investigate-a-dataset-template

June 20, 2020

1 Project: FBI Gun Dataset Analysis

1.1 Table of Contents

Introduction

We will be analyzing FBI Gun dataset in this project and we will particularly investigate following questions:

- Which state has the heighest number of handgun and longgun ownership?
- Which are the top 10 state that has maximum number of guns ?
- Which state has the heighest number of gun ownership on the basis of the population of state ?
- Which state has heighest increase in gun ownership on the basis of population of state ?
- Observe the trend of change of gun ownership ?

[1]:
```
#Import essential libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Libraries that are essential for us to perform data analysis is imported here.

Data Wrangling and Data Cleaning

In this section, we will load the data, check for cleanliness, and then trim and clean our dataset for analysis. We will document our steps carefully and justify our cleaning decisions as well.

1.1.1 General Properties

[2]:
```python
#lets read the datas
gun=pd.read_excel('gun_data.xlsx')
census=pd.read_csv('U.S. Census Data.csv')
```

Here we are reading the two datasets and now we will view the datas it contains. It will help us understand our data and help us to generate ideas on how to answer the research questions we have posed.

[3]:
```python
#Lets view some datas from top
gun.head()
```

[3]:
```
     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]
```

We are going to need months,state, permit, permit_recheck, handgun, and long_gun column only because they will only be required to answer our research question successfully.

[4]:
```
#Lets view some datas from the end
gun.tail()
```

[4]:
```
         month          state  permit  permit_recheck  handgun  long_gun  \
12480  1998-11       Virginia     0.0             NaN     14.0       2.0
12481  1998-11     Washington     1.0             NaN     65.0     286.0
12482  1998-11  West Virginia     3.0             NaN    149.0     251.0
12483  1998-11      Wisconsin     0.0             NaN     25.0     214.0
12484  1998-11        Wyoming     8.0             NaN     45.0      49.0

      other  multiple  admin  prepawn_handgun  …  returned_other  \
12480   NaN         8    0.0              NaN  …             NaN
12481   NaN         8    1.0              NaN  …             NaN
12482   NaN         5    0.0              NaN  …             NaN
12483   NaN         2    0.0              NaN  …             NaN
12484   NaN         5    0.0              NaN  …             NaN

      rentals_handgun  rentals_long_gun  private_sale_handgun  \
12480             NaN               NaN                   NaN
12481             NaN               NaN                   NaN
12482             NaN               NaN                   NaN
12483             NaN               NaN                   NaN
12484             NaN               NaN                   NaN

      private_sale_long_gun  private_sale_other  return_to_seller_handgun  \
12480                   NaN                 NaN                       NaN
12481                   NaN                 NaN                       NaN
12482                   NaN                 NaN                       NaN
12483                   NaN                 NaN                       NaN
12484                   NaN                 NaN                       NaN

      return_to_seller_long_gun  return_to_seller_other  totals
12480                       NaN                     NaN      24
12481                       NaN                     NaN     361
12482                       NaN                     NaN     408
12483                       NaN                     NaN     241
12484                       NaN                     NaN     107

[5 rows x 27 columns]
```

Here, we see nan values, they might be required to be deleted or filled later on.They will be handeled as required

[5]:
```
#Lets view number of rows and colums
gun.shape
```

[5]: (12485, 27)

So, there are 12485 datas in this dataset along with 27 columns.

[6]:
```
#Lets view summary statistics
gun.describe()
```

[6]:

```
             permit  permit_recheck        handgun       long_gun  \
count  12461.000000     1100.000000   12465.000000   12466.000000
mean    6413.629404     1165.956364    5940.881107    7810.847585
std    23752.338269     9224.200609    8618.584060    9309.846140
min        0.000000        0.000000       0.000000       0.000000
25%        0.000000        0.000000     865.000000    2078.250000
50%      518.000000        0.000000    3059.000000    5122.000000
75%     4272.000000        0.000000    7280.000000   10380.750000
max   522188.000000   116681.000000  107224.000000  108058.000000

             other      multiple         admin  prepawn_handgun  \
count  5500.000000  12485.000000  12462.000000     10542.000000
mean    360.471636    268.603364     58.898090         4.828021
std    1349.478273    783.185073    604.814818        10.907756
min       0.000000      0.000000      0.000000         0.000000
25%      17.000000     15.000000      0.000000         0.000000
50%     121.000000    125.000000      0.000000         0.000000
75%     354.000000    301.000000      0.000000         5.000000
max   77929.000000  38907.000000  28083.000000       164.000000

       prepawn_long_gun  prepawn_other  …  returned_other  rentals_handgun  \
count      10540.000000    5115.000000  …     1815.000000       990.000000
mean           7.834156       0.165591  …        1.027548         0.076768
std           16.468028       1.057105  …        4.386296         0.634503
min            0.000000       0.000000  …        0.000000         0.000000
25%            0.000000       0.000000  …        0.000000         0.000000
50%            1.000000       0.000000  …        0.000000         0.000000
75%            8.000000       0.000000  …        0.000000         0.000000
max          269.000000      49.000000  …       64.000000        12.000000

       rentals_long_gun  private_sale_handgun  private_sale_long_gun  \
count        825.000000           2750.000000            2750.000000
mean           0.087273             14.936000              11.602909
std            0.671649             71.216021              54.253090
min            0.000000              0.000000               0.000000
25%            0.000000              0.000000               0.000000
50%            0.000000              0.000000               0.000000
```

```
75%          0.000000             2.000000              4.000000
max         12.000000          1017.000000            777.000000

       private_sale_other  return_to_seller_handgun  \
count         2750.000000               2475.000000
mean             1.030182                  0.402020
std              4.467843                  1.446568
min              0.000000                  0.000000
25%              0.000000                  0.000000
50%              0.000000                  0.000000
75%              0.000000                  0.000000
max             71.000000                 28.000000

       return_to_seller_long_gun  return_to_seller_other         totals
count                2750.000000             2255.000000   12485.000000
mean                    0.441818                0.105987   21595.725911
std                     1.528223                0.427363   32591.418387
min                     0.000000                0.000000       0.000000
25%                     0.000000                0.000000    4638.000000
50%                     0.000000                0.000000   12399.000000
75%                     0.000000                0.000000   25453.000000
max                    17.000000                4.000000  541978.000000

[8 rows x 25 columns]
```

WE can see details such as in average,1165 permit has been rechecked.In average there are 5940 guns and 7810 handguns and so on.

[7]:
```python
#Lets view null value and datatype of each column
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
```

The month column is stated as object whill shall be changed later on. There are lots of null value that shall be handeled further on.

[8]:
```
#Lets view some datas from census , from top
census.head()
```

[8]:
```
                                               Fact Fact Note    Alabama  \
0      Population estimates, July 1, 2016,  (V2016)       NaN  4,863,300
1  Population estimates base, April 1, 2010,  (V2…       NaN  4,780,131
2  Population, percent change - April 1, 2010 (es…       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]
```

[9]:
```
#Lets view some data from the end
census.tail()
```

[9]:
```
   Fact                                         Fact Note Alabama Alaska  \
80   FN             Footnote on this item in place of data     NaN    NaN
81  NaN                                      Not available     NaN    NaN
82    S    Suppressed; does not meet publication standards     NaN    NaN
83    X                                     Not applicable     NaN    NaN
84    Z  Value greater than zero but less than half uni…     NaN    NaN

   Arizona Arkansas California Colorado Connecticut Delaware  …  \
80     NaN      NaN        NaN      NaN         NaN      NaN  …
81     NaN      NaN        NaN      NaN         NaN      NaN  …
82     NaN      NaN        NaN      NaN         NaN      NaN  …
83     NaN      NaN        NaN      NaN         NaN      NaN  …
84     NaN      NaN        NaN      NaN         NaN      NaN  …

   South Dakota Tennessee Texas Utah Vermont Virginia Washington  \
80          NaN       NaN   NaN  NaN     NaN      NaN        NaN
81          NaN       NaN   NaN  NaN     NaN      NaN        NaN
82          NaN       NaN   NaN  NaN     NaN      NaN        NaN
83          NaN       NaN   NaN  NaN     NaN      NaN        NaN
84          NaN       NaN   NaN  NaN     NaN      NaN        NaN

   West Virginia Wisconsin Wyoming
80           NaN       NaN     NaN
81           NaN       NaN     NaN
82           NaN       NaN     NaN
83           NaN       NaN     NaN
84           NaN       NaN     NaN

[5 rows x 52 columns]
```

Looking at the data, we will only require population census from 2010 and 2016,in order to answer our research question.We will remove all other rows lateron.

[10]:
```
#Select the columns required for our data analysis
gun = gun[gun.columns[0:6]]
gun.head(10)
```

[10]:
```
     month                 state   permit  permit_recheck  handgun  long_gun
0  2017-09               Alabama  16717.0             0.0   5734.0    6320.0
1  2017-09                Alaska    209.0             2.0   2320.0    2930.0
```

```
2  2017-09                Arizona   5069.0            382.0  11063.0    7946.0
3  2017-09               Arkansas   2935.0            632.0   4347.0    6063.0
4  2017-09             California  57839.0              0.0  37165.0   24581.0
5  2017-09               Colorado   4356.0              0.0  15751.0   13448.0
6  2017-09            Connecticut   4343.0            673.0   4834.0    1993.0
7  2017-09               Delaware    275.0              0.0   1414.0    1538.0
8  2017-09   District of Columbia      1.0              0.0     56.0       4.0
9  2017-09                Florida  10784.0              0.0  39199.0   17949.0
```

Here, we have selected the columns that are going to be used in this data analysis.

[11]:
```
#Lets change datatype of month and the name of the column
gun['month'] = pd.to_datetime(gun['month'])

gun.rename(columns={"month": "date"},inplace=True)
gun.head()
```

[11]:
```
        date       state   permit  permit_recheck  handgun  long_gun
0 2017-09-01     Alabama  16717.0             0.0   5734.0    6320.0
1 2017-09-01      Alaska    209.0             2.0   2320.0    2930.0
2 2017-09-01     Arizona   5069.0           382.0  11063.0    7946.0
3 2017-09-01    Arkansas   2935.0           632.0   4347.0    6063.0
4 2017-09-01  California  57839.0             0.0  37165.0   24581.0
```

Previously, we had observed the datatype of the month column to be object, so we changed that to datetime and to make it more convenient we changed the column name from month to date.

[12]:
```
gun.info()
gun.permit_recheck.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12485 entries, 0 to 12484
Data columns (total 6 columns):
date              12485 non-null datetime64[ns]
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
dtypes: datetime64[ns](1), float64(4), object(1)
memory usage: 585.4+ KB
```

[12]: 11385

Since the null value of permit_recheck is large , lets fillna with average of permit_recheck instead of dropping it and then have a look at stat once more.We might or might not use the permit recheck lateron

[13]:
```
#Replace na with mean value and check the summary stat
gun.permit_recheck.fillna((gun['permit_recheck'].mean()),inplace=True)
gun.describe()
```

[13]:

	permit	permit_recheck	handgun	long_gun
count	12461.000000	12485.000000	12465.000000	12466.000000
mean	6413.629404	1165.956364	5940.881107	7810.847585
std	23752.338269	2736.848174	8618.584060	9309.846140
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	1165.956364	865.000000	2078.250000
50%	518.000000	1165.956364	3059.000000	5122.000000
75%	4272.000000	1165.956364	7280.000000	10380.750000
max	522188.000000	116681.000000	107224.000000	108058.000000

[14]:
```
#look at no. of rows and column after taking the required columns only
gun.shape
```

[14]: (12485, 6)

So, now we have 12485 datas and 6 columns.

[15]:
```
#drop na value in gun dataset
gun= gun.dropna()
```

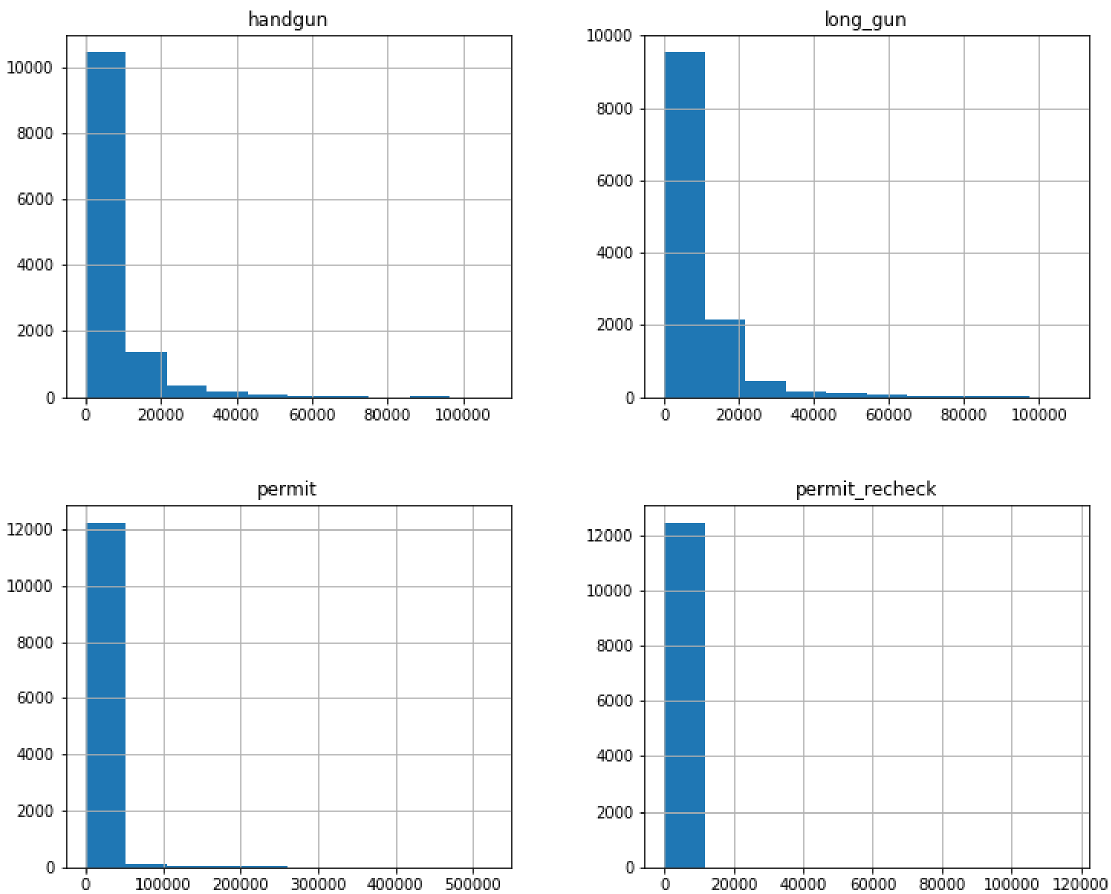
Here we have removed the all data containing nan value. And since the no. of these value is low, it will not have any adverse effect on our data analysis.

[16]:
```
#lets look for duplicate rows
gun.duplicated().sum()
```

[16]: 0

There are no duplicate rows.

[17]:
```
#lets look at histograms for gun data
gun.hist(figsize=(12,10));
```



[18]:
```
# final number of rows and column in gun dataset
gun.shape
```

[18]: (12461, 6)

Now, Lets go on towards census data.

[19]:
```
#Lets remove factnote and fact

census.drop(columns=['Fact Note',"Fact"],inplace=True)
```

Here, we have removed the Fact Note and Fact columns.

[20]:
```
reqd_cen = census.loc[[0,3]]
reqd_cen = reqd_cen.transpose()
reqd_cen = reqd_cen.rename(columns={0: 'pop_2016', 3: 'pop_2010'})
reqd_cen = reqd_cen.reset_index()
reqd_cen = reqd_cen.rename(columns={"index": "state"})
```

Here, we have selected the rows that are required for our data analysis and ignored all

other datas.We have changed the row to column and column to row , reset the index and set the index name to state for column containing all the states, we have done this to bring the uniformity in dataframe in relation to gun dataframe

[21]:
```
#check for null value and datatypes
reqd_cen.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 3 columns):
state       50 non-null object
pop_2016    50 non-null object
pop_2010    50 non-null object
dtypes: object(3)
memory usage: 1.3+ KB
```

Since, the datatype of pop__2016 and pop__2010 are object, we have to change the data types to float.

[22]:
```
#Change datatype
reqd_cen['pop_2016'] = reqd_cen['pop_2016'].str.replace(',', '').astype(float)
reqd_cen['pop_2010'] = reqd_cen['pop_2010'].str.replace(',', '').astype(float)
```

[23]:
```
#confirm datatype, null value and the changes
reqd_cen.info()
reqd_cen.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 3 columns):
state       50 non-null object
pop_2016    50 non-null float64
pop_2010    50 non-null float64
dtypes: float64(2), object(1)
memory usage: 1.3+ KB
```

[23]:

	state	pop_2016	pop_2010
0	Alabama	4863300.0	4779736.0
1	Alaska	741894.0	710231.0
2	Arizona	6931071.0	6392017.0
3	Arkansas	2988248.0	2915918.0
4	California	39250017.0	37253956.0

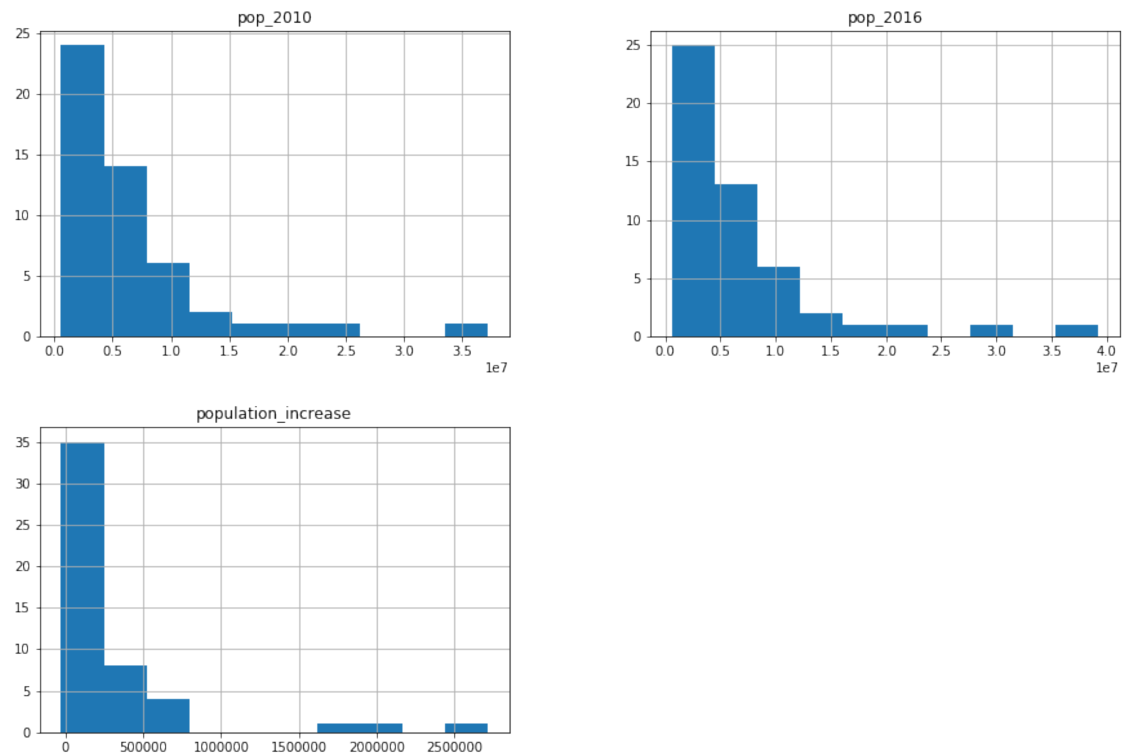
[24]:
```
#lets add new column for the increase in population from 2010 to 2016
reqd_cen["population_increase"] = (reqd_cen["pop_2016"] - reqd_cen["pop_2010"] )
reqd_cen.head()
```

[24]:

	state	pop_2016	pop_2010	population_increase
0	Alabama	4863300.0	4779736.0	83564.0
1	Alaska	741894.0	710231.0	31663.0
2	Arizona	6931071.0	6392017.0	539054.0
3	Arkansas	2988248.0	2915918.0	72330.0
4	California	39250017.0	37253956.0	1996061.0

[25]:

```
#lets look at all histogram for reqd_cen data
reqd_cen.hist(figsize=(15,10));
```



Since we have brought uniformity in both data. We can now merge the datas.

[26]:

```
#lets merge data
df = pd.merge(gun, reqd_cen)
df.head(5)
```

[26]:

	date	state	permit	permit_recheck	handgun	long_gun	pop_2016	\
0	2017-09-01	Alabama	16717.0	0.0	5734.0	6320.0	4863300.0	
1	2017-08-01	Alabama	19733.0	4.0	6289.0	6045.0	4863300.0	
2	2017-07-01	Alabama	18042.0	1.0	6046.0	4790.0	4863300.0	
3	2017-06-01	Alabama	19508.0	89.0	8275.0	4782.0	4863300.0	
4	2017-05-01	Alabama	18538.0	313.0	7198.0	4559.0	4863300.0	

```
   pop_2010  population_increase
0  4779736.0              83564.0
1  4779736.0              83564.0
2  4779736.0              83564.0
3  4779736.0              83564.0
4  4779736.0              83564.0
```

Here, we have successfully merged the data. And, although the population is shown for all dates , there would be no problem as we will be taking population of 2016 and 2010 for the dates ranging in only 2016 and 2010 respectively while analysing the data.

Exploratory Data Analysis

- Now that we've trimmed and cleaned our data, we're ready to move on to exploration.

1.1.2 Question 1 : Which state has the heighest number of handgun and longgun ownership ?

[27]:

```python
#Lets create new column
df["total_guns"] = df["handgun"] + df["long_gun"]
df.head()
#sort the datas by date and total gun and view the data
sort_guns = df.sort_values(by=['date','total_guns'], ascending=False)
sort_guns.head(8)
```

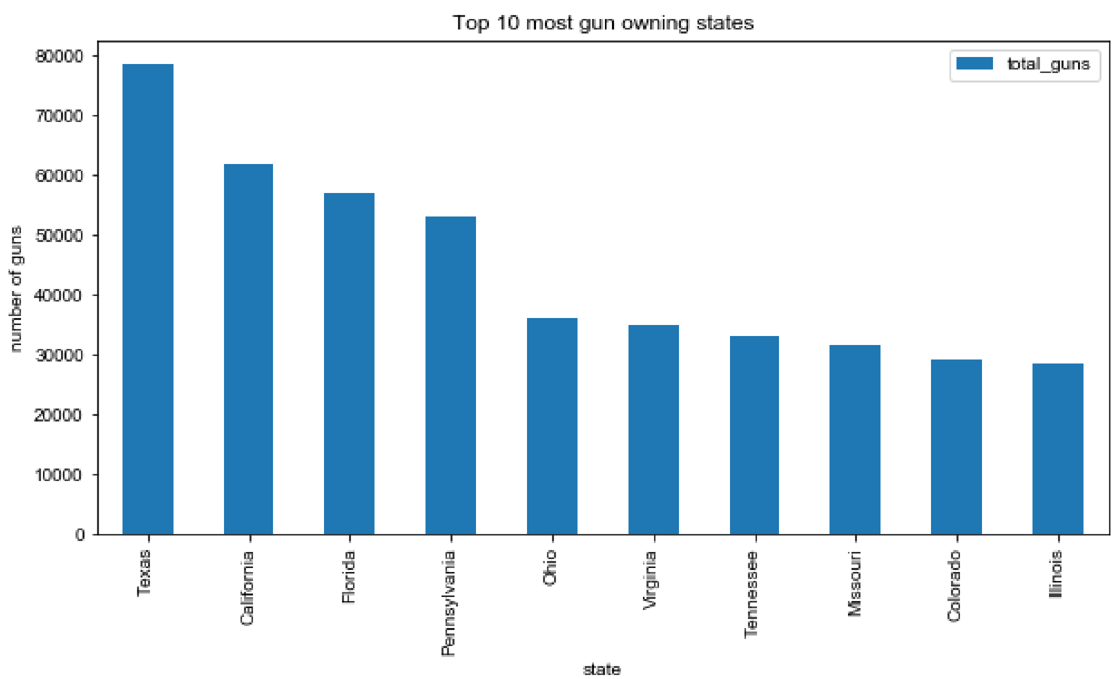
[27]:

```
             date         state   permit  permit_recheck  handgun  long_gun  \
9533   2017-09-01         Texas  31390.0             0.0  39119.0   39416.0
908    2017-09-01    California  57839.0             0.0  37165.0   24581.0
1816   2017-09-01       Florida  10784.0             0.0  39199.0   17949.0
8398   2017-09-01  Pennsylvania  23144.0             0.0  39825.0   13222.0
7717   2017-09-01          Ohio   8741.0           490.0  21085.0   14998.0
10214  2017-09-01      Virginia    585.0             0.0  19676.0   15075.0
9306   2017-09-01     Tennessee  16887.0             0.0  19219.0   13746.0
5447   2017-09-01      Missouri    791.0             0.0  16993.0   14395.0

         pop_2016    pop_2010  population_increase  total_guns
9533   27862596.0  25145561.0            2717035.0     78535.0
908    39250017.0  37253956.0            1996061.0     61746.0
1816   20612439.0  18801310.0            1811129.0     57148.0
8398   12784227.0  12702379.0              81848.0     53047.0
7717   11614373.0  11536504.0              77869.0     36083.0
10214   8411808.0   8001024.0             410784.0     34751.0
9306    6651194.0   6346105.0             305089.0     32965.0
5447    6093000.0   5988927.0             104073.0     31388.0
```

As of 2017-09-01, Texas has the heighest gun ownership by state.

1.1.3 Research question 2 : Which are the top 10 state that has maximum number of guns ?

[28]:
```
top_10 = sort_guns[['state','total_guns']][:10]
#sorting datas
sorted_guns = top_10['total_guns'].sort_values(ascending=False)[:10]

# Create state and total gun  which will be used as X-axis and Y-axis values in␣
↪bar graph.
high_guns1=pd.DataFrame()
state=[]
total_guns=[]

# Fill the vallues from raw data to the lists.
for i in sorted_guns.index:
    state.append(df.loc[i,'state'])
    total_guns.append(sorted_guns.loc[i])
high_guns1['state']=state
high_guns1['total_guns']=total_guns
high_guns1.set_index('state',inplace=True)

# Plot
high_guns1.plot(kind ='bar',figsize=(10,5))
plt.title('Top 10 most gun owning states');
plt.ylabel('number of guns');
sns.set_style('darkgrid')
```



Top 10 states which has maximum no. of guns as of 2017 is Texas, California,Florida, and so on . It is as listed in the histogram above.

1.1.4 Research Question 3 : Which 10 state has the heighest number of gun ownership on the basis of the population of state ?

[29]:
```
#Lets add two new columns
df["Gun_proportion_16"]= df["total_guns"] / df["pop_2016"]
df["Gun_proportion_10"]= df["total_guns"] / df["pop_2010"]
df.head(2)
```

[29]:
```
         date    state   permit  permit_recheck  handgun  long_gun   pop_2016  \
0  2017-09-01  Alabama  16717.0             0.0   5734.0    6320.0  4863300.0
1  2017-08-01  Alabama  19733.0             4.0   6289.0    6045.0  4863300.0

    pop_2010  population_increase  total_guns  Gun_proportion_16  \
0  4779736.0              83564.0     12054.0           0.002479
1  4779736.0              83564.0     12334.0           0.002536

   Gun_proportion_10
0           0.002522
1           0.002580
```

Since, the census for 2016, was of date july 1 2016, we will look at the population to gun ratio on this day. And for 2010, april 1 2010 is taken

[30]:
```
high_pro_16 = df.query("date == '2016-07-01'")
#high proportion in 2016
high_pro_16 = high_pro_16.sort_values(by=['Gun_proportion_16'], ascending=False)
high_pro_16.head(10)
```

[30]:
```
             date          state  permit  permit_recheck  handgun  long_gun  \
241    2016-07-01         Alaska   215.0             0.0   2898.0    2816.0
3873   2016-07-01      Louisiana  2595.0             0.0  21637.0   12252.0
6369   2016-07-01  New Hampshire  3882.0             0.0   5200.0    3716.0
5688   2016-07-01        Montana  1356.0             0.0   2894.0    3882.0
9320   2016-07-01      Tennessee  1915.0         11933.0  26276.0   16118.0
9093   2016-07-01   South Dakota  1179.0             0.0   2490.0    3004.0
10681  2016-07-01  West Virginia  1992.0             0.0   6417.0    5134.0
1149   2016-07-01       Colorado  6372.0             0.0  18765.0   15176.0
8185   2016-07-01         Oregon    21.0             0.0  14284.0   10507.0
11135  2016-07-01        Wyoming   597.0             0.0   1619.0    1769.0

        pop_2016   pop_2010  population_increase  total_guns  \
241     741894.0   710231.0              31663.0      5714.0
3873   4681666.0  4533372.0             148294.0     33889.0
```

```
6369   1334795.0  1316470.0            18325.0     8916.0
5688   1042520.0   989415.0            53105.0     6776.0
9320   6651194.0  6346105.0           305089.0    42394.0
9093    865454.0   814180.0            51274.0     5494.0
10681  1831102.0  1852994.0           -21892.0    11551.0
1149   5540545.0  5029196.0           511349.0    33941.0
8185   4093465.0  3831074.0           262391.0    24791.0
11135   585501.0   563626.0            21875.0     3388.0

       Gun_proportion_16  Gun_proportion_10
241             0.007702           0.008045
3873            0.007239           0.007475
6369            0.006680           0.006773
5688            0.006500           0.006848
9320            0.006374           0.006680
9093            0.006348           0.006748
10681           0.006308           0.006234
1149            0.006126           0.006749
8185            0.006056           0.006471
11135           0.005786           0.006011
```

We can observe that in 2016, Alaska has the heighest gun ownership in terms of population.

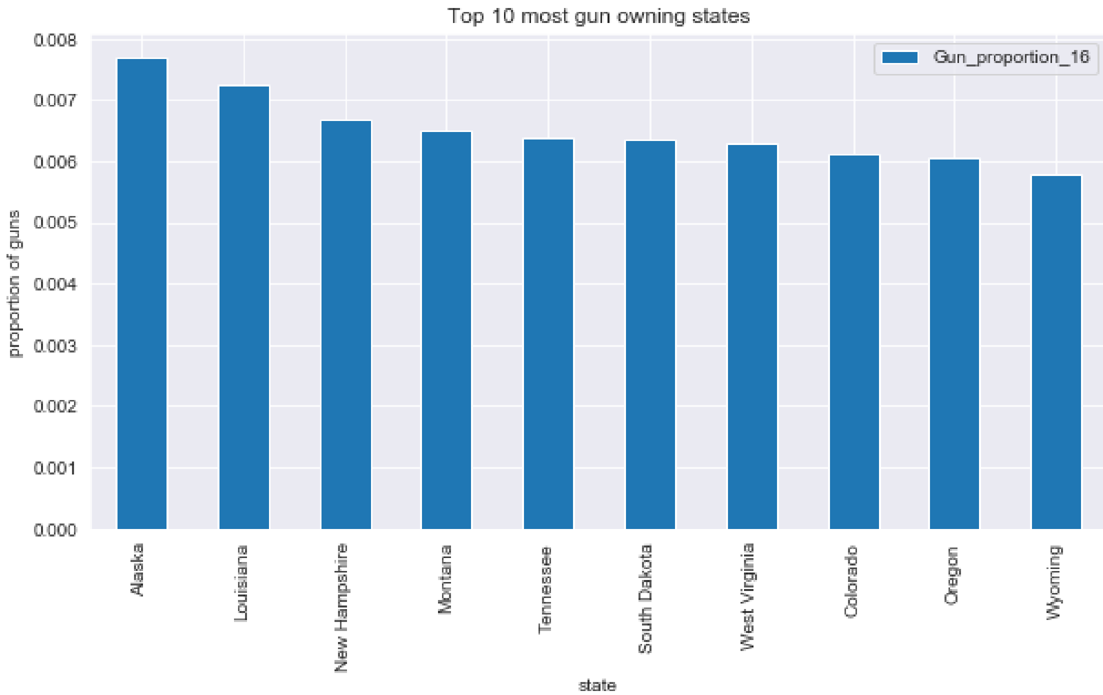
[31]:
```python
high_pro_10 = df.query("date == '2010-04-01'")
#high proportion in 2010
high_pro_10 = high_pro_10.sort_values(by=['Gun_proportion_10'], ascending=False)
high_pro_10.head(10)
```

[31]:
```
             date          state  permit  permit_recheck  handgun  long_gun  \
316    2010-04-01         Alaska     0.0     1165.956364   2650.0    3136.0
5763   2010-04-01        Montana   906.0     1165.956364   2172.0    3824.0
10303  2010-04-01       Virginia     0.0     1165.956364  25259.0   18158.0
11210  2010-04-01        Wyoming   532.0     1165.956364   1295.0    1700.0
9168   2010-04-01   South Dakota     0.0     1165.956364   1396.0    2785.0
10756  2010-04-01  West Virginia     0.0     1165.956364   3927.0    4534.0
7579   2010-04-01   North Dakota   608.0     1165.956364    888.0    2004.0
1224   2010-04-01       Colorado     0.0     1165.956364  10998.0    9403.0
8260   2010-04-01         Oregon    35.0     1165.956364   7445.0    8065.0
8487   2010-04-01   Pennsylvania   211.0     1165.956364      1.0   49644.0

        pop_2016   pop_2010  population_increase  total_guns  \
316     741894.0   710231.0              31663.0      5786.0
5763   1042520.0   989415.0              53105.0      5996.0
10303  8411808.0  8001024.0             410784.0     43417.0
11210   585501.0   563626.0              21875.0      2995.0
9168    865454.0   814180.0              51274.0      4181.0
```

```
10756   1831102.0   1852994.0             -21892.0      8461.0
7579     757952.0    672591.0              85361.0      2892.0
1224    5540545.0   5029196.0             511349.0     20401.0
8260    4093465.0   3831074.0             262391.0     15510.0
8487   12784227.0  12702379.0              81848.0     49645.0

       Gun_proportion_16  Gun_proportion_10
316             0.007799           0.008147
5763            0.005751           0.006060
10303           0.005161           0.005426
11210           0.005115           0.005314
9168            0.004831           0.005135
10756           0.004621           0.004566
7579            0.003816           0.004300
1224            0.003682           0.004057
8260            0.003789           0.004048
8487            0.003883           0.003908
```

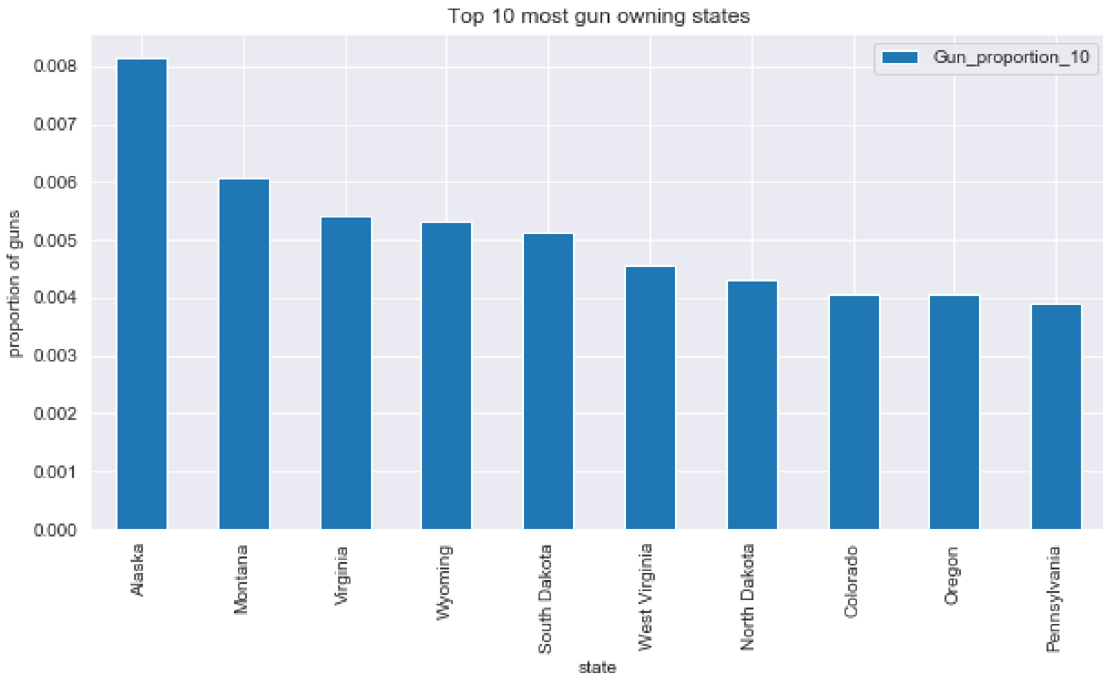
We can observe that in 2010, Alaska has the heighest gun ownership in terms of population to gun ratio..

[32]:
```
sorted_guns1 = high_pro_16['Gun_proportion_16'].sort_values(ascending=False)[:
↪10]

# Create state and total gun proportion for 2016 list which will be used as␣
↪X-axis and Y-axis values in bar graph.
high_guns2=pd.DataFrame()
state=[]
Gun_proportion_16=[]

# Fill the vallues from raw data to the lists.
for i in sorted_guns1.index:
    state.append(df.loc[i,'state'])
    Gun_proportion_16.append(sorted_guns1.loc[i])
high_guns2['state']=state
high_guns2['Gun_proportion_16']=Gun_proportion_16
high_guns2.set_index('state',inplace=True)

# Plot
high_guns2.plot(kind ='bar',figsize=(10,5))
plt.title('Top 10 most gun owning states');
plt.ylabel('proportion of guns');
sns.set_style('darkgrid')
```



Here, we can see top 10 states with population to gun proportion in 2016. Still Alaska ranks first.

[33]:
```
sorted_guns2 = high_pro_10['Gun_proportion_10'].sort_values(ascending=False)[:
 ↪10]

# Create state and total gun proportion for 2010 list which will be used as␣
 ↪X-axis and Y-axis values in bar graph.
high_guns3=pd.DataFrame()
state=[]
Gun_proportion_10=[]

# Fill the vallues from raw data to the lists.
for i in sorted_guns2.index:
    state.append(df.loc[i,'state'])
    Gun_proportion_10.append(sorted_guns2.loc[i])
high_guns3['state']=state
high_guns3['Gun_proportion_10']=Gun_proportion_10
high_guns3.set_index('state',inplace=True)

# Plot
high_guns3.plot(kind ='bar',figsize=(10,5))
plt.title('Top 10 most gun owning states');
plt.ylabel('proportion of guns');
sns.set_style('darkgrid')
```



Here, we can see top 10 states with population to gun proportion in 2010 in terms of population to gun ratio.

1.1.5 Research Question 4 : Which state has heighest increase in gun ownership on the basis of population of state ?

[34]:
```
#add new column
df["changed_prop"] = (df["Gun_proportion_16"] - df["Gun_proportion_10"])
df.head()
```

[34]:
```
         date    state   permit  permit_recheck  handgun  long_gun   pop_2016  \
0  2017-09-01  Alabama  16717.0             0.0   5734.0    6320.0  4863300.0
1  2017-08-01  Alabama  19733.0             4.0   6289.0    6045.0  4863300.0
2  2017-07-01  Alabama  18042.0             1.0   6046.0    4790.0  4863300.0
3  2017-06-01  Alabama  19508.0            89.0   8275.0    4782.0  4863300.0
4  2017-05-01  Alabama  18538.0           313.0   7198.0    4559.0  4863300.0

    pop_2010  population_increase  total_guns  Gun_proportion_16  \
0  4779736.0              83564.0     12054.0           0.002479
1  4779736.0              83564.0     12334.0           0.002536
2  4779736.0              83564.0     10836.0           0.002228
3  4779736.0              83564.0     13057.0           0.002685
4  4779736.0              83564.0     11757.0           0.002417

   Gun_proportion_10  changed_prop
```

```
0            0.002522     -0.000043
1            0.002580     -0.000044
2            0.002267     -0.000039
3            0.002732     -0.000047
4            0.002460     -0.000042
```

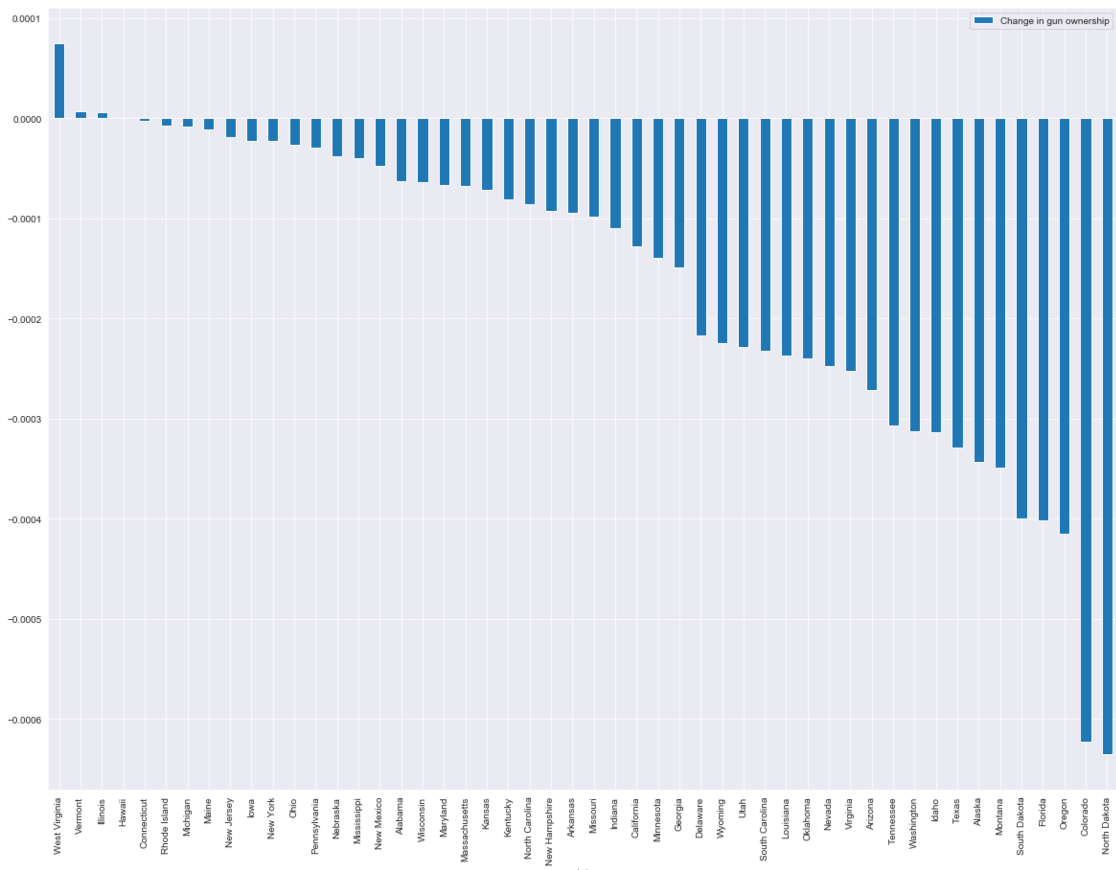
[35]:
```
inc_pro_16 = df.query("date == '2016-07-01'")
#changed proportion in 2016
new = inc_pro_16.sort_values(by=['changed_prop'], ascending=False)

new.head(12)
```

[35]:
```
            date          state    permit  permit_recheck  handgun  long_gun  \
10681 2016-07-01  West Virginia    1992.0             0.0   6417.0    5134.0
10001 2016-07-01        Vermont       0.0             0.0   1293.0    1201.0
2738  2016-07-01       Illinois  125075.0          8969.0  21421.0   11881.0
2284  2016-07-01         Hawaii    1563.0             0.0      0.0       0.0
1376  2016-07-01    Connecticut   14156.0             0.0  11328.0    4015.0
8639  2016-07-01   Rhode Island       0.0             0.0   1133.0     951.0
4780  2016-07-01       Michigan   15869.0          3753.0  11308.0    8095.0
4099  2016-07-01          Maine     540.0             0.0   3426.0    3026.0
6596  2016-07-01     New Jersey       0.0             0.0   5708.0    4155.0
3192  2016-07-01           Iowa    9391.0            11.0    186.0    2227.0
7050  2016-07-01       New York    3738.0             0.0  10900.0   13073.0
7731  2016-07-01           Ohio   11762.0            55.0  27876.0   17720.0

         pop_2016    pop_2010  population_increase  total_guns  \
10681   1831102.0   1852994.0             -21892.0     11551.0
10001    624594.0    625741.0              -1147.0      2494.0
2738   12801539.0  12830632.0             -29093.0     33302.0
2284    1428557.0   1360301.0              68256.0         0.0
1376    3576452.0   3574097.0               2355.0     15343.0
8639    1056426.0   1052567.0               3859.0      2084.0
4780    9928300.0   9883640.0              44660.0     19403.0
4099    1331479.0   1328361.0               3118.0      6452.0
6596    8944469.0   8791894.0             152575.0      9863.0
3192    3134693.0   3046355.0              88338.0      2413.0
7050   19745289.0  19378102.0             367187.0     23973.0
7731   11614373.0  11536504.0              77869.0     45596.0

       Gun_proportion_16  Gun_proportion_10  changed_prop
10681           0.006308           0.006234      0.000075
10001           0.003993           0.003986      0.000007
2738            0.002601           0.002596      0.000006
2284            0.000000           0.000000      0.000000
1376            0.004290           0.004293     -0.000003
8639            0.001973           0.001980     -0.000007
```

4780	0.001954	0.001963	-0.000009
4099	0.004846	0.004857	-0.000011
6596	0.001103	0.001122	-0.000019
3192	0.000770	0.000792	-0.000022
7050	0.001214	0.001237	-0.000023
7731	0.003926	0.003952	-0.000026

We can observe that, west virginia has the heighest increase of gun ownership.

[36]:
```
new.plot.bar(y='changed_prop',x='state',figsize=(20,15),label="Change in gun␣
↪ownership" );
```

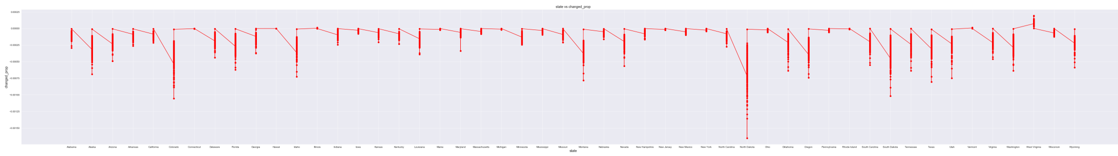


whereas, the most decrease of gun ownership can be seen in north dakota.

1.1.6 Research Question 5 : Observe the trend of change of gun ownership ?

[37]:
```
#lets plot a line chart to see what is happening in every state
plt.figure(figsize=(80,10))
plt.plot(df['state'], df['changed_prop'], color='red', marker='o')
plt.title('state vs changed_prop', fontsize=14)
```

```
plt.xlabel('state', fontsize=14)
plt.ylabel('changed_prop', fontsize=14)
plt.grid(True)
plt.show()
```



We can observe that the overall trend of gun ownership has been decreasing as the points in ever city is falling .

Conclusions

Following observations were made from the above dataset :

- As of 2017-09-01, Texas has the heighest gun ownership by state.
- Top 10 states which has maximum no. of guns as of 2017 is Texas, California,Florida, and so on . It is as listed in the histogram above in question 2 .
- We can see top 10 states with population to gun proportion in 2010 , where Alaska ranks first.
- In 2016, Alaska has the heighest gun ownership in terms of population to gun ratio, yet again.
- We can observe that, West Virginia has the heighest increase of gun ownership from 2010 to 2016.
- The most decrease of gun ownership can be seen in North Dakota.
- We can observe that the overall trend of gun ownership is decreasing.

[ ]:

```
```