Predicting Post-Release Interactions with Mental Health Systems

Project Repository: https://github.com/dssg/stablegeniuses-mlpp2018

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SUMMARY

Potentially thousands of people are released from our Nation's jails and prisons every day with undetected and untreated mental health disorders. While re-entry is challenging for any inmate, it is particularly so for these individuals. Two-thirds of released inmates with severe mental illnesses are either rearrested or hospitalized within 18 months of their release.[1] Our paper seeks to help Johnson County jail identify released inmates who will have an interaction with the mental health system within a year of release in order to provide specialized services and programs to help these individuals successfully reintegrate into society.

1. BACKGROUND & INTRODUCTION

In the United States, it's estimated that 2 million individuals experiencing severe mental illnesses are booked into jails every year.[2] That number dwarfs the number of seriously ill individuals admitted into state psychiatric services: county jails and state prisons house 10 times more individuals with serious mental illnesses than do state psychiatric hospitals.[3] In 44 of the 50 states, a prison or jail is the single largest 'mental institution.'[4]

To their credit, prison and jail systems in the United States have largely adopted best practices for screening inmates for mental health disorders at intake; however, recent studies have found these guidelines have poor rates of detection, including one study that found that only 32.5% of inmates with severe mental illnesses are detected at intake.[5]

This creates two issues – county jails like Johnson County jail are likely to house inmates with undiagnosed mental health disorders, whose problems may consequently worsen; and thousands of people with undetected and untreated mental health disorders are released daily from jails back into their communities, which may be unprepared to deal with the additional strain on their resources.

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[1] Hartwell, S. PhD. (2008). Community Reintegration of Persons with SMI Post Incarceration. *Center for Mental Health Services Research, Department of Psychiatry University of Massachusetts Medical School.* Retrieved from: https://www.umassmed.edu/globalassets/center-for-mental-health-services-research/documents/products-publications/issue-briefs/human-rights/community-reintegration-of-persons-with-smi-post-incarceration.pdf

[2] Hutton, M. (2017). *The Lack of Federal Funding for Mental Health and the Criminalization of Mental Illness*. Psyche. Retrieved from: https://psyche.media/the-lack-of-federal-funding-for-mental-health-and-the-criminalization-of-mental-illness

[3] AbuDagga, A., Carome, M., Fuller Torrey, E., Phatdouang, A., & Wolfe, S. (2016). Individuals with Serious Mental Illnesses in County Jails: A Survey of Jail Staff's Perspectives. *Public Citizen and The Treatment Advocacy Center*. Retrieved from: http://www.treatmentadvocacycenter.org/storage/documents/jail-survey-report-2016.pdf

[4] Insel, T. (2014). A Misfortune, Not a Crime. National Institute for Mental Health. Retrieved from: https://www.nimh.nih.gov/about/directors/thomas-insel/blog/2014/a-misfortune-not-a-crime.shtml

[5] Colman, I., Martin, M., McKenzie, K., & Simpson, A. (2013). Mental Health Screening Tools in Correctional Institutions: A Systematic Review. *BMC Psychiatry* 13:275. Retrieved from: https://bmcpsychiatry.biomedcentral.com/articles/10.1186/1471-244X-13-275

2. RELATED WORK

A significant amount of effort has been dedicated to identifying, diverting, or treating people with mental health disorders in order to prevent recidivism. In particular, several studies have tried to predict the relationship between recidivism rates and mental health interventions, including: the impact of mental health courts in reducing recidivism rates,[6] how wraparound services mitigate recidivism,[7] and predicting recidivism based on mental health diagnosis and race.[8] Additionally, a separate machine learning analysis using this same data focused on identifying individuals with mental health disorders prior to an interaction with the criminal justice system.[9]

Our analysis fills a small gap within this field of study. Comparatively little research has been done to understand how likely a recently released inmate is to access mental health services. Understanding which released inmates will access mental health services post-release will allow for more targeted interventions that could help smooth out the re-entry process for these individuals and reduce recidivism.[10]

3. PROBLEM FORMULATION & SOLUTION OVERVIEW

Our project attempted to build a model that can be used to identify people in the Johnson County jail system who are at risk of entering the county mental health system after their release from jail. Our goal was to identify inmates who would enter the county mental health system within one year of their release, based on information available to the jail system at the time of their release.

4. DATA DESCRIPTION

Our focus is on data held by Johnson County on inmates at the time of their release from jail.

Our outcome label depends on whether or not an individual goes on to access mental health services in the year after their release from jail.

We focus on data contained in the 'bookings' table; each row represents an instance of an inmate being released from jail. This means that individuals are represented multiple times in the table. Since the bookings represent different points in time, the data for individuals change from booking to booking, so we focus on individual bookings, rather than individuals. Since we are interested in

[6] Binder, R. & McNiel, D. (2007). Effectiveness of a Mental Health Court in Reducing Criminal Recidivism and Violence. *The American Journal of Psychiatry*, 164:9, 1395-1403.

[7] Gaylor, R., Kerbs, J., Koroloff, K., Pullmann, M., Sieler, D., & Veach-White, E. (2006). Juvenile Offenders with Mental Health Needs: Reducing Recidivism Using Wraparound. *Crime & Delinquency*, 52:3, 375-397.

[8] Forehand, R, & Wierson, M. (1995). Predicting Recidivism in Juvenile Delinquents: The Role of Mental Health Diagnoses and the Qualification of Conclusions by Race. *Behavior Research and Therapy*, 33:1, 63-67.

[9] Bauman, M., Boxer, K., Ghani, R., Haynes, L., Helsby, J., Lin, T., Naveed, H., Salomon, E., Schneweis, C., Sullivan, R., & Yoder, S. (2017). Reducing Incarceration Through Prioritized Intervention. Retrieved from: https://dssg.uchicago.edu/wp-content/uploads/2017/03/reducing-incarceration-prioritized.pdf

[10] Hartwell, S. PhD. (2008). Community Reintegration of Persons with SMI Post Incarceration. *Center for Mental Health Services Research, Department of Psychiatry University of Massachusetts Medical School.* Retrieved from: https://www.umassmed.edu/globalassets/center-for-mental-health-services-research/documents/products-publications/issue-briefs/human-rights/community-reintegration-of-persons-with-smi-post-incarceration.pdf

making a prediction at the time of release from jail, we are able to make use of all of the information contained in each row.

We join this table on the county mental health table to obtain information on every individual's mental health history, if any. We then get mental health information for every individual prior to their release date.

Our data ends in 2016; since this is the last year we have labeled outcomes, we reserve the data from 2015 for our test set and use data from 2010 - 2014 for our training sets.

The 2010-2014 training data comprises 21749 "release events". Approximately 3% of those released go on to access county mental health services within a year of their release.

5. METHODS

5.1 Features

We generate features based on information available about a given inmate at the time of their release. This includes information about the circumstances of their arrest and booking, including the type of case (whether criminal, juvenile, or domestic-violence related), the date of their arrest, whether they made bail (and the amount, and who posted bail), and the agency responsible for the arrest, among others. Using an inmate's history in the jail system (prior to a specific release event), we generated features tracking the number of times they had been in jail previously and the amount of time they had spent in jail.

We also included features based on basic demographic information collected during the intake process (race, gender, age, location, among others). This information is available for virtually every "release event" (although residence information is missing for about 1600 residents).

We also make use of information gathered from the "Level of Service Inventory - Revised", a questionnaire administered to inmates at intake. This data is available for nearly 8000 inmates.

Finally, we incorporated information on an inmate's history with the mental (prior to a specific release event). We generated features based on the number of times the inmate had accessed the mental health system previously and the amount of time they spent in the system. We also included information on an inmate's past diagnoses and the source of their referral to the mental health system. Of the rows in our training set, 4231 are associated with past mental health data.

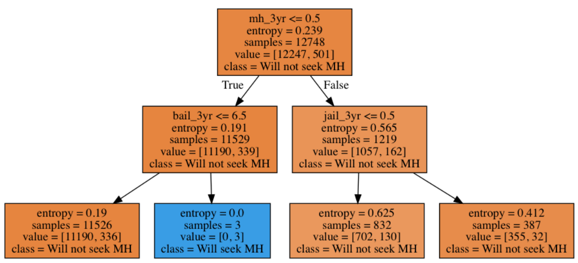
5.2 Model Selection & Evaluation Methodology

Johnson County had resources to pilot an intervention program for the 200 riskiest individuals for their recidivism prevention program; we will use this number as a reference for a comparable, hypothetical program aimed at mental health interventions.

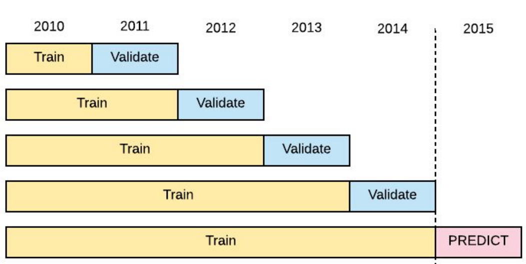
Since the resources available for targeted individual services are limited, we need to prioritize precision when selecting a model.

We needed to establish a baseline comparator to evaluate the usefulness of the model. We used two different methods for such a comparator. First, we built a naïve model that predicted that individuals would enter the mental health system after their release from jail if they had any contact with the mental health system in the previous three years. Second, we built a simplified version of our full model by creating a two level decision tree using only basic features involving contact with both the county jail and mental health systems.

The classification using the simple decision tree is shown below.



Given data on 2010 to 2015, we reserve the final year of data to make a final prediction. We train each of the models across successively increasing time chunks, validating them using one year of data immediately following the training period. This framework enables us to detect changes in model performance over time and anomalies for any given testing period.



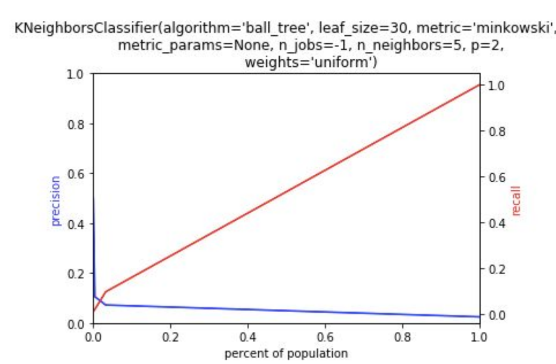
We notice that the baseline decreases for later time periods, and performance of our models is impacted as a result.

Validation Set	Baseline	Mental Health	Simple Tree
2011	3.4	15.5	15.5
2012	2.2	17.6	14.3
2013	1.3	4.6	4.6
2014	1.3	4.3	4.3
2015	2.4	7.9	7.9

6. EVALUATION

When selecting models, we prioritize those with precision at the top 50% of the highest performing models at our metric of interest, which is precision at 5%. Given that each validation set contains approximately 4000 releases, the top 5% yields roughly the top 200 riskiest individuals targeted for intervention.

Our highest performing model trained on our full data from 2010 to 2014 and validated using 2015 data is K-Nearest Neighbors with 5 neighbors. 25% of its predictions are accurate when we intervene on the top 5%. This is 10 times as accurate as a random intervention and 3 times as accurate as the simple models' predictions.



The following table summarizes the mean precision and AUC-ROC of each of the models we have tested.

Model Type	Precision at Top 5%	AUC-ROC
AB	11.2	0.57
DT	13.3	0.55
KNN	13.0	0.58
LR	13.6	0.56
RF	10.1	0.6

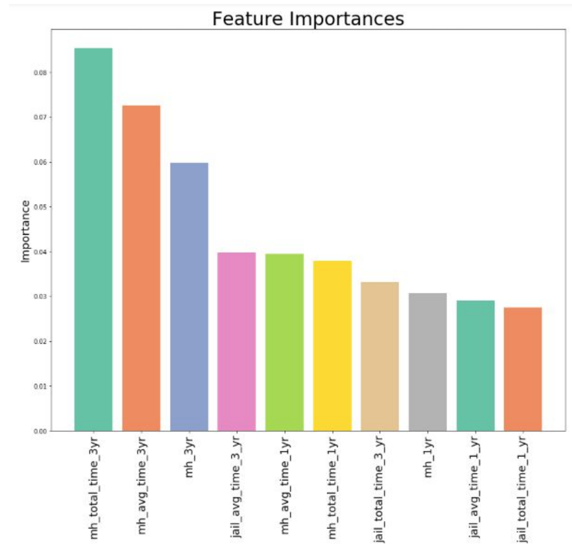
We found that Decision Trees and Logistic Regression lead to few distinct risk scores and are not suitable for our analysis if we aim to consistently classify individuals based on a relative ranking of their risk score. Ensemble methods like boosting and random forests mitigate this problem to an extent and yield predictions with lower variance.

While random forest has a lower precision compared to other models, its high AUC-ROC score suggests it may be a good model to use if Johnson County were to expand its resources to intervene on a higher number of people.

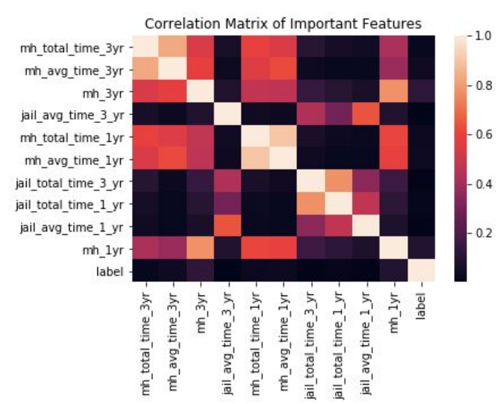
7. RESULTS

Our most consistent finding across all time splits is that prior mental health history is the most important factor in predicting future mental health encounters.

The following are the ten most important features computed using a random forest of trees trained on the full training set from 2010-2014. The importances are calculated by the mean decrease in node impurity of each attribute over all trees. We use a random forest for this analysis due to its robustness across different trees in the forest.



We then plot a correlation matrix of the important features to see their correlation with the outcome variable. As expected, we find that an individual's three year mental health history is the most strongly correlated with the label.



8. RECOMMENDATIONS

Johnson County officials are planning to use the results of this analysis to conduct proactive mental health outreach to 200 inmates. We recommend they focus their efforts in the following areas to produce better outcomes for people who could have future interactions with the mental health system.

1) Launch a voluntary pilot program modeled after the Threshold Justice Program in Chicago, which connects releasees with community-based housing, primary physical and mental health care treatment, and job assessments and placements. This model has reduced arrests among our target population by 89%, jail time by 86%, and hospitalizations by 76%.[11]
2) For releasees who choose not to participate in the pilot program, help them enroll in Medicaid prior to their release date. Simply having Medicaid access cut return trips to jail by 16% for mentally ill releasees in Washington and Florida.[12]
3) Since previous interactions with the mental health system predict post-release interactions, Johnson County jail should endeavor to improve upon the detection of individuals with mental health illnesses at intake and provide them with appropriate resources within the jail.

9. LIMITATIONS

This study has several important limitations that must be considered when analyzing the results and attempting to improve the models in future work.

One of the most concerning limitations of this work is that it is significantly biased on race and gender. For both females and African-Americans, the false omission and false positive rates are both outside the bounds of fairness. This means that females and African Americans that have an interaction with the mental health system within year of release are classified as not having had that interaction. Our models are also biased in the other direction, females and African-Americans who have not had an interaction with the mental health system are often classified as having had that interaction.

Attribute Name	Attribute Value	False Discovery Disparity	False Positive Disparity	False Omission Disparity	False Negative Disparity	Precision
Race	AMERICAN INDIAN OR ALASKA NATIVE	NaN	0.000000	0.000000	NaN	NaN
Race	ASIAN	NaN	0.000000	0.000000	NaN	NaN
Race	BLACK OR AFRICAN AMERICAN	1.009695	$\boxed{0.759908}$	$\boxed{0.623497}$	0.996944	0.052632
Race	WHITE	1.000000	1.000000	1.000000	1.000000	0.061728
Sex	FEMALE	0.921134	$\boxed{1.498108}$	$\boxed{2.636512}$	0.921317	0.108108
Sex	MALE	1.000000	1.000000	1.000000	1.000000	0.031746

This bias is emblematic of broader issues of bias and racial distortions inherent in the criminal justice system.

A second limitation is the small size of the population that we know to access services post-release. In our training sets, no more than 3% of 'release events' result in an interaction with the mental health system within a year of release. Using such a small subset of the training data to build a predictive model could lead to issues of

[11] Thresholds: The Justice Program. Retrieved June 2, 2018 from: http://www.thresholds.org/our-work/programs/justice-program/

[12] Artiga, S., Gates, A., & Rudowitz, R. (2014). Health Coverage and Care for the Adult Criminal Justice-Involved Population. Henry H. Kaiser Family Foundation. Retrieved from: https://www.kff.org/uninsured/issue-brief/health-coverage-and-care-for-the-adult-criminal-justice-involved-population/

overfitting – particularly with classifiers prone to overfitting like Decision Trees.

Any future work based on this analysis should prioritize finding ways to control for the bias built into our data, build a larger dataset with more post-release mental health interactions, and potentially incorporate EMS data to understand the events that led to mental health interactions post-release.

10. REFERENCES

AbuDagga, A., Carome, M., Fuller Torrey, E., Phatdouang, A., & Wolfe, S. (2016). Individuals with Serious Mental Illnesses in County Jails: A Survey of Jail Staff's Perspectives. *Public Citizen and The Treatment Advocacy Center*. Retrieved from: http://www.treatmentadvocacycenter.org/storage/documents/jail-survey-report-2016.pdf

Bauman, M., Boxer, K., Ghani, R., Haynes, L., Helsby, J., Lin, T., Naveed, H., Salomon, E., Schneweis, C., Sullivan, R., & Yoder, S. (2017). Reducing Incarceration Through Prioritized Intervention. Retrieved from: https://dssg.uchicago.edu/wp-content/uploads/2017/03/reducing-incarceration-prioritized.pdf

Binder, R. & McNiel, D. (2007). Effectiveness of a Mental Health Court in Reducing Criminal Recidivism and Violence. *The American Journal of Psychiatry*, 164:9, 1395-1403.

Colman, I., Martin, M., McKenzie, K., & Simpson, A. (2013). Mental Health Screening Tools in Correctional Institutions: A Systematic Review. *BMC Psychiatry* 13:275. Retrieved from: https://bmcpsychiatry.biomedcentral.com/articles/10.1186/1471-244X-13-275

Forehand, R, & Wierson, M. (1995). Predicting Recidivism in Juvenile Delinquents: The Role of Mental Health Diagnoses and the Qualification of Conclusions by Race. *Behavior Research and Therapy*, 33:1, 63-67.

Gaylor, R., Kerbs, J., Koroloff, K., Pullmann, M., Sieler, D., & Veach-White, E. (2006). Juvenile Offenders with Mental Health Needs: Reducing Recidivism Using Wraparound. Crime & Delinquency, 52:3, 375-397.

Hartwell, S. PhD. (2008). Community Reintegration of Persons with SMI Post Incarceration. *Center for Mental Health Services Research, Department of Psychiatry University of Massachusetts Medical School.* Retrieved from: https://www.umassmed.edu/globalassets/center-for-mental-health-services-research/documents/products-publications/issue-briefs/human-rights/community-reintegration-of-persons-with-smi-post-incarceration.pdf

Hutton, M. (2017). *The Lack of Federal Funding for Mental Health and the Criminalization of Mental Illness*. Psyche. Retrieved from: https://psyche.media/the-lack-of-federal-funding-for-mental-health-and-the-criminalization-of-mental-illness

Insel, T. (2014). A Misfortune, Not a Crime. National Institute for Mental Health. Retrieved from: https://www.nimh.nih.gov/about/directors/thomas-insel/blog/2014/a-misfortune-not-a-crime.shtml

Thresholds: The Justice Program. Retrieved June 2, 2018 from: http://www.thresholds.org/our-work/programs/justice-program/

Artiga, S., Gates, A., & Rudowitz, R. (2014). Health Coverage and Care for the Adult Criminal Justice-Involved Population. Henry H. Kaiser Family Foundation. Retrieved from: https://www.kff.org/uninsured/issue-brief/health-coverage-and-care-for-the-adult-criminal-justice-involved-population/