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CAPP30254: Machine Learning for Public Policy
Spring 2019

HW 1
DIAGNOSTIC ASSIGNMENT

Notes

- Representative code snippets are interspersed with analysis and explanations below; all code is available on GitHub: `https://github.com/satejsoman/capp30254/tree/master/hw1/code`.
- Sources for data and techniques are cited at the end of this report.

1 Data Acquisition & Analysis

1.1 Chicago Open Data Portal

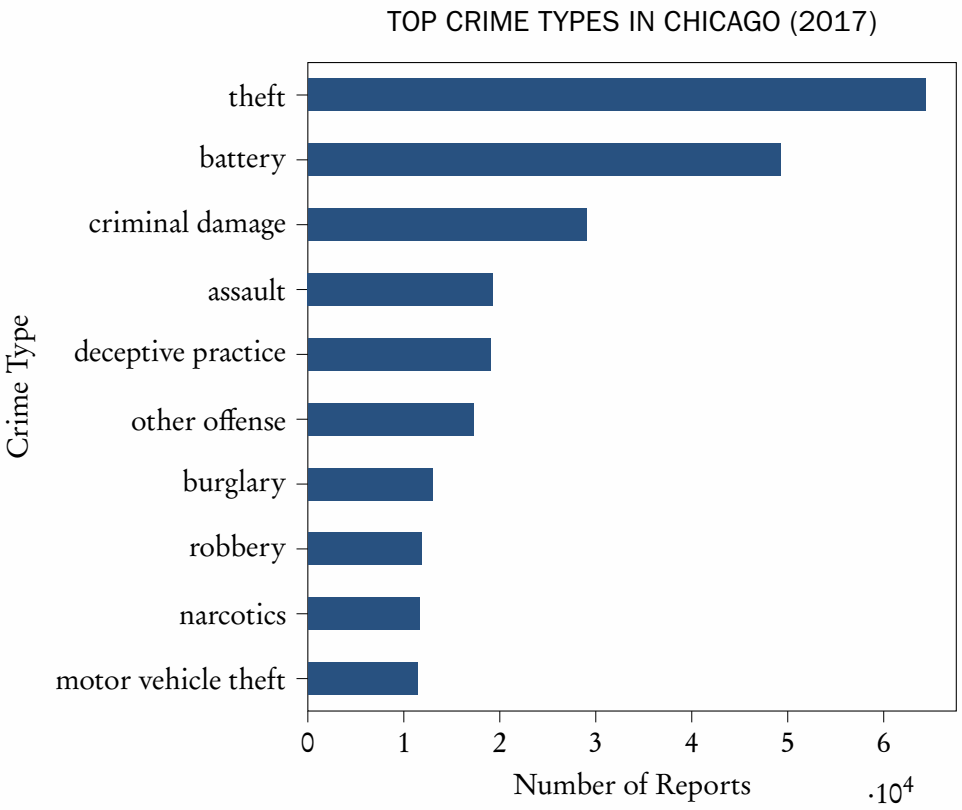
Chicago crime data is available, filtered by year, from the Chicago Data Portal (`https://data.cityofchicago.org/browse?category=Public%20Safety`). We can download this data and load it into a Pandas `DataFrame`:

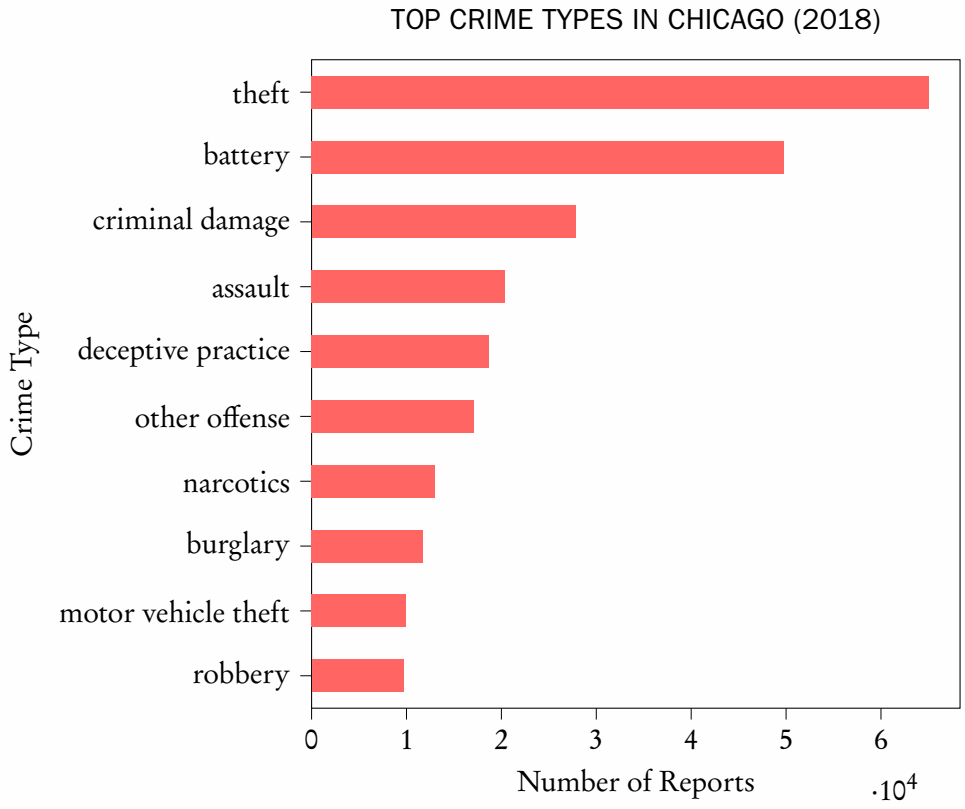
```
from pathlib import Path

import pandas as pd
import requests

# download crime data if we don't have it locally
base_url = "https://data.cityofchicago.org/api/views/{}/rows.csv?accessType=DOWNLOAD"
crime_resources = {
    2017: (Path("./crime_data_2017.csv"), "3i3m-jwuy"),
    2018: (Path("./crime_data_2018.csv"), "d62x-nvdr"),
}

for (year, (path, identifier)) in crime_resources.items():
    if not path.exists():
        url = base_url.format(identifier)
        print("{} data not found locally, downloading from {}".format(year, url))
        response = requests.get(url)
        with path.open("wb") as f:
            f.write(response.content)

crime_stats = pd.concat([
    pd.read_csv(crime_resources[2017][0]),
    pd.read_csv(crime_resources[2018][0])
])
```

1.2 Summary Statistics for Crime Report Data, 2017-2018

year	2017	2018	AVG
number of reported crimes	268094	266246	267170

year	2017	2018	OVERALL
crimes involving an arrest	19.53%	19.75%	19.64%
crimes considered domestic	15.90%	16.39%	16.14%


TOP CRIME TYPES IN CHICAGO (2017)
theft
battery
criminal damage
assault
deceptive practice
other offense
burglary
robbery
narcotics
motor vehicle theft
Crime Type
0
1
2
3
4
5
6
Number of Reports
·10^4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2 Data Augmentation & APIs

2.1 Chicago Crime Reports, Augmented with ACS Demographic Information

To pull in data from the American Community Survey, we need to identify which census tract each crime report corresponds to. This correspondence can be found by performing a *spatial join*: with shapefiles representing the geometry of each Chicago-area census tracts as a polygon, each crime report's latitude/longitude pair can be assigned to a census tract based on which geometry contains the report's coordinates. Census tract shapefiles are available from the City of Chicago's Data Portal.

```
from shapely.geometry import Point
import geopandas as gpd

def assign_census_tracts(crime_stats):
    boundary_shp = "./Boundaries - Census Blocks -
        2000/geo_export_8e9f6d85-3c5b-429f-b625-25afcc3dea85.shp"
    census_tracts = gpd.read_file(boundary_shp).drop(columns=["perimeter", "shape_area",
        "shape_len"])
    # restrict geocoding to valid locations
    crime_stats = crime_stats[crime_stats["Location"].notna()]
    crime_stats["geometry"] = crime_stats.apply(lambda row: Point(row["Longitude"],
        row["Latitude"]), axis = 1)
    return gpd.tools.sjoin(gpd.GeoDataFrame(crime_stats), census_tracts, how="inner")
```

With the census tracts assigned, we can query the Census Bureau's API via DataMade's `census` Python package to find representative data about each census tract. We'll need the following ACS variables to pull in demographic data:

ACS VARIABLE NAME	LABEL
B01003_001E	total population
B02001_003E	race (Black or African American alone)
B03003_001E	Hispanic or Latino origin
B19013_001E	median household income in the past 12 months
B22002_001E	receipt of food stamps/SNAP in the past 12 months by children under 18

```
from census import Census

census_client = Census(census_api_key)

illinois = "17"
cook_county = "031"
acs_vars = {
    "NAME" : "tract_name",
    "B01003_001E": "total_pop",
    "B02001_003E": "black_pop",
    "B03003_003E": "hispanic_pop",
    "B19013_001E": "median_income",
    "B22002_001E": "child_snap"
}

tract_numbers = set(crime_stats["census_tra"].to_list())
```

```
response = census_client.acs5.state_county_tract(list(acs_vars.keys()), illinois, cook_county,
    Census.ALL)
demography = pd.DataFrame([elem for elem in response if elem["tract"] in
    tract_numbers]).rename(columns=acs_vars)
# normalize by population
demography[["black_pct", "hispanic_pct", "child_snap_pct"]] = demography[["black_pop",
    "hispanic_pop", "child_snap"]].div(demography.total_pop, axis=0)
demography["tract"] = pd.to_numeric(demography["tract"])
demography.set_index("tract")
crime_stats["census_tra"] = pd.to_numeric(crime_stats["census_tra"])
crime_stats = crime_stats.merge(demography, left_on=["census_tra"], right_on=["tract"])

demographic_vars = ["black_pct", "hispanic_pct", "child_snap_pct", "median_income"]

# battery
crime_stats[crime_stats["Primary Type"] == "BATTERY"][demographic_vars].describe()
# homicide
crime_stats[crime_stats["Primary Type"] == "HOMICIDE"][demographic_vars].describe()

# homicide over time
crime_stats[(crime_stats["Primary Type"] == "HOMICIDE") & (crime_stats["Year"] ==
    2017)][demographic_vars].describe()
crime_stats[(crime_stats["Primary Type"] == "HOMICIDE") & (crime_stats["Year"] ==
    2018)][demographic_vars].describe()

# deceptive practice vs. sex offense
crime_stats[crime_stats["Primary Type"] == "DECEPTIVE PRACTICE"][demographic_vars].describe()
crime_stats[crime_stats["Primary Type"] == "SEX OFFENSE"][demographic_vars].describe()
```

2.1.1 What types of blocks have reports of “Battery”?

% BLACK	% HISPANIC	% CHILDREN ON SNAP	MEDIAN INCOME
0.590492	0.197004	0.373272	43079.587196

The typical block with incidents of battery is generally roughly 60% Black and 20% Hispanic. On average, 37% of children receive food stamps, and the median income is about $43,000.

2.1.2 What types of blocks get “Homicide”?

% BLACK	% HISPANIC	% CHILDREN ON SNAP	MEDIAN INCOME
0.732555	0.172105	0.352350	35031.494636

The typical block with incidents of battery is generally roughly 73% Black and 17% Hispanic. On average, 35% of children receive food stamps, and the median income is about $35,000.

2.1.3 Does that change over time in the data you collected?

2017 Homicide characteristics:

% BLACK	% HISPANIC	% CHILDREN ON SNAP	MEDIAN INCOME
0.728826	0.185749	0.353375	34954.426374

2018 Homicide characteristics:

% BLACK	% HISPANIC	% CHILDREN ON SNAP	MEDIAN INCOME
0.736974	0.155940	0.351134	35122.81250

Comparing the 2017 to 2018 statistics, the characterization of the typical block for homicide stays effectively the same.

2.1.4 What is the difference in blocks that get "Deceptive Practice" vs "Sex Offense"?

Deceptive Practice:

% BLACK	% HISPANIC	% CHILDREN ON SNAP	MEDIAN INCOME
0.359146	0.182752	0.425968	65201.237182

Sex Offense:

% BLACK	% HISPANIC	% CHILDREN ON SNAP	MEDIAN INCOME
0.413284	0.255555	0.385575	52807.952566

Comparing the block characteristics between the two crime types, blocks with deceptive practice reports tend to have a higher median income (though also a higher percentage of children receiving food assistance). They also tend to have fewer Black or Hispanic residents than blocks with sex offense reports.

3 Analysis & Communication

3.1 Changes in Crime, 2017-2018

By aggregating over the year of each report, or by the primary type of each reported crime, we can develop an overview of how crime has changed overall, and of how rates of each type of crime are changing.

```
def summarize_changes(crime_stats):
    # overall changes
    crime_stats.groupby("Year").size().to_frame().T
    (100 * crime_stats.groupby("Year").size().pct_change()).to_frame().T

    # changes per type
    100 * crime_stats.groupby(["Primary Type",
        "Year"]).size().unstack().T.pct_change().stack().sort_values(ascending=False)
```

First, let us look at overall changes in crime:

year	2017	2018	% CHANGE
number of reports	268094	266246	-0.68931

The percentage change in overall crime is negligible; the total crime rate is effectively stable across 2017-2018.

Additionally, we can look at how each type of crime changed:

PRIMARY TYPE	% CHANGE, 2017-2018
concealed carry license violation	115.942029
human trafficking	55.555556
non-criminal (subject specified)	50.000000
public indecency	40.000000
liquor law violation	39.790576
interference with public officer	20.165746
weapons violation	16.303884
narcotics	11.399897
intimidation	11.258278
stalking	7.978723
sex offense	7.609756
assault	5.563902
gambling	5.235602
criminal trespass	1.350558
battery	1.152111
theft	1.140726
crim sexual assault	-0.061425
other offense	-0.592094
obscenity	-1.149425
deceptive practice	-1.624179
offense involving children	-1.718819
prostitution	-2.312925
non-criminal	-2.631579
criminal damage	-4.255905
public peace violation	-8.611482
burglary	-9.783863
kidnapping	-11.052632
motor vehicle theft	-12.440821
homicide	-13.313609
arson	-16.216216
robbery	-18.472678
other narcotic violation	-90.909091

Clearly, not all types of crimes are changing at the same rates. Concealed carry license violations more than doubled between 2017 and 2018, while other narcotic violations dropped by 90%.

3.2 Analysis of Jacob Ringer's Claims

Jacob Ringer, a candidate for alderman for the 43rd Ward, claims:

> Let's break down the Chicago Police Department's report for the month leading up to July 26, 2018, compared to the same week [*sic*] in 2017:
>
> - Robberies – up 21 percent over the same time-frame in 2017
> - Aggravated batteries – up 136 percent
> - Burglaries – an increase of 50 percent
> - Motor vehicle theft – up 41 percent.
>
> All told, crime rose 16 percent in the same 28-day time period in just one year.

To evaluate Ringer's claims, we can filter down the relevant ward, and isolate the time periods he analyzes.

```
import datetime

one_month = datetime.timedelta(days = 28) # "same 28-day time period in just one year"
target17 = datetime.datetime(year=2017, month=7, day=26)
target18 = datetime.datetime(year=2018, month=7, day=26)

crime_stats = crime_stats[crime_stats["Ward"] == 43]
crime_stats["Date"] = pd.to_datetime(ward_crime_stats["Date"])
crime_stats = crime_stats[
    ((target17 - one_month <= crime_stats["Date"]) & (crime_stats["Date"] <= target17)) |
    ((target18 - one_month <= crime_stats["Date"]) & (crime_stats["Date"] <= target18))
]

# overall changes
crime_stats.groupby("Year").count()["ID"]
crime_stats.groupby("Year").count()["ID"].pct_change()

crime_stats = crime_stats[crime_stats["Primary Type"].isin(["ROBBERY", "BATTERY", "BURGLARY",
    "MOTOR VEHICLE THEFT"])]
crime_agg_2017 = crime_stats[crime_stats["Year"] == 2017]["Primary Type"].value_counts()
crime_agg_2018 = crime_stats[crime_stats["Year"] == 2018]["Primary Type"].value_counts()
crime_agg_2017.name, crime_agg_2018.name = "2017", "2018"
pd.DataFrame([crime_agg_2017, crime_agg_2018])
```

Calculated changes in crime for the 43rd ward:

			ACTUAL	CLAIMED
year	2017	2018	% CHANGE	% CHANGE
all crimes	340	378	+11.18 %	+16 %
battery	38	33	-13.16 %	+136 %
robbery	17	8	-52.94 %	+21 %
burglary	16	13	-18.75 %	+50 %
motor vehicle theft	5	10	+100.00 %	+41 %

Further, Ringer claims:

> But take a look at the year-to-date number and you'll see how crime has affected our local neighborhoods in a four-year period:
>
> - Rose 10 percent since 2017
> - Rose 22 percent since 2016

Since we have data for 2017 and 2018, we can analyze the first claim in this section:

```
def analyze_ward_to_date(crime_stats, ward=43, target_month=7, target_day=26):
    year_start = lambda year: datetime.datetime(year=year, month=1, day=1)
    to_date = lambda year: datetime.datetime(year=year, month=target_month, day=target_day)
    crime_stats = crime_stats[crime_stats["Ward"] == ward]
    crime_stats["Date"] = pd.to_datetime(crime_stats["Date"])
    crime_stats = crime_stats[
        ((year_start(2017) <= crime_stats["Date"]) & (crime_stats["Date"] <= to_date(2017))) |
        ((year_start(2018) <= crime_stats["Date"]) & (crime_stats["Date"] <= to_date(2018)))
    ]

    crime_stats.groupby("Year").size()
    crime_stats.groupby("Year").size().pct_change()
analyze_ward_to_date(crime_stats, ward=43, target_month=7, target_day=26)
analyze_ward_to_date(crime_stats, ward=43, target_month=12, target_day=31)
```

			ACTUAL	CLAIMED
year	2017	2018	% CHANGE	% CHANGE
year-to-date number of reports in ward 43	2148	2359	+9.823%	+10%

Ringer's claim about the comparison of crime reports from the start of the year to 26 July of each year is correct. However, there is no reason why 26 July is a useful cut-off in analyzing crime rates. Looking at crime reports in ward 43 for *the whole year* indicates crime reports rose by 7.55%. In general, while some of Ringer's claims are directionally correct, his crime statistics should be rejected overall, and we cannot trust any conclusions made from these statistics.

3.3 Key Findings

1. The total amount of crime in Chicago is effectively constant across the time period 2017-2018.
2. The majority of crime across the time period analyzed is dominated by incidents of: theft, battery, criminal damage, and assault.
3. The proportion of motor vehicle theft and narcotics crimes are growing from 2017 to 2018, while robbery incidents are proportionally decreasing.
4. The fastest-growing (specific) types of crime are: concealed carry license violation, human trafficking, public indecency and liquor law violations. Crime prevention efforts should focus on these categories.
5. Crime types whose prevalence is falling include: homicide, arson, robbery, and other narcotic violation.

3.4 Caveats & Limitations

Some caveats apply to this analysis:

- Demographic information comes from the American Community Survey, in which responses are voluntary. These data may therefore be incomplete or flawed due to non-response.
- Statistics solely about crime are from a two-year window; a more comprehensive analysis would take into account several years of crime statistics.

4 Probability Exercise

4.1 Probabilities of Crime Type for a Call from a Given Address

We can aggregate the crime types for the given block to see that battery is the most probably report type for the block at 2111 S Michigan Ave. The overall probabilities can also be calculated:

```
def analyze_crime_for_block(crime_stats, block_address):
    return 100 * crime_stats[crime_stats["Block"].str.contains(block_address)]["Primary
        Type"].value_counts(normalize=True)

analyze_crime_for_block(crime_stats, "021XX S MICHIGAN")
```

PRIMARY TYPE	PROBABILITY
battery	26.667%
other offense	21.667%
criminal damage	10.000%
theft	10.000%
assault	10.000%
deceptive practice	10.000%
robbery	3.333%
motor vehicle theft	3.333%
burglary	1.667%
public peace violation	1.667%
criminal trespass	1.667%

4.2 Theft in Garfield Park vs. Uptown

The City of Chicago's Data Portal indicated that Garfield Park corresponds to community areas 26 and 27 and Uptown to community area 3. With this mapping, we can aggregate community areas over reports of theft and find the probabilities:

```
def theft_probabilities(crime_stats, areas):
    return 100 * crime_stats[crime_stats["Primary Type"] == "THEFT"]["Community
        Area"].value_counts(normalize=True)[[float(a) for a in areas]]

theft_probabilities(crime_stats, [26, 27, 3])
```

COMMUNITY AREA	PROBABILITY OF ORIGIN, GIVEN THEFT CALL
26.0	0.937%
27.0	0.990%
3.0	1.510%

The total probability of the call being from Garfield Park is 1.927%, which is 0.42 percentage points more likely than Uptown.

4.3 Calculation under Simulated Frequencies

We can use Bayes' Theorem to calculate the conditional probabilities:

$$P(A \mid B) = \frac{P(B \mid A) P(A)}{P(A)}$$

From the problem statement, we know:

$$P(\text{GARFIELD PARK}) = \frac{600}{1000} = 0.6$$

$$P(\text{UPTOWN}) = \frac{400}{1000} = 0.4$$

$$P(\text{BATTERY}) = \frac{100 + 160}{1000} = 0.26$$

$$P(\text{BATTERY} \mid \text{GARFIELD PARK}) = \frac{100}{600} = 0.16667$$

$$P(\text{BATTERY} \mid \text{UPTOWN}) = \frac{160}{400} = 0.4$$

Therefore,

$$P(\text{GARFIELD PARK} \mid \text{BATTERY}) = \frac{P(\text{BATTERY} \mid \text{GARFIELD PARK}) P(\text{GARFIELD PARK})}{P(\text{BATTERY})}$$

$$= \frac{0.16667 \cdot 0.6}{0.26} = 0.3846$$

$$P(\text{UPTOWN} \mid \text{BATTERY}) = \frac{P(\text{BATTERY} \mid \text{UPTOWN}) P(\text{UPTOWN})}{P(\text{BATTERY})}$$

$$= \frac{0.4 \cdot 0.4}{0.26} = 0.6154$$

From these calculations, a call about battery is 23% more likely to come from Uptown than from Garfield Park.

Sources