Modeling Criminal Sentencing Disparities in Harris County

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Github Repository:
https://github.com/jasirrahman/DSCI-303-Project

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ABSTRACT

The Harris County criminal system is rife with disparities. Despite making up just 19% of the population, black people comprised 45% of bookings in Harris County jail from 2015-2018 [1]. Nationally, this is in line with disparities in criminal justice outcomes, which tends to favor white, affluent defendants over people of color and lower-income defendants [2]. This paper aims to employ machine learning techniques to investigate what demographic outcomes are predictive of harsher sentencing in Harris County. We leverage a robust publicly available dataset from the Harris County Clerk's Office with over 200,000 Harris County Court case outcomes to create multivariate regression models. First, we estimate sentencing harshness based solely on the facts of the case, then we estimate the effect of defendant demographics on sentencing outcomes. Including defendant demographics in our model does not improve model performance, suggesting more work to be done for machines to accurately estimate disparities.

1 Introduction

The Harris County criminal justice system is one of the largest in the United States. For the past decade Harris County processed nearly 100,000 criminal cases annually [3]. Despite being the most diverse county in the country, disparities in the Harris County criminal justice system remain present. Black people are vastly overrepresented in Harris County jail, making up 45% of bookings from 2015-2018, despite making up just 19% of the population. In Harris County non-citizens are 50 percent more likely to be sentenced to jail or prison time than citizens [4]. Non-citizens are also, on average, sentenced to 18 percent longer periods of incarceration for the same offense [4]. Given the extent to which disparities occur on an individual basis, there has been much scrutiny on Harris County Judges and the court system to ensure equitable sentencing. Such a debate caused a sea change in the Harris County judiciary, as misdemeanor reforms were implemented in 2019 in attempts to curb disparities. However, the felony system remains unchanged and bias remains a problem to be addressed by judges..

2 Related Work

The causes of criminal justice sentencing disparities are contested by researchers and political actors, resulting in different philosophies by which the justice system operates. On the one hand, Sampson and Lauritsen (1997) write that disparities in the number of people of color in jail have been linked to higher rates of criminal activity by those groups, which are shaped by historical disparities in income and educational attainment [5]. On the other hand, when controlling for systemic factors, Spohn (2013) writes that people of color face disproportionately harsher sentences than similarly situated White defendants [2]. The United States Sentencing Commission investigated sentencing data in the United States from 2017-2021 and found that compared with White men, Black men receive 13.4% longer sentences and Hispanic men receive 11.2% longer sentences [6]. Clair & Winter of Harvard University (2017) find that the majority of judges (76%) report that such disparities are (at least in part) caused by bias at the judge level [7].

Recent advances in Machine Learning have been increasingly applied in criminal justice contexts, supposedly as a means to eliminate human biases present in the system. The most notable example is the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) system, which has recently been implemented by human judges to provide guidance for sentencing based on estimated recidivism rates. Estimating sentencing using machine learning in such a way has come under scrutiny for simply attempting to predict outcomes based on data that is inherently biased – producing biased results under the veneer of empiricism that is associated with machines. Propublica published a report on COMPAS' recidivism estimators, finding that COMPAS overestimated the rate at which black defendants recidivate while underestimating the recidivism rate of white defendants [8]. Aside from bias, another critique of COMPAS and many other AI models that are used for sentencing and recidivism prediction is that of transparency. In a 2022 literature review of machines that have been trained to predict recidivism, Travaini et al. write, "The latest machine learning models are like 'black boxes' because they have such a complex design that users cannot understand how an AI system converts data into decisions" [9].

We are thus left with a criminal justice system that we know is broken from decades of research, and novel technologies with the ability to accurately estimate bias that is simultaneously either a) influenced by human bias or b) too complex for humans to truly understand. There is hope, however, for models that are more interpretable to be leveraged to estimate sentencing bias within the criminal justice system. Angelino et al. (2018) of MIT construct linear models for recidivism and find accuracy scores for such simple models were comparable to that of COMPAS [10].

Similarly, we aim to leverage simple linear models to estimate sentencing harshness and understand what demographics count in the process.

3 Methods

Using publicly available data from the Harris County Clerk's website, we examine criminal cases in Harris County over a period of ten years from 2010 - 2019. We choose this period because it provides a large set of observations prior to the COVID-19 pandemic, which temporarily altered the criminal justice system in Harris County. We restrict our analysis to the Harris County District Courts which adjudicate felonies. due to greater variability in sentencing for felonies (ranging from 180 days to life in prison).

Using Python we filter our dataset down to meet the specifications above and after further data cleaning (removing null values, etc.) the dataset of over 3,000,000 rows is reduced to 235,334 that we analyze.

In order to create an evaluable model, it was necessary to operationalize our measurement of sentence harshness. Such a scaling technique was initially developed by the Administrative Office of the U.S. District Court (1967), which created a continuous measure to scalarize the previously nebulous concept of harshness. Tiffany, Avichai, and Peters (1975) created "a slightly modified version of a scale created by the Administrative Office" to express sentence severity quantitatively. Their "TAP" index, which consists of 12 levels weighted to reflect overall severity, scales from 0-50, with higher scores weighted to greater lengths of jail time, and lower scores accounting for probation and fines [11]. Ostrom et al. (2004) concluded that there are three principles guiding judge sentences: 1) judges tend to repeat sentences, 2) judges divide sentences in distinct increments (e.g. 6 months, 12 months, etc.), and 3) judges create uneven intervals at higher sentencing levels because they discount long-term disutility at the end of a sentence [12]. We conclude that the TAP index meets these criteria, and is presented in Table 1-1 below. Our aim in implementing TAP as a measure of harshness is to interpret magnitude and direction of demographic variables on TAP beyond feature importance.

We apply the TAP index to each row of our dataset to assign a measurement of harshness for each observation. Because criminal sentences of lower severity as measured by TAP occur at significantly higher rates (mean TAP score was 7.21 out of 50), we use box-cox to standardize the skew of TAP scores for analysis. This

We create two regression models: 1) a simple model with case-related variables, and 2) an enhanced model with demographic variables. We compare both models against the baseline – the mean TAP score of all defendants – to estimate the effects of the facts of the case and demographics on sentencing.

Our first model (Model 1) aims to estimate theoretical sentencing "all else equal". That is, discounting potential bias from demographic information (e.g. race, sex, etc.) and unobservable variance (e.g. judge interpretation), what ought the sentences be based on the theoretical underpinnings of sentencing. In criminal courts, there are three components that theoretically determine sentencing: the level of the crime, defendant pleas, and recidivism. Judges in Texas are provided schedules that guide sentencing based on the severity of felony charges, with each succeeding grade receiving a more severe punishment. In Texas there are five felony levels (from least to most severe): State Jail (Class S), Class C, Class B, Class A, and Capital. To expedite adjudication, the state will often offer plea deals for those who plead guilty to a crime, resulting in shorter sentences for defendants. Based on the dataset's disposition labels – which indicate the final outcome of a court case – we isolate which offenders plead guilty in their case. Under Texas law, the court is required to take prior offenses into account when sentencing. We estimate the rate at which defendants recidivate by counting prior occurrences of each defendant in the sentencing data.[1] 59.2% of the cases examined in the data involved a defendant that had been convicted of a prior offense. Given recidivism is so prevalent in the data, and is legally bound to be a factor in sentencing. The model specification for *Model 1* is as follows:

$$TAP = \beta_0 + \beta_1(\text{Level: Class B}) + \beta_2(\text{Level: Class C}) + \beta_3(\text{Level: Class S}) + \beta_4(\text{Level: Class S}) + \beta_5(\text{Plea: Guilty}) + \beta_6(\text{Number of Past Offenses})$$

We hypothesized that *Model 1* would predict sentencing moderately better than baseline, as it accounts for factors which would theoretically and legally determine sentencing.

Our second model (Model 2) aims to approximate real-world sentencing, taking into account the following factors: 1) race, 2) sex, and 3) immigration status. The model specification for Model 2 is as follows:

$$TAP = \beta_0 + \beta_1(\text{Level: Class B}) + \beta_2(\text{Level: Class C}) + \beta_3(\text{Level: Class S}) + \beta_4(\text{Level: Class S}) + \beta_5(\text{Plea: Guilty}) + \beta_6(\text{Number of Past Offenses}) + \beta_7(\text{Race: Black}) +$$

[1] It should be noted that we calculate the recidivism count for each defendant over the period of 1990-2019, prior to subsetting the data to the study period of 2010-2019. This ensures that our estimate of recidivism includes crimes that occurred prior to the study period.

β_8(Race: Native American) + β_9(Race: White) + β_9(Sex: Female) + β_9(Citizenship: Citizen)

We hypothesized that *Model 2* improves upon *Model 1*, as it controls for factors that are found to be historical drivers of disparities in criminal sentencing in Harris County and nationally. In particular, we predict that the racial categorization of "Black" will significantly predict greater TAP scores when compared to the category of "White," and that the citizenship categorization of "Citizen" will significantly predict lower TAP scores when compared to the category of "Noncitizen."

To test our models we run 10-fold cross-validation and compute the average mean-squared error (MSE) and R^2 across the folds for each model to determine which variables improve predictions. Because we use box-cox transformation to normalize TAP scores, we report box-cox transformed coefficients in our model tables (see Appendix), but reverse transform TAP scores when reporting out results of our models.

4 Results

Baseline

For our baseline model we use a linear model to compare the average box-cox transformed TAP score across all observations against individual box-cox transformed TAP scores for each observation. The mean box-cox transformed TAP score of the data was 1.44, which when reverse transformed is equivalent to a TAP score of 4.51 – around 7 months in prison. When running this mean score in a linear model, the MSE is 0.91 and the R^2 is -0.0002. This model does not predict sentencing outcomes in any meaningful way. The R^2 is a negative value because predicting the average yields an R^2 of 0, and the adjusted R^2 penalizes adding any additional variables.

Model 1

Model 1 moderately predicts TAP scores, improving significantly over baseline (see Appendix). Following 10-fold cross-validation, the following mean statistics are returned across the 10 folds: Average Training MSE: 0.5450; Average Testing MSE: 0.5486; Average Training Adjusted R^2: 0.4022; Average Testing Adjusted R^2: 0.3903. A moderate R^2 demonstrates that *Model 1*, controlling for solely the facts relating to the case, moderately predicts sentencing harshness as measured by TAP, but fails to capture the majority of the variance. The MSE values indicate that the model predicts TAP scores within around 0.5 box-cox transformed TAP points (1.6 true TAP points) of the true value. The baseline box-cox transformed TAP predicted for a first-time offender who plead not guilty to a Class A felony charge was 2.68, which when reverse transformed is a TAP score of 18.29. A TAP score in this range corresponds to jail sentences between 5 and 10 years.

All variables except for Past Offense Number have significant p-values ($p < 0.05$), which runs contrary to our hypothesis. This lack of statistical significance suggests that recidivism and sentence harshness do not have a linear relationship. In the field, if a judge sees that a defendant has prior criminal convictions, the number of prior convictions may not be as determinative of sentencing as say length of time since last conviction or previous conviction crime type. Felony charges of class B and C have statistically significant, positive correlations with box-cox transformed TAP scores (0.10 and 0.04, respectively), but the slim margins indicate no true relationship between these lower crime types and sentencing outcomes. A Class S felony charge, however, has a statistically significant, negative relationship with TAP scores (coefficient of -1.13). This translates to TAP scores three points lower than baseline, or prison sentences around five years in length (2-3 years below the baseline of a Grade A Felony). This may seem like a gross overestimate, given that Class S felonies typically have a maximum sentence length of two years. However, this estimate may be confounded by the high rate of recidivism in the dataset. Texas Penal Code § Title 3, Chapter 12, Subchapter A. Sec. 12.35(c)(2) specifies that those convicted of a Class S felony with prior arrests are required to be charged with a Class C felony, which may have sentences between two and ten years. The final variable to note is guilty plea, which in line with theory and court observations has a negative statistically significant association (-0.73) with TAP scores. This translates to sentences that are two years shorter than baseline.

Model 2

Model 2 only marginally improves prediction over *Model 1*, but illuminates unique relationships between demographics. Following 10-fold cross-validation, the following mean statistics are returned across the 10 folds: Average Training MSE: 0.5447; Average Testing MSE: 0.5463; Average Training Adjusted R^2: 0.4101; Average Testing Adjusted R^2: 0.4001. The baseline box-cox transformed TAP predicted for a first-time offender who plead not guilty to a Class A felony charge was 2.57, which when reverse transformed is a TAP score of 16.25. A TAP score in this range corresponds to a jail sentence slightly longer than 5 years. It should be noted that the constant of this model, which predicts the TAP score of an Asian-American noncitizen male who has committed a Class A Felony, is less than that of the constant of *Model 1.* The differences derived from the inclusion of racial, sex, and citizenship data do not meaningfully improve on *Model 1*, which strictly predicted based on facts of the case. The constant The coefficient for Past Offense Number jumps from barely different from 0 to 0.17, equivalent to a one point TAP score increase. It should be noted that the mean recidivism rates for defendants of different races varies drastically. In our dataset, 69.1% of Black defendants had at least one prior offense, much higher than White (49.7%), Asian (38.1%), or Native American (33.7%) defendants.

Upon accounting for demographics, the effect of guilty plea becomes insignificant. Interestingly, across all demographics included in this model, the extent to which the rate of guilty pleas differs across demographics (that is, across all race, sex, citizenship categories) is within 5%, and no demographic group when considered as a whole has a guilty plea rate less than 90%.

Among racial groups, the categorization of White has a slim, negative effect on sentencing outcomes relative to baseline (-0.106), while categorizations of Black and Native American have slim positive effects (0.144 & 0.09, respectively). These coefficients generally align with trends in racial bias that have been observed in the court system. From this model, a white defendant with a prior offense will have lighter sentencing outcomes than a first-time black defendant charged with the same crime.

The differences in sentencing for those categorized as Female was negligible (-0.0006), suggesting little disparities in sentencing based on sex.

The effect of being categorized as having citizenship had a relatively large effect on harshness, yielding a coefficient of -0.76 which translates to TAP score reductions of over two points. From this model, a citizen with three prior offenses will receive lighter sentences than a noncitizen with no criminal record who committed the same crime.

5 Discussion

While predictive power is not improved holistically from *Model 1* to *Model 2*, examining individual coefficient differences yields interesting insights into the operations of the criminal justice system. Guilty pleas becoming insignificant upon accounting for demographics suggests that some demographics have different relationships with plea deals than others. Indeed, some evidence suggests that Black defendants don't benefit from plea deals at all [13]. Exploration of demographics with larger impacts on TAP scores – namely race and citizenship status – provide potential future steps for researchers. We note that recidivism rates are significantly higher for Black defendants, which may be a function of the greater policing of black neighborhoods and previously existing disparities. This suggests that the relationship between recidivism and race may be entangled, causing us to underestimate race as a factor. Examining citizenship status, more sophisticated data about the nature of the documentation status of these individuals – for example, whether one is an undocumented immigrant or has a green card – would contribute to a greater understanding of judge interpretations of offenses by noncitizens.

Our models may also lend themselves towards individual analyses of judge behavior. Clair and Winter of Harvard (2017) write, "Judges reported two groupings of strategies for dealing with racial disparities at different stages of the criminal-court process," which they define as "interventionist" and "non-interventionist [7]. Interventionists challenge the conduct of others in the court, accounting for potential bias from other actors such as the prosecution and arresting officer. Non-interventionists tend to defer to other actors and stick more to prescribed sentencing guidelines. *Model 1* and *Model 2* are similar to the non-interventionist interventionist styles, respectively, as *Model 1* sticks to the fundamental factors of sentencing, and *Model 2* attempts to estimate demographic influence. Future researchers may benefit from adjusting the models to create a classifier to identify these different types of judges and estimate how different styles may influence sentencing outcomes.

We suggest that Harris County investigate further the impact of the demographic relationships listed above on sentencing outcomes. Given that 97% of sentences in the data are given after plea deals, it is imperative to understand how plea deals impact sentencing with marginalized populations to ensure equitable sentencing. Understanding how over policing impacts relative recidivism rates may aid in re-examining the role of recidivism as one of the three primary factors in sentencing. Finally, more research ought to be invested into inequities based on citizenship status that are not currently accounted for with the current Harris County data.

6 Conclusion

It is clear that there is a problem of bias in the American criminal justice system. While machines like COMPAS have shown promise in ameliorating such problems, the "black box" nature of such machines does not provide information about where disparities manifest and how to combat them. This project aims to translate the human decision-making process into an interpretable machine to identify disparities in the Harris County judicial system. Using linear regression, we explore sentencing in Harris County based on facts of the case (Model 1) and demographics (Model 2). While including demographics does not improve upon our initial model, we provide an interpretable model which lends itself to future exploration of more complex factors of sentencing, such as plea bargaining direction, entanglements of recidivism and race, and differences across noncitizen populations.

CONTRIBUTIONS

Andrew Kim led the project's data preparation and analysis, focusing on data cleaning and feature engineering. He also contributed to building the regression models, interpreting the results, and synthesizing findings for the report. Jasir Rahman led the theoretical underpinnings of the paper through background research and contextual understanding of the TAP score. He also contributed to the regression modeling process, developed data visualizations to support the analysis, and took lead on reporting results.

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APPENDIX

TABLE 1: TAP SCORES

Sentence	Score
Suspended Sentence Probation w/o supervision	0
Fine only; Probation with supervision, 1-12 months	1
Probation with supervision, 13-36 months	2
Probation with supervision, over 36 months	3
Split sentences, Delayed probation	4
Imprisonment, 7-12 months	5
Imprisonment, 13-24 months	7
Imprisonment, 24-36 months	10
Imprisonment, 37-48 months	12
Imprisonment, 49-60 months	14
Imprisonment, 61-120 months	25
Imprisonment, over 120 months	50

MODEL 1 RESULTS

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              TAP SCORE   R-squared:                       0.402
Model:                            OLS   Adj. R-squared:                  0.402
Method:                 Least Squares   F-statistic:                 3.168e+04
Date:                Thu, 12 Dec 2024   Prob (F-statistic):               0.00
Time:                        02:15:58   Log-Likelihood:            -2.6268e+05
No. Observations:              235420   AIC:                         5.254e+05
Df Residuals:                  235414   BIC:                         5.254e+05
Df Model:                           5
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
CONSTANT                 2.6811      0.011    236.409      0.000       2.659       2.703
FELONY B                 0.1007      0.005     19.754      0.000       0.091       0.111
FELONY C                 0.0375      0.005      7.596      0.000       0.028       0.047
FELONY S                -1.1372      0.004   -279.124      0.000      -1.145      -1.129
PAST OFFENSE NUMBER     -0.0002      0.000     -0.729      0.466      -0.001       0.000
GUILTY PLEA             -0.7343      0.011    -65.700      0.000      -0.756      -0.712
==============================================================================
Omnibus:                    28761.831   Durbin-Watson:                   1.942
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13148.663
Skew:                           0.405   Prob(JB):                         0.00
Kurtosis:                       2.173   Cond. No.                         80.5
==============================================================================
```

MODEL 2 RESULTS

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              TAP SCORE   R-squared:                       0.410
Model:                            OLS   Adj. R-squared:                  0.410
Method:                 Least Squares   F-statistic:                 1.508e+04
Date:                Thu, 12 Dec 2024   Prob (F-statistic):               0.00
Time:                        02:16:03   Log-Likelihood:            -2.4181e+05
No. Observations:              216816   AIC:                         4.836e+05
Df Residuals:                  216805   BIC:                         4.838e+05
Df Model:                          10
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
CONSTANT                 2.5766      0.022    115.893      0.000       2.533       2.620
FELONY B                 0.1022      0.005     19.145      0.000       0.092       0.113
FELONY C                 0.0391      0.005      7.582      0.000       0.029       0.049
FELONY S                -1.1371      0.004   -265.606      0.000      -1.146      -1.129
PAST OFFENSE NUMBER      0.1747      0.018      9.549      0.000       0.139       0.211
GUILTY PLEA             -0.0401      0.089     -0.452      0.652      -0.214       0.134
BLACK                    0.1444      0.018      7.931      0.000       0.109       0.180
NATIVE AMERICAN          0.0921      0.004     21.107      0.000       0.084       0.101
WHITE                   -0.1058      0.006    -17.767      0.000      -0.117      -0.094
FEMALE                  -0.0006      0.000     -1.930      0.054      -0.001    8.67e-06
CITIZEN                 -0.7622      0.012    -65.391      0.000      -0.785      -0.739
==============================================================================
Omnibus:                    29119.320   Durbin-Watson:                   1.946
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            12437.694
Skew:                           0.403   Prob(JB):                         0.00
Kurtosis:                       2.148   Cond. No.                         446.
==============================================================================
```