Unlocking Opportunities: A Blueprint for Implementing a Recidivism-Reducing Algorithm in Job-Training Selection for Ex-Offenders.

Highlights:

* The city decided to allocate job-training resources for ex-offenders as a solution to prison overcrowding, but currently has no system in place to decide who receives these resources.
* We recommend the implementation of our new algorithm as an equitable and economical way to decide which ex-offenders the city should allocate job-training resources to.
* Upon analysis of the economic and social costs at both the individual and societal level, we found that the benefits outweigh the potential costs of implementing this algorithm.

Background:

Ever since the War on Crimes, War on Drugs and other tough-on-crime strategies were implemented, incarceration rates in the US have skyrocketed (1). As a result, prisons all over the country face the consequences of overcrowding. The shortage of already little resources that prisons can provide incarcerated individuals are exasperated by this, stripping people in custody of any chance to gain the skills necessary to reenter mainstream society and avoid recidivating.

Our city responded by creating a job-training program for ex-offenders, offering them tools to prevent re-offending. The program includes resume-writing, interview techniques, specific job-related technical skill teachings, and networking events with local organizations and companies. Many ex-offenders were already unemployed before being arrested due to factors including low levels of education and family background, making this program an essential part in ending the cycle of unemployment and crime.

Research has found that vocational training programs do not work on all ex-offenders, they tend to work better on non-violent offenders (2). How do we ensure that we enroll the people who are most receptive and have the highest likelihood of successfully completing the job-training program? We propose our algorithm as a solution.

The Algorithm:

Data for the algorithm comes from COMPAS, including information from 6,162 ex-offenders with features such as demographics like age, sex, and race in addition to details about their crime and time in prison. Taking these and other features of an individual as input, our algorithm gives us a simple output: a “yes” or “no” to the question, “Is this person very likely to recidivate?”

The algorithm is based on a model which helps us figure out the likelihood of an event by using an S-shaped curve that begins flat at a zero value, rises steeply in the middle, and settles at a value of one (with zero being “no” and one being “yes” for the question above). The model predicts everyone to be on some part of this line, so the final decision we needed to make about the model is where to mark the threshold, or decision boundary on this S-curve for which all the points above it would be categorized as “yes”, and the rest are categorized as “no”.

Cost-Benefit Analysis:

Though we care about the algorithm’s accuracy, we argue that it’s more important for it to accurately predict the people who don’t recidivate because those are the people we will be providing job-training resources to. If the model predicted that someone will not recidivate but they actually do, that would not only mean that the city resources we spent for this person would go to waste (about $5,000 per person), but that we would also be paying more to keep this person in prison (national average of $43,716 per year) in addition to the costs of the crime they commit (average of $109,682). On the other hand, if the model had predicted that someone was likely to recidivate, but it turns out that this person wouldn’t have, we would again be spending money on keeping this person incarcerated ($43,716), but the greater social cost is that this individual will now lose years of their life in prison and have a much more difficult time reentering society, altering their whole course of life (median yearly income of $57,537, assuming 3% income tax, $1,726).

With these values in mind, we can explore a simple cost-benefit analysis (see table 1). If we stick with the default threshold value of 50% for our model, we would see 418 people who are categorized as high risk of recidivating who end up recidivating, 204 people who are high risk and did not recidivate, 285 people who are low risk and recidivated, and 633 people who are low risk and did not recidivate (see figure 1). Equation 1 shows the breakdown of how this would result in a net loss of $99,601,347 per year, compared to imprisoning everyone which would cost $257,515,720.

Recommendations:

We found that the optimum threshold value is 55%, where the total cost is $45,695,562 while also maintaining a model accuracy of around 69% for all racial groups (see figure 2). One problem we found in our model is that the algorithm disproportionately discriminates against Black ex-offenders. Compared to other racial groups, the model predicts a larger proportion Black ex-offenders to be high risk. The 55% threshold seems to balance out the racial disparities, but they do still exist. We recommend the use of this algorithm in combination with human specialists who can mitigate the racial bias of this algorithm.

Overall, this algorithm would reduce the amount of time that a human would spend sorting through various cases to decide who should receive the job-training resources, while also optimizing government spending. The model’s racial bias is a mitigable issue and a human specialist would be able to catch small errors that a model cannot fully capture.

Sources (not part of official document):

1. Hodge, J. and Dholakia, N. (2021). Fifty Years Ago Today, President Nixon Declared the War on Drugs. Vera Institute of Justice, vera.org, June 17. <https://www.vera.org/news/fifty-years-ago-today-president-nixon-declared-the-war-on-drugs>
2. Bollinger, C.R. and Yelowitz, A. (2021). Targeting Intensive Job Assistance to Ex-Offenders by the Nature of Offense: Results from a Randomized Control Trial. Institute of Labor Economics (IZA), Discussion Paper Series, IZA DP No. 14078, January. <https://docs.iza.org/dp14078.pdf>
3. McCollister, K.E., French, M.T., Fang, H (2010). The Cost of Crime to Society: New Crime-Specific Estimates for Policy and Program Evaluation. Drug Alcohol Depend. April 1; 108(1-2): 98–109. doi:10.1016/j.drugalcdep.2009.12.002. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2835847/pdf/nihms170575.pdf>
4. Prison Policy Initiative. Economics of Incarceration: The economic drivers and consequences of mass incarceration. <https://www.prisonpolicy.org/research/economics_of_incarceration/>

Table 1. Financial Cost of Predicted and Real Recidivism (immediate + 1 year in)

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| --- | --- | --- |
|  | High risk of recidivating | Low risk of recidivating |
| Recidivated | Prison TP  -$43,716 | Program costs, cost of crime, prison FN  -$5,000 + -$109,681 + -$43,716 = -$158,397 |
| Did not recidivate | Prison, lost income tax FP  -$109,681 + -$1,726= -$167,218 | Program costs, income tax from job revenue TN  -$5,000 + $1,726 = -$3,274 |

Note: We assume that the job-training program costs $5,000 per capita, crimes cost an average of $109,682 per unit crime, keeping someone imprisoned for a year costs $43,716, and the income tax revenue from a yearly median household income of a Philadelphian is $1,726.

Formula 1: 418\*-$43,716 + 204\*-$167,218 + 285\*-$158,397 + 633 \* -$3,274 =-$99,601,347.

