Preventing Interactions with the Juvenile Justice System

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ABSTRACT

Interactions with the criminal justice system severely impact the lives and future of young people. Extensive research has shown that early-intervention programs aimed at preventing such interactions are effective at combating juvenile delinquency [6, 11]. This suggests that early and better intervention targeting can have a significant, positive impact on those likely to enter the criminal justice systems as children. The Milwaukee Public School systems currently uses a rule-based system to target students that are at high-risk for entering the criminal justice system. We have built an adaptable and scalable model to predict which students are most at-risk of interacting with the criminal justice system. The model achieves 30% precision in the top 1%, significantly outperforming both a random baseline (6% precision @ 1%) and the current rule-based system (6% precision @ 1%). In addition to generating a list of students in need of extra support, our system also helps MPS identify factors that are predictive of juvenile interaction with the criminal justice system to help schools develop personalized interventions.

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1 INTRODUCTION

Historically, the juvenile-justice system was meant to rehabilitate delinquent youth to become productive citizens.[1] However, research shows that students, especially inner city youth, have trouble reintegrating back into society once they have had a significant interaction with the juvenile justice system. Teenagers who interact with the system are likely to experience significant negative life outcomes such as a decreased likelihood of high school graduation [1], an increased likelihood of committing crimes in early adulthood [2], and a significantly higher mortality rate [5].

The City of Milwaukee, Wisconsin, in particular, is afflicted by both low graduation rates and high rates of juvenile crime. While juvenile arrest rates have been steadily decreasing nationally, Milwaukee's arrest rates have increased by 163% between the years of 2011 and 2015, the last-year recorded. Similarly, the State of Wisconsin has a high school graduation rate of 88% but Milwaukee Public Schools' (MPS) graduation rate was only 58% in 2015. In response, the Milwaukee Police Department (MPD) has commissioned several task forces focused on reducing juvenile crime [7] and MPS has designed broad interventions that aim to increase Milwaukee's graduation rate[2].

1.1 Current System in Milwaukee

MPS currently employs three tiers of interventions for at-risk youth. Tier 1 consists of school-level interventions such as regular assemblies reminding students of behavioral expectations. Tier 2 consists of targeted interventions to support students who are not responding to Tier 1. An example of a Tier 2 level intervention is the Check-In/Check-Out (CICO) program: a student checks in briefly each morning and afternoon with a designated school staff member who determines whether the student is ready for class and, if required, whether the student will remain with them for further assistance and guidance. Tier 3 interventions are intense and personalized, they are intended for students not responding to Tier 2 intervention. One example is the RENEW program, a structured school-to-career transition planning and individualized wrap-around process for youth with emotional and behavioral challenges. Due to resource constraints, the number of students receiving Tier 3 interventions

[1] A brief history can be found in [8].
[2] For example, https://www.cityyear.org/milwaukee/our-work/our-approach

can be no more than one to five percent of the total student population.

To identify at-risk youth, MPS evaluates student attendance, behavior, and curricular performance (the "ABCs"). If a student is flagged as at risk in two of these three categories, they are recommended to a Tier 2 intervention. Whether a student is flagged depends on their age and the severity of the problem. For instance, the flags for behavior are as follows:

- For students in kindergarten through grade 8, one Office Discipline Referrals (ODRs) in the past 20 school days or one out-of-school suspension in the past 90 days;
- For students in grades 9 through 12, three ODRs in the past 20 school days, or two out-of-school suspensions in past 90 school days.

Once a student is flagged, the school's Building Intervention Team considers additional data such as the nature of the ODR, credits, grades, attendance, teacher input, work samples, observation, etc., to determine whether a student should receive an intervention, and if so, at which tier. This system currently flags 22,000 students without any prioritization or ranking. Currently, the school district has the capacity to intervene with 5,000 students every year. Thus, the current system makes it untenable to match students effectively with the available interventions.

1.2 Problem Formulation

Our aim is two-fold. First, we want to provide MPS with a risk-score for current students that provide's insight into a student's risk of interacting with the criminal justice system in the next three years. It is important to note that the list of students and their associated risk scores is generated to allow the school system to match students with various support programs to ensure they stay in school, graduate on time, and avoid the criminal justice system. This ties into the current community-based crime prevention methods that are already in place in Milwaukee. Second, we want to understand what features are most predictive of high or low risk scores. We used juvenile and adult criminal justice data through Milwaukee's pioneering DataShare platform[3], as well as data from Milwaukee Public Schools (see Section 2). Many studies suggest that poor school performance and early truancy lead to juvenile delinquency [3], but prior to this the education records and criminal justice records have not been combined to build predictive models of delinquency.

We framed the problem as a binary classification problem to predict which students will have an interaction with the criminal justice system in the next three years. We find that the students who are assigned a high risk score (in the top decile) by our system are four to five times more likely to have an interaction with the criminal justice system in the future than those with lower scores (bottom 9 deciles). In addition, unlike the existing system that assigns a binary (at risk or not) flag to students, our model allows the school to use the risk scores to prioritize students for appropriate interventions.

[3]http://milwaukeedata.org/

2 DATA SOURCES

2.1 Milwaukee Public Schools

The Milwaukee Public School's (MPS) data includes information on demographics, attendance, discipline, assessment, and school programs for students enrolled between 2004 and 2015. Demographic data covers race, gender, birth date, mailing address and school name per student identified by a unique student key. There are over 1.5 million demographic records for more than 300,000 students during the data collection period. Ideally, a new record is generated every time any of the fields change. One reason for multiple records per student is that Milwaukee has a highly mobile population with many students changing schools and home addresses from year to year. There are also 100,000 more students present in the demographic dataset than are present in the other datasets. In consultation with MPS, we noted that while we identify students by unique student keys, in some cases, when a student leaves the school district and re-enters at a later time, they will be registered as a new student with a new student key. This was an important consideration in the entity resolution stage as there are not actually 300,000 unique students represented in the MPS data.

Attendance data includes daily attendance records for each student, with a row representing a day that a student was in attendance at their school. There are approximately 127 million records covering 179,780 students by unique student key.

Discipline data includes date and nature (e.g., classroom disruption, weapons related) of the disciplinary event. The file contains over 100,000 records which are recorded at the event-level and represents 97,000 students.

Assessment data includes descriptions of all tests taken (e.g., date taken, subject) as well as students' scores. There are more than 5 million records representing 194,415 students. This includes repeated standardized testing such as Measures of Academic Progress (MAP) which are administered multiple times a year for students from kindergarten through high school, as well as college admissions tests such as the Scholastic Aptitude Test (SAT) which are administered once per student.

Finally, school programs records include information on the type (e.g., HeadStart, Special Education, Mckinney Vento) and the dates students were enrolled in these programs.

2.2 Milwaukee District Attorney's Office

Data from the Milwaukee District Attorney's (MDA) covers all juvenile and adult interactions with the criminal justice system from 2009 to 2015 where the case was referred to the DA's Office. Once probable cause for criminal behavior is developed by law enforcement, a juvenile can be assigned to an informal diversion, advised and released, transported to a homeless shelter/detox service or referred to a psychiatric crisis team. If the juvenile is arrested and booked, they are eventually ordered to the DA's office. Since the criminal justice data we have originates from the DA's office, it is important to note the limitations. From arrest to when a juvenile enters into the records at the DA's office, there are multiple endpoints at which the juvenile can exit the system. For example, they can be released to community service or if it is a municipal case (i.e. not a misdemeanor or a felony) they can be ordered to civil court and released. This means that only serious crimes are represented in the MDA data. After a charging decision is made by the DA, the office prepares the case and it proceeds to court. After a bond hearing and a preliminary hearing the plea negotiation process is initiated or the case proceeds to trial. If found guilty, the juvenile might be put on probation, end up in a juvenile detention center or pay a fine. The DA's office serves the county and therefore covers a wider range of people than the citywide school district. The MDA data represents 9,500 individuals. It contains information such as the name of the defendant, as well as demographic variables such as date of birth, gender and race. The dataset also contains information on the severity of the offense separated into felony, misdemeanor, and forfeiture.

2.3 Data Cleaning

In the MPS data, demographic details were standardized at the student level. For example, 'Black or African American' or 'African-Am' are used to refer to African American students. Such discrepancies were identified and normalized. Since new demographic records are generated often, there were many students who have multiple different values for their race or gender due to data entry errors. We standardized these records by taking the last non-null record for every student and propagating it back over time.

3 MATCHING THE DATASETS

In order to identify and link unique individuals within the MDA data, we matched within the datasets and created IDs for each person. We assumed that individuals having the same first name, last name, and date of birth were the same person. However, simply matching on these fields across the MPS and MDA data sets yielded no matches due to variations in formatting. Additionally, names are captured in two different formats in the two datasets. For the MDA dataset, there is only a single name field, for instance "Smith, P. Jones". In the MPS dataset, there are separate fields for first, last and middle names. Additionally, in the MDA data, the same individual may be booked multiple times leading to variation in how the name may be entered each time. For example, a name might be misspelled, only the first part of a hyphenated name might be included, or an apostrophe might be used one time and replaced by a space the second time.

In order to improve the matching rate, we cleaned the first and lame name fields to make them more uniform by removing midddle initials, whitespace, commas, quotations marks, hypens and suffixes. Based on input from the MPS and MAD, we expected an 80% match rate between the two datasets. After this initial cleaning, we only achieved a 25% match rate. Recognizing that there might be some variation due to spelling errors or the use of nicknames, we computed the Jaro-Winkler distance for the first name and last name fields. If all three cleaned fields match exactly, we consider the record to belong to the same individual. If one or zero of the fields match exactly, we do *not* consider the records as belonging to the same individual. If two of the three fields match exactly, then we consider the records belonging to the same individual whenever:

- both names match, the birth dates share the same year and otherwise differ by a single character
- one of the two name fields match and the birth date match, and Jaro-Winkler distance [10] between the mismatched names is at least 0.8.

First Name	Last Name	DOB	JW Dist
Reginald	Grey	2004-08-03	0.8333
Reginald	Gray	2004-08-03	
Khabaugh	Musgrave	1993-10-22	0.9629
Khabaugh	Musgraves	1993-10-22	

Table 1: Matching Logic: A Jaro-Winkler distance cut-off of 0.8 suggests that these are records for two individuals.

Two examples of individuals considered the same are illustrated in Table 1.

Lastly, noting that there might be some birth dates that were entered incorrectly, we allowed for some fuzziness. With an exact match on first name, last name, and the *year* of birth, we allowed up to a 1 digit difference in the month and day. For example: `2010-0`**`2`**`-04` and `2010-0`**`3`**`-04` is a match but `2004-11-`**`09`** and `2004-11-`**`22`** is not considered a match.

The MDA data contained one row per case per charge. If an individual is charged with multiple charges for the same incident, this will be reflected in multiple rows with the exact same information but with different charges. We want to identify individuals within the data set and match case number to a unique Person ID. Starting with 96,066 rows in the juvenile data, we identified 15,451 distinct cases by DA Case Numbers. After applying the matching logic above, we identified 9,451 unique individuals and assigned them a Person ID which was then appended to the original dataset.

After identifying unique individuals within the MDA data, these individuals were matched to MPS data. We again applied the same logic as above. We successfully linked 86% of individuals with a DA record to the MPS data. Since it is possible that individuals who have an MDA record did not attend schools in Milwaukee (e.g. out-of-state offenders), we believe that 86% is a reasonable match rate. Future work includes using more sophisticated machine learning based record linkage approaches to improve the matching process.

4 FEATURE GENERATION

A lot of the features considered were generated in consultation with our partners or with reference to the literature on juvenile delinquency. Much of the literature suggests that certain immutable factors such as sex, ethnicity and socioeconomic status are prime predictors for delinquency [9]. Thus, we created demographic features that capture information relevant to classic predictors of delinquency. Furthermore, victims of child abuse and neglect are primed for interacting with the juvenile justice system later in life [9]. This information was captured from the MDA using CHIPS data. Additionally, there is a causal link between truancy and absenteeism, and this was captured by discipline and attendance features (ex: number of disciplinary incidents in the last year, number of days absent in the last two years, average attendance over the years, maximum number of disciplinary incidents per year). We generated 98 features in total.

Table 2: Grid Search Parameters for Model Selection

Models and Hyperparameters
Logistic Regression C: 0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10 Penalty: L1, L2
Random Forest Classifier Number of Estimators: 1, 10, 100, 1000, 10000 Max Depth: 1, 5, 10, 20, 50, 100 Max Features: Square root, log2 Minimum Samples at Split: 2, 5, 10
K Nearest Neighbors Classifier N Neighbors: 1, 5, 10, 25, 50, 100 Weights: uniform, distance Algorithm: auto, ball tree, kd tree
Decision Tree Classifier Criterion: gini, entropy
AdaBoost Classifier Algorithm: SAMME, SAMME.R Number of Estimators: 1, 10, 100, 1000, 10000
SGD Classifier Loss: hinge, log, perceptron Penalty: L2 L1, Elasticnet
Extra Trees Classifier Number of Estimators: 1, 10, 100, 1000, 10000 Criterion: gini, entropy Max Depth: 1, 5, 10, 20, 50, 100 Max Features: sqrt, log2 Min Samples Split: 2, 5, 10

5 METHODS

As described earlier, we formulated our problem as predicting whether a currently enrolled student is at risk of interacting with the criminal justice system in the next 3 years. We implemented the following models using scikitlearn and a variety of hyperparameters: Random Forests (RF), Adaboost (AB), Logistic Regression (LR), Support Vector Machines (SVM), and Decision Trees (DT). Table 2) shows the model and hyperparameter space over which we searched.

6 MODEL EVALUATION

We validated our models using temporal validation by creating training and test sets that are temporally disjoint. For example, if we are predicting an interaction with the criminal justice system in the years 2010-2012, the models are trained on all the data up to the end of 2009 and then the model predicts a risk score for all students as of the beginning of 2010 that provides their risk of having a criminal justice interaction from 2010 to 2012.

7 MODEL PERFORMANCE

We evaluate the model performance based on two criteria:

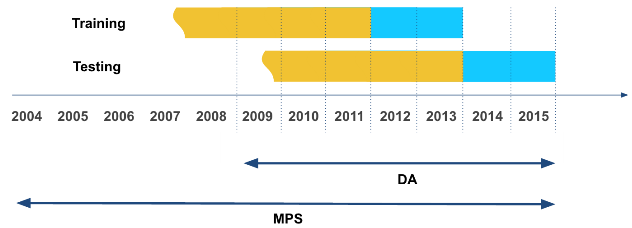

Figure 1: Illustration of temporal validation strategy

(1) Precision in the top 1%: We want the model to be as accurate as possible in the top 1% of the predictions since that is the intervention capacity of MPS. MPS has the resources to administer Tier 3 interventions to no more than 1 to 5% of the school population. Focusing on the 1% threshold allows us to better match students with the limited intervention resources available to the school district.
(2) Stability of that performance over time: We want a model that is stable in terms of Precision at 1% over time so it can be used consistently without risking drastic performance changes.

To achieve those two goals, we selected the 50 best performing models based on precision at 1%. We then selected models that are consistently among the top 50 across each time period. We found that Random Forests with the following hyperparameters performed the best based on these two criteria:

- `n_estimators = 200`
- `max_depth = 10`
- `min_samples_split = 5`
- `max_features = 0.33`
- `criterion = entropy`

The precision-recall curves for this model are shown in figure 2. At 1% of the population, the precision is 0.3 and the recall is about 0.1. This is extremely encouraging - taking the top 1% of the model predictions allows us to identify 10% of all the at-risk students at 30% precision. This is significantly (more than 10 times) higher than a random baseline which would get 2.8% precision (there are 300,000 students and only 8500 juvenile offenders).

8 ANALYSIS OF RESULTS

In this section, we take the best performing model and show some diagnostics we performed to understand and validate the model further.

8.1 Risk Scores

Figure 3 is a log-plot of the risk scores generated by the best model selected.

8.2 Evaluating the predictions by score decile

Figure 4 shows a decile plot that compares the actual number of positive labels in each decile versus the predicted number. A well-performing model will have both values as close to each other as possible in every decile and the number of predicted positive labels should go down as the risk score goes down. As we can see from

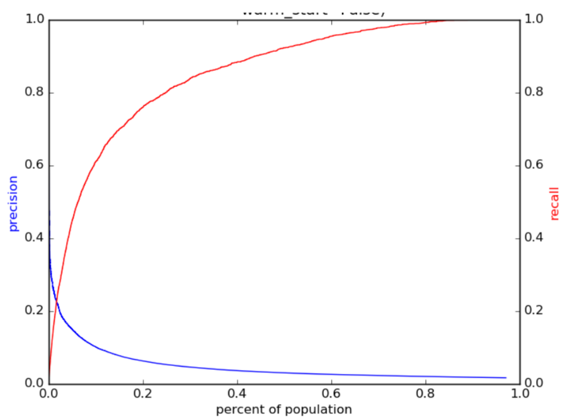

Figure 2: Precision and Recall Curves for our best performing Random Forest Model

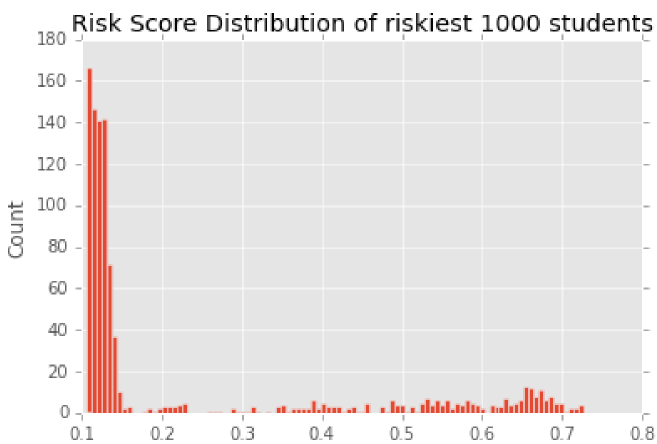

Figure 3: Risk Score Distribution of the riskiest 1000 students

the graph, that is the case for our best performing model which gives us confidence in the risk scores.

8.3 Comparison to current MPS approach

As our goal was to help the school targeting interventions for the relevant students, we compared our model results to the method the schools use to flag students who need intervention. Students are flagged as "generally at risk" using a rule-based method based on the number of suspensions and office discipline referrals as well as their current grade level[4]. We implemented MPS's tier-2 intervention as the baseline and calculated the performance in terms of precision, recall and percent of students that they flag. The current system flags 22,000 students, and 1300 of those flagged actually have an interaction with the criminal justice system 3 (precision of 5.9%). Compared to this, our model can identify the same number of at-risk students while only flagging 33% as many students. If we allow

	Flags	Correctly Identifies
Heuristic Method	22000	1310
Our Model	12000	1630

Table 3: Comparing the baseline method to the best performing model, we note that precision increases from 6% for the current system to 14% for the best model.

our model to flag as many students as the current method, we can identify 46% more students who will go on to interact with the criminal justice system. This shows the effectiveness of our system compared to the current methods being used in MPS today.

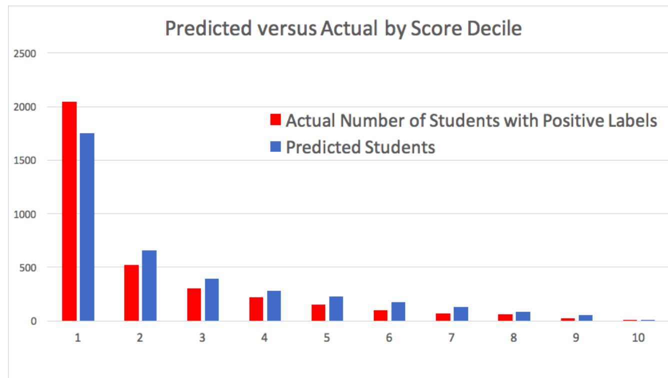

Figure 4: Comparing the predicted versus actual by score decile. We can see that model is performing very well in estimating the number of true positives in each decile

8.4 Feature Importances

The features that are most important in the best performing model are:

1. Number of "Child In Need of Protective Services" (CHIPS) record
2. Age
3. Number of discipline incidents in last 2 years
4. Average absence days over the years

The number of CHIPS record is generated from the DA data set. A record is created if a child is abused or neglected by their parent and the case was logged in MDA. This feature consistently shows up as one of the top features in our best performing model. It is important to note that this is not necessarily causal relationship. It is possible that the number of CHIPS records are correlated with other attributes of a juvenile and are showing up as highly predictive. Age is also very predictive compared to other features. This makes intuitive sense as a 15-year-old is generally more likely to commit an offense than a 8-year-old. Number of discipline incidents in the last 2 years and average absence days over the years are also among the top features, which is consistent with the findings in the literature [4] that state that absenteeism and truancy are often causes for delinquency. Interestingly, common demographic features such as gender and race are noticeably absent from the top features. This is

[4] The details can be found here: http://mps.milwaukee.k12.wi.us/en/Families/Family-Services/Intervention—PBIS/PBIS.htm

often the case since behavioral attributes are often more predictive than demographics but both have high correlation in practice.

To further investigate whether the number of CHIPS records are masking the contribution of other demographic variables, we examine the cross-tabs of number of CHIPS records and race. The result is presented in table 4. Comparing the racial make-up for students with at least one CHIPS record, we find that African Americans tend to have a higher fraction, and lower fraction of Hispanic students with at least 1 record. Together, the result suggests that African American are more likely, Hispanics are less likely and Whites are no more and no less likely to have more CHIPS records.

8.5 Future Work

The existing system only predicts interaction with the juvenile criminal justice system. A natural next step is to expand the label set to include adult interactions as well. We would also like to broaden the definition of interaction by incorporating arrest data. For example, it was reported that there were approximately 16000 arrests of juveniles in 2012, but based on the DA case data we only have information about 1923 incidents in 2012. Currently, we are only able to predict severe offenses, by including arrest data we can focus on models that would predict any interaction at all with the criminal justice systems. Many juveniles are often cited and released into the custody of their parents for minor offenses and currently our labels do not capture this kind of interaction. Another extension for this work would be to re-frame the problem as a multi-class prediction problem and predict classes of offense by severity. It would be interesting to investigate whether features have different predictive power in predicting certain classes of offenses.

Another area of future work is to generate more features using other data sets that are on the DataShare platform such as health and family data. The incorporation of health and family data would allow us to incorporate other likely predictive factors. For instance, the health dataset contains information on students' blood lead levels and vaccination status.

The premise of building a system such as ours is that we assume there exist interventions that are effective at reducing the risk of students having an interaction with the juvenile justice system. Our machine learning system can then identify students who should be matched with those interventions in order to improve their outcomes. A critical future endeavor is to 1) validate that assumption and determine whether existing interventions are in fact effective at reducing the risk, especially for high risk students and 2) determine which students are not responding to existing interventions and work with experts to create new interventions. Having a system that can accurate assess the future risk allows effective evaluation of existing interventions and supports the development of new ones, thus improving outcomes that we care about.

9 CONCLUSIONS

In this paper, we show that using school records, we can accurately identify students who are at risk of future juvenile criminal justice interactions. Experiments on historical data show that our model performs significantly better than the existing early warning system being used at Milwaukee Public Schools. If we allow our model to flag as many students as the current MPS method, we can identify 46% more students who will go on to interact with the criminal justice system. To the best of our knowledge this work represents the first data-driven approach to address the problem of juvenile deliquency using both school and criminal justice data. WE are currently working with the city of Milwaukee to implement this system and design intervention pilots and field trials.

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REFERENCES

[1] Anna Aizer and Joseph J. Doyle Jr. 2015. Juvenile Incarceration, Human Capital and Future Crime: Evidence from Randomly-Assigned Judges. *The Quarterly Journal of Economics* (February 2015).

[2] J. Bernburg and M. Krohn. 2003. Labeling, life chances, and adult crime: The direct and indirect effects of official intervention in adolescence on crime in early adulthood. *Criminology* 41 (2003), 1287–1316.

[3] Paul J Hirschfield and Joseph Gasper. 2011. The relationship between school engagement and delinquency in late childhood and early adolescence. *Journal of Youth and Adolescence* 40, 1 (2011), 3–22.

[4] B. Jacob and L. Lefgren. 2003. Are idle hands the devil's workshop? Incapacitation, concentration, and juvenile crime. *American Economic Review* 93, 5 (2003), 1560–1577.

[5] R. Ramchand, A. Morral, and K. Becker. 2003. Seven-Year Life Outcomes of Adolescent Offenders in Los Angeles. *American Journal of Public Health* 99, 5 (2003), 863fi?!870.

[6] A.J. Reynolds, J.A. Temple, D.L. Robertson, and E.A. Mann. Long-term effects of an early childhood intervention on educational achievement and juvenile arrest. *J. Amer. Med. Assn.* 285, 18 (????), 2339–2346.

[7] Ashley Sears. Alarming statistics, devastating consequences: MPD task force committed to reducing juvenile crime, year = 2016, url = http://fox6now.com/2016/03/02/alarming-statistics-devastating-consequences-mpd-task-force-committed-to-reducing-juvenile-crime/, urldate = 2016-03-02. (????).

[8] Howard N. Snyder and Melissa Sickmund. 1999. Juvenile justice system structure and process. In *Juvenile offenders and victims: 1999 national report*. Office of Juvenile Justice and Delinquency Prevention, Washington, D.C., Chapter 4, 84–109.

[9] Terence P Thornberry and Marvin D Krohn. 2001. The Development of Delinquency. In *Handbook of youth and justice*. Springer, 289–305.

[10] W. E. Winkler. 1990. String Comparator Metrics and Enhanced Decision Rules in the Fellegi-Sunter Model of Record Linkage. *Proc. Sec. Survey Res. Meth.* (1990), 354–359.

[11] E. Zigler, C. Taussig, and K. Black. 1992. Early childhood intervention. A promising preventative for juvenile delinquency. *Amer. Psychologist* 47, 8 (1992), 997–1006.

No. CHIPS records	0	1-10	11- 20	21- 30	31- 40	41-50
African-American	79840 (53.11%)	1185 (65.65%)	246 (68.14%)	78 (69.64%)	41	31
American Indian or Alaska Native	487 (0.32%)	13 (1.11%)	4 (1.05%)	0	0	0
Asian	7953 (5.29%)	13 (0.72%)	5 (1.39%)	0	0	0
Hispanic	33770 (22.46%)	287 (15.90%)	58 (16.07%)	3 (2.68%)	8	1
Native American	1062 (0.71%)	17 (0.94%)	1 (0.28%)	18 (16.07%)	1	2
White	25276 (16.81%)	280(15.51%)	40 (11.08%)	12 (10.71%)	5	6
Other	1943 (1.29%)	10 (0.55%)	7 (1.94%)	1 (0.89%)	0	0

*The figure within the parenthesis denotes the fraction of overall cases. The table is using all data up to year 2013.

Table 4: Number of CHIPS record by Race