Using Machine Learning to Predict Recidivism Risk in the Colombian Prison System

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Abstract

Recidivism represents an expensive risk for society, not only because of crimes committed but also due to the costs of incarceration in a country with high levels of overcrowding. Every day, judges face a decision of whether the defendants must be deprived of freedom based on a prediction of what a defendant would do if released. The importance of that decision, combined with recent and rich data on Colombian inmates in the Prison System, makes this problem an ideal application for machine learning. In this paper, I expand the efforts of recent literature on how computer algorithms can be used to improve judges' decisions about the incarceration of defendants by using predictions about the risk of recidivism amongst released ex-convicted people. The main contribution of this paper suggests that there is a potential mis-prediction of the recidivism risk when deciding who to incarcerate and who not to. Potential welfare gains could be achieved, measured as reductions in crime and jailing rates. Moreover, these predictions can be used to develop public policies that address the growing prison overcrowding problem by suggesting an early release of less risky inmates based on the algorithm prediction.

Keywords: Recidivism, machine learning, prison system, overcrowding, Colombia.

1. Introduction

A significant fraction of crimes are committed by ex-convicts. In particular, Fazel and Wolf (2015) do a systematic review of the recidivism after 5 years of the release and found that the country with the highest rates is the United Kingdom at 72% followed by France at 59%, and the United States at 55%. In Colombia, as mentioned by Garzon et al. (2018), different sources and definitions make it difficult to provide just one number. Measured as the people who are re-captured, in 2016 31% of those captured had previous records. On the other hand, concerning the prison population, the National Penitentiary and Prison System (INPEC, by its Spanish initials) calculates that from the 179,024 people in the prison system, 8.6% are re-offenders. With the database used in this paper, I estimated that 17% of released people re-enter the prison between 2010 and 2016, 7.9% do it in one year, and 13% within the two years after the release [1].

According to Colombian law, when a person is suspected of a crime and is captured, a judge must decide if he should wait for the ascription of charges in jail or at home, considering several conditions stated in the Code of Criminal Procedure. Judges are, therefore, faced with very complex decisions, which should consider the risk of the defendant obstructing the procedure, the risk for the victim or the society if the defendant commits a crime and the risk of not appearing in the penal process. This decision requires the judge to consider other factors that could affect the decision. If the judge mis-predicts these risks, he could end up putting in jail a person who does not need to be deprived of his freedom but could have other restriction measures stated in the Code of Criminal Procedure, such as home jailing or electronic monitoring.

These kinds of complicated human decisions can be imperfect since they are based on limited experience and lack of use of all the information available. Errors in risk prediction are more costly with the actual overcrowding problem in Colombia since it imposes a broad burden on the judicial system if more people are sent to jail. As overcrowding rates were about 51% in 2016 (INPEC, 2017), the prison conditions have been deteriorating, and the delay of a judgment could be difficult for syndicated people waiting for the judges to decide if they are convicted or not. Also, many high-risk inmates could get out of prison without even being convicted due to the expiration of terms because their time in prison is greater than indicated by law. Indeed, 32.62% of those released between 2010 and 2016, did not were convicted but still spent, on average, 317 days in prison. This could be evidence of the

[1] These estimates are similar to those found by Tobón (2017)

expiration of terms produced by the burden of the judicial system.

With large volumes of data and recent computational tools for analyzing that data, we could address this decision problem by predicting the recidivism risk and ranking the most and least risky convicts. Because of the nature of the decision, machine learning (ML) surges as an ideal approach to identifying patterns in data and making predictions to aid complicated decisions. As stated in Kleinberg et al. (2017), machine learning has been proven beneficial not only to develop algorithms capable of face or voice recognition but also in the economic literature to compare and improve human decisions in the judicial system, in preventing crime (such as in The Economist (2018)), and has a long tradition as a robust statistical method (Berk, 2012, 2017).

This paper makes two unique contributions. Firstly, it applies advanced statistical methods based on machine learning to aid judges in their decision-making process. It is worth noting, however, that determining whether model-assisted predictions improve decision quality is a sensitive matter due to uncontrollable external factors affecting decision-making, as several authors have pointed out (Kleinberg et al., 2017). Yet, as Berk (2012) suggests, machine learning predictions can be included as part of the decision-makers' information pool, thereby improving their performance.

Secondly, this paper proposes a recidivism prediction tool to evaluate the impact of data-assisted decision-making on the chronic overcrowding that plagues the Colombian prison system. In this respect, I suggest implementing a smart de-incarceration method as mentioned in Berk (2017) to reduce overcrowding levels in Colombia without increasing crime rates.

The rest of this paper is organized as follows. Section 2 reviews previous works on human decisions, machine predictions, and recidivism determinants. Later, section 3 presents the data about events of imprisonment and how those are framed in the Colombian Prison System. In section 4, the methodology is presented, after which the results about the fitting of the models and the comparison with judges' decisions are made in section 5. Section 6 presents the proposal of a tool to assess risk and its possible impact, and section 7 concludes.

2. Literature review and previous applications

I contribute mainly to two branches of Literature. The former is the one that has used machine learning asses whether human decisions can be improved (Kleinberg et al., 2017). The latter is related to the study of recidivism, about which the relevant literature has focused on the causal effects of different prison conditions (Tobón, 2017). Hence, the main contributions of this paper are the prediction of the recidivism risk in a developing country such as Colombia -as well as the relevant factors- using machine learning techniques and the proposal of a risk assessment tool intended to reduce the characteristic overcrowding of the Colombian Prison System.

Regarding the first branch of literature mentioned above, using predictions to improve the decisions made has been deeply rooted in psychology and criminology (Kleinberg, 2017). Ohlin and Duncan (1949), for example, propose an index to measure the efficiency of prediction and conclude that it is necessary to investigate the possibilities of prediction in criminology rigorously. Likewise, Meehl (1954) and Meehl et al (1989) compare actuarial methods with clinical methods, indicating that actuarial methods (methods based on statistics applied in risk assessment) can be superior.

More recent applications have studied predictions in contexts such as the effect of the doctorate admissions committees (PhD) on the future success of Ph.D. students in economics (Athey et al 2007) or to advise administrators on the prediction of future productivity to take it into account in hiring decisions, with spatial applications on police hiring or duration of teachers (Chalfin et al 2016). This literature concludes that ML algorithms have proven to be helpful in the decision-making process.

These applications connect with the pioneering work of Richard Berk on the use of machine learning to predict the risk of committing a crime for ex-convicted people. Accordingly, to Berk (2012), Pennsylvania began to use ML predictions to inform the parole release decision. The paper aims to evaluate the impact of those decisions on recidivism. Although the predictions have no effect on release rates because the release decisions are not displaced but reinforced by predictions, algorithms reduce recidivism within two years after release.

Finally, Kleinberg et al. (2017) study whether machine learning improves judges' decisions about fail-to-attendance (FTA) risk. They overcome the omitted variable problem by using a quasi-random approach to the assignment of cases to judges. With the exogenous variation of the leniency of judges, they prove that machine learning certainly could help improve judges' decisions by reducing incarceration at the same level of crime or reducing crime with the same level of incarceration. Unlike Kleinberg et al. (2017), who use data of arrests in New York City, I observe the outcome after the release of each event of imprisonment. Therefore, I focus on the risk that the person will re-enter prison in different time horizons.

Concerning the second line of literature related to the study of recidivism, (Tobón, 2017) makes a good revision of the recidivism determinants. The author establishes mixed evidence about the prison conditions and recidivism. Studies like Chen and Shapiro (2007) show that inmates assigned to maximum security facilities do not have lower recidivism rates; on the other hand, Di Tella and Schargorsdky (2013), who studied electronic monitoring and recidivism, found that offenders under electric monitoring have lower recidivism rates than those who went to prison. On the other hand, Kuzienko (2013) shows that a greater time of imprisonment is related to greater recidivism risk. Finally, Tobón (2017) mention that Bayer et al (2009) study the effects of imprisonment on young people and found that imprisonment is causally related to greater participation in criminal activities.

3. Data and context

3.1. Data

The data used to analyze the recidivism of people come from the Integral Systematization of the Prison and Penitentiary System (SISIPEC of the INPEC). This database is the same as that used in Tobón (2017) and has information about the prison population between 2009 and 2016. That is to say, the database allows to identify the inmates in the prison system in 2009 (stock), and after that, I observe the flows of people entering the prison system, with the cutoff point as the most recent date for which data are available, which is October 2016. To ensure accuracy, each instance of imprisonment is treated as a separate event rather than lumped together. This is necessary as individuals may have multiple incarcerations for distinct offenses. For instance, those who have previously been released from prison typically have an average of 1.3 instances of incarceration on file.

The database has the information of the person, the reasons for his imprisonment, and other characteristics of the passage through the prison. Regarding personal information, I have data on gender, nationality, the educational level reached, if the person has minor children, and the location of the family. Regarding imprisonment, I have the date of admission to the last center, the date of exit -if it has already left-, the situation of each event, that is to say, if it is condemned or unionized, the previous convictions, the months of condemnation of the event of imprisonment and the crime for which he entered the system, for each event. Interestingly, and to demonstrate the use of extramural benefits, the base identifies whether the person has electronic monitoring, probation, or other benefits.

Additionally, concerning the characteristics associated with prison time, it is known if the person has previous sanctions, if he receives visits, if he participated in rehabilitation programs, or if he received any benefit, such as electronic monitoring or home detention. There is also information on whether the inmate is in a third-generation center, which is the last built and has better conditions of seclusion than the other older centers, such as better facilities or, in some cases, less overcrowding. The levels of overcrowding are obtained from the monthly reports of the INPEC.

Machine learning algorithms were utilized to improve the prison and penitentiary system. Three variables were created to measure recidivism and evaluate the performance of the models. The selection of the predictors of recidivism was made based on the literature and also based on two methodologies for the selection of variables, which is detailed later in section 4. The three outcomes are dichotomous variables that indicate whether a person has recidivated and vary depending on the period necessary for them to be observed again in the database.

The first and most basic measure of interest is re-entry, which considers whether the prisoner enters the prison system again at some time after his release, regardless of whether it is close to the time horizon of analysis (October 2016). That is to say, it is a variable that classifies if the person leaves his detention event and enters the prison system again -convicted or not- before October 2016. The other recidivism measures proposed are more restrictive with the time given to the person to re-offend, that is, to reappear in the database of the INPEC. In this case, the imprisonment events are filtered in such a way that the data allows the observation of different time horizons: one year for the second measure and two years for the third measure. For example, for the second measure, imprisonment events are filtered such that the time between their departure and the cut-off date is greater than or equal to one year. Similarly, the third measure takes the value of 1 if the person recurs two years after leaving prison and 0 otherwise. The observation is dropped if the time between the departure and the cut-off date is less than the horizon of each measurement (1 or 2 years).

From the initial sample of 466,037 incarceration events, I remain with a final sample of 263,633 events for the re-entry variable at some point after the release, 225,746 for the recidivism in 1 year, and 184,544 for the two-year recidivism. The main reason for the difference in the number of data is that the rest of the events were active by October 2016 since they were still in detention, and it has yet to be observed whether these people will re-offend. However, the prison population, especially those syndicated but not convicted, will be used to determine the level of risk for the proposal of a rule that allows for intelligent de-incarceration.

3.2. Institutional and Regulatory Framework

In Colombia, the law establishes a series of procedures to consider when deciding on custodial measures or granting extramural benefits. In particular, Law 906 of 2004 issued the

Code of Criminal Procedure (CPP, by its initials in Spanish), which defines these procedures for judges. Although the final decisions on imprisonment may be due to the consideration of factors not observable in the data and only observable to the judges, they must be in accordance with the principles and procedures stipulated in the law. According to the CPP, when a person is accused of committing a crime, in the assignment of a security measure, the judge considers one of the following requirements: 1) That the measure is necessary to prevent the accused from obstructing the exercise of justice, 2) If the accused constitutes a danger to the safety of society or the victim, 3) It is likely that the accused will not appear in the process (Article 308).

The Code of Criminal Procedure also establishes that there are two types of insurance measures: private and non-custodial (Art 307, Law 906 of 2004). These measures may be requested by the victims or by the prosecution, and according to paragraph 2 of Law 1760 of 2015, it must be proved before a pre-trial control judge, that the privative measures must be imposed when the non-exclusive measures are insufficient. It is also established in Article 310 that the judge must assess circumstances of dange,r to the community such as: the continuity of the criminal activity or connection with criminal organizations, the nature of the crimes that are imputed and their amount, the fact of being accused with some measure of insurance or enjoying a substitute mechanism for the penalty, and the existence of current convictions. Additionally, he is given preventive detention if the accused has been captured in the last 3 years (counted from the new capture) when no preclusion or acquittal has been given in the preceding case (numeral 4, article 313).

It is essential for this work to also determine the considerations that judges have when offering extramural benefits, that is, non-privative of freedom measures of assurance, such as electronic monitoring or confinement in residence. Article 314 of the CPP states that the judge may offer the benefit of confinement in residence when evaluating whether the place of residence is sufficient for the purposes of the assurance measure, if the person is over 65 years of age (depending on the crime), if the person is close to giving birth, or if you are responsible for a child under 12 with a disability. Non-custodial measures may also be imposed if the principal penalty of the crime is not the deprivation of freedom, or in less serious crimes, or when the minimum penalty is less than four years (Article 315, CPP). If the conditions of the non-custodial insurance measure are breached, the Judge may rule the incarceration in a prison establishment, depending on the severity of the non-compliance.

Finally, Article 317 of the CPP decrees that the defendants will be released when the penalty is served or when the accused has been exonerated when the principle of opportunity is applied [2]. Additionally, they can be released if 160 days have elapsed since the accusation was formulated without submission, 120 days have passed without initiating the hearing of the oral trial, or 150 days have gone by without the hearing of the reading of the judgment. Paragraph 1 of Law 1760 of 2015 specifies that the security measure must not exceed one year and can only be doubled if there are more than three defendants or cases of corruption. Once the term expires, a Warranty Control Judge can replace the freedom-privative security measure with non-privative measures. It is worth noting that, following Law 1786 of 2016, the time will not be accounted for if there are any delaying measures in the suspect's defense.

3.3. Descriptive Statistics

In this subsection the characteristics of the database are presented, differentiating between those who are already out of prison and those still inside. The data used to train the models takes only the released people because for those who are still in prison, I cannot assume if will re-offend or not. From the 446,037 events of imprisonment 36% where still in prison by the cut-off date, 6.9% among those 295.942 released were recidivist in 1 year, 9.8% in 2 years, and 17.6% after release.

Table 3.3.1 shows the mean of all the four class predictors of the recidivism described in section 4. The first column shows the values for the population still in prison by October of 2016, column 2 shows all the released people's characteristic values, and 3 to 5 columns show the characteristics of those who were released but re-offend within different time horizons. Recidivism is more common in people with property crimes such as robberies than in other more several crimes like homicides and other violent for which more people are still in prison.

It is important to highlight that the characteristics of the re-offenders are different from those who are in prison and from all the released. for example, the mean of sanctions is up to double among those who re-offend than in those who are still in prison and higher than the mean of all the released. Also, about the 70% percent of those who re-offend have already re-offended before and more times than the other released.

4. Methodological Strategy

As we saw in Section 3, different classification or regression algorithms can be implemented to predict recidivism thanks to the availability of data on incarceration events. In this document, three classification algorithms (GBM, XGBoost, and Random Forest) and

[2]Which is the circumstances under which the Attorney General can suspend or waive criminal prosecution, stipulated in Article 324 of the Code of Criminal Procedure

Table 3.3.1 Descriptive Statistics

Variable	Is in Prison? Yes	No	Re-offender? 1y	2y	Anytime
N	170,095	295,942	20,514	29,235	52,268
Personal Characteristics					
Male	0.897	0.895	0.944	0.939	0.933
age_entry	32.329	32.526	27.904	28.251	28.612
Primary Education	0.621	0.621	0.571	0.573	0.578
Secondary Education	0.305	0.294	0.379	0.376	0.368
Tertiary Education	0.043	0.051	0.019	0.021	0.023
Visits	0.680	0.583	0.625	0.603	0.571
Minors	0.810	0.774	0.753	0.762	0.771
Judicial Characteristics					
Convicted	0.646	0.674	0.651	0.646	0.641
Days in prison	-	-	645.27	640.54	649.74
Criminal Characteristics					
Already recidivist	0.208	0.221	0.778	0.774	0.677
Previous times	0.179	0.110	0.270	0.222	0.208
Homicide	0.192	0.100	0.063	0.064	0.072
Assault	0.016	0.029	0.025	0.026	0.027
Property crime	0.321	0.460	0.667	0.651	0.622
Other violent crimes	0.083	0.066	0.039	0.041	0.045
Time in Prison					
Rehab Work	0.260	0.372	0.360	0.348	0.348
Rehab Study	0.265	0.481	0.544	0.520	0.503
Rehab Teaching	0.010	0.017	0.008	0.008	0.009
Sanctions	0.132	0.099	0.312	0.287	0.239
Overcrowding	-	-	71.917	68.960	69.267

one of regression (Logit) are explored, and the best one is chosen according to their performance and the precedents found in the literature. Although the results of each model will be presented, it is not the objective of this paper to make an exhaustive comparison of the algorithms and their characteristics but to apply this prediction methodology to a real problem such as recidivism, and where there is a wide possibility of improvement for decision making. One of the advantages of using this type of non-parametric models is that they do not assume a normal distribution for the data, in addition two of the algorithms used are based on boosting, which is a technique to improve the prediction rules by means of a weighted sum of the results obtained when applying the prediction to several samples in an iterative way, allowing to reduce the variance (Sutton, 2005). On the other hand, the estimates are carried out in free software R, using the statistical package ”Caret” which is specialized in the implementation of ML. The empirical strategy established in this paper is based on three steps. First, the sample is randomly separated into 70% of data for training and 30% for the test set, to prevent the algorithm from out-perform just by over-fitting. Subsequently, the prediction algorithm is trained to make a prediction $\hat{y}_i$ that is obtained and adjusted to the function of inputs $m(X_i)$ that measures the probability of the outcomes -any of the recidivism measures, which are dichotomous- to take the value of 1. In this sense, we have for each imprisonment event i:

$$Pr(y_i = 1|X_i) = m(X_i) \tag{1}$$

Where y_i is one of the three recidivism outcomes that take the value of 1 if for that incarceration event i a new admission to a prison establishment is observed, and 0 otherwise: re-entry (anytime recidivism), recidivism in 1 year, recidivism in 2 years. The set of predictors X_i contains characteristics of the person (sex, age at the time of entry, educational level, if has children or receives visits), from the judicial situation (if he was convicted or not), criminal capital information (whether has been in prison before, how many times, and the crime characteristics related to that imprisonment event), the characteristics of its time in prison (days incarcerated, whether has had sanctions, or if he is in a rehabilitation program), and the characteristics of the prison (whether the reclusion establishment is third generation one and the level of overcrowding in it).

Although all these predictors are supported in the literature, sociodemographic, cognitive and psychological factors, prior criminal behavior and environmental factors -such as family and peer effects- (Monnery, 2014) and prison conditions as peer-effects (Bayer et al, 2009) are highlighted. Also, an empirical validation of the choice of the variables is made using stepwise regression: forward selection and backward elimination in a logit model. Backward elimination is a method that starts with all the variables selected according to the literature and iteratively removes each variable to improve the model. On the other side, forward selection starts with no variables and adds them testing its significance and leaving those who improve the model. The results of the marginal effects of the logit model on the probability of return to prison are shown in table 1 for the variable re-entry at any time after the release.

The results suggest that nearly all the variables selected were relevant in explaining recidivism and its impact, except for visits, if the crime is a homicide, or if the inmate was prosecuted in the oral penal accusatory system. Interestingly, if the inmate has sanctions, the probability of re-entering prison increases by 11.63 percentage points, ceteris paribus. The stronger predictor is being a recidivist, which increases the probability of returning to prison

Table 4.1. Logit results- complete and stepwise method

	(1)	(2)	(3)
	re_entry	re_entry	re_entry
Days Intern	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Times Prev Entry	-0.10***	-0.10***	-0.10***
	(0.00)	(0.00)	(0.00)
Convicted	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Male	0.05***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)
Rehab Work	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Rehuc Estudio	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Rehab Teach	-0.02***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)
Educ Primary	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)
Educ Secondary	-0.01*	-0.01*	-0.01*
	(0.00)	(0.00)	(0.00)
Educ Tertiary	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)
Visits	-0.00		
	(0.00)		
Minors	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
Sanctions	0.12***	0.12***	0.12***
	(0.00)	(0.00)	(0.00)
Avg Overcrowding	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Homicide	0.00*		
	(0.00)		
Assault	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Property Crime	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)
Other Violent	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)
Age Entry	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Penal Acusatory Syst	-0.00		
	(0.00)		
Penal Code	-0.15***	-0.15***	-0.15***
	(0.01)	(0.01)	(0.01)
Third Generation	-0.05***	-0.05***	-0.05***
	(0.00)	(0.00)	(0.00)
Months Conviction	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Recidivist	0.29***	0.29***	0.29***
	(0.00)	(0.00)	(0.00)
Observations	263,633	263,633	263,633

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

by 28.7 percentage points, holding other variables constant. Since almost all the variables were important in explaining crime and given its importance in literature, homicides, penal accusatory system, and visits were included as predictors by which to control in the prediction algorithms.

4.1. Logit Regression

In cases where the outcome is a binary response, a regression model could be fit to the predictors X_i. Unlike the Ordinary Least Squares regression (OLS), which has heteroskedasticity problems and predictions out of the range between 0 and 1, Logit can estimate the relationship between independent variables and the probability of success (dependent variable=1), predicting it within the plausible range of 0 to 1. Logit is used in the vast majority of applications along with probit models, and the marginal change associated with it depends on the level of X_i (Wooldridge, 2009)

According to Greene (2012), in the logit model, the probability $Pr(y_i = 1|X_i)$ is a logistic function of the parameters and the data such as:

$$Pr(Y = 1|X) = \frac{exp(x'\beta)}{(1 + exp(x'\beta)} = \Lambda(x'\beta) \tag{2}$$

Where $\Lambda(.)$ denotes the logistic cumulative distribution function. This is a method based on maximum likelihood estimation, that is to say, where the probability of having the sample extrapolated to the population is maximized (Wooldridge, 2009). In the previous subsection, this model was implemented and the marginal effects were reported. This partial effect is obtained from derivate $Pr(Y = 1\ X)$ with respect to X.

4.2. Random Forest

Random Forest (RF) is a machine learning method that combines tree predictors, where each tree depends on a random vector sampled independently and identically distributed to all the trees in the forest of classification. It was introduced and created by Kam (1995) in Bell Labs, and was modified by Breiman (2001) for classification and regression application to construct a collection of trees controlling its variance. RF is a substantial modification of Bagging, which is a technique designed to reduce the variance of the prediction; it builds a collection of trees and averages them. It is widely used because is simple to train and tune (Hastie et al., 2009).

After the generation of trees of classification, the observations are evaluated and the winning category is assigned due to the majority vote. This winning category is calculated in accordance with the cutoff value of the category (Osowski & Siwek, (2016); Mejia & Montes (n.d.). RF uses out-of-bag (OOB) sample that, for each observation, constructs its random forest predictor by averaging only trees of the samples in which the observation did not appear, and the training is terminated once the OOB error stabilizes.

4.3. Gradient Boosted Decision Trees - GBM

The predictions with better performance were those constructed with gradient-boosted decision trees (GBM). This algorithm was developed by Friedman (1999). Simultaneously, Mason et al (1999) enlarged the gradient boosting perspective to be an iterative optimization of a cost function pointing in the negative gradient direction. As stated in Kleinberg et al (2018), this algorithm is essentially averaging multiple decision trees sequentially built on the training data, and in each iteration, the importance of the observations that have been predicted poorly is increased (up-weight) by the sequence of trees up to that point. I can increase the complexity of the algorithm by changing the depth of each tree, the number of trees, and the weighting scheme. These parameters are selected using a fivefold cross-validation method, which selects the optimal model to be used on all the training set.

4.4. Extreme Gradient Boosting - XGBoost

This is an efficient and scalable implementation of gradient boosting from Friedman (1999), like GBM. Is generally 10 times faster than GBM (Chen & He, 2018). It uses a more regularized model to control over-fitting. One of the authors (Tianqi Chen) has recently said that the algorithm is intended to push up the limits of the computation resources (Chen, 2018). Since its differences with GBM rely more on computational than theoretical reasons, XGBoost algorithm is estimated, and its performance is good but GBM is preferred because academic literature has used it in similar approaches to the one in this paper, for example, Kleinberg et al. (2018) uses GBM to estimate the Fail to Attend risk to the hearing in New York. In any case, the results of GBM and XGBoost are very similar.

5. Results

This section presents the results of the performance of the models proposed previously. After training all the models for each one of the three outcome variables, the performance of the algorithms is proven in the test set. The metric considered to train the algorithms was the Area under the Receiver Operating Characteristic (ROC), named AUC by its English acronym. As stated in Salfner et al (2010) and in Nettleman (1988), this area measures the precision of the prediction since the ROC curve represents the relation between the true positive rate ($TPR = Sensitivity$) and the false positive rate ($FPR = 1 - Specificity$), therefore:

$$TPR = \frac{\#TruePositives}{\#TruePositives + \#FalsePositives} \tag{3}$$

$$FPR = \frac{\#FalsePositives}{\#FalsePositives + \#TrueNegatives} \tag{4}$$

Considering the positive class to be if the inmate re-offends, the true positive rate measures the proportion of re-offenders that the algorithm classifies as such. On the other hand, a false positive rate indicates how likely is that the algorithm identifies as a recidivist a person who will not re-offend. In contrast, the specificity captures the proportion of non-recidivists that the algorithm predicts as such. If the AUC is 0.5, the model has a prediction capacity similar to what could be achieved by flipping a coin, which is to say, a prediction by chance. It is desirable for the ROC curve — that discriminates between failures and non-failures — to be closer to the upper left corner of the ROC space because then the model will be more accurate (Salfner et al, 2010).

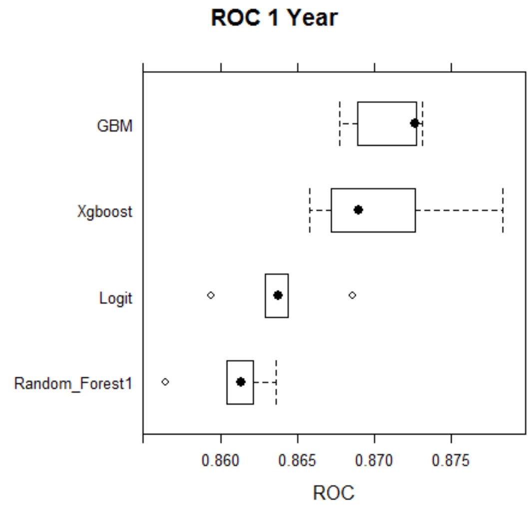
One challenge arises at first with respect to the classes' imbalance when doing the classification in the testing set: since the percentage of released people that reoffend is low (13%), the sensitivity was too low (nearly 20% at its best). This was a big problem because the algorithm was classifying a great proportion of recidivists as not recidivists, and then the algorithm could be useless in determining who does not represent a risk for society. To overcome this problem, I found in the "caret" package two possible ways to deal with class. One of them was to change the metric to "Kappa" as it is a measure to estimate accuracy with a low percentage of samples in one class, and the second was a subsample for class imbalance (Kuhn, 2018). Changing the metric did not solve the problem, but subsampling did. The subsample technique implemented was down-sampling. This approach subsetted all the classes in the training set so that their class frequencies matched the least prevalent class, and the sensitivity improved considerably. Performance results and the variable importance are shown next.

5.1. Adjustment and performance of the algorithms

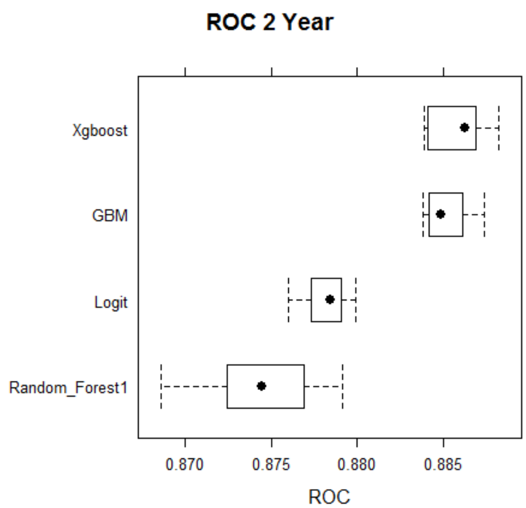
After running the algorithms, the best performance in the resampling was achieved by GBM and XGBoost. Figure 6.1 shows the AUC distribution over the different measures of recidivism. The results are notably worse in Logit and Random Forest specifications for the three outcomes of interest.

The results of the performance of the model on the test set are summed up in table 5.1. Although the results don't vary much, the accuracy is greater in the models that predict

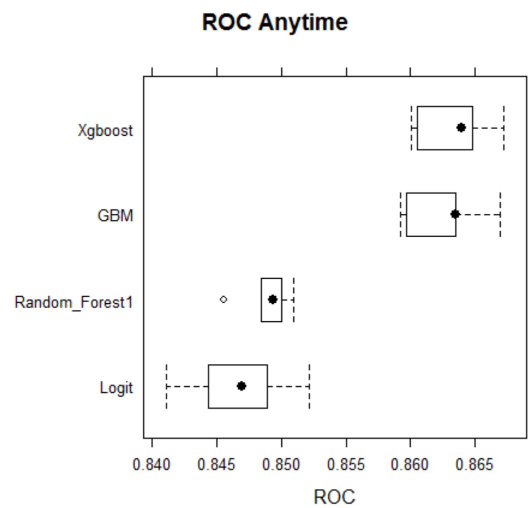
Figure 5.1.1 ROC results for the three outcomes



(a) 1 Year recidivism



(b) 2 Year recidivism



(c) Any time recidivism

recidivism without considering the time horizon (achieving its maximum value with GBM). On the other hand, sensitivity was generally better in the recidivism model within a year after release; these results for GBM suggest that for recidivism in one or two years, the algorithm predicts correctly that a released person will re-enter prison 82% of the time. Similarly, the percentage of correct classified classes (accuracy) is about 80%.

Figure 5.1.2 presents the outcomes of our analysis of the significance of variables in the recidivism model post-release. The most crucial factor is whether the individual has a history

Table 5.1. Performance of models and algorithms

Algorithm	Model	Performance measures of algorithms on test set			
		Accuracy	Sensitivity	Specificity	AUC
Logit	Recidivism 1Y	80.93%	80.57%	80.96%	86.61%
	Recidivism 2Y	82.78%	80.92%	83.07%	87.68%
	Re Entry Anytime	83.05%	71.14%	85.54%	84.72%
Random Forest	Recidivism 1Y	79.31%	81.99%	79.07%	86.21%
	Recidivism 2Y	81.74%	81.79%	81.73%	87.53%
	Re Entry Anytime	81.27%	73.55%	82.29%	84.82%
GBM	Recidivism 1Y	80.12%	82.99%	79.86%	87.38%
	Recidivism 2Y	82.60%	82.49%	82.62%	88.58%
	Re Entry Anytime	83.38%	73.02%	85.54%	86.26%
XGBoost	Recidivism 1Y	80.14%	83.30%	79.86%	87.47%
	Recidivism 2Y	82.78%	82.22%	82.86%	88.69%
	Re Entry Anytime	83.22%	73.08%	85.34%	86.23%

of imprisonment (recidivist), followed by age at entry, average overcrowding level, sanctions, and the number of days interned. These essential variables are standard to all algorithms. Beyond the top six predictors, the ranking of importance varies between algorithms but with less than 25%.

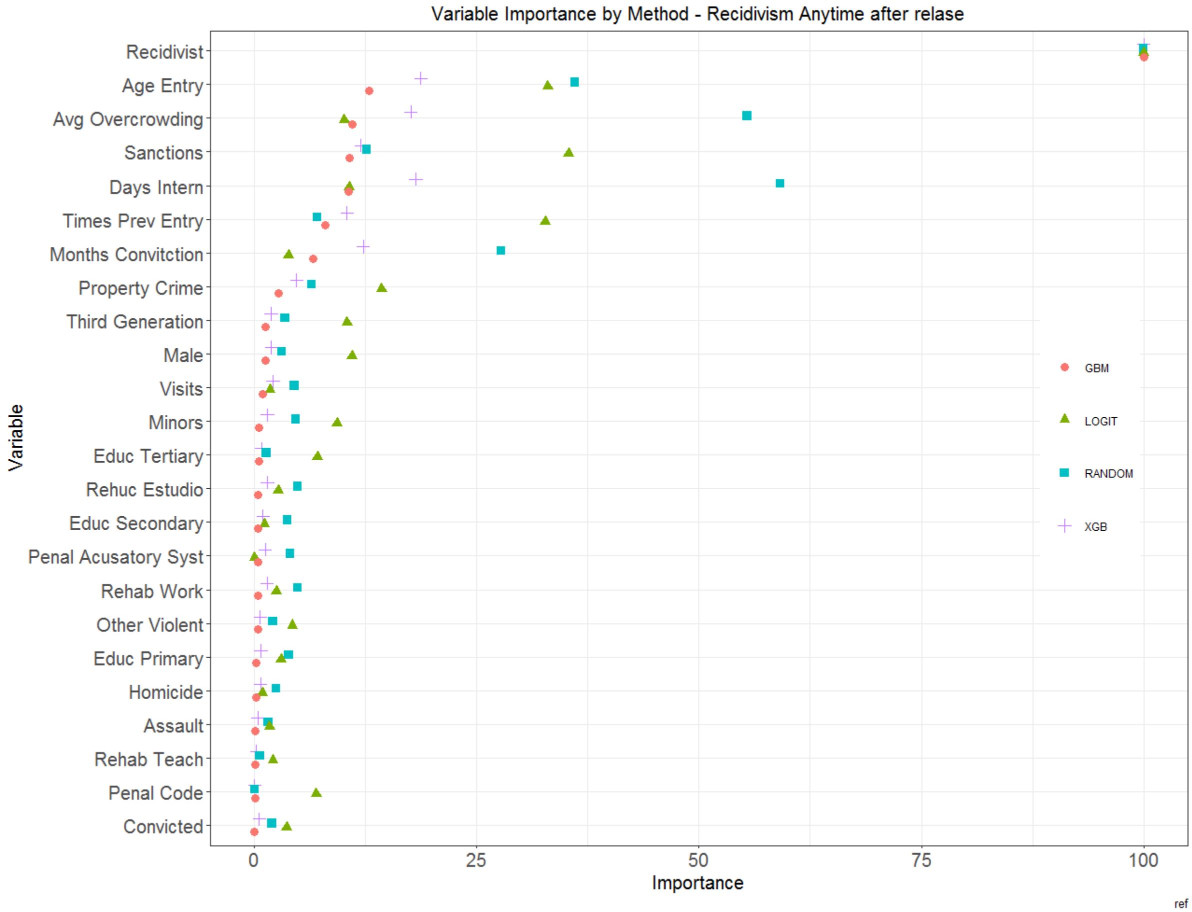
5.2. Risk predicted by ML and judges decisions

How risky are the people who are offered non-privative benefits? As established in the code of criminal procedure, judges can offer extramural benefits such as home prison or electronic monitoring. Based on the ML procedure, I predict the class probabilities of the GBM algorithm to compare and describe the most and least risky quintile in terms of recidivism risk within any time after the release.

The results for the class predictions and the mean of class probabilities are shown in figure 5.2.1. Among those who finish their time in prison without being convicted, the algorithm predicts that 23.53% of them (91,197 in total) will re-offend. Similarly, among the 24% of those granted extra-mural benefits, the algorithm predicts that 25.4% of them will re-offend anytime after release.

This does not necessarily mean that judges are making bad decisions about who will be re-incarcerated because they can be pursuing other objectives or could be facing other judicial restrictions or, as stated in Kleinberg et al. (2017), there could be non-observable variables influencing their decisions. Nonetheless, this is worrisome since Article 310 of the

Figure 5.1.2 Variable importance for Any time recidivism



Code of Criminal Procedure establishes that judges must value the risk for the community due to the continuity of the accused's criminal activities. Also, since many syndicated people come out of prison after a long time and without being convicted, the risk to society may be more prominent due to the overloaded judicial system.

The results in table 5.2.2 are quite interesting because describe the characteristics of the least and most risky released so far in five risk-ordered recidivism groups. With nearly 52,727 people in each group, the 5th quintile represents the 20% of the sample that has the greatest probability of re-offending after release, and the 1st quintile groups the least risky people.

The released people predicted to be riskier (5th quintile) re-enter the prison at a greater rate, have on average 28 years, had more entries to the prison than anyone else, and have been less time in prison (594 days on average), have minor children in less proportion, and commit the most sanction among groups of risk. On the other hand, the recidivism of the 1st quintile is lower, yet spend more time in prison.

Table 5.2.1 ML predictions and judicial status

	Predicted classification of recidivism (row percentage) (Training + Test Set)			Mean of predicted risk
Convicted?	Non-recidivist	Recidivist	Total	
No	76.47%	23.53%	91,197	0.387
Yes	74.62%	25.38%	172,436	0.352
Benefits?				
No	75.47%	24.53%	199,365	0.368
Yes	74.60%	25.40%	64,268	0.353
Total	198,410	65,226	263,633	0.364

Table 5.2.2 Descriptive statistics by levels of risk

	Quintiles of predicted risk (mean of var)					Total
Variables	1st	2nd	3rd	4th	5th	
Re entry	1.7%	4.2%	7.5%	14.5%	59.1%	17.4%
Convicted	83.1%	60.5%	55.8%	61.5%	66.1%	65.4%
Age at entry	42.634	36.302	29.089	25.873	28.624	32.504
Previos times	0.01	0.01	0.03	0.19	0.38	0.12
Already recidivist	0.6%	1.3%	3.0%	19.0%	89.3%	22.6%
Male	81.9%	84.6%	92.0%	96.3%	93.8%	89.7%
Days in prison	1029.614	721.449	648.101	675.173	594.671	733.802
Has minores	83.6%	80.4%	74.1%	75.5%	76.2%	78.0%
Has sanctions	1.0%	2.0%	3.9%	13.0%	30.7%	10.1%

6. A Public Policy Tool to Asses Risk

One of the advantages and still underused characteristics of machine learning algorithms is their potential application in prevention policies in underdeveloped countries. In accordance with the approach of this paper, a possible solution for the overload of the judicial system and the high and increasing levels of overcrowding, is to help judges in the decision they make about incarceration or release.

To face the problem of overcrowding in the prison system, a risk-ranked releasing rule is proposed to be implemented. To do this, the predicted class probabilities of the GBM model developed here could order syndicated people (who comply with the requirements of the law) from the least to the most risky and release all the persons that are below a threshold limit.

According to the institutional framework, this proposal could be achieved in practice since the Constitutional Court of Colombia has precedents of attempting to establish an equilibrium rule to reduce overcrowding. In the sentences T-153 of 1998 and T-388 of 2013, the state of unconstitutional affairs in the prison system was declared because of the poor prison conditions of the penitentiary establishments, and the judgment T-762 of 2015 reiterated that the conditions that inmates have to face are not constitutional. The Court ordered the application of two rules of equilibrium in which basically the establishments could not receive people if that implies raising the occupation level. This is to say that the entrance is only allowed if the number of syndicated or convicted people to enter is less than the number of people who exit the last week.

This has not been implemented since is difficult to decide if another person should leave the prison just so the new inmate could get in. Also, is not clear how the rule will decrease the levels of overcrowding. The tool proposed here could be useful to decide whether is better for a person to wait for its trial at home, based on their predicted risk. As many people whose risk level we do not know are already getting out of prison for expiration of terms, this tool could be a good idea.

In the literature, there has been a precedent of machine learning prediction being used to forecast risk and make decisions. Berk (2012) shows that in Pennsylvania, a tool is used to inform parole release decisions. This paper evaluates the impact of such tools in different outcomes to argue the desirability of their implementation in other contexts. This evaluation's results show a reduction of recidivism within two years after the arrest. The conclusion presented here is that more information is better, so the people in charge of making such complicated decision is more informed about uncertainty.

An idea similar to the one proposed in this document is the tool used in the United States to improve the fight against crime and the administration of the criminal justice system, based on the "Moneyball" theory. The idea of Moneyball arises from using statistics and data in baseball games to help teams win games. This idea was extended to applications in the criminal justice system to improve decision-making processes and make the system's administration more efficient.

One of the people who has used the Moneyball approach is Cyrus Vance Jr's, New York district attorney elected in 2009, who had as an initiative to transform the way in which prosecutors fight crime to develop what he called "intelligence-driven prosecution"(accusation-based on intelligence). Vance, along with attorney Chauncey Parker and the Police Department, developed a structure called the Crime Strategies Unit (CSU), which became a database of 9,000 chronic criminals with a criminal record. The data is entered into the

Arrest Alert System (SAA), and when a suspect is investigated, any interested prosecutor receives an email from the SAA with the alert detailing the person. This system is complemented by the Crime Prevention System, which focuses on violent crimes and collects all the details about the offender. With all the information available, Parker proposed Moneyball's approach to determining who should focus efforts and who should be referred to jails or correctional facilities (Brown, 2014). In this last aspect, the system developed in New York is assimilated to the one proposed here, in that observable information of people is used to determine their risk profile using quantitative tools.

7. Conclusions

In this paper, I present the ideal use of machine learning algorithms in complex systems such as the Colombian judicial system. I review different models to predict the likelihood of recidivism observed, and I evaluate the metrics of performance in order to choose the best performing according to the Area Under Curve the Receiver Operating Characteristic Curve (AUC). The probability of correctly identifying a recidivist as such is near 82%. The model chosen for its performance and for being widely used in the literature was gradient-boosted decision Trees (GBM).

The results suggest good behavior in the models proposed for different re-offending time horizons. Additionally, it was determined that the most important variables within the recidivism prediction were if the person already had previous recidivism, the level of overcrowding to which he is exposed, and if he has been sanctioned.

With the predictions of the algorithms, we proceed to compare the decisions that the judges make with regard to the extra-mural benefits, and we observe that there is a possibility of improvement while the total of people to whom the benefits are offered predicts that about 25% returns to re-offend.

On the other hand, given the structural failures that have resulted (and have been) from the congestion of the judicial system, such as overcrowding, a release rule based on the predicted probability of recidivism is proposed. In this sense, setting free to the 20% of the population less risky could be beneficial while reducing overcrowding and the probability of committing crimes will be less than that reported

Further analysis could include estimating an equilibrium model to achieve less overcrowding and crime. For this purpose, a cost-benefit analysis could be useful to determine the change in society's welfare since having a person in prison is costly, but society could also be affected if it is released since the crime rate could increase. Since the average risk of the least risky quintile is less than the average risk of persons already in extra-mural benefits, the least risky recidivism risk could be less harmful.

References

References

Susan Athey, Lawrence F Katz, Alan B Krueger, Steven Levitt, and James Poterba. What Does Performance in Graduate School Predict? Graduate Economics Education and Student Outcomes. *American Economic Review*, 97(2):512–518, apr 2007. ISSN 0002-8282. doi: 10.1257/aer.97.2.512. URL `http://pubs.aeaweb.org/doi/10.1257/aer.97.2.512`.

Patrick Bayer, Randi Hjalmarsson, and David Pozen. Building Criminal Capital behind Bars: Peer Effects in Juvenile Corrections [*]. *Quarterly Journal of Economics*, 124(1):105–147, feb 2009. ISSN 0033-5533. doi: 10.1162/qjec.2009.124.1.105. URL `https://academic.oup.com/qje/article-lookup/doi/10.1162/qjec.2009.124.1.105`.

Richard Berk. An impact assessment of machine learning risk forecasts on parole board decisions and recidivism. *Journal of Experimental Criminology*, 13(2):193–216, jun 2017. ISSN 1573-3750. doi: 10.1007/s11292-017-9286-2. URL `http://link.springer.com/10.1007/s11292-017-9286-2`.

Richard A. Berk. *Criminal justice forecasts of risk : a machine learning approach*. Springer, 2012. ISBN 9781461430858.

Leo Breiman. Random Forests. *Machine Learning*, 45(1):5–32, 2001. ISSN 08856125. doi: 10.1023/A:1010933404324. URL `http://link.springer.com/10.1023/A:1010933404324`.

Chip Brown. Cyrus Vance Jr.'s 'Moneyball' Approach to Crime - The New York Times, 2014. URL `https://www.nytimes.com/2014/12/07/magazine/cyrus-vance-jrs-moneyball-approach-to-crime.html`.

Aaron Chalfin, Oren Danieli, Andrew Hillis, Zubin Jelveh, Michael Luca, Jens Ludwig, and Sendhil Mullainathan. Productivity and Selection of Human Capital with Machine Learning. *American Economic Review*, 106(5):124–127, may 2016. ISSN 0002-8282. doi: 10.1257/aer.p20161029. URL `http://pubs.aeaweb.org/doi/10.1257/aer.p20161029`.

Tianqi Chen. What is the difference between the R gbm (gradient boosting machine) and xgboost (extreme gradient boosting)?, 2015. URL `https://www.quora.com/`

What-is-the-difference-between-the-R-gbm-gradient-boosting-machine-and-xgboost-extrem answer/Tianqi-Chen-1?srid=8Zehttps://www.quora.com/What-is-the-difference-between-the-R-gbm-gradient-boosting-machine-and-xgboo.

Tianqi Chen and Tong He. xgboost : eXtreme Gradient Boosting. *R package version 0.4-2*, pages 1–4, 2015. URL https://cran.r-project.org/web/packages/xgboost/vignettes/xgboost.pdf.

Congreso de la República Colombia. Ley 906 de 2004, 2004. URL http://www.alcaldiabogota.gov.co/sisjur/normas/Norma1.jsp?i=14787.

Congreso de la República de Colombia. Ley 1760 de 2015 Nivel Nacional, 2015. URL http://www.alcaldiabogota.gov.co/sisjur/normas/Norma1.jsp?i=62277{\#}1.

Corporación Andina de Fomento (CAF). Por una América Latina más segura: Una nueva perspectiva para prevenir y controlar el delito. Technical report, CAF, 2014. URL www.caf.com.

R M Dawes, D Faust, and P E Meehl. Clinical versus actuarial judgment. *Science (New York, N.Y.)*, 243(4899):1668–74, mar 1989. ISSN 0036-8075. doi: 10.1126/SCIENCE.2648573. URL http://www.ncbi.nlm.nih.gov/pubmed/2648573.

DMLC. Introduction to Boosted Trees — xgboost 0.71 documentation, 2015. URL http://xgboost.readthedocs.io/en/latest/model.html.

Seena Fazel and Achim Wolf. A Systematic Review of Criminal Recidivism Rates Worldwide: Current Difficulties and Recommendations for Best Practice. *PLOS ONE*, 10(6):e0130390, jun 2015. ISSN 1932-6203. doi: 10.1371/journal.pone.0130390. URL http://dx.plos.org/10.1371/journal.pone.0130390.

Jerome H. Friedman. Greedy Function Approximation : A Gradient Boosting Machine 1 Function estimation 2 Numerical optimization in function space. *North*, 1(3):1–10, 1999. ISSN 00905364. doi: 10.2307/2699986. URL http://www.jstor.org/stable/2699986.

Juan Carlos Garzon, María Victoria Llorente, and Manuela Suárez. ¿Qué hacer con la reincidencia delincuencial? El problema y sus posibles soluciones. Technical report, Fundación Ideas para la Paz, Bogota, 2018. URL http://cdn.ideaspaz.org/media/website/document/5ae0ab974baff.pdf.

William H. Greene. *Econometric analysis*, volume 3. Prentice Hall, 1997. ISBN 978-0-02-346602-1. doi: 10.1198/jasa.2002.s458.

Trevor Hastie, Robert Tibshirani, and J. H. (Jerome H.) Friedman. *The elements of statistical learning : data mining, inference, and prediction.* Springer, second edition, 2009. ISBN 9780387848570.

Tin Kam. *Proceedings of the third International Conference on Document Analysis and Recognition : August 14-16, 1995, Montréal, Canada.* IEEE Computer Society Press, 1995. ISBN 0818671289. URL `https://dl.acm.org/citation.cfm?id=844379.844681`.

Kan Nishida. Introduction to Extreme Gradient Boosting in Exploratory, 2017. URL `https://blog.exploratory.io/introduction-to-extreme-gradient-boosting-in-exploratory-7bbec554ac7`.

Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer. Prediction Policy Problems. *American Economic Review*, 105(5):491–495, may 2015. ISSN 0002-8282. doi: 10.1257/aer.p20151023. URL `http://pubs.aeaweb.org/doi/10.1257/aer.p20151023`.

Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan. Human Decisions and Machine Predictions*. *The Quarterly Journal of Economics*, 133(1):237–293, aug 2017. ISSN 0033-5533. doi: 10.1093/qje/qjx032. URL `http://academic.oup.com/qje/article/doi/10.1093/qje/qjx032/4095198/Human-Decisions-and-Machine-Predictions`.

Author Max Kuhn, Jed Wing, Steve Weston, and Andre Williams. The caret Package, 2007. URL `http://topepo.github.io/caret/index.html`.

Llew Mason, Jonathan Baxter, Peter Bartlett, and Marcus Frean. Boosting Algorithms as Gradient Descent in Function Space. *Advancies in neural information processing systems*, 1999. URL `http://maths.dur.ac.uk/{~}dma6kp/pdf/face{\_}recognition/Boosting/Mason99AnyboostLong.pdf`.

Paul E. Meehl. *Clinical versus statistical prediction: A theoretical analysis and a review of the evidence.* University of Minnesota Press, Minneapolis, 1954. doi: 10.1037/11281-000. URL `http://content.apa.org/books/11281-000`.

Benjamin Monnery. The determinants of recidivism among ex-prisoners: a survival analysis on French data. *European Journal of Law and Economics*, 39(1):37–56, feb

2015. doi: 10.1007/s10657-014-9442-3. URL http://link.springer.com/10.1007/s10657-014-9442-3.

Mary D. Nettleman. Receiver Operator Characteristic (ROC) Curves. *Infection Control and Hospital Epidemiology*, 9(8):374–377, aug 1988. ISSN 0899823X. doi: 10.2307/30145466. URL https://www.jstor.org/stable/info/10.2307/30145466.

Lloyd E. Ohlin and Otis Dudley Duncan. The Efficiency of Prediction in Criminology. *American Journal of Sociology*, 54(5):441–452, mar 1949. ISSN 0002-9602. doi: 10.1086/220398. URL https://www.journals.uchicago.edu/doi/10.1086/220398.

Felix Salfner, Maren Lenk, and Miroslaw Malek. A survey of online failure prediction methods. *ACM Computing Surveys*, 42(3):1–42, mar 2010. doi: 10.1145/1670679.1670680. URL http://portal.acm.org/citation.cfm?doid=1670679.1670680.

Krzysztof Siwek and Stanisław Osowski. Data mining methods for prediction of air pollution. *International Journal of Applied Mathematics and Computer Science*, 26(2):467—-478, jan 2016. ISSN 2083-8492. doi: 10.1515/amcs-2016-0033. URL http://content.sciendo.com/view/journals/amcs/26/2/article-p467.xml.

Clifton D Sutton. Classification and Regression Trees, Bagging, and Boosting, 2004. ISSN 01697161. URL http://mason.gmu.edu/{~}csutton/vt6.pdf.

The Economist. How data-driven policing threatens human freedom - Open Future, 2018. URL https://www.economist.com/open-future/2018/06/04/how-data-driven-policing-threatens-human-freedom?cid1=cust/ddnew/email/n/n/2018065n/owned/n/n/ddnew/n/n/n/nLA/Daily{_}Dispatch/email{\&}etear=dailydispatch{\&}utm{_}source=newsletter{\&}utm{_}medium=email{\&}utm{_}campaign=Dai.

Santiago Tobón. Three Essays on Crime Policy and Development -Poor Prison Conditions, Human Capital and Recidivism. 2017. URL https://papers.ssrn.com/sol3/papers.cfm?abstract{_}id=2921477.

Jeffrey M. Wooldridge. *Introductory econometrics : a modern approach*. South-Western, fourth edition, 2009. ISBN 130527010X.