pset1_individualexercises_Wright

April 25, 2021

1 0. Load packages and imports

[55]:
```
## basic functionality
import pandas as pd
import numpy as np
import re
import plotnine
from plotnine import *

## repeated printouts
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

2 Individual portion

Use the same `sentencing_cleaned` data for this portion.

In the group portion, you investigated one form of disparity: probation versus incarceration.

Here, you'll investigate a second type of disparity—the length of a defendant's sentence—and also investigate how variation between different judges in the severity of the sentence relates to disparities.

2.1 3.1 Filter to incarceration and construct a sentence length variable (6 points)

Defendants can be sentenced to different lengths for probation, but for simplicity:

- Filter to sentences that involve incarceration (same Illinois Department of Corrections logic as above)
- Filter out non-numeric sentence lengths (e.g., Term, Pounds, or Dollars)
- Filter to Black or White defendants

Then, follow the instructions in the codebook (combining `COMMITMENT_TERM` with `COMMITMENT_UNIT`) to create a standard sentence length in days column (`senlength_derived`). To simplify, you can assume that:

- 1 hour = 1/24th of a day
- 1 year = 365 days
- 1 month = 30.5 days

- 1 week = 7 days
- Natural life = difference between the age of 100 and the defendant's age at incident (cleaned; if missing, code to age 20); note that this is a simplification since age at incident != age at sentencing

Print the following cols for an example of each type (eg an example of originally hours; an example of natural life): `COMMITMENT_TERM`, `COMMITMENT_UNIT`, `age_derived` and your new standardized sentence length column

Print the summary of that sentence length column using the .describe() command

[56]:
```
sentencing = pd.read_csv("~/qss20_mywork/pset1/sentencing_cleaned.csv")
```

```
/opt/conda/lib/python3.8/site-packages/IPython/core/interactiveshell.py:3165:
DtypeWarning: Columns (10,11,14,16,23,25,41,43,44,45,46,47) have mixed
types.Specify dtype option on import or set low_memory=False.
```

[57]:
```
sentencing = sentencing[sentencing["COMMITMENT_TYPE"]== "Illinois Department of␣
↪Corrections"]
sentencing = sentencing[~sentencing["COMMITMENT_UNIT"].
↪isin(["Term","Pounds","Dollars"])]
sentencing = sentencing[sentencing["is_white_derived"] |␣
↪sentencing["is_black_derived"]]

sentencing["COMMITMENT_TERM"] = pd.to_numeric(sentencing["COMMITMENT_TERM"])

terms = [sentencing["COMMITMENT_UNIT"] == "Hours",
         sentencing["COMMITMENT_UNIT"] == "Year(s)",
         sentencing["COMMITMENT_UNIT"] == "Months",
         sentencing["COMMITMENT_UNIT"] == "Weeks",
         sentencing["COMMITMENT_UNIT"] == "Days",
         (sentencing["COMMITMENT_UNIT"] == "Natural Life") &␣
↪(sentencing['AGE_AT_INCIDENT'].notnull()),
         (sentencing["COMMITMENT_UNIT"] == "Natural Life") &␣
↪(sentencing['AGE_AT_INCIDENT'].isna())]

units = [sentencing["COMMITMENT_TERM"] / 24,
         sentencing["COMMITMENT_TERM"] * 365,
         sentencing["COMMITMENT_TERM"] * 30.5,
         sentencing["COMMITMENT_TERM"] * 7,
         sentencing["COMMITMENT_TERM"],
         100-sentencing['AGE_AT_INCIDENT'],
         80]

sentencing["senlength_derived"] = np.select(terms, units, None)

sentencing["senlength_derived"] = pd.to_numeric(sentencing["senlength_derived"])
```

[58]:
```python
sentencing.groupby("COMMITMENT_UNIT")[["COMMITMENT_TERM", "senlength_derived"]].
↪first()
sentencing["senlength_derived"].describe()
```

[58]:

	COMMITMENT_TERM	senlength_derived
COMMITMENT_UNIT		
Days	90.0	90.000000
Hours	1.0	0.041667
Months	18.0	549.000000
Natural Life	1.0	70.000000
Weeks	2.0	14.000000
Year(s)	62.0	22630.000000

[58]:
```
count     44639.000000
mean       1438.190193
std        2018.256817
min           0.000000
25%         457.500000
50%        1095.000000
75%        1460.000000
max      147825.000000
Name: senlength_derived, dtype: float64
```

2.2 3.2 Examine disparities in length within the same judge and offense category: no adjustment (2 points)

- Filter to narcotics offenses
- For each judge with at least 20 Black and at least 20 white defendants, plot the (1) median sentence length for Black defendants and (2) median sentence length for white defendants (factor variable on x axis for each judge_id who qualifies; group by race)
- Write a 1-2 sentence interpretation - if we assume that cases/defendants are randomly assigned to sentencing judges, what might this suggest about the role of judicial discretion in these disparities?

[59]:
```python
sentencing = sentencing[sentencing["simplified_offense_derived"] == "Narcotics"]

judge_groupings = sentencing.groupby("judgeid_derived").agg({"is_black_derived":
↪ "sum", "is_white_derived": "sum"})
judge_groupings3_2 = judge_groupings[(judge_groupings.is_black_derived>= 20) &␣
↪(judge_groupings.is_white_derived>= 20)]
judge_groupings3_2
```

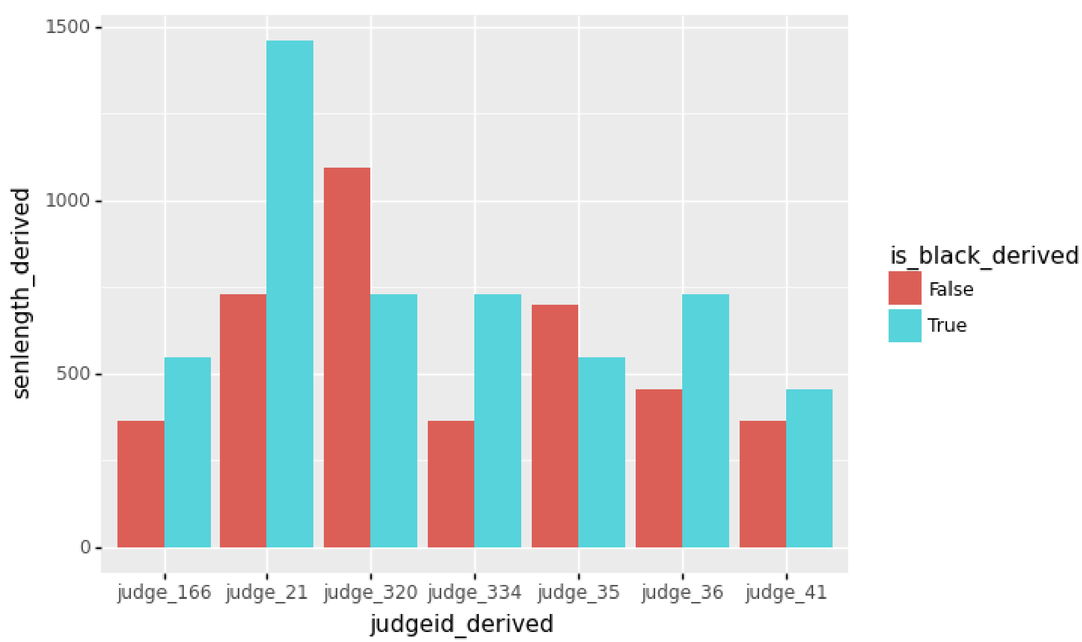
[59]:

	is_black_derived	is_white_derived
judgeid_derived		
judge_166	21	24
judge_21	21	31

judge_320	260	21
judge_334	117	25
judge_35	74	20
judge_36	389	28
judge_41	28	51

[60]:
```
mediansenlength = sentencing[sentencing["judgeid_derived"].isin(judge_groupings3_2.index)]
mediansenlength = mediansenlength.groupby(["judgeid_derived", "is_black_derived"]).senlength_derived.median().to_frame().reset_index()
#mediansenlength

plot = ggplot(mediansenlength, aes(x="judgeid_derived", y = "senlength_derived", fill = "is_black_derived")) + geom_bar(stat="identity", position = "dodge")
plot
```



[60]:
```
<ggplot: (8728065314100)>
```

All but two judges gave longer median sentences to black defendants compared to white ones. In particular, judge_21 tended to give far longer sentences in general than many of their peers - but black defendants' median sentences were nearly double that of their white counterparts. Given that we assume cases are randomly assigned, this implies judicial discretion is a major part of the disparities in sentencing.

2.3 3.3 Examine disparities in length within the same judge and offense category: constructing matched pairs (6 points)

Focus on `judgeid_derived` = `judge_21` and the same narcotics offenses. For each defendant, you want to construct "matched groups" of defendants who:

- Are the same exact age
- Are the same gender
- Differ in race from the focal defendant

Use code to find any/all matched defendants for each focal defendant. Print a table that compares the sentence length for focal compared to others and comment on what other things you'd like to match on if we had a larger dataset

[61]:
```
sentencing = sentencing[sentencing["judgeid_derived"] == "judge_21"]

for i in range(0, sentencing.shape[0]):

    matches = sentencing[sentencing["age_derived"] == sentencing.
 ↪iloc[i]["age_derived"]]
    matches = matches[matches["GENDER"] == sentencing.iloc[i]["GENDER"]]
    matches = matches[matches["RACE"] != sentencing.iloc[i]["RACE"]]
    matches = matches.append(sentencing.iloc[i])
    matches[["age_derived", "GENDER", "RACE", "senlength_derived"]]
#Last row of each table is the focal defendant - tables with only one row means␣
 ↪no matched defendants exist
#with a larger dataset, it would be very interesting to see the judge's race,␣
 ↪age and gender as well
```

[61]:

	age_derived	GENDER	RACE	senlength_derived
58381	21.0	Male	Black	1460.0
412	21.0	Male	White	1095.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
6904	17.0	Male	White	1095.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
57019	33.0	Male	Black	8760.0
21175	33.0	Male	White	1825.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
30015	20.0	Female	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
61939	32.0	Male	Black	1460.0
61940	32.0	Male	Black	1460.0
61941	32.0	Male	Black	1460.0
61942	32.0	Male	Black	1460.0
32289	32.0	Male	White	2190.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
61939	32.0	Male	Black	1460.0
61940	32.0	Male	Black	1460.0
61941	32.0	Male	Black	1460.0
61942	32.0	Male	Black	1460.0
32301	32.0	Male	White	2190.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
61939	32.0	Male	Black	1460.0
61940	32.0	Male	Black	1460.0
61941	32.0	Male	Black	1460.0
61942	32.0	Male	Black	1460.0
32302	32.0	Male	White	2190.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
40632	36.0	Male	White	1825.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
79738	29.0	Male	Black	1460.0
41448	29.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
43109	22.0	Male	Black	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
58381	21.0	Male	Black	1460.0
44766	21.0	Male	White	2555.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
44894	34.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
45804	19.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
47562	22.0	Male	Black	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
81801	24.0	Male	Black	2190.0
81892	24.0	Male	Black	2190.0
47992	24.0	Male	White	730.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
74782	25.0	Male	White	365.0
48366	25.0	Male	Black	1095.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
74782	25.0	Male	White	365.0
48546	25.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
81801	24.0	Male	Black	2190.0
81892	24.0	Male	Black	2190.0
49418	24.0	Male	White	730.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
66907	28.0	Male	Black	1825.0
49532	28.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
50482	42.0	Male	Black	2190.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
63152	23.0	Male	White	365.0
51346	23.0	Male	Black	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
51777	35.0	Male	Black	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
81801	24.0	Male	Black	2190.0
81892	24.0	Male	Black	2190.0
53700	24.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
55416	41.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
56480	36.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
21175	33.0	Male	White	1825.0
57019	33.0	Male	Black	8760.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
57502	27.0	Male	Black	730.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
57587	28.0	Female	White	730.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
57589	28.0	Female	White	730.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
412	21.0	Male	White	1095.0
44766	21.0	Male	White	2555.0
61379	21.0	Male	White	365.0
58381	21.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
60872	35.0	Female	White	730.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
58381	21.0	Male	Black	1460.0
61379	21.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
32289	32.0	Male	White	2190.0
32301	32.0	Male	White	2190.0
32302	32.0	Male	White	2190.0
61939	32.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
32289	32.0	Male	White	2190.0
32301	32.0	Male	White	2190.0
32302	32.0	Male	White	2190.0
61940	32.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
32289	32.0	Male	White	2190.0
32301	32.0	Male	White	2190.0
32302	32.0	Male	White	2190.0
61941	32.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
32289	32.0	Male	White	2190.0
32301	32.0	Male	White	2190.0
32302	32.0	Male	White	2190.0
61942	32.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
51346	23.0	Male	Black	365.0
63152	23.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
64674	26.0	Male	Black	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
49532	28.0	Male	White	365.0
66907	28.0	Male	Black	1825.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
67513	25.0	Female	White	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
79738	29.0	Male	Black	1460.0
67872	29.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
68219	24.0	Female	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
68358	30.0	Female	White	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
73082	39.0	Female	White	1095.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
74317	22.0	Male	Black	1095.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
48366	25.0	Male	Black	1095.0
48546	25.0	Male	Black	1460.0
74782	25.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
74872	23.0	Female	White	2190.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
77484	34.0	Female	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
41448	29.0	Male	White	365.0
67872	29.0	Male	White	365.0
79738	29.0	Male	Black	1460.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
80366	31.0	Male	White	365.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
47992	24.0	Male	White	730.0
49418	24.0	Male	White	730.0
53700	24.0	Male	White	365.0
81801	24.0	Male	Black	2190.0

[61]:

	age_derived	GENDER	RACE	senlength_derived
47992	24.0	Male	White	730.0
49418	24.0	Male	White	730.0
53700	24.0	Male	White	365.0

```
81892          24.0   Male  Black            2190.0
```

3 4. Optional challenge: looking at judge characteristics

The previous exercises showed large differences in sentences between judges/differences in disparities. You become interested in how the judge's own demographic attributes are correlated with sentencing. Going back to the judge's name (`SENTENCE JUDGE`), parse their first name and try to probabilistically infer his or her gender. Then, investigate whether disparities differ between "likely female" and "likely male" judges.