Predicting Recidivism with Demographic and Criminal Records

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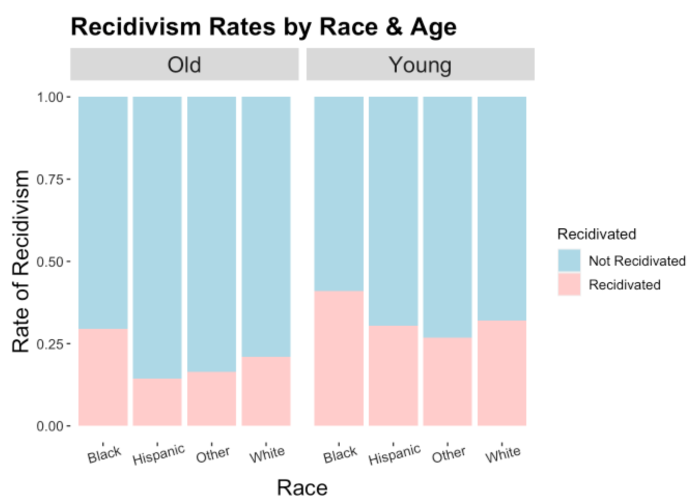
Background & Significance

In the past several decades, the United States Justice System has demanded change in the traditional sentencing process. Many legal scholars have called for statistical modeling as a form of judicial reform, and an alternative to the inherent bias of judges and juries in court (Broward County Clerk's Office, 2021). Especially in the context of the Black Lives Matter movement and increasing support to defund the police due to racial discrimination, promoting equality in our judicial system is particularly relevant today (Levin, 2020). Across the country, various court systems have begun to integrate machine learning models to determine sentencing lengths, bond amounts, and other aspects of defendants' freedom. For example, Florida has used a model from Northpointe to determine bond lengths, and has served as a trial for heavy integration of these data models. However, a recent ProPublica study has since exposed the flaws in these models. Despite basing conviction on over one hundred questions that do not directly address race, it is evident that instead of bridging the underlying bias in our judicial system, this model has extenuated racial differences, with disproportionately harsh scores for African American citizens, even when other factors are controlled (Angwin et al., 2016).

With rising criticism for these statistical models, we decided to create our own data model to predict recidivism. We explored whether recidivism can be accurately predicted, and how these predictions vary between races. Specifically, we wanted to test the sensitivity and specificity of a 'race-blind' model, like the one from Northpointe, for black and white Americans. With the results of this study, we hoped to gain insight into the inherent racial bias in these data models and provide direction for how these models can be improved in the future to better serve the justice system as an equitable indicator of recidivism likelihood.

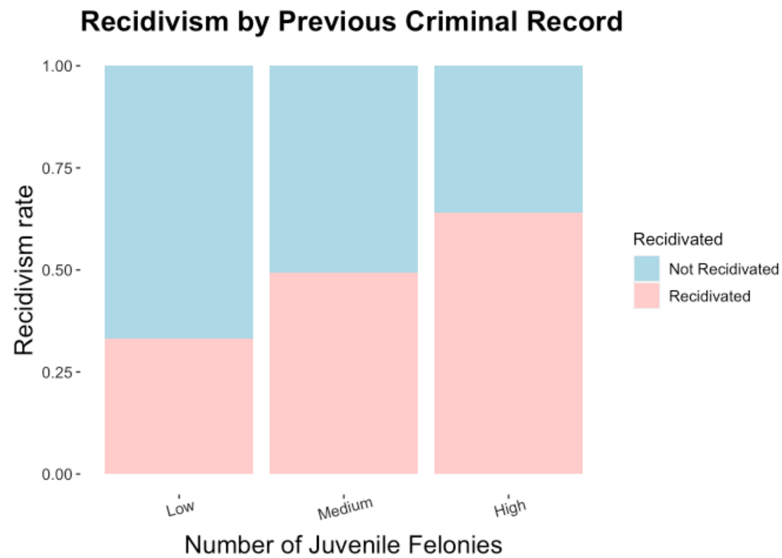
Methodology

Our model examined a dataset of over 7,800 observations from the Broward County Clerk's Office. In this dataset, each observation represents an individual person, with many variables describing their demographic background and criminal record. The data has sufficient representation of black and white residents, but limited records for other races and certain demographic groups. Because of these limitations, we manipulated the data for easier visualization. For both race and marital status, we consolidated many of the underrepresented groups into an 'Other' category. For example, there were too few Asian and Native American people to draw meaningful conclusions; therefore, we grouped these together in the 'Other' category.



Before building the model, we created several figures to shape our modeling and analysis. In 'Recidivism Rates by Age & Race,' the graphs are faceted by age, with 'Old' representing individuals who are over 45 and 'Young' containing those under 45. In this data set, younger individuals have higher recidivism rates across all races, and African-American citizens have higher recidivism rates than other racial groups. These trends have clear limitations; however, they provided us insight into the racial and age-based disparities which may be reflected in our model.

For 'Recidivism by Previous Criminal Record', we consolidated the data from the juvenile felony counts into low (0 or one), medium (two or three), and high (more than three), in order to easily visualize the data. Although limited in scope, juvenile felony counts can provide basic insights into the influence of criminal history on recidivism. This graph reflects an increasing likelihood of recidivism with a higher rate of juvenile felonies.

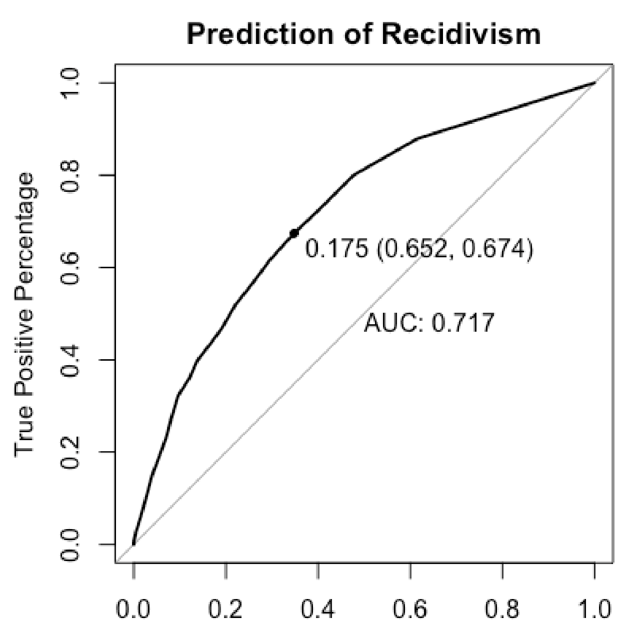


Figures like these demonstrate the importance of including both demographic variables like age as well as variables pertaining to criminal history in our data model. Although we used categorical variables to make these visualizations, we used the quantitative version of variables like age and juvenile felony count in our model for increased accuracy.

Based on our initial exploration, our model used a combination of demographic factors and criminal history to predict recidivism. We cleaned the data, reducing data to eleven explanatory variables, and selected the quantitative version of variables like age. After this cleaning, the dataset was split into testing and training data. Using a random forest, we created a series of 500 binary trees to predict whether or not an individual would recidivate. Each tree represents a bootstrapped sample by evaluating five random variables at each node and creating a split based on the variable with the best predictive ability. With this random forest, we used an ROC curve to evaluate the accuracy of the model and determine the best threshold for our model to have the highest accuracy. By applying this model to different races, we evaluated the present bias.

Results

The first model was created from the training dataset and gave us a threshold of 0.183. In other words, if a defendant returned a score of greater than 0.183, the model would predict them to recidivate. Therefore, we created an updated model that incorporated this threshold of 0.183. After applying our updated model to the testing data, we created the following ROC curve with an AUC of 0.717.



With this model, we also evaluated the sensitivity and specificity by race (see

Tables 1 and 2 in the Appendix). The sensitivity for African-American citizens is 0.748 compared to 0.599 for their white peers. Specificity is much higher for white citizens (0.716) than African-American ones (0.562).

Discussion of research, limitations, reasonableness of assumptions, possibilities for future work

We created this model in order to understand the underlying racial bias in statistical modeling for recidivism. By analyzing the sensitivity and specificity of this data, this bias is clear. In the context of recidivism, a sensitive test will be more likely to predict that someone will recidivate, at the expense of being specific. In other words, the higher sensitivity for African-American people means that our model is more likely to predict that African-Americans are going to recidivate, and thus a higher frequency of false accusations (false positives). Higher specificity for whites means that the model is less likely to commit false accusations for whites, but more likely to let future criminals walk free (false negatives). Obviously, the racial implications of this are huge, as the model disproportionately condemns African-American defendants at a higher rate than the white defendants. Therefore, while the model itself is not explicitly racist, there is clear underlying influence of systemic racism as we integrate explanatory variables like juvenile felony counts and prior sentencing.

Beyond the inaccuracy of this model, which falsely predicts hundreds of cases of recidivism, there are other clear limitations on this dataset. Primarily, this data set is over seven years old, not random, and sourced from a single county in Florida. Crime behaviors and trends may vary significantly between rural regions and urban ones, between states, and even between different counties in Florida. Furthermore, factors such as cultural, political, and economic change may influence criminal behavior, making this data from 2013-2014 less applicable today. Additionally, the assumption that variables are completely independent is a large one which degrades the quality of this model. In the context of the US policing system, it is naive to assume that race and gender will not influence policing and thus felony rates. These connections help to explain the disparities in sensitivity and specificity described above.

Finally, when modeling for recidivism rates, it is essential to evaluate the weight of false positives and false negatives in this context. A false positive is a false prediction of recidivation whereas a false negative fails to predict recidivation. In this context, false positives are much more serious, considering the presumption of innocence in our justice system. Future researchers may choose to use a measure other than the AUC, which tends to be less accurate when there are large disparities between the cost of false positives and false negatives.

While this model provides interesting insights into recidivism in Broward County, Florida, it fails to provide an accurate prediction of recidivation. Instead, it supports the results of the ProPublica analysis, pointing towards the limitations of statistical modeling in the justice system. Measures other than the AUC may serve as stronger metrics to create these models. By using variables, coefficients, and other factors to account for the underlying racial biases, researchers may create more effective tools for the judicial system to support equality down the road.

References

Angwin, Julia, et al. “Machine Bias.” *ProPublica*, 9 March 2019, www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

Broward County Clerk’s Office, “COMPAS Recidivism Risk Score Data and Analysis”, ProPublica Data Store, ProPublica, November 2019, https://www.propublica.org/datastore/dataset/compas-recidivism-risk-score-data-and-analysis, Accessed 18 March 2021.

Levin, Sam. “Movement to Defund Police Gains 'Unprecedented' Support across US.” *The Guardian*, Guardian News and Media, 4 June 2020, www.theguardian.com/us-news/2020/jun/04/defund-the-police-us-george-floyd-budgets.

Appendix

Table 1: Actual Recidivation versus Predicted Recidivation (Caucasian)

	Predicted to Recidivate	Predicted to Not Recidivate
Recidivated	151	101
Did Not Recidivate	184	464

Table 2: Actual Recidivation versus Predicted Recidivation (African-American)

	Predicted to Recidivate	Predicted to Not Recidivate
Recidivated	433	146
Did Not Recidivate	372	478