 non-null     float64
 13  Black or African American alone, percent, July 1, 2016,  (V2016)
50 non-null     float64
 14  American Indian and Alaska Native alone, percent, July 1, 2016,
(V2016)                50 non-null     float64
 15  Asian alone, percent, July 1, 2016,  (V2016)
50 non-null     float64
 16  Native Hawaiian and Other Pacific Islander alone, percent, July 1,
2016,  (V2016)       50 non-null     object
 17  Two or More Races, percent, July 1, 2016,  (V2016)
50 non-null     float64
 18  Hispanic or Latino, percent, July 1, 2016,  (V2016)
50 non-null     float64
 19  White alone, not Hispanic or Latino, percent, July 1, 2016,  (V201
6)                     50 non-null     float64
 20  Veterans, 2011-2015
50 non-null     int64
 21  Foreign born persons, percent, 2011-2015
50 non-null     float64
 22  Housing units,  July 1, 2016,  (V2016)
50 non-null     int64
 23  Housing units, April 1, 2010
50 non-null     int64
 24  Owner-occupied housing unit rate, 2011-2015
50 non-null     float64
```

```
 25  Median value of owner-occupied housing units, 2011-2015
50 non-null     int64
 26  Median selected monthly owner costs -with a mortgage, 2011-2015
50 non-null     int64
 27  Median selected monthly owner costs -without a mortgage, 2011-2015
50 non-null     int64
 28  Median gross rent, 2011-2015
50 non-null     int64
 29  Building permits, 2016
50 non-null     int64
 30  Households, 2011-2015
50 non-null     int64
 31  Persons per household, 2011-2015
50 non-null     float64
 32  Living in same house 1 year ago, percent of persons age 1 year+, 2
011-2015              50 non-null     float64
 33  Language other than English spoken at home, percent of persons age
5 years+, 2011-2015  50 non-null     float64
 34  High school graduate or higher, percent of persons age 25 years+,
2011-2015             50 non-null     float64
 35  Bachelor's degree or higher, percent of persons age 25 years+, 201
1-2015                50 non-null     float64
 36  With a disability, under age 65 years, percent, 2011-2015
50 non-null     float64
 37  Persons  without health insurance, under age 65 years, percent
50 non-null     float64
 38  In civilian labor force, total, percent of population age 16 years
+, 2011-2015          50 non-null     float64
 39  In civilian labor force, female, percent of population age 16 year
s+, 2011-2015         50 non-null     float64
 40  Total accommodation and food services sales, 2012 ($1,000)
50 non-null     int64
 41  Total health care and social assistance receipts/revenue, 2012
($1,000)                 50 non-null     int64
 42  Total manufacturers shipments, 2012 ($1,000)
50 non-null     object
 43  Total merchant wholesaler sales, 2012 ($1,000)
50 non-null     int64
 44  Total retail sales, 2012 ($1,000)
50 non-null     int64
 45  Total retail sales per capita, 2012
50 non-null     int64
 46  Mean travel time to work (minutes), workers age 16 years+, 2011-20
15                    50 non-null     float64
 47  Median household income (in 2015 dollars), 2011-2015
50 non-null     int64
 48  Per capita income in past 12 months (in 2015 dollars), 2011-2015
50 non-null     int64
 49  Persons in poverty, percent
50 non-null     float64
 50  Total employer establishments, 2015
50 non-null     int64
 51  Total employment, 2015
50 non-null     int64
 52  Total annual payroll, 2015 ($1,000)
50 non-null     int64
 53  Total employment, percent change, 2014-2015
```

```
50 non-null     object
 54  Total nonemployer establishments, 2015
50 non-null     int64
 55  All firms, 2012
50 non-null     int64
 56  Men-owned firms, 2012
50 non-null     int64
 57  Women-owned firms, 2012
50 non-null     int64
 58  Minority-owned firms, 2012
50 non-null     int64
 59  Nonminority-owned firms, 2012
50 non-null     int64
 60  Veteran-owned firms, 2012
50 non-null     int64
 61  Nonveteran-owned firms, 2012
50 non-null     int64
 62  Population per square mile, 2010
50 non-null     float64
 63  Land area in square miles, 2010
50 non-null     float64
 64  FIPS Code
50 non-null     object
dtypes: float64(31), int64(30), object(4)
memory usage: 25.8+ KB
```

In [246]:
```
df_gun.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12485 entries, 0 to 12484
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   month                      12485 non-null  object 
 1   state                      12485 non-null  object 
 2   permit                     12461 non-null  float64
 3   permit_recheck             1100 non-null   float64
 4   handgun                    12465 non-null  float64
 5   long_gun                   12466 non-null  float64
 6   other                      5500 non-null   float64
 7   multiple                   12485 non-null  int64  
 8   admin                      12462 non-null  float64
 9   prepawn_handgun            10542 non-null  float64
 10  prepawn_long_gun           10540 non-null  float64
 11  prepawn_other              5115 non-null   float64
 12  redemption_handgun         10545 non-null  float64
 13  redemption_long_gun        10544 non-null  float64
 14  redemption_other           5115 non-null   float64
 15  returned_handgun           2200 non-null   float64
 16  returned_long_gun          2145 non-null   float64
 17  returned_other             1815 non-null   float64
 18  rentals_handgun            990 non-null    float64
 19  rentals_long_gun           825 non-null    float64
 20  private_sale_handgun       2750 non-null   float64
 21  private_sale_long_gun      2750 non-null   float64
 22  private_sale_other         2750 non-null   float64
 23  return_to_seller_handgun   2475 non-null   float64
 24  return_to_seller_long_gun  2750 non-null   float64
 25  return_to_seller_other     2255 non-null   float64
 26  totals                     12485 non-null  int64  
dtypes: float64(23), int64(2), object(2)
memory usage: 2.6+ MB
```

In [247]:
```
df_cesus.describe()
```

Out[247]:

	Population estimates, July 1, 2016, (V2016)	Population estimates base, April 1, 2010, (V2016)	Population, percent change - April 1, 2010 (estimates base) to July 1, 2016, (V2016)	Population, Census, April 1, 2010	Persons under 5 years, percent, July 1, 2016, (V2016)	Persons under 5 years, percent, April 1, 2010	Persons under 18 years, percent, July 1, 2016, (V2016)	
count	5.000000e+01	5.000000e+01	50.000000	5.000000e+01	50.000000	50.000000	50.00000	5
mean	6.448927e+06	6.163127e+06	0.041800	6.162876e+06	0.061600	0.065460	0.22750	
std	7.271769e+06	6.848463e+06	0.033811	6.848235e+06	0.006612	0.007579	0.01977	
min	5.855010e+05	5.637670e+05	-0.012000	5.636260e+05	0.048000	0.051000	0.19000	
25%	1.850106e+06	1.833003e+06	0.016250	1.833004e+06	0.058000	0.062000	0.21650	
50%	4.559320e+06	4.436412e+06	0.040500	4.436370e+06	0.061000	0.065000	0.22750	
75%	7.198768e+06	6.680362e+06	0.063750	6.680312e+06	0.064000	0.069750	0.23675	
max	3.925002e+07	3.725452e+07	0.127000	3.725396e+07	0.083000	0.095000	0.30200	

In [248]:
```
df_gun.describe()
```

Out[248]:

	permit	permit_recheck	handgun	long_gun	other	multiple
count	12461.000000	1100.000000	12465.000000	12466.000000	5500.000000	12485.000000
mean	6413.629404	1165.956364	5940.881107	7810.847585	360.471636	268.603364
std	23752.338269	9224.200609	8618.584060	9309.846140	1349.478273	783.185073
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	865.000000	2078.250000	17.000000	15.000000
50%	518.000000	0.000000	3059.000000	5122.000000	121.000000	125.000000
75%	4272.000000	0.000000	7280.000000	10380.750000	354.000000	301.000000
max	522188.000000	116681.000000	107224.000000	108058.000000	77929.000000	38907.000000

In [249]:
```
# lets try and look at the column names to see what data are we dealing
 with

for i, v in enumerate(df_cesus.columns):
    print(i,v)
```

```
0 Population estimates, July 1, 2016,  (V2016)
1 Population estimates base, April 1, 2010,  (V2016)
2 Population, percent change - April 1, 2010 (estimates base) to July
1, 2016,  (V2016)
3 Population, Census, April 1, 2010
4 Persons under 5 years, percent, July 1, 2016,  (V2016)
5 Persons under 5 years, percent, April 1, 2010
6 Persons under 18 years, percent, July 1, 2016,  (V2016)
7 Persons under 18 years, percent, April 1, 2010
8 Persons 65 years and over, percent,  July 1, 2016,  (V2016)
9 Persons 65 years and over, percent, April 1, 2010
10 Female persons, percent,  July 1, 2016,  (V2016)
11 Female persons, percent, April 1, 2010
12 White alone, percent, July 1, 2016,  (V2016)
13 Black or African American alone, percent, July 1, 2016,  (V2016)
14 American Indian and Alaska Native alone, percent, July 1, 2016,  (V2
016)
15 Asian alone, percent, July 1, 2016,  (V2016)
16 Native Hawaiian and Other Pacific Islander alone, percent, July 1, 2
016,  (V2016)
17 Two or More Races, percent, July 1, 2016,  (V2016)
18 Hispanic or Latino, percent, July 1, 2016,  (V2016)
19 White alone, not Hispanic or Latino, percent, July 1, 2016,  (V2016)
20 Veterans, 2011-2015
21 Foreign born persons, percent, 2011-2015
22 Housing units,  July 1, 2016,  (V2016)
23 Housing units, April 1, 2010
24 Owner-occupied housing unit rate, 2011-2015
25 Median value of owner-occupied housing units, 2011-2015
26 Median selected monthly owner costs -with a mortgage, 2011-2015
27 Median selected monthly owner costs -without a mortgage, 2011-2015
28 Median gross rent, 2011-2015
29 Building permits, 2016
30 Households, 2011-2015
31 Persons per household, 2011-2015
32 Living in same house 1 year ago, percent of persons age 1 year+, 201
1-2015
33 Language other than English spoken at home, percent of persons age 5
years+, 2011-2015
34 High school graduate or higher, percent of persons age 25 years+, 20
11-2015
35 Bachelor's degree or higher, percent of persons age 25 years+, 2011-
2015
36 With a disability, under age 65 years, percent, 2011-2015
37 Persons  without health insurance, under age 65 years, percent
38 In civilian labor force, total, percent of population age 16 years+,
2011-2015
39 In civilian labor force, female, percent of population age 16 years
+, 2011-2015
40 Total accommodation and food services sales, 2012 ($1,000)
41 Total health care and social assistance receipts/revenue, 2012 ($1,0
00)
42 Total manufacturers shipments, 2012 ($1,000)
43 Total merchant wholesaler sales, 2012 ($1,000)
44 Total retail sales, 2012 ($1,000)
45 Total retail sales per capita, 2012
46 Mean travel time to work (minutes), workers age 16 years+, 2011-2015
```

```
47 Median household income (in 2015 dollars), 2011-2015
48 Per capita income in past 12 months (in 2015 dollars), 2011-2015
49 Persons in poverty, percent
50 Total employer establishments, 2015
51 Total employment, 2015
52 Total annual payroll, 2015 ($1,000)
53 Total employment, percent change, 2014-2015
54 Total nonemployer establishments, 2015
55 All firms, 2012
56 Men-owned firms, 2012
57 Women-owned firms, 2012
58 Minority-owned firms, 2012
59 Nonminority-owned firms, 2012
60 Veteran-owned firms, 2012
61 Nonveteran-owned firms, 2012
62 Population per square mile, 2010
63 Land area in square miles, 2010
64 FIPS Code
```

In [250]:

```
for i, v in enumerate(df_gun.columns):
    print(i,v)
```

```
0 month
1 state
2 permit
3 permit_recheck
4 handgun
5 long_gun
6 other
7 multiple
8 admin
9 prepawn_handgun
10 prepawn_long_gun
11 prepawn_other
12 redemption_handgun
13 redemption_long_gun
14 redemption_other
15 returned_handgun
16 returned_long_gun
17 returned_other
18 rentals_handgun
19 rentals_long_gun
20 private_sale_handgun
21 private_sale_long_gun
22 private_sale_other
23 return_to_seller_handgun
24 return_to_seller_long_gun
25 return_to_seller_other
26 totals
```

Upon observation of data manually, I came to observe that the states are not consistent in both the data. Upon observing the Census data source I found out 5 states that are not present in the Gun data namely Guam, Puerto Rico, District of Columbia, Virgin Islands, and Mariana Islands. We will have to eliminate to avoid unneccessary confusion in analysis.

In [251]:
```
# removing the data related to all that 5 states from the Guns data
print(df_gun.state.nunique())

df_gun = df_gun[df_gun.state!='Guam']
df_gun = df_gun[df_gun.state!='Puerto Rico']
df_gun = df_gun[df_gun.state!='District of Columbia']
df_gun = df_gun[df_gun.state!='Virgin Islands']
df_gun = df_gun[df_gun.state!='Mariana Islands']
```

```
55
```

In [252]:
```
df_cesus.dtypes
```

Out[252]:
```
Population estimates, July 1, 2016,  (V2016)
int64
Population estimates base, April 1, 2010,  (V2016)
int64
Population, percent change - April 1, 2010 (estimates base) to July 1,
2016,  (V2016)     float64
Population, Census, April 1, 2010
int64
Persons under 5 years, percent, July 1, 2016,  (V2016)
float64
Persons under 5 years, percent, April 1, 2010
float64
Persons under 18 years, percent, July 1, 2016,  (V2016)
float64
Persons under 18 years, percent, April 1, 2010
float64
Persons 65 years and over, percent,  July 1, 2016,  (V2016)
float64
Persons 65 years and over, percent, April 1, 2010
float64
Female persons, percent,  July 1, 2016,  (V2016)
float64
Female persons, percent, April 1, 2010
float64
White alone, percent, July 1, 2016,  (V2016)
float64
Black or African American alone, percent, July 1, 2016,  (V2016)
float64
American Indian and Alaska Native alone, percent, July 1, 2016,  (V201
6)                  float64
Asian alone, percent, July 1, 2016,  (V2016)
float64
Native Hawaiian and Other Pacific Islander alone, percent, July 1, 201
6,  (V2016)          object
Two or More Races, percent, July 1, 2016,  (V2016)
float64
Hispanic or Latino, percent, July 1, 2016,  (V2016)
float64
White alone, not Hispanic or Latino, percent, July 1, 2016,  (V2016)
float64
Veterans, 2011-2015
int64
Foreign born persons, percent, 2011-2015
float64
Housing units,  July 1, 2016,  (V2016)
int64
Housing units, April 1, 2010
int64
Owner-occupied housing unit rate, 2011-2015
float64
Median value of owner-occupied housing units, 2011-2015
int64
Median selected monthly owner costs -with a mortgage, 2011-2015
int64
Median selected monthly owner costs -without a mortgage, 2011-2015
int64
Median gross rent, 2011-2015
```

```
int64
Building permits, 2016
int64
Households, 2011-2015
int64
Persons per household, 2011-2015
float64
Living in same house 1 year ago, percent of persons age 1 year+, 2011-2
015                float64
Language other than English spoken at home, percent of persons age 5 ye
ars+, 2011-2015    float64
High school graduate or higher, percent of persons age 25 years+, 2011-
2015               float64
Bachelor's degree or higher, percent of persons age 25 years+, 2011-201
5                  float64
With a disability, under age 65 years, percent, 2011-2015
float64
Persons  without health insurance, under age 65 years, percent
float64
In civilian labor force, total, percent of population age 16 years+, 20
11-2015            float64
In civilian labor force, female, percent of population age 16 years+, 2
011-2015           float64
Total accommodation and food services sales, 2012 ($1,000)
int64
Total health care and social assistance receipts/revenue, 2012 ($1,000)
int64
Total manufacturers shipments, 2012 ($1,000)
object
Total merchant wholesaler sales, 2012 ($1,000)
int64
Total retail sales, 2012 ($1,000)
int64
Total retail sales per capita, 2012
int64
Mean travel time to work (minutes), workers age 16 years+, 2011-2015
float64
Median household income (in 2015 dollars), 2011-2015
int64
Per capita income in past 12 months (in 2015 dollars), 2011-2015
int64
Persons in poverty, percent
float64
Total employer establishments, 2015
int64
Total employment, 2015
int64
Total annual payroll, 2015 ($1,000)
int64
Total employment, percent change, 2014-2015
object
Total nonemployer establishments, 2015
int64
All firms, 2012
int64
Men-owned firms, 2012
int64
```

```
Women-owned firms, 2012
int64
Minority-owned firms, 2012
int64
Nonminority-owned firms, 2012
int64
Veteran-owned firms, 2012
int64
Nonveteran-owned firms, 2012
int64
Population per square mile, 2010
float64
Land area in square miles, 2010
float64
FIPS Code
object
dtype: object
```

In [253]:
```
df_gun.dtypes
```

Out[253]:
```
month                          object
state                          object
permit                        float64
permit_recheck                float64
handgun                       float64
long_gun                      float64
other                         float64
multiple                        int64
admin                         float64
prepawn_handgun               float64
prepawn_long_gun              float64
prepawn_other                 float64
redemption_handgun            float64
redemption_long_gun           float64
redemption_other              float64
returned_handgun              float64
returned_long_gun             float64
returned_other                float64
rentals_handgun               float64
rentals_long_gun              float64
private_sale_handgun          float64
private_sale_long_gun         float64
private_sale_other            float64
return_to_seller_handgun      float64
return_to_seller_long_gun     float64
return_to_seller_other        float64
totals                          int64
dtype: object
```

In [254]:
```
# Checking for duplicates

sum(df_cesus.duplicated())
```

Out[254]:
```
0
```

In [255]:
```
sum(df_gun.duplicated())
```

Out[255]: 0

In [256]:
```
# Check if any value is Nan in the dataframe and how many columns have N
an values

df_cesus.isnull().any().any(), sum(df_cesus.isnull().any())
```

Out[256]: (False, 0)

In [257]:
```
df_cesus.isnull().any()
```

Out[257]:
```
Population estimates, July 1, 2016,  (V2016)
False
Population estimates base, April 1, 2010,  (V2016)
False
Population, percent change - April 1, 2010 (estimates base) to July 1,
2016,  (V2016)     False
Population, Census, April 1, 2010
False
Persons under 5 years, percent, July 1, 2016,  (V2016)
False
Persons under 5 years, percent, April 1, 2010
False
Persons under 18 years, percent, July 1, 2016,  (V2016)
False
Persons under 18 years, percent, April 1, 2010
False
Persons 65 years and over, percent,  July 1, 2016,  (V2016)
False
Persons 65 years and over, percent, April 1, 2010
False
Female persons, percent,  July 1, 2016,  (V2016)
False
Female persons, percent, April 1, 2010
False
White alone, percent, July 1, 2016,  (V2016)
False
Black or African American alone, percent, July 1, 2016,  (V2016)
False
American Indian and Alaska Native alone, percent, July 1, 2016,  (V201
6)                  False
Asian alone, percent, July 1, 2016,  (V2016)
False
Native Hawaiian and Other Pacific Islander alone, percent, July 1, 201
6,  (V2016)         False
Two or More Races, percent, July 1, 2016,  (V2016)
False
Hispanic or Latino, percent, July 1, 2016,  (V2016)
False
White alone, not Hispanic or Latino, percent, July 1, 2016,  (V2016)
False
Veterans, 2011-2015
False
Foreign born persons, percent, 2011-2015
False
Housing units,  July 1, 2016,  (V2016)
False
Housing units, April 1, 2010
False
Owner-occupied housing unit rate, 2011-2015
False
Median value of owner-occupied housing units, 2011-2015
False
Median selected monthly owner costs -with a mortgage, 2011-2015
False
Median selected monthly owner costs -without a mortgage, 2011-2015
False
Median gross rent, 2011-2015
```

```
False
Building permits, 2016
False
Households, 2011-2015
False
Persons per household, 2011-2015
False
Living in same house 1 year ago, percent of persons age 1 year+, 2011-2
015                 False
Language other than English spoken at home, percent of persons age 5 ye
ars+, 2011-2015    False
High school graduate or higher, percent of persons age 25 years+, 2011-
2015                False
Bachelor's degree or higher, percent of persons age 25 years+, 2011-201
5                   False
With a disability, under age 65 years, percent, 2011-2015
False
Persons  without health insurance, under age 65 years, percent
False
In civilian labor force, total, percent of population age 16 years+, 20
11-2015             False
In civilian labor force, female, percent of population age 16 years+, 2
011-2015            False
Total accommodation and food services sales, 2012 ($1,000)
False
Total health care and social assistance receipts/revenue, 2012 ($1,000)
False
Total manufacturers shipments, 2012 ($1,000)
False
Total merchant wholesaler sales, 2012 ($1,000)
False
Total retail sales, 2012 ($1,000)
False
Total retail sales per capita, 2012
False
Mean travel time to work (minutes), workers age 16 years+, 2011-2015
False
Median household income (in 2015 dollars), 2011-2015
False
Per capita income in past 12 months (in 2015 dollars), 2011-2015
False
Persons in poverty, percent
False
Total employer establishments, 2015
False
Total employment, 2015
False
Total annual payroll, 2015 ($1,000)
False
Total employment, percent change, 2014-2015
False
Total nonemployer establishments, 2015
False
All firms, 2012
False
Men-owned firms, 2012
False
```

```
Women-owned firms, 2012
False
Minority-owned firms, 2012
False
Nonminority-owned firms, 2012
False
Veteran-owned firms, 2012
False
Nonveteran-owned firms, 2012
False
Population per square mile, 2010
False
Land area in square miles, 2010
False
FIPS Code
False
dtype: bool
```

In [258]:

```
df_gun.isnull().any().any(), sum(df_gun.isnull().any())
```

Out[258]:

```
(True, 21)
```

In [259]:

```
df_gun.isnull().any()
```

Out[259]:

```
month                         False
state                         False
permit                         True
permit_recheck                 True
handgun                       False
long_gun                      False
other                          True
multiple                      False
admin                          True
prepawn_handgun                True
prepawn_long_gun               True
prepawn_other                  True
redemption_handgun             True
redemption_long_gun            True
redemption_other               True
returned_handgun               True
returned_long_gun              True
returned_other                 True
rentals_handgun                True
rentals_long_gun               True
private_sale_handgun           True
private_sale_long_gun          True
private_sale_other             True
return_to_seller_handgun       True
return_to_seller_long_gun      True
return_to_seller_other         True
totals                        False
dtype: bool
```

In [260]:
```
df_cesus.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 50 entries, Alabama to Wyoming
Data columns (total 65 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Population estimates, July 1, 2016,  (V2016)
50 non-null     int64
 1   Population estimates base, April 1, 2010,  (V2016)
50 non-null     int64
 2   Population, percent change - April 1, 2010 (estimates base) to Jul
y 1, 2016,  (V2016)   50 non-null     float64
 3   Population, Census, April 1, 2010
50 non-null     int64
 4   Persons under 5 years, percent, July 1, 2016,  (V2016)
50 non-null     float64
 5   Persons under 5 years, percent, April 1, 2010
50 non-null     float64
 6   Persons under 18 years, percent, July 1, 2016,  (V2016)
50 non-null     float64
 7   Persons under 18 years, percent, April 1, 2010
50 non-null     float64
 8   Persons 65 years and over, percent,  July 1, 2016,  (V2016)
50 non-null     float64
 9   Persons 65 years and over, percent, April 1, 2010
50 non-null     float64
 10  Female persons, percent,  July 1, 2016,  (V2016)
50 non-null     float64
 11  Female persons, percent, April 1, 2010
50 non-null     float64
 12  White alone, percent, July 1, 2016,  (V2016)
50 non-null     float64
 13  Black or African American alone, percent, July 1, 2016,  (V2016)
50 non-null     float64
 14  American Indian and Alaska Native alone, percent, July 1, 2016,
(V2016)                50 non-null     float64
 15  Asian alone, percent, July 1, 2016,  (V2016)
50 non-null     float64
 16  Native Hawaiian and Other Pacific Islander alone, percent, July 1,
2016,  (V2016)       50 non-null     object
 17  Two or More Races, percent, July 1, 2016,  (V2016)
50 non-null     float64
 18  Hispanic or Latino, percent, July 1, 2016,  (V2016)
50 non-null     float64
 19  White alone, not Hispanic or Latino, percent, July 1, 2016,  (V201
6)                     50 non-null     float64
 20  Veterans, 2011-2015
50 non-null     int64
 21  Foreign born persons, percent, 2011-2015
50 non-null     float64
 22  Housing units,  July 1, 2016,  (V2016)
50 non-null     int64
 23  Housing units, April 1, 2010
50 non-null     int64
 24  Owner-occupied housing unit rate, 2011-2015
50 non-null     float64
```

```
 25  Median value of owner-occupied housing units, 2011-2015
50 non-null     int64
 26  Median selected monthly owner costs -with a mortgage, 2011-2015
50 non-null     int64
 27  Median selected monthly owner costs -without a mortgage, 2011-2015
50 non-null     int64
 28  Median gross rent, 2011-2015
50 non-null     int64
 29  Building permits, 2016
50 non-null     int64
 30  Households, 2011-2015
50 non-null     int64
 31  Persons per household, 2011-2015
50 non-null     float64
 32  Living in same house 1 year ago, percent of persons age 1 year+, 2
011-2015              50 non-null     float64
 33  Language other than English spoken at home, percent of persons age
5 years+, 2011-2015  50 non-null     float64
 34  High school graduate or higher, percent of persons age 25 years+,
2011-2015             50 non-null     float64
 35  Bachelor's degree or higher, percent of persons age 25 years+, 201
1-2015                50 non-null     float64
 36  With a disability, under age 65 years, percent, 2011-2015
50 non-null     float64
 37  Persons  without health insurance, under age 65 years, percent
50 non-null     float64
 38  In civilian labor force, total, percent of population age 16 years
+, 2011-2015          50 non-null     float64
 39  In civilian labor force, female, percent of population age 16 year
s+, 2011-2015         50 non-null     float64
 40  Total accommodation and food services sales, 2012 ($1,000)
50 non-null     int64
 41  Total health care and social assistance receipts/revenue, 2012
($1,000)                 50 non-null     int64
 42  Total manufacturers shipments, 2012 ($1,000)
50 non-null     object
 43  Total merchant wholesaler sales, 2012 ($1,000)
50 non-null     int64
 44  Total retail sales, 2012 ($1,000)
50 non-null     int64
 45  Total retail sales per capita, 2012
50 non-null     int64
 46  Mean travel time to work (minutes), workers age 16 years+, 2011-20
15                    50 non-null     float64
 47  Median household income (in 2015 dollars), 2011-2015
50 non-null     int64
 48  Per capita income in past 12 months (in 2015 dollars), 2011-2015
50 non-null     int64
 49  Persons in poverty, percent
50 non-null     float64
 50  Total employer establishments, 2015
50 non-null     int64
 51  Total employment, 2015
50 non-null     int64
 52  Total annual payroll, 2015 ($1,000)
50 non-null     int64
 53  Total employment, percent change, 2014-2015
```

```
50 non-null     object
 54  Total nonemployer establishments, 2015
50 non-null     int64
 55  All firms, 2012
50 non-null     int64
 56  Men-owned firms, 2012
50 non-null     int64
 57  Women-owned firms, 2012
50 non-null     int64
 58  Minority-owned firms, 2012
50 non-null     int64
 59  Nonminority-owned firms, 2012
50 non-null     int64
 60  Veteran-owned firms, 2012
50 non-null     int64
 61  Nonveteran-owned firms, 2012
50 non-null     int64
 62  Population per square mile, 2010
50 non-null     float64
 63  Land area in square miles, 2010
50 non-null     float64
 64  FIPS Code
50 non-null     object
dtypes: float64(31), int64(30), object(4)
memory usage: 25.8+ KB
```

In [261]:
```
df_gun.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11350 entries, 0 to 12484
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   month                      11350 non-null  object 
 1   state                      11350 non-null  object 
 2   permit                     11348 non-null  float64
 3   permit_recheck             1000 non-null   float64
 4   handgun                    11350 non-null  float64
 5   long_gun                   11350 non-null  float64
 6   other                      5000 non-null   float64
 7   multiple                   11350 non-null  int64  
 8   admin                      11348 non-null  float64
 9   prepawn_handgun            9597 non-null   float64
 10  prepawn_long_gun           9595 non-null   float64
 11  prepawn_other              4650 non-null   float64
 12  redemption_handgun         9600 non-null   float64
 13  redemption_long_gun        9598 non-null   float64
 14  redemption_other           4650 non-null   float64
 15  returned_handgun           2000 non-null   float64
 16  returned_long_gun          1950 non-null   float64
 17  returned_other             1650 non-null   float64
 18  rentals_handgun            900 non-null    float64
 19  rentals_long_gun           750 non-null    float64
 20  private_sale_handgun       2500 non-null   float64
 21  private_sale_long_gun      2500 non-null   float64
 22  private_sale_other         2500 non-null   float64
 23  return_to_seller_handgun   2250 non-null   float64
 24  return_to_seller_long_gun  2500 non-null   float64
 25  return_to_seller_other     2050 non-null   float64
 26  totals                     11350 non-null  int64  
dtypes: float64(23), int64(2), object(2)
memory usage: 2.4+ MB
```

Tip: You should *not* perform too many operations in each cell. Create cells freely to explore your data. One option that you can take with this project is to do a lot of explorations in an initial notebook. These don't have to be organized, but make sure you use enough comments to understand the purpose of each code cell. Then, after you're done with your analysis, create a duplicate notebook where you will trim the excess and organize your steps so that you have a flowing, cohesive report.

Tip: Make sure that you keep your reader informed on the steps that you are taking in your investigation. Follow every code cell, or every set of related code cells, with a markdown cell to describe to the reader what was found in the preceding cell(s). Try to make it so that the reader can then understand what they will be seeing in the following cell(s).

Data Cleaning

In [262]:
```
# After discussing the structure of the data and any problems that need
 to be
#   cleaned, perform those cleaning steps in the second part of this sec
tion.


# Lets start cleaning process by dropping the unnecessary data points.

df_cesus.drop_duplicates(inplace=True)
sum(df_cesus.duplicated())
```

Out[262]: 0

In [263]:
```
df_gun.drop_duplicates(inplace=True)
sum(df_gun.duplicated())
```

Out[263]: 0

In [264]:
```
'''
A good analysis are with good aesthetics and to get to that, we will hav
e to change the column names into a uniform
case and make it all into lower for convenience
'''

df_cesus.rename(columns = lambda x: x.lower(), inplace=True)
df_cesus.head()
```

Out[264]:

	population estimates, july 1, 2016, (v2016)	population estimates base, april 1, 2010, (v2016)	population, percent change - april 1, 2010 (estimates base) to july 1, 2016, (v2016)	population, census, april 1, 2010	persons under 5 years, percent, july 1, 2016, (v2016)	persons under 5 years, percent, april 1, 2010	persons under 18 years, percent, july 1, 2016, (v2016)	persons under 18 years, percent, april 1, 2010
State								
Alabama	4863300	4780131	0.017	4779736	0.060	0.064	0.226	0.237
Alaska	741894	710249	0.045	710231	0.073	0.076	0.252	0.264
Arizona	6931071	6392301	0.084	6392017	0.063	0.071	0.235	0.255
Arkansas	2988248	2916025	0.025	2915918	0.064	0.068	0.236	0.244
California	39250017	37254522	0.054	37253956	0.063	0.068	0.232	0.250

In [ ]:

In [266]:
```
# Now let us replace NaN with specific string

df_cesus.fillna('No Record', inplace=True)

df_cesus.isnull().any()
```

Out[266]:
```
population estimates, july 1, 2016,  (v2016)
False
population estimates base, april 1, 2010,  (v2016)
False
population, percent change - april 1, 2010 (estimates base) to july 1,
2016,  (v2016)     False
population, census, april 1, 2010
False
persons under 5 years, percent, july 1, 2016,  (v2016)
False
persons under 5 years, percent, april 1, 2010
False
persons under 18 years, percent, july 1, 2016,  (v2016)
False
persons under 18 years, percent, april 1, 2010
False
persons 65 years and over, percent,  july 1, 2016,  (v2016)
False
persons 65 years and over, percent, april 1, 2010
False
female persons, percent,  july 1, 2016,  (v2016)
False
female persons, percent, april 1, 2010
False
white alone, percent, july 1, 2016,  (v2016)
False
black or african american alone, percent, july 1, 2016,  (v2016)
False
american indian and alaska native alone, percent, july 1, 2016,  (v201
6)                  False
asian alone, percent, july 1, 2016,  (v2016)
False
native hawaiian and other pacific islander alone, percent, july 1, 201
6,  (v2016)         False
two or more races, percent, july 1, 2016,  (v2016)
False
hispanic or latino, percent, july 1, 2016,  (v2016)
False
white alone, not hispanic or latino, percent, july 1, 2016,  (v2016)
False
veterans, 2011-2015
False
foreign born persons, percent, 2011-2015
False
housing units,  july 1, 2016,  (v2016)
False
housing units, april 1, 2010
False
owner-occupied housing unit rate, 2011-2015
False
median value of owner-occupied housing units, 2011-2015
False
median selected monthly owner costs -with a mortgage, 2011-2015
False
median selected monthly owner costs -without a mortgage, 2011-2015
False
median gross rent, 2011-2015
```

```
False
building permits, 2016
False
households, 2011-2015
False
persons per household, 2011-2015
False
living in same house 1 year ago, percent of persons age 1 year+, 2011-2
015                  False
language other than english spoken at home, percent of persons age 5 ye
ars+, 2011-2015    False
high school graduate or higher, percent of persons age 25 years+, 2011-
2015                 False
bachelor's degree or higher, percent of persons age 25 years+, 2011-201
5                    False
with a disability, under age 65 years, percent, 2011-2015
False
persons  without health insurance, under age 65 years, percent
False
in civilian labor force, total, percent of population age 16 years+, 20
11-2015              False
in civilian labor force, female, percent of population age 16 years+, 2
011-2015             False
total accommodation and food services sales, 2012 ($1,000)
False
total health care and social assistance receipts/revenue, 2012 ($1,000)
False
total manufacturers shipments, 2012 ($1,000)
False
total merchant wholesaler sales, 2012 ($1,000)
False
total retail sales, 2012 ($1,000)
False
total retail sales per capita, 2012
False
mean travel time to work (minutes), workers age 16 years+, 2011-2015
False
median household income (in 2015 dollars), 2011-2015
False
per capita income in past 12 months (in 2015 dollars), 2011-2015
False
persons in poverty, percent
False
total employer establishments, 2015
False
total employment, 2015
False
total annual payroll, 2015 ($1,000)
False
total employment, percent change, 2014-2015
False
total nonemployer establishments, 2015
False
all firms, 2012
False
men-owned firms, 2012
False
```

```
women-owned firms, 2012
False
minority-owned firms, 2012
False
nonminority-owned firms, 2012
False
veteran-owned firms, 2012
False
nonveteran-owned firms, 2012
False
population per square mile, 2010
False
land area in square miles, 2010
False
fips code
False
dtype: bool
```

In [267]:

```
# Let us do the same thing with df_gun also.

col_gun = df_gun.iloc[:, np.r_[2:7,8:26]].columns

for c in col_gun:
    col_mean = df_gun[c].mean()
    df_gun[c].fillna(col_mean, inplace=True)

df_gun.isnull().any()
```

Out[267]:

```
month                         False
state                         False
permit                        False
permit_recheck                False
handgun                       False
long_gun                      False
other                         False
multiple                      False
admin                         False
prepawn_handgun               False
prepawn_long_gun              False
prepawn_other                 False
redemption_handgun            False
redemption_long_gun           False
redemption_other              False
returned_handgun              False
returned_long_gun             False
returned_other                False
rentals_handgun               False
rentals_long_gun              False
private_sale_handgun          False
private_sale_long_gun         False
private_sale_other            False
return_to_seller_handgun      False
return_to_seller_long_gun     False
return_to_seller_other        False
totals                        False
dtype: bool
```

In [268]:
```
# when we are dealing with dates, to perform any calculations based on i
t, we will need to have them into standard
# format using datetime package

df_gun.month = pd.to_datetime(df_gun['month'], errors='coerce')


df_gun.head()
```

Out[268]:

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple	admin	prepa
0	2017-09-01	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0	
1	2017-09-01	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0	
2	2017-09-01	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0	
3	2017-09-01	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.0	
4	2017-09-01	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0	

In [ ]:

Exploratory Data Analysis

Tip: Now that you've trimmed and cleaned your data, you're ready to move on to exploration. Compute statistics and create visualizations with the goal of addressing the research questions that you posed in the Introduction section. It is recommended that you be systematic with your approach. Look at one variable at a time, and then follow it up by looking at relationships between variables.

Research Question 1 Which state has the highest total purchases in April 2010 and April 2015?

In [144]:
```
'''
For a particular question we want per highest guns and for that we will
 require a specific table so I am creating it
'''



df_gun_q1 = df_gun[['month','state','totals']]


print(df_gun_q1.head())

print('q1 df shape:', df_gun_q1.shape)
```

```
       month       state  totals
0 2017-09-01     Alabama   32019
1 2017-09-01      Alaska    6303
2 2017-09-01     Arizona   28394
3 2017-09-01    Arkansas   17747
4 2017-09-01  California  123506
q1 df shape: (11350, 3)
```

In [145]:
```
df_gun_q1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11350 entries, 0 to 12484
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   month   11350 non-null  datetime64[ns]
 1   state   11350 non-null  object
 2   totals  11350 non-null  int64
dtypes: datetime64[ns](1), int64(1), object(1)
memory usage: 674.7+ KB
```

In [146]:
```
# lets extract 2010 data and 2015 data.

q1_2010 = df_gun_q1[df_gun_q1['month'] == '2010-04-01']
print(q1_2010.head())
print('\n')
q1_2015 = df_gun_q1[df_gun_q1['month'] == '2015-04-01']
print(q1_2015.head())
```

```
           month       state  totals
4895  2010-04-01     Alabama   20791
4896  2010-04-01      Alaska    6411
4897  2010-04-01     Arizona   16578
4898  2010-04-01    Arkansas   14563
4899  2010-04-01  California   80750


           month       state  totals
1595  2015-04-01     Alabama   46971
1596  2015-04-01      Alaska    7030
1597  2015-04-01     Arizona   24762
1598  2015-04-01    Arkansas   17135
1599  2015-04-01  California  114686
```

In [147]:
```
print(q1_2010.describe())
print('\n')
print(q1_2015.describe())
```

```
            totals
count      50.0000
mean    24517.7400
std     34280.1673
min       963.0000
25%      7197.5000
50%     15242.5000
75%     26335.5000
max    211261.0000


              totals
count      50.000000
mean    33925.100000
std     42696.000686
min      1329.000000
25%      9988.500000
50%     20781.500000
75%     37886.000000
max    253890.000000
```

In [148]:
```
q1_join = pd.merge(q1_2010, q1_2015, on='state', how='outer')
```

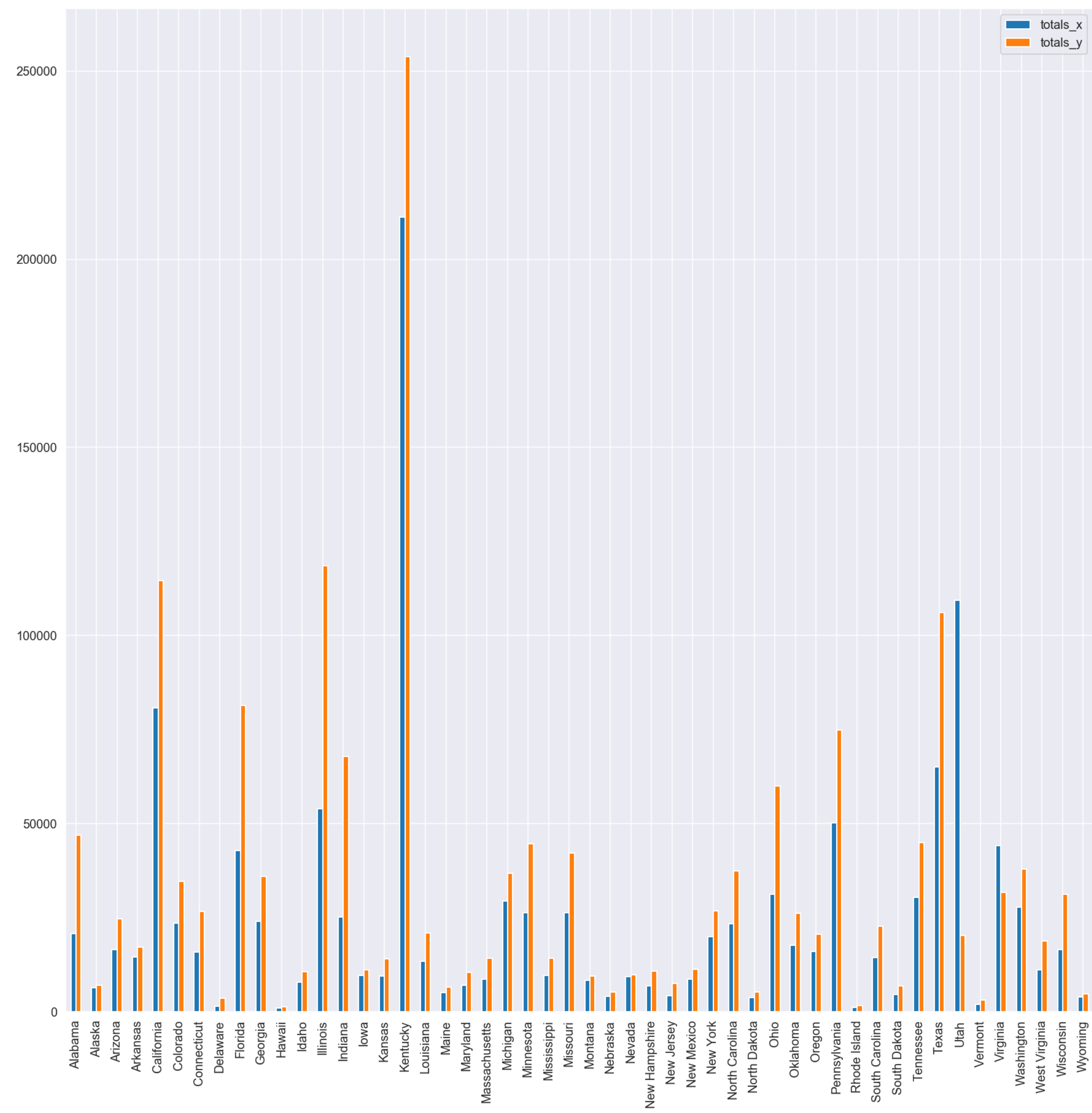
In [149]:
```
q1_join.head()
```

Out[149]:

	month_x	state	totals_x	month_y	totals_y
0	2010-04-01	Alabama	20791	2015-04-01	46971
1	2010-04-01	Alaska	6411	2015-04-01	7030
2	2010-04-01	Arizona	16578	2015-04-01	24762
3	2010-04-01	Arkansas	14563	2015-04-01	17135
4	2010-04-01	California	80750	2015-04-01	114686

In [150]:
```
q1_join.plot(x='state', y=["totals_x","totals_y"], kind='bar', figsize =
(15,15))
```

Out[150]: <matplotlib.axes._subplots.AxesSubplot at 0x1a28a18fd0>



In [275]:
```
kent_2010 = q1_join[q1_join.state =='Kentucky']['totals_x']
kent_2015 = q1_join[q1_join.state =='Kentucky']['totals_y']

print("The number of firearms sold in Kentucky in 2010 is ", kent_2010);
print("The number of firearms sold in Kentucky in 2015 is ", kent_2015);
```

```
The number of firearms sold in Kentucky in 2010 is  16    211261
Name: totals_x, dtype: int64
The number of firearms sold in Kentucky in 2015 is  16    253890
Name: totals_y, dtype: int64
```

Insight:

> When comparing the overall sales of april month in 2010 and 2015, the state of Kentucky has emerged as highest weapons selling state. The difference between sales of 2010 and 2015 in the state of Kentucky is around 41,000 firearms.

Research Question 2:

What is per capita firearm sales for all states in April 2010 vs July 2016?

In [289]:
```
# Continue to explore the data to address your additional research
#   questions. Add more headers as needed if you have more questions to
#   investigate.

''' So now we have a question which will require us data from both df_ce
nsus and df_gun. So we try and get a small
    dataframe with only relevant columns and get the visualization that
 can lead to answer to our question.

'''

q3 = df_gun[['state','month', 'totals']]

q3= q3[q3['month']=='2016-07-01']

q3
```

Out[289]:

	state	month	totals
770	Alabama	2016-07-01	48927
771	Alaska	2016-07-01	6793
772	Arizona	2016-07-01	34496
773	Arkansas	2016-07-01	19378
774	California	2016-07-01	190218
775	Colorado	2016-07-01	43094
776	Connecticut	2016-07-01	29755
777	Delaware	2016-07-01	4494
779	Florida	2016-07-01	125208
780	Georgia	2016-07-01	49183
782	Hawaii	2016-07-01	1565
783	Idaho	2016-07-01	12154
784	Illinois	2016-07-01	168227
785	Indiana	2016-07-01	88340
786	Iowa	2016-07-01	11937
787	Kansas	2016-07-01	14140
788	Kentucky	2016-07-01	363085
789	Louisiana	2016-07-01	41063
790	Maine	2016-07-01	7702
792	Maryland	2016-07-01	12228
793	Massachusetts	2016-07-01	20480
794	Michigan	2016-07-01	40142
795	Minnesota	2016-07-01	43368
796	Mississippi	2016-07-01	21907
797	Missouri	2016-07-01	46637
798	Montana	2016-07-01	9869
799	Nebraska	2016-07-01	5429
800	Nevada	2016-07-01	11785
801	New Hampshire	2016-07-01	13068
802	New Jersey	2016-07-01	10074
803	New Mexico	2016-07-01	12219
804	New York	2016-07-01	29513
805	North Carolina	2016-07-01	44123
806	North Dakota	2016-07-01	5470

	state	month	totals
807	Ohio	2016-07-01	63148
808	Oklahoma	2016-07-01	25946
809	Oregon	2016-07-01	24813
810	Pennsylvania	2016-07-01	86137
812	Rhode Island	2016-07-01	2368
813	South Carolina	2016-07-01	32730
814	South Dakota	2016-07-01	7406
815	Tennessee	2016-07-01	57653
816	Texas	2016-07-01	127207
817	Utah	2016-07-01	17608
818	Vermont	2016-07-01	2674
820	Virginia	2016-07-01	43574
821	Washington	2016-07-01	47887
822	West Virginia	2016-07-01	16791
823	Wisconsin	2016-07-01	38922
824	Wyoming	2016-07-01	4585

In [290]:
```
q3.reset_index(drop=True, inplace=True)   # removed the usual index for
 aesthetics
q3
```

Out[290]:

	state	month	totals
0	Alabama	2016-07-01	48927
1	Alaska	2016-07-01	6793
2	Arizona	2016-07-01	34496
3	Arkansas	2016-07-01	19378
4	California	2016-07-01	190218
5	Colorado	2016-07-01	43094
6	Connecticut	2016-07-01	29755
7	Delaware	2016-07-01	4494
8	Florida	2016-07-01	125208
9	Georgia	2016-07-01	49183
10	Hawaii	2016-07-01	1565
11	Idaho	2016-07-01	12154
12	Illinois	2016-07-01	168227
13	Indiana	2016-07-01	88340
14	Iowa	2016-07-01	11937
15	Kansas	2016-07-01	14140
16	Kentucky	2016-07-01	363085
17	Louisiana	2016-07-01	41063
18	Maine	2016-07-01	7702
19	Maryland	2016-07-01	12228
20	Massachusetts	2016-07-01	20480
21	Michigan	2016-07-01	40142
22	Minnesota	2016-07-01	43368
23	Mississippi	2016-07-01	21907
24	Missouri	2016-07-01	46637
25	Montana	2016-07-01	9869
26	Nebraska	2016-07-01	5429
27	Nevada	2016-07-01	11785
28	New Hampshire	2016-07-01	13068
29	New Jersey	2016-07-01	10074
30	New Mexico	2016-07-01	12219
31	New York	2016-07-01	29513
32	North Carolina	2016-07-01	44123
33	North Dakota	2016-07-01	5470

	state	month	totals
34	Ohio	2016-07-01	63148
35	Oklahoma	2016-07-01	25946
36	Oregon	2016-07-01	24813
37	Pennsylvania	2016-07-01	86137
38	Rhode Island	2016-07-01	2368
39	South Carolina	2016-07-01	32730
40	South Dakota	2016-07-01	7406
41	Tennessee	2016-07-01	57653
42	Texas	2016-07-01	127207
43	Utah	2016-07-01	17608
44	Vermont	2016-07-01	2674
45	Virginia	2016-07-01	43574
46	Washington	2016-07-01	47887
47	West Virginia	2016-07-01	16791
48	Wisconsin	2016-07-01	38922
49	Wyoming	2016-07-01	4585

In [291]:
```
q3['population_july2016'] = df_cesus['population estimates, july 1, 201
6,  (v2016)'].values
q3.head()
```

Out[291]:

	state	month	totals	population_july2016
0	Alabama	2016-07-01	48927	4863300
1	Alaska	2016-07-01	6793	741894
2	Arizona	2016-07-01	34496	6931071
3	Arkansas	2016-07-01	19378	2988248
4	California	2016-07-01	190218	39250017

In [288]:
```
q3_2010_april = df_gun[['state','month', 'totals']]

q3_2010_april = q3_2010_april[q3_2010_april['month']=='2010-04-01']

q3_2010_april.reset_index(drop=True, inplace=True)

q3_2010_april
```

Out[288]:

	state	month	totals
0	Alabama	2010-04-01	20791
1	Alaska	2010-04-01	6411
2	Arizona	2010-04-01	16578
3	Arkansas	2010-04-01	14563
4	California	2010-04-01	80750
5	Colorado	2010-04-01	23609
6	Connecticut	2010-04-01	15922
7	Delaware	2010-04-01	1439
8	Florida	2010-04-01	42794
9	Georgia	2010-04-01	24065
10	Hawaii	2010-04-01	963
11	Idaho	2010-04-01	7814
12	Illinois	2010-04-01	53929
13	Indiana	2010-04-01	25232
14	Iowa	2010-04-01	9720
15	Kansas	2010-04-01	9529
16	Kentucky	2010-04-01	211261
17	Louisiana	2010-04-01	13373
18	Maine	2010-04-01	5073
19	Maryland	2010-04-01	6992
20	Massachusetts	2010-04-01	8748
21	Michigan	2010-04-01	29383
22	Minnesota	2010-04-01	26351
23	Mississippi	2010-04-01	9702
24	Missouri	2010-04-01	26289
25	Montana	2010-04-01	8367
26	Nebraska	2010-04-01	4141
27	Nevada	2010-04-01	9294
28	New Hampshire	2010-04-01	6911
29	New Jersey	2010-04-01	4215
30	New Mexico	2010-04-01	8599
31	New York	2010-04-01	19906
32	North Carolina	2010-04-01	23378
33	North Dakota	2010-04-01	3726

	state	month	totals
34	Ohio	2010-04-01	31312
35	Oklahoma	2010-04-01	17750
36	Oregon	2010-04-01	16031
37	Pennsylvania	2010-04-01	50249
38	Rhode Island	2010-04-01	1199
39	South Carolina	2010-04-01	14441
40	South Dakota	2010-04-01	4561
41	Tennessee	2010-04-01	30453
42	Texas	2010-04-01	65012
43	Utah	2010-04-01	109391
44	Vermont	2010-04-01	2053
45	Virginia	2010-04-01	44137
46	Washington	2010-04-01	27816
47	West Virginia	2010-04-01	11180
48	Wisconsin	2010-04-01	16471
49	Wyoming	2010-04-01	4013

In [292]:

```
q3_2010_april['population_april2010'] = df_cesus['population estimates b
ase, april 1, 2010,  (v2016)'].values
q3_2010_april.head()
```

Out[292]:

	state	month	totals	population_april2010
0	Alabama	2010-04-01	20791	4780131
1	Alaska	2010-04-01	6411	710249
2	Arizona	2010-04-01	16578	6392301
3	Arkansas	2010-04-01	14563	2916025
4	California	2010-04-01	80750	37254522

In [293]:
```
''' we will calulate the per capita percentage by summing all the states
and then try showing a graph of the changed
from 2010 till 2016

'''

q3['total_2010'] = q3_2010_april['totals'].values
q3['population_april2010'] = q3_2010_april['population_april2010'].value
s

q3
```

Out[293]:

	state	month	totals	population_july2016	total_2010	population_april2010
0	Alabama	2016-07-01	48927	4863300	20791	4780131
1	Alaska	2016-07-01	6793	741894	6411	710249
2	Arizona	2016-07-01	34496	6931071	16578	6392301
3	Arkansas	2016-07-01	19378	2988248	14563	2916025
4	California	2016-07-01	190218	39250017	80750	37254522
5	Colorado	2016-07-01	43094	5540545	23609	5029324
6	Connecticut	2016-07-01	29755	3576452	15922	3574114
7	Delaware	2016-07-01	4494	952065	1439	897936
8	Florida	2016-07-01	125208	20612439	42794	18804592
9	Georgia	2016-07-01	49183	10310371	24065	9688680
10	Hawaii	2016-07-01	1565	1428557	963	1360301
11	Idaho	2016-07-01	12154	1683140	7814	1567650
12	Illinois	2016-07-01	168227	12801539	53929	12831574
13	Indiana	2016-07-01	88340	6633053	25232	6484136
14	Iowa	2016-07-01	11937	3134693	9720	3046869
15	Kansas	2016-07-01	14140	2907289	9529	2853129
16	Kentucky	2016-07-01	363085	4436974	211261	4339344
17	Louisiana	2016-07-01	41063	4681666	13373	4533479
18	Maine	2016-07-01	7702	1331479	5073	1328364
19	Maryland	2016-07-01	12228	6016447	6992	5773786
20	Massachusetts	2016-07-01	20480	6811779	8748	6547813
21	Michigan	2016-07-01	40142	9928300	29383	9884129
22	Minnesota	2016-07-01	43368	5519952	26351	5303924
23	Mississippi	2016-07-01	21907	2988726	9702	2968103
24	Missouri	2016-07-01	46637	6093000	26289	5988928
25	Montana	2016-07-01	9869	1042520	8367	989414
26	Nebraska	2016-07-01	5429	1907116	4141	1826334
27	Nevada	2016-07-01	11785	2940058	9294	2700691
28	New Hampshire	2016-07-01	13068	1334795	6911	1316461
29	New Jersey	2016-07-01	10074	8944469	4215	8791953
30	New Mexico	2016-07-01	12219	2081015	8599	2059198
31	New York	2016-07-01	29513	19745289	19906	19378110
32	North Carolina	2016-07-01	44123	10146788	23378	9535688
33	North Dakota	2016-07-01	5470	757952	3726	672591

	state	month	totals	population_july2016	total_2010	population_april2010
34	Ohio	2016-07-01	63148	11614373	31312	11536727
35	Oklahoma	2016-07-01	25946	3923561	17750	3751615
36	Oregon	2016-07-01	24813	4093465	16031	3831072
37	Pennsylvania	2016-07-01	86137	12784227	50249	12702857
38	Rhode Island	2016-07-01	2368	1056426	1199	1052940
39	South Carolina	2016-07-01	32730	4961119	14441	4625410
40	South Dakota	2016-07-01	7406	865454	4561	814195
41	Tennessee	2016-07-01	57653	6651194	30453	6346298
42	Texas	2016-07-01	127207	27862596	65012	25146100
43	Utah	2016-07-01	17608	3051217	109391	2763888
44	Vermont	2016-07-01	2674	624594	2053	625741
45	Virginia	2016-07-01	43574	8411808	44137	8001041
46	Washington	2016-07-01	47887	7288000	27816	6724545
47	West Virginia	2016-07-01	16791	1831102	11180	1853011
48	Wisconsin	2016-07-01	38922	5778708	16471	5687289
49	Wyoming	2016-07-01	4585	585501	4013	563767

In [294]:

```
# Now let us calculate the capita percentage for 2010 and 2016, and we w
ill use it to plot a graph

capita_10 = q3.total_2010.sum()/q3.population_april2010.sum()

print("Per capita firearms for April 2010 is ", capita_10)

capita_16 = q3.totals.sum()/q3.population_july2016.sum()

print("Per capita firearms for July 2016 is ", capita_16)
```

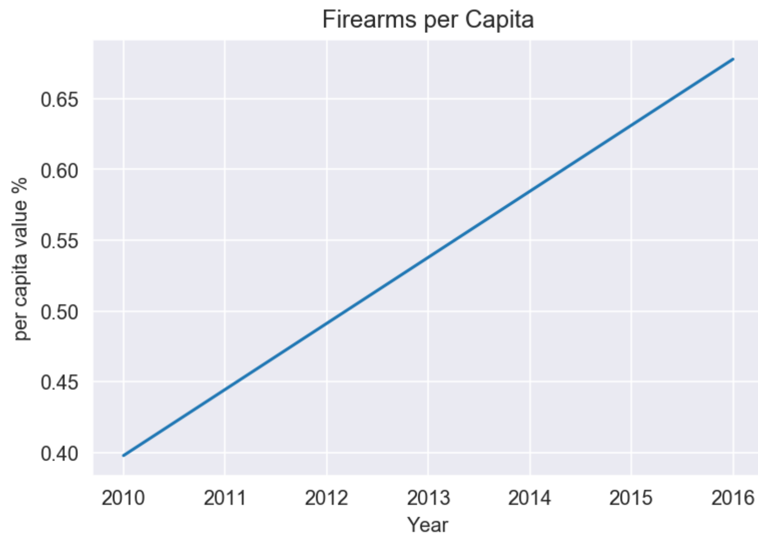
```
Per capita firearms for April 2010 is  0.003978133320178106
Per capita firearms for July 2016 is  0.006777933902633841
```

In [295]:

```
# We see that value upon simple division are too small and we should try
and get percentage values by multiplying
# those values with 100.

capita_10 = capita_10*100
capita_16 = capita_16*100

print("new capita_10: ", capita_10)
print("new capita_16: ", capita_16)
```

```
new capita_10:  0.3978133320178106
new capita_16:  0.677793390263384
```

In [296]:
```
# Now we will try to plot the graph to see the change

years = [2010,2016]
capita_values = [capita_10, capita_16]

plt.title("Firearms per Capita")
plt.xlabel('Year')
plt.ylabel('per capita value %')
plt.plot(years,capita_values)
plt.show()
```



Insights:

> The graph shows us the increase in per capita ownership of firearms. The per-capita value (percentage value) in April 2010 is 0.38 and it goes on to 0.678 in July 2016.
>
> Number of things to be considered for this visual.
>
> - This chart is a nation-wide chart and does give us a birds-eye view.
> - At state level this graph's slope will vary and hence the insights cannot be generalized.
> - Also, we are using 2 point of time (i.e. April 2010 and July 2016), whereas we have no information about how this per capita relationship will vary over the 6 years between 2010 and 2016. Again, this insight cannot be generalized.

In [ ]:

Conclusions

> **Tip**: Finally, summarize your findings and the results that have been performed. Make sure that you are clear with regards to the limitations of your exploration. If you haven't done any statistical tests, do not imply any statistical conclusions. And make sure you avoid implying causation from correlation!
>
> **Tip**: Once you are satisfied with your work here, check over your report to make sure that it is satisfies all the areas of the rubric (found on the project submission page at the end of the lesson). You should also probably remove all of the "Tips" like this one so that the presentation is as polished as possible.

Submitting your Project

> Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).
>
> Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.
>
> Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

In [ ]:

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

In [ ]:

In [ ]: