

FBI_Gun_Date

December 20, 2021

1 Project: Investigate a Dataset - [FBI_Gun_Data]

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Introduction

1.1.1 Dataset Description

In this notebook, we will analyze data for two related data sets:

1- Gun Data (NICS Data), this data comes from the FBI's National Instant Criminal Background Check System, it is a system that contains people who are allowed to own weapons and people who have a criminal history. Our data is columns that contains the number of firearm checks by month, state, type, and totals.

2-Census Data: It contains several variables at the state level.variables may be have one data point per state , or have data for more than one year, columns(fact,fact note,states).

1.1.2 Questions:

- 1- How much growth rate in gun registration in each state?
- 2- What is the over all trend in gun phrchases?
- 3- How many persons are permitted to own gun in last date?
- 4- How many persons are permitted versus not permitted to own gun in Arizona state in last date?
- 5- How much quantity of each types of guns?
- 6- in which state did men owned firms by maximum number of gun in 2012?
- 7- How many gun registered in all states in 2017?
- 8- how many gun registered in each state i 2000?
- 9- What is the average of guns registered in each states since 1998?
- 10- How many guns registered in Texas in 2017?
- 11- What is the total revenue of all fims in all states in 2012?

```
In [1]: #import packages
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import datetime

In [2]: # Upgrade pandas to use dataframe.explode() function.
#!pip install --upgrade pandas==0.25.0
```

Data Wrangling

```
In [3]: # Loading DataFrames
# read_csv to read and load csv file
# read_excel to read and load xlsx file
df_census = pd.read_csv('US_Census_Data.csv')
df_gun = pd.read_excel('gun_data.xlsx')

In [4]: # print out first 5 rows of census data
df_census.head()
```

```
Out[4]:
```

					Fact	Fact	Note	Alabama	\
0	Population estimates, July 1, 2016, (V2016)						NaN	4,863,300	
1	Population estimates base, April 1, 2010, (V2010)						NaN	4,780,131	
2	Population, percent change - April 1, 2010 (estimated)						NaN	1.70%	
3	Population, Census, April 1, 2010						NaN	4,779,736	
4	Persons under 5 years, percent, July 1, 2016, ...						NaN	6.00%	
	Alaska	Arizona	Arkansas	California	Colorado	Connecticut	Delaware	\	
0	741,894	6,931,071	2,988,248	39,250,017	5,540,545	3,576,452	952,065		
1	710,249	6,392,301	2,916,025	37,254,522	5,029,324	3,574,114	897,936		
2	4.50%	8.40%	2.50%	5.40%	10.20%	0.10%	6.00%		
3	710,231	6,392,017	2,915,918	37,253,956	5,029,196	3,574,097	897,934		
4	7.30%	6.30%	6.40%	6.30%	6.10%	5.20%	5.80%		
	...	South Dakota	Tennessee	Texas	Utah	Vermont	Virginia	\	
0	...	865454	6651194	27,862,596	3,051,217	624,594	8,411,808		
1	...	814195	6346298	25,146,100	2,763,888	625,741	8,001,041		
2	...	0.063	0.048	10.80%	10.40%	-0.20%	5.10%		
3	...	814180	6346105	25,145,561	2,763,885	625,741	8,001,024		
4	...	0.071	0.061	7.20%	8.30%	4.90%	6.10%		
	Washington	West Virginia	Wisconsin	Wyoming					
0	7,288,000	1,831,102	5,778,708	585,501					
1	6,724,545	1,853,011	5,687,289	563,767					
2	8.40%	-1.20%	1.60%	3.90%					
3	6,724,540	1,852,994	5,686,986	563,626					
4	6.20%	5.50%	5.80%	6.50%					

[5 rows x 52 columns]

```
In [5]: # info() to show some general information of data
        # there are missing values
        # there are incorrect data types
        # shape(85,52)
        df_census.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85 entries, 0 to 84
Data columns (total 52 columns):
Fact                80 non-null object
Fact Note           28 non-null object
Alabama             65 non-null object
Alaska              65 non-null object
Arizona             65 non-null object
Arkansas            65 non-null object
California           65 non-null object
Colorado            65 non-null object
Connecticut         65 non-null object
Delaware            65 non-null object
Florida             65 non-null object
Georgia             65 non-null object
Hawaii              65 non-null object
Idaho               65 non-null object
Illinois            65 non-null object
Indiana             65 non-null object
Iowa                65 non-null object
Kansas              65 non-null object
Kentucky            65 non-null object
Louisiana           65 non-null object
Maine               65 non-null object
Maryland            65 non-null object
Massachusetts       65 non-null object
Michigan            65 non-null object
Minnesota           65 non-null object
Mississippi         65 non-null object
Missouri            65 non-null object
Montana             65 non-null object
Nebraska            65 non-null object
Nevada              65 non-null object
New Hampshire       65 non-null object
New Jersey          65 non-null object
New Mexico          65 non-null object
New York            65 non-null object
North Carolina      65 non-null object
North Dakota        65 non-null object
Ohio                65 non-null object
Oklahoma            65 non-null object
Oregon              65 non-null object
```

```

Pennsylvania      65 non-null object
Rhode Island      65 non-null object
South Carolina    65 non-null object
South Dakota      65 non-null object
Tennessee         65 non-null object
Texas             65 non-null object
Utah              65 non-null object
Vermont           65 non-null object
Virginia          65 non-null object
Washington        65 non-null object
West Virginia     65 non-null object
Wisconsin         65 non-null object
Wyoming           65 non-null object
dtypes: object(52)
memory usage: 34.6+ KB

```

```

In [6]: # see number of columns that contain missing values (NaN)
        df_census.isnull().any().sum()

```

```

Out[6]: 52

```

```

In [7]: # number of missing values
        df_census.isnull().sum().sum()

```

```

Out[7]: 1062

```

```

In [8]: # which columns have missing and count it
        df_census.isnull().sum()

```

```

Out[8]: Fact      5
        Fact Note  57
        Alabama   20
        Alaska    20
        Arizona   20
        Arkansas  20
        California 20
        Colorado  20
        Connecticut 20
        Delaware  20
        Florida   20
        Georgia   20
        Hawaii    20
        Idaho     20
        Illinois  20
        Indiana   20
        Iowa      20
        Kansas    20
        Kentucky  20

```

```

Louisiana      20
Maine          20
Maryland       20
Massachusetts  20
Michigan       20
Minnesota      20
Mississippi    20
Missouri       20
Montana        20
Nebraska       20
Nevada         20
New Hampshire  20
New Jersey     20
New Mexico     20
New York       20
North Carolina 20
North Dakota   20
Ohio           20
Oklahoma       20
Oregon         20
Pennsylvania   20
Rhode Island   20
South Carolina 20
South Dakota   20
Tennessee     20
Texas          20
Utah           20
Vermont        20
Virginia       20
Washington     20
West Virginia  20
Wisconsin      20
Wyoming        20
dtype: int64

```

```

In [9]: # there are three duplicates values
df_census.duplicated().sum()

```

```

Out[9]: 3

```

```

In [10]: # do the same with df_gun
df_gun.head()

```

```

Out[10]:
   month      state  permit  permit_recheck  handgun  long_gun  other \
0  2017-09  Alabama  16717.0             0.0   5734.0   6320.0  221.0
1  2017-09   Alaska    209.0             2.0   2320.0   2930.0  219.0
2  2017-09  Arizona   5069.0            382.0  11063.0   7946.0  920.0
3  2017-09  Arkansas  2935.0            632.0   4347.0   6063.0  165.0
4  2017-09 California  57839.0             0.0  37165.0  24581.0 2984.0

```

	multiple	admin	prepawn_handgun	...	returned_other	rentals_handgun	\
0	317	0.0	15.0	...	0.0	0.0	
1	160	0.0	5.0	...	0.0	0.0	
2	631	0.0	13.0	...	0.0	0.0	
3	366	51.0	12.0	...	0.0	0.0	
4	0	0.0	0.0	...	0.0	0.0	

	rentals_long_gun	private_sale_handgun	private_sale_long_gun	\
0	0.0	9.0	16.0	
1	0.0	17.0	24.0	
2	0.0	38.0	12.0	
3	0.0	13.0	23.0	
4	0.0	0.0	0.0	

	private_sale_other	return_to_seller_handgun	return_to_seller_long_gun	\
0	3.0	0.0	0.0	
1	1.0	0.0	0.0	
2	2.0	0.0	0.0	
3	0.0	0.0	2.0	
4	0.0	0.0	0.0	

	return_to_seller_other	totals
0	3.0	32019
1	0.0	6303
2	0.0	28394
3	1.0	17747
4	0.0	123506

[5 rows x 27 columns]

```
In [11]: # show general information
# missing values
# incorrect data types
# shape(12485,27)
df_gun.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12485 entries, 0 to 12484
Data columns (total 27 columns):
month                12485 non-null object
state                12485 non-null object
permit              12461 non-null float64
permit_recheck      1100 non-null float64
handgun             12465 non-null float64
long_gun            12466 non-null float64
other                5500 non-null float64
multiple            12485 non-null int64
```

```

admin                12462 non-null float64
prepawn_handgun      10542 non-null float64
prepawn_long_gun     10540 non-null float64
prepawn_other        5115 non-null float64
redemption_handgun   10545 non-null float64
redemption_long_gun  10544 non-null float64
redemption_other     5115 non-null float64
returned_handgun     2200 non-null float64
returned_long_gun    2145 non-null float64
returned_other       1815 non-null float64
rentals_handgun      990 non-null float64
rentals_long_gun     825 non-null float64
private_sale_handgun 2750 non-null float64
private_sale_long_gun 2750 non-null float64
private_sale_other   2750 non-null float64
return_to_seller_handgun 2475 non-null float64
return_to_seller_long_gun 2750 non-null float64
return_to_seller_other 2255 non-null float64
totals               12485 non-null int64
dtypes: float64(23), int64(2), object(2)
memory usage: 2.6+ MB

```

```

In [12]: # number of columns has missing values
df_gun.isnull().any().sum()

```

```

Out[12]: 23

```

```

In [13]: # number of missing values
df_gun.isnull().sum().sum()

```

```

Out[13]: 154595

```

```

In [14]: # which columns contain missing value
df_gun.isnull().sum()

```

```

Out[14]: month                0
state                        0
permit                      24
permit_recheck             11385
handgun                     20
long_gun                    19
other                       6985
multiple                    0
admin                       23
prepawn_handgun             1943
prepawn_long_gun            1945
prepawn_other               7370
redemption_handgun          1940

```

```

redemption_long_gun      1941
redemption_other         7370
returned_handgun         10285
returned_long_gun        10340
returned_other           10670
rentals_handgun          11495
rentals_long_gun         11660
private_sale_handgun      9735
private_sale_long_gun     9735
private_sale_other        9735
return_to_seller_handgun  10010
return_to_seller_long_gun 9735
return_to_seller_other    10230
totals                   0
dtype: int64

```

```

In [15]: # check duplicates value
         # there are no duplicates
         df_gun.duplicated().sum()

```

```

Out[15]: 0

```

1.1.3 Data Cleaning

```

In [16]: # fixing data type
         # we need to convert type of states column in census data from object type to float type
         # but state data separated by (,) then when we try convert this data using extract and a
         # data will converted as minimum float number
         # to solve this we remove sympol like , and % then convert it
         # but astype() method can't convert string to float(its NaN value)
         # first we fill NaN with type of same data because float object has no attribute split
         # after convert, we get NaN again then we fill it again by mean, that is better.

         #for column in df_census.columns[2:]:
         #    df_census[column]=df_census[column].str.extract('(\d+)').astype(float)
         #    df_census[column]= pd.to_numeric(df_census[column],errors='coerce')
         #    df_census[column]=df_census[column].replace(',','').str.extract('(\d)').astype(float)

         df_census.fillna('1,111',inplace=True)

         for column in df_census.columns[2:]:
             df_census[column]=df_census[column].apply(lambda x:x.split()[0].replace(',',''))
             df_census[column]=df_census[column].apply(lambda x:x.split()[0].replace('%',''))
             df_census[column]=df_census[column].str.extract('(\d+)').astype(float)

         df_census.replace('1,111',np.NaN, inplace=True)
         df_census.replace(1111.0, np.NaN, inplace=True)

```



```
In [17]: # confirm changes
df_census.head(66)
```

```
Out[17]:
```

	Fact	\
0	Population estimates, July 1, 2016,	(V2016)
1	Population estimates base, April 1, 2010,	(V2...
2	Population, percent change - April 1, 2010 (es...	
3	Population, Census, April 1, 2010	
4	Persons under 5 years, percent, July 1, 2016, ...	
5	Persons under 5 years, percent, April 1, 2010	
6	Persons under 18 years, percent, July 1, 2016,...	
7	Persons under 18 years, percent, April 1, 2010	
8	Persons 65 years and over, percent, July 1, 2...	
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...	
14	American Indian and Alaska Native alone, perce...	
15	Asian alone, percent, July 1, 2016,	(V2016)
16	Native Hawaiian and Other Pacific Islander alo...	
17	Two or More Races, percent, July 1, 2016,	(V2...
18	Hispanic or Latino, percent, July 1, 2016,	(V...
19	White alone, not Hispanic or Latino, percent, ...	
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, ...	
26	Median selected monthly owner costs -with a mo...	
27	Median selected monthly owner costs -without a...	
28	Median gross rent, 2011-2015	
29	Building permits, 2016	
..	...	
36	With a disability, under age 65 years, percent...	
37	Persons without health insurance, under age 6...	
38	In civilian labor force, total, percent of pop...	
39	In civilian labor force, female, percent of po...	
40	Total accommodation and food services sales, 2...	
41	Total health care and social assistance receip...	
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 ag...	
47	Median household income (in 2015 dollars), 201...	
48	Per capita income in past 12 months (in 2015 d...	

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
65	NaN

	Fact Note	Alabama	Alaska \
0	NaN	4863300.0	741894.0
1	NaN	4780131.0	710249.0
2	NaN	1.0	4.0
3	NaN	4779736.0	710231.0
4	NaN	6.0	7.0
5	NaN	6.0	7.0
6	NaN	22.0	25.0
7	NaN	23.0	26.0
8	NaN	16.0	10.0
9	NaN	13.0	7.0
10	NaN	51.0	47.0
11	NaN	51.0	48.0
12	(a)	69.0	66.0
13	(a)	26.0	3.0
14	(a)	0.0	15.0
15	(a)	1.0	6.0
16	(a)	0.0	1.0
17	NaN	1.0	7.0
18	(b)	4.0	7.0
19	NaN	65.0	61.0
20	NaN	363170.0	69323.0
21	NaN	3.0	7.0
22	NaN	2230185.0	310658.0
23	NaN	2171853.0	306967.0
24	NaN	68.0	63.0
25	NaN	125500.0	250000.0
26	NaN	1139.0	1827.0
27	NaN	345.0	554.0
28	NaN	717.0	1146.0

29		NaN	15001.0	1503.0
..	
36		NaN	11.0	8.0
37		NaN	10.0	15.0
38		NaN	58.0	67.0
39		NaN	53.0	65.0
40		(c)	7576462.0	2221335.0
41		(c)	26039632.0	6375483.0
42		(c)	124809759.0	NaN
43		(c)	57746565.0	5216303.0
44		(c)	58564965.0	10474275.0
45		(c)	12145.0	14320.0
46		NaN	24.0	19.0
47		NaN	43623.0	72515.0
48		NaN	24091.0	33413.0
49		NaN	17.0	9.0
50	Includes data not distributed by county.		98540.0	20907.0
51	Includes data not distributed by county.		1634391.0	267999.0
52	Includes data not distributed by county.		67370353.0	15643303.0
53	Includes data not distributed by county.		1.0	0.0
54		NaN	322025.0	55521.0
55		NaN	374153.0	68032.0
56		NaN	203604.0	35402.0
57		NaN	137630.0	22141.0
58		NaN	92219.0	13688.0
59		NaN	272651.0	51147.0
60		NaN	41943.0	7953.0
61		NaN	316984.0	56091.0
62		NaN	94.0	1.0
63		NaN	50645.0	570640.0
64		NaN	1.0	2.0
65		NaN	NaN	NaN

	Arizona	Arkansas	California	Colorado	Connecticut	\
0	6931071.0	2988248.0	39250017.0	5540545.0	3576452.0	
1	6392301.0	2916025.0	37254522.0	5029324.0	3574114.0	
2	8.0	2.0	5.0	10.0	0.0	
3	6392017.0	2915918.0	37253956.0	5029196.0	3574097.0	
4	6.0	6.0	6.0	6.0	5.0	
5	7.0	6.0	6.0	6.0	5.0	
6	23.0	23.0	23.0	22.0	21.0	
7	25.0	24.0	25.0	24.0	22.0	
8	16.0	16.0	13.0	13.0	16.0	
9	13.0	14.0	11.0	10.0	14.0	
10	50.0	50.0	50.0	49.0	51.0	
11	50.0	50.0	50.0	49.0	51.0	
12	83.0	79.0	72.0	87.0	80.0	
13	4.0	15.0	6.0	4.0	11.0	

14	5.0	1.0	1.0	1.0	0.0
15	3.0	1.0	14.0	3.0	4.0
16	0.0	0.0	0.0	0.0	0.0
17	2.0	2.0	3.0	3.0	2.0
18	30.0	7.0	38.0	21.0	15.0
19	55.0	72.0	37.0	68.0	67.0
20	505794.0	220953.0	1777410.0	391725.0	199331.0
21	13.0	4.0	27.0	9.0	13.0
22	2961003.0	1354762.0	14060525.0	2339118.0	1499116.0
23	2844526.0	1316299.0	13680081.0	2212898.0	1487891.0
24	62.0	66.0	54.0	64.0	67.0
25	167500.0	111400.0	385500.0	247800.0	270500.0
26	1343.0	1019.0	2155.0	1577.0	2067.0
27	380.0	327.0	500.0	419.0	833.0
28	913.0	677.0	1255.0	1002.0	1075.0
29	35578.0	9474.0	102350.0	38974.0	5504.0
..
36	8.0	12.0	6.0	7.0	7.0
37	11.0	9.0	8.0	8.0	5.0
38	59.0	58.0	63.0	67.0	67.0
39	54.0	53.0	57.0	62.0	62.0
40	13996635.0	4307264.0	90830372.0	13617654.0	9542068.0
41	37055881.0	15792628.0	248953592.0	29488161.0	29573119.0
42	51243473.0	62712925.0	512303164.0	50447098.0	55160095.0
43	69437272.0	31256110.0	666652186.0	77034971.0	161962244.0
44	84716542.0	36815256.0	481800461.0	67815200.0	51632467.0
45	12927.0	12483.0	12665.0	13073.0	14381.0
46	24.0	21.0	28.0	24.0	25.0
47	50255.0	41371.0	61818.0	60629.0	70331.0
48	25848.0	22798.0	30318.0	32217.0	38803.0
49	16.0	17.0	14.0	11.0	9.0
50	136352.0	65175.0	908120.0	161737.0	89232.0
51	2295186.0	1003113.0	14325377.0	2253795.0	1503102.0
52	102671393.0	39451191.0	856954246.0	117539555.0	92555072.0
53	2.0	1.0	3.0	3.0	1.0
54	451951.0	198380.0	3206958.0	480847.0	272809.0
55	499926.0	231959.0	3548449.0	547352.0	326693.0
56	245243.0	123158.0	1852580.0	284554.0	187845.0
57	182425.0	75962.0	1320085.0	194508.0	106678.0
58	135313.0	35982.0	1619857.0	85849.0	56113.0
59	344981.0	189029.0	1819107.0	442365.0	259614.0
60	46780.0	25915.0	252377.0	51722.0	31056.0
61	427582.0	192988.0	3176341.0	469524.0	281182.0
62	56.0	56.0	239.0	48.0	738.0
63	113594.0	52035.0	155779.0	103641.0	4842.0
64	4.0	5.0	6.0	8.0	9.0
65	NaN	NaN	NaN	NaN	NaN

	Delaware	...	South Dakota	Tennessee	Texas \
0	952065.0	...	865454.0	6651194.0	27862596.0
1	897936.0	...	814195.0	6346298.0	25146100.0
2	6.0	...	0.0	0.0	10.0
3	897934.0	...	814180.0	6346105.0	25145561.0
4	5.0	...	0.0	0.0	7.0
5	6.0	...	0.0	0.0	7.0
6	21.0	...	0.0	0.0	26.0
7	22.0	...	0.0	0.0	27.0
8	17.0	...	0.0	0.0	12.0
9	14.0	...	0.0	0.0	10.0
10	51.0	...	0.0	0.0	50.0
11	51.0	...	0.0	0.0	50.0
12	70.0	...	0.0	0.0	79.0
13	22.0	...	0.0	0.0	12.0
14	0.0	...	0.0	0.0	1.0
15	4.0	...	0.0	0.0	4.0
16	0.0	...	0.0	0.0	0.0
17	2.0	...	0.0	0.0	1.0
18	9.0	...	0.0	0.0	39.0
19	62.0	...	0.0	0.0	42.0
20	71213.0	...	63742.0	462414.0	1539655.0
21	8.0	...	0.0	0.0	16.0
22	426149.0	...	383838.0	2919671.0	10753629.0
23	405885.0	...	363438.0	2812133.0	9977436.0
24	71.0	...	0.0	0.0	62.0
25	231500.0	...	140500.0	142100.0	136000.0
26	1537.0	...	1210.0	1181.0	1432.0
27	445.0	...	433.0	359.0	460.0
28	1018.0	...	655.0	764.0	882.0
29	5804.0	...	5686.0	36157.0	165853.0
..
36	8.0	...	0.0	0.0	8.0
37	6.0	...	0.0	0.0	18.0
38	63.0	...	0.0	0.0	64.0
39	59.0	...	0.0	0.0	57.0
40	2148437.0	...	1873699.0	12499013.0	54480811.0
41	7003251.0	...	6211731.0	42383683.0	145035130.0
42	22597384.0	...	16882647.0	139960482.0	702603073.0
43	5628914.0	...	20411059.0	111718421.0	691242607.0
44	14456001.0	...	13791827.0	91641605.0	356116376.0
45	15763.0	...	16550.0	14194.0	13666.0
46	25.0	...	16.0	24.0	25.0
47	60509.0	...	50957.0	45219.0	53207.0
48	30554.0	...	26747.0	25227.0	26999.0
49	11.0	...	0.0	0.0	15.0
50	24852.0	...	26511.0	133344.0	569091.0
51	397385.0	...	353540.0	2507205.0	10239710.0

52	21305227.0	...	13812997.0	110481280.0	521095797.0
53	1.0	...	0.0	0.0	3.0
54	60734.0	...	64006.0	495703.0	2205149.0
55	73418.0	...	81314.0	550453.0	2356748.0
56	38328.0	...	42418.0	302249.0	1251696.0
57	23964.0	...	23722.0	195694.0	866678.0
58	14440.0	...	4101.0	105234.0	1070392.0
59	54782.0	...	74228.0	434025.0	1224845.0
60	7206.0	...	8604.0	59379.0	213590.0
61	60318.0	...	66219.0	469392.0	2057218.0
62	460.0	...	10.0	153.0	96.0
63	1948.0	...	75811.0	41234.0	261231.0
64	10.0	...	46.0	47.0	48.0
65	NaN	...	NaN	NaN	NaN

	Utah	Vermont	Virginia	Washington	West Virginia \
0	3051217.0	624594.0	8411808.0	7288000.0	1831102.0
1	2763888.0	625741.0	8001041.0	6724545.0	1853011.0
2	10.0	0.0	5.0	8.0	1.0
3	2763885.0	625741.0	8001024.0	6724540.0	1852994.0
4	8.0	4.0	6.0	6.0	5.0
5	9.0	5.0	6.0	6.0	5.0
6	30.0	19.0	22.0	22.0	20.0
7	31.0	20.0	23.0	23.0	20.0
8	10.0	18.0	14.0	14.0	18.0
9	9.0	14.0	12.0	12.0	16.0
10	49.0	50.0	50.0	50.0	50.0
11	49.0	50.0	50.0	50.0	50.0
12	91.0	94.0	70.0	80.0	93.0
13	1.0	1.0	19.0	4.0	3.0
14	1.0	0.0	0.0	1.0	0.0
15	2.0	1.0	6.0	8.0	0.0
16	1.0	NaN	0.0	0.0	NaN
17	2.0	1.0	2.0	4.0	1.0
18	13.0	1.0	9.0	12.0	1.0
19	78.0	93.0	62.0	69.0	92.0
20	134332.0	44708.0	706539.0	564864.0	150021.0
21	8.0	4.0	11.0	13.0	1.0
22	1054164.0	329525.0	3491054.0	3025685.0	886640.0
23	979709.0	322539.0	3364939.0	2885677.0	881917.0
24	69.0	71.0	66.0	62.0	72.0
25	215900.0	217500.0	245000.0	259500.0	103800.0
26	1428.0	1535.0	1711.0	1731.0	966.0
27	388.0	641.0	433.0	511.0	293.0
28	887.0	895.0	1116.0	1014.0	643.0
29	22662.0	1771.0	31132.0	44077.0	2544.0
..
36	6.0	10.0	7.0	8.0	14.0

37	9.0	4.0	10.0	6.0	6.0
38	67.0	66.0	64.0	63.0	53.0
39	59.0	63.0	60.0	58.0	49.0
40	4789281.0	1564272.0	17795901.0	14297278.0	4036333.0
41	14521857.0	4457996.0	47705003.0	43966889.0	12259395.0
42	50046429.0	9315494.0	96389872.0	131530601.0	24553072.0
43	30927885.0	6450076.0	86613641.0	83313366.0	14295437.0
44	38024486.0	9933751.0	110002385.0	118924049.0	22637923.0
45	13317.0	15868.0	13438.0	17243.0	12201.0
46	21.0	22.0	27.0	26.0	25.0
47	60727.0	55176.0	65015.0	61062.0	41751.0
48	24686.0	29894.0	34152.0	31762.0	23450.0
49	10.0	11.0	11.0	11.0	17.0
50	75463.0	21121.0	197384.0	182913.0	36993.0
51	1203954.0	266363.0	3198718.0	2602408.0	565435.0
52	51453266.0	10615093.0	165788897.0	149258789.0	22159084.0
53	4.0	2.0	1.0	2.0	1.0
54	216280.0	60312.0	576446.0	444135.0	88136.0
55	251419.0	75827.0	653193.0	541522.0	114435.0
56	132163.0	41270.0	353012.0	262650.0	63112.0
57	76269.0	23417.0	236290.0	187677.0	39065.0
58	24423.0	2354.0	185043.0	92807.0	5777.0
59	218826.0	70491.0	450109.0	426697.0	104785.0
60	18754.0	8237.0	76434.0	49331.0	12912.0
61	219807.0	63317.0	548439.0	461401.0	94960.0
62	33.0	67.0	202.0	101.0	77.0
63	82169.0	9216.0	39490.0	66455.0	24038.0
64	49.0	50.0	51.0	53.0	54.0
65	NaN	NaN	NaN	NaN	NaN

	Wisconsin	Wyoming
0	5778708.0	585501.0
1	5687289.0	563767.0
2	1.0	3.0
3	5686986.0	563626.0
4	5.0	6.0
5	6.0	7.0
6	22.0	23.0
7	23.0	24.0
8	16.0	15.0
9	13.0	12.0
10	50.0	48.0
11	50.0	49.0
12	87.0	92.0
13	6.0	1.0
14	1.0	2.0
15	2.0	1.0
16	0.0	0.0

17	1.0	2.0
18	6.0	10.0
19	81.0	84.0
20	381940.0	48505.0
21	4.0	3.0
22	2668444.0	270600.0
23	2624358.0	261868.0
24	67.0	69.0
25	165800.0	194800.0
26	1402.0	1348.0
27	532.0	386.0
28	776.0	789.0
29	19274.0	1727.0
..
36	8.0	8.0
37	6.0	13.0
38	67.0	67.0
39	63.0	62.0
40	10303256.0	1644844.0
41	40680625.0	3291478.0
42	177728926.0	10783794.0
43	77066883.0	5597891.0
44	78201822.0	9446043.0
45	13656.0	16388.0
46	21.0	18.0
47	53357.0	58840.0
48	28340.0	29803.0
49	11.0	11.0
50	139500.0	21040.0
51	2503532.0	219881.0
52	112406494.0	10094010.0
53	2.0	NaN
54	341935.0	48140.0
55	432980.0	62427.0
56	236252.0	30039.0
57	133859.0	19344.0
58	40507.0	4077.0
59	379934.0	55397.0
60	39830.0	6470.0
61	370755.0	51353.0
62	105.0	5.0
63	54157.0	97093.0
64	55.0	56.0
65	NaN	NaN

[66 rows x 52 columns]

In [18]: *# fixing NaN values*


```

# first one to fill numerical NaN with mean
# second one to fill string NaN with any word like non
# and confirm changes
df_census.fillna(df_census.mean(), inplace=True)
df_census.fillna('non',inplace=True)
df_census.isnull().any().sum()

```

Out[18]: 0

```

In [19]: # drop duplicates and confirm changes
df_census.drop_duplicates(inplace=True)
df_census.duplicated().sum()

```

Out[19]: 0

```

In [20]: # convert time in month column to datetime
# confirm changes
df_gun['month'] = pd.to_datetime(df_gun['month'])
df_gun['month'].dtype

```

Out[20]: dtype('<M8[ns]')

```

In [21]: # fixing missing value and confirm changes
df_gun.fillna(df_gun.mean(), inplace=True)
df_gun.isnull().any().sum()

```

Out[21]: 0

```

In [22]: # confirm census data after cleaning
df_census.head(66)

```

```

Out[22]:

```

		Fact \
0	Population estimates, July 1, 2016, (V2016)	
1	Population estimates base, April 1, 2010, (V2...	
2	Population, percent change - April 1, 2010 (es...	
3	Population, Census, April 1, 2010	
4	Persons under 5 years, percent, July 1, 2016, ...	
5	Persons under 5 years, percent, April 1, 2010	
6	Persons under 18 years, percent, July 1, 2016,...	
7	Persons under 18 years, percent, April 1, 2010	
8	Persons 65 years and over, percent, July 1, 2...	
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...	
14	American Indian and Alaska Native alone, perce...	
15	Asian alone, percent, July 1, 2016, (V2016)	
16	Native Hawaiian and Other Pacific Islander alo...	

17 Two or More Races, percent, July 1, 2016, (V2...
 18 Hispanic or Latino, percent, July 1, 2016, (V...
 19 White alone, not Hispanic or Latino, percent, ...
 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, ...
 26 Median selected monthly owner costs -with a mo...
 27 Median selected monthly owner costs -without a...
 28 Median gross rent, 2011-2015
 29 Building permits, 2016
 ..
 36 With a disability, under age 65 years, percent...
 37 Persons without health insurance, under age 6...
 38 In civilian labor force, total, percent of pop...
 39 In civilian labor force, female, percent of po...
 40 Total accommodation and food services sales, 2...
 41 Total health care and social assistance receip...
 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 ag...
 47 Median household income (in 2015 dollars), 201...
 48 Per capita income in past 12 months (in 2015 d...
 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
 65 non

	Fact	Note	Alabama	Alaska \
0		non	4863300.0	7.418940e+05
1		non	4780131.0	7.102490e+05

2	non	1.0	4.000000e+00
3	non	4779736.0	7.102310e+05
4	non	6.0	7.000000e+00
5	non	6.0	7.000000e+00
6	non	22.0	2.500000e+01
7	non	23.0	2.600000e+01
8	non	16.0	1.000000e+01
9	non	13.0	7.000000e+00
10	non	51.0	4.700000e+01
11	non	51.0	4.800000e+01
12	(a)	69.0	6.600000e+01
13	(a)	26.0	3.000000e+00
14	(a)	0.0	1.500000e+01
15	(a)	1.0	6.000000e+00
16	(a)	0.0	1.000000e+00
17	non	1.0	7.000000e+00
18	(b)	4.0	7.000000e+00
19	non	65.0	6.100000e+01
20	non	363170.0	6.932300e+04
21	non	3.0	7.000000e+00
22	non	2230185.0	3.106580e+05
23	non	2171853.0	3.069670e+05
24	non	68.0	6.300000e+01
25	non	125500.0	2.500000e+05
26	non	1139.0	1.827000e+03
27	non	345.0	5.540000e+02
28	non	717.0	1.146000e+03
29	non	15001.0	1.503000e+03
..
36	non	11.0	8.000000e+00
37	non	10.0	1.500000e+01
38	non	58.0	6.700000e+01
39	non	53.0	6.500000e+01
40	(c)	7576462.0	2.221335e+06
41	(c)	26039632.0	6.375483e+06
42	(c)	124809759.0	6.965095e+05
43	(c)	57746565.0	5.216303e+06
44	(c)	58564965.0	1.047428e+07
45	(c)	12145.0	1.432000e+04
46	non	24.0	1.900000e+01
47	non	43623.0	7.251500e+04
48	non	24091.0	3.341300e+04
49	non	17.0	9.000000e+00
50	Includes data not distributed by county.	98540.0	2.090700e+04
51	Includes data not distributed by county.	1634391.0	2.679990e+05
52	Includes data not distributed by county.	67370353.0	1.564330e+07
53	Includes data not distributed by county.	1.0	0.000000e+00
54	non	322025.0	5.552100e+04

55	non	374153.0	6.803200e+04
56	non	203604.0	3.540200e+04
57	non	137630.0	2.214100e+04
58	non	92219.0	1.368800e+04
59	non	272651.0	5.114700e+04
60	non	41943.0	7.953000e+03
61	non	316984.0	5.609100e+04
62	non	94.0	1.000000e+00
63	non	50645.0	5.706400e+05
64	non	1.0	2.000000e+00
65	non	5644810.4	6.965095e+05

	Arizona	Arkansas	California	Colorado	Connecticut \
0	6.931071e+06	2.988248e+06	3.925002e+07	5.540545e+06	3.576452e+06
1	6.392301e+06	2.916025e+06	3.725452e+07	5.029324e+06	3.574114e+06
2	8.000000e+00	2.000000e+00	5.000000e+00	1.000000e+01	0.000000e+00
3	6.392017e+06	2.915918e+06	3.725396e+07	5.029196e+06	3.574097e+06
4	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	5.000000e+00
5	7.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	5.000000e+00
6	2.300000e+01	2.300000e+01	2.300000e+01	2.200000e+01	2.100000e+01
7	2.500000e+01	2.400000e+01	2.500000e+01	2.400000e+01	2.200000e+01
8	1.600000e+01	1.600000e+01	1.300000e+01	1.300000e+01	1.600000e+01
9	1.300000e+01	1.400000e+01	1.100000e+01	1.000000e+01	1.400000e+01
10	5.000000e+01	5.000000e+01	5.000000e+01	4.900000e+01	5.100000e+01
11	5.000000e+01	5.000000e+01	5.000000e+01	4.900000e+01	5.100000e+01
12	8.300000e+01	7.900000e+01	7.200000e+01	8.700000e+01	8.000000e+01
13	4.000000e+00	1.500000e+01	6.000000e+00	4.000000e+00	1.100000e+01
14	5.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00
15	3.000000e+00	1.000000e+00	1.400000e+01	3.000000e+00	4.000000e+00
16	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
17	2.000000e+00	2.000000e+00	3.000000e+00	3.000000e+00	2.000000e+00
18	3.000000e+01	7.000000e+00	3.800000e+01	2.100000e+01	1.500000e+01
19	5.500000e+01	7.200000e+01	3.700000e+01	6.800000e+01	6.700000e+01
20	5.057940e+05	2.209530e+05	1.777410e+06	3.917250e+05	1.993310e+05
21	1.300000e+01	4.000000e+00	2.700000e+01	9.000000e+00	1.300000e+01
22	2.961003e+06	1.354762e+06	1.406052e+07	2.339118e+06	1.499116e+06
23	2.844526e+06	1.316299e+06	1.368008e+07	2.212898e+06	1.487891e+06
24	6.200000e+01	6.600000e+01	5.400000e+01	6.400000e+01	6.700000e+01
25	1.675000e+05	1.114000e+05	3.855000e+05	2.478000e+05	2.705000e+05
26	1.343000e+03	1.019000e+03	2.155000e+03	1.577000e+03	2.067000e+03
27	3.800000e+02	3.270000e+02	5.000000e+02	4.190000e+02	8.330000e+02
28	9.130000e+02	6.770000e+02	1.255000e+03	1.002000e+03	1.075000e+03
29	3.557800e+04	9.474000e+03	1.023500e+05	3.897400e+04	5.504000e+03
...
36	8.000000e+00	1.200000e+01	6.000000e+00	7.000000e+00	7.000000e+00
37	1.100000e+01	9.000000e+00	8.000000e+00	8.000000e+00	5.000000e+00
38	5.900000e+01	5.800000e+01	6.300000e+01	6.700000e+01	6.700000e+01
39	5.400000e+01	5.300000e+01	5.700000e+01	6.200000e+01	6.200000e+01

40	1.399664e+07	4.307264e+06	9.083037e+07	1.361765e+07	9.542068e+06
41	3.705588e+07	1.579263e+07	2.489536e+08	2.948816e+07	2.957312e+07
42	5.124347e+07	6.271292e+07	5.123032e+08	5.044710e+07	5.516010e+07
43	6.943727e+07	3.125611e+07	6.666522e+08	7.703497e+07	1.619622e+08
44	8.471654e+07	3.681526e+07	4.818005e+08	6.781520e+07	5.163247e+07
45	1.292700e+04	1.248300e+04	1.266500e+04	1.307300e+04	1.438100e+04
46	2.400000e+01	2.100000e+01	2.800000e+01	2.400000e+01	2.500000e+01
47	5.025500e+04	4.137100e+04	6.181800e+04	6.062900e+04	7.033100e+04
48	2.584800e+04	2.279800e+04	3.031800e+04	3.221700e+04	3.880300e+04
49	1.600000e+01	1.700000e+01	1.400000e+01	1.100000e+01	9.000000e+00
50	1.363520e+05	6.517500e+04	9.081200e+05	1.617370e+05	8.923200e+04
51	2.295186e+06	1.003113e+06	1.432538e+07	2.253795e+06	1.503102e+06
52	1.026714e+08	3.945119e+07	8.569542e+08	1.175396e+08	9.255507e+07
53	2.000000e+00	1.000000e+00	3.000000e+00	3.000000e+00	1.000000e+00
54	4.519510e+05	1.983800e+05	3.206958e+06	4.808470e+05	2.728090e+05
55	4.999260e+05	2.319590e+05	3.548449e+06	5.473520e+05	3.266930e+05
56	2.452430e+05	1.231580e+05	1.852580e+06	2.845540e+05	1.878450e+05
57	1.824250e+05	7.596200e+04	1.320085e+06	1.945080e+05	1.066780e+05
58	1.353130e+05	3.598200e+04	1.619857e+06	8.584900e+04	5.611300e+04
59	3.449810e+05	1.890290e+05	1.819107e+06	4.423650e+05	2.596140e+05
60	4.678000e+04	2.591500e+04	2.523770e+05	5.172200e+04	3.105600e+04
61	4.275820e+05	1.929880e+05	3.176341e+06	4.695240e+05	2.811820e+05
62	5.600000e+01	5.600000e+01	2.390000e+02	4.800000e+01	7.380000e+02
63	1.135940e+05	5.203500e+04	1.557790e+05	1.036410e+05	4.842000e+03
64	4.000000e+00	5.000000e+00	6.000000e+00	8.000000e+00	9.000000e+00
65	6.042079e+06	3.162765e+06	4.686571e+07	5.907422e+06	6.449429e+06

	Delaware	...	South Dakota	Tennessee	Texas \
0	9.520650e+05	...	8.654540e+05	6.651194e+06	2.786260e+07
1	8.979360e+05	...	8.141950e+05	6.346298e+06	2.514610e+07
2	6.000000e+00	...	0.000000e+00	0.000000e+00	1.000000e+01
3	8.979340e+05	...	8.141800e+05	6.346105e+06	2.514556e+07
4	5.000000e+00	...	0.000000e+00	0.000000e+00	7.000000e+00
5	6.000000e+00	...	0.000000e+00	0.000000e+00	7.000000e+00
6	2.100000e+01	...	0.000000e+00	0.000000e+00	2.600000e+01
7	2.200000e+01	...	0.000000e+00	0.000000e+00	2.700000e+01
8	1.700000e+01	...	0.000000e+00	0.000000e+00	1.200000e+01
9	1.400000e+01	...	0.000000e+00	0.000000e+00	1.000000e+01
10	5.100000e+01	...	0.000000e+00	0.000000e+00	5.000000e+01
11	5.100000e+01	...	0.000000e+00	0.000000e+00	5.000000e+01
12	7.000000e+01	...	0.000000e+00	0.000000e+00	7.900000e+01
13	2.200000e+01	...	0.000000e+00	0.000000e+00	1.200000e+01
14	0.000000e+00	...	0.000000e+00	0.000000e+00	1.000000e+00
15	4.000000e+00	...	0.000000e+00	0.000000e+00	4.000000e+00
16	0.000000e+00	...	0.000000e+00	0.000000e+00	0.000000e+00
17	2.000000e+00	...	0.000000e+00	0.000000e+00	1.000000e+00
18	9.000000e+00	...	0.000000e+00	0.000000e+00	3.900000e+01
19	6.200000e+01	...	0.000000e+00	0.000000e+00	4.200000e+01

20	7.121300e+04	...	6.374200e+04	4.624140e+05	1.539655e+06
21	8.000000e+00	...	0.000000e+00	0.000000e+00	1.600000e+01
22	4.261490e+05	...	3.838380e+05	2.919671e+06	1.075363e+07
23	4.058850e+05	...	3.634380e+05	2.812133e+06	9.977436e+06
24	7.100000e+01	...	0.000000e+00	0.000000e+00	6.200000e+01
25	2.315000e+05	...	1.405000e+05	1.421000e+05	1.360000e+05
26	1.537000e+03	...	1.210000e+03	1.181000e+03	1.432000e+03
27	4.450000e+02	...	4.330000e+02	3.590000e+02	4.600000e+02
28	1.018000e+03	...	6.550000e+02	7.640000e+02	8.820000e+02
29	5.804000e+03	...	5.686000e+03	3.615700e+04	1.658530e+05
..
36	8.000000e+00	...	0.000000e+00	0.000000e+00	8.000000e+00
37	6.000000e+00	...	0.000000e+00	0.000000e+00	1.800000e+01
38	6.300000e+01	...	0.000000e+00	0.000000e+00	6.400000e+01
39	5.900000e+01	...	0.000000e+00	0.000000e+00	5.700000e+01
40	2.148437e+06	...	1.873699e+06	1.249901e+07	5.448081e+07
41	7.003251e+06	...	6.211731e+06	4.238368e+07	1.450351e+08
42	2.259738e+07	...	1.688265e+07	1.399605e+08	7.026031e+08
43	5.628914e+06	...	2.041106e+07	1.117184e+08	6.912426e+08
44	1.445600e+07	...	1.379183e+07	9.164160e+07	3.561164e+08
45	1.576300e+04	...	1.655000e+04	1.419400e+04	1.366600e+04
46	2.500000e+01	...	1.600000e+01	2.400000e+01	2.500000e+01
47	6.050900e+04	...	5.095700e+04	4.521900e+04	5.320700e+04
48	3.055400e+04	...	2.674700e+04	2.522700e+04	2.699900e+04
49	1.100000e+01	...	0.000000e+00	0.000000e+00	1.500000e+01
50	2.485200e+04	...	2.651100e+04	1.333440e+05	5.690910e+05
51	3.973850e+05	...	3.535400e+05	2.507205e+06	1.023971e+07
52	2.130523e+07	...	1.381300e+07	1.104813e+08	5.210958e+08
53	1.000000e+00	...	0.000000e+00	0.000000e+00	3.000000e+00
54	6.073400e+04	...	6.400600e+04	4.957030e+05	2.205149e+06
55	7.341800e+04	...	8.131400e+04	5.504530e+05	2.356748e+06
56	3.832800e+04	...	4.241800e+04	3.022490e+05	1.251696e+06
57	2.396400e+04	...	2.372200e+04	1.956940e+05	8.666780e+05
58	1.444000e+04	...	4.101000e+03	1.052340e+05	1.070392e+06
59	5.478200e+04	...	7.422800e+04	4.340250e+05	1.224845e+06
60	7.206000e+03	...	8.604000e+03	5.937900e+04	2.135900e+05
61	6.031800e+04	...	6.621900e+04	4.693920e+05	2.057218e+06
62	4.600000e+02	...	1.000000e+01	1.530000e+02	9.600000e+01
63	1.948000e+03	...	7.581100e+04	4.123400e+04	2.612310e+05
64	1.000000e+01	...	4.600000e+01	4.700000e+01	4.800000e+01
65	1.203696e+06	...	1.195122e+06	8.342865e+06	4.004406e+07

	Utah	Vermont	Virginia	Washington	West Virginia \
0	3.051217e+06	6.245940e+05	8.411808e+06	7.288000e+06	1.831102e+06
1	2.763888e+06	6.257410e+05	8.001041e+06	6.724545e+06	1.853011e+06
2	1.000000e+01	0.000000e+00	5.000000e+00	8.000000e+00	1.000000e+00
3	2.763885e+06	6.257410e+05	8.001024e+06	6.724540e+06	1.852994e+06
4	8.000000e+00	4.000000e+00	6.000000e+00	6.000000e+00	5.000000e+00

5	9.000000e+00	5.000000e+00	6.000000e+00	6.000000e+00	5.000000e+00
6	3.000000e+01	1.900000e+01	2.200000e+01	2.200000e+01	2.000000e+01
7	3.100000e+01	2.000000e+01	2.300000e+01	2.300000e+01	2.000000e+01
8	1.000000e+01	1.800000e+01	1.400000e+01	1.400000e+01	1.800000e+01
9	9.000000e+00	1.400000e+01	1.200000e+01	1.200000e+01	1.600000e+01
10	4.900000e+01	5.000000e+01	5.000000e+01	5.000000e+01	5.000000e+01
11	4.900000e+01	5.000000e+01	5.000000e+01	5.000000e+01	5.000000e+01
12	9.100000e+01	9.400000e+01	7.000000e+01	8.000000e+01	9.300000e+01
13	1.000000e+00	1.000000e+00	1.900000e+01	4.000000e+00	3.000000e+00
14	1.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	0.000000e+00
15	2.000000e+00	1.000000e+00	6.000000e+00	8.000000e+00	0.000000e+00
16	1.000000e+00	7.208260e+05	0.000000e+00	0.000000e+00	1.710532e+06
17	2.000000e+00	1.000000e+00	2.000000e+00	4.000000e+00	1.000000e+00
18	1.300000e+01	1.000000e+00	9.000000e+00	1.200000e+01	1.000000e+00
19	7.800000e+01	9.300000e+01	6.200000e+01	6.900000e+01	9.200000e+01
20	1.343320e+05	4.470800e+04	7.065390e+05	5.648640e+05	1.500210e+05
21	8.000000e+00	4.000000e+00	1.100000e+01	1.300000e+01	1.000000e+00
22	1.054164e+06	3.295250e+05	3.491054e+06	3.025685e+06	8.866400e+05
23	9.797090e+05	3.225390e+05	3.364939e+06	2.885677e+06	8.819170e+05
24	6.900000e+01	7.100000e+01	6.600000e+01	6.200000e+01	7.200000e+01
25	2.159000e+05	2.175000e+05	2.450000e+05	2.595000e+05	1.038000e+05
26	1.428000e+03	1.535000e+03	1.711000e+03	1.731000e+03	9.660000e+02
27	3.880000e+02	6.410000e+02	4.330000e+02	5.110000e+02	2.930000e+02
28	8.870000e+02	8.950000e+02	1.116000e+03	1.014000e+03	6.430000e+02
29	2.266200e+04	1.771000e+03	3.113200e+04	4.407700e+04	2.544000e+03
..
36	6.000000e+00	1.000000e+01	7.000000e+00	8.000000e+00	1.400000e+01
37	9.000000e+00	4.000000e+00	1.000000e+01	6.000000e+00	6.000000e+00
38	6.700000e+01	6.600000e+01	6.400000e+01	6.300000e+01	5.300000e+01
39	5.900000e+01	6.300000e+01	6.000000e+01	5.800000e+01	4.900000e+01
40	4.789281e+06	1.564272e+06	1.779590e+07	1.429728e+07	4.036333e+06
41	1.452186e+07	4.457996e+06	4.770500e+07	4.396689e+07	1.225940e+07
42	5.004643e+07	9.315494e+06	9.638987e+07	1.315306e+08	2.455307e+07
43	3.092788e+07	6.450076e+06	8.661364e+07	8.331337e+07	1.429544e+07
44	3.802449e+07	9.933751e+06	1.100024e+08	1.189240e+08	2.263792e+07
45	1.331700e+04	1.586800e+04	1.343800e+04	1.724300e+04	1.220100e+04
46	2.100000e+01	2.200000e+01	2.700000e+01	2.600000e+01	2.500000e+01
47	6.072700e+04	5.517600e+04	6.501500e+04	6.106200e+04	4.175100e+04
48	2.468600e+04	2.989400e+04	3.415200e+04	3.176200e+04	2.345000e+04
49	1.000000e+01	1.100000e+01	1.100000e+01	1.100000e+01	1.700000e+01
50	7.546300e+04	2.112100e+04	1.973840e+05	1.829130e+05	3.699300e+04
51	1.203954e+06	2.663630e+05	3.198718e+06	2.602408e+06	5.654350e+05
52	5.145327e+07	1.061509e+07	1.657889e+08	1.492588e+08	2.215908e+07
53	4.000000e+00	2.000000e+00	1.000000e+00	2.000000e+00	1.000000e+00
54	2.162800e+05	6.031200e+04	5.764460e+05	4.441350e+05	8.813600e+04
55	2.514190e+05	7.582700e+04	6.531930e+05	5.415220e+05	1.144350e+05
56	1.321630e+05	4.127000e+04	3.530120e+05	2.626500e+05	6.311200e+04
57	7.626900e+04	2.341700e+04	2.362900e+05	1.876770e+05	3.906500e+04

58	2.442300e+04	2.354000e+03	1.850430e+05	9.280700e+04	5.777000e+03
59	2.188260e+05	7.049100e+04	4.501090e+05	4.266970e+05	1.047850e+05
60	1.875400e+04	8.237000e+03	7.643400e+04	4.933100e+04	1.291200e+04
61	2.198070e+05	6.331700e+04	5.484390e+05	4.614010e+05	9.496000e+04
62	3.300000e+01	6.700000e+01	2.020000e+02	1.010000e+02	7.700000e+01
63	8.216900e+04	9.216000e+03	3.949000e+04	6.645500e+04	2.403800e+04
64	4.900000e+01	5.000000e+01	5.100000e+01	5.300000e+01	5.400000e+01
65	3.142726e+06	7.208260e+05	8.711424e+06	8.875524e+06	1.710532e+06

	Wisconsin	Wyoming
0	5.778708e+06	5.855010e+05
1	5.687289e+06	5.637670e+05
2	1.000000e+00	3.000000e+00
3	5.686986e+06	5.636260e+05
4	5.000000e+00	6.000000e+00
5	6.000000e+00	7.000000e+00
6	2.200000e+01	2.300000e+01
7	2.300000e+01	2.400000e+01
8	1.600000e+01	1.500000e+01
9	1.300000e+01	1.200000e+01
10	5.000000e+01	4.800000e+01
11	5.000000e+01	4.900000e+01
12	8.700000e+01	9.200000e+01
13	6.000000e+00	1.000000e+00
14	1.000000e+00	2.000000e+00
15	2.000000e+00	1.000000e+00
16	0.000000e+00	0.000000e+00
17	1.000000e+00	2.000000e+00
18	6.000000e+00	1.000000e+01
19	8.100000e+01	8.400000e+01
20	3.819400e+05	4.850500e+04
21	4.000000e+00	3.000000e+00
22	2.668444e+06	2.706000e+05
23	2.624358e+06	2.618680e+05
24	6.700000e+01	6.900000e+01
25	1.658000e+05	1.948000e+05
26	1.402000e+03	1.348000e+03
27	5.320000e+02	3.860000e+02
28	7.760000e+02	7.890000e+02
29	1.927400e+04	1.727000e+03
..
36	8.000000e+00	8.000000e+00
37	6.000000e+00	1.300000e+01
38	6.700000e+01	6.700000e+01
39	6.300000e+01	6.200000e+01
40	1.030326e+07	1.644844e+06
41	4.068062e+07	3.291478e+06
42	1.777289e+08	1.078379e+07


```

43  7.706688e+07  5.597891e+06
44  7.820182e+07  9.446043e+06
45  1.365600e+04  1.638800e+04
46  2.100000e+01  1.800000e+01
47  5.335700e+04  5.884000e+04
48  2.834000e+04  2.980300e+04
49  1.100000e+01  1.100000e+01
50  1.395000e+05  2.104000e+04
51  2.503532e+06  2.198810e+05
52  1.124065e+08  1.009401e+07
53  2.000000e+00  6.921724e+05
54  3.419350e+05  4.814000e+04
55  4.329800e+05  6.242700e+04
56  2.362520e+05  3.003900e+04
57  1.338590e+05  1.934400e+04
58  4.050700e+04  4.077000e+03
59  3.799340e+05  5.539700e+04
60  3.983000e+04  6.470000e+03
61  3.707550e+05  5.135300e+04
62  1.050000e+02  5.000000e+00
63  5.415700e+04  9.709300e+04
64  5.500000e+01  5.600000e+01
65  8.099572e+06  6.921724e+05

```

[66 rows x 52 columns]

```

In [23]: # confirm nics data after cleaning
df_gun.head()

```

```

Out[23]:      month      state  permit  permit_recheck  handgun  long_gun  other  \
0  2017-09-01    Alabama  16717.0           0.0    5734.0    6320.0    221.0
1  2017-09-01     Alaska    209.0           2.0    2320.0    2930.0    219.0
2  2017-09-01    Arizona   5069.0          382.0   11063.0    7946.0    920.0
3  2017-09-01   Arkansas   2935.0          632.0    4347.0    6063.0    165.0
4  2017-09-01  California  57839.0           0.0   37165.0   24581.0   2984.0

      multiple  admin  prepawn_handgun  ...  returned_other  rentals_handgun  \
0         317    0.0           15.0  ...           0.0           0.0
1         160    0.0           5.0  ...           0.0           0.0
2         631    0.0          13.0  ...           0.0           0.0
3         366   51.0          12.0  ...           0.0           0.0
4           0    0.0           0.0  ...           0.0           0.0

      rentals_long_gun  private_sale_handgun  private_sale_long_gun  \
0           0.0           9.0           16.0
1           0.0          17.0           24.0
2           0.0          38.0           12.0
3           0.0          13.0           23.0

```

```

4          0.0          0.0          0.0

    private_sale_other  return_to_seller_handgun  return_to_seller_long_gun  \
0          3.0          0.0          0.0
1          1.0          0.0          0.0
2          2.0          0.0          0.0
3          0.0          0.0          2.0
4          0.0          0.0          0.0

    return_to_seller_other  totals
0          3.0    32019
1          0.0    6303
2          0.0    28394
3          1.0    17747
4          0.0   123506

```

[5 rows x 27 columns]

```

In [24]: # show some general properties
df_census.describe()

```

```

Out[24]:

```

	Alabama	Alaska	Arizona	Arkansas	California	
count	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01	
mean	5.644810e+06	6.965095e+05	6.042079e+06	3.162765e+06	4.686571e+07	
std	1.778849e+07	2.217958e+06	1.739900e+07	9.604165e+06	1.408072e+08	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	
25%	2.325000e+01	2.050000e+01	2.625000e+01	2.150000e+01	3.250000e+01	
50%	4.713400e+04	2.152400e+04	8.192450e+04	3.867650e+04	2.040780e+05	
75%	5.644810e+06	6.965095e+05	6.042079e+06	3.162765e+06	4.686571e+07	
max	1.248098e+08	1.564330e+07	1.026714e+08	6.271292e+07	8.569542e+08	

	Colorado	Connecticut	Delaware	Florida	Georgia	
count	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01	
mean	5.907422e+06	6.449429e+06	1.203696e+06	1.905439e+07	1.101339e+07	
std	1.784105e+07	2.189089e+07	3.797209e+06	5.638734e+07	3.246234e+07	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	
25%	2.400000e+01	2.275000e+01	2.275000e+01	2.625000e+01	2.725000e+01	
50%	7.323900e+04	4.745800e+04	1.986350e+04	1.376200e+05	7.715000e+04	
75%	5.907422e+06	6.449429e+06	1.203696e+06	1.905439e+07	1.101339e+07	
max	1.175396e+08	1.619622e+08	2.259738e+07	3.370745e+08	1.748394e+08	

	...	South Dakota	Tennessee	Texas	Utah	
count	...	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01	
mean	...	1.195122e+06	8.342865e+06	4.004406e+07	3.142726e+06	
std	...	3.573824e+06	2.490916e+07	1.262991e+08	9.412073e+06	
min	...	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	
25%	...	0.000000e+00	0.000000e+00	3.600000e+01	3.100000e+01	
50%	...	2.511650e+04	5.229900e+04	1.897215e+05	4.270650e+04	

75%	...	1.195122e+06	8.342865e+06	4.004406e+07	3.142726e+06
max	...	2.041106e+07	1.399605e+08	7.026031e+08	5.145327e+07

	Vermont	Virginia	Washington	West Virginia	Wisconsin \
count	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01	8.200000e+01
mean	7.208260e+05	8.711424e+06	8.875524e+06	1.710532e+06	8.099572e+06
std	2.019675e+06	2.588748e+07	2.672587e+07	4.717679e+06	2.579573e+07
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	3.950000e+01	2.925000e+01	2.750000e+01	3.100000e+01	2.400000e+01
50%	2.226900e+04	7.072450e+04	6.375850e+04	3.051550e+04	4.693200e+04
75%	7.208260e+05	8.711424e+06	8.875524e+06	1.710532e+06	8.099572e+06
max	1.061509e+07	1.657889e+08	1.492588e+08	2.455307e+07	1.777289e+08

	Wyoming
count	8.200000e+01
mean	6.921724e+05
std	1.996627e+06
min	0.000000e+00
25%	2.425000e+01
50%	2.542150e+04
75%	6.921724e+05
max	1.078379e+07

[8 rows x 50 columns]

In [25]: *# show some general properties*
df_gun.describe()

Out[25]:

	permit	permit_recheck	handgun	long_gun \
count	12485.000000	12485.000000	12485.000000	12485.000000
mean	6413.629404	1165.956364	5940.881107	7810.847585
std	23729.495816	2736.848174	8611.677589	9302.758891
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	1165.956364	868.000000	2079.000000
50%	522.000000	1165.956364	3067.000000	5130.000000
75%	4338.000000	1165.956364	7277.000000	10374.000000
max	522188.000000	116681.000000	107224.000000	108058.000000

	other	multiple	admin	prepawn_handgun \
count	12485.000000	12485.000000	12485.000000	12485.000000
mean	360.471636	268.603364	58.898090	4.828021
std	895.634628	783.185073	604.257419	10.023040
min	0.000000	0.000000	0.000000	0.000000
25%	163.000000	15.000000	0.000000	0.000000
50%	360.471636	125.000000	0.000000	1.000000
75%	360.471636	301.000000	0.000000	4.828021
max	77929.000000	38907.000000	28083.000000	164.000000

	prepawn_long_gun	prepawn_other	...	returned_other \
count	12485.000000	12485.000000	...	12485.000000
mean	7.834156	0.165591	...	1.027548
std	15.130888	0.676584	...	1.672013
min	0.000000	0.000000	...	0.000000
25%	0.000000	0.000000	...	1.027548
50%	3.000000	0.165591	...	1.027548
75%	7.834156	0.165591	...	1.027548
max	269.000000	49.000000	...	64.000000

	rentals_handgun	rentals_long_gun	private_sale_handgun \
count	12485.000000	12485.000000	12485.000000
mean	0.076768	0.087273	14.936000
std	0.178589	0.172556	33.418596
min	0.000000	0.000000	0.000000
25%	0.076768	0.087273	14.936000
50%	0.076768	0.087273	14.936000
75%	0.076768	0.087273	14.936000
max	12.000000	12.000000	1017.000000

	private_sale_long_gun	private_sale_other	return_to_seller_handgun \
count	12485.000000	12485.000000	12485.000000
mean	11.602909	1.030182	0.402020
std	25.458626	2.096565	0.643964
min	0.000000	0.000000	0.000000
25%	11.602909	1.030182	0.402020
50%	11.602909	1.030182	0.402020
75%	11.602909	1.030182	0.402020
max	777.000000	71.000000	28.000000

	return_to_seller_long_gun	return_to_seller_other	totals
count	12485.000000	12485.000000	12485.000000
mean	0.441818	0.105987	21595.725911
std	0.717129	0.181592	32591.418387
min	0.000000	0.000000	0.000000
25%	0.441818	0.105987	4638.000000
50%	0.441818	0.105987	12399.000000
75%	0.441818	0.105987	25453.000000
max	17.000000	4.000000	541978.000000

[8 rows x 25 columns]

```
In [26]: # show data in Fact column
df_census['Fact']
```

```
Out[26]: 0      Population estimates, July 1, 2016, (V2016)
1      Population estimates base, April 1, 2010, (V2...
2      Population, percent change - April 1, 2010 (es...
```

3 Population, Census, April 1, 2010
 4 Persons under 5 years, percent, July 1, 2016, ...
 5 Persons under 5 years, percent, April 1, 2010
 6 Persons under 18 years, percent, July 1, 2016,...
 7 Persons under 18 years, percent, April 1, 2010
 8 Persons 65 years and over, percent, July 1, 2...
 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...
 14 American Indian and Alaska Native alone, perce...
 15 Asian alone, percent, July 1, 2016, (V2016)
 16 Native Hawaiian and Other Pacific Islander alo...
 17 Two or More Races, percent, July 1, 2016, (V2...
 18 Hispanic or Latino, percent, July 1, 2016, (V...
 19 White alone, not Hispanic or Latino, percent, ...
 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, ...
 26 Median selected monthly owner costs -with a mo...
 27 Median selected monthly owner costs -without a...
 28 Median gross rent, 2011-2015
 29 Building permits, 2016
 ...
 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
 65 non
 66 NOTE: FIPS Code values are enclosed in quotes ...
 67 Value Notes
 68 1
 69 Fact Notes
 70 (a)
 71 (b)

```

74                                     (c)
75                                     Value Flags
76                                     -
77                                     D
78                                     F
79                                     FN
80                                     non
81                                     S
82                                     X
83                                     Z
84
Name: Fact, Length: 82, dtype: object

```

```

In [27]: # check columns in df_gun to understand data
df_gun.columns

```

```

Out[27]: Index(['month', 'state', 'permit', 'permit_recheck', 'handgun', 'long_gun',
               'other', 'multiple', 'admin', 'prepawn_handgun', 'prepawn_long_gun',
               'prepawn_other', 'redemption_handgun', 'redemption_long_gun',
               'redemption_other', 'returned_handgun', 'returned_long_gun',
               'returned_other', 'rentals_handgun', 'rentals_long_gun',
               'private_sale_handgun', 'private_sale_long_gun', 'private_sale_other',
               'return_to_seller_handgun', 'return_to_seller_long_gun',
               'return_to_seller_other', 'totals'],
              dtype='object')

```

Exploratory Data Analysis

```

In [28]: # summary(it takes long time but you can run it !!!!)

```

```

# pd.plotting.scatter_matrix(df_gun, figsize=(50,50));

```

Research Question 1 (How much growth in gun registration in each state?)

```

In [29]: # grouped data by month, state to show total registration
filt = df_gun.groupby(['month', 'state'])['totals'].sum()

```

```

In [30]: # calculate growth rating by subtract total registration in current date from total reg
growth = filt.loc[df_gun['month'].max()] - filt.loc[df_gun['month'].min()]

```

```

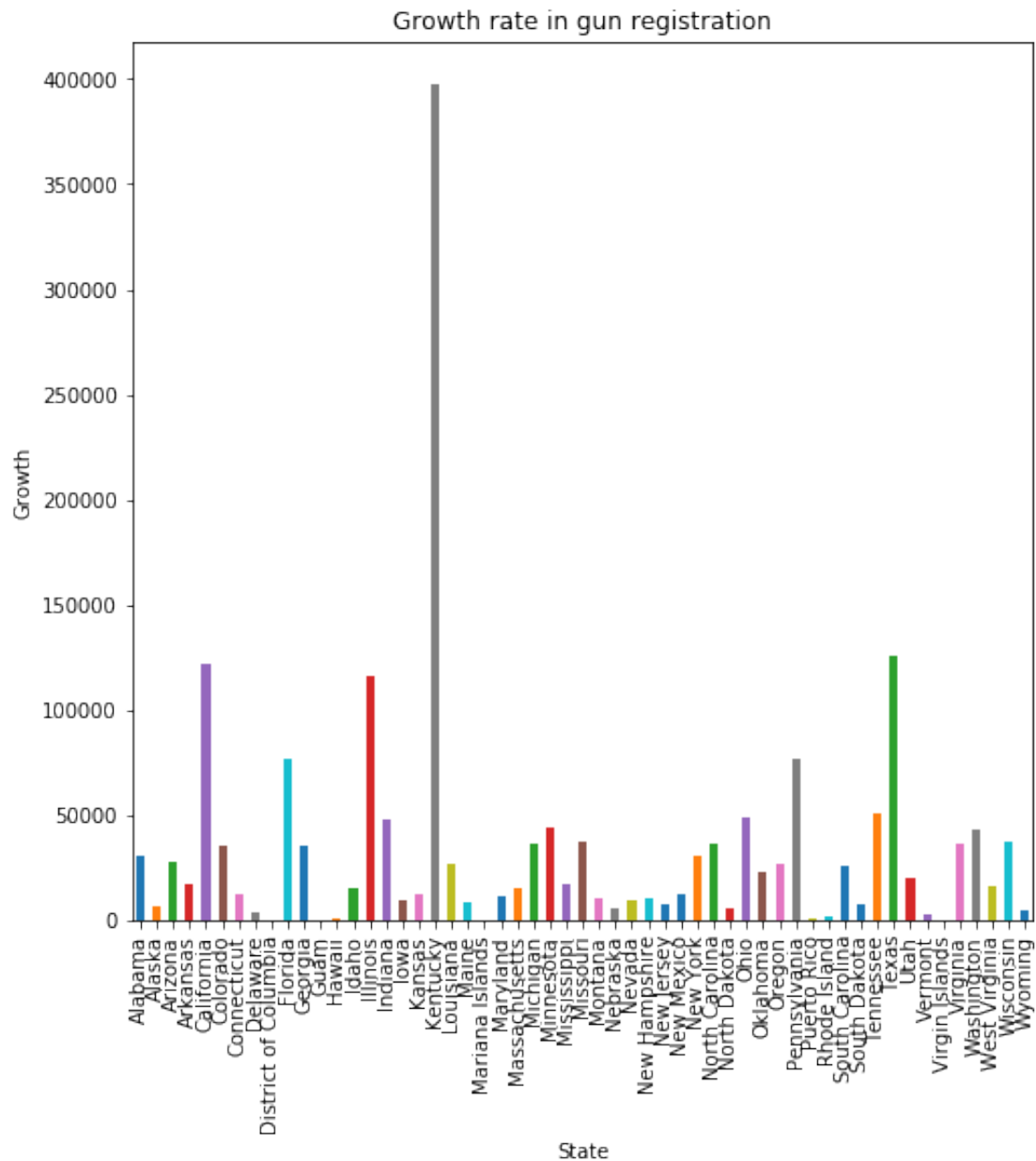
In [31]: # visualize result
growth_plot = growth.plot(kind='bar', figsize=(8,8), title='Growth rate in gun registra
growth_plot.set_xlabel('State')
growth_plot.set_ylabel('Growth')

```

```

Out[31]: Text(0,0.5,'Growth')

```



```
In [32]: # show max and min growth
         growth[growth==growth.max()],growth[growth==growth.min()]
```

```
Out[32]: (state
          Kentucky      397866
          Name: totals, dtype: int64, state
          Virgin Islands    9
          Name: totals, dtype: int64)
```

Maximum growth registration in (Kentucky) equal (397866)

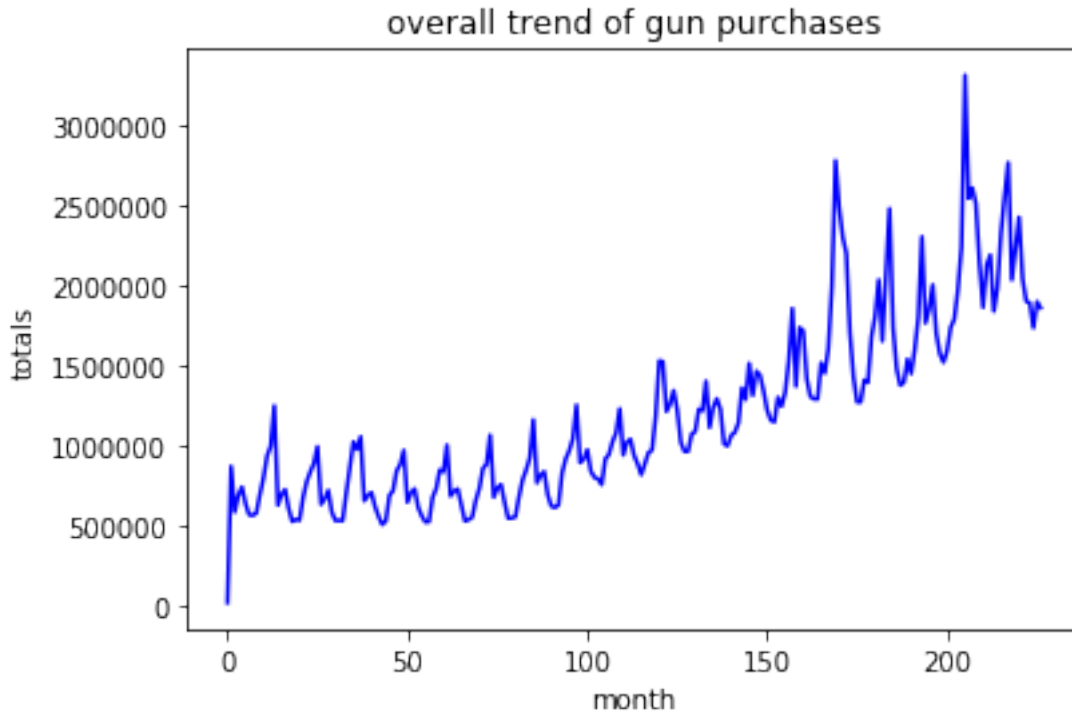
Minimum growth registration in (Virgin) equal (9)

Research Question 2 (what is the overall trend of gun purchases?)

```
In [33]: # grouped data to show totals respect month
df_gun_trend = df_gun.groupby('month')['totals'].sum()
#df_gun.month.dt.year.unique()

In [34]: # visualize result using matplotlib
ind = np.arange(len(df_gun_trend))

plt.plot(ind,df_gun_trend, color='blue')
plt.title('overall trend of gun purchases')
plt.ylabel('totals')
plt.xlabel('month')
plt(figsize=(10,10))
```



overall trend of purchases is constantly increasing.

Research Question 3 (how many persons are permitted to own gun in last date)

```
In [35]: # see last date
df_gun.month.max()

Out[35]: Timestamp('2017-09-01 00:00:00')
```



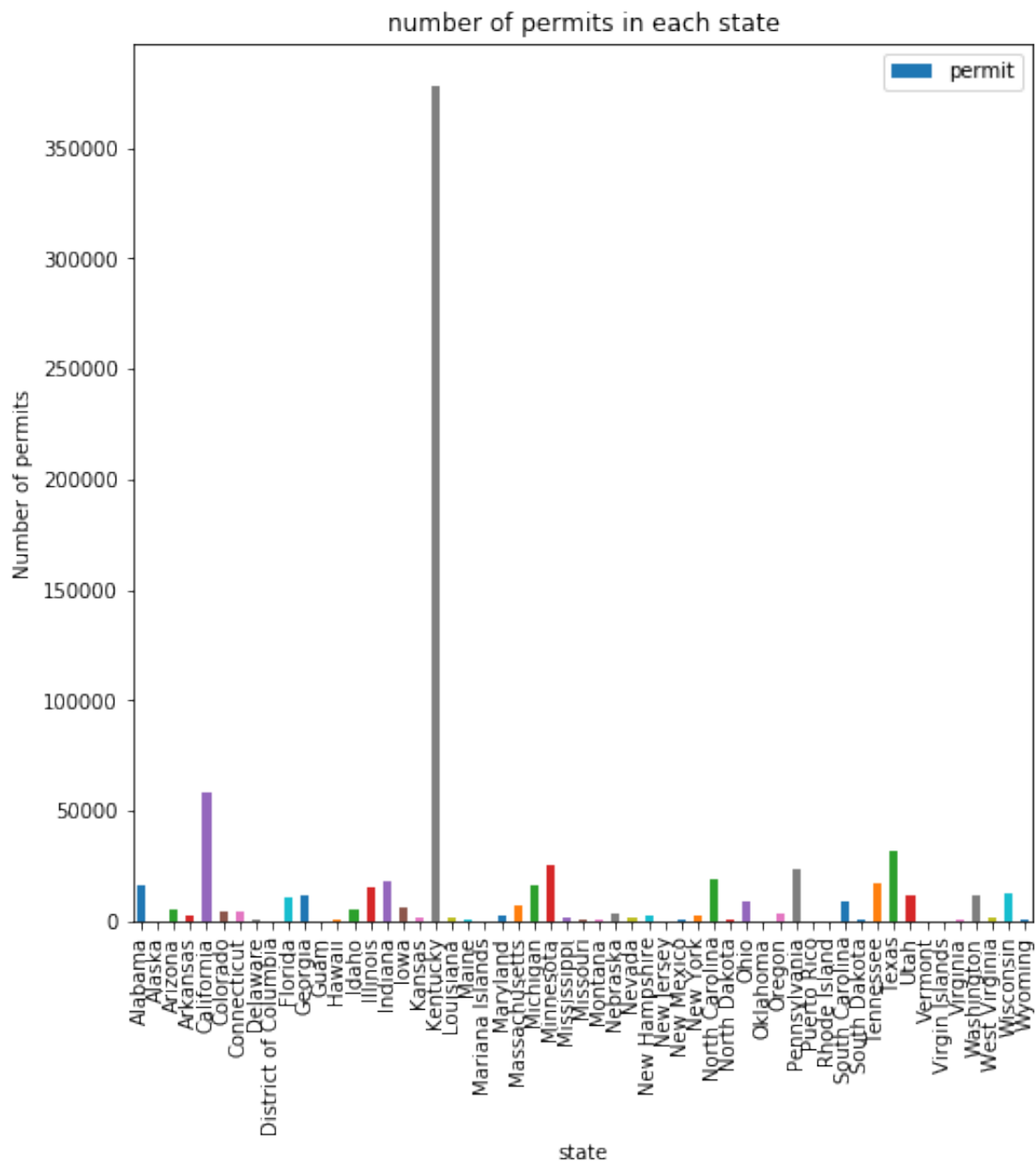
```

In [36]: # filter data by last date
df_permit = df_gun.query('month == "2017-09"')[['permit', 'permit_recheck', 'state']]

In [37]: # visualize result
permit_plot = df_permit.plot(x='state', y='permit', kind='bar', figsize=(8,8), title='num
permit_plot.set_ylabel('Number of permits')

Out[37]: Text(0,0.5,'Number of permits')

```



```

In [38]: # how many permitted in all state except Kentucky state
df_permit.permit.sum() - df_permit.permit.max()

```

```
Out[38]: 383238.0
```

Kentucky state has high permit.

persons permitted to own gun in (Kentucky state) equal to approximately person permitted to own gun in (ALL) other states

Research Question 4 (How many persons are permitted versus not permitted in (Arizona state) in last date ?)

```
In [39]: # filter data by Arizona state
```

```
Arizona_filt = df_permit.query('state == "Arizona"')
```

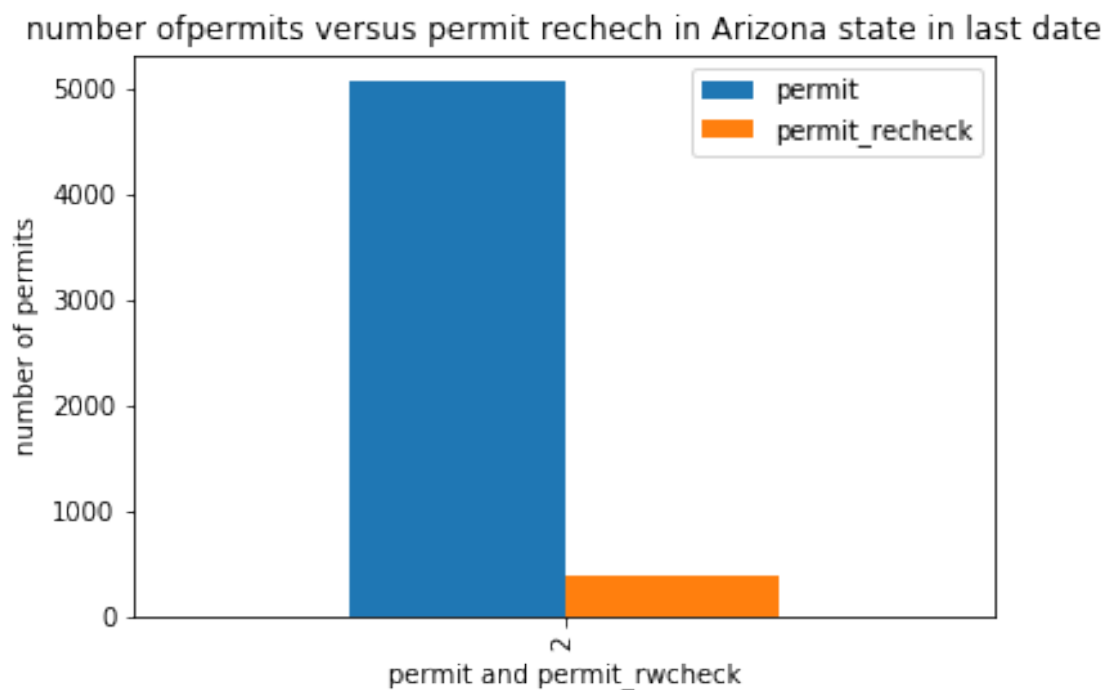
```
In [40]: # visualize result
```

```
Arizona_permit_plot = Arizona_filt.plot(kind='bar', title='number of permits versus perm
```

```
Arizona_permit_plot.set_ylabel('number of permits')
```

```
Arizona_permit_plot.set_xlabel('permit and permit_rwcheck')
```

```
Out[40]: Text(0.5,0,'permit and permit_rwcheck')
```



```
In [41]: Arizona_filt.sum()
```

```
Out[41]: permit          5069
permit_recheck         382
state              Arizona
dtype: object
```

total permit in Arizona in 09-2017: 5069

total permut_recheck in Arizona in 09-2017: 382

Research Question 5 (quantity types of guns)

```
In [42]: # select type of guns and sum
df_gun_type = df_gun.iloc[:,4:26].sum()
df_gun_type
```

```
Out[42]: handgun          7.417190e+07
long_gun                9.751843e+07
other                   4.500488e+06
multiple                3.353513e+06
admin                   7.353427e+05
prepawn_handgun         6.027785e+04
prepawn_long_gun        9.780943e+04
prepawn_other           2.067409e+03
redemption_handgun      5.093511e+06
redemption_long_gun     7.482665e+06
redemption_other        2.266339e+04
returned_handgun        3.697149e+05
returned_long_gun       9.435633e+04
returned_other          1.282894e+04
rentals_handgun         9.584444e+02
rentals_long_gun        1.089600e+03
private_sale_handgun    1.864760e+05
private_sale_long_gun   1.448623e+05
private_sale_other      1.286182e+04
return_to_seller_handgun 5.019222e+03
return_to_seller_long_gun 5.516100e+03
return_to_seller_other   1.323244e+03
dtype: float64
```

```
In [43]: # index to use it in visualization using matplotlib
# labels to use it in visualization using matplotlib
# function return selected rows of type
```

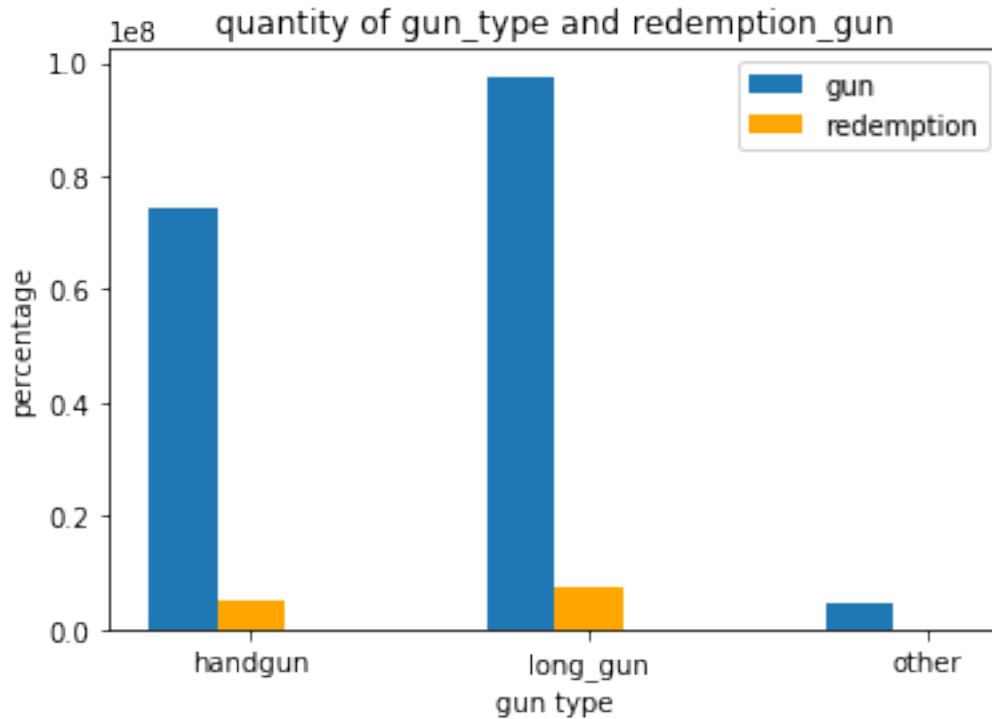
```
ind=np.arange(3)
labels=['handgun','long_gun','other']
def return_rwo(a,b):
    return df_gun_type.iloc[a:b]
```

```
In [44]: # visualize guns with redemption guns alone because they have high quantity

plt.bar(ind,return_rwo(0,3),width=0.2,label='gun')
plt.bar(ind+0.2,return_rwo(8,11),color='orange',width=0.2,label='redemption')
plt.legend()
plt.xticks(ind+0.2,labels);
```

```
plt.xlabel('gun type')
plt.ylabel('percentage')
plt.title('quantity of gun_type and redemption_gun')
```

Out[44]: Text(0.5,1,'quantity of gun_type and redemption_gun')



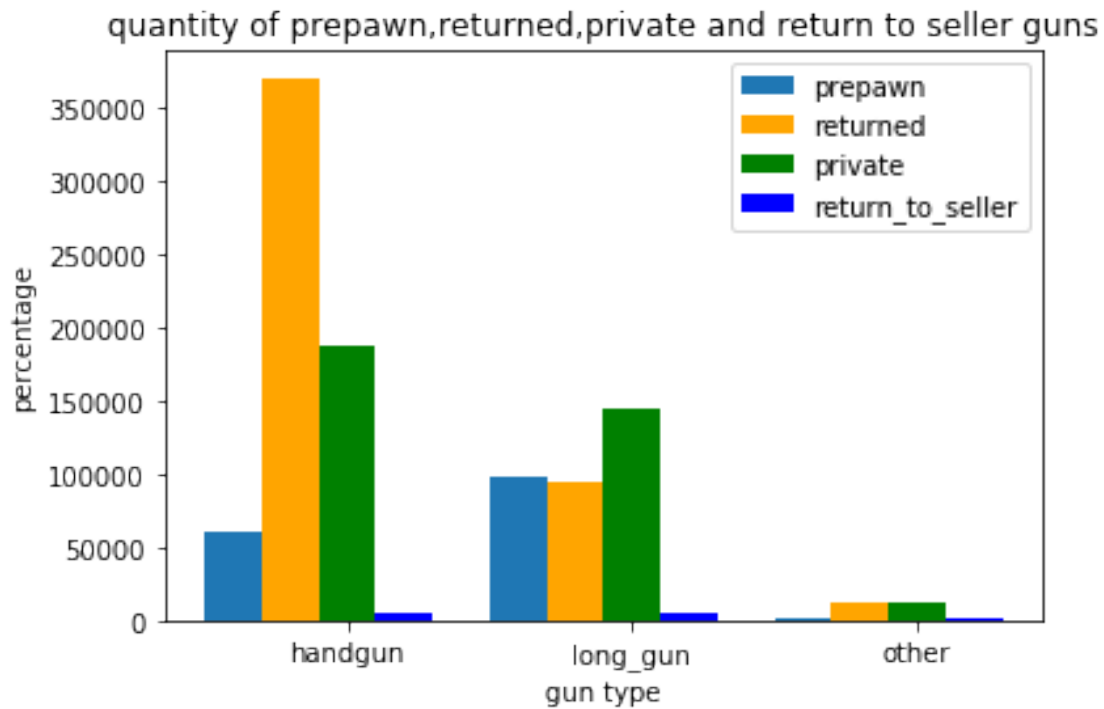
In [45]: *# visualize other types*

```
plt.bar(ind,return_rwo(5,8),width=0.2,label='prepawn')
#plt.bar(ind+0.2,return_rwo(8,11),width=0.2,color='red')
plt.bar(ind+0.2,return_rwo(11,14),width=0.2,color='orange',label='returned')
#plt.bar(np.arange(2)+0.6,return_rwo(14,16),width=0.2,color='pink')
plt.bar(ind+0.4,return_rwo(16,19),width=0.2,color='green',label='private')
plt.bar(ind+0.6,return_rwo(19,22),width=0.2,color='blue',label='return_to_seller')

plt.legend()

plt.xticks(ind+0.4,labels);
plt.xlabel('gun type')
plt.ylabel('percentage')
plt.title('quantity of prepawn,returned,private and return to seller guns')
```

Out[45]: Text(0.5,1,'quantity of prepawn,returned,private and return to seller guns')



long_gun have maximum quantity in (gun_type, redemption, prepawn)

hand_gun have maximum quantity in (returned, private, return_to_seller)

Research Question 6 (In which state did men owned firms by maximum number of gun in 2012?)

```
In [46]: # select row 56 that contain data who men_owed firms(2012)
# max_: max number of gun
# state: list contain states have the maximum number of gun
# for loop: loop for compare column number to maximum number and store column name have
# maximum number of gun

df_men_owed_firms = df_census.iloc[56:57,2:]

max_ = df_men_owed_firms.max(axis=1)
state=[]
for column in df_men_owed_firms.columns:
    if (df_men_owed_firms[column] == max_).any():
        max_ = df_men_owed_firms[column]
        state.append(column)
state,max_

Out[46]: (['California'], 56      1852580.0
          Name: California, dtype: float64)
```

maximum number of guns that men owned firms in 2012 owned in Nebraska state

Research Question 7 (How many guns registered in 2017 in all states?)

```
In [47]: # copy df_gun
         # append year column in new dataframe from month column
         # filter data by year 2017 and select only totals registration
         # calculate sum of totals in 2017 dataframe

df_copy = df_gun.copy()
df_copy['year'] = df_copy['month'].dt.year
df_copy.query('year == "2017"')['totals'].sum()
```

Out[47]: 17990528

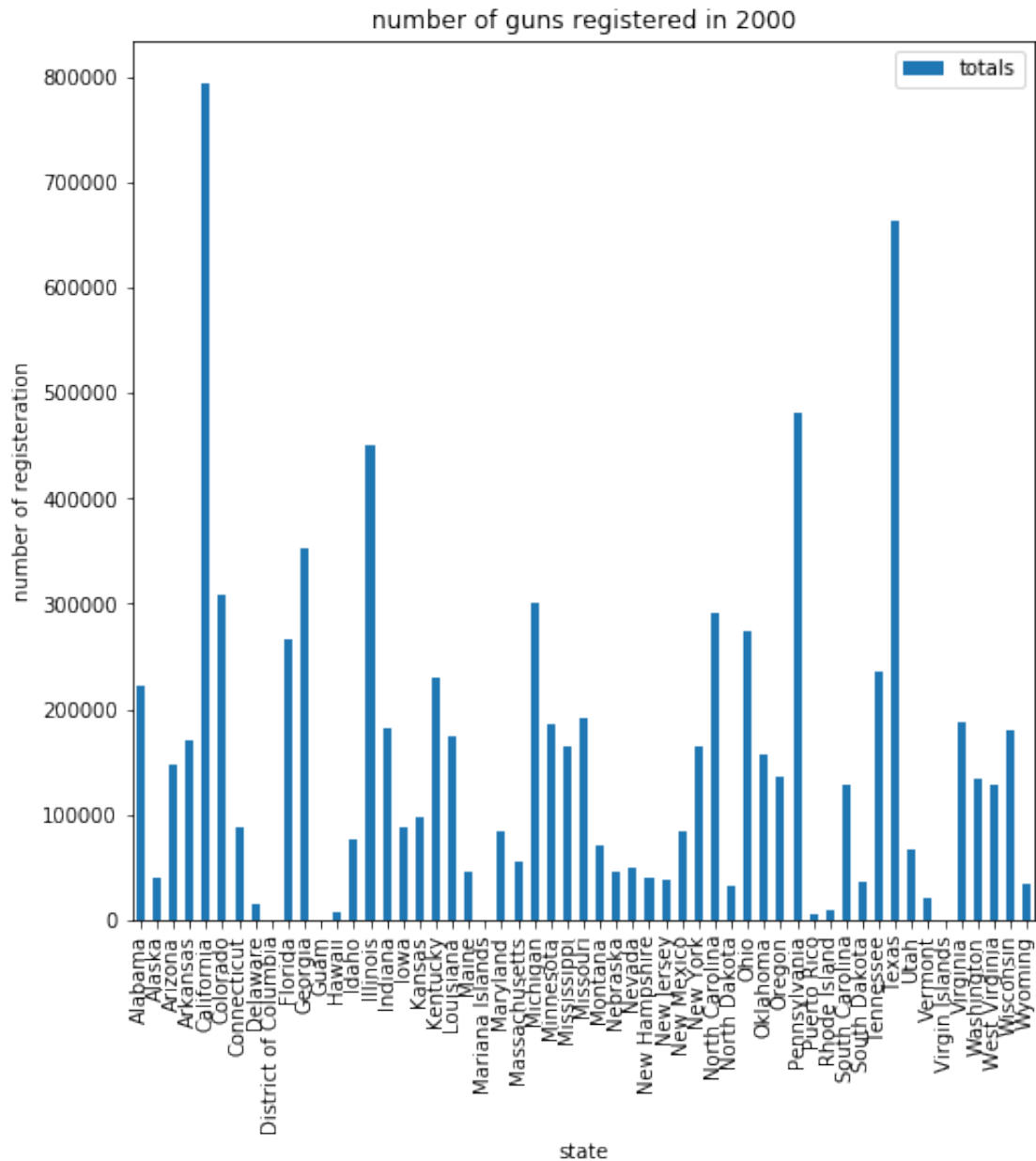
there are 17990528 guns registered in all state in 2017

Research Question 8 (How many guns registered in 2000 in each state?)

```
In [48]: # filter data by year 2000 and select only state and totals columns
         # grouped data by state
         # visualize result

filter_2000 = df_copy.query('year == "2000"')[['state','totals']]
group = filter_2000.groupby('state').sum()
filter_2000_plot = group.plot(kind='bar',figsize=(8,8), title='number of guns registered')
filter_2000_plot.set_ylabel('number of registration')
```

Out[48]: Text(0,0.5,'number of registration')



```
In [49]: group.max()
```

```
Out[49]: totals      794506
dtype: int64
```

California has the highest number of guns registration in 2000

Research Question 9 (Average guns registered in each state since 1998)

```
In [50]: # filter data by state and select only totals column
         # calculate mean in totals column in all date
```

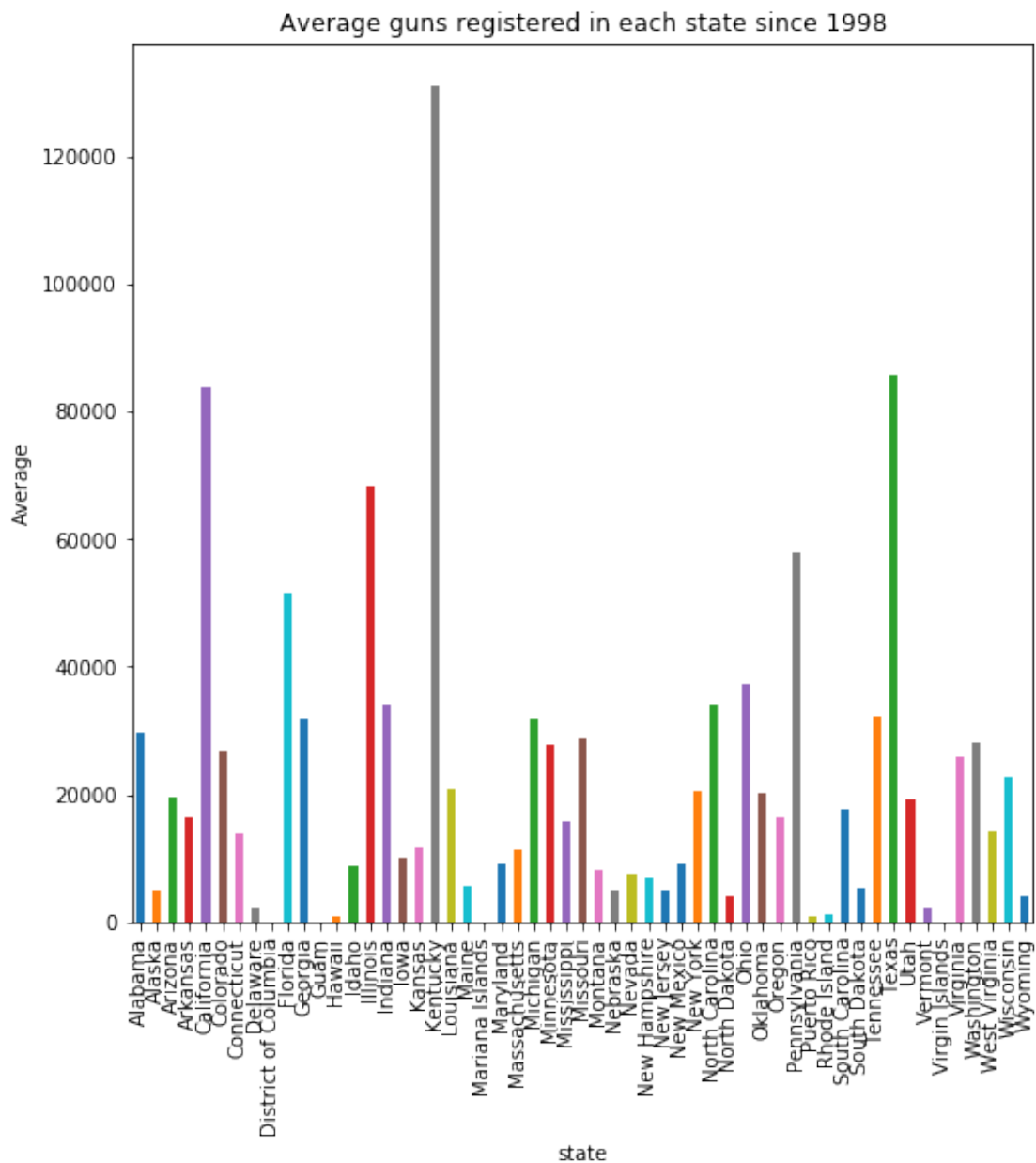
```
total_filter = df_gun.groupby('state')['totals'].mean()
total_filter.mean()
```

Out[50]: 21595.725911093308

In [51]: *# visualize result*

```
total_filter_plot = total_filter.plot(kind='bar',figsize=(8,8), title='Average guns reg
total_filter_plot.set_ylabel('Average')
```

Out[51]: Text(0,0.5,'Average')



Kentucky has the highest average of gun registration since 1998

California and Texas have the same average of gun registration

Research Question 10 (How many guns registered in 2017 in Texas)?

```
In [52]: # filter data by year 2017 and Texas state and select only totals column
        # calculate sum of totals
```

```
df_copy.query('year=="2017" and state=="Texas"')['totals'].sum()
```

```
Out[52]: 1074971
```

there are 1074971 gun registrations in Texas in 2017

Research Question 11 (What is the total revenue of all firms in all state in 2012?)

```
In [53]: # select row 55 in df_census that contain revenue of firms in 2012
        # calculate sum of revenue
```

```
df_census.iloc[55,2:].sum()
```

```
Out[53]: 27744592.0
```

27744592 is the total revenue of all firms in all states in 2012

Conclusions

from the previous analyzes we draw some important conclusions in several aspects:

growth in gun registration

> 1- the highest growth rate in gun registration in KENTUCKY state (growth = 397899) from 1998 to 2017.

> 2- the lowest growth rate in VIRGIN state (growth = 9).

> 3- growth rate in CALIFORNIA,ILINOIS and TEXAS veryvclise and ranks third of growth.

registration

> 1- there are 17990528 total guns registered in all states in 2017.

> 2- CALIFORNIA has the highest number of guns registration in 2000.

> 3- KENTUCKY has the highest average of gun registration since 1998.

> 4- CALIFORNIA and TEXAS have the same average of gun registration.

> 5- there are 1074971 gun registered in TEXAS in 2017.

overall trend

> overall trend of gun purchases is constantly increasing and quickly.

> permits

> 1- KENTUCKY state has the highest number of permits.

> 2- number of permits in KENTUCKY is equal approximately number of permits in all other states.

> 3- number of permits in ARIZONA in 09-2017 is 5069.

> 4- number of permits recheck in ARIZONA in 09-2017 is 382.

quantities of guns types

- > 1- long_gun has the highest quantity in (gun type, redemption, and prepawn)
- > 2- hand_gun has the highest quantity in (returned, private, and return_to_seller) > **other**
- > 1- the highest number of guns that men owned firms buy in 2017 was in NEBRASKA state.
- > 2- the total revenue of all firms in all states in 2012 equal 27744592.

1.1.4 Limitations

1- in census data, all columns contain missing values, and the majority of columns contain 20 missing value out of 85 rows. meaning that approximately 25% of the data are missing and this is an exaggeration.

2- there are 154595 missing in the gun data, this represents about 45% of the total values, this is a very large number even if we try to complete it using appropriate methods, the result will still be somewhat inaccurate.

3- in gun data, there are months of specific years that have not been recorded, and there are also states that have not been recorded.

4- the numeric values in census data separated by a comma, this makes converting them into float more difficult, and when doing this in the best way, there are completely inaccurate values and this changes the accuracy of the result.

```
In [54]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[54]: 255
```