Interpretable Classification Models for Recidivism Prediction

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Abstract

We investigate a long-debated question, which is how to create predictive models of recidivism that are sufficiently accurate, transparent, and interpretable to use for decision-making. This question is complicated as these models are used to support different decisions, from sentencing, to determining release on probation, to allocating preventative social services. Each use case might have an objective other than classification accuracy, such as a desired true positive rate (TPR) or false positive rate (FPR). Each (TPR, FPR) pair is a point on the receiver operator characteristic (ROC) curve. We use popular machine learning methods to create models along the full ROC curve on a wide range of recidivism prediction problems. We show that many methods (SVM, Ridge Regression) produce equally accurate models along the full ROC curve. However, methods that designed for interpretability (CART, C5.0) cannot be tuned to produce models that are accurate and/or interpretable. To handle this shortcoming, we use a new method known as SLIM (Supersparse Linear Integer Models) to produce accurate, transparent, and interpretable models along the full ROC curve. These models can be used for decision-making for many different use cases, since they are just as accurate as the most powerful black-box machine learning models, but completely transparent, and highly interpretable.

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Keywords: recidivism, machine learning, interpretability, scoring systems

1 Introduction

Forecasting has been used for criminology applications since the 1920s (Borden 1928, Burgess 1928) when various factors derived from age, race, prior offense history, employment, grades, and neighborhood background were used to estimate success of parole. Many things have changed since then, including the fact that we have developed machine learning methods that can produce accurate predictive models, and have collected large high-dimensional datasets on which to apply them.

Recidivism prediction is still extremely important. In the United States, for instance, a minority of individuals commit the majority of the crimes (Wolfgang 1987): these are the “power few” of Sherman (2007) on which we should focus our efforts. Clearly, we want to ensure that public resources are directed towards the right individuals, whether these resources are correctional facilities or preventative social services. Milgram (2014) recently discussed the critical importance of accurately predicting if an individual who is released on bail poses a risk to public safety, pointing out that high-risk individuals are being released 50% of the time while low-risk individuals are being released less often then they should be (Milgram 2014). Her observations are in line with longstanding work on clinical versus actuarial judgment, which shows that humans, on their own, are not as good at risk assessment as statistical tools (Dawes et al. 1989, Grove and Meehl 1996). This is the reason that several U.S. states have mandated the use of predictive models for sentencing decisions (Pew Center of the...
There has been some controversy as to whether sophisticated machine learning methods (such as random forests, Breiman 2001b, Berk et al. 2009, Ritter 2013) are necessary to produce accurate predictive models of recidivism, or if traditional approaches such as logistic regression would suffice (see, e.g., Tollenaar and van der Heijden 2013, Berk and Bleich 2013, Bushway 2013). Random forests may produce accurate predictive models, but these models effectively operate as a “black-box,” where it is difficult to understand how the input variables are combined to produce a predicted outcome. If a simpler, transparent, but equally accurate predictive model could be developed, it would be more usable and defensible for all different decision-making applications. There is a clear precedent for using such models in criminology (Steinhart 2006, Andrade 2009) where some have argued that a “decent transparent model that is actually used will outperform a sophisticated system that predicts better but sits on a shelf” (Ridgeway 2013). This discussion is captured nicely by Bushway (2013), who described a discrepancy between papers of Berk and Bleich (2013) and Tollenaar and van der Heijden (2013). Berk and Bleich (2013) claim we need sophisticated machine learning methods due to their substantial benefits in accuracy, whereas Tollenaar and van der Heijden (2013) claim that these methods are not necessary and that logistic regression is sufficient. In this work, we show that the answer to the question is far more subtle than a simple yes or no.

In particular, the answer depends on how the models are going to be used for decision-making. For each use case (e.g., sentencing, parole decisions, policy interventions) one might need a decision point at a different level of the true positive rate (TPR) and false positive rate (FPR) (see also Ritter 2013). Each (TPR, FPR) pair is a point on the receiver operator characteristic (ROC) curve. To determine if one method is better than another, one must consider the appropriate point along the ROC curve for decision-making. As we will show in this paper, for a wide range of recidivism prediction problems, many machine learning methods (support vector machines, random forests) produce equally accurate predictive models along the full ROC curve. However, there are trade-offs between accuracy, transparency, and interpretability: methods that are designed to yield transparent models (CART, C5.0) cannot be tuned to produce as accurate models along the full ROC curve, and do not always yield models that are interpretable. This is not to say that interpretable models for recidivism prediction do not exist. The fact that many machine learning methods produce models with similar levels of predictive accuracy indicates that there is a large class of approximately-equally-accurate predictive models (called the “Rashomon” effect by Breiman 2001a) and, in this case, there may exist interpretable models that also attain the same level of accuracy. Finding these models that are accurate and interpretable, however, is computationally challenging.

In this paper, we explore whether such accurate-yet-interpretable models exist and how to find them. To this end, we use a powerful new machine learning method known as a Supersparse Linear Integer Model (SLIM, see Ustun et al. 2013, Ustun and Rudin 2014, 2015). SLIM is designed to produce models that are highly accurate but simple enough to make predictions by hand, without the use of a calculator or computer. We use SLIM to produce accurate transparent models along the full ROC curve. These models can be used for decision-making for many different cases; they are just as accurate as the most powerful black-box machine learning models, but completely transparent and highly interpretable. Black box models are indefensible. One may not agree with a particular transparent model, but one can at least have a clear idea of what it is doing.

The remainder of our paper is structured as follows. In Section 2 we discuss related work. In Section 3 we describe how we derived eight recidivism prediction problems and provide simple insights into each problem. In Section 4 we compare the accuracy and interpretability of models produced by the eight machine learning methods on the eight recidivism prediction problems, and include examples of accurate and interpretable SLIM models for each problem. In Appendix A we discuss the impact of using race-related input variables. In Appendix C we present accurate and interpretable models that were created using a new rule-based method.
known as Falling Rule Lists. We include additional results related to the accuracy and interpretability of models from different methods in Appendix D.

With this manuscript, all of our code will be published for the purpose of reproducibility and clarity to show how data were processed and how models were trained. We invite others to build on our work and adapt our methodology to produce interpretable models for recidivism prediction on future applications.

2 Related Work

We discuss related work in both criminal justice and in machine learning.

2.1 Related Work in Criminal Justice

Since the 1920's (Borden 1928, Burgess 1928, Tibbitts 1931), predictive models for recidivism have been in widespread use in different countries and areas of the criminal justice system, spurred on by continued research into the superiority of actuarial judgment (Dawes et al. 1989, Grove and Meehl 1996) as well as a desire to efficiently use limited public resources (Clements 1996, Simon 2005). Countries that currently use risk assessment tools include: Canada (Hanson and Thornton 2003); the Netherlands (Tollenaar and van der Heijden 2013); the U.K. (Howard et al. 2009); and the U.S (Turner et al. 2009). Applications of these tools can be seen in evidence-based sentencing (Hoffman 1994), correction / prison administration (Belfrage et al. 2000), informing release on parole (Pew Center of the States, Public Safety Performance Project 2011), determining the level of supervision during parole (Barnes and Hyatt 2013), determining appropriate sanctions for parole violations (Turner et al. 2009), and targeted policy interventions (Lowenkamp and Latessa 2004).

In this work, we consider predictive models for general recidivism (recidivism of any crime type) as well as crime-specific recidivism. Risk assessment tools for general recidivism risk prediction include: the Salient Factor Score (Hoffman and Adelberg 1980, Hoffman 1994), the Offender Group Reconviction Scale (Copas and Marshall 1998, Maden et al. 2006, Howard et al. 2009), the Statistical Information of Recidivism scale (Nafekh and Motiuk 2002), and the Level of Service/Case Management Inventory (Andrews and Bonta 2000). Crime-specific applications include risk assessment tools for domestic violence (see, e.g., the Spousal Abuse Risk Assessment of Kropp and Hart 2000), sexual violence (see, e.g., Hanson and Thornton 2003, Langton et al. 2007), and general violence (see, e.g., Historical Clinical and Risk Management tool of Webster et al. 1997, or the Structured Assessment of Violence Risk in Youth tool of Borum 2006).

The majority of recidivism risk assessment tools were produced using logistic regression and substantially modified for the purposes of interpretability (see, e.g., the recommendations of Gottfredson and Snyder 2005). These approaches have led to serious issues in practice (see, e.g., Gottfredson and Moriarty 2006, for a detailed overview). In particular, risk assessments are not well suited for decision-making because they output risk estimates as opposed to prediction. Risk estimates can be converted to predicted outcomes by imposing a threshold (i.e. classify a prisoner as “high-risk” if the predicted probability of arrest > 70%). Many tools use the risk estimate to produce several outcomes (e.g., “low risk,” “medium risk” and “high risk) with thresholds that are decided arbitrarily (Hannah-Moffat 2013). This makes it difficult, if not impossible, to assess predictive accuracy. Netter (2007), for instance, mentions that “the possibility of making a prediction error (false positive or false negative) using a risk tool is probable, but not easily determined.” This problem is further exacerbated by the fact that the performance of each tool is reported using statistics that do not immediately relate to predictive accuracy. In many cases, performance is measured using in-sample error (i.e., “training” error) or in-sample AUC, despite the fact that the out-of-sample TPR/FPR at the decision-making point is far more relevant. There
has been continued interest in more principled evaluation methods for these programs in recent years (see for instance the review papers of [Skeem and Monahan 2011], [Hanson and Morton-Bourgon 2009]).

Predictive models for recidivism have been used extensively, especially for parole decisions and sentencing. In the 1970s, for instance, the United States Parole Commission began using an actuarial measurement built from 2,497 prisoners to inform parole decisions, called the Salient Factor Score (SFS) (Hoffman and Adelberg 1980). A follow-up study showed that the SFS had been fairly accurate in the first twenty years of its implementation (Hoffman 1994). Since 1987, the United States Sentencing Commission’s Federal Sentencing Guidelines has mandated the use of a predictive recidivism measure for sentencing, in particular, the Criminal History Category (CHC) ([U.S. Sentencing Commission 1987]). A series of reports compared the CHC and SFS along various dimensions ([U.S. Sentencing Commission 2004], [2005]). We remark that the form of all of these models are linear models with integer coefficients like the ones we develop in this paper; of course, the CHC and SFS were not built using the sophisticated optimization techniques we use. Unlike the CHC and SFS, our models are created in a completely automated way, for each crime type, which implies that our tools can be used for population-specific models, or other datasets. The studies found that the AUC was 0.70 for the CHC and 0.73 for the SFS ([U.S. Sentencing Commission 2005]), which are within the range of the values we report in Section 4.4 (0.66 – 0.72 depending on the method). Note that our dataset is slightly different; it is over five times the size of that used for the USSC’s recidivism study, and we predict for 3 years rather than 2 years.

2.2 Related Work in Statistics and Machine Learning

Many current criminologists and statisticians still depend heavily on traditional statistical tools such as logistic regression, e.g., the work of [Penner et al. 2013]. They consider in-sample performance, rather than the machine learning perspective of considering out-of-sample performance on a held-out test set; the machine learning perspective handles problems with overfitting and multiple testing, and it is well-known that only reporting in-sample accuracy can be very misleading. There are some works that consider machine learning approaches, and in particular, classification trees. For instance the work of [Steadman et al. 2000] favors classification trees over logistic regression due to its similarity to the clinical method of decision making. Stalans et al. (2004) also found that decision trees are better than logistic regression for prediction of violent recidivism, and Silver and Chow-Martin (2002) used trees as a meta-learner over multiple existing recidivism models. Berk et al. (2005) conducted a study that helped the Los Angeles Sheriff’s Department develop a simple and practical screener for forecasting domestic violence, also showing that decision trees were more accurate than logistic regression. Berk and Bleich (2014) used classification trees CART to provide a prototype of risk forecasting for sentencing. We extensively consider decision trees in this study, but we find there are flaws in the standard decision tree algorithms and implementations that other methods do not have. In particular, these decision tree methods are greedy and do not produce optimal solutions; they also cannot easily be tuned to different decision points. As an aside, in Appendix C we present an empirical result using a new non-greedy tree-like algorithm called Falling Rule Lists ([Wang and Rudin 2014]) that is optimized for both accuracy and sparsity; this method’s good result indicates that the problem is with the CART and decision tree algorithms, and is not a problem pertaining to tree-like models in general.

Random forests ([Breiman 2001b]) is another popular method that produces very complex black-box models: Neuilly et al. (2011) found that random forests were better for prediction of recidivism for homicide offenders; Berk et al. (2006) used the method to forecast a prisoner’s likelihood to commit a serious misconduct while incarcerated; Berk et al. (2009) used it to forecast potential murders for criminals on probation or parole; and Berk and Sorenson used random forests to forecast domestic violence and help inform court decisions at arraignment.

The work of Tollenaar and van der Heijden (2013) provides somewhat of an exception to the works on
machine learning for recidivism, by claiming that machine learning approaches do not outperform classical statistical modeling approaches, and that they both perform similarly. Our findings are similar in some ways to those of Tollenaar and van der Heijden (2013) in that for some decision points, we find that all methods - machine learning methods and classical statistical methods - have essentially the same performance. This “Rashomon” effect (Breiman 2001a) can be exploited to find models that are accurate but also are beneficial in other ways, such as interpretability. We agree with the commentary of Yang et al. (2010) who noted that for many problems, many prediction methods perform approximately the same, and in that case, one should use another measure to gauge how useful a model is. (Yang et al. 2010 was not a machine learning study however.) Our findings disagreed with Tollenaar and van der Heijden (2013) in an important way. Specifically, we find that for some decision points, the choice of algorithm is extremely important.

There are some works on the topic of handling issues such as race in predictive modeling (e.g., Gottfredson and Jarjoura 1996, Berk 2009), and broadly, guidelines on constructing and understanding models. Gottfredson and Moriarty (2006) provide a set of warnings for those using statistical tools to create predictions (though the evaluation of performance that they recommend differs from our approach). For instance, it is clearly true that all of our results are conditioned on our dataset. It is easily possible to change the conditioning by re-running our code on a subset of our data, or on recidivism data from another source.

3 Data and Preliminary Analysis

The recidivism prediction problems in our paper were all derived from the “Recidivism of Prisoners Released in 1994” database, which was put together by the U.S. Department of Justice, Bureau of Justice Statistics (2014). Each problem is a binary classification problem with \( N = 33796 \) prisoners and \( P = 49 \) input variables, where the goal is to predict if a prisoner will be arrested for a certain type of crime within 3 years of being released from prison. In what follows, we describe the original database, explain how we created each prediction problem, and provide insights. The “Recidivism of Prisoners Released in 1994” database (U.S. Department of Justice, Bureau of Justice Statistics 2014) is the largest publicly available database on prisoner recidivism in the United States. It tracks a sample of 38,624 prisoners for 3 years following their release from prison in 1994. These prisoners are randomly sampled from the population of all prisoners released from 15 major states and account for two-thirds of prisoners that were released from prison in the U.S. in 1994.

The database is composed of 38,624 rows and 6,427 columns, where each column represents a prisoner and each row represents a field of information for a given prisoner. The 6,427 columns consist of 91 fields that were recorded before or during release from prison in 1994 (e.g., date of birth, effective sentence length), and 64 fields that were repeatedly recorded for up to 99 different points in the 3 year follow-up period (e.g., if a prisoner was arrested until that point). The information for each prisoner is sourced from record of arrest and prosecution (RAP) sheets kept by state law enforcement agencies and/or the FBI. A detailed descriptive analysis of the database was carried out by statisticians at the U.S. Bureau of Justice Statistics (Langan and Levin 2002). This study restricted its attention to 33,796 of the 38,624 prisoners to exclude extraordinary or unrepresentative release cases. To mirror the approach of Langan and Levin (2002), we also restricted our attention to the same subset of prisoners.

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1 Other studies that use this database include Bhati and Piquero (2007), Bhati (2007), Zhang et al. (2009).

2 The states in the database include: Arizona, California, Delaware, Florida, Illinois, Maryland, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Texas, and Virginia.

3 To be selected for the analysis of Langan and Levin (2002), a prisoner had to be alive during the 3 year follow-up period, and had to have been released from prison in 1994 for an original sentence that was at least 1 year or longer. Prisoners with certain release types - release to custody/detainer/warrant, absent without leave, escape, transfer, administrative release, and release on appeal - were excluded.
This dataset also has serious flaws which we point out below (almost every data set has serious flaws of some kind). For our dataset, many important factors that could be used to predict recidivism are missing, and many included factors are noisy enough that they were not useful for prediction in our preliminary experiments. The information about education levels is extremely minimal; we do not even know whether each prisoner attended college, or completed high school, and the information about courses in prison is only an indicator of whether the inmate took any education or vocation courses at all. Also there is no family history for each prisoner (e.g., foster care), and no record of visitors while in prison (e.g., indicators of caring family members or friends). There is no information about reentry programs, or employment history. For instance, we have only an indicator that someone was once a drug or alcohol abuser, but we have little details about the drug treatment or the extent of drug abuse. While some of these factors, such as drug/alcohol treatment and in prison vocational programs, exist, data is highly incomplete and therefore excluded from our analysis. For example, for drug treatment, less than 14% of the prisoners had a valid entry. The rest were “unknown.” In order for the study to include as many prisoners as possible, we chose to exclude factors with extremely sparse information.

Furthermore, there are more detailed categories of the crimes reported (e.g. fatal violence can be broken than into 6 categories), but we did not find those to be useful in preliminary analysis; an avenue of further investigation would be to consider these features further; however, without the education and family information, it is not clear that this would be worthwhile. The major benefits of this dataset over others are: (i) it is publicly available, benefiting reproducibility (ii) it is large (iii) its criminal history records are fairly complete. Indeed, the BJS study by Langan and Levin (2002) also split the crimes into exactly the same major categories that we did.

3.1 Prediction Problems

Input Variables: We derived a total of \( P = 49 \) input variables. We encoded each input variable as a binary rule of the form \( x_{ij} \in \{0, 1\} \) where \( x_{ij} = 1 \) if condition \( j \) holds true about prisoner \( i \), allowing us to encode highly nonlinear functions of the original variables. For clarity, we refer to input variables in the text using italicized font (e.g., \( \text{female} \)). We provide a summary of all input variables in Table 1. The final set of input variables represents known risk factors (Bushway and Piehl 2007, Crow 2008) and have been used in risk assessment tools since 1928 (see, e.g., Borden 1928, U.S. Sentencing Commission 2005, Berk et al. 2006, Baradaran 2013). Specifically, the variables are based on: 1) information about prison release in 1994 (e.g., \( \text{time\_served} \), \( \text{age\_at\_release} \), \( \text{infraction} \)); 2) information from past arrests, sentencing, and convictions (e.g., \( \text{prior\_arrests} \geq 1 \), \( \text{any\_prior\_jail\_time} \)); 3) history of substance abuse (e.g., \( \text{alcohol\_abuse} \)) 4) gender (e.g., \( \text{female} \)). Thus our actuarial tools assess static recidivism risk in the sense that a) the information is easily accessible to law enforcement officials (all above information can be found in state RAP sheets); and b) the input variables do not include socioeconomic factors such as race, which would directly eliminate the potential to use these tools in applications such as sentencing – we study the effects of using race as an input variable in Appendix A.

Outcome Variables: We created eight recidivism prediction problems by encoding a binary outcome variable \( y_i \in \{-1, +1\} \), where \( y_i = +1 \) if a prisoner is arrested for a particular type of crime within 3 years after being released from prison; and \( y_i = -1 \) otherwise. For clarity, we refer to each prediction problem in the text using typewriter font (e.g., \( \text{arrest} \)). We provide details on the recidivism prediction problems that we consider in

\footnote{Note that the \( \text{prior\_arrests} \) variable does not count the crime for which they were released from prison in 1994; thus, about 12% of the prisoners in the dataset have \( \text{no\_prior\_arrests} = 1 \) even though they had to have been arrested at least once the crime for which they were released from prison in 1994.}

\footnote{Static recidivism risk assessment tools use risk factors that do not change over time (see, e.g., Tollenaar and van der Heijden 2013, Hannah-Moffat 2013 for a discussion).}
| Input Variable | \( P(x_{ij} = 1) \) | Definition |
|----------------|----------------|-------------|
| female         | 0.06           | prisoner \( i \) is female |
| prior_alcohol_abuse | 0.20         | prisoner \( i \) has history of alcohol abuse |
| prior_drug_abuse  | 0.16           | prisoner \( i \) has history of drug abuse |
| age_at_release <= 17 | 0.00     | prisoner \( i \) was \( \leq 17 \) years old at release in 1994 |
| age_at_release > 24 & <= 29 | 0.19     | prisoner \( i \) was \( 18-24 \) years old at release in 1994 |
| age_at_release > 29 & <= 39 | 0.21     | prisoner \( i \) was \( 25-29 \) years old at release in 1994 |
| age_at_release > 39 & <= 60 | 0.21     | prisoner \( i \) was \( 30-39 \) years old at release in 1994 |
| released_unconditional | 0.11     | prisoner \( i \) released at expiration of sentence |
| released_conditional | 0.97     | prisoner \( i \) released by parole or probation |
| released_other   | 0.02           | prisoner \( i \) released by other means |
| time_served <= 6mo | 0.23     | prisoner \( i \) served \( \leq 6 \) months |
| time_served > 6 & <= 12mo | 0.20     | prisoner \( i \) served \( 7-12 \) months |
| time_served > 12 & <= 24mo | 0.23     | prisoner \( i \) served \( 13-24 \) months |
| time_served > 24 & <= 60mo | 0.25     | prisoner \( i \) served \( 25-60 \) months |
| time_served > 60mo | 0.10     | prisoner \( i \) served \( \geq 61 \) months |
| infraction_in_prison | 0.24      | prisoner \( i \) has a record of misconduct in prison |
| age_at_arrest <= 17 | 0.14     | prisoner \( i \) was \( \leq 17 \) years old at 1st arrest |
| age_at_arrest > 24 & <= 29 | 0.61     | prisoner \( i \) was \( 18-24 \) years old at 1st arrest |
| age_at_arrest > 29 & <= 39 | 0.10     | prisoner \( i \) was \( 25-29 \) years old at 1st arrest |
| age_at_arrest > 39 & <= 60 | 0.09     | prisoner \( i \) was \( 30-39 \) years old at 1st arrest |
| age_at_arrest > 60 | 0.04     | prisoner \( i \) was \( \geq 40 \) years at 1st arrest |
| age_at_confinement <= 17 | 0.03     | prisoner \( i \) was \( \leq 17 \) years old at 1st confinement |
| age_at_confinement > 24 & <= 29 | 0.46     | prisoner \( i \) was \( 18-24 \) years old at 1st confinement |
| age_at_confinement > 29 & <= 39 | 0.18     | prisoner \( i \) was \( 25-29 \) years old at 1st confinement |
| age_at_confinement > 39 & <= 60 | 0.21     | prisoner \( i \) was \( 30-39 \) years old at 1st confinement |
| age_at_confinement > 60 | 0.12     | prisoner \( i \) was \( \geq 40 \) years at 1st confinement |
| prior_arrests_for_drug | 0.47     | prisoner \( i \) was once arrested for drug offense |
| prior_arrests_for_property | 0.67     | prisoner \( i \) was once arrested for property offense |
| prior_arrests_for_public_order | 0.62     | prisoner \( i \) was once arrested for public order offense |
| prior_arrests_for_general_violence | 0.52     | prisoner \( i \) was once arrested for general violence |
| prior_arrests_for_domestic_violence | 0.04     | prisoner \( i \) was once arrested for domestic violence |
| prior_arrests_for_sexual_violence | 0.03     | prisoner \( i \) was once arrested for sexual violence |
| prior_arrests_for_fatal_violence | 0.01     | prisoner \( i \) was once arrested for fatal violence |
| prior_arrests_for_multiple_types | 0.77     | prisoner \( i \) was once arrested for multiple types of crime |
| prior_arrests_for_felony | 0.84     | prisoner \( i \) was once arrested for a felony |
| prior_arrests_for_misdemeanor | 0.49     | prisoner \( i \) was once arrested for a misdemeanor |
| prior_arrests_for_local_ordinance | 0.01     | prisoner \( i \) was once arrested for local ordinance |
| prior_arrests_with_firearms_involving | 0.09     | prisoner \( i \) was once arrested or an incident involving firearms |
| prior_arrests_with_child_involved | 0.17     | prisoner \( i \) was once arrested for an incident involving children |
| no_prior_arrests | 0.12     | prisoner \( i \) has no prior arrests |
| prior_arrests >= 1 | 0.88     | prisoner \( i \) has at least 1 prior arrest |
| prior_arrests >= 2 | 0.78     | prisoner \( i \) has at least 2 prior arrests |
| prior_arrests >= 5 | 0.60     | prisoner \( i \) has at least 5 prior arrests |
| multiple_prior_prison_time | 0.43     | prisoner \( i \) has been to prison multiple times |
| any_prior_jail_time | 0.47     | prisoner \( i \) has been to jail at least once |
| multiple_prior_jail_time | 0.29     | prisoner \( i \) has been to prison multiple times |
| any_prior_probation_or_fine | 0.42     | prisoner \( i \) has been on probation or paid a fine at least once |
| multiple_prior_probation_or_fine | 0.22     | prisoner \( i \) has been on probation or paid a fine multiple times |

Table 1: Overview of input variables for all prediction problems. Each input variable is a binary rule of the form \( x_{ij} \in \{0, 1\} \). We list conditions required for \( x_{ij} = 1 \) under the Definition column.
| Problem          | P(yᵢ = +1) | Outcome Variable                                                                 |
|------------------|------------|----------------------------------------------------------------------------------|
| arrest           | 59.0%      | yᵢ = +1 if prisoner i is arrested for any offense within 3 years of release from prison |
| drug             | 20.0%      | yᵢ = +1 if prisoner i is arrested for drug-related offense (e.g., possession, trafficking) within 3 years of release from prison |
| property         | 25.2%      | yᵢ = +1 if prisoner i is arrested for a property-related offense (e.g., burglary, larceny, arson, fraud) within 3 years of release from prison |
| public_order     | 27.9%      | yᵢ = +1 if prisoner i is arrested for a public order offense (e.g., weapons possession, DUI) within 3 years of release from prison |
| general_violence | 19.1%      | yᵢ = +1 if prisoner i is arrested for a violent offense (e.g., robbery, aggravated assault) within 3 years of release from prison |
| domestic_violence| 3.5%       | yᵢ = +1 if prisoner i is arrested for domestic violence within 3 years of release from prison |
| sexual_violence  | 3.0%       | yᵢ = +1 if prisoner i is arrested for sexual violence within 3 years of release from prison |
| fatal_violence   | 0.7%       | yᵢ = +1 if prisoner i is arrested for murder or manslaughter within 3 years of release from prison |

Table 2: Overview of recidivism prediction problems.

Table 2 shows that the percentages $P(yᵢ = +1)$ in Table 2 do not add up to 100% because a prisoner could be arrested for multiple types of crime within a single incident (e.g., both drug and public order offenses), and could also be arrested multiple times over the 3 year follow-up period.

The final problems that we consider include: an arrest for any crime (arrest); an arrest for a drug-related offense (drug); an arrest for a property-related offense (property); an arrest for a public order-related offense (public_order); or an arrest for a certain type of violent offense (general_violence, domestic_violence, sexual_violence, fatal_violence).

### 3.2 Conditional Probabilities for Each Outcome and Variable

Table 3 lists the conditional probabilities $P(y = 1|x_j = 1)$ between the outcome variable $y$ and each input variable $x_j$ for all prediction problems. Using this table, we can identify strong associations between the input and output for each prediction problem. These associations can help uncover insights into each problem and also help qualitatively validate predictive models in Section 4.5. Consider, for instance, arrest. Here, we can see that prisoners who are released from prison at a later age are less likely to be arrested (as the probability for arrest decreases monotonically as age_at_release increases). This also appears to be the case for prisoners who were first confined (e.g., sent to prison or jail) at an older age (see, e.g., age_of_first_confinement). In addition, we can also see that prisoners with more prior arrests have a higher likelihood of being arrested (as the probability for arrest increases monotonically with prior_arrests).

Similar insights can be made for crime-specific prediction problems. In drug, for instance, we see that prisoners who were previously arrested for a drug-related offense are more likely to be arrested for a drug-related offense (32%) than those who were previously arrested for any other type of offense. Likewise, looking at domestic_violence, we see that the prisoners with the greatest probability of being arrested for a domestic violence crime are those with a history of domestic violence (13%).

We formulated mutually exclusive outcome variables for violent offenses as different types of violence are treated differently within the U.S. legal system. In other words, $yᵢ = +1$ for general_violence does not necessarily imply $yᵢ = +1$ for domestic_violence, sexual_violence, fatal_violence).
Table 3: Table of conditional probabilities for all input variables (row) and prediction problems (columns). Each cell represents the conditional probability $P(y = +1|x = +1)$ where $x$ is the input variable that is specified in the row and $y$ is the outcome variable for the prediction problem specified in the column.
3.3 Association Rules

We produce insights similar to those in Section 3.2 using a more principled approach by mining association rules. Association rules, also known as “IF-THEN” rules, are simple and powerful predictive models that can be produced using search techniques or optimization techniques.

Good association rules are characterized by large values of \textit{support}, \textit{confidence}, and \textit{lift}. To define this terminology, consider a rule such as “IF \(a\) THEN \(b\).” We denote this rule as \(a \rightarrow b\), and refer to \(a\) as the “IF condition” and refer to \(b\) as “THEN condition.” The \textbf{support} of \(a \rightarrow b\) is the empirical probability \(\hat{P}(a \text{ and } b)\), that is, the proportion of observations where the conditions \(a\) and \(b\) are both satisfied. The \textbf{confidence} of \(a \rightarrow b\) is the empirical probability \(\hat{P}(b | a)\), that is, the proportion of observations for which condition \(b\) is satisfied given \(a\) is satisfied. The \textbf{lift} of \(a \rightarrow b\) is the ratio \(\frac{\hat{P}(b | a)}{\hat{P}(b)}\). Lift measures the ability of condition \(a\) to “target” the population where condition \(b\) is satisfied: if the lift of \(a \rightarrow b\) is equal to 1, then outcome \(b\) could be predicted equally well if we had assumed that \(a\) and \(b\) were independent; if the lift of \(a \rightarrow b\) greater than 1 then event \(a\) has some effect on predicting event \(b\).

To illustrate these concepts, consider the following association rule:

\[
\text{IF age at release 18 to 24 AND prior arrests } \geq 5 \text{ THEN } y = +1
\]

The support of this rule is 0.07, which that 7% of prisoners were released from prison between the ages of 18 to 24, had at least 5 prior arrests, and were arrested within 3 years of being released from prison. The confidence of this rule is 0.83, which means that if a prisoner was released from prison between the ages of 18 to 24 and had at least 5 prior arrests, then there was an 83% chance that this person would be arrested within 3 years of being released from prison. Lastly, the lift of this rule is 1.41, which means that prisoners released from prison between the ages of 18 to 24 and had at least 5 prior arrests have a higher chance of being rearrested than other prisoners, i.e., the prisoners age at release and arrest history makes the conditional probability of arrest 1.41 times higher than if arrest was independent of these conditions.

Results

We list 24 interesting association rules for the arrest problem in Table 4, and provide a graphical representation of their lift and support in Figure 1. Here, the IF conditions are formulated using combinations of input variables \((i.e. \ x_j = 1 \text{ and } x_k = 1)\) and the THEN condition is that a prisoner is arrested within 3 years of being released from prison \((i.e. \ a \text{ positive outcome } y = +1)\). The rules from Figure 1 are provided in Table 4. These rules have the highest levels of lift and confidence with a minimum support of 5\% \((i.e., \ the \ rule \ applied \ to \ at \ least \ 1690 \ of \ the \ 33796 \ prisoners \ in \ our \ dataset)\). This threshold value was chosen so the rules do not reflect spurious correlations. Rules A – E were produced by mining the most powerful single-variable predictors for arrest \(\hat{5}\) Rules F – X were produced by mining two variables rules that use at least one of the input variables from Rules A – E \(\hat{5}\). Out of all these rules, Rule F performs the best with a confidence of 0.83 and a lift of 1.41. As it turns out, Rule F is often exploited by some of the best models we find for arrest as we often find patterns similar to “age at release 18 to 24 AND prior arrests \(\geq 5\)” in our predictive models \((\text{see, e.g., Figure 6 in Section 4.5})\).

\footnote{These rules were generated with the \texttt{arules} package \cite{Hahsler2014} in R 3.1.1. Note that the choice of package does not matter, as mining rules through search techniques is deterministic, so all packages produce the same rules.}

\footnote{Rules A–E attain the highest lift among 1 variable rules with a support of at least 5\% and a confidence of at least 0.70.}

\footnote{Rules F–X attain the highest possible lift, as well as support at least 5\% and confidence at least 0.75.}
Interesting observations can also be made from the discovered rules. Recall that jail is a much less severe punishment than prison. Considering Rule L and Rule M in Table 4, we can see that prisoners with multiple jail time and have any past probations or fines are just as likely to be arrested as those with multiple jail time and multiple prior prison records - despite multiple_prior_prison_time being a indicator of much more severe past actions than any.prior.probation.or.fine.

4 Prediction Methodology and Empirical Results

In what follows we discuss cost-sensitive classification for imbalanced problems, provide an overview of techniques and provide empirical results.

4.1 Imbalanced Problems and Cost-Sensitive Classification

The majority of classification problems that we consider in this paper are imbalanced in the sense that the data contain a relatively small number of examples from one class and a relatively large number of examples from the other.

Imbalanced classification problems necessitate changes in the way that we train classification models as well as the way that we evaluate their performance. Consider, for instance, a heavily imbalanced problem such as fatal_violence where only $P(y_i = +1) = 0.4\%$ of individuals are arrested within 3 years of being released from prison. In this case, a method that maximizes overall classification accuracy is likely to produce a model that predicts no one will be arrested for fatal offenses – a result that is not surprising given that the trivial model is 99.6\% accurate on the overall population. Unfortunately, this model will never be able to identify individuals that are arrested for fatal offenses, and will actually be 0\% accurate on the population of interest.

In order to provide a clear measure of performance of classification model on imbalanced problems, we assess the accuracy of a model on the positive and negative classes separately. In our experiments, we report the class-based accuracy of each model using metrics known as the true positive rate (TPR), which reflects the
| Rule | IF Condition | Lift | Support | Confidence |
|------|--------------|------|---------|------------|
| A    | multiple_prior_jail_time | 1.24 | 0.21   | 0.73       |
| B    | age_1st_arrest ≤ 17 | 1.23 | 0.10   | 0.73       |
| C    | multiple_prior_probation_or_fine | 1.20 | 0.16   | 0.71       |
| D    | age_at_release_18_to_24 | 1.20 | 0.14   | 0.71       |
| E    | prior_arrests ≥ 5 | 1.19 | 0.42   | 0.70       |
| F    | age_at_release_18_to_24 AND prior_arrests ≥ 5 | 1.41 | 0.07   | 0.83       |
| G    | multiple_prior_jail_time AND multiple_prior_probation_or_fine | 1.30 | 0.08   | 0.77       |
| H    | age_1st_arrest ≤ 17 AND prior_arrests ≥ 5 | 1.28 | 0.08   | 0.76       |
| I    | multiple_prior_jail_time AND time_served ≤ 6mo | 1.34 | 0.06   | 0.79       |
| J    | multiple_prior_jail_time AND age_1st_confinement_18_to_24 | 1.29 | 0.12   | 0.76       |
| K    | multiple_prior_jail_time AND prior_arrests_for_misdemeanor | 1.28 | 0.15   | 0.76       |
| L    | multiple_prior_jail_time AND multiple_prior_prison_time | 1.28 | 0.13   | 0.75       |
| M    | multiple_prior_jail_time AND any_prior_probation_or_fine | 1.27 | 0.13   | 0.75       |
| N    | age_1st_arrest ≤ 17 AND prior_arrests_for_misdemeanor | 1.32 | 0.07   | 0.78       |
| O    | age_1st_arrest ≤ 17 AND any_prior_jail_time | 1.28 | 0.06   | 0.76       |
| P    | age_1st_arrest ≤ 17 AND age_1st_confinement_18_to_24 | 1.28 | 0.05   | 0.75       |
| Q    | multiple_prior_probation_or_fine AND age_1st_confinement_18_to_24 | 1.31 | 0.08   | 0.77       |
| R    | age_at_release_18_to_24 AND prior_arrests_for_misdemeanor | 1.34 | 0.06   | 0.79       |
| S    | age_at_release_18_to_24 AND any_prior_jail_time | 1.34 | 0.06   | 0.79       |
| T    | age_at_release_18_to_24 AND prior_arrests ≥ 2 | 1.32 | 0.10   | 0.78       |
| U    | age_at_release_18_to_24 AND prior_arrests_for_multiple_types | 1.30 | 0.10   | 0.76       |
| V    | prior_arrests ≥ 5 AND age_at_release_25_to_29 | 1.31 | 0.10   | 0.77       |
| W    | prior_arrests ≥ 5 AND age_1st_confinement_18_to_24 | 1.28 | 0.21   | 0.76       |
| X    | prior_arrests ≥ 5 AND time_served ≤ 6mo | 1.28 | 0.11   | 0.76       |

Table 4: IF-THEN rules mined for arrest. The IF conditions are listed in the table, and the THEN condition for all rules is the outcome \( y = +1 \), which indicates that a prisoner is arrested within 3 years of being released from prison.
accuracy on the positive class, and the false positive rate (FPR), which reflects the error rate on negative class. For a given classification model, we compute these quantities as

\[ TPR = \frac{1}{N^+} \sum_{i \in I^+} \mathbb{1} \left[ \hat{y}_i = +1 \right] \quad \text{and} \quad FPR = \frac{1}{N^-} \sum_{i \in I^-} \mathbb{1} \left[ \hat{y}_i = +1 \right], \]

where \( \hat{y}_i \) denotes the predicted outcome for example \( i \), \( N^+ \) denotes the number of examples in the positive class \( I^+ = \{ i : y_i = +1 \} \), and \( N^- \) denotes the number of examples from the negative class \( I^- = \{ i : y_i = -1 \} \). Ideally, a classification model should have high TPR and low FPR (i.e. TPR close to 1 and FPR = 0).

Most classification methods can be adapted to yield a model that is more accurate on the positive class, but only if we are willing to sacrifice some accuracy on examples from the negative class, and vice-versa. To illustrate the trade-off of classification accuracy between positive and negative classes, we plot all models produced by a given method as points on a receiver operating characteristic (ROC) curve, which plots the TPR on the vertical axis and the FPR on the horizontal axis. Having constructed an ROC curve, we then assess the overall performance of each method by calculating the area under the ROC curve (AUC).

4.2 Overview of Classification Methods

We compared the performance of models from eight different classification methods, including those previously used for recidivism prediction (see Section 2.2) or that ranked among the “top 10 algorithms in data mining” (Wu et al. 2008). We restricted our attention to methods with publicly-available software packages that allowed us to specify misclassification costs for positive and negative classes.

- **C5.0 Trees and C5.0 Rules**: C5.0 is an updated version of the popular C4.5 algorithm (Quinlan 2014, Kuhn and Johnson 2013) that can create decision trees and rule sets.

- **Classification and Regression Trees (CART)**: CART is a popular method to create decision trees through recursive partitioning of the input variables (Breiman et al. 1984), which is a predecessor to C5.0.

- **L1 and L2-Penalized Logistic Regression**: State-of-the-art variants of logistic regression that penalize the coefficients to prevent overfitting (Friedman et al. 2010). L1-penalized methods are typically used to create linear models that are sparse (Tibshirani 1996, Hesterberg et al. 2008).

10 We note that AUC is a summary statistic that is frequently misused in the context of classification problems. It is true that a method that with AUC = 1 always produces models that are more accurate than a method with AUC = 0. Other than this simple case, however, it is not possible to state that a method with high AUC always produces models that are more accurate than a method with low AUC.
• **Random Forests**: A popular “black-box” method that makes predictions using a large ensemble of “weak” classification trees. The method was originally developed by [Breiman (2001b)] but is widely used for recidivism prediction (see, e.g., [Berk et al. 2009] [Ritter 2013]).

• **Support Vector Machines**: A popular “black-box” method for non-parametric linear classification. The Radial Basis Function (RBF) kernel allows the method to handle classification problems where the decision-boundary may be non-linear (see, e.g., [Cristianini and Shawe-Taylor 2000] [Berk and Bleich 2014]).

• **Supersparse Linear Integer Models**: A new method to create scoring systems that are optimized for accuracy and sparsity ([Ustun and Rudin 2015]). We provide a short overview in the following section.

### 4.2.1 Supersparse Linear Integer Models

A Supersparse Linear Integer Model (SLIM) is a new optimization-based method for creating *scoring systems* – that is, linear classification models that only require users to add, subtract and multiply a few small numbers to make a prediction ([Ustun and Rudin 2015]).

Scoring systems are widely used because they allow users to make quick predictions, without the use of a computer, and without extensive training in statistics (see, e.g., [Webster et al. 1997] [Webster 2013] for applications in criminology). These models are often more interpretable than traditional linear models because they are highly sparse and use a small number of integer coefficients. Such characteristics allow users to easily gauge the influence of one input variable with respect to the others – by catering to the fact that most humans are seriously limited in the number of cognitive entities they can handle at once (7 ± 2 according to [Miller 1984]), and seriously limited in estimating the association between three or more variables ([Jennings et al. 1982]).

SLIM scoring systems are linear classification models of the form:

\[
\hat{y}_i = \begin{cases} 
+1 & \text{if } \sum_{j=1}^{P} \lambda_j x_{ij} > \lambda_0 \\
-1 & \text{if } \sum_{j=1}^{P} \lambda_j x_{ij} \leq \lambda_0.
\end{cases}
\]

Here, \(\lambda_1, \ldots, \lambda_P\) represent the coefficients (i.e. the “points” for input variables 1, \ldots, \(P\)), and \(\lambda_0\) represents an intercept (i.e. the “threshold score” that has to be surpassed to predict \(\hat{y}_i = +1\)). The values of the coefficients are fitted from data by solving a discrete optimization problem of the form:

\[
\min_{\lambda} \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[y_i \neq \hat{y}_i] + C_0 \sum_{j=1}^{P} \mathbb{1}[\lambda_j \neq 0] + \epsilon \sum_{j=1}^{P} |\lambda_j| \\
\text{s.t.} \quad (\lambda_0, \lambda_1, \ldots, \lambda_P) \in \mathcal{L}.
\]

Here, the objective directly minimizes the error rate \(\frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[y_i \neq \hat{y}_i]\) and directly penalizes the number of non-zero terms \(\sum_{j=1}^{P} \mathbb{1}[\lambda_j \neq 0]\). The constraints restrict coefficients to a small set of bounded integers and may include additional conditions to tailor the accuracy and interpretability of the final scoring system. We note that the objective also includes a *tiny* penalty on the absolute value of the coefficients to restrict coefficients to coprime values without affecting accuracy or sparsity.\(^{11}\)

\(^{11}\)To illustrate the use of this penalty, consider a classifier such as \(\hat{y} = \text{sign}(x_1 + x_2)\). If SLIM only minimized the misclassification...
SLIM differs from state-of-the-art machine learning methods because it directly optimizes accuracy and sparsity, without making approximations that other methods make for scalability (e.g., the use of convex loss functions). By avoiding these approximations, SLIM sacrifices the ability to fit a model within seconds in a way that scales to extremely large datasets. In return, however, it gains the ability to produce accurate models that are far more practical and interpretable than the state-of-the-art.

SLIM also has the unique ability to address operational constraints related to accuracy and interpretability, without the need for parameter tuning (e.g., it can directly produce scoring systems with explicit limits on the false positive rate, or the number of input variables in the final model). In our experiments, we trained the following version of SLIM:

\[
\min_{\lambda} \frac{W^+}{N} \sum_{i \in I^+} \mathbb{1}[y_i \neq \hat{y}_i] + \frac{W^-}{N} \sum_{i \in I^-} \mathbb{1}[y_i \neq \hat{y}_i] + C_0 \sum_{j=1}^{P} \mathbb{1}[\lambda_j \neq 0] + \epsilon \sum_{j=1}^{P} |\lambda_j|
\]

s.t. \[
\sum_{j=1}^{P} \mathbb{1}[\lambda_j \neq 0] \leq 8
\]
\[
\lambda_j \in \{-10, \ldots, 10\} \text{ for } j = 1, \ldots, P
\]
\[
\lambda_0 \in \{-100, \ldots, 100\}.
\]

Here, we constrained each coefficient \(\lambda_j\) to an integer between \(-10\) and \(10\), we constrained the threshold \(\lambda_0\) to an integer between \(-100\) and \(100\), and we restricted the number of non-zero coefficients to at most 8, similar to the number of cognitive entities humans can handle (Miller 1956). These choices were intended to create a model that would allow users to make predictions without a computer or calculator, and to be able to easily assess how joint values of input variables affected the predicted outcome. The \(C_0\) parameter was set to a sufficiently small value so that SLIM would not sacrifice accuracy for sparsity; given \(W^+, W^-\) we can set \(C_0\) to any value \(0 < C_0 < \min\{W^-, W^+\}/NP\) to ensure this condition. The \(\epsilon\) parameter was set to a sufficiently small value so that SLIM would produce a model with coprime coefficients without affecting accuracy or sparsity; given \(W^+, W^-\) and \(C_0\), we can set \(\epsilon\) to any value \(0 < \epsilon < C_0/\max\{\sum_{j=1}^{P} |\lambda_j|\}\) to ensure this condition.

One cannot expect the same level of accuracy or constraint satisfaction by manually rounding or adjusting logistic regression coefficients, manually searching over integer points in a high dimensional space can be highly suboptimal.

### 4.3 Experimental Design

We provide an overview of the methods, software, and settings that we used to produce prediction models for all problems in Table 5.

We ran each method on each problem for 19 values of \(W^+\) as well as method-specific free parameters. By default, we chose values of \(W^+ \in \{0.050, \ldots, 1.950, 2.000\}\) (i.e. cost ratios between 1:39 and 39:1). This range was inappropriate for problems with a significant class imbalance as all methods produced trivial models. For significantly imbalanced problems, such as domestic_violence, sexual_violence, we instead used values of \(W^+ \in \{1.905, \ldots, 1.995\}\) (i.e. cost ratios between 19:1 and 199:1). In the case of fatal_violence, which was extremely imbalanced, we used \(W^+ \in \{1.9905, \ldots, 1.9995\}\) (i.e. cost ratios between 209:1 and 3999:1).

rate and the number of terms, then \(\hat{y} = \text{sign}(2x_1 + 2x_2)\) would have the same objective value as \(\hat{y} = \text{sign}(x_1 + x_2)\) because it makes the same predictions and has the same number of non-zero coefficients. Since coefficients are restricted to a discrete set, we use this tiny penalty on the absolute value of these coefficients so that SLIM chooses the classifier with the smallest (coprime) coefficients, \(\hat{y} = \text{sign}(x_1 + x_2)\).
For each problem, each method, each value of $W^+$, and each instance of the method-specific free parameters, we trained a total of 11 models: 1 model using all of the data to assess interpretability, and 10 models using subsets of the data to assess the predictive accuracy through 10-fold cross-validation (10-CV). We generated the folds once, and used the same folds for each problem so as to allow for comparisons across algorithms and problems.

We constructed an ROC curve for each method by plotting the 10-CV mean TPR and 10-CV mean FPR of the produced model for each distinct value of $W^+$. For methods such as Lasso, Ridge and SVM RBF, where we trained multiple models for each value of $W^+$ with different settings of the free parameters, we selected a single model for each of the $W^+$ values by choosing the instance that minimized the weighted mean 10-CV test error. This resulted in optimistic performance for these methods, as we discuss shortly.

We trained all models on a 12-core 2.7GHZ Intel Nehalem CPU with 48GB RAM. We trained all methods other than SLIM using publicly available packages in R 3.1.1 (R Core Team 2014) without imposing any time constraints. We trained SLIM by solving mixed-integer programming problems (MIP) with the CPLEX 12.6 API in MATLAB 2014a. We set a time limit of 1 hour for each MIP and solved 11 MIPs in parallel. Thus, it took 19 hours to train all of the SLIM models required to produce an ROC curve for a single problem. This was comparable to the time required to train models with RF and SVM RBF: these methods required 40–60 minutes to train models at each value of $W^+$, and 12–20 hours to produce all models required to create an ROC curve.

Our design differs from split-sample designs where a substantial portion of the data is reserved for used as a test set (see, e.g., Tollenaar and van der Heijden 2013, Berk et al. 2014). We chose to forgo allocating a test set because it would have substantially reduced the number of examples in the minority class for heavily imbalanced problems such as fatal_violence. This design may have resulted in optimistic performance for Lasso, Ridge and SVM RBF as we set the free parameters for these methods using 10-CV statistics. However, it had the benefit of producing 10 separate estimates of predictive accuracy, and final predictive models that were trained with as much data as possible, and provided us with a measure of uncertainty on unseen data.

4.4 Observations on Predictive Accuracy

We show the ROC curves for all methods on all prediction problems in Figures 2 and 3 and summarize the 10-CV test AUC of each method in Table 6. We include a table with the 10-CV training AUC in Appendix D.1. We make the following important observations, which we believe carries over to a large class of problems beyond recidivism prediction:

- All methods did well on the general recidivism prediction problem arrest. In this case, we observe only small differences in predictive accuracy of different methods: all methods (other than CART) attain a test AUC above 0.70; the highest test 10-CV test AUC was achieved by SVM RBF (0.74). This multiplicity of good models reflects the Rashomon effect of Breiman (2001b).

- Major differences between methods appeared in terms of their performance on imbalanced prediction problems. We expected different methods respond differently to changes in the misclassification costs, and therefore trained each method over a large range of possible misclassification costs. Even so, it was difficult (if not impossible) to tune certain methods to produce models at certain points of the ROC curve – especially in problems with significant class imbalance (e.g., fatal_violence).

- SVM RBF, LARS Lasso and LARS Ridge were able to produce accurate models at different points on the ROC curve on most problems. SVM RBF usually achieved the highest AUC on most problems (e.g., arrest,

---

12 There is little guidance on how much data to allocate for a test set (see e.g. Faraway 2014 for a discussion.)
| Method                | Acronym | Software | Free Parameters and Settings |
|----------------------|---------|----------|-----------------------------|
| CART Decision Trees  | CART    | rpart    | 19 values of $W^+$           |
| C5.0 Decision Trees  | C5.0T   | e50      | 19 values of $W^+$           |
| C5.0 Decision Rules  | C5.0R   | e50      | 19 values of $W^+$           |
| Logistic Regression  | Lasso   | glmnet   | 19 values of $W^+ \times 100$ values of $L_1$-penalty chosen by glmnet |
| Logistic Regression  | Ridge   | glmnet   | 19 values of $W^+ \times 100$ values of $L_2$-penalty chosen by glmnet |
| Random Forests       | RF      | randomForest | 19 values of $W^+$     |
| Support Vector Machines (Radial Basis Kernel) | SVM RBF | e1071 | 19 values of $W^+ \times 7$ values of $C \in (10^{-3}, \ldots, 10^3)$ |
| SLIM Scoring Systems | SLIM    | CPLEX 12.6 | 19 values of $W^+$; $C_0, \epsilon, \mathcal{L}$ set to find most accurate model with $\leq 8$ coefficients where $\lambda_0 \in \{-100, \ldots, 100\}$ and $\lambda_j \in \{-10, \ldots, 10\}$ |

Table 5: Methods, software and free parameters used to create models for each problem. The values of $W^+$ are problem-specific.

We find that these methods do respond well to cost-sensitive tuning, but that it is difficult to find appropriate misclassification costs for highly imbalanced problems such as sexual_violence, domestic_violence and fatal_violence.

- C5.0T, C5.0R and CART were unable to produce accurate models at different points on the ROC curve on any imbalanced problems. We found that these methods do not respond well to cost-sensitive tuning, and that this issue becomes markedly more severe as problems become more imbalanced. For drug, property, and general_violence, for instance, these methods could not produce models with high TPR. For sexual_violence and domestic_violence, these methods almost always produced trivial models that always predict $y = 0$ (resulting in AUCs of 0.5). This result may be attributed to the greedy nature of the algorithms that are being used to fit the trees, as opposed to the use of tree models in general. The issue is unlikely to be software-related as it affects both C5.0 and CART, and has been observed by others (see, e.g., Goh and Rudin 2014).

In Appendix C, we present a model from a new machine learning algorithm called Falling Rule Lists, which is a non-greedy method for producing tree-like models; the model is much higher quality than the CART and C5.0 models, indicating that there do exist good non-trivial rule-based models for imbalanced problems.

- Random Forests – while being able to produce accurate models at certain points on the ROC curve – tend to overfit on all problems. To see this, we can compare the difference in performance between the testing accuracy in Table 6 (usually near 0.7) and the training AUC in Table 13 (usually near 1.0). The overfitting could be due to settings in the randomForest package in R, or the use of a cost-sensitive approach (Berk et al. 2006 mentions that random forests may be better-suited to tackle imbalanced problems using sampling-based approaches that oversample the minority class.) The settings in the R package cannot easily be fixed without tuning in a huge parameter space, which itself grows exponentially with the number of parameters.

- SLIM performs well despite being restricted to a relatively small class of simple linear models (e.g., mod-
Table 6: Test AUC for all methods on all prediction problems. Each cell contains the 10-CV mean test AUC (top), as well as the 10-CV minimum and maximum test AUC (bottom).

| Problem       | Lasso | Ridge | C5.0R | C5.0T | CART | RF  | SVM RBF | SLIM |
|---------------|-------|-------|-------|-------|------|-----|---------|------|
| arrest        | 0.74  | 0.73  | 0.72  | 0.71  | 0.66 | 0.72| 0.74    | 0.70 |
|               | 0.73 - 0.75 | 0.72 - 0.74 | 0.71 - 0.73 | 0.70 - 0.73 | 0.65 - 0.67 | 0.71 - 0.73 | 0.73 - 0.75 | 0.68 - 0.72 |
| drug          | 0.71  | 0.72  | 0.63  | 0.63  | 0.50 | 0.69| 0.73    | 0.69 |
|               | 0.68 - 0.74 | 0.69 - 0.74 | 0.59 - 0.66 | 0.61 - 0.65 | 0.50 - 0.50 | 0.67 - 0.70 | 0.71 - 0.75 | 0.67 - 0.72 |
| property      | 0.71  | 0.70  | 0.66  | 0.66  | 0.50 | 0.69| 0.73    | 0.67 |
|               | 0.69 - 0.73 | 0.68 - 0.73 | 0.65 - 0.67 | 0.63 - 0.67 | 0.50 - 0.50 | 0.67 - 0.71 | 0.70 - 0.74 | 0.65 - 0.70 |
| public_order  | 0.69  | 0.69  | 0.65  | 0.65  | 0.53 | 0.68| 0.70    | 0.66 |
|               | 0.68 - 0.70 | 0.68 - 0.71 | 0.64 - 0.67 | 0.64 - 0.66 | 0.51 - 0.54 | 0.66 - 0.70 | 0.69 - 0.73 | 0.64 - 0.67 |
| general_violence | 0.68 | 0.69  | 0.57  | 0.57  | 0.50 | 0.65| 0.70    | 0.67 |
|               | 0.67 - 0.70 | 0.67 - 0.71 | 0.55 - 0.58 | 0.56 - 0.60 | 0.50 - 0.50 | 0.63 - 0.67 | 0.69 - 0.72 | 0.66 - 0.70 |
| domestic_violence | 0.70 | 0.73  | 0.50  | 0.50  | 0.50 | 0.55| 0.72    | 0.70 |
|               | 0.67 - 0.72 | 0.68 - 0.75 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.55 - 0.58 | 0.69 - 0.75 | 0.57 - 0.74 |
| sexual_violence | 0.66 | 0.66  | 0.50  | 0.50  | 0.50 | 0.51| 0.66    | 0.67 |
|               | 0.64 - 0.70 | 0.63 - 0.70 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.49 - 0.53 | 0.63 - 0.70 | 0.63 - 0.74 |
| fatal_violence | 0.51  | 0.51  | 0.50  | 0.50  | 0.50 | 0.51| 0.50    | 0.62 |
|               | 0.50 - 0.53 | 0.50 - 0.52 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.53 | 0.50 - 0.51 | 0.56 - 0.68 |

4.5 Observations on Interpretability

Interpretable predictive models provide “a qualitative understanding of the relationship between joint values of the input variables and the resulting predicted response value,” (Hastie et al. 2009). In assessing the interpretability of various models, we distinguish between transparent models, which provide a textual or visual representation of the relationship between input variables and the predicted outcome (CART, C5.0R, C5.0, Lasso, Ridge), and black-box models, which do not (RF, SVM RBF).

Trade-offs Between Accuracy and Interpretability

Most of the methods that we tested for are unable to produce a prediction model that is both accurate and interpretable along the full ROC curve. In fact, we find the only methods that can consistently produce accurate models along the full ROC curve and also have the potential for interpretability are SLIM and Lasso. Among the remaining methods:
**Figure 2:** ROC curves for general recidivism-related prediction problems. We plot SLIM models using large blue dots. All models perform similarly except for C5.0R, C5.0T, and CART.
Figure 3: ROC curves for violence-related prediction problems. We plot SLIM models using large blue dots. Here C5.0R, C5.0T, and CART performed poorly, and for \text{fatal violence}, all methods except SLIM performed poorly.
• Methods such as RF and SVM RBF produce “black box” models that do not provide a comprehensible representation of the relationship between input variables and the predicted outcome.

• Ridge produces models that are accurate and transparent. The models produced by ridge provide a clear representation of the relationship between input variables and the predicted outcome. However, they do not allow users to understand how joint values of the input variables affect the predicted outcome since they use all of the \( P = 49 \) input variables; these models are not sparse.

• Tree and rule-based methods such as CART, C5.0T and C5.0R are generally unable to produce to models that attain high degrees of accuracy. Even on balanced problems such as arrest where these methods are able to produce accurate models, however, we find that these models are complicated and use a very large number of rules or leaves (similar behavior for C5.0T/C5.0R is also observed by, for instance, Lim et al. [2000]). As we show in Appendix D.2, it was not reasonably possible to obtain a C5.0R/C5.0T/CART model with at most 8 rules or 8 leaves for almost every prediction problem. While it may be possible to simplify the models that we obtained through these methods through heuristic post-processing methods (e.g., pruning), it is not likely to benefit the accuracy of the model (and can drastically change the TPR or FPR).

On the Interpretability of Equally Accurate Transparent Models

To assess the interpretability of different models, we provide a comparison of predictive models produced by SLIM, Lasso and CART for the arrest problem in Figures 4–6. This example provide a nice basis for comparison as all three methods are able to produce a model at roughly the same decision point, and with the same degree of sparsity. We include similar comparisons for other prediction problems in Appendix D.3. We make the following observations:

• All three models attain similar levels of predictive accuracy. Test TPR values ranged between 73-78% and test FPR values ranged between 45-47%. There may not exist a classification model that can attain a substantially higher accuracy. The highest test TPR attained by models with test FPR \( \leq 50\% \) was produced by the SVM RBF model which had a TPR of 80%.

• The SLIM model is highly sparse and uses 4 input variables. The small integer coefficients allow users to make quick predictions without a computer or calculator (see, e.g., Figure 7). Further, they allow users to easily gauge the importance of different input variables and provide a natural rule-based interpretation. In this case, for example, the SLIM model effectively says “predict arrest for any crime if age at release is \( \leq 24 \) or prior arrests \( \geq 5 \), unless the age at first confinement \( \geq 40 \).”

• The CART model allows users to make hands-on predictions. In comparison to the SLIM model, however, the hierarchical structure of the CART model makes it difficult to gauge the relationship of each input variable on the predicted outcome. Consider, for instance, the relationship between age at release and the outcome. In this case, users are immediately aware that there is an effect, as the model branches on the variables \( \text{age at release} \geq 40 \) and \( \text{age at release 18 to 24} \). However, the effect is difficult to comprehend since it depends on prior arrests and prior jail time: if \( \text{prior arrests} \geq 5 = 1 \) and \( \text{age at release 18 to 24} = 1 \) then the model predicts \( \hat{y} = +1 \); if \( \text{prior arrests} \geq 5 = 0 \) and \( \text{age at release} \geq 40 = 0 \) then \( \hat{y} = +1 \); however, if \( \text{prior arrests} \geq 5 = 0 \) and \( \text{age at release} \geq 40 = 1 \) then \( \hat{y} = +1 \) only if \( \text{multiple prior jail time} = 1 \). Such issues

\[\text{13}\]

For this comparison, we considered any transparent model with at most 8 coefficients (Lasso), 8 rules (C5.0R) or 8 leaves (C5.0T, CART) and had a test FPR less than or equal to that of the SLIM model (48%). We report the models that attained the highest test TPR among all such models. Here, neither C5.0R nor C5.0R could produce an acceptable model with 8 rules or 8 leaves.
Figure 4: SLIM model for arrest. This model has a training TPR/FPR of 78.4%/47.1%, and a mean 10-CV test TPR/FPR of 78.0%/48.3%.

\[ 2 \text{age}_{at\text{-}release} \leq 24 + 2 \text{prior\_arrests} \geq 5 - 2 \text{age\_1st\_confinement} \geq 40 - 1 \]

Figure 5: Lasso model for arrest. This model has a training TPR/FPR of 73.7%/45.2%, and a mean 10-CV test TPR/FPR of 73.2%/44.9%.

do not affect linear models, such as SLIM and Lasso, where users can immediately gauge the direction and strength of the relationship between a input variable and the predicted outcome by the size and sign of a coefficient.

Scoring Systems for Recidivism Prediction

We present one of the SLIM scoring systems for each of the prediction problems that we consider in Figures 7 through 14. Many of these models exhibit the same “rule-like” interpretability discussed in the previous section (see, e.g., drug in Figure 8, which effectively predicts that a person will be arrested for a drug-related offense if he/she has had any prior arrests and was at most 17 years old when released from prison). For completeness, we include baseline comparisons with other transparent models in Appendix D.3.

Note that the models below are not causal, meaning that one cannot change a single feature and evaluate the change in the predictions; a person with one feature that is different may also have other correlated features that are not accounted for when changing one feature at a time. One can argue why or why not these models make sense, whereas a black box model (such as SVM) is indefensible; a black box model is often so complex that printing one on a page of this manuscript would not be possible.

5 Conclusion

Our paper merges two perspectives on recidivism modeling: the first is to obtain accurate predictive models using the most powerful machine learning tools available, and the second is to create models that are interpretable, in fact, small enough to fit on an index card. We used a set of features that are commonly accessible to police officers and judges, and performed a comparison of different machine learning methods. Our findings show that there are (potentially major) advantages of using new machine learning tools like SLIM. SLIM produces models that are just as accurate as the more complicated black box algorithms; however, they are also much more interpretable, they can be customized automatically to follow criminological knowledge, and they can be directly useful in decision-making. These models can be dependably generated for any given decision point along the ROC curve.
Figure 6: CART model for arrest. This model has a training TPR/FPR of 77.7%/45.4%, and a mean 10-CV test TPR/FPR of 77.9%/45.9%.

**PREDICT ARREST FOR ANY OFFENSE IF SCORE > 1**

| Rule                                      | Points | Score |
|-------------------------------------------|--------|-------|
| age_at_release ≤ 24                      | ±2     |       |
| prior_arrests ≥ 5                        | ±2     |       |
| age_1st_confinement ≥ 40                 | -3     |       |

**ADD POINTS FROM ROWS 1-3  SCORE =  ......**

Figure 7: SLIM scoring system for arrest. This model has a training TPR/FPR of 78.4%/47.1%, and a mean 10-CV test TPR/FPR of 78.0%/48.3%.

**PREDICT ARREST FOR DRUG OFFENSE IF SCORE > 1**

| Rule                                      | Points | Score |
|-------------------------------------------|--------|-------|
| prior_arrests_for_drugs                  | ±2     |       |
| age_at_release ≥ 18                      | ±2     |       |

**ADD POINTS FROM ROWS 1-2  SCORE =  ......**

Figure 8: SLIM scoring system for drug. This model has a training TPR/FPR of 75.5%/40.3%, and a mean 10-CV test TPR/FPR of 70.5%/37.7%.

**PREDICT ARREST FOR PROPERTY OFFENSE IF SCORE > 1**

| Rule                                      | Points | Score |
|-------------------------------------------|--------|-------|
| prior_arrests_for_property              | ±3     |       |
| prior_arrests ≥ 1                        | ±1     |       |
| prior_arrests_for_sexual                | ±2     |       |

**ADD POINTS FROM ROWS 1-3  SCORE =  ......**

Figure 9: SLIM scoring system for property. This model has a training TPR/FPR of 69.4%/41.3%, and a mean 10-CV test TPR/FPR of 72.7%/44.8%.
**PREDICT ARREST FOR PUBLIC ORDER OFFENSE IF SCORE > 1**

|   |   |   |
|---|---|---|
| 1. | prior_arrests_for_public_order | 2 points |
| 2. | prior_arrests_for_general_violence | 2 points |
| 3. | prior_arrests≥1 | -2 points |

**ADD POINTS FROM ROWS 1-3  SCORE =   **

*Figure 10:* SLIM scoring system for public_order. This model has a training TPR/FPR of 55.9%/36.4%, and a mean 10-CV test TPR/FPR of 55.0%/34.5%.

**PREDICT ARREST FOR VIOLENT OFFENSE IF SCORE > 1**

|   |   |   |
|---|---|---|
| 1. | age_at_release≤17 | 2 points |
| 2. | prior_arrests_for_fatal_violence | 2 points |
| 3. | prior_arrests_for_general_violence | 2 points |
| 4. | age_1st_confainment≥40 | -2 points |
| 5. | age_1st_arrest≥40 | -4 points |

**ADD POINTS FROM ROWS 1-5  SCORE =   **

*Figure 11:* SLIM scoring system for general_violence. This model has a training TPR/FPR of 73.4%/44.2%, and a mean 10-CV test TPR/FPR of 73.9%/45.1%.

**PREDICT ARREST FOR FATAL VIOLENCE IF SCORE > 1**

|   |   |   |
|---|---|---|
| 1. | prior_arrests_for_multiple_types_of_crime | 4 points |
| 2. | released_other | 2 points |
| 3. | age_1st_arrest≥40 | -2 points |
| 4. | age_at_release_30_to_39 | -2 points |
| 5. | age_at_release_25_to_29 | -4 points |
| 6. | age_at_release_great_than_40 | -6 points |
| 7. | female | -8 points |

**ADD POINTS FROM ROWS 1-7  SCORE =   **

*Figure 12:* SLIM scoring system for fatal_violence. This model has a training TPR/FPR of 90.5%/63.7%, and a mean 10-CV test TPR/FPR of 81.3%/61.3%. The reason for the “released_other” term appearing in the model is unclear, though as Table 3 shows, the type of release indeed has predictive power. The codebook for the dataset has little explanation for the meaning of this variable, other than that it excludes conditional releases such as parole and probation release, unconditional releases such as expiration of sentence or commutation and pardon, and releases by death or transfer. This term actually appears in some models (see Figure [12](#)), indicating that it is worthwhile to further investigate this variable for either data quality or more information.
**Predict Arrest for Sexual Offense If Score > 9**

|   | Description                                   | Points | Score |
|---|------------------------------------------------|--------|-------|
| 1 | prior_arrests_for_sexual                      | 6      |       |
| 2 | age_at_release_25_to_29                       | 6      | +     |
| 3 | age_at_release_18_to_24                       | 4      | +     |
| 4 | age_at_release_≥30                            | 4      | +     |
| 5 | prior_arrests_for_local_ord                   | 4      | +     |
| 6 | released_unconditional                        | 2      | +     |
| 7 | age_1st_arrest_≥40                            | -2     | +     |

Add points from rows 1-7. Score = ....

**Figure 13:** SLIM scoring system for sexual. This model has a training TPR/FPR of 59.9%/28.7%, and a mean 10-CV test TPR/FPR of 58.9%/28.6%.

**Predict Arrest for Domestic Violence If Score > 17**

|   | Description                                   | Points | Score |
|---|------------------------------------------------|--------|-------|
| 1 | prior_arrests_for_felony                      | 8      |       |
| 2 | prior_arrests_for_misdemeanor                 | 6      | +     |
| 3 | prior_arrests_for_general_violence            | 6      | +     |
| 4 | age_at_release_18_to_24                       | 4      | +     |
| 5 | female                                        | -4     | +     |
| 6 | infraction_in_prison                          | -6     | +     |

Add points from rows 1-6. Score = ....

**Figure 14:** SLIM scoring system for domestic_violence. This model has a training TPR/FPR of 65.5%/27.6%, and a mean 10-CV test TPR/FPR of 73.1%/39.9%.
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A The Impact of Race

As discussed earlier, we chose not to include race as an input variable in our prediction problems. Some studies have shown that race is important for accurate recidivism prediction (Petersilia and Turner 1987; Berk 2009).

We wanted to know the answers to two questions. First, whether including race as a feature would lead to more accurate predictions. Second, whether we could predict race from the features that we already had. If we could predict race well from our current set of features, this would show that race information could be implicitly included in any model we might construct. The results that follow show: (i) including race does not substantially increase prediction accuracy for our problems, and (ii) race can be predicted fairly well from the features we already have. These results indicate that most of the information necessary to predict recidivism is already included in the features we have, and these features also include relevant information for predicting race.

To address whether race provided an increase in accuracy for predicting recidivism, we re-ran all methods other than SLIM on all new versions of each prediction problem that included three additional race-related input variables: white, black, hispanic. Table 7 summarizes the results for all methods on all prediction problems. The values in the table represent the percentage increase in AUC when models are trained with race-related input variables. As shown, the differences for most methods are negligible. In the cases of SVM RBF and Ridge, the accuracy increased slightly. In the case of RF, including race decreases accuracy (most likely because it exacerbates the overfitting problem).

To determine whether race could be predicted from the current variables, we used three different race options (white, black, hispanic) as outcomes and predicted each race as a function of our features. ROC plots are provided in Figure 15, showing that race can be predicted much better than random guessing. This is not a surprise, as we already know that blacks tend to have longer criminal histories than whites. On the other hand, we remark that we could not predict race perfectly with the features we have - in fact, our predictions (for all methods) were far from perfect. This means that not all of the information about race is contained in the features we have.

B Additional Association Rules

For fatal violence, it was difficult to produce accurate predictive models due to high class imbalance in the prediction problem. To give insights into the logic behind fatal violence prediction, we have listed some related rules in Table 10. Here, we note that the low support does not necessarily reflect a bad rule since prisoners being arrested for fatal violence make up only about 2% of the dataset.

C Falling Rule Lists for Imbalanced Problems

As we discuss in Section 4.4, it is difficult to use traditional tree and rule-based methods to create non-trivial models on imbalanced classification problems such as sexual violence. Here, we aim to show that there exist rule-based models that perform well on such problems by training falling rule lists. (Wang and Rudin 2014).
Figure 15: ROC curves for predicting white, black and hispanic using the standard set of input variables.
The percentage increase in 10-CV test AUC due to the inclusion of race-related indicator variables such as white, black and hispanic. This represents the percent increase in 10-CV test AUC reported in Tables 8 and 9.

| Problem                | Lasso | Ridge | C5.0R | C5.0T | CART | RF   | SVM RBF |
|------------------------|-------|-------|-------|-------|------|------|---------|
| arrest                 | 0.8%  | 0.8%  | 0.3%  | 0.1%  | 0.0% | -1.6%| 0.5%    |
|                        | 0.49 - 0.79% | 0.47 - 0.87% | -0.14 - 0.71% | -0.86 - 0.65% | 0.00 - 0.00% | -1.54 - 1.54% | 0.07 - 0.87% |
| drug                   | 1.0%  | 1.1%  | 1.6%  | 1.5%  | 0.0% | -4.4%| 0.8%    |
|                        | 1.88 - 1.14% | 1.27 - 1.28% | 5.50 - 0.30% | 2.90 - 0.25% | 0.00 - 0.00% | -4.19 - 3.98% | 0.95 - 0.99% |
| property               | 0.8%  | 0.4%  | 0.8%  | 0.0%  | 0.0% | -4.2%| 0.5%    |
|                        | 0.69 - 0.44% | 0.71 - 0.29% | -2.00 - 0.62% | -0.36 - 0.90% | 0.00 - 0.00% | -3.97 - 4.32% | 0.84 - 0.48% |
| public_order           | 0.6%  | 0.9%  | 0.1%  | 0.0%  | 0.0% | -3.0%| 0.4%    |
|                        | 0.08 - 1.05% | 0.56 - 1.36% | 0.38 - 1.18% | -0.11 - 0.67% | 0.00 - 0.00% | -5.79 - 6.33% | 1.25 - 1.33% |
| general_violence       | 0.6%  | 0.9%  | 0.1%  | 0.0%  | 0.0% | -6.2%| 0.8%    |
|                        | 1.2%  | 0.8%  | 0.0%  | 0.0%  | 0.0% | -6.6%| 1.6%    |
| domestic_violence      | 0.6%  | 0.9%  | 0.1%  | 0.0%  | 0.0% | -1.4%| -0.3%   |
| sexual_violence        | 0.0%  | 0.1%  | 0.0%  | 0.0%  | 0.0% | -1.4%| -0.3%   |
| fatal_violence         | 0.0%  | 1.9%  | 0.0%  | 0.0%  | 0.0% | -0.4%| 0.1%    |
|                        | 0.00 - 0.98% | 2.11 - 1.77% | 0.00 - 0.00% | 0.00 - 0.00% | 0.48 - 0.30% | 0.00 - 0.73% |

Table 7: The percentage increase in 10-CV test AUC for the baseline methods on all prediction problems using the standard set of input variables.
### Table 9: 10-CV test AUC for the baseline methods on all prediction problems using the standard set of input variables along with the race-related indicator variables white, black and hispanic.

| Problem     | Lasso  | Ridge  | C5.0R | C5.0T | CART  | RF    | SVM  | RBF  |
|-------------|--------|--------|-------|-------|-------|-------|------|------|
| arrest      | 0.74   | 0.74   | 0.72  | 0.71  | 0.66  | 0.71  | 0.71 | 0.74 |
|             | 0.73 - 0.75 | 0.72 - 0.75 | 0.70 - 0.73 | 0.70 - 0.73 | 0.65 - 0.67 | 0.70 - 0.72 | 0.73 - 0.76 |
| drug        | 0.72   | 0.73   | 0.64  | 0.64  | 0.50  | 0.66  | 0.74 |
|             | 0.69 - 0.75 | 0.70 - 0.75 | 0.62 - 0.66 | 0.63 - 0.65 | 0.50 - 0.50 | 0.64 - 0.67 | 0.71 - 0.76 |
| property    | 0.72   | 0.71   | 0.65  | 0.65  | 0.50  | 0.66  | 0.73 |
|             | 0.69 - 0.73 | 0.69 - 0.73 | 0.63 - 0.67 | 0.63 - 0.67 | 0.50 - 0.50 | 0.65 - 0.68 | 0.71 - 0.75 |
| public_order| 0.69   | 0.69   | 0.65  | 0.65  | 0.53  | 0.66  | 0.70 |
|             | 0.68 - 0.70 | 0.68 - 0.71 | 0.63 - 0.67 | 0.63 - 0.67 | 0.51 - 0.54 | 0.65 - 0.68 | 0.69 - 0.73 |
| general_violence | 0.69 | 0.69 | 0.57 | 0.57 | 0.50 | 0.61 | 0.71 |
|             | 0.67 - 0.71 | 0.67 - 0.72 | 0.55 - 0.58 | 0.56 - 0.59 | 0.50 - 0.50 | 0.60 - 0.62 | 0.70 - 0.73 |
| domestic_violence | 0.71 | 0.73 | 0.50 | 0.50 | 0.50 | 0.52 | 0.74 |
|             | 0.68 - 0.73 | 0.69 - 0.75 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.53 | 0.71 - 0.77 |
| sexual      | 0.66   | 0.66   | 0.50  | 0.50  | 0.50  | 0.50  | 0.66 |
|             | 0.64 - 0.70 | 0.63 - 0.70 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.51 | 0.63 - 0.70 |
| fatal_violence | 0.51 | 0.52 | 0.50 | 0.50 | 0.50 | 0.51 | 0.50 |
|             | 0.50 - 0.53 | 0.51 - 0.53 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.54 | 0.50 - 0.51 |

### Table 10: IF-THEN rules mined for fatal_violence. We list the IF condition in the table, and the THEN condition for each rule is the outcome $y = +1$, which indicates that a prisoner is arrested for a fatal offense within 3 years of being released from prison.

| Rule | IF Condition | Lift  | Support | Confidence |
|------|--------------|-------|---------|------------|
| A    | age_at_release 18 to 24 | 1.89  | 0.002   | 0.01       |
| B    | age_1st_confinement 18 to 24 | 1.37  | 0.004   | 0.009      |
| C    | prior_arrests for general violence | 1.27  | 0.004   | 0.008      |
| D    | prior_arrests ≥ 5 | 1.18  | 0.005   | 0.008      |
| E    | prior_arrests for multiple types | 1.16  | 0.006   | 0.008      |
| F    | age_at_release 18 to 24 AND prior_arrests for multiple types | 2.30  | 0.002   | 0.02       |
| G    | age_at_release 18 to 24 AND prior_arrests for felony | 2.30  | 0.002   | 0.01       |
| H    | age_at_release 18 to 24 AND prior_arrests ≥ 1 | 2.01  | 0.002   | 0.01       |
| I    | age_at_release 18 to 24 AND time_served ≥ 61mo | 1.91  | 0.002   | 0.01       |
| J    | age_1st_confinement 18 to 24 AND prior_arrests for general violence | 1.62  | 0.003   | 0.01       |
Falling rule lists are ordered lists of IF-THEN rules. Here, rules are ordered so that the confidence of each rule decreases as we go down the list. In this way, the highest rule applies to the group of individuals that have the highest risk, the second highest rule applies to a group of individuals with the second highest risk, and so on.

We present a falling rule list for the arrest problem in Table 11 learned from the algorithm of Wang and Rudin (2014). This model was trained using rules with at most two input variables and a support of at least 5%. The rules listed within this model have the form “IF a THEN b” where b denotes a positive outcome y = +1. In Table 11, support refers to the percentage of remaining examples that satisfy the IF conditions and probability refers to percentage of these examples where the outcome variable is positive. This model shows that the highest risk prisoners are those who were released between ages 18 and 24, and who have at least 5 prior arrests – this is aligned with the association rule (Rule F) that we found in Section 3.3. Once those individuals are removed, the second highest risk prisoners are 25–29 year olds with at least 5 prior arrests, etc. The risk of each group decreases as one move down the rules. Rule 15 represents the default rule. If an individual does not fall under any of risk groups determined by Rules 1-14, then his/her risk of arrest is 0.21.

We present a falling rule list for the sexual violence problem in Table 12. A visual comparison of falling rule list and SLIM’s performance for the above two models is presented in Figure 16. The model achieves comparable accuracy to the best models presented in Section 4.4 for this problem. This is in contrast to tree and rule-based methods such as C5.0T, C5.0R and CART. Thus, the difference in performance cannot be attributed to the class of models that are being fit (logical tree-like models), but to the fitting process itself. In comparison to traditional rule-based methods such as C5.0, falling rule lists choose and order the rules without using a greedy approach. In particular, falling rule lists are not constructed in an iterative splitting process where the data are recursively split into smaller pieces. Rather, the method aims to optimize over choices of rules as well as the ordering of the rules within the list. This allows falling rule lists to maintain a nice balance between accuracy and interpretability, even for imbalanced problems.
| Conditions                                                                 | Probability | Support |
|---------------------------------------------------------------------------|-------------|---------|
| IF prior_arrests_for_sexual AND age_1st_confinement_18_to_24              | 0.07        | 0.12    |
| ELSE IF prior_arrests_for_sexual AND prior_arrests >= 5                  | 0.07        | 0.16    |
| ELSE IF prior_arrests_for_sexual                                          | 0.04        | 0.31    |
| ELSE IF age_1st_confinement_18_to_24 AND prior_arrests_for_general_violence | 0.03        | 0.26    |
| ELSE default                                                              | 0.01        |         |

Table 12: Falling rule list for sexual_violence. This model has a 10-CV test AUC of 0.689 and a training AUC of 0.688.

Figure 16: Comparison of the ROC curve of Falling Rule List and SLIM for arrest and sexual_violence for one fold.
Table 13: Training AUC for all methods on all prediction problems. We report the 10-CV mean training AUC. The ranges underneath each cell represent the 10-CV minimum and maximum.

| Problem        | Lasso | Ridge | C5.0R | C5.0T | CART | RF   | SVM RBF | SLIM |
|----------------|-------|-------|-------|-------|------|------|---------|------|
| domestic_violence | 0.70  | 0.73  | 0.50  | 0.50  | 0.50 | 0.97 | 0.73    | 0.70 |
|                 | 0.70 - 0.71 | 0.73 - 0.74 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.97 - 0.97 | 0.71 - 0.74 | 0.58 - 0.73 |
| drug            | 0.71  | 0.72  | 0.65  | 0.66  | 0.50 | 0.97 | 0.75    | 0.70 |
|                 | 0.71 - 0.72 | 0.72 - 0.72 | 0.63 - 0.66 | 0.65 - 0.67 | 0.50 - 0.50 | 0.97 - 0.98 | 0.75 - 0.76 | 0.68 - 0.71 |
| fatal_violence  | 0.51  | 0.51  | 0.50  | 0.50  | 0.50 | 1.00 | 0.50    | 0.65 |
|                 | 0.50 - 0.53 | 0.50 - 0.52 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 1.00 - 1.00 | 0.50 - 0.51 | 0.63 - 0.66 |
| general_violence | 0.69  | 0.69  | 0.58  | 0.60  | 0.50 | 0.98 | 0.73    | 0.68 |
|                 | 0.68 - 0.69 | 0.69 - 0.69 | 0.57 - 0.59 | 0.59 - 0.61 | 0.50 - 0.50 | 0.97 - 0.98 | 0.72 - 0.73 | 0.66 - 0.68 |
| property        | 0.71  | 0.70  | 0.68  | 0.69  | 0.50 | 0.97 | 0.75    | 0.67 |
|                 | 0.71 - 0.72 | 0.70 - 0.71 | 0.67 - 0.69 | 0.68 - 0.70 | 0.50 - 0.50 | 0.97 - 0.97 | 0.75 - 0.75 | 0.66 - 0.69 |
| public_order    | 0.69  | 0.69  | 0.67  | 0.68  | 0.53 | 0.97 | 0.72    | 0.66 |
|                 | 0.68 - 0.69 | 0.69 - 0.69 | 0.66 - 0.68 | 0.67 - 0.69 | 0.51 - 0.53 | 0.97 - 0.97 | 0.72 - 0.72 | 0.63 - 0.68 |
| arrest          | 0.74  | 0.73  | 0.73  | 0.74  | 0.66 | 0.96 | 0.77    | 0.70 |
|                 | 0.74 - 0.74 | 0.73 - 0.73 | 0.73 - 0.73 | 0.73 - 0.74 | 0.66 - 0.67 | 0.96 - 0.96 | 0.77 - 0.77 | 0.67 - 0.71 |
| sexual          | 0.66  | 0.67  | 0.50  | 0.50  | 0.50 | 0.98 | 0.66    | 0.68 |
|                 | 0.66 - 0.67 | 0.66 - 0.69 | 0.50 - 0.50 | 0.50 - 0.50 | 0.50 - 0.50 | 0.98 - 0.99 | 0.66 - 0.66 | 0.67 - 0.69 |

D Additional Results

D.1 Additional Results on Predictive Accuracy

Table 13 provides the training AUC performance for all methods on all prediction problems.

D.2 ROC Curves for Transparent Methods with Model Size Constraints

Figure 17 provides ROC curves for all models that had a maximum size of 8 terms.

D.3 Model-Based Comparisons

D.3.1 drug

This is the SLIM model for drug. This model has a training TPR/FPR of 75.5%/40.3%, and a mean 10-CV test TPR/FPR of 70.5%/37.7%.

\[
\begin{align*}
2 \text{ prior arrests for drug} & \quad - \quad 2 \text{ age at release}_{18-24} & \quad - \quad 2 \text{ age at release}_{25-29} \\
- \quad 2 \text{ age at release}_{30-39} & \quad - \quad 2 \text{ age at release}_{\geq 40} & \quad + \quad 1.
\end{align*}
\]

This is the Lasso model for drug. This model has a training TPR/FPR of 73.3%/36.9%, and a mean 10-CV test TPR/FPR of 73.1%/36.8%.

\[
\begin{align*}
1.01 \text{ prior arrests for drug} & \quad + \quad 0.09 \text{ prior arrests for property} & \quad + \quad 0.08 \text{ prior arrests for misdemeanor} \\
+ \quad 0.07 \text{ prior arrests}_{\geq 5} & \quad + \quad 0.06 \text{ age 1st confinement}_{18-24} & \quad - \quad 1.05.
\end{align*}
\]
**Figure 17:** ROC curves for general recidivism-related prediction problems. We consider only transparent models with a maximum model size of 8. We plot SLIM models using large blue dots.
Figure 18: ROC curves for violence-related prediction problems. We consider only transparent models with a model size of 8. We plot SLIM models using large blue dots.
| Problem          | Lasso | Ridge | C5.0R | C5.0T | CART | SLIM |
|------------------|-------|-------|-------|-------|------|------|
| domestic.violence| 0.70  | 0.00  | 0.00  | 0.00  | 0.50 | 0.70 |
|                  | 0.68-0.72 | 0.00-0.00 | 0.00-0.00 | 0.00-0.00 | 0.50-0.50 | 0.57-0.74 |
| drug             | 0.69  | 0.00  | 0.53  | 0.00  | 0.50 | 0.69 |
|                  | 0.67-0.72 | 0.00-0.00 | 0.50-0.56 | 0.00-0.00 | 0.50-0.50 | 0.67-0.72 |
| fatal.violence   | 0.51  | 0.00  | 0.00  | 0.00  | 0.50 | 0.62 |
|                  | 0.50-0.53 | 0.00-0.00 | 0.00-0.00 | 0.00-0.00 | 0.50-0.50 | 0.56-0.68 |
| general.violence | 0.69  | 0.00  | 0.50  | 0.50  | 0.50 | 0.67 |
|                  | 0.67-0.70 | 0.00-0.00 | 0.50-0.52 | 0.50-0.51 | 0.50-0.50 | 0.66-0.70 |
| property         | 0.70  | 0.00  | 0.50  | 0.50  | 0.50 | 0.67 |
|                  | 0.67-0.71 | 0.00-0.00 | 0.50-0.50 | 0.50-0.50 | 0.50-0.50 | 0.65-0.70 |
| public_order     | 0.67  | 0.00  | 0.53  | 0.00  | 0.53 | 0.66 |
|                  | 0.65-0.68 | 0.00-0.00 | 0.52-0.53 | 0.00-0.00 | 0.51-0.54 | 0.64-0.67 |
| arrest           | 0.70  | 0.00  | 0.00  | 0.00  | 0.66 | 0.70 |
|                  | 0.69-0.70 | 0.00-0.00 | 0.00-0.00 | 0.00-0.00 | 0.65-0.67 | 0.68-0.72 |
| sexual           | 0.66  | 0.00  | 0.00  | 0.00  | 0.50 | 0.67 |
|                  | 0.64-0.71 | 0.00-0.00 | 0.00-0.00 | 0.00-0.00 | 0.50-0.50 | 0.63-0.74 |

**Table 14:** Test AUC for transparent methods on all prediction problems. We report the 10-CV mean test AUC. The ranges underneath each cell represent the 10-CV minimum and maximum.
D.3.2 property
This is the SLIM model for property. This model has a training TPR/FPR of 69.4%/41.3%, and a mean 10-CV test TPR/FPR of 72.7%/44.8%.

\[
\begin{align*}
3 \text{ prior}_\text{arrests}_\text{for_property} & - 2 \text{ prior}_\text{arrests}_\text{for sexual} - \text{ prior}_\text{arrests}_\geq 1 \\
- & 1. 
\end{align*}
\]

This is the Lasso model for property. This model has a training TPR/FPR of 74.4%/44.1%, and a mean 10-CV test TPR/FPR of 67.9%/39.8%.

\[
\begin{align*}
0.68 \text{ prior}_\text{arrests}_\text{for_property} & + 0.22 \text{ prior}_\text{arrests}_\geq 5 & + 0.03 \text{ prior}_\text{arrests}_\text{for misdemeanor} \\
- & 0.90. 
\end{align*}
\]

D.3.3 public order
This is the SLIM model for public order. This model has a training TPR/FPR of 55.9%/36.4%, and a mean 10-CV test TPR/FPR of 55.0%/34.5%.

\[
\begin{align*}
2 \text{ prior}_\text{arrests}_\text{for_public_order} & + 2 \text{ prior}_\text{arrests}_\text{for general violence} & - 2 \text{ prior}_\text{arrests}_\geq 1 \\
- & 1. 
\end{align*}
\]

This is the Lasso model for public order. This model has a training TPR/FPR of 61.8%/33.9%, and a mean 10-CV test TPR/FPR of 62.1%/34.1%.

\[
\begin{align*}
0.45 \text{ prior}_\text{arrests}_\text{for_public_order} & + 0.39 \text{ prior}_\text{arrests}_\text{for misdemeanor} & + 0.14 \text{ prior}_\text{arrests}_\text{for property} \\
+ 0.14 \text{ prior}_\text{arrests}_\geq 5 & + 0.13 \text{ prior}_\text{arrests}_\text{for general violence} & + 0.10 \text{ age}_\text{at release}_\text{18 to 24} \\
+ 0.04 \text{ age}_\text{at first confinement}_\text{18 to 24} & - 0.20 \text{ age}_\text{at release}_\geq 40 & - 0.88. 
\end{align*}
\]

This is the CART model for public order. This model has a training TPR/FPR of 8.8%/2.5%, and a mean 10-CV test TPR/FPR of 7.1%/1.9%.

D.3.4 general violence
This is the SLIM model for general violence. This model has a training TPR/FPR of 73.4%/44.2%, and a mean 10-CV test TPR/FPR of 73.9%/45.1%.
This is the Lasso model for \textit{general violence}. This model has a training TPR/FPR of 73.1\%/43.1\%, and a mean 10-CV test TPR/FPR of 73.3\%/43.8\%.

\begin{align*}
2 \text{ age}_\text{at}_\text{release} \leq 17 &+ 2 \text{ prior}_\text{arrests}_\text{for}_\text{fatal}_\text{violence} &+ 2 \text{ prior}_\text{arrests}_\text{for}_\text{general}_\text{violence} \\
- 4 \text{ age}_1\text{st}_\text{arrest} \geq 40 &- 2 \text{ age}_1\text{st}_\text{confinement} \geq 40 &- 1.
\end{align*}

This is the SLIM model for \textit{domestic violence}. This model has a training TPR/FPR of 65.5\%/27.6\%, and a mean 10-CV test TPR/FPR of 73.1\%/39.9\%.

\begin{align*}
8 \text{ prior}_\text{arrests}_\text{for}_\text{felony} &+ 6 \text{ prior}_\text{arrests}_\text{for}_\text{misdemeanor} &+ 6 \text{ prior}_\text{arrests}_\text{for}_\text{general}_\text{violence} \\
+ 4 \text{ age}_\text{at}_\text{release} \geq 25 &- 4 \text{ infraction}_\text{in}_\text{prison} &- 4 \text{ female} \\
- 17.
\end{align*}

This is the Lasso model for \textit{domestic violence}. This model has a training TPR/FPR of 72.0\%/32.7\%, and a mean 10-CV test TPR/FPR of 72.1\%/32.8\%.

\begin{align*}
0.63 \text{ prior}_\text{arrests}_\text{for}_\text{general}_\text{violence} &+ 0.09 \text{ prior}_\text{arrests}_\text{for}_\text{misdemeanor} &+ 0.08 \text{ age}_1\text{st}_\text{confinement} \geq 25 \\
+ 0.04 \text{ prior}_\text{arrests}_\text{for}_\text{property} &- 0.65.
\end{align*}

\textbf{D.3.5} \textit{domestic violence}

This is the SLIM model for \textit{domestic violence}. This model has a training TPR/FPR of 59.9\%/28.7\%, and a mean 10-CV test TPR/FPR of 58.9\%/28.6\%.

\begin{align*}
6 \text{ age}_\text{at}_\text{release} \geq 25 &+ 6 \text{ prior}_\text{arrests}_\text{for}_\text{sexual} &+ 4 \text{ age}_\text{at}_\text{release} \geq 25 \\
+ 4 \text{ age}_\text{at}_\text{release} \geq 30 &+ 4 \text{ age}_\text{at}_\text{release} \geq 40 &+ 4 \text{ prior}_\text{arrests}_\text{for}_\text{local}_\text{ord} \\
+ 2 \text{ released}_\text{unconditional} &- 2 \text{ age}_1\text{st}_\text{arrest} \geq 40 &- 9.
\end{align*}

This is the Lasso model for \textit{sexual violence}. This model has a training TPR/FPR of 57.5\%/26.9\%, and a mean 10-CV test TPR/FPR of 57.3\%/27.4\%.

\begin{align*}
1.09 \text{ prior}_\text{arrests}_\text{for}_\text{sexual} &+ 0.28 \text{ prior}_\text{arrests}_\text{for}_\text{general}_\text{violence} &+ 0.23 \text{ age}_1\text{st}_\text{confinement} \geq 30 \\
+ 0.09 \text{ infraction}_\text{in}_\text{prison} &+ 0.07 \text{ prior}_\text{arrests}_\text{for}_\text{property} &+ 0.05 \text{ prior}_\text{arrests}_\text{with}_\text{child}_\text{involved} \\
- 0.07 \text{ prior}_\text{arrests}_\text{for}_\text{drugs} &- 0.01 \text{ age}_\text{at}_\text{release} \geq 40 &- 1.09.
\end{align*}

\textbf{D.3.6} \textit{sexual violence}

This is the SLIM model for \textit{fatal violence}. This model has a training TPR/FPR of 90.5\%/63.7\%, and a mean 10-CV test TPR/FPR of 81.3\%/61.3\%.

\begin{align*}
4 \text{ prior}_\text{arrests}_\text{for}_\text{multiple}_\text{types}_\text{of}_\text{crime} &- 8 \text{ female} &- 6 \text{ age}_\text{at}_\text{release} \geq 40 \\
- 4 \text{ age}_\text{at}_\text{release} \geq 25 &- 2 \text{ age}_\text{at}_\text{release} \geq 30 &- 2 \text{ age}_1\text{st}_\text{arrest} \geq 40 \\
- 2 \text{ released}_\text{unconditional} &- 2 \text{ released}_\text{conditional} &+ 3.
\end{align*}