Reimagining the Justice System After Incarceration

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Abstract
Criminal justice reform is one of the most topical issues in the United States today. Half of the people released from prison return within three years. There must be a change to help people re-enter society after being released. In order to see what factors are most important in classifying who returns to prison, I utilize two models: logistic and support vector machine. I found that the model's two most important variables related to a job. This finding provided support for the “ban the box” policy.

Introduction:

Criminal justice reform is a topical issue in the United States. Almost two million people are incarcerated in the United States (Wagner, n.d.). Of those nearly two million, fifty-five thousand are serving life in prison sentences (Nellis, 2022). That means that most people currently incarcerated will be released in the future. With that being said, the United States Sentencing Commission found that in 2010 around half of the people released from prison were rearrested, a pattern that has stayed consistent with previous cohorts (United States Sentencing Commission, 2021). This in itself is alarming, but it is primarily given that one of the criminal justice system's four goals is rehabilitation. Unfortunately, the criminal justice system fails half of those who go through it. To reform the system, we must see what is not working. We need to see which variables account for someone returning to prison. I will analyze what variables best predict recidivism, guided by my research question: What factors account for recidivism after release? Doing this will help direct focus on which areas need special support when developing and funding a reentry program to best help those reentering society.

Background:

Many studies have looked at individual factors' effects on reentry. One factor that has gotten much attention is education. Education programs have successfully reduced recidivism in many areas where they have been implemented. One prominent initiative is the Bard Prison Initiative (BPI) in New York. (Spivey-Jones, 2022). BPI provides education for associate's degrees and bachelor's degrees. In 2022, they said that only 8.7% of students who earn associate degrees will be re-arrested, which falls to 3.1% when participants get their bachelor's degrees. Studies like Fogarty & Giles examination of education and recidivism in the United States have also reinforced these findings and shown that education still reduces recidivism even when it is a basic to secondary education program (Fogarty & Giles, 2018). This study reaffirms previous studies' findings while building on the findings by taking publication bias into account. This study was done well; however, to fully understand what makes a successful re-entry, one must focus on more than just education.

Another factor that is heavily analyzed in a recidivism context is housing security. One study conducted by Jacobs & Gottlieb based in San Francisco found that housing factors throughout probation predicted recidivism for the individual (Jacobs & Gottlieb, 2020). This study was good; however, the data was only from people in San Francisco, so it may only apply to some places. Another issue is that many people with secure housing, once released from prison, return to the areas they were arrested in because that is where their families are. A pilot study was conducted in Maryland called MOVE to address this (Kirk et al., 2017). In this study, there were three groups. One group received free housing away from their prior location; one moved from their prior location without costs paid for, and the control group. They found that recidivism was lowest in the group that received free housing away from their prior location and was lower in the group that just moved away compared to the control. However, this study only had 30 participants between the two groups and 30 in the control so the results may not be accurate when looking at a larger population.

One final factor that is examined is employment's effect on recidivism. A study conducted by Skardhamar and Telle in 2012 looked at reentry in Norway and found that obtaining employment after release does reduce recidivism (Skardhamar and Telle). This theory has been projected onto United States prisons a lot, with most people citing this article; however, prisons in Norway are vastly different from the United States, so it may not be accurate to cast those findings onto a US population. With this being said, a similar study was conducted in the United States, not with work after incarceration but a work history before incarceration. They found that recent work history reduces recidivism (Kolbeck, Bellair, & Lopez 2022). These findings were not what the authors initially intended to look at since their research question was to see if race was a moderating factor between employment and recidivism.

Data:

I will use the National Institute of Justice data on the Office of Justice Programs website. The dataset is called the "NIJ's Recidivism Challenge Full Dataset," and it contains almost 26,000 observations, where each observation is a person (NIJ, 2021). It was added to the Office of Justice's registry of datasets on July 15th, 2021, and was last revised that day. It has just over 50 variables. Some interesting variables include gender, education level, if they were gang-affiliated, prior arrests and convictions for different crimes, if they have changed residences, how many jobs they have had, if they had been rearrested within one, two, or three years, and many other interesting variables. One limitation of this dataset is that it has been shown that recidivism is reduced when individuals move to a different area after incarceration; however, no variable captures that in this data.

Table One

	Count	Mean	Std	Min	25%	50%	75%	Mmax
Recidivism within three years	25835.0	0.577	0.494	0.0	0.0	1.0	1.0	1.0
Prior Probation Revocations	25835.0	0.146	0.353	0.0	0.0	0.0	0.0	1.0
Prior Parole Revocations	25835.0	0.096	0.294	0.0	0.0	0.0	0.0	1.0
Domestic Violence Charges	25835.0	0.165	0.371	0.0	0.0	0.0	0.0	1.0
Gang Affiliated	25835.0	0.152	0.359	0.0	0.0	0.0	0.0	1.0
Gender Male	25835.0	0.877	0.328	0.0	1.0	1.0	1.0	1.0
Supervision Risk Score	25360.0	6.082	2.381	1.0	4.0	6.0	8.0	10.0
Percent Days Employed	25373.0	0.482	0.425	0.0	0.0	0.476	0.969	1.0

Table One shows descriptive statistics for some of the variables that will be significant concerning recidivism. Each variable is binary except for Supervision Risk Score, a discrete variable up to 10. Looking at the means, we see that the data is about 87% male with an average risk score of six. We can also see that 15% of individuals have prior probation revocations, domestic violence charges, and gang affiliation. The count for supervision risk score and percent days employed seems about 500 observations smaller than other variables, which indicates missing values; however, not enough to be significant. Finally, about 57% of people return to prison after three years, which aligns with the national recidivism rate.

Table Two

	Count	Unique	Top	Freq
Age at Release	25835	7	23-27	5176
Race	25835	2	BLACK	14847
Supervision Level First	24115	3	Standard	9983
Education Level	25835	3	High School Diploma	11390
Dependents	25835	4	0	8037
Prison Offense	22558	5	Property	8284
Prison Years	25835	4	1-2 years	8084
Prior Arrest Felony	25835	11	Ten or more	6140
Prior Arrest Violent	25835	4	0	11049

Table Two shows the descriptive statistics for categorical variables of interest, specifically their unique values, top value observed, and frequency of the top value observed. Interestingly, there were only two unique values for race in this data. Further investigation found that it was encoded as either Black or White. This categorization could be an issue if this model were used for other data that included other identities. In this data, Black is the top identity, with just under 15,000 individuals identifying as Black.

Table Three

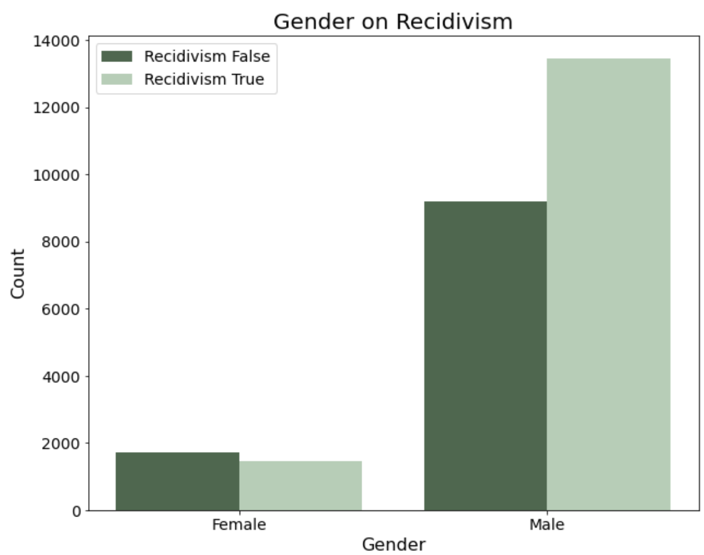
Education Level	Count
Less Than High School Diploma	9840
High School Diploma	11390
At Least Some College	4605

Education has proved to be a factor in recidivism, so I included table three which shows an individual count of each education level. The most common level of education was less than high school, and the least common education level was at least some college.

Table Four

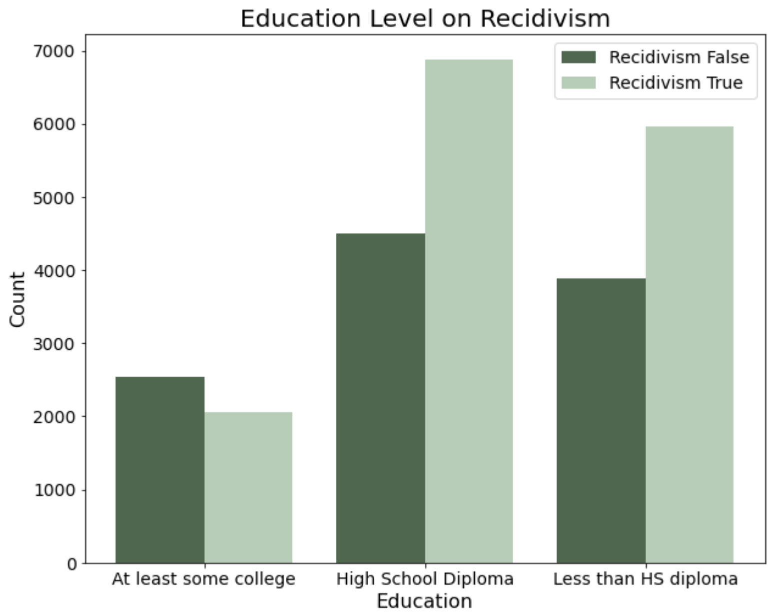
Prison Offense	Count
Property	8284
Violent/Non-Sex	5475
Violent/ Sex	830
Drug	5190
Other	2779

When looking at prison offense, I wanted to ensure that all had a significant number of observations. Table 4 shows the count of each offense in the data set. Violent/ Sex has the least; however, it still has a significant amount.



Graph One

Initial exploration for gender and recidivism is shown in graph one. There are significantly more men incarcerated, and men's recidivism rate is higher than women's. Initial exploration for education level and recidivism is shown below in graph two. There are more incarcerated people with a high school diploma or less, and recidivism rates are higher than at least some college education.



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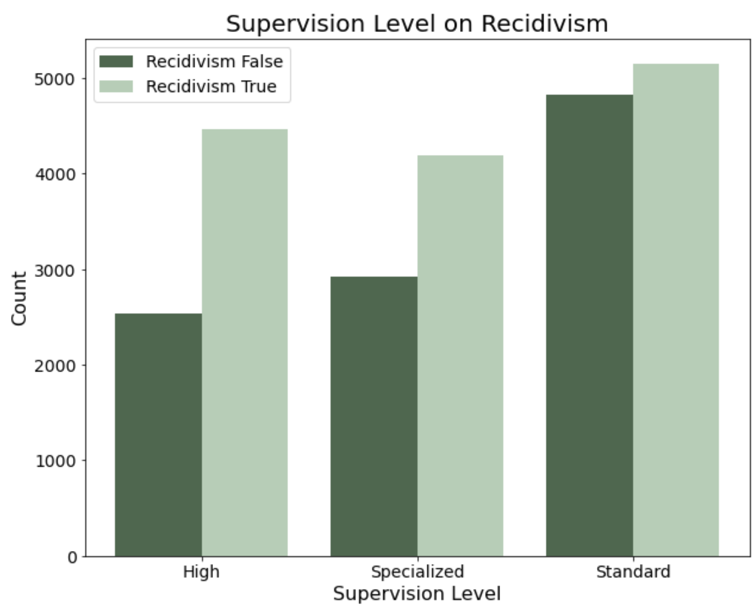
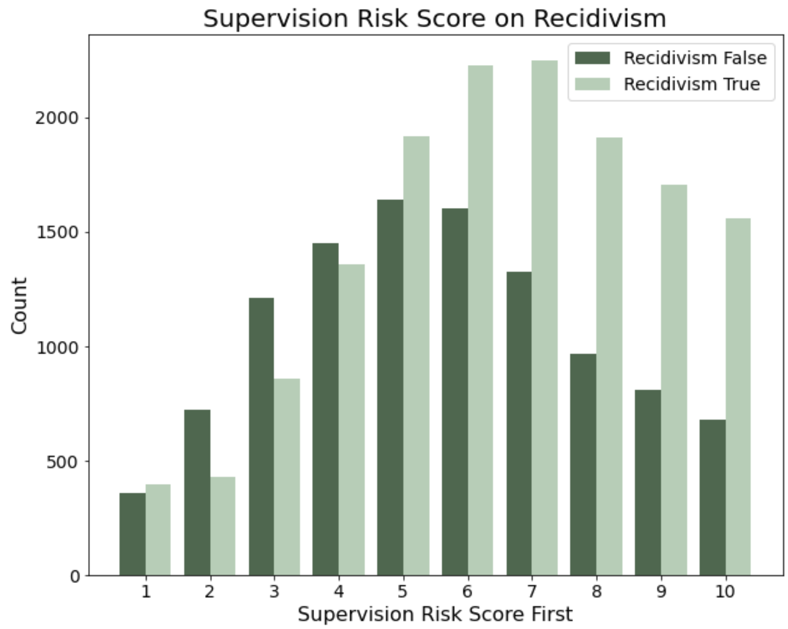
Graph Two



Graph Three

Initial exploration for supervision level and recidivism is shown in graph three. There is the smallest gap between the count of people who return to prison and those that do not at the standard supervision level. The most significant gap is in high supervision. More people return to prison at all levels than those who do not.



Graph Four

Initial exploration for supervision risk score and recidivism is shown in graph four. Seemingly, individuals with higher risk scores return to prison more often than those with lower risk scores.

Methodology:

To see what factors greatest impact recidivism, I first need to estimate a model that classifies whether or not someone returns to prison. For this model, the target variable is Recidivism within three years. In order to classify individuals, I am going to use variables that have been proven to reduce recidivism, including education level and percentage of time employed. I will also use the variables gender, supervision risk score, and prison offense to determine outcome as well.

I plan on using a logistic regression for my parametric model. Logistic regression is a supervised learning method that uses maximum likelihood to estimate the class. When doing this, the model finds the probability of the dependent variable being true given the independent variables. Since I am trying to infer which individuals return to prison, and the outcome is a binary true or false, that is the best parametric method. There was a study done in 2013 that predicted burglary using logistic regression (Antolos et al., 2013). They predicted occurrence probability based on factors like day of the week, time of day, and repeated victimization. Their model had varying significance depending on the distance from the epicenter. Another study compared models when predicting criminality and found that a logistic regression performed best (Tollenaar & van der Heijden, 2012). Therefore, using this model to determine class will be an excellent parametric model.

For my non-parametric model, I will use Support Vector Machine (SVM). Support vector machine is a model that uses training instances called support vectors to distinguish between the classifications for the dependent variable with the goal of maximizing the distance between the two classifications. I chose this model because of its ability to quantify uncertainty. Since there is a probability that an individual does not go back to prison, quantifying uncertainty is essential. This model was also used in the earlier study comparing models and performed well (Tollenaar & van der Heijden, 2012). A separate study used SVM to predict recidivism in 2010 (Wang et al., 2010). In this study, they used nine variables, including race, alcohol use, and marital status, to predict recidivism on a data set of about 1500 observations, and the model performed well. Given my variables, these are the two best methods to use for inferring if someone goes back to prison.

I began by hand-picking variables through domain knowledge and a literature review for each model. I picked the variables: gender, dependents, prior parole revocations, prior probation revocations, age at release, supervision risk score, supervision level, education level, prison years, prior felony arrests, prior misdemeanor arrests, program attendances, and percent days employed. Using these variables, I ran the model to determine the model's baseline scores. After this, I scaled the variables since there was a mix of binary variables and variables ranging from one to over ten. I re-ran the models with the scaled data and saw an improvement in the accuracy of the model. Then, I used the sci-kit learn feature selector to choose a number of variables ranging from two to fifteen. I found that the models that performed the best were when it picked ten variables. The variables picked were: gender, age at release, gang affiliated, prior misdemeanor arrests, prior property arrests, prior parole violations, mental health/ sexual assault condition, positive THC drug test, percent days employed, and jobs per year. After this, I re-ran the models with these variables scaled as the scaled variables performed better in the hand-picked variable models.

Once this was finished, I determined the feature importance in the highest-performing model by calculating the score, accuracy, and recall of the full model, then iterating through, removing one column and recalculating each score. I subtracted the new score from the score of the full model to get the effect without that column.

Results:

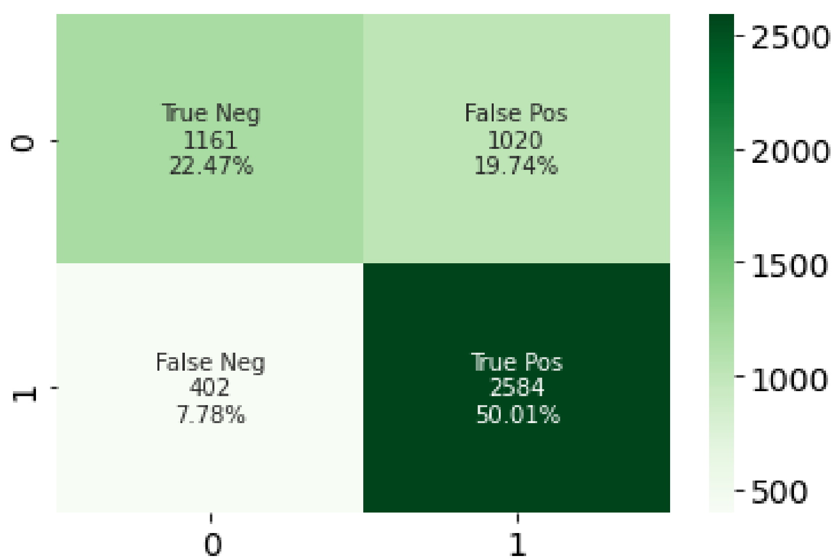
Two of the main metrics for model evaluation that I utilized were accuracy and recall. Accuracy is the proportion of times the model correctly identified the recidivism outcome. Recall is the number of times the model correctly identified an individual going back to prison over the total number of instances in the data where someone goes back to prison (this includes instances where the model was correct and incorrect in its classification). The initial results of the model's score and accuracy using scaling are shown in Table five below.

MODEL	HAND-PICKED LOGISTIC REGRESSION	HAND-PICKED SVM	AUTO-SELECTED LOGISTIC REGRESSION	AUTO-SELECTED SVM
ACCURACY	.678	.694	.707	.725
RECALL	.795	.838	.813	.865

Table Five

The results show that the auto-selected variable models outperformed the hand-picked models in both logistic regression and support vector machine. The SVM model also outperformed the logistic regression in both the hand-picked and auto-selected models. Therefore, the best model was the auto-selected SVM model, with an accuracy score of .725 and a recall score of .865.

Another important model evaluation I utilized was each model's confusion matrix. The confusion matrix shows the instances where the model was correct and the number of falsely classified instances. The confusion matrix for the auto-selected support vector machine is shown below.



Graph Five

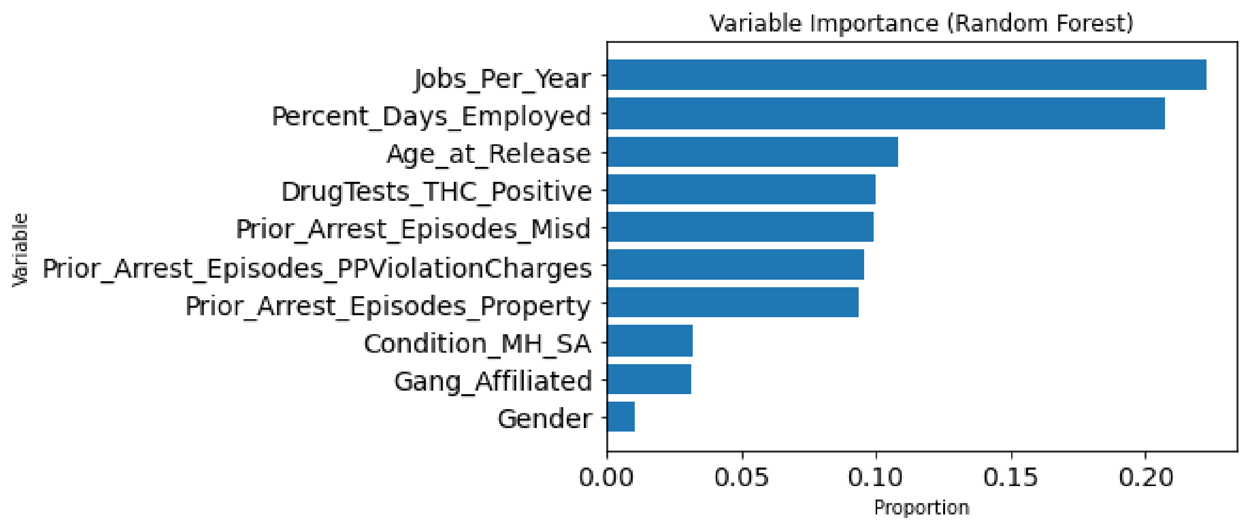
The 50% of the model's identification is true positive instances where the individual returns to prison. It could better identify true negative instances, as it misses about half of true negatives. Since this model is not used to determine who is released from prison but to identify what features may cause someone to return, identifying true positives is more important than overall accuracy. Thus, this model is adequate to look at feature importance for recidivism.

Since the auto-selected SVM performed the best, I used this model to calculate the feature importance for recall, accuracy, and precision. Precision is the proportion of true recidivism cases that were identified correctly. These results are compiled into Table six, shown below.

COLUMN NAME	RECALL	ACCURACY	PRECISION
JOBS PER YEAR	.0311	.0250	.0147
PERCENT DAYS EMPLOYED	.0224	.0414	.0338
AGE AT RELEASE	.0114	.0121	.0084
MENTAL HEALTH/ SEXUAL ABUSE CONDITION	.0084	.0039	.0009
PRIOR PROPERTY ARRESTS	.0077	.0100	.0076
THC POSITIVE DRUG TESTS	.0067	-.0009	-.0034
PRIOR MISDEMEANOR ARRESTS	.0037	.0021	.0009
PRIOR PAROLE VIOLATION CHARGES	0.000	.0074	.0075
GENDER	-.0003	.0017	.0020
GANG AFFILIATED	-.0057	.0006	.0026

Table Six

This table is sorted in descending order by recall score. We can see that the two most significant variables across recall, accuracy, and precision are jobs per year and percent days employed. I also used the random forests feature importance on the auto-selected variables to ensure these findings were sound. The results are shown in the graph below.



Graph Six

This graph also has jobs per year and percent days employed as the top two important variables. It also has a similar order to the order in Table six, showing that the findings are sound for this data.

Discussion:

The feature importance in SVM and random forest showed that jobs per year and percent days employed were the most important variables. For SVM, it changed the model accuracy by .02 and .04, respectively. When looking at random forest, the proportion was over .20 for both variables. This is interesting because these are two variables indicating employment status. Not only this, but these variables were significantly more important than any of the other variables. This shows the importance of obtaining a job after being released from prison. When reimagining incarceration, we must think about programs and policies that will better serve rehabilitation. With this in mind, one policy we can consider is ‘ban the box.’ Ban the box is a policy that aims to eliminate the box on applications where someone has to check if they have been incarcerated. There is a stigma around incarceration, so many people see that box checked in the initial application and do not want to give people formerly incarcerated the chance to work, so they will not receive an interview. Eliminating this box would give more people a fair chance when searching for jobs after incarceration. Since we can see a significant relationship between employment and recidivism, looking at programs and policies, like ban the box, that promote more accessible access to jobs post-incarceration should be at the forefront of lawmakers' agendas.

There are some limitations regarding the data that was used. The first limitation is that variables known to be significant were not included in the dataset. For example, receiving an education while incarcerated and moving away from the area where they were arrested after release are two variables known to be significant but not included in the dataset.

Additionally, this study looked at the important features for recidivism using a federal incarceration database. Future research could involve similar methods while looking at data on a state level. Ban the box is a policy implemented by each state, so it may be more compelling to see if this trend can be seen in state-level data when advocating for a policy at the state level.

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