cogs9_proj

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1 Cogs9 Project: For the SDPD in 2019, is there a significant difference in the likelihood of someone being stopped according to their race?

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1.1 Analysis

For our analysis method, we'll be using python pandas - link to repository- https://github.com/AndrewCheng2002/Cogs-9-Project

[1]:
```
#Modules
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
import datetime

%matplotlib inline
plt.style.use('fivethirtyeight')
```

Data Collection: How do we get data to preform analysis on?

When answering a data science question, our first tasks is to gather the data itself. However not just any data will suffice and in order to get an accurate, unbiased and ethical model, we need ensure that our data is sufficient and representative of the population.(San Diego in 2019) We needed to find a source that was reliable to ensure fairness and correct represenation as well as one that was large enough to not be affected by outliers. After spending lots time and deliberation we settled on using RIPA (An act passed by the government that requires police departments to publish their data regarding stops, arrests, etc.) to get data on race and stop information. We simply downloaded the data off the RIPA website which was conviently in csv format. In addition to race and stop data we also need data of specific race demographics, in this case, we decided to use the US census. Even though we are analyzing the SDPD in 2019, which not a census year(every decade), we felt that the predictive algorithms used by the US government were trustworthy and sufficient enough to get an accerate representation of the population demographic. Because there's was no quick download function and the fact that we're only analyzing 7 races, we decided it was easier to just webscrapped the information and put it in a table.

[2]:
```
#We made pandas read the RIPA csv files we downloaded
data_race_raw = pd.read_csv('ripa_race_datasd.csv')
data_stops_raw = pd.read_csv('ripa_stops_datasd.csv', low_memory = False)

#For the census we webscrapped the information and manually inserted in a table
data_census_race = pd.DataFrame({'percentage of population': [42.8,6.4,30.3,2.
↪9,16.7,.5,.4]},
index = ['White','Black/African American','Hispanic/Latino/a','Middle Eastern␣
↪or South Asian','Asian','Native American','Pacific Islander'])
```

[3]:
```
data_race_raw
```

[3]:
```
        stop_id  pid                    race
0          2443    1                   White
1          2444    1                   White
2          2447    1       Hispanic/Latino/a
3          2447    2       Hispanic/Latino/a
4          2448    1                   White
…             …    …                       …
394970   356019    1  Black/African American
394971   356025    1  Black/African American
394972   356080    1                   White
394973   356300    1  Black/African American
394974   356303    1  Black/African American

[394975 rows x 3 columns]
```

[4]:
```
data_stops_raw
```

[4]:
```
        stop_id        ori agency  exp_years   date_stop time_stop  \
0          2443  CA0371100     SD         10  2018-07-01  00:01:37
1          2444  CA0371100     SD         18  2018-07-01  00:03:34
2          2447  CA0371100     SD          1  2018-07-01  00:05:43
3          2447  CA0371100     SD          1  2018-07-01  00:05:43
4          2448  CA0371100     SD          3  2018-07-01  00:19:06
…             …          …    …          …           …         …
391129   356019  CA0371100     SD          1  2020-09-30  23:05:00
391130   356025  CA0371100     SD          1  2020-09-30  23:38:00
391131   356080  CA0371100     SD         18  2020-09-30  15:31:00
391132   356300  CA0371100     SD         18  2020-09-30  19:30:00
391133   356303  CA0371100     SD          1  2020-09-30  19:37:52

        stopduration  stop_in_response_to_cfs  officer_assignment_key  \
0                 30                        0                       1
```

```
1                10                          0                       1
2                15                          1                      10
3                15                          1                      10
4                 5                          0                       1
…               …                       …                       …
391129            7                          1                       1
391130           30                          1                       1
391131            5                          0                       1
391132          180                          1                       1
391133           45                          0                       1

                                       assignment  …  \
0       Patrol, traffic enforcement, field operations  …
1       Patrol, traffic enforcement, field operations  …
2                                               Other  …
3                                               Other  …
4       Patrol, traffic enforcement, field operations  …
…                                                 …  …
391129  Patrol, traffic enforcement, field operations  …
391130  Patrol, traffic enforcement, field operations  …
391131  Patrol, traffic enforcement, field operations  …
391132  Patrol, traffic enforcement, field operations  …
391133  Patrol, traffic enforcement, field operations  …

                  beat_name  pid isstudent perceived_limited_english  \
0         Pacific Beach 122    1         0                         0
1         Mission Beach 121    1         0                         0
2           El Cerrito 822    1         0                         0
3           El Cerrito 822    2         0                         0
4          Ocean Beach 614    1         0                         0
…                       …  …       …                       …
391129      Harborview 527    1         0                         0
391130    Core-Columbia 524    1         0                         0
391131         Unknown 999    1         0                         0
391132  Carmel Mountain 232    1         0                         0
391133      Golden Hill 517    1         0                         0

       perceived_age  perceived_gender gender_nonconforming gend  gend_nc  \
0                 25              Male                    0    1      NaN
1                 25              Male                    0    1      NaN
2                 30              Male                    0    1      NaN
3                 30            Female                    0    2      NaN
4                 23              Male                    0    1      NaN
…               …               …                  …  …      …
391129            50            Female                    0    2      NaN
391130            35              Male                    0    1      NaN
391131            60              Male                    0    1      NaN
```

```
391132           25            Male                   0    1      NaN
391133           28            Male                   0    1      NaN

       perceived_lgbt
0                  No
1                  No
2                  No
3                  No
4                  No
…               …
391129             No
391130             No
391131             No
391132             No
391133             No

[391134 rows x 29 columns]
```

[5]:
```
data_census_race
```

[5]:
```
                               percentage of population
White                                              42.8
Black/African American                              6.4
Hispanic/Latino/a                                  30.3
Middle Eastern or South Asian                       2.9
Asian                                              16.7
Native American                                     0.5
Pacific Islander                                    0.4
```

Data Wrangling: How do we make our data useable

As of now, our raw data has a lot of information that we don't really need to answer our data science question. (For the SDPD in 2019, is there is significant difference in the likely hood of someone being stopped according to their race?) The columns that we need consists of the **races** of the people stopped and the **date**. (to restrict our time interval) In order to do this and combine it into one table, we need to first drop all the columns in the stops data we aren't using and merge that table to the race table at the **stop_id**.

Then we have to remove duplicates that arise from the merge. The reason why the merge creates duplicates is because multiple people can be stopped at one stop_id represented by the **pid**(person id) which means that there will be an addition copy of the stop_id from the dates table. (Has unique stops and doesn't account for pid) In addition to removing duplicates, we have to set the final table to only contain stop_ids with a date in 2019. To this, we need to convert the dates in the date column to something we can read, such as a **datetime**. After converting the date column of strings to a datetime, we can restrict the table to only include stops from the year 2019.

[6]:
```
data_race = data_race_raw.set_index('stop_id')
data_race
```

[6]:
```
          pid                   race
stop_id
2443        1                  White
2444        1                  White
2447        1      Hispanic/Latino/a
2447        2      Hispanic/Latino/a
2448        1                  White
…         …                      …
356019      1  Black/African American
356025      1  Black/African American
356080      1                  White
356300      1  Black/African American
356303      1  Black/African American

[394975 rows x 2 columns]
```

[7]:
```
data_date = pd.DataFrame().assign(date = data_stops_raw.get('date_stop'),␣
↪stop_id = data_stops_raw.get('stop_id')).set_index('stop_id')
data_date
```

[7]:
```
               date
stop_id
2443     2018-07-01
2444     2018-07-01
2447     2018-07-01
2447     2018-07-01
2448     2018-07-01
…               …
356019   2020-09-30
356025   2020-09-30
356080   2020-09-30
356300   2020-09-30
356303   2020-09-30

[391134 rows x 1 columns]
```

[8]:
```
#Merge race data set with the dates from the stop data set with the stop_id
data_merged = data_race.merge(data_date,left_index = True, right_index = True)
data_merged
```

[8]:
```
          pid                   race        date
stop_id
2443        1                  White  2018-07-01
2444        1                  White  2018-07-01
2447        1      Hispanic/Latino/a  2018-07-01
2447        1      Hispanic/Latino/a  2018-07-01
2447        2      Hispanic/Latino/a  2018-07-01
```

```
…       …                        …          …
356019     1  Black/African American  2020-09-30
356025     1  Black/African American  2020-09-30
356080     1                   White  2020-09-30
356300     1  Black/African American  2020-09-30
356303     1  Black/African American  2020-09-30

[595128 rows x 3 columns]
```

[9]:
```
#Remove Duplicates
data_final = data_merged.drop_duplicates()

#Get the year from the date string
def to_year(date):
    dt = datetime.datetime.strptime(date,'%Y-%m-%d')
    return dt.year

#Include data within subjected time interval
data_final = data_final[data_final.get('date').apply(to_year) == 2019]
data_final
```

[9]:
```
         pid                           race        date
stop_id
84362      1               Hispanic/Latino/a  2019-01-01
84364      1                           White  2019-01-01
84369      1          Black/African American  2019-01-01
84372      2               Hispanic/Latino/a  2019-01-01
84376      1  Middle Eastern or South Asian  2019-01-01
…        …                              …           …
254761     8                           White  2019-12-31
254771     2                           White  2019-12-31
254776     1                 Native American  2019-12-31
255002     4                           White  2019-12-31
255002     5                           White  2019-12-31

[8398 rows x 3 columns]
```

Exploratory/Descriptive Analysis: What does our data say?

Now that we have our data neated sorted and ready to use, lets use that to answer our question. In order to do that we started off by producing some basic descriptive analysis to get a general idea of the trend of our data. For the descriptive analysis, we decided to compare the percentages of each race stopped versus the percentages of each race's demographic to see if there was any significant difference between the two. To do this, we created a new table showing the percentage of each race stopped and then merged the demographic table to that table. Then generate basic statistics that comparet the two distributions such as the absolute mean difference, the standard deviation of the absolute differences, and the range of the absolute differences.

[10]:
```
#Generate Race Percentages Table from the data wrangled data_final
race_percentage = data_final.groupby('race').count()/data_final.shape[0]*100
race_percentage = race_percentage.drop(columns = ['date']).
 ↪rename(columns={'pid':'percentage stopped'})
race_percentage
```

[10]:

race	percentage stopped
Asian	10.431055
Black/African American	20.159562
Hispanic/Latino/a	22.552989
Middle Eastern or South Asian	8.001905
Native American	3.346035
Pacific Islander	6.215766
White	29.292689

Now we see that there's a difference between the two distributions in the following table below.

[11]:
```
#Now merge the census data and sort by lowest population to highest
race_census_percentage = race_percentage.merge(data_census_race,left_index =␣
 ↪True,right_index = True)
race_census_percentage = race_census_percentage.sort_values('percentage of␣
 ↪population', ascending = True)
race_census_percentage
```

[11]:

	percentage stopped	percentage of population
Pacific Islander	6.215766	0.4
Native American	3.346035	0.5
Middle Eastern or South Asian	8.001905	2.9
Black/African American	20.159562	6.4
Asian	10.431055	16.7
Hispanic/Latino/a	22.552989	30.3
White	29.292689	42.8

Basic Statistics generated below:

[12]:
```
difference = race_census_percentage.get('percentage␣
 ↪stopped')-race_census_percentage.get('percentage of population')
mean_abs_diff = abs(difference).mean()
std_abs_diff = np.std(abs(difference))
range_abs_diff = abs(difference).max()-abs(difference).min()
print('mean abs diff: '+ str(mean_abs_diff) +'%, std abs diff: ' +␣
 ↪str(std_abs_diff) + '%, range abs diff: ' + str(range_abs_diff)+'%')
```

```
mean abs diff: 7.863790698465621%, std abs diff: 3.8944448367344955%, range abs
diff: 10.913527030245294%
```

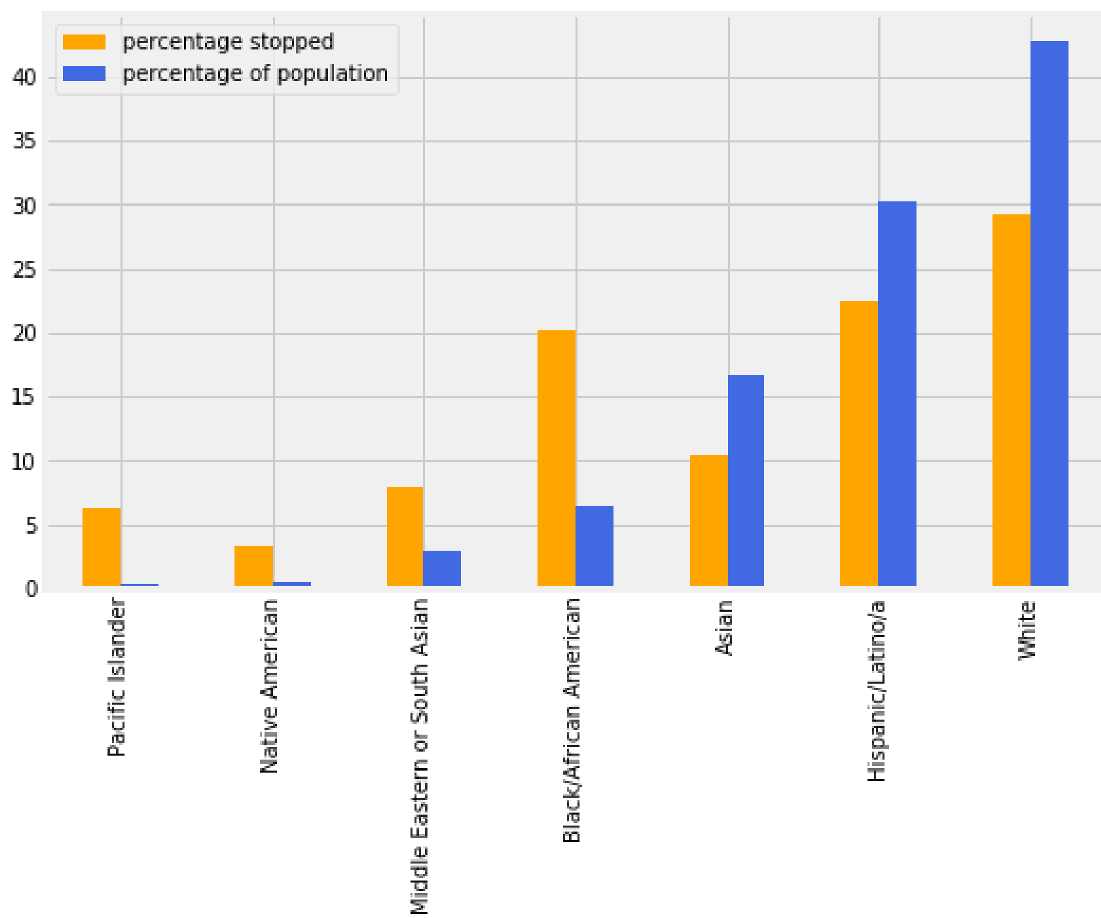
Our descriptive analysis shows that there's a decent chance that race is correlated with the likely-hood of being stopped by the police in San Diego with the mean difference from the demographic being 7.86%. Assuming that these results are realiable(proven later in our statistical analysis), we can then use this to justify or disprove our hypothesis that blacks and hispanics are stopped more frequently by the police compared to other races.

Data Visualization: What does the data show us

Once we completed some basic analysis, the next step is to visualize the data and see how each races compares to it's demographic. With Pandas it's really easy and simple to perform since we already have a completed table from our exploratory analysis and data wrangling we did. We decided to make a grouped bar graph to compare the distribution of two categorical variables. We decided to choose blue and orange as the colors and make the graph a bit wider to make it easier on the eyes. As you can see, miniorities are stopped much more often than the rest of the races, especially in Black/African American and much less in Asian and White which supports our hypothesis. However, Hispanics/Latinos are surprisingly stopped less relative to their population according to the visualization which goes against our hypothesis.

[13]:
```
race_census_percentage.plot(kind = 'bar', figsize = [8,5],color =␣
↪['orange','royalblue'])
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe129689c88>



Statistical Analysis: How do we know that our results are trustworthy

After performing exploratory analysis to generate basic statistics and producing a visualization, we need to make sure that these results are valid and significant. In order to achieve this we will perform a hypothesis test and calculate a confidence interval and p-value for our statistic.

- Null: There is no significant difference between the percentage of races stopped respective to their demographic
- Alternate: There is a significant difference between the percentage of race stopped respective to their demographic

[14]:
```
#Test Statistic will be the Mean Difference
test_stat = mean_abs_diff
test_stat
```

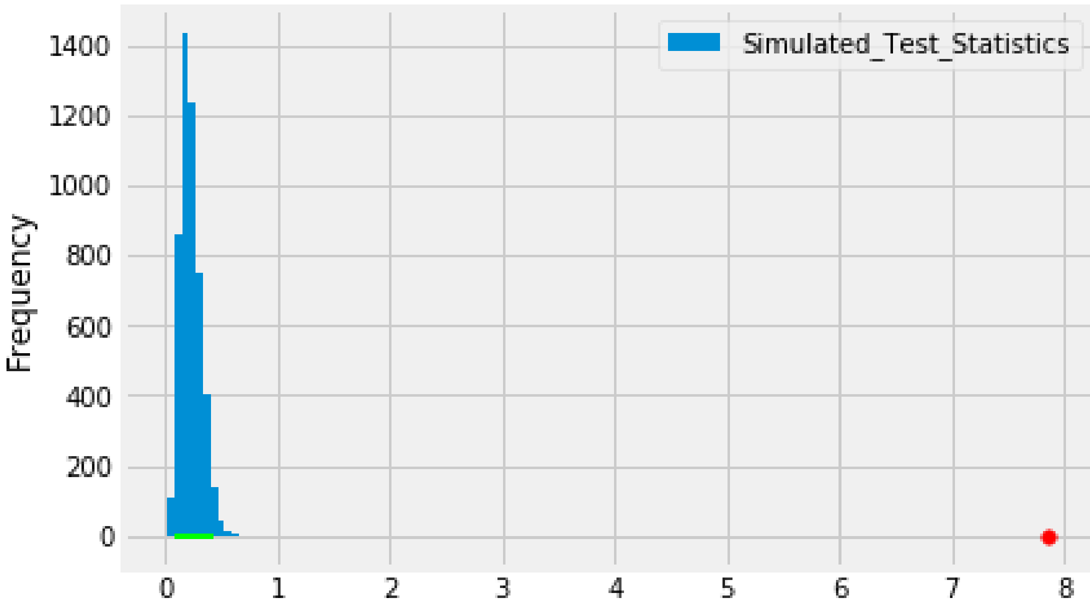
[14]:
```
7.863790698465621
```

[15]:
```
#We'll generate about 5000 sample test stats using the census data to create a␣
↪95% confidence interval

num_repetitions = 5000
population = data_final.shape[0]

simulated_test_stats = np.array([])

for i in range(num_repetitions):
    model_proportions = race_census_percentage.get('percentage of population')/
↪100
    sample = np.random.multinomial(population, model_proportions)/population
    sim_test_stat = abs(model_proportions-sample).mean()*100
    simulated_test_stats = np.append(simulated_test_stats, sim_test_stat)

simulated_test_stats
```

[15]:
```
array([0.28257748, 0.2145817 , 0.17443609, …, 0.3521927 , 0.11246215,
       0.17691967])
```

[16]:
```
#Lets look at the distribution and generate the 95% confidence interval
t = pd.DataFrame().assign(Simulated_Test_Statistics = simulated_test_stats)
t.plot(kind='hist')

confidence_interval = [np.percentile(simulated_test_stats,2.5),np.
↪percentile(simulated_test_stats,97.5)]
plt.scatter(test_stat, 0, color='red', s=30);
plt.plot(confidence_interval,[0,0], color = 'lime', linewidth = 2)
print('Confidence Interval: [' + str(confidence_interval[0]) +', ' +␣
↪str(confidence_interval[1]) + ']')
```

```
Confidence Interval: [0.09025873507297717, 0.4387075153948224]
```



[17]:
```
#Now lets generate a p value
p_value = np.count_nonzero(simulated_test_stats >= test_stat)/
↪simulated_test_stats.shape[0]
print('p value: ' + str(p_value))
```

```
p value: 0.0
```

We reject the null, therefore the difference in the percentage of races being stopped is statistically significant. With this test, we are confident to use the results as justification to prove if our hypothesis is correct or incorrect.

Geospatial Analysis: Is there any bais in our data due to the location of the stops

In this analysis we compare the total distribution of the San Diego police stops to the total demographic of San Diego to see if there's any difference between the two. However, the police may not uniformly partol each district of San Diego. For example, police might be active in urban areas where minorities may make up more of the population as opposed to subarbs where most of the populations are whites, hispanics, and asians. We'll perform a geospatial analysis to see if the frequency a police stops at a location has an effect on the mean difference of races to demographic stopped. This will tell us if there's any bias in our data and how severe it is.

[31]:
```
#Data Wrangling
data_loc = pd.DataFrame().assign(stop_id = data_stops_raw.
↪get('stop_id'),location = data_stops_raw.get('beat_name'))
data_loc = data_loc.set_index('stop_id')
data_geo = data_final.merge(data_loc,left_index = True, right_index = True)
```

```
data_geo = data_geo.drop_duplicates()
data_geo
```

[31]:

```
             pid                            race        date            location
stop_id
84362          1               Hispanic/Latino/a  2019-01-01  Cherokee Point 839
84364          1                           White  2019-01-01        La Jolla 124
84369          1          Black/African American  2019-01-01     Ocean Beach 614
84372          2               Hispanic/Latino/a  2019-01-01   Pacific Beach 122
84376          1  Middle Eastern or South Asian  2019-01-01   Pacific Beach 122
…            …                               …           …                   …
254761         8                           White  2019-12-31    East Village 521
254771         2                           White  2019-12-31   Logan Heights 512
254776         1                 Native American  2019-12-31   Mission Beach 121
255002         4                           White  2019-12-31     Ocean Beach 614
255002         5                           White  2019-12-31     Ocean Beach 614

[8398 rows x 4 columns]
```

[38]:

```
#Analysis
geo_percentages = data_geo.groupby('location').count()
geo_percentages = geo_percentages.assign(frequency = geo_percentages.
 ↪get('pid')).drop(columns=['pid','race','date'])
geo_percentages
```

[38]:

```
                           frequency
location
Adams North 814                    8
Allied Gardens 322                16
Alta Vista 439                     2
Azalea/Hollywood Park 835         14
Balboa Park 531                  118
…                                …
University City 115               53
University Heights 624            35
Unknown 999                       69
Valencia Park 432                 30
Wooded Area 617                    1

[122 rows x 1 columns]
```

[ ]: