Data Bootcamp Final Project: The Relationship Between Private Prisons, Incarceration, and Political Parties in the United States

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The first private prison in the U.S. came into existance in 1984. Since then, the number of private prisons and people incarcerated in private prisons has increased dramatically. There have been many studies on the quality of private prisons over public prisons, typically looking at internal variables such as financing, security and opperations. There is a lot of controversy regarding the ethics of private prisons, as well as their quality. However, there has been less exploration of the broad, macro-level trends of private prisons, specifically in relation to all prisons and politics.

In this project, I will analyze the change in people incarcerated in private prisons over time and people, relative to the change in total people incarcerate. Secondly, I will normalize the number data of people incarcerated by state relative to the population of that state. Finally I will look at where most private prisons are located and see if there is a relationship between the states in which private prisons are concentrated and that state's political leaning.

The data behind this project comes from the Bureau of Justice Statistics ('https://www.bjs.gov/index.cfm?ty=nps'), (JBS), for information on incarceration rates, number of private prisons, and location of private prisons; Pew Research Center ('http://www.pewforum.org/religious-landscape-study/compare/party-affiliation/by/state/#') for information about party affiliation by state.

I will download the data from the Bureau of Justice Statistics ('https://www.bjs.gov/index.cfm?ty=nps') from their website into an excel sheet. I will do the same for Pew Research Center ('http://www.pewforum.org/religious-landscape-study/compare/party-affiliation/by/state/#').

Steps:

Step One: Private Prisons v. All Prisons in the United States First, I will examine the change in number of people in private prisons over time, compared to total people in prisons on a Natinoal level. To do this I will read two data sets from the Bureau of Justice Statistics ('https://www.bjs.gov/index.cfm?ty=nps'). One contains information on the number of people incarcerating in private prisons over tiem from 1999 to 2016. The other data set contains information on the number of people incarcerated in all prisons over time from 1999 to 2016. This data set contains indevidual state data, state prison data, federal prison data, and total data regarding people incarcerated in private prisons. For this part I will only be looking at the national statistics, not indevidiual state statistics.

Step Two: Private Prisons v. All Prisons by State Next, I will be using that same private prison data set from the Bureau of Justice Statistics ('https://www.bjs.gov/index.cfm?ty=nps'), as well as the Census API. I will be using the Census API to access state population from 2015. For this section I will be examining the number of private prisons in each state. I will use the population data from the Census API to normalize the number of people in private prisons relative to that state's popualtion.

Step Two: Location of Private Prisons v. Political Leaning by State Finally, I will be comparing the location of private prisons in the United States to the political leaning of that state. I will be using data from Pew Research Center ('http://www.pewforum.org/religious-landscape-study/compare/party-affiliation/by/state/#') for state political leaning and the normalized data from Step Two.

In [432]:
```
# Here I am importing the packages that I need
     # This helps displays things nicely
from IPython.display import display, Image

# This is my key tool to manipulate data-set
import pandas as pd

# Helps plot
import matplotlib.pyplot as plt

 # Helps numerical operations
import numpy as np
import os


# Needed for geopandas to run which I will be using in Step three
import fiona

# Main geopandas
import geopandas as gpd

 # Needed for shape-files - Step three
from shapely.geometry import Point, Polygon

# This helps make a nice inset
from mpl_toolkits.axes_grid1.inset_locator import zoomed_inset_axes
from mpl_toolkits.axes_grid1.inset_locator import mark_inset
```

Step One: Private Prisons v. All Prisons in the United States

Private Prison Data

First, I am going to read and reformat the data on Private Prisons and All Prisons and then merge them into one, easy to read chart

In [433]:
```
# Here I am reading the data set from JBS about people in private prison
s
private_custody = pd.read_excel('QT_private_prisons_total.xlsx')
```

In [434]:
```
# Reformatting - I am only taking the national statistics, not stat by s
tate statistics for this section
private_custody = private_custody[:4].T.reset_index().drop('index', axis
=1).drop([1]).T.set_index([0])
```

In [435]:
```
# Reformatting and renaming columns
private_custody = private_custody.T.rename(columns={'Jurisdiction':'Yea
r'})
```

In [436]:
```
# This is how it looks so far
private_custody.head()
```

Out[436]:

	Year	U.S. total	Federal/a	State
2	1999	68960	3828	65132
3	2000	91579	15524	76055
4	2001	86421	12736	73685
5	2002	88370	14732	73638
6	2003	90123	16281	73842

In [437]:
```
# I am making a list to add to private_custody to distinguish what data
 is refering to people in private prisons
    # versus people in all prisons once I merge the two data sets togeth
er
private_type = ['Private', 'Private', 'Private', 'Private',
                'Private', 'Private', 'Private', 'Private',
                'Private', 'Private', 'Private', 'Private',
                'Private', 'Private', 'Private', 'Private',
                'Private', 'Private',]
```

In [438]:
```
# Adding the list to private_prisons
private_custody['Prison Type'] = private_type
```

In [439]:
```
# Reformatting
private_custody = private_custody.T.reset_index()
```

In [440]:
```
# The data was not perfectly clean, some of the state names had /a at th
e end of them
    # This is a function to eliminate /a from the end of the State names
for i in private_custody[0]:
    if (i[-2:] == '/a'):
        p = i[0:-2]
        if i[0:-2] == p:
            private_custody[0].replace(to_replace=i, value = p, inplace=
True)
```

In [441]:
```
# Here it is - ready to merge with the next set, which I am about to go
 format
private_custody.head()
```

Out[441]:

	0	2	3	4	5	6	7	8	9	10	1
0	Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
1	U.S. total	68960	91579	86421	88370	90123	92569	107433	113697	124150	12948
2	Federal	3828	15524	12736	14732	16281	18709	27046	27726	31310	33162
3	State	65132	76055	73685	73638	73842	73860	80387	85971	92840	96320
4	Prison Type	Private	Private	Private	Private	Private	Private	Private	Private	Private	Private

Total Prison Data

In [442]:
```
# Reading JBS data set on total people in all prisons
prison_custody = pd.read_excel('QT_custody_prisons_total.xlsx')
```

In [443]:
```
# Reformatting, chanign column names
prison_custody = prison_custody[:4].T.reset_index().drop([1]).T.set_inde
x([0]).T.rename(columns={'Inmates '+
                             'in custody of state or'+
                             ' federal correctional facilities, '+
                             'including private prison facilities, '+
                             'December 31, 1999-2016/a': 'Year'}).drop(
'Jurisdiction', axis=1)
```

In [444]:
```
# How it looks so far
prison_custody.head()
```

Out[444]:

	Year	U.S. total	Federal	State
2	1999	1.28156e+06	125682	1.15588e+06
3	2000	1.3173e+06	140064	1.17724e+06
4	2001	1329806	149852	1179954
5	2002	1367361	158216	1209145
6	2003	1394115	168144	1225971

In [445]:
```
# Same as with private_custody - making a list to distinguish this as da
ta pertaining to ALL prisons
prison_type = ['Total', 'Total', 'Total', 'Total',
               'Total', 'Total', 'Total', 'Total',
               'Total', 'Total', 'Total', 'Total',
               'Total', 'Total', 'Total', 'Total',
               'Total', 'Total']
```

In [446]:
```
# Adding to prison_custody
prison_custody['Prison Type'] = prison_type
```

In [447]:
```
# Reformatting
prison_custody = prison_custody.T.reset_index()
```

In [448]:
```
# Now we are ready to merge prison_custody and private_custody
prison_custody.head()
```

Out[448]:

	0	2	3	4	5	6	7	8	
0	Year	1999	2000	2001	2002	2003	2004	2005	200
1	U.S. total	1.28156e+06	1.3173e+06	1329806	1367361	1394115	1421816	1447435	148
2	Federal	125682	140064	149852	158216	168144	177600	186364	190
3	State	1.15588e+06	1.17724e+06	1179954	1209145	1225971	1244216	1261071	129
4	Prison Type	Total	Total	Total	Total	Total	Total	Total	Tota

In [449]:
```
# Merging prison_custody and private custody into a new data set called
 tot
tot = prison_custody.merge(private_custody, on=[0], how="outer")
```

In [450]:
```
# Reformatting tot and creatting a new variable called total to be the r
eformatted data frame
total = tot.set_index([0]).T.set_index(['Prison Type', 'Year']).unstack(
'Prison Type').T
```

In [451]:
```
# Transposing
total = total.T
```

Reformatted Chart: Private Prisons v. Total Prisons

This chart contains the U.S. total (i.e both state and federal prisons) as well as the totals for State and Federal prisons independant of eachother

In [452]:
```
# Here is the final reformatted data set
    # As you can see, this chart is split into three sections - all pris
ons (U.S. total),
        # Federal prisons ('Federal'), and State Prisons ('State')
            # From there the data is separated by if Private vs Total
 (i.e. all prisons)
total
```

Out[452]:

0	U.S. total		Federal		State	
Prison Type	**Private**	**Total**	**Private**	**Total**	**Private**	**Total**
Year						
1999	68960	1.28156e+06	3828	125682	65132	1.15588e+06
2000	91579	1.3173e+06	15524	140064	76055	1.17724e+06
2001	86421	1329806	12736	149852	73685	1179954
2002	88370	1367361	14732	158216	73638	1209145
2003	90123	1394115	16281	168144	73842	1225971
2004	92569	1421816	18709	177600	73860	1244216
2005	107433	1447435	27046	186364	80387	1261071
2006	113697	1488380	27726	190844	85971	1297536
2007	124150	1513390	31310	197285	92840	1316105
2008	129482	1522953	33162	198414	96320	1324539
2009	129333	1524650	34087	205087	95246	1319563
2010	127945	1521413	33830	206968	94115	1314445
2011	130972	1504986	38546	214774	92426	1290212
2012	137220	1483913	40446	216915	96774	1266998
2013	133363	1485266	41159	214989	92204	1270277
2014	131723	1479300	40017	209561	91706	1269739
2015	126272	1440722	34934	195622	91338	1245100
2016	128323	1417017	34159	188311	94164	1228706

Normalized Data

Next, I am going to normalize each column against its own minimum and maximum to create a range between 0 and 1 so that the data is easier to analyze

In [453]:
```
# These are functions that will populate the lists below with the normal
ized values of each column
        # That way I can join the lists together to create a new data fr
ame with the normalized data

tot_p = []
tot_t = []

fed_p = []
fed_t = []

sta_p = []
sta_t = []

for item in total['U.S. total'].Private:
    mn = total['U.S. total'].Private.min()
    mx = tot_p_max = total['U.S. total'].Private.max()
    p = (item - mn)/(mx - mn)
    tot_p.append(p)
for item in total['U.S. total'].Total:
    mn = total['U.S. total'].Total.min()
    mx = tot_p_max = total['U.S. total'].Total.max()
    p = (item - mn)/(mx - mn)
    tot_t.append(p)
for item in total['Federal'].Private:
    mn = total['Federal'].Private.min()
    mx = tot_p_max = total['Federal'].Private.max()
    p = (item - mn)/(mx - mn)
    fed_p.append(p)
for item in total['Federal'].Total:
    mn = total['Federal'].Total.min()
    mx = tot_p_max = total['Federal'].Total.max()
    p = (item - mn)/(mx - mn)
    fed_t.append(p)
for item in total['State'].Private:
    mn = total['State'].Private.min()
    mx = tot_p_max = total['State'].Private.max()
    p = (item - mn)/(mx - mn)
    sta_p.append(p)
for item in total['State'].Total:
    mn = total['State'].Total.min()
    mx = tot_p_max = total['State'].Total.max()
    p = (item - mn)/(mx - mn)
    sta_t.append(p)
```

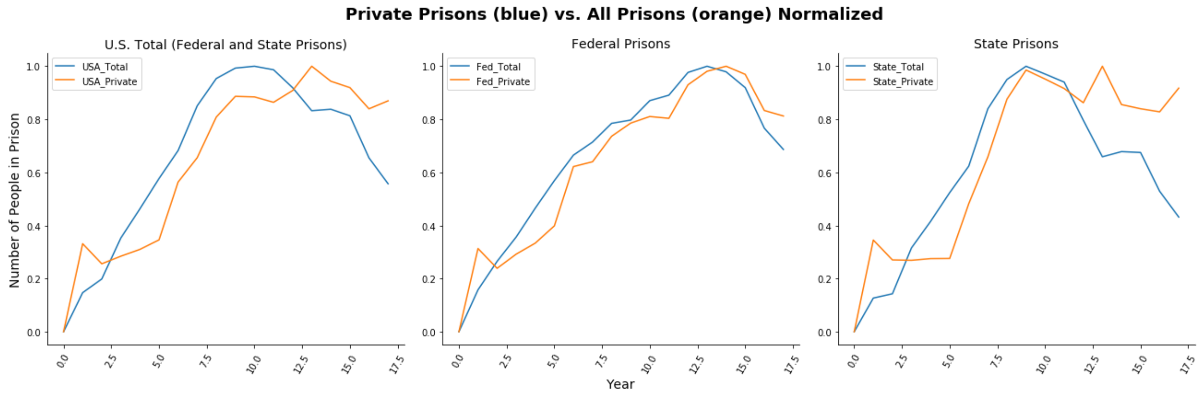
In [454]:
```
# This is the dataframe I am creating with the above lists
normal = pd.DataFrame({'USA_Private': tot_p, 'USA_Total': tot_t, 'Fed_Pr
ivate': fed_p, 'Fed_'+
                       'Total': fed_t, 'State_Private': sta_p, 'State_To
tal': sta_t,})
```

In [455]:
```
# Here is what the data frame looks like
    # This is the number of people incarcerated over time, normalized to
 each columns own data

normal
```

Out[455]:

	Fed_Private	Fed_Total	State_Private	State_Total	USA_Private	USA_Total
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.313305	0.157640	0.345206	0.126656	0.331365	0.147040
2	0.238622	0.264926	0.270305	0.142748	0.255801	0.198470
3	0.292090	0.356603	0.268820	0.315823	0.284354	0.352960
4	0.333583	0.465424	0.275267	0.415585	0.310035	0.463018
5	0.398623	0.569070	0.275836	0.523761	0.345869	0.576971
6	0.621950	0.665132	0.482112	0.623695	0.563624	0.682360
7	0.640165	0.714237	0.658587	0.839898	0.655391	0.850796
8	0.736171	0.784837	0.875672	0.949994	0.808526	0.953680
9	0.785781	0.797212	0.985652	1.000000	0.886639	0.993019
10	0.810560	0.870354	0.951710	0.970497	0.884456	1.000000
11	0.803675	0.890971	0.915966	0.940152	0.864122	0.986684
12	0.930005	0.976533	0.862588	0.796473	0.908468	0.919108
13	0.980901	1.000000	1.000000	0.658836	1.000000	0.832420
14	1.000000	0.978889	0.855572	0.678278	0.943495	0.837986
15	0.969409	0.919393	0.839833	0.675088	0.919470	0.813444
16	0.833249	0.766609	0.828203	0.529002	0.839613	0.654745
17	0.812488	0.686473	0.917515	0.431801	0.869660	0.557230

In [533]:
```
# These are three graphs showing the number of people in all prisons and
 only private over time,
    # separated by all prisons, Federal prisons, and State prisons

fig, ax = plt.subplots(nrows = 1, ncols = 3, figsize = (18,5))

fig.tight_layout()

ax[0].plot(normal['USA_Total'])
ax[0].plot(normal['USA_Private'])

ax[1].plot(normal['Fed_Total'])
ax[1].plot(normal['Fed_Private'])

ax[2].plot(normal['State_Total'])
ax[2].plot(normal['State_Private'])


ax[0].tick_params(axis='x', rotation=60)
ax[1].tick_params(axis='x', rotation=60)
ax[2].tick_params(axis='x', rotation=60)

# Eliminating the upper and right frame of the graphs
ax[0].spines["top"].set_visible(False)
ax[0].spines["right"].set_visible(False)

ax[1].spines["top"].set_visible(False)
ax[1].spines["right"].set_visible(False)


ax[2].spines["top"].set_visible(False)
ax[2].spines["right"].set_visible(False)

ax[0].set_ylabel("Number of People in Prison", fontsize=14)
ax[1].set_xlabel("Year", fontsize=14)

# Labeling each graph
ax[0].set_title('U.S. Total (Federal and State Prisons)', fontsize=14)
ax[1].set_title('Federal Prisons', fontsize=14)
ax[2].set_title('State Prisons', fontsize=14)

# Labeling the whole thing
fig.suptitle("Private Prisons (blue) vs. All Prisons (orange) Normalize
d",
             fontsize=18, fontweight='bold', y = 1.1)

ax[0].legend()
ax[1].legend()
ax[2].legend()


plt.show()
```



Step Two: Private Prisons v. All Prisons by State

In this step I am going to use the same data set, but this time I will be looking at the data on a state level rather than a national level

In [457]:
```
# Reading the data set into a new variable
state_private = pd.read_excel('QT_private_prisons_total.xlsx')
```

In [458]:
```
# Reformatting - this time saving only the state data
state_private = state_private.T.reset_index().drop(['ind'+
                'ex', 1, 2, 3, 55, 56, 57, 58, 59, 60, 61, 62], axis = 1
).drop([0])
```

In [459]:
```
state_private = state_private.set_index([0]).T
```

In [460]:
```
# This is a function to rid any of the state names of additional charact
ers they may have at the end
p=[]
for i in (state_private.Year):
    if (i[-2:] == '/b') or (i[-2:] == '/e'):
        p = i[0:-2]
        if i[0:-2] == p:
            state_private.Year.replace(to_replace=i, value = p, inplace=
True)
```

In [461]:
```
# Cleaning up the data set to make sure all values are numbers
state_private.replace(to_replace="/", value=0, inplace = True)
state_private.replace(to_replace="--", value=0, inplace=True)
state_private.replace(to_replace=".", value=0, inplace=True)
```

In [462]:
```
# Filling empty cells with 0
state_private.fillna(0, inplace=True)
```

In [463]:
```
# Making sure column headers are strings to access them more easily
state_private.columns = state_private.columns.map(str)
state_private = state_private.rename(columns={'1999.0':'1999'})
```

In [464]:
```
state_private.set_index('Year', inplace=True)
```

Normalized Data

For this section, I am normalizing the data based on population size to get a better representation of the relative number of people incarcerated in private prisons as compared to all prisons

For this step I am utilizing the Census API to pull population data - due to the data available with this API and the scope of this project, I am only looking at 2015 for this section

In [465]:
```
# Here I am importing the Census API
from census import Census
from us import states
```

In [466]:
```
# This is my api_key
my_api_key = '34e40301bda77077e24c859c6c6c0b721ad73fc7'

# object c has methods associated with it to use the Census API
c = Census(my_api_key)
```

In [467]:
```
# This grabs the geographical name, B01001_001E which is the population
    # This grabs data from all of the States

code = ("NAME","B01001_001E")
state_pop_2015 = c.acs5.get(code, {'for': 'state:* '}, year=2015)

# This creates a data frame with the data I grabbed from the API
state_pop_2015 = pd.DataFrame(state_pop_2015)

# Here I renamed B01001_001E
state_pop_2015.rename(columns={'B01001_001E':'Pop_2015'}, inplace=True)
```

In [468]:
```
# Here I am merging state_pop_2015 with state_private
state_private = state_private.reset_index().merge(state_pop_2015, left_o
n='Year', right_on='NAME', how="outer")
```

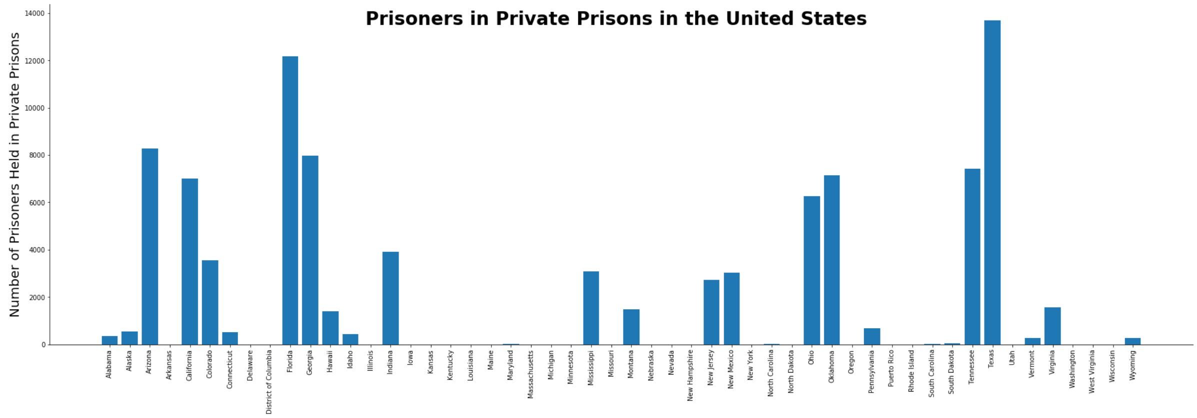
In [469]:
```
# Reformatting
state_private_2015 = state_private.T.reset_index()[17:21].T.set_index([2
0]).T.set_index('NAME').T.drop('2016', axis=1)
```

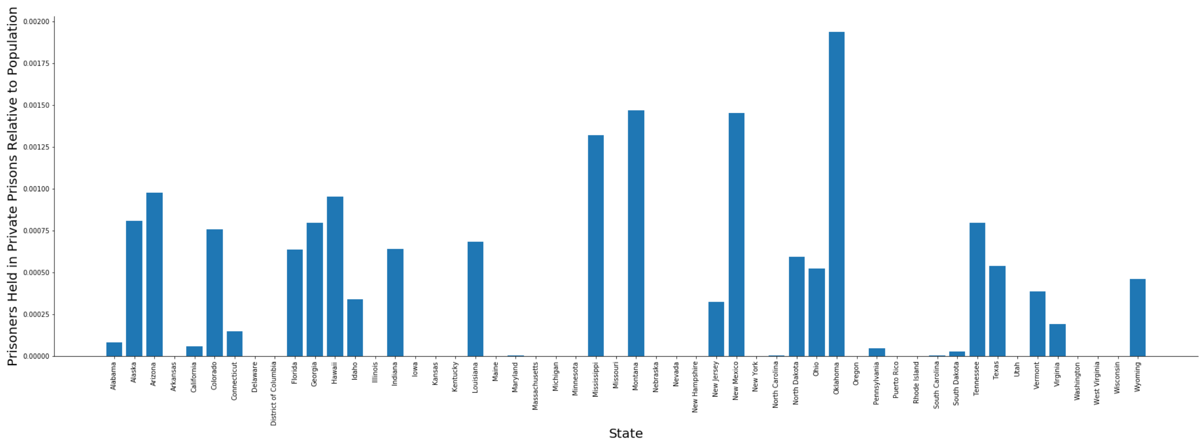
In [470]:
```
# Here I am creating a new column in my data frame called norman_2015
    # normal_2015 has the same data about prisoners held in private pris
ons, relative to population size
state_private_2015['normal_2015'] = state_private_2015['2015']/state_pri
vate_2015['Pop_2015']
```

In [479]:
```
# Here I am reformatting the private prisons 2015 normalized data set so
 it can be graphed seamlesly
state_private_2015 = state_private_2015.reset_index()
state_private_2015.columns = state_private_2015.columns.map(str)
state_private_2015.rename(columns={'20':'State'}, inplace=True)
```

Below are two graphs. This first graph was made with 2015 data NOT normalized by population. The second graph WAS made with 2015 data, normalized by population.

In [480]:
```
# Creting my graphs in 2 rows and 1 column
fig, ax = plt.subplots(nrows = 2, ncols = 1, figsize = (25,17))

fig.tight_layout(h_pad=12, w_pad=12)

ax[0].bar(state_private_2015['State'], state_private['2016'])
ax[1].bar(state_private_2015['State'], state_private_2015['normal_2015'
])

# Rotating the State names on the x-axis
ax[0].tick_params(axis='x', rotation=90)
ax[1].tick_params(axis='x', rotation=90)

# Making clear names to distinguish between the charts
ax[0].set_ylabel('Number of Prisoners Held in Private Prisons', fontsize
=20) # Set the y label
ax[1].set_ylabel('Prisoners Held in Private Prisons Relative to Populati
on', fontsize=20) # Set the y label

# Making more labels
ax[1].set_xlabel("State", fontsize=20) # Set the x label

# Titling the graphs
fig.suptitle("Prisoners in Private Prisons in the United States",
             fontsize=28, fontweight='bold')

# Eliminating the upper and right frame of the graphs
ax[0].spines["top"].set_visible(False)
ax[0].spines["right"].set_visible(False)

ax[1].spines["top"].set_visible(False)
ax[1].spines["right"].set_visible(False)

#California, Florida, Hawaii, Louisiana, Mississippi, Montana, New Mexic
o, North Dakota

plt.show()
```





Step Three: Location of Private Prisons v. Political Leaning by State

In this step I am going to use data from Pew Research to create a graph that illustrates the political leaning of the States in the United States

Then, I will use the normalized number of people inprivate prisons in 2015 data from Step Two and create a map that shows which states have the most people incarcerated in private prisons, relative to the population

In [481]:
```
# Here I am loading the shape file that will enable me to create my Maps
cwd = os.getcwd()
regions_shape = cwd + "/shape_file/USstates/cb_2017_us_state_500k.shx"
```

In [482]:
```
regions_shape
```

Out[482]:
```
'/Users/rachelrub/Documents/DataBootcamp/FinalProject/shape_file/USstat
es/cb_2017_us_state_500k.shx'
```

In [483]:
```
# I am reading the shap file into a data frame I am calling USA_map
USA_map = gpd.read_file(regions_shape)
```

In [484]:
```
# Here is what it looks like
USA_map.head(5)
```

Out[484]:

	STATEFP	STATENS	AFFGEOID	GEOID	STUSPS	NAME	LSAD	ALAND	
0	54	01779805	0400000US54	54	WV	West Virginia	00	62265662566	4
1	17	01779784	0400000US17	17	IL	Illinois	00	143784114293	6
2	24	01714934	0400000US24	24	MD	Maryland	00	25150696145	6
3	16	01779783	0400000US16	16	ID	Idaho	00	214048160737	2
4	50	01779802	0400000US50	50	VT	Vermont	00	23873457570	1

In [485]:
```
# Now, I am loading the data from Pew Research about State political lea
ning
political_leaning = pd.read_excel('PEW_political_leading.xlsx')
```

In [486]:
```
# Here it is
political_leaning.head()
```

Out[486]:

	State	Republican/lean Rep.	No Lean	Democrat/lean Dem.	Sample Size
0	Alabama	0.52	0.13	0.35	511
1	Alaska	0.39	0.29	0.32	310
2	Arizona	0.40	0.21	0.39	653
3	Arkansas	0.46	0.16	0.38	311
4	California	0.30	0.21	0.49	3697

In [487]:

```
# Now, I am merging the political leaning data with the USA_map data frame
USA_map = USA_map.merge(political_leaning, left_on='NAME', right_on='State', how="outer")
```

In [488]:

```
# Here is is, merged
USA_map.head()
```

Out[488]:

	STATEFP	STATENS	AFFGEOID	GEOID	STUSPS	NAME	LSAD	ALAND	
0	54	01779805	0400000US54	54	WV	West Virginia	00	62265662566	4
1	17	01779784	0400000US17	17	IL	Illinois	00	143784114293	6
2	24	01714934	0400000US24	24	MD	Maryland	00	25150696145	6
3	16	01779783	0400000US16	16	ID	Idaho	00	214048160737	2
4	50	01779802	0400000US50	50	VT	Vermont	00	23873457570	1

In [489]:

```
# Here is state_private_2015 from Sept Two
state_private_2015.head()
```

Out[489]:

NAME	index	State	2015	Pop_2015	normal_2015
0	0	Alabama	398	4.83062e+06	8.23911e-05
1	1	Alaska	593	733375	0.00080859
2	2	Arizona	6471	6.64193e+06	0.000974265
3	3	Arkansas	0	2.95821e+06	0
4	4	California	2195	3.84215e+07	5.71295e-05

In [490]:
```
# Now I am going to merge
USA_map = USA_map.merge(state_private_2015, left_on='NAME', right_on='St
ate', how="outer")
```

In [491]:
```
# Here is the fully merged USA_map
USA_map.head()
```

Out[491]:

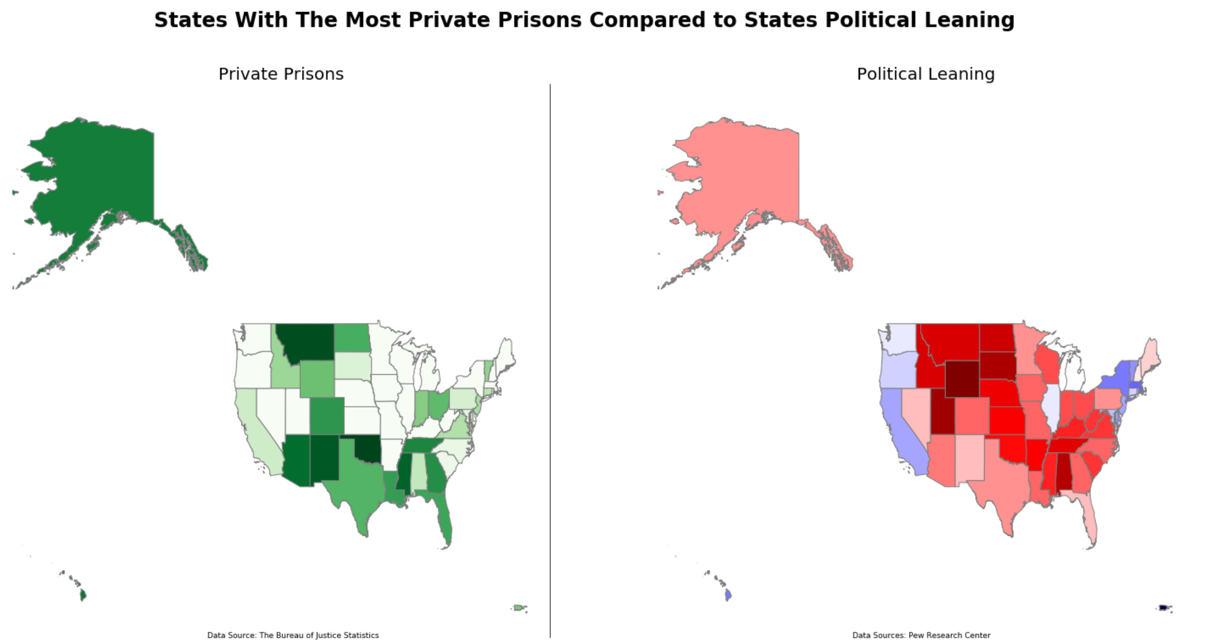
	STATEFP	STATENS	AFFGEOID	GEOID	STUSPS	NAME	LSAD	ALAND	
0	54	01779805	0400000US54	54	WV	West Virginia	00	62265662566	4
1	17	01779784	0400000US17	17	IL	Illinois	00	143784114293	6
2	24	01714934	0400000US24	24	MD	Maryland	00	25150696145	6
3	16	01779783	0400000US16	16	ID	Idaho	00	214048160737	2
4	50	01779802	0400000US50	50	VT	Vermont	00	23873457570	1

In [492]:
```
# I am making sure that all the columnns in USA_map are strings so that
 I can access them more easily
USA_map.columns = USA_map.columns.map(str)
```

In [493]:
```
fig, ax = plt.subplots(nrows = 1, ncols = 2, figsize=(25,12))

# This first map is the map of the number of people incarcerated in priv
ate prisons in each state,
    # relative to the population of that state, in 2015

USA_map.plot(ax = ax[0], # So the geopandas has a built in plot feature,
 we just pass our "ax to it
             edgecolor='tab:grey',
             column='normal_2015',
             cmap='Greens',
             alpha = 1) # Transparent

# This second map is a dipiction of the political leaning of the United
 States of America, by state

USA_map.plot(ax = ax[1], # So the geopandas has a built in plot feature,
 we just pass our "ax to it
             edgecolor='tab:grey',
             column='Republican/lean Rep.',
             cmap='seismic',
             alpha = 1) # Transparent

# Setting the bounds of the map so that it fits the frame better
ax[0].set_xlim([-170, -60])
ax[0].set_ylim([15, 75])

ax[1].set_xlim([-170, -60])
ax[1].set_ylim([15, 75])

# Making the right boarder of the left map visible to separate the maps
ax[0].spines["right"].set_visible(True)

# Making the rest of the boarders invisible
ax[0].spines["left"].set_visible(False)
ax[0].spines["top"].set_visible(False)
ax[0].spines["bottom"].set_visible(False)

ax[1].spines["right"].set_visible(False)
ax[1].spines["left"].set_visible(False)
ax[1].spines["top"].set_visible(False)
ax[1].spines["bottom"].set_visible(False)

ax[0].get_xaxis().set_visible(False)
ax[0].get_yaxis().set_visible(False)

ax[1].get_xaxis().set_visible(False)
ax[1].get_yaxis().set_visible(False)

# Labeling the Maps
ax[0].set_title('Private Prisons', fontsize=20)
ax[1].set_title('Political Leaning', fontsize=20)

# Labeling the whole thing
```

```
fig.suptitle("States With The Most Private Prisons Compared to States Po
litical Leaning",
             fontsize=24, fontweight='bold')

# Citing my sources
ax[0].text(-130,15, "Data Source: The Bureau of Justice Statistics",font
size=9)
ax[1].text(-130,15, "Data Sources: Pew Research Center",fontsize=9)

plt.show()
```

```
/Users/rachelrub/anaconda3/lib/python3.6/site-packages/matplotlib/color
s.py:489: RuntimeWarning: invalid value encountered in less
  np.copyto(xa, -1, where=xa < 0.0)
```



Conclusion

My evaluation post analysis:

- **Step 1**: In step one Private prisons and all prisons seem to be traveling along very similar trajectories.
- **Step 2**: In step two, it was apparent how impactful normalizing by state population was in interpreting the data. Some states, like California, went from having being seemingly dominant in its private prison population, however when adjusted to the population of California itself, the significance decreased dramatically. Similarly, state like Montana became more significant upon normalizing the data. There may not be many people in private prisons in Montana, however there simply are ot that many people in Montana, so when population was taken into account, Montana had a higher people in private prisons relative to population ratio.
- **Step 3**: I was predicting that Republican leaning states would have more people in private prisons. However, while there is quite a bit of overlap between dominant private prison states and Republican leaning states, the graphs are significantly different.

Next steps would be to delve deeper into the types of prisosn that are private versus the types of prisons that are public, to take into account variables that perhaps contributed to some element of ommitted variable bias in this report.