Predicting Foster Care Outcomes in the United States with the National Youth in Transition Database

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Abstract

The National Youth in Transition Database (NYTD) hosts one of the largest sources of information on youth aging out of the foster care system in the United States. It covers nearly 10 years and consists of basic demographic information coupled with outcome data and independent living service (ILS) utilization for thousands of individuals. While past work has identified ILS as an impactful measure on positive adult outcomes in foster youth, other work has shown that utilization of these services varies based on demographics and location. This project aims to identify to what extent independent living services influence youth outcomes with respect to demographic data. In this report, we will focus on substance abuse referrals to analyze indicators for high-risk behavior in youth who may lack adequate support systems. Out of our five classification models, we determine the random forest classifier has the highest performance for substance abuse referral prediction and maintains fairness across genders, races, and geographic regions. After feature selection, our random forest classifier achieves significant improvements in the run time and most scoring metrics. Across all five models, we identified that having a connection to an adult and current school enrollment increases the likelihood of substance abuse referral. On the other hand, educational aid, public food assistance, and other public financial assistance may deter referral, meaning youth who receive these forms of aid may have lower rates of substance abuse.

1 Introduction

In 2015, the United Nations set the 17 Sustainable Development Goals [Nations, 2018]. SDG 1 aims to eliminate poverty in all forms and to empower the most vulnerable. In the United States, foster youth, particularly those transitioning out of the foster care system are amongst the most vulnerable.

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After entering the foster care system, youth often are moved around from home to home. Due to the shortage of foster homes, youth often are even placed in motels and hotels. This continuous movement not only prevents youth from making friends and connections but also affects their education. By the time youth in foster care reach their junior year, more than a third will have switched schools at least five times. With each move, it is estimated that on average, youth lose four to six months of academic progress. When these kids age out of the system at 18, they are left disconnected, alone and often without even a high school degree. In fact, only 58% of young people in foster care graduate from high school. In contrast, 92% of young adults in the US graduate high school. [Preston, 2021]. These kids are more likely to abuse drugs, become homeless, and pregnant, in other words: perpetuate the cycle of poverty. Adverse outcomes for transitioning youth is a large-scale problem. In 2020, the United States Foster Care System served more than a half million youth, 20% of which are in high school and are transitioning into adulthood. For this reason, the foster care system must identify at-risk youth to help prevent negative outcomes before aging out of the system.
In 2006, the John H. Chafee Foster Care Independence Program was launched to promote positive foster care outcomes Bureau [2021]. This provided state-level funding to establish independent living services (ILS) that aid transitioning youth. Additionally, the program launched a data collection program, called the National Youth in Transition Database (NYTD) that allowed the federal Administration for Children and Families to track ILS utilization in conjunction with foster youth outcomes.

1.1 Motivation

Currently, service providers do not have overarching information regarding the outcomes resulting from their services. This lack of clarity and most importantly, explainability, makes service resource allocation often ineffective or inefficient. The goal of this paper is to understand the relationship between services used and adverse outcomes. We hope to understand under which circumstances each service leads to reduced adverse outcomes to identify at-risk youth as soon as possible. This information can aid service providers to allocate their limited resources more effectively and maximize their positive effects on some of the most vulnerable of our society, foster youth.

1.2 Goals

While the NYTD collects data on services and youth outcomes on financial self-sufficiency, educational attainment, connection with adults, homelessness, high-risk behaviors, and access to health insurance, we will be focusing on *substance abuse referrals*.

In this project, we will utilize independent living services (ILS), demographics, and federal aid to predict whether or not youth will receive a substance abuse referral. Our goal is to utilize these models to identify which features are correlated with referrals. In addition to feature importance, we will analyze our results to ensure our models perform fairly across gender, race, and geographic region groups.
We will not treat substance abuse referrals as a proxy for substance abuse because we acknowledge that referrals are highly correlated with mentoring and connection to adults. Instead, we want to understand the underlying factors that drive substance abuse referral in order to identify youth who abuse substances but **do not** have an adult to refer them to substance abuse services. Ultimately, we are interested in understanding what features are risk and protective factors in positively identifying youth with a substance use disorder.

2 Related Works

Many works have examined the NYTD to understand the driving factors of youth outcomes. Sphiegal and Ocasio used 2-step cluster analysis to categorize transitioning youth into five distinct designations: resilience, substance abuse, multiple problems, incarceration only, and homelessnes [Shpiegel and Ocasio, 2015]. This work implies that foster care outcomes are reliant on multiple features including demographics and home-life stability. Additionally, this work implies that youth require particular services specific to their outcome. Importantly, this paper identified that substance abuse referrals were highly correlated with mentor support and school enrollment. This shows a weakness in how substance abuse is tracked amongst foster youth and points to a need to identify

Table 1: Summary of Cohort by Year

Cohort Year	Number of Records	Number of Features
2011	58,729	51
2014	52,569	51
2017	40,700	51
2020	21,430	50

youth who may not have close connection to adults.

In addition to clustering methods that characterize the NYTD, other work has utilized regression models to analyze overall service utilization. This is relevant because we are interested in understanding how services impact service referrals. Yan et. al. determined that youth age, youth time in foster care, and youth resident state determine which service the particular youth will receive using gradient-boosted trees (GBT) [Yan et al., 2021]. Further, their GBT framework showed promising results for maintaining overall model fairness across racial groups. Our aim is to build on service prediction research by utilizing service as a feature to determine the impact of such services on youth. For instance, Kim. et. al. employed three different logistic regression models to determine whether or not ILS has a positive impact on high school education, post-secondary education, and employment in transition youth [Kim et al., 2019]. While these researchers outline a framework to analyze the impact of services, we aim to incorporate fairness analysis to assess the extent to which demographic factors alone, in addition to services with these factors, can drive transitioning youth behavior. Additionally, instead of analyzing specific outcomes, we are interested in the identification of high-risk behaviors with substance abuse referrals.

Our work extends past previous work because we are targeting substance abuse referrals, an outcome that has yet to be thoroughly explored in NYTD outcome prediction research. Additionally, we will utilize machine learning methods that extend beyond classic models used in the past work to provide more methods to study outcome prediction. Finally, we will address fairness concerns and ensure our models assess each sub-population equitably.

3 Data

3.1 NYTD Youth Outcomes Dataset

We combined multiple NYTD Outcomes studies from the following cohorts: 2011 (all waves), 2020 (wave 1), 2014 (all waves), and 2017 (waves 1 & 2). This data includes demographic information (date of birth, identifying race, gender, location), date of survey, foster care status, government assistance, health insurance, housing status, employment, and other outcome-related information (number of children, marital status, incarceration, and substance abuse). We summarize each cohort by year below. In total, this accounts for 99,697 unique individuals. Collections were performed across all 50 states, Washington D.C. and Puerto Rico. In years post-2011, follow-up cohorts included adults who had been surveyed as 17-year-olds. In addition to these individuals, data from those (not previously surveyed) between the ages of 19 and 22 who transitioned out of the system were additionally collected. It is also important to note that the administration of surveys varied in format by state (online, in-person, over the phone). Across all cohorts, there were 58 unique features. Table 2 summarizes the feature contents.

3.2 NYTD Services Utilization Dataset

We extracted service utilization through the NYTD Services 2020 dataset, which includes service utilization records between 2011-2020. In total there were 1,698,819 records, 488,944 were completed by unique participants, represented by 40 features. We found that approximately 98% of individuals were surveyed 1-9 times, with the average between 2 and 3 surveys per participant. The highest number of surveys completed by one individual was 21 (See Figure 1). Participants were offered financial incentives for each survey completed.

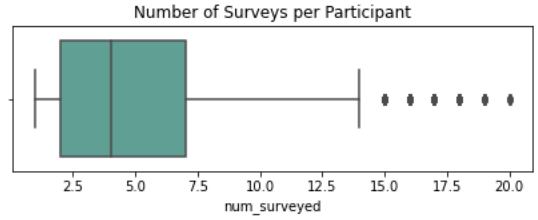

Figure 1: The Distribution of Number of Times Survey was Taken Among Participants

In addition to demographic information (date of birth, location, identified race, gender, outcomes cohort, if applicable) on each participant, each record included 15 offered independent living services. See Table 2 for more information.

4 Data Processing

Service utilization was extracted from the NYTD Services 2020 dataset. A total of 15 service utilization features were extracted for all individuals. For each record in every NYTD Outcomes cohort, the individual was matched to the history of service utilization, if it existed. For example, if a person received X service in 2008, Y service in 2012, and Z survey in 2016, and if the outcomes survey was conducted in 2014, only service X and Y would be recorded.

After merging the service utilization with outcomes data, all the waves were merged for a total of 112,257 individuals. For duplicated individuals (i.e. individuals who took the survey several times between 2011-2020), only the most recent survey was kept, amounting to 62,828 individuals.

Next, 23 features with more than 25% missingness within their cohort and duplicate information (e.g. 'stfips' and 'st') were dropped. To better summarize specific features, age was estimated by finding the number of days between the first day of the month and year of surveying and date of birth. After calculating age, other time related features were dropped to avoid duplicate information, leaving a total of 50 features.

We then removed 3119 individuals who declined to share racial identification when surveyed. This is because we later calculated model performance for particular demographic groups so it was necessary to remove individuals with unavailable demographic information. For each individual, there was an identified race (including self-identified unknown race) and state location. Additionally, 32 individuals with unknown encoding and 1 individual with low compliance were removed. Last, we removed 26,670 individuals with either declined or null outcome responses and 48 individuals with incomplete survey participation. In total, after running the mentioned filters, 32958 individuals and 48 features remained.

Finally, we one-hot-encoded the categorical data and pruned features that indicated the response was declined. For example, if the possible categories were "yes," "no," or "declined," we removed the one-hot-encoded feature corresponding to the "declined" response. In other words, the response for individuals who declined fit neither into the category "yes" or "no." In total, 152 features remained. Of these, 8 features were outcome targets in education, employment status, incarceration, homelessness status, and substance abuse. Additionally, 30 of these features were on service utilization. For a more detailed description of features, see Table 2.

The target features that we examined include information pertaining to the following categories (See Table 2 for more details):

- Education level
- Incarceration
- Substance Abuse
- Employement

Table 2: Summary of features in post-processed NYTD dataset

Feature Label	Verbatim Feature Description	Categories	Missingness
age	Estimated age	1	0.0
st	State or district of residence	52	0.0
sex	Identified Sex	2	0.0
outcmfcs	Fostercare status	2	0
amiakn	American Indian Or Alaskan Native	2	9.1e-05
blkafram	Black Or African American	2	9.1e-05
asian	Asian	2	9.1e-05
hawaiipi	Native Hawaiian Or Other Pacific Islander	2	9.1e-05
white	White	2	0.0
raceunkn	Race - Unknown	2	0.0
hisorgin	Hispanic or Latino Ethnicity	2	0.03
emplyskills	Employment Related Skills	2	9.1e-3
educaid	Education Aid	2	1.2e-2
pubfinac	Public Financial Assistance	2	6.6e-2
pubfoodas	Public Food Assistance	3	6.5e-3
othrfinas	Other Financial Support	2	1.3e-2
currenroll	Current Enrollment And Attendance	2	6.3e-3
cnctadult	Connection ToAdult	2	9.1e-3
children	Child status	2	9.3e-3
marriage	Marriage at Child's birth	3	3.6e-3
medicaid	Medicaid	3	2.3e-2
othrhlthin	Other Health Insurance Coverage	4	6.8e-3
medicalin	Health Insurance Type: Medical	4	2.7e-3
mentlhlhin	Health Insurance Type: Mental Health	2	2.4e-3
prescripin	Health Indusrance Type: Prescription Drugs	2	2.5e-3
baseline	Youth is in Baseline Population	2	0.0
specedsv	Services: Special Education	2	1.9e-2
ilnasv	Services: Independent Living Needs Assessment	2	1.7e-2
acsuppsv	Services: Academic Support	2	1.7e-2
psedsuppsv	Services: Post-Secondary Educational Support	2	1.8e-2
careersv	Services: Career Preparation	2	1.7e-2
emplytrsv	Services: Employment Programs	2	1.8e-2
budgetsv	Services: Financial Management	2	1.7e-2
housesv	Services: Home Management Training	2	1.7e-2
hlthedsv	Services: Health Education And Risk Prevention	2	1.7e-2
famsuppsv	Services: Family Education	2	1.7e-2
mentorsv	Services: Mentoring	2	1.8e-2
silsv	Services: Supervised Independent Living	2	1.7e-2
rmbrdtasv	Services: Housing Financial Assistance	2	1.8e-2
edufinasv	Services: Education Financial Assistance	2	1.8e-2
othrfinasv	Services: Other Financial Assistance	2	1.8e-2
highcert	Target: Post-high school education	2	1.8e-2
homeless	Target: Homelessness Status	2	0.0
subabuse	Target: Substance Abuse Referral	2	0.0
incarc	Target: Incarceration Status	2	0.0
currfte	Target: Current full-time employment	2	0.0
currpte	Target: Current half-time employment	2	0.0

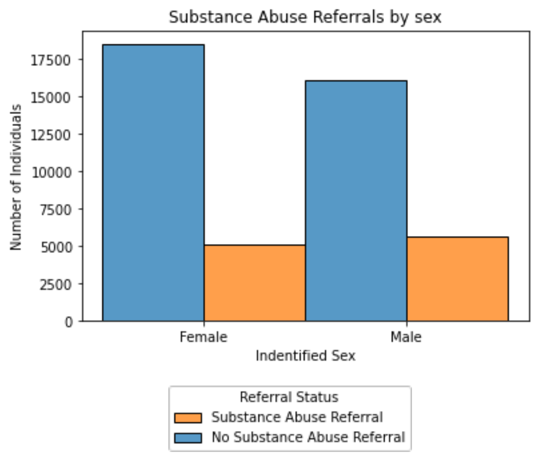

Figure 2: Gender Distribution for Referral Rates

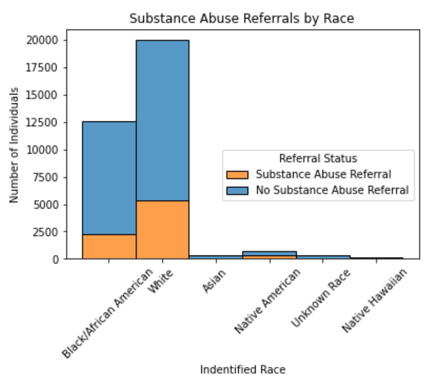

Figure 3: Racial Distribution for Referral Rates

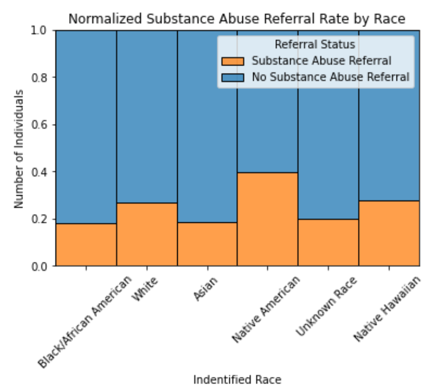

Figure 4: Normalized Referral Rates by Race

5 Data Exploration

This section covers our data exploration with our fully processed dataset.

Before modeling, we wanted to examine bias within our dataset. Overall there is a 24% referral rate in our dataset. However, because referral rates are given by counselors, these can often be biased. Hence, we examined referral rates within particular demographics. In total, we found some evidence of demographic bias.

Across individuals, overall there were 23608 female individuals, totaling a 27.7% referral rate within females. Similarly, there were 21756 male individuals, resulting in a 35.0% referral rate in males. See Figure 2 for more details. There is a significant difference in referral rates for males and females with a z score = -7.0245 ($p < 0.05$).

Regarding the racial distribution of our dataset, we have an imbalanced dataset with more Black/African American and European individuals than other racial groups. See Figure 3 for the racial distribution of individuals, without multiracial individuals. However, within each racial group, there is variation in referral rates. Notably, there is a significant difference in referral rates between Europeans and Black/African Americans with a z-score of z = 7.09998 (p ¡ 0.05). The other racial groups have too small of a sample size to determine significance. Table 3 summarizes referral rates across racial groups.

When looking at the regional breakdown of the dataset, we see there is very little variation in referral rates. See Figure 5 for the distribution.

Table 3: Racial Distribution for Referral Rates

Race Identifier	Number of Individuals	Referral Rate
White	19947	0.27
Black/African American	1289	0.18
Native American	725	0.40
Unknown	376	0.20
Asian American	336	0.19
Native Hawaiian	100	0.28

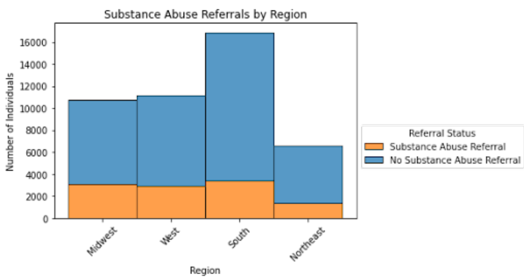

Figure 5: Regional Distribution for Referral Rates

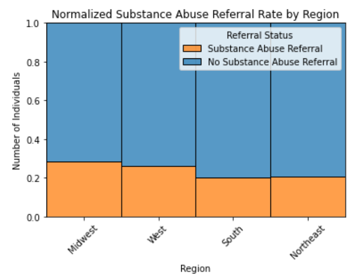

Figure 6: Normalized Referral Rates

One important aspect that we would like to look for in our modeling is the impact of location on substance abuse referrals. In general, services are localized to states, meaning most states only offer a specific subset of the fifteen services. This can be observed in Figure 7. For example ”rmbrdtasv” or Housing Financial Assistance Service has practically no utilization in west coast states. This implies these states do not offer this service OR do not offer this service to 17-year-olds.

Finally, we wanted to see how substance abuse referrals are correlated with other target youth outcomes. As noted before, we are using substance abuse referrals as a proxy for other target youth outcomes. Overall substance abuse referrals are positively correlated with incarceration and homelessness status, which are considered negative youth outcomes. We cannot determine any correlation between employment and high school graduation because our sample is comprised of 17-year-olds. Hence, utilizing substance abuse referrals as a proxy for positive outcomes is not an accurate representation of our data.

To address the target class imbalance of our dataset, we attempted multiple techniques to improve the performance of our modelings including oversampling, undersampling, and stratified sampling during cross-validation. In the end, we determined that Synthetic Minority Oversampling Technique (SMOTE) with edited nearest neighbors (ENN) with stratified sampling during cross-validation yielded the highest model performance. Because SMOTE interpolates between similar observations, we ran the dataset with and without services to assess the relationship between features. Additionally, due to the messy signal within our dataset, ENN improves our models by removing instances close to the decision boundary, hence improving classification. Table 4 summarizes the target class before and after sampling. After SMOTE-ENN, our datasets has around a 3:2 ratio of positive class (substance abuse referrals) and negative class (no substance abuse referrals).

Table 4: Final Dataset After SMOTE and ENN

Dataset	Positive-Negative Ratio	N. Individuals	N. Features
BEFORE Balancing Foster Outcomes	1:3.21	45364	111
AFTER Balancing Foster Outcomes	1:69:1	24790	111
AFTER Balancing Foster Outcomes + Services	1:62:1	38031	141

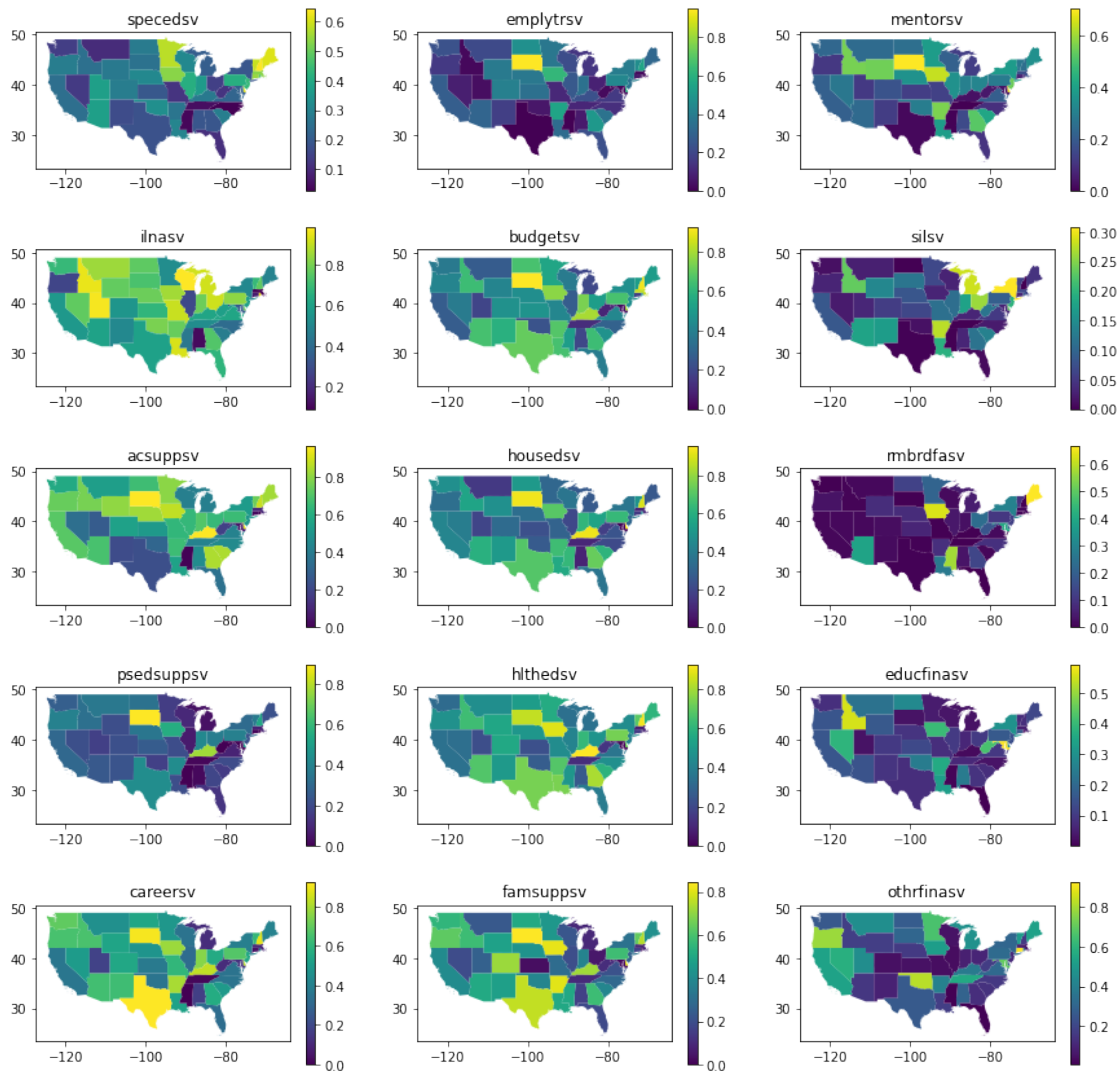

Figure 7: Service Utilization Per State

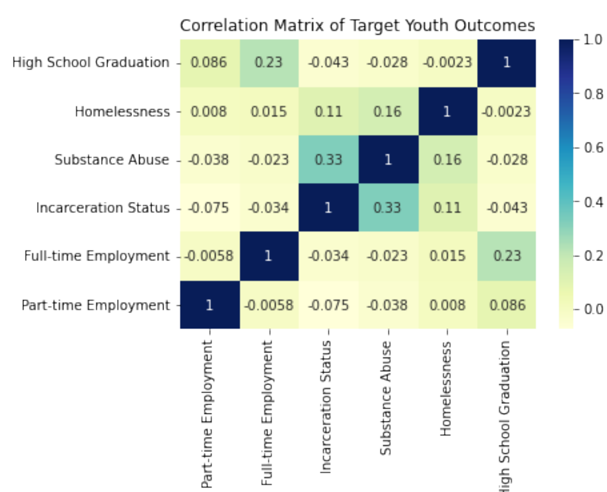

Figure 8: Correlation of substance abuse referrals to other target outcomes

6 Results

In this section, we will cover our experiments for substance abuse prediction. As a baseline, we utilize foster care data, excluding service data, to determine substance abuse referrals. We did this for the following reasons: 1) specific foster care services may be correlated with incarceration status and 2) we wanted to understand the extent to which non-service related features can impact foster care outcomes. We then compared these results to the training of the models with the inclusion of the 15 services described in the Data Processing section.

In our experiments, we wanted to use a mix of classification methods previously utilized in the literature and our own proposed methods. In total, we utilized support vector machines (SVMs), logistic regression, random forest, gradient-boosted trees, and artificial neural networks. All classification methods were validated with 5-fold cross-validation. As scoring metrics, true negative rate (TNR), false positive rate (FPR), true positive rate (TPR), and false negative rate (FNR), in addition to the average area under the receiver operating characteristic, and the average f1 scores (the harmonic mean of precision and recall) are shown in Table 5 for substance abuse referral prediction without service utilization.

Table 5: Substance abuse prediction without services

Model	Without Services					
	TNR	FPR	TPR	FNR	AUC	F1
Logistic Regression	0.67	0.33	0.67	0.33	0.67(7.1e-3)	0.72(4.1e-3)
Linear SVM	0.90	0.10	0.81	0.19	0.85(5.6e-3)	0.86(3.2e-3)
XGBoost	0.62	0.38	0.93	0.07	0.77(7.8e-3)	0.87(4.5e-3)
Random Forest	**0.94**	**0.04**	**0.98**	**0.02**	**0.96(2.2e-3)**	**0.97(1.6e-3)**
Artificial Neural Network	0.85	0.15	0.91	0.09	0.88(3.6e-2)	0.90(3.1e-2)

Table 6: Substance abuse prediction with services

Model	With Services					
	TNR	FPR	TPR	FNR	AUC	F1
Logistic Regression	0.66	0.34	0.70	0.30	0.68(7.3e-3)	0.73(5.0e-3)
Linear SVM	0.92	0.08	0.77	0.23	0.85(2.1e-3)	0.85(1.9e-3)
XGBoost	0.64	0.36	0.91	0.09	0.77(3.6e-3)	0.85(1.8e-3)
Random Forest	**0.88**	**0.12**	**0.96**	**0.04**	**0.92(2.9e-3)**	**0.94(1.7e-3)**
Artificial Neural Network	0.84	0.16	0.86	0.14	0.84(3.7-2)	0.88(3.0e-2)

These results suggest the ability to classify educational attainment with non-service utilization features alone. In fact, due to the localization of services to states, this suggests that location may encode service utilization, hence explaining why we are able to predict referrals without utilization. However when we look at referral prediction with the addition of services, we see similar model performance to prediction without services, with some models decreasing in referral prediction (See Table 6). This implies that service utilization may have a messy relationship with referrals, hence the lower prediction accuracy. Out of these models, the random forest classifier consistently performs the best out of our five models.

Before feature selection and feature importance, we wanted to analyze bias within our models' predictions. We compared false negative rates and false positive rates for key demographics including gender, race, and location. Despite slight bias within referral rates for our data, our best performing model, the **random forest classifier**, has consistent false negative and false positive rates across all genders, races, and regions.

Table 7: Assessing false negative and false positive rate across gender and race

Model		Gender (FNR/FPR)		Race (FNR/FPR)	
	All	Female	Male	White	Non-White
Logistic Regression	0.33/0.33	0.33/0.33	0.32/0.34	0.33/0.33	0.33/0.33
Linear SVM	0.19/0.10	0.19/0.10	0.20/0.10	0.19/0.11	0.19/0.10
XGBoost	0.07/0.38	0.07/0.37	0.06/0.39	0.07/0.38	0.07/0.38
Random Forest	**0.02/0.06**	**0.02/0.06**	**0.02/0.07**	**0.02/0.07**	**0.02/0.06**
Artificial Neural Network	0.09/0.15	0.1/0.16	0.1/0.15	0.1/0.15	0.11/0.16

Table 8: Assessing false negative and false positive rate across geographic regions

Model		Region (FNR/FPR)			
	All	West	Northeast	South	Midwest
Logistic Regression	0.33/0.33	0.33/0.33	0.33/0.32	0.33/0.33	0.32/0.34
Linear SVM	0.19/0.10	0.17/0.11	0.22/0.07	0.23/0.11	0.20/0.11
XGBoost	0.07/0.38	0.06/0.38	0.07/0.34	0.08/0.39	0.07/0.39
Random Forest	**0.02/0.07**	**0.02/0.04**	**0.02/0.04**	**0.02/0.06**	**0.02/0.06**
Artificial Neural Network	0.09/0.15	0.1/0.14	0.11/0.17	0.11/0.16	0.11/0.16

6.1 Feature Selection

For feature selection of our dataset, we experimented with multiple selection methods before settling upon recursive feature elimination due to our means of evaluating our models' performances. Because we were using a small set of scoring metrics, we were able to perform an analysis of which features consistently remained after optimizing for each metric with a particular model. Since the random forest was our highest-performing model, we built 5 different pruned random forest models, each optimized for accuracy, precision, AUC, recall, and F1 scores respectively, we found a subset of 61 of the previous 141 features to remain across all 5 models. This became our transformed data set.

Table 9: Substance abuse prediction with selected features

Model	Percent Change After Feature Selection				
	FPR	FNR	AUC	F1	Runtime
Logistic Regression	-11.9%	+1082.2%	-0.6%	-3.3%	-62.1%
Linear SVM	+21.7%	-9.1%	-4.6%	+1.2%	-9.7%
XGBoost	-21.3%	+27.3%	+0.1%	-1.7%	-40.9%
Random Forest	**-45.4%**	**+15.2%**	**+1.5%**	**+2.0%**	**-14.0%**
Artificial Neural Network	-6.3%	+30.8%	-1.4%	-3.3%	-4.4%

Using this transformed dataset, we reran the models to evaluate improvements to runtime and performance. As can be seen in Table 9, the most notable changes were in the model runtimes, while changes in most performance metrics were typically insignificant. The consistent significant changes in performance were reflected in volatile changes to FPR and FNR.

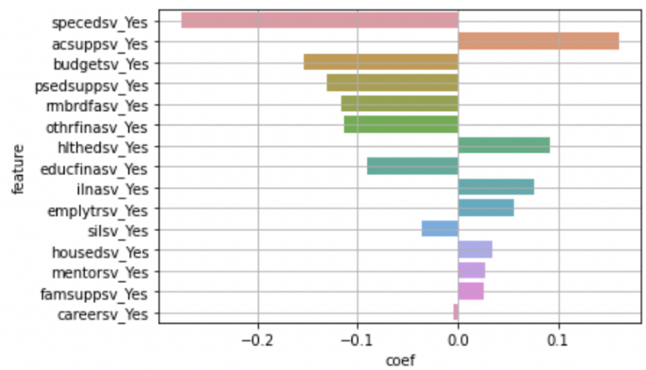

Figure 9: SVM Coefficients for Services

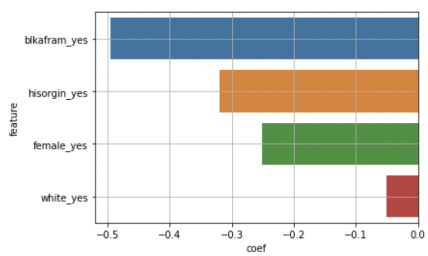

Figure 10: SVM Coefficients for Demographic Factors

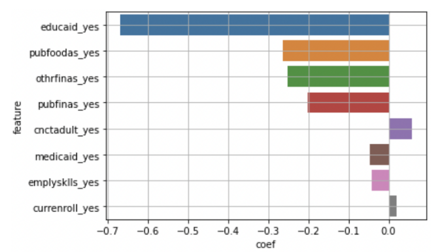

Figure 11: SVM Coefficients for Public Services Features

6.2 Feature Importance

We assessed feature importance in two primary ways: SVM coefficients and Permutation Importance for three of the models. The coefficients from the SVM model are shown in Figures 9, 10, and 11. The results for Permutation Importance are shown in Figure 12.

As seen, the foster care services with the most negative coefficients are the special education service and the budget and financial management assistance service (Fig. 9). According to our SVM model, individuals using these services have the lowest referral rates. In contrast, academic support services have an extremely positive coefficient. This is initially quite counter-intuitive but, we attribute this large positive coefficient to academic services being a service that builds a strong

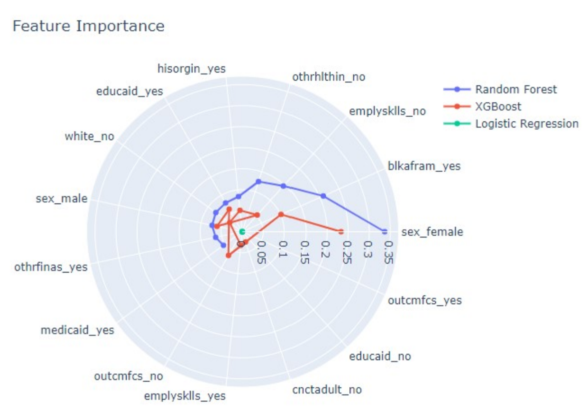

Figure 12: Permutation Feature Importance

connection between the student and an adult. Due to this relationship, individuals who actually abuse substances **and** who have an adult mentor in their lives have a higher likelihood of being referred. This is consistent with previous literature.

Services that lower substance abuse rates may be protective factors while services that foster a connection to adults will increase the likelihood of referral (See Fig. 11). This makes our features difficult to interpret without domain expertise. That being said, with our knowledge of ILS, we conclude from our SVM coefficients that academic services have a key influence on substance abuse referral rates as they can indicate a support system for the individual. On the other hand, services such as special education and budget and financial management assistance strongly decrease the likelihood of referral most likely due to their impacts on reducing actual substance use. The Random Forest, XGBoost, and Logistic Regression models show that individuals who identify as female are less likely to receive a referral for substance abuse. Further, these models confer with the SVM results (see Fig. 12). However, this result does not necessarily imply that females are being under-referred or that females have lower rates of substance abuse. More domain expertise is required to gain additional insight into the demographic feature importance. However, we can conclude that specific services, like academic services, may increase the rate of referral due to the connectivity they foster whereas other services may decrease the rate of referral due to a decrease in substance use. Though our results highlight the importance of gender, academic support and financial management; domain expertise is required to further asses the degree of connection each foster service provides thus whether the change in referral rates is due to increased connection *or* an intrinsic decrease in substance use.

7 Conclusion

In total, we developed a fair method to predict substance abuse referrals for 17-year-olds in the NYTD using ILS utilization, demographics, federal aid, and other foster care-related features. We found the random forest classifier had the highest performance and assessed each population equitably. After feature importance, we identified having a connection to an adult and school enrollment as factors that positively correlated with referral and receiving educational aid, public food assistance, and other financial assistance as factors that negatively correlated with referral. These features will help future researchers positively identify youth with substance abuse problems and potentially little adult support.

7.1 Limitations

One large caveat in our experimental design is that our models are targeting substance abuse referrals. This relies on counselors or adult figures to accurately assess youth equally. However, if these individuals prefer to give referrals to specific youth (or a subgroup of youth), our models may perpetuate biases and hence youth who actually need referrals may not receive help (false negative). On the contrary, youth who may not need substance abuse disorder services may be incorrectly offered services (false positive), resulting in inefficient resource allocation. Consequently, the factors that are important in classification may be biased towards a specific demographic. However, given our data, our model does not have inconsistent false positive and false negative rates across demographic groups. Until more comprehensive surveying is done, this is as close as we can get to identifying youth who may benefit from substance abuse services.

Additionally, the implications of a false negatives and false positives in practice brings into consideration the results of our feature selection. Since using only the selected features for classification increased FPR and decreased FNR (or vice versa) while resulting in massive time savings, domain experts should consider the ethics of using a more streamlined input if it means that it could yield inefficiencies in resource allocation or even negative youth outcomes.

Finally, in our conclusions, we make the assumption that youth who have adult support and youth who do not have adult support will have similar risk/protective factors for substance abuse disorder. In other words, we assume adult support (found as a feature in the outcomes survey) is what makes these youth more likely to get referred. Because our data is biased in that those with high-risk behavior and with more adult support in their lives are more likely to get referred to substance abuse service, there is no way to account for the unknown interaction between adult support and other features that may impact substance abuse referral. That being said, our feature importance analysis will set a baseline for research to identify high-risk youth without strong adult support.

7.2 Extension

Our model can be used to identify factors that correlate with substance abuse referrals. Prior to using these features to identify youth, we would like to consult a domain expert in social sciences to identify which features are related to elevated referral rate (such as academic services or close connection to adult) and which features are driving substance abuse. This will help disentangle our results so that we can utilize these features to identify youth that may need substance abuse services but do not have an adult to refer them to help.

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