QSS20_Finalpset1_Individual_You-Chi_Liu

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1 0. Load packages and imports

[80]:
```
## basic functionality
import pandas as pd
import numpy as np
import re
from matplotlib import pyplot as plt


## 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.

[81]:
```
sentencing_cleaned=pd.read_csv("sentencing_cleaned.csv")
```

```
/opt/conda/lib/python3.8/site-packages/IPython/core/interactiveshell.py:3165:
DtypeWarning: Columns (10,11,16,25) have mixed types.Specify dtype option on
import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

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

[82]:
```
#Filter to sentences that involve incarceration (same Illinois Department of␣
↪Corrections logic as above)

incar = sentencing_cleaned[sentencing_cleaned['COMMITMENT_TYPE'].str.
↪fullmatch("Illinois Department of Corrections", na = False)].copy()


#Filter out non-numeric sentence lengths (e.g., Term, Pounds, or Dollars)
non_num = incar['COMMITMENT_UNIT'].isin(['Term', 'Pounds', 'Dollars'])
incar = incar[~non_num].copy()


# Filter to Black or White defendants
incar = incar[(incar['is_black_derived']== True)| (incar['is_white_derived']==␣
↪True)].copy()
```

[84]:
```
#Then, follow the instructions in the codebook (combining COMMITMENT_TERM with␣
↪COMMITMENT_UNIT)
#to create a standard sentence length in days column (senlength_derived)
##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

incar['COMMITMENT_TERM'] = incar['COMMITMENT_TERM'].astype('string').str.
↪replace('\.0', '').astype(float)

incar['age_derived'].fillna(value = 20, inplace = True)
```

```
incar["age_new"]=incar['age_derived']*365


incar['commitment_unit_clean'] = incar['COMMITMENT_UNIT'].map({"Year(s)":365,␣
↪"Weeks":7,"Hours":1/24 , "Months":30.5 , "Days":1 }).
↪fillna(incar['COMMITMENT_UNIT'])

incar['commitment_unit_clean']=np.where(incar.COMMITMENT_UNIT=="Natural Life",
                                        ␣
↪36500-incar['age_new'],incar['commitment_unit_clean'])


incar["senlength_derived"]= incar["commitment_unit_clean"] *␣
↪incar["COMMITMENT_TERM"]
```

```
<ipython-input-84-6a354fae18d6>:7: FutureWarning: The default value of regex
will change from True to False in a future version.
  incar['COMMITMENT_TERM'] =
incar['COMMITMENT_TERM'].astype('string').str.replace('\.0', '').astype(float)
```

[85]:
```
#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

result = incar.groupby('COMMITMENT_UNIT').apply(lambda x: x.sample(1)).
↪reset_index(drop=True)
result_final = result[["COMMITMENT_UNIT","COMMITMENT_TERM", "age_derived",␣
↪"senlength_derived"]]
result_final
```

[85]:

	COMMITMENT_UNIT	COMMITMENT_TERM	age_derived	senlength_derived
0	Days	145.0	58.0	145.0
1	Hours	1.0	22.0	0.041667
2	Months	14.0	52.0	427.0
3	Natural Life	1.0	29.0	25915.0
4	Weeks	2.0	23.0	14.0
5	Year(s)	7.0	21.0	2555.0

[86]:
```
#Print the summary of that sentence length column using the .describe() command
incar["senlength_derived"].describe()
```

[86]:
```
count     58289.0
unique      235.0
```

```
top         365.0
freq      14456.0
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?

[87]:
```
# Filter to narcotics offenses

incar = incar[incar['simplified_offense_derived']=="Narcotics"]

organized = incar.groupby(["judgeid_derived"])["is_black_derived",␣
↪"is_white_derived"].sum().reset_index()

organized =␣
↪organized[(organized['is_black_derived']>=20)&(organized['is_white_derived']>=20)]

# print(organized)

judge_list =␣
↪["judge_133","judge_166","judge_177","judge_20","judge_21","judge_279","judge_320"
            ,"judge_334","judge_35","judge_36","judge_41"]

incar = incar[incar['judgeid_derived'].isin(judge_list)]

incar['senlength_derived'] = incar['senlength_derived'].astype(float)

organized2= incar.groupby(["judgeid_derived","is_black_derived"]).
↪agg({'senlength_derived': 'median'}).reset_index()
final=organized2.pivot(index="judgeid_derived", columns="is_black_derived",␣
↪values="senlength_derived").plot(kind="bar")
final.legend(["White", "Black"])
plt.title('Comparison of Median Sentence Length By Race Determined By Selected␣
↪Judges')
plt.xlabel('Judges')
plt.ylabel('Median Sentence Length(Days)')
plt.show()
```

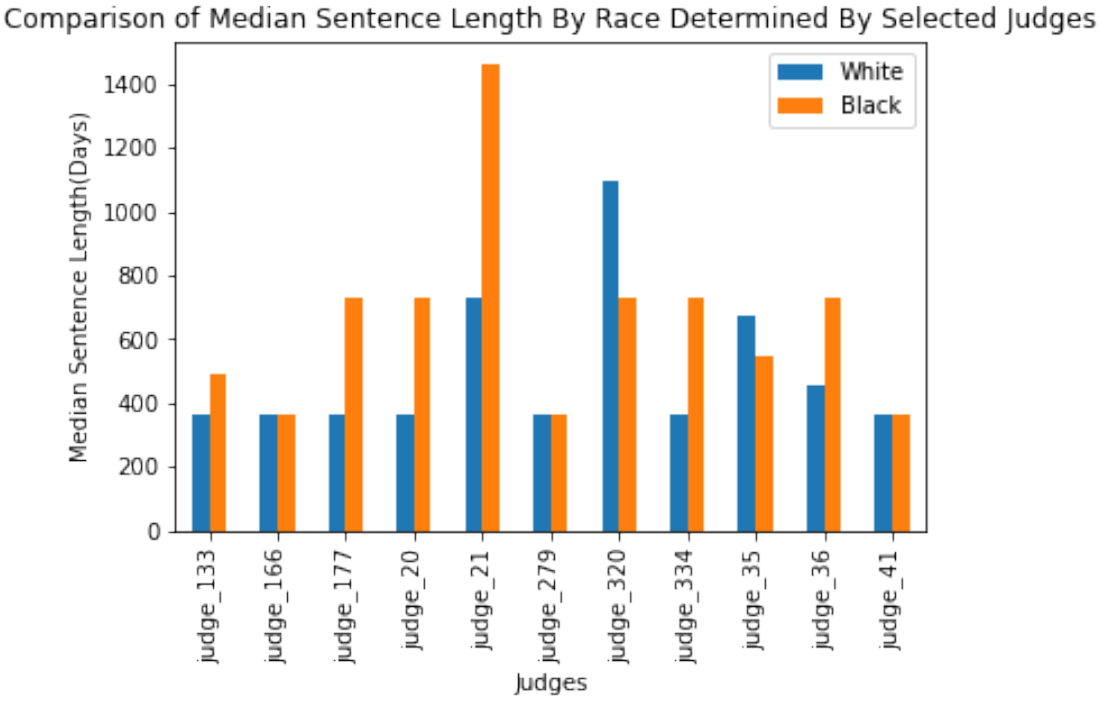
```
<ipython-input-87-d58177cf93ad>:5: FutureWarning: Indexing with multiple keys
(implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  organized = incar.groupby(["judgeid_derived"])["is_black_derived",
"is_white_derived"].sum().reset_index()
```

[87]:
```
<matplotlib.legend.Legend at 0x7fdd721b10a0>
```

[87]:
```
Text(0.5, 1.0, 'Comparison of Median Sentence Length By Race Determined By
Selected Judges')
```

[87]:
```
Text(0.5, 0, 'Judges')
```

[87]:
```
Text(0, 0.5, 'Median Sentence Length(Days)')
```



[88]:
```
# 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?

## From the plot "Comparison of Median Sentence Length By Race Determined By␣
↪Selected Judges," we can notice quite
## clearly that Black has disproportionately higher median sentence legths as␣
↪among the eleven
```

```
## judges, 5 judges gave a higher sentence length for Black with 3 judges␣
 ↪giving equal sentence length. This contrast
## and interesting result from the plot can possible suggest the bias and␣
 ↪racism underlined and influenced the judical
## discretion that then widen the racial disparities and challenge the idea of␣
 ↪"fairness" in law. However, it is
## important to note that although median is statistically more representative,␣
 ↪the sentence length can still be skewed
## to a extent of outliers who commit more severe crime and have a long␣
 ↪sentence length.
```

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

[89]:
```
judges_example = incar.loc[incar['judgeid_derived'] == "judge_21"]

def proximate_defendent(data,i):
    defendant_lookfor = data.iloc[i]
    other_defendants = data.loc[data['CASE_ID'] != defendant_lookfor['CASE_ID']]
    same_stuff = other_defendants.loc[other_defendants["age_derived"] ==␣
 ↪defendant_lookfor["age_derived"]]
    same_stuff = same_stuff.loc[same_stuff["is_male_derived"] ==␣
 ↪defendant_lookfor["is_male_derived"]]
    same_stuff = same_stuff.loc[same_stuff["is_white_derived"] !=␣
 ↪defendant_lookfor["is_white_derived"]]
    table = pd.DataFrame()
    table["match_CASE_ID"] = same_stuff.CASE_ID
    table["match_is_male"] = same_stuff.is_male_derived
    table["match_is_white"] = same_stuff.is_white_derived
    table["match_age"] = same_stuff.age_derived
    table["match_senlength"] = same_stuff.senlength_derived
    table["focal_CASE_ID"] = defendant_lookfor.CASE_ID
    table["focal_is_male"] = defendant_lookfor.is_male_derived
    table["focal_is_white"] = defendant_lookfor.is_white_derived
    table["focal_age"] = defendant_lookfor.age_derived
    table["focal_senlength"] = defendant_lookfor.senlength_derived
```

```
    return(table)

original = pd.DataFrame()


for i in range(0, judges_example.shape[0]):
    if proximate_defendent(judges_example, i).shape[0] > 0:
        individuals = proximate_defendent(judges_example, i)
        original = pd.concat([original,individuals])

original.sample(n=20)
original.shape[0]
```

[89]:

	match_CASE_ID	match_is_male	match_is_white	match_age	\
48546	402664055531	True	False	25.0	
53700	404580508998	True	True	24.0	
32289	396452543476	True	True	32.0	
47992	402439955301	True	True	24.0	
32301	396455774278	True	True	32.0	
61942	407704401578	True	False	32.0	
53700	404580508998	True	True	24.0	
61940	407703520450	True	False	32.0	
104703	424062396620	True	False	24.0	
32301	396455774278	True	True	32.0	
81892	415163150361	True	False	24.0	
81801	415127464675	True	False	24.0	
61379	407493077705	True	True	21.0	
81892	415163150361	True	False	24.0	
412	213700128228	True	True	21.0	
81801	415127464675	True	False	24.0	
32302	396456361697	True	True	32.0	
61939	407703373595	True	False	32.0	
67872	409877997576	True	True	29.0	
32289	396452543476	True	True	32.0	

	match_senlength	focal_CASE_ID	focal_is_male	focal_is_white	\
48546	1460.0	412483493163	True	True	
53700	365.0	415127464675	True	False	
32289	2190.0	407703373595	True	False	
47992	730.0	415127464675	True	False	
32301	2190.0	407703814159	True	False	
61942	1460.0	396455774278	True	True	
53700	365.0	415163150361	True	False	
61940	1460.0	396452543476	True	True	
104703	365.0	402439955301	True	True	
32301	2190.0	407703520450	True	False	
81892	2190.0	402439955301	True	True	

```
81801            2190.0   404580508998          True           True
61379             365.0   406322205406          True          False
81892            2190.0   404580508998          True           True
412              1095.0   406322205406          True          False
81801            2190.0   402981555331          True           True
32302            2190.0   407703373595          True          False
61939            1460.0   396452543476          True           True
67872             365.0   414327840987          True          False
32289            2190.0   407704401578          True          False

        focal_age  focal_senlength
48546        25.0            365.0
53700        24.0           2190.0
32289        32.0           1460.0
47992        24.0           2190.0
32301        32.0           1460.0
61942        32.0           2190.0
53700        24.0           2190.0
61940        32.0           2190.0
104703       24.0            730.0
32301        32.0           1460.0
81892        24.0            730.0
81801        24.0            365.0
61379        21.0           1460.0
81892        24.0            365.0
412          21.0           1460.0
81801        24.0            730.0
32302        32.0           1460.0
61939        32.0           2190.0
67872        29.0           1460.0
32289        32.0           1460.0
```

[89]:
```
62
```

[28]:
```
# Comment on what other things you'd like to match on if we had a larger dataset
## If we had a larger dataset, I would like to match the education level and␣
 ↪income of each focal and the matches.
## I think it would be interesting to analyze how education and income level␣
 ↪can correlate with the sentence length.
```

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.

[ ]: