Problem Set 1 Section 6 (KC Harris)

March 4, 2022

Link to Section 3: https://datahub.berkeley.edu/user/kc1558628/notebooks/Problem%20Set%201%20(KC%20Ha

Link to Section 4,5: https://datahub.berkeley.edu/user/kc1558628/notebooks/Problem%20Set%201%20(KC%20H

[20]:
```
# import libraries
# !pip install folium --upgrade

from numpy.random import *
import pandas as pd
import numpy as np
from collections import Counter
import matplotlib.pyplot as plt
import os
%matplotlib inline

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
from IPython.core.display import HTML

def multi_table(table_list):
    ''' Acceps a list of IpyTable objects and returns a table which contains␣
 ↪each IpyTable in a cell
    '''
    return HTML(
        '<table><tr style="background-color:white;">' +
        ''.join(['<td>' + table._repr_html_() + '</td>' for table in␣
 ↪table_list]) +
        '</tr></table>'
    )


# Incident Report Data
sfpd_ir_2018_2022 = os.path.
 ↪join('Sample_10k_Police_Department_Incident_Reports__2018_to_Present.csv')
ir = pd.read_csv(sfpd_ir_2018_2022)
ir_2019 = ir[ir['Incident Year'] == 2019]
```

```
calls_serv_18_22 = os.path.
 ↪join('Law_Enforcement_Dispatched_Calls_for_Service__Real-Time.csv')
calls = pd.read_csv(calls_serv_18_22)
```

1 6) Discussion Questions

6.1) Based on the evidence from this lab assignment, why do you think "hotspots" policing became more popular in the last few decades? What are the pros and cons to this kind of approach?

To the point about the last few decades - "hotspot policing" has it's foundations in theories that emerged (or returned) in the 1980s as relevant to crime control, all following the publishing of Crime Prevention Through Environmental Design (CPTED) in the early 1970s. The first official study happened in Minneapolis began in in 1988 and showed that there was a modest deterrent effect (Sherman and Weisburd 1995). Within the next 10-20 years, a majority of police departments in the US were conducting some kind of mapping and area-based approach to patrols and policing.

In the context of this assignment and it's review of neighborhood/police district and time of day/week/year/etc correlations, I would argue that hotspot policing definitely presents itself as an appealing alternative to indiscriminate or randomized patrols. There are clearly (this being a weighted term) areas where crime concentrates, particularly within or along neighborhood lines that are already likely well defined within officer's pre-existing beats. And if we can decently argue that this is a moderate deterrent, even better! There's not only a more effective allocation of resources, but slight crime reduction.

However, other research has shown that these effects are mixed. In a recent NBER research paper (Chalfin et al 2020) data from 250 cities between 1981-2018 shows that while hotspot policing can be a deterrent, it has also had reduced effects in cities with predominantly black populations, and increased arrest rates for petty crimes (which black populations are disproportionately arrested for). The slight (and still in question) deterrence of crime should not come at the cost of even more increased discriminatory practice and criminalization, and this creates a major flaw in CPTED's application.

As a side note, some of the aforementioned theories that contributed to CPTED's prevelance are listed below: * Routine Activity theory * Situational Crime Prevention Theory * Broken Windows Theory * Crime Opportunity Theory * Social Disorganization Theory * Crime Pattern Theory

Sherman, L. W., & Weisburd, D. (1995). General detterent effects of police patrol in crime hot spots: randomized, controlled trial. Justice Quarterly 12(4), 625-648. https://static1.squarespace.com/static/5d809efd96f5c906aaf61f3d/t/601c032236cf8d4a7ccd459f/1612448549602/G

Chalfin, A., Hansen, B., Weisburst, E. K., Williams, M. C., & Jr. (2020, December 14). Police force size and civilian race. NBER. Retrieved March 2, 2022, from https://www.nber.org/papers/w28202?utm_source=npr_newsletter&utm_medium=email&utm_content=2021C

6.2) Comment on what sorts of incidents get reported in this database.

For instance, do you see a lot of reports about things like white collar crime? How do you think incident categories are selected? As data scientists, what kinds of ethical and legal concerns should we be aware of when we construct these sorts of datasets?

```
[6]: ir['Incident Code'].unique()
```

```
[6]: array([ 6244, 64085,  6372, 16623,  6362, 68060, 65015,  6371,  7041,
         4134, 71000, 65010, 64070, 15200, 19057, 64015,  3014,  6314,
         6242,  6224, 27195, 71012, 74000, 28160,  5073, 64020,  4104,
         7023, 27170, 71013, 16625,  9031, 28150, 51040, 19020, 16120,
         6374, 26170,  7044,  7045, 27400,  5072,  6361,  9027,  5051,
         7021,  5041,  3474, 15161,  5043,  6301, 68020, 72000,  6151,
        28100,  9320,  6241, 27175, 16652, 63010, 12030,  4012, 15162,
        28135,  4011,  3044,  5071, 62030, 27065, 28140,  6394,  6302,
        15300,  9024, 26031, 75000, 75030, 12080, 62050, 27130,  6243,
        15151, 65016, 10050,  5081, 19024,  4154,  7025, 26030,  6364,
         7046, 16710, 28161,  7020, 11012, 10115, 27090,  5015, 61030,
        26080,  6363, 68069,  4014,  4170, 15150,  5083, 75025,  6113,
         7100, 16650,  5011,  6234, 30200,  5014,  3084, 26120,  6303,
        68050, 28165,  4073,  7200, 65050,  7052, 27100,  6373, 15201,
        16660, 16110,  5023,  3071,  3074,  7043, 16010, 16662,  9026,
        62071,  3042,  5031,  6304, 71010,  5153, 62020,  4092,  4013,
        64002, 15155, 12015,  4144,  3012,  3094, 68000,  3401,  5251,
        16632,  5141, 30210,  9029,  6154, 26200,  3081, 13075, 27068,
        64010,  6153, 27131,  6223, 62060,  6246, 68030,  9110,  3011,
         5013, 12008, 28092, 26028,  4081, 64001,  5052, 16030,  4138,
        19090,  6313,  9250,  6126, 12168,  6221, 65020,  6114, 26150,
         3031,  5053,  3072, 15303,  7055, 30140,  5021,  9015, 19050,
        60010, 12130, 16420, 16780, 11017,  5151, 71024,  9020,  4033,
         9262, 16654,  5042, 12027, 12173,  4136,  9016,  9215, 71011,
        27198, 19055, 12120, 28010, 65021,  6383, 62040,  3061, 16664,
        16220,  5062,  3021,  3073,  9173,  6233, 30155,  9150, 64060,
         3043, 10149, 27172,  9310,  7026,  3441,  3414, 14040,  6112,
         6152, 27080, 19070, 16705, 61040, 27300, 10125, 27010, 26029,
        12100,  5061,  3411,  3013, 19010,  5173, 30011,  4022,  6400,
        16704,  4114,  9166, 16645, 30190, 26063,  7054,  4023,  5171,
        64000, 16210, 26032, 51041,  6222, 27110, 51050,  5082, 65030,
        26145,  6240,  9164,  6125,  3473, 64065,  9340,  4021, 27020,
        16100, 19022, 26036,  6312, 19400,  3024, 64072, 12060,  5143,
         3461,  5012,  4064, 26040, 11016,  4082, 26141,  4074, 30080,
         5131, 13111, 27177,  4024, 16622,  3034, 19031, 16621,  5033,
         4083,  3472, 15095, 27199,  5112, 73000, 16230,  4091, 19028,
        10040,  3054,  3424,  5172, 13060,  6220, 19089, 64003, 27171,
        15400, 62010,  7053, 64090, 64080, 65060, 12166, 27145, 10120,
         9264, 28120,  9040, 13045,  3494,  6111,  6230, 15401, 73010,
        10025, 10045,  3051,  6231, 19081, 26020, 15165, 19080, 11013,
        65056,  7022,  3421, 14042, 16130, 10090,  7024,  5271, 60190,
        10110,  3023, 16740,  6232, 14020, 15160, 64040,  7051,  9269,
        28166, 10015,  6300,  6381, 27071, 16630, 14043,  4084,  7056,
        13115, 14052, 27140, 16629,  3492,  6360, 26100, 26142,  4124,
         1160, 30030, 16040, 13030, 16020, 65057, 26105, 28130, 16620,
```

```
        65055, 26149,  4080, 51030, 12110, 16430,  5161, 28110,  4145,
         6315,  5152])
```

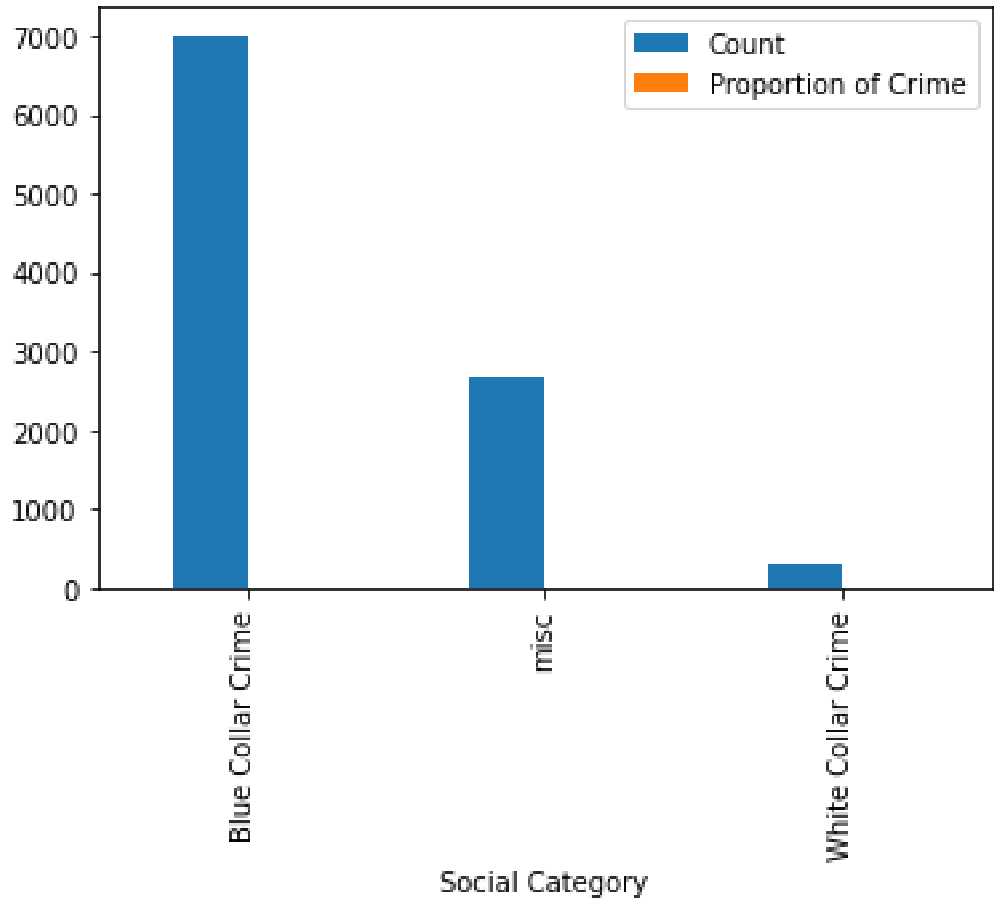
[12]:
```
ir_crime_simple = ir[['Incident ID', 'Incident Category', 'Incident␣
 ↪Subcategory', 'Resolution']].copy()

ir_crime_simple['Social Category'] = (ir_crime_simple['Incident Category'])

def crime_classifier(df, col):
    df[col].replace({'Larceny Theft': 'Blue Collar Crime',
                    'Arson': 'Blue Collar Crime',
                    'Assault': 'Blue Collar Crime',
                    'Burglary': 'Blue Collar Crime',
                    'Case Closure': 'misc',
                    'Civil Sidewalks': 'misc',
                    'Commercial Sex Acts': 'Blue Collar Crime',
                    'Courtesy Report': 'Blue Collar Crime',
                    'Disorderly Conduct': 'Blue Collar Crime',
                    'Drug Offense': 'Blue Collar Crime',
                    'Drug Violation': 'Blue Collar Crime',
                    'Embezzlement': 'White Collar Crime',
                    'Fire Report': 'misc',
                    'Forgery And Counterfeiting': 'White Collar Crime',
                    'Fraud': 'White Collar Crime',
                    'Homicide': 'Blue Collar Crime',
                    'Human Trafficking (A), Commercial Sex Acts': 'White Collar␣
 ↪Crime',
                    'Human Trafficking, Commercial Sex Acts': 'White Collar␣
 ↪Crime',
                    'Lost Property': 'misc',
                    'Malicious Mischief': 'Blue Collar Crime',
                    'Miscellaneous Investigation': 'misc',
                    'Missing Person': 'misc',
                    'Motor Vehicle Theft': 'Blue Collar Crime',
                    'nan': 'misc',
                    'Non-Criminal': 'misc',
                    'Offences Against The Family And Children': 'Blue Collar␣
 ↪Crime',
                    'Other Miscellaneous': 'misc',
                    'Other Offenses': 'misc',
                    'Other': 'misc',
                    'Prostitution': 'Blue Collar Crime',
                    'Rape': 'Blue Collar Crime',
                    'Recovered Vehicle': 'misc',
                    'Robbery': 'Blue Collar Crime',
                    'Sex Offense': 'Blue Collar Crime',
                    'Stolen Property': 'Blue Collar Crime',
```

```
                      'Suicide': 'misc',
                      'Suspicious Occ': 'Blue Collar Crime',
                      'Suspicious': 'Blue Collar Crime',
                      'Traffic Collision': 'misc',
                      'Traffic Violation Arrest': 'misc',
                      'Vandalism': 'Blue Collar Crime',
                      'Vehicle Impounded': 'misc',
                      'Vehicle Misplaced': 'misc',
                      'Warrant': 'Blue Collar Crime',
                      'Weapons Carrying Etc': 'Blue Collar Crime',
                      'Weapons Offense': 'Blue Collar Crime'}, inplace=True)


crime_classifier(ir_crime_simple, 'Social Category')


# https://stackoverflow.com/questions/17071871/
 ↪how-do-i-select-rows-from-a-dataframe-based-on-column-values
ir_crime_simple_blue_collar = ir_crime_simple.loc[ir_crime_simple['Social␣
 ↪Category'].isin(['Blue Collar Crime'])]
ir_crime_simple_white_collar = ir_crime_simple.loc[ir_crime_simple['Social␣
 ↪Category'].isin(['White Collar Crime'])]
ir_crime_simple_misc = ir_crime_simple.loc[ir_crime_simple['Social Category'].
 ↪isin(['misc'])]

ir_crime_simple_grouped = ir_crime_simple.groupby(['Incident Category']).size().
 ↪to_frame(name = 'Count').sort_values("Count", ascending = False).
 ↪reset_index()
ir_crime_simple_grouped_social = ir_crime_simple.groupby(['Social Category']).
 ↪size().to_frame(name = 'Count').sort_values("Count", ascending = False)
ir_crime_simple_grouped_social['Proportion of Crime'] =␣
 ↪ir_crime_simple_grouped_social['Count']/
 ↪sum(ir_crime_simple_grouped_social['Count'])


ir_crime_simple_grouped_social
ir_crime_simple_grouped_social.plot.bar()
```

[12]:

```
                    Count  Proportion of Crime
Social Category
Blue Collar Crime    7004             0.701031
misc                 2669             0.267140
White Collar Crime    318             0.031829
```

[12]: <AxesSubplot:xlabel='Social Category'>



[5]:
```
ir_crime_simple_grouped['Social Category'] = (ir_crime_simple_grouped['Incident␣
↪Category'])
crime_classifier(ir_crime_simple_grouped, 'Social Category')

ir_crime_simple_grouped.sort_values(['Social Category', 'Count'],␣
↪ascending=[True, False])
```

[5]:

	Incident Category	Count	Social Category
0	Larceny Theft	2936	Blue Collar Crime
2	Malicious Mischief	717	Blue Collar Crime
3	Assault	634	Blue Collar Crime
4	Burglary	605	Blue Collar Crime
6	Motor Vehicle Theft	510	Blue Collar Crime
8	Warrant	319	Blue Collar Crime
11	Drug Offense	248	Blue Collar Crime
13	Suspicious Occ	213	Blue Collar Crime
14	Robbery	196	Blue Collar Crime
15	Disorderly Conduct	166	Blue Collar Crime

16	Offences Against The Family And Children	162	Blue Collar Crime
21	Weapons Offense	66	Blue Collar Crime
23	Stolen Property	59	Blue Collar Crime
24	Weapons Carrying Etc	54	Blue Collar Crime
25	Courtesy Report	40	Blue Collar Crime
27	Arson	25	Blue Collar Crime
28	Vandalism	24	Blue Collar Crime
32	Prostitution	13	Blue Collar Crime
34	Sex Offense	9	Blue Collar Crime
37	Drug Violation	5	Blue Collar Crime
40	Suspicious	1	Blue Collar Crime
41	Rape	1	Blue Collar Crime
42	Homicide	1	Blue Collar Crime
10	Fraud	257	White Collar Crime
26	Forgery And Counterfeiting	37	White Collar Crime
31	Embezzlement	19	White Collar Crime
38	Human Trafficking (A), Commercial Sex Acts	4	White Collar Crime
43	Human Trafficking, Commercial Sex Acts	1	White Collar Crime
1	Other Miscellaneous	722	misc
5	Non-Criminal	571	misc
7	Recovered Vehicle	391	misc
9	Lost Property	278	misc
12	Missing Person	215	misc
17	Traffic Violation Arrest	121	misc
18	Miscellaneous Investigation	91	misc
19	Other Offenses	81	misc
20	Other	73	misc
22	Case Closure	59	misc
29	Civil Sidewalks	20	misc
30	Traffic Collision	19	misc
33	Fire Report	12	misc
35	Vehicle Impounded	7	misc
36	Suicide	5	misc
39	Vehicle Misplaced	4	misc

When we look at the number of crimes per Incident Category, it's obvious that 'white collar' crimes are substantially less reported on. They only occupy about 3% of the IRs in this dataset - with 'blue collar' crimes at about 70% and the in-between category of 'misc' in a distant second. Even the most common white collar crime, fraud, is still less than half of the most common miscallaneous category and behind the 8th ranking most common ir, warrants, at 319 in the blue collar category.

This absolutely speaks to how the IR system is designed. The collection/analysis of this data, and it's inherent eventual use in the field, is designed by the SFPD Crime Strategies Unit. Looking at the monthly crime report here (https://www.sanfranciscopolice.org/sites/default/files/2021-02/SFPDCompstat.20210211.pdf) and the city's crime dashboard here (https://www.sanfranciscopolice.org/stay-safe/crime-data/crime-dashboard) reveals that the design is largely centered on two categories: Violent Crime, and Property Crime. Both of these predominantly consist of Incident Categories that count as blue collar, and as a result create a system that is disproportionately focused on blue collar crime.

But this is a very broad way to think about the flaws of this system: instead we should consider that white collar crimes have a number of differentiating factors that make them difficult to report on/arrest for: 1) that white collar criminals are usually higher income and/or have access to better tools 2) both property crime and violent crime occur in person, while most white collar crimes are more remote or are in person for substantially less time and less often 3) criminal activity that is harder to track/know about will likely get less funding and attention from police departments and 4) criminal activity like this might also be in the realm of other organizations (the FBI for example) and only involve the police when arrests, evidence, or local warrants are involved.

There are obligations as criminologists, data scientists, lawmakers, and law enforcement officials that come into play when certain crime is weighted in this way. The way we collect and organize data becomes the way the world is understood - and if we do this in a way that is not equitable, the world slowly becomes warped. More specifically, if we do not make a point to represent white collar crime as prominently as blue collar crime where appropriate, we risk contributing to the subtle (and not so subtle) narratives where these crimes simply don't exist. And in particular, to the ones where the blue collar crimes are the only thing we CAN see. This affects existing discriminatory feedback loops in public perception, social funding, and law enforcement practices that will continue to disproportionaly affect low income and minority groups most and distort future data.

******As a side note, this doesn't even address the fact that the above NBER paper (Chalfin et al 2020) found that hotspot policing increased arrest rates for petty crimes. This also disproportionately impacts people of color.

6.3) What other sorts of data would help improve your analysis?

I'd be interested in creating a choropleth map showing number of calls per neighborhood, and then overlaying that with our current map from 4.1 of incident reports. Or possibly overlaying the choropleth map of total crimes in each neighborhood from 5.1 with bubbles for each neighborhood who's size correlated to the number of calls they'd had? We could access this data here: https://data.sfgov.org/Public-Safety/Law-Enforcement-Dispatched-Calls-for-Service-Close/2zdj-bwza

On top of that, I'd also be interested in seeing if we could merge this IR dataset with this closed Dispatched Calls for Service dataset, and create the same charts as above. We could also use the matched datasets to find rates of which incident categories most often got called about. https://data.sfgov.org/Public-Safety/Law-Enforcement-Dispatched-Calls-for-Service-Close/2zdj-bwza

We could also merge this with census data for SF, and look at median income per neighborhood, population density per neighborhood, etc. Although I'm having trouble finding geographically specific information from the census - right now I can only find information for SF as a whole. I'll need to look into this more.