Gun Fatalities in the United States

Data Bootcamp - Undergraduate - Fall 2018

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In the past year, the United States has witnessed hightened tensions surrounding the US Constitution's 2nd ammendment regarding the right to bare arms. Politicians and civilians equally have become more divided on the topic after several shootings in public spaces and schools have taken the life of innocent Americans. In this project, we dive deep into the gun fatalities in the US to understand who are those that are being most affected. As our main source of data we used Five Thirty Eight's reasearch on gun fatalities from 2012 to 2014. We will also be using a complementary data source from the Washington Post.

We've split up this into three seperate parts: The first part will discuss the most common cause of gun deaths in the US: suicides. We want to dive deep into the demographics of suicides and develop an informed hypothesis about what are the major causes of suicide in the US. The second part analyzes homicides in the United States. We'll also investigate the demographics on homicides in the country to see who is more prone to gun violence in our country. The third part will look specifically into homicides by police officers and will investigate the claim that police officers are more prone to using deadly force against minority races such as blacks and hispanics versus majority race.

In [1]:

```
import pandas as pd  # data package
import numpy as np
import matplotlib.pyplot as plt # graphics
import statsmodels.api as sm
%matplotlib inline
```

In [18]:

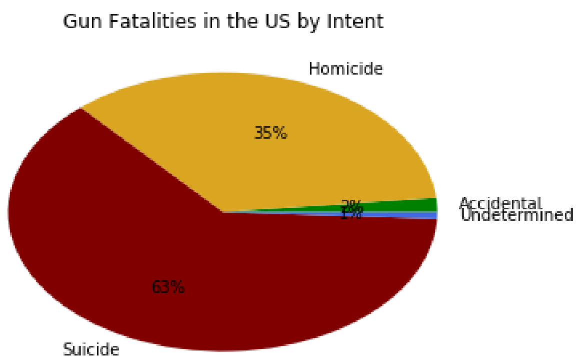
```
#Reading the Five Thirty-Eight file and cleaning the dataframe to be able to work with it
guns = (pd.read_csv('https://raw.githubusercontent.com/fivethirtyeight/guns-data/master/full_data.csv')
        .sort_values(['year','month']).rename(columns={'Unnamed: 0':'id'}).drop('hispanic',axis=1))
#We also cleaned the file to sort the deaths by year and month and renamed the first column to be the id.
#We dropped one more column that we found uneccesary for this project
```

In [62]:

```
#Creating a pivot table that describes the number of deaths by year by intent
intents = guns.pivot_table(index='intent',columns='year',values='id',aggfunc=len)
intents['average'] = intents.mean(axis=1) #Adds a column that averages the fatalities per intent over the three years
fig,ax = plt.subplots()
intents['average'].plot.pie(y=' ',ax=ax,autopct='%1.0f%%', colors=['green','goldenrod','maroon','royalblue'])
ax.set_title('Gun Fatalities in the US by Intent')
ax.set_ylabel(' ')
```

Out[62]:

```
Text(0,0.5,' ')
```



In [64]:

```
intents
```

Out[64]:

year	2012	2013	2014	average
intent				
Accidental	548	505	586	546.333333
Homicide	12093	11674	11409	11725.333333
Suicide	20666	21175	21334	21058.333333
Undetermined	256	281	270	269.000000

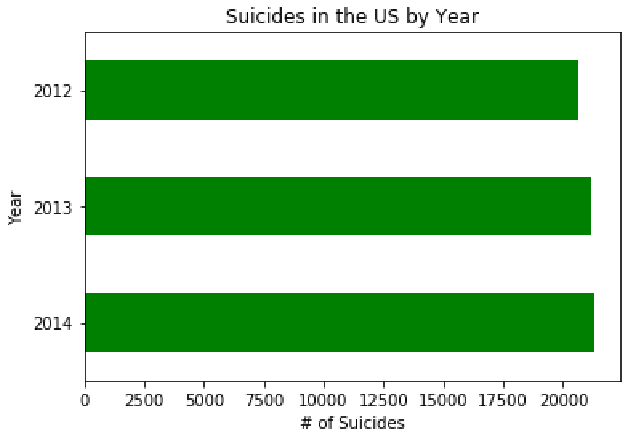
Suicides

In [65]:

```
suicides = guns.loc[guns['intent']=='Suicide']# Filtering for all deaths with homicidal intent
fig,ax = plt.subplots()
suicides['year'].value_counts().plot.barh(ax = ax,color='green')
ax.set_title('Suicides in the US by Year')
ax.set_xlabel('# of Suicides')
ax.set_ylabel('Year')
```

Out[65]:

```
Text(0,0.5,'Year')
```

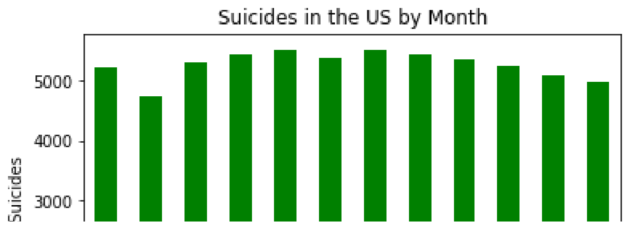


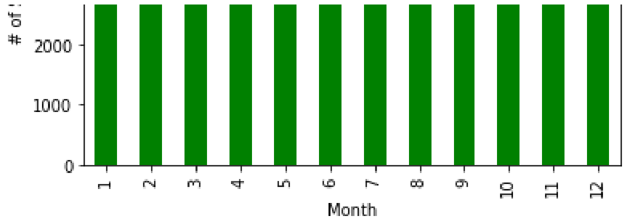
In [75]:

```
fig,ax = plt.subplots()
suicides['month'].value_counts().sort_index().plot.bar(ax = ax,color='green')
ax.set_title('Suicides in the US by Month')
ax.set_ylabel('# of Suicides')
ax.set_xlabel('Month')
```

Out[75]:

```
Text(0.5,0,'Month')
```



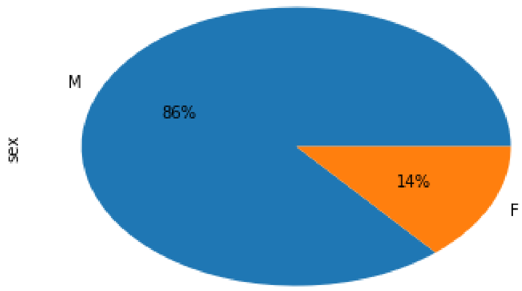


In [5]:

```
suicides['sex'].value_counts().plot.pie(autopct='%1.0f%%')
```

Out[5]:

<matplotlib.axes._subplots.AxesSubplot at 0x1c0d22b9b0>

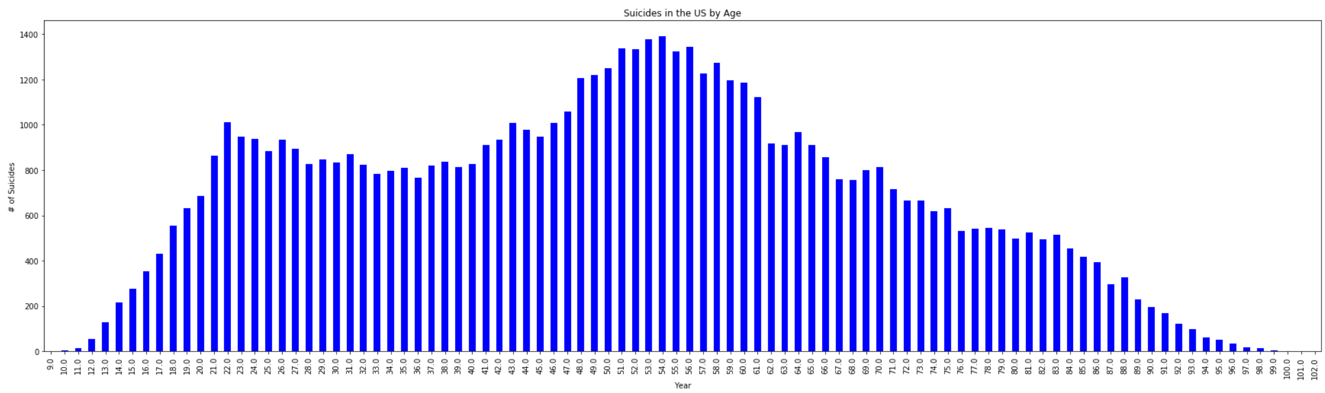


In [67]:

```
fig,ax = plt.subplots()
suicides['age'].value_counts().sort_index().plot.bar(ax = ax,color='blue',figsize=(30,8))
ax.set_title('Suicides in the US by Age')
ax.set_ylabel('# of Suicides')
ax.set_xlabel('Year')
```

Out[67]:

Text(0.5,0,'Year')

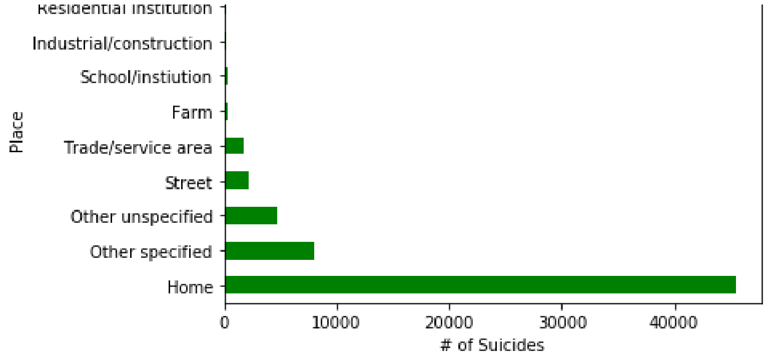


In [68]:

```
fig,ax = plt.subplots()
suicides['place'].value_counts().plot.barh(ax = ax,color='green')
ax.set_title('Suicides in the US by Place')
ax.set_xlabel('# of Suicides')
ax.set_ylabel('Place')
```

Out[68]:

Text(0,0.5,'Place')

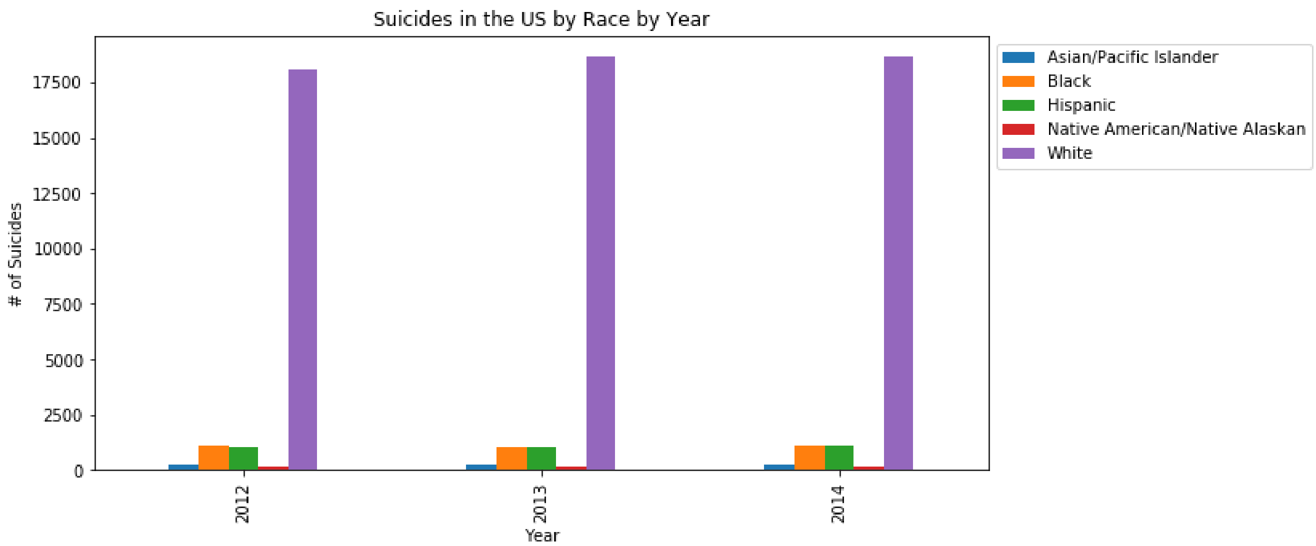


In [72]:

```
suicide_race=suicides.pivot_table(index='year',columns='race',values='id',aggfunc=len)
fig,ax = plt.subplots()
suicide_race.sort_index().plot.bar(ax=ax,figsize=(10,5))
ax.set_title('Suicides in the US by Race by Year')
ax.set_ylabel('# of Suicides')
ax.set_xlabel('Year')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[72]:

```
<matplotlib.legend.Legend at 0x1c1fd29d68>
```

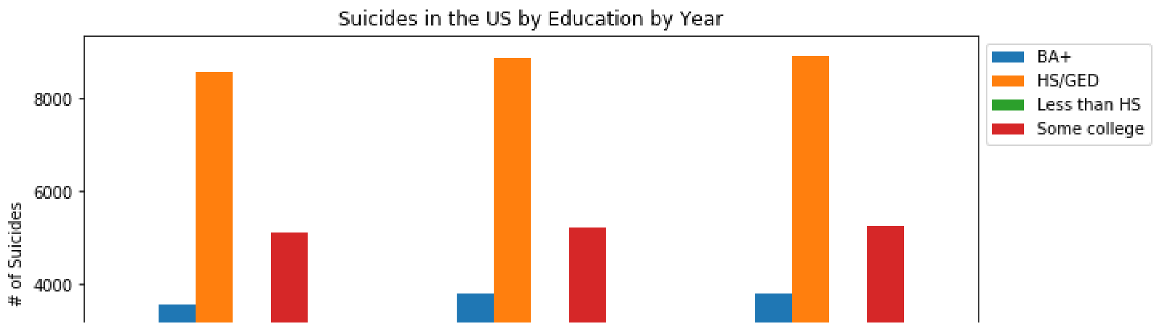


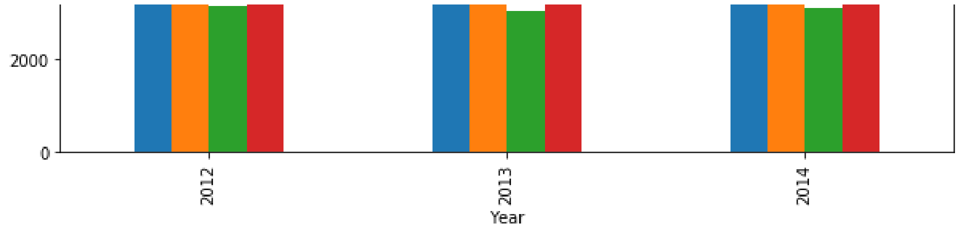
In [71]:

```
suicide_education=suicides.pivot_table(index='year',columns='education',values='id',aggfunc=len)
fig,ax = plt.subplots()
suicide_education.sort_index().plot.bar(ax=ax,figsize=(10,5))
ax.set_title('Suicides in the US by Education by Year')
ax.set_ylabel('# of Suicides')
ax.set_xlabel('Year')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[71]:

```
<matplotlib.legend.Legend at 0x1c1fc40240>
```





From the graphs above, we can easily see that suicide rates increased between 2012 and 2014. Feburary has the lowest number of suicides, while May and July have the highest. 86% of reported suicides in US between 2012 and 2014 were male, while only 14% were female. Most suicides happen at home, possibly because most people feel safest and/or most stressed there. Most reported suicides were by white people. Suicide rates among high school graduates and college graduates increased between 2012 and 2014. The age group with the highest suicide rate was 51-60, with 54 year olds forming the peak. There is a smaller, yet significant peak at the age of 22. All this leads us to believe that many, if not most, of these suicides might have been caused by employement issues, debt issues, mid-life crises etc.

Homicides

The second largest intent group within gun deaths in America is homicide. We've already seen that gun deaths in the United States tend to be more common among men than women and we don't suspect that this could be any different when narrowing down the deaths to homicides. However, something we want to explore within this category is race. For the past decades, our media has focused a lot on violence in minoirty communities such as black and hispanic

In [8]:

```
homicide = guns.loc[guns['intent'] == 'Homicide'] # Filtering for all deaths with homicidal intent
#Creating a data frame for the number of homicides per year per race
hom_race = homicide.pivot_table(index='year',columns='race',values='id',aggfunc=len)
hom_race
```

Out[8]:

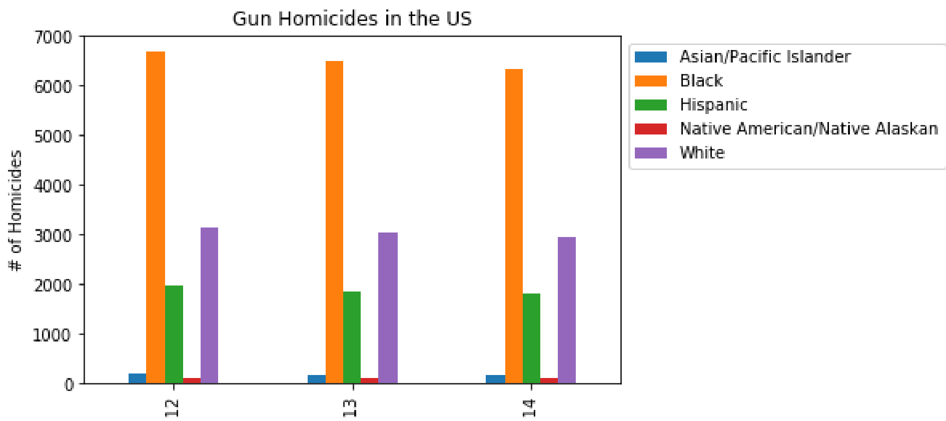
race	Asian/Pacific Islander	Black	Hispanic	Native American/Native Alaskan	White
year					
2012	205	6676	1971	105	3136
2013	181	6503	1836	97	3057
2014	173	6331	1827	124	2954

In [9]:

```
fig,ax = plt.subplots()
hom_race.plot.bar(ax = ax)
ax.set_title('Gun Homicides in the US')
ax.set_ylabel('# of Homicides')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[9]:

<matplotlib.legend.Legend at 0x1c1ad027f0>



The information above confirms what popular media has been saying. More than double the amount of black people in America die by gun shot than white people. But the data from the CDC enables us to dig deeper into who is perpetrating the homicide, specifically, deaths perpetrated by police officers. A controversial topic in popular media today has been the huge racial disparities in how US police use force. The data from the CDC might enable us to dig deeper into how each race is being treated differently by US police.

In [10]:

```
#Creating a dataframe for homicides in which police was involved per race per year
hom_pol = homicide.loc[homicide['police']==1].pivot_table(index='year',columns='race',values='id',a
ggfunc=len)
hom_pol['total']= hom_pol.sum(axis=1)
hom_pol['%Black'] = hom_pol['Black']/hom_pol['total']
hom_pol['%Hispanic'] = hom_pol['Hispanic']/hom_pol['total']
hom_pol
```

Out[10]:

race	Asian/Pacific Islander	Black	Hispanic	Native American/Native Alaskan	White	total	%Black	%Hispanic
year								
2012	10	121	101	10	229	471	0.256900	0.214437
2013	11	129	86	4	237	467	0.276231	0.184154
2014	9	106	95	11	243	464	0.228448	0.204741

In [11]:

```
hom_pol.mean()
```

Out[11]:

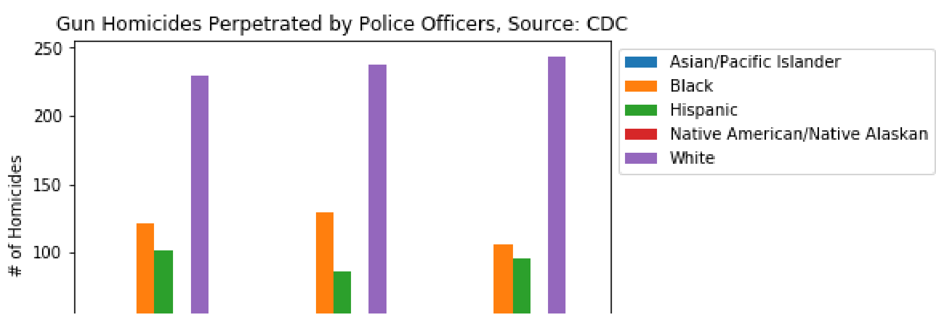
```
race
Asian/Pacific Islander             10.000000
Black                             118.666667
Hispanic                           94.000000
Native American/Native Alaskan      8.333333
White                             236.333333
total                             467.333333
%Black                              0.253860
%Hispanic                           0.201111
dtype: float64
```

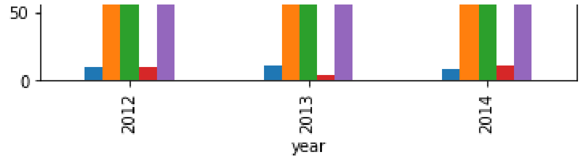
In [12]:

```
fig,ax = plt.subplots()
hom_pol[['Asian/Pacific Islander','Black','Hispanic', 'Native American/Native Alaskan', 'White']].
plot.bar(ax = ax)
ax.set_title('Gun Homicides Perpetrated by Police Officers, Source: CDC')
ax.set_ylabel('# of Homicides')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[12]:

```
<matplotlib.legend.Legend at 0x1c1ad2a898>
```



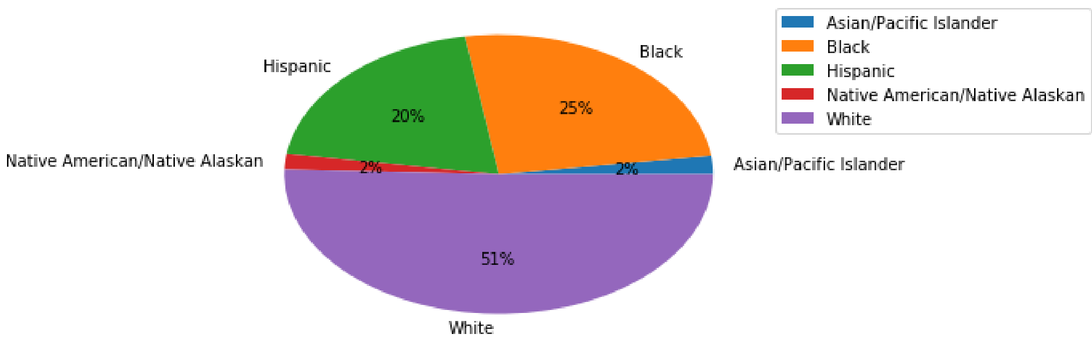


In [51]:

```
#Creating a dataset that transposes the pervious one, putting the years as columns and the races a
s rows
trans_hom_pol = hom_pol[['Asian/Pacific Islander','Black','Hispanic', 'Native American/Native
Alaskan', 'White']].transpose()
#Adding one more column for the average number of homicides per race for the three years
trans_hom_pol['Average']=trans_hom_pol.mean(axis=1)
#Plotting the average % of homicides per race
fig,ax = plt.subplots()
trans_hom_pol.plot.pie(y='Average',ax=ax,autopct='%1.0f%%')
ax.set_ylabel('')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[51]:

```
<matplotlib.legend.Legend at 0x1c1e4d1ba8>
```



It is interesting to see that fatal police shootings happen more often with white people than minority populations. Simply looking at the total number of fatalities per race is not accurate because it assumes that the US population is composed by an equal amount of people from each race. According to the Census Bureau, the US population is composed of 64% whites, 12% black and 16% hispanic or latino. Nevertheless, Black and Hispanic populations represent 25% and 20% of fatal police shootings on average each year respectively.

However, we have to keep in mind that this data is reported by the Center for Disease Control, a government agency who benefits from misrepresenting or undereporting data such as fatal police shootings. Thus we decided to consult another source for data on fatal police shootings. Although the data from the Washington Post only has data after 2014, it is impossible to match both sources. However, according to the CDC, fatal police shootings by race have remained relatively constant as shown below. Thus, we could expect the data from the Washington Post to be similar to that of the CDC. Below we analyze the data from the Washington Post and compare it to that of the CDC:

In [27]:

```
#Reading data from the Washington Post on shootings by police officers
wp_guns = pd.read_csv('https://raw.githubusercontent.com/washingtonpost/data-police-
shootings/master/fatal-police-shootings-data.csv')
#Creating a column out of the first 4 characters of the string in 'Date' for the year of the homic
ide
wp_guns['year'] = wp_guns['date'].str.slice(0,4)
#Creating a column out of the 6th and 7th characters of the string in 'Date' for the month of the
homicide
wp_guns['month'] = wp_guns['date'].str.slice(5,7)
#Dropping the column date
wp_guns['date'].drop
wp_guns
```

Out[27]:

	id	name	date	manner_of_death	armed	age	gender	race	city	state	signs_of_mental_illn
			2015-								

	id	name	date	manner_of_death	armed	age	gender	race	city	state	signs_of_mental_illn
0	3	Tim Elliot	01-02	shot	gun	53.0	M	A	Shelton	WA	True
1	4	Lewis Lee Lembke	2015-01-02	shot	gun	47.0	M	W	Aloha	OR	False
2	5	John Paul Quintero	2015-01-03	shot and Tasered	unarmed	23.0	M	H	Wichita	KS	False
3	8	Matthew Hoffman	2015-01-04	shot	toy weapon	32.0	M	W	San Francisco	CA	True
4	9	Michael Rodriguez	2015-01-04	shot	nail gun	39.0	M	H	Evans	CO	False
5	11	Kenneth Joe Brown	2015-01-04	shot	gun	18.0	M	W	Guthrie	OK	False
6	13	Kenneth Arnold Buck	2015-01-05	shot	gun	22.0	M	H	Chandler	AZ	False
7	15	Brock Nichols	2015-01-06	shot	gun	35.0	M	W	Assaria	KS	False
8	16	Autumn Steele	2015-01-06	shot	unarmed	34.0	F	W	Burlington	IA	False
9	17	Leslie Sapp III	2015-01-06	shot	toy weapon	47.0	M	B	Knoxville	PA	False
10	19	Patrick Wetter	2015-01-06	shot and Tasered	knife	25.0	M	W	Stockton	CA	False
11	21	Ron Sneed	2015-01-07	shot	gun	31.0	M	B	Freeport	TX	False
12	22	Hashim Hanif Ibn Abdul-Rasheed	2015-01-07	shot	knife	41.0	M	B	Columbus	OH	True
13	25	Nicholas Ryan Brickman	2015-01-07	shot	gun	30.0	M	W	Des Moines	IA	False
14	27	Omarr Julian Maximillian Jackson	2015-01-07	shot	gun	37.0	M	B	New Orleans	LA	False
15	29	Loren Simpson	2015-01-08	shot	NaN	28.0	M	W	Huntley	MT	False
16	32	James Dudley Barker	2015-01-08	shot	shovel	42.0	M	W	Salt Lake City	UT	False
17	36	Artago Damon Howard	2015-01-08	shot	unarmed	36.0	M	B	Strong	AR	False
18	37	Thomas Hamby	2015-01-08	shot	gun	49.0	M	W	Syracuse	UT	False
19	38	Jimmy Foreman	2015-01-09	shot	gun	71.0	M	W	England	AR	False
20	325	Andy Martinez	2015-01-09	shot	gun	33.0	M	H	El Paso	TX	False
21	42	Tommy Smith	2015-01-11	shot	gun	39.0	M	W	Arcola	IL	True
22	43	Brian Barbosa	2015-01-11	shot	gun	23.0	M	H	South Gate	CA	False
23	45	Salvador Figueroa	2015-01-11	shot and Tasered	gun	29.0	M	H	North Las Vegas	NV	False
		John									

	id	name	date	manner_of_death	armed	age	gender	race	city	state	signs_of_mental_illn
24	46	John Edward O'Keefe	2015-01-13	shot	gun	34.0	M	W	Albuquerque	NM	False
25	48	Richard McClendon	2015-01-13	shot	knife	43.0	M	W	Jourdanton	TX	True
26	49	Marcus Golden	2015-01-14	shot	NaN	24.0	M	B	St. Paul	MN	False
27	50	Michael Goebel	2015-01-14	shot	NaN	29.0	M	W	Franklin County	MO	False
28	51	Mario Jordan	2015-01-14	shot	gun	34.0	M	B	Chesapeake	VA	True
29	52	Talbot Schroeder	2015-01-14	shot	knife	75.0	M	W	Old Bridge	NJ	False
...	...	...	...	...	...	...	...	...	...	...	...
3871	4241	Ricardo Galvan	2018-11-30	shot	gun	37.0	M	H	Ogden	UT	False
3872	4239	Demontry Floytra Boyd	2018-12-01	shot and Tasered	knife	43.0	M	B	Las Vegas	NV	False
3873	4240	John Young	2018-12-01	shot	meat cleaver	65.0	M	NaN	Pensacola	FL	False
3874	4272	Jarvis Randall	2018-12-01	shot	straight edge razor	30.0	M	B	Tamarac	FL	True
3875	4269	Anthony Ray Borden-Cortez	2018-12-04	shot	toy weapon	18.0	M	H	Ogden	UT	False
3876	4270	David Alejandro Molina	2018-12-05	shot	gun	27.0	M	H	Napa	CA	False
3877	4271	TK TK	2018-12-05	shot	knife	NaN	M	NaN	Philadephia	PA	False
3878	4276	Paul Ridgeway	2018-12-05	shot	gun	41.0	M	NaN	Martinez	CA	False
3879	4279	Anthony M. Edwards	2018-12-05	shot	knife	33.0	M	NaN	Richmond	VA	False
3880	4275	Dimaggio McDonough	2018-12-06	shot	gun	53.0	M	NaN	Henry County	GA	False
3881	4277	Benjamin David Larson	2018-12-06	shot	gun	42.0	M	W	Redding	CA	False
3882	4287	Jason O'Bannon	2018-12-06	shot	gun	46.0	M	W	Pahrump	NV	True
3883	4281	Jesus Lainez	2018-12-07	shot	unknown weapon	51.0	M	H	Fort Pierce	FL	False
3884	4286	James N. Robertson	2018-12-08	shot	knife	41.0	M	NaN	West Wendover	NV	False
3885	4282	Joshua Boyd	2018-12-09	shot	gun	24.0	M	NaN	Savannah	GA	False
3886	4283	Christopher Deandre Mitchell	2018-12-09	shot	gun	23.0	M	NaN	Torrance	CA	False
3887	4284	Terry Don King	2018-12-09	shot	gun	50.0	M	NaN	Springdale	AR	False
3888	4285	Shane	2018-	shot	gun	41.0	M	W	Noble	OK	False

	id	name	date	manner_of_death	armed	age	gender	race	city	state	signs_of_mental_illn
3889	4289	TK TK	2018-12-10	shot	knife	NaN	M	NaN	Fredonia	NY	True
3890	4290	Kyle Hart	2018-12-10	shot	knife	33.0	M	NaN	Redwood City	CA	True
3891	4288	Kaley Gay	2018-12-11	shot	gun	25.0	F	NaN	Bibb County	GA	False
3892	4291	TK TK	2018-12-11	shot	gun	NaN	F	NaN	Puna	HI	False
3893	4292	TK TK	2018-12-11	shot	undetermined	NaN	M	NaN	Rangley	CO	False
3894	4293	Marcus Neal	2018-12-11	shot	knife	47.0	M	NaN	Buffalo	NY	True
3895	4295	Haze Connor Martin	2018-12-11	shot	knife	22.0	M	W	Pope County	AR	False
3896	4296	Tameka LaShay Simpson	2018-12-11	shot	gun	27.0	F	B	Calhoun	GA	False
3897	4297	Demario Bass	2018-12-12	shot	vehicle	29.0	M	B	St. Louis	MO	False
3898	4298	Jason Emerson Connell	2018-12-12	shot	gun	43.0	M	W	Jacksonville	FL	False
3899	4299	Dylan Parker Thomas	2018-12-12	shot	toy weapon	18.0	M	W	Jacksonville	FL	False
3900	4300	TK TK	2018-12-12	shot	gun	NaN	M	NaN	Albuquerque	NM	False

3901 rows × 16 columns

In [28]:

```
#Creating a dataframe with police homicides per year per race according to the Washington Post
wp_race = wp_guns.pivot_table(index='year',columns='race',values='id',aggfunc=len).drop('2018')
wp_race ['total'] = wp_race.sum(axis=1)
wp_race.columns = ['Asian', 'Black','Hispanic','Native American','Other','White','total']
wp_race
```

Out[28]:

	Asian	Black	Hispanic	Native American	Other	White	total
year							
2015	14	259	172	9	15	497	966
2016	15	234	160	16	11	466	902
2017	16	223	179	22	6	459	905

In [29]:

```
wp_race.mean()
```

Out[29]:

```
Asian               15.000000
Black              238.666667
Hispanic           170.333333
Native American     15.666667
Other               10.666667
```

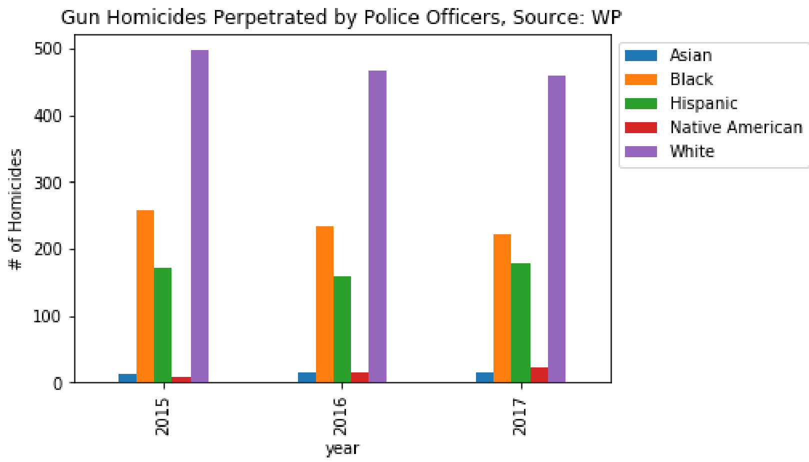
```
White              474.000000
total              924.333333
dtype: float64
```

In [30]:

```
fig,ax = plt.subplots()
wp_race[['Asian', 'Black','Hispanic','Native American','White']].plot.bar(ax=ax)
ax.set_title('Gun Homicides Perpetrated by Police Officers, Source: WP')
ax.set_ylabel('# of Homicides')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[30]:

```
<matplotlib.legend.Legend at 0x1c0c6f4710>
```

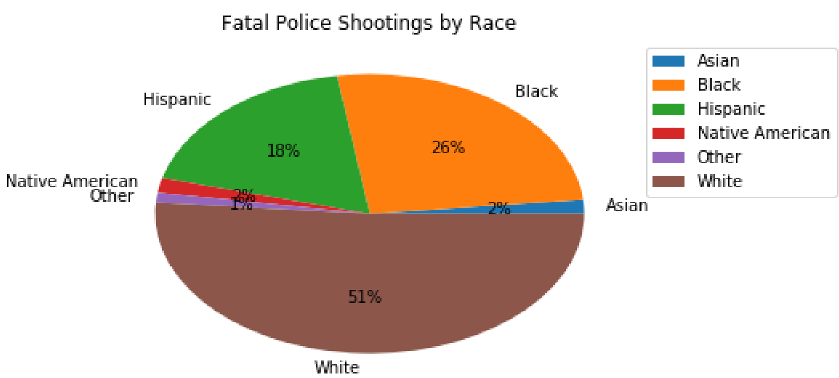


In [78]:

```
trans_wp_race = wp_race.transpose().drop('total')
trans_wp_race['Average']=trans_wp_race.mean(axis=1)
fig,ax = plt.subplots()
trans_wp_race.plot.pie(y='Average',ax=ax,autopct='%1.0f%%')
ax.set_ylabel('')
ax.set_title('Fatal Police Shootings by Race')
ax.legend(bbox_to_anchor=(1,1),loc=0) #sets the legend of the bar graph outside the plot
```

Out[78]:

```
<matplotlib.legend.Legend at 0x1c202c1320>
```



The data from the Washington Post is consistent with the CDC in terms of pecentage of fatal shootings by race. Police shooting of white people are significantly more common than those of Black or Hispanic. However, the CDC appears to be massively underreporting fatal shootings for all races. According to the Washington Post, there is an average of 924.33 fatal police shootings per year from 2015 through 2017 while the CDC reported an average of 467.33 fatal police shootings per year.

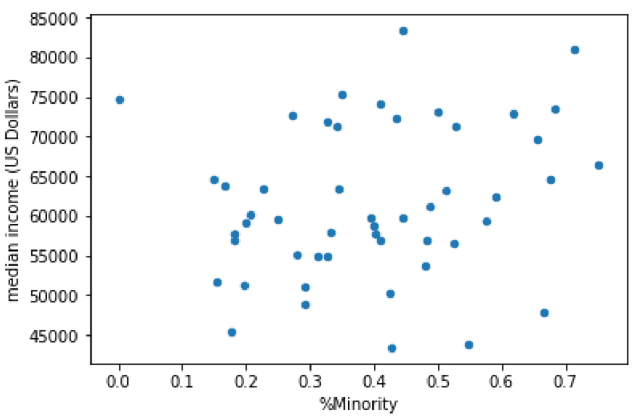
The data from the Washington Post enables us to analyze these police shooting furthermore. We continue with the hypothesis that minorities are more prominent to get shot by police officers than other races. We know that minority populations tend to be poorer than others. Thus, we want to analyze how the percentage of police shootings per race correlate to the median income by state. To do so, we have to import more data that will provide us with the median income by state and run a regression model to see how do so, we have to import more data that will provide us with the median income by state and run a regression model to see how these two variables compare to each other.

In [74]:

```
#Creating a dictionary and dataframe based on states and their abbreviations
states = {'AK': 'Alaska','AL': 'Alabama','AR': 'Arkansas','AS': 'American Samoa','AZ':
'Arizona','CA': 'California',
        'CO': 'Colorado','CT': 'Connecticut','DC': 'District of Columbia','DE': 'Delaware','FL': 'F
lorida',
        'GA': 'Georgia','GU': 'Guam','HI': 'Hawaii','IA': 'Iowa','ID': 'Idaho','IL': 'Illinois','IN
': 'Indiana',
        'KS': 'Kansas','KY': 'Kentucky','LA': 'Louisiana','MA': 'Massachusetts','MD': 'Maryland','M
E': 'Maine',
        'MI': 'Michigan','MN': 'Minnesota','MO': 'Missouri','MP': 'Northern Mariana Islands','MS':
'Mississippi',
        'MT': 'Montana','NA': 'National','NC': 'North Carolina','ND': 'North Dakota','NE': 'Nebrask
a',
        'NH': 'New Hampshire','NJ': 'New Jersey','NM': 'New Mexico','NV': 'Nevada','NY': 'New York'
,'OH': 'Ohio',
        'OK': 'Oklahoma','OR': 'Oregon','PA': 'Pennsylvania','PR': 'Puerto Rico','RI': 'Rhode Islan
d',
        'SC': 'South Carolina','SD': 'South Dakota','TN': 'Tennessee','TX': 'Texas','UT': 'Utah','V
A': 'Virginia',
        'VI': 'Virgin Islands','VT': 'Vermont','WA': 'Washington','WI': 'Wisconsin','WV': 'West Vir
ginia',
        'WY': 'Wyoming'}
state = pd.DataFrame(states, index=[1]).transpose().reset_index().rename(columns={'index':'abbrev',
1:'state'})
#Reading data on median income per state
state_income = pd.read_excel('/Users/javierbeltranena/Downloads/median-household-income-
state.xlsx')
#Merging data on median income per state and state abbreviations
state_income = state_income.merge(state, how='inner', on='state')
#Creating a data frame with police homicides per state per race
state_homs = wp_guns.pivot_table(index='state',columns='race',values='id',aggfunc=len).fillna(0)
#Merging the past dataframe with the median income per state
state_hom_inc = state_homs.merge(state_income,how='inner',left_on='state',right_on='abbrev').set_in
dex('state')
#Creating a column for the percentage of police homicides who were not White
state_hom_inc['%Minority']= 1-((state_hom_inc['W']+state_hom_inc['A'])/(state_hom_inc['A']+ state_h
om_inc['B']
    + state_hom_inc['H'] + state_hom_inc['N'] + state_hom_inc['O'] + state_hom_inc['W']))
state_hom_inc[['median income (US Dollars)','%Minority']].plot.scatter(x='%Minority',y='median inc
ome (US Dollars)')
```

Out[74]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c201ceeb8>
```



In [33]:

```
regression = sm.OLS(state_hom_inc['%Minority'],state_hom_inc['median income (US Dollars)'])
results = regression.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              %Minority   R-squared:                       0.845
```

```
Model:                            OLS   Adj. R-squared:                  0.841
Method:                 Least Squares   F-statistic:                     266.3
Date:                Wed, 19 Dec 2018   Prob (F-statistic):           1.92e-21
Time:                        14:58:50   Log-Likelihood:                 17.725
No. Observations:                  50   AIC:                            -33.45
Df Residuals:                      49   BIC:                            -31.54
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
median income (US Dollars)  6.346e-06   3.89e-07     16.317      0.000    5.56e-06    7.13e-06
==============================================================================
Omnibus:                        0.125   Durbin-Watson:                   1.862
Prob(Omnibus):                  0.939   Jarque-Bera (JB):                0.118
Skew:                          -0.096   Prob(JB):                        0.943
Kurtosis:                       2.858   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

By running the regression model and looking at the graph, we can see that there is no correlation among bot factors. Perhaps analyzing this at such a broad level like state is not necesarilly accurate. Unfortunately we were unable to find complete accurate date for all the cities in which police shootings have occured according to the Washington Post and thus, narrowing this down to a city level is not possible.

Conclusion

From the first part of our investigation, we have seen that the most common causes of suicides are probably income an employment related, or possibly due to mid-life crises. We can say this because most suicides are by white males around the age of 54. From the second part of our research, we have seen that most of the victims of gun homicides are black, although this population decreased from 6,676 to 6,331 between 2012 and 2014. From the third part of our research, we have seen that the CDC dramatically underreports police-related gun shootings. For example, while the CDC reported only 464 fatal police shootings in 2014 (with a decreasing trend), the Washington Post reported 966 fatal police shootings by 2015, which constitutes a growth of almost 107% from one year to the next one. We also learned that, although most victims of police shootings are white (51%), when compared to the US population demographics, black and hispanic communities experience more police brutality. Thus, we wanted to prove that minority populations, who typically earn less, are more vulnerable to police shootings. We did so by comparing the percentage of minority fatal shootings by police officers per state to median income by state. However, regressions at a state level showed no correlation between these two.

Further investigations could go deeper into the correlations between minority police shootings versus median income at a city or county level, which might show a greater correlation. Furthermore, more analysis could be done on the topic of suicide if information about the victims' income and workplace was available. This could enable us to perform some sort of automated machine learning that could identify factors that drive suicide rate and consequently potential suicide victims so that the US could take preventive measures.

Link to the GitHub: https://github.com/jjbeltranena/GunFatalitiesUnitedStates