

# **Predicting Recidivism in Connecticut**

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## **Abstract**

In the past ten years, all states combined reported annual spendings of \$50 billion (fluctuating +-\$2 billion per year) on inmate expenses. Leveraging predictive analysis and machine learning to find patterns in arrest data would empower law enforcement to predict which crimes to expect at any given time, which will reduce criminal activity and lead to less money spent on imprisonment. This research has been conducted with Connecticut convictions to help understand the type of crimes that occur in the area that this research was coordinated. Due to the fact that the Connecticut's conviction dataset is publicly accessible, but not available for direct download, custom software tools must be created to scrape the CT judicial website to get our data in a structured format that can be stored in a SQL database and analyzed with R programming. Information that can be gathered through analysis consists of (but is not limited to) common crimes in any given area and/or season, relationships between crimes, and estimations of recidivism for criminals.

## **Introduction**

Crime is inevitable in society, and sanctions for criminals are not cheap. Between 2002 and 2010 all states combined ran up a costly bill that ranged between \$48.4 and \$53.4 billion per year [1]. It costs ~\$29,000 per year to keep one offender incarcerated, and ~\$2,750 per year for post-release monitoring programs per offender [2]. To decrease the expensive sanctions cost, states would rather free prisoners on a post-release monitoring program such as parole. Post-release monitoring programs may sound like a win-win situation, however, many of these parolee's are not reformed from these programs and are likely to be rearrested and be a detriment to society.

There are two main ways offenders are released from prison: conditionally and unconditionally. Unconditional releases simply occur when a prisoners' sentence ends – there is no post-release supervision. Conditional releases are a bit more complicated and can be either discretionary or mandatory. Discretionary releases require prisoners to be screened by a parole board to see if they've been reformed and are ready to go back into society. Mandatory releases are obtained by prisoners who were on a program while serving their prison sentence that allowed them to earn "good-time credits" for an early release. Prisoners released on discretionary parole are less likely to be arrested than mandatory and unconditional release offenders – 60% of unconditional and mandatory release offenders were rearrested within two years of release, and 54% of discretionary parolee's were arrested within two years after their release [3]. In addition, the Bureau of Justice Statistics reported in 2005 that out of all the ex-parolees that committed a crime within 5 years of their release, 36.8% of these offenders were rearrested within 6 months of release, and 56.7% were rearrested within their first year of release [4].

Prisoners are often released early from sentences on monitoring programs like parole, however, many of these early-released prisoners end up back in prison. Releasing inmates prematurely allows them another chance to negatively affect society.

The Connecticut judicial website (<http://www.jud2.ct.gov/crdockets/parm1.aspx>) holds information about Connecticut court cases for the past 10 years. Each case is identified by a unique docket number. Docket numbers are composed of the court code, type of offense, year of offense, case number, and a suffix. Cases can be looked up by docket number, which will give a detailed summary regarding the court case. This detailed summary includes defendant information, docket information, and charge information. Information about the defendant consists of defendant first and last name, birth

year, and representing attorney. Docket information tells the arresting agency (typically police departments in the town that the crime was committed,) original arrest date, and sentenced date. Finally, all charges are listed with statute number, description, class (A, B, C, etc.,) type (felony/misdemeanor,) occurrences, offense date, plea, verdict finding, verdict date, and any fines/fees that the defendant was ordered to pay. **Figure 1** is a screenshot of a random docket on the CT judicial website that contains the aforementioned data. The data enclosed in the red box is 'metadata' about the case, blue box is the actual charges that the offender was charged with, green is the docket number I used as a join key between the case and metadata SQL tables, and purple is the composite key used to uniquely identify offenders.

In this paper, we will explore the process of creating a queryable database containing Connecticut judicial records, along with tools/models that allows the analysis and prediction of crimes in Connecticut. These tools will weigh offender's likelihood of being rearrested, which will affect how an offending criminal is sentenced.

|  |  |
|--|--|
| <b>Defendant Information</b>                                 |  |
| <b>Last, First:</b> [REDACTED]                               | <b>Represented By:</b> 402884 KM GLEASON                 |
| <b>Birth Year:</b> 1968                                      |  |
| <b>Docket Information</b>                                    |  |
| <b>Docket No:</b> N23N-MV08-0046598-S                        | <b>Original Arresting Agency:</b> LOCAL POLICE NEW HAVEN |
| <b>Court:</b> New Haven GA 23                                |  |
| <b>Costs:</b>  | <b>Original Arrest Date:</b> 3/14/2008                   |
|  | <b>Sentenced Date:</b> 9/16/2008                         |
| <b>Overall Sentence Information</b>                          |  |
| A Violation of Probation (1st) was disposed of on 08/31/2010 |  |
| Probation Continued  |  |

| Statute   | Description                    | Class Type | Occ | Offense Date | Plea   | Verdict Finding | Verdict Date | Fine     | Fee(s) |
|---|--------------------------------|------------|-----|--------------|--------|-----------------|--------------|----------|--------|
| 14-227a   | ILL Opn Mv Under Infl Alc/Drug |            | 1   | 3/14/2008    | Guilty | Guilty          | 9/16/2008    | \$500.00 | \$0.00 |
| <b>Sentenced:</b> 6 Months Jail, Execution Suspended, Probation 18 Months |                                |            |     |              |        |                 |              |          |        |
| 53a-32  | Violation Of Probation         |            | 1   |              | Guilty | Guilty          | 8/31/2010    | \$0.00   | \$0.00 |

through the local MySQL database, which created several boolean fields for each court case. These fields corresponded to: hasDrugCharges, hasWeaponCharge, hasBurglaryCharge, hasExecutionSuspended, and hasProbation.

### Understanding the dataset

Analysis in this project occurs in three different modules. The first module consisted of creating dashboards for the dataset. These dashboards helped illustrate the amount and type of data I was working with. These dashboards also supported 'drilling down' for a more detailed view of court records that a business user would be interested in viewing. These graphs and dashboards were modeled in Excel and the Business Analytic tool, Tableau.

### Finding patterns

The second module entailed using the IBM SPSS Modeler tool for data mining. Given the dataset and user-specified input/output fields, IBM Modeler helps identify the best predictive models for complex relationships in the dataset. After running my original dataset through the IBM SPSS Modeler with unsatisfying results, I decided I needed to go back to the data preparation phase to add boolean fields that would help predict patterns.

## Crime correlation

The final module consisted of using R to finalize my analysis. R utilized the data gained from modules 1 and 2 to create appropriate data models to perform statistical tests on. R allowed me to utilize the previously-created boolean values of the dataset to create a contingency table, which helped me find correlations between crimes that are likely to occur together. A fisher test was then applied to these contingency tables to statistically prove and support my findings.

Based on the information and patterns found throughout the analysis phase, a recidivism calculator has been generated that will give each offender a 'recidivism score.' Higher recidivism scores represent higher chances of the offender being rearrested. The formula for this calculation consists of three components of an offender: amount of previous cases, amount of times in jail, and probation violations. In conjunction with the aforementioned factors, a logistic regression model was used against a boolean value, representing whether or not that offender was re-sentenced within five years after their initial arrest. The exact formula for calculating recidivism scores is revealed in the results section of this paper.

All of the tools created and used for preparing the dataset used in this project are located on my GitHub at <https://github.com/dimattiami/CT-Judicial-Analysis>. The dataset in MySQL format (dump.txt) used in this project is available for download on my webserver at <http://osbuddy.pro/ct-jud/>.

## Results

The data preparation process is illustrated in **Figure 2**. After eliminating any duplicate cases, 308,360 out of 408,205 cases were retained, with a total of 536,991 charges across 141,017 different offenders. **Table 1** represents a breakdown of the amount of charges in each court case, and the corresponding amount of occurrences.

CT Judicial Website → local HTML files → Python parsing → MySQL → Java → MySQL

**Figure 2:** data preparation process

**Table 1:** Frequency table for number of number of charges in each court case

| # of charges | 1       | 2      | 3      | 4    | 5    | 6   | 7   | 8   | 9  | 10 | >10 |
|--------------|---------|--------|--------|------|------|-----|-----|-----|----|----|-----|
| Frequency    | 207,672 | 61,916 | 26,947 | 7138 | 3084 | 928 | 380 | 128 | 52 | 35 | 36  |

Several tests were performed on this dataset to reproduce previous findings, including a correlation between drug and weapon charges (**table 2**.) Only .014% of drug charges contained weapons. There were no major correlations found between drugs and weapons in this dataset, which is discussed further in the discussion section of this paper. However, after running Fisher's exact test for count data, a small p-value of 0.00958 was calculated. A similar test was conducted to find correlations between weapon and burglary charges (**table 3**.) with the majority of weapon charges not being related to burglaries with a p-value of <2.2e-16.

**Table 2:** 98.5% of drug charges did not contain weapons, while only .015% of drug charges contained weapons.

|           | weaponfalse | weapontrue |
|-----------|-------------|------------|
| drugfalse | 0.0         | 0.0        |
| drugtrue  | 0.98534916  | 0.01465084 |

**Table 3:** 5.9% of weapon charges were related to burglaries

|             | burglaryfalse | burglarytrue |
|-------------|---------------|--------------|
| weaponfalse | 0.0           | 0.0          |
| weapontrue  | 0.94076935    | 0.05923065   |

**Figure 3** represents the recidivism calculator that was discussed in the previous section. Higher recidivism scores represent higher chances of an offender to be rearrested. Recidivism score is calculated by multiplying three times the amount of previous cases an offender has, multiplying 2 by the amount of times the offender has been in jail, and then the amount of times an offender has probation violations multiplied by 1.5.

|  |
|--|
| $\text{recidivism score} = 3 * \text{amt of previous cases} + 2 * \text{timesInJail} + 1.5 * \text{probationViolationOccurrences}$ |
|--|

**Figure 3:** weighted recidivism calculator

**Figure 4** is a tree-map that represents the most occurring crimes per season (darker color/bigger square means more occurrences.) The biggest issue in summer for law enforcement was assault of the 3<sup>rd</sup> degree, spring and winter had the most arrests for driving under the influencing, and autumn's largest issue was larceny of the 6<sup>th</sup> degree.

Before wrapping up my results, since our school is located in Willimantic, I'd like to reflect on the arrests made by the Willimantic police department. First thing that I'd like to point out are the age of offenders at the time of their arrests. The top ten ages of offenders in Willimantic are 26, 22, 23, 24, 25, 30, 21, 28, 27, and 29 with occurrences (arrest counts) of 149, 149, 138, 136, 130, 129, 126, 122, 118, 115, respectively; people in their mid-twenties are likely to offend in Willimantic. The top five offenses that occurred in Willimantic were breach of peace 2<sup>nd</sup> degree (504 occurrences,) failure to appear 2<sup>nd</sup> degree (393 occurrences,) driving under the influence (356 occurrences,) assault 3<sup>rd</sup> degree (314 occurrences,) and possession of narcotics (312 occurrences.)



aforementioned keys to create a composite 'PersonID' unique identifier for each person in the database. I noticed several times that offenders had similar names and birth years, but had different PersonID's. After further investigation, these people with similar PersonIDs were actually the same person – they just had misspellings in their name. Another issue that revolves around using first name, last name, and birth year as a unique identifier is that if two offenders have the same name and birth year (very unlikely,) there will be inconsistencies when analyzing individual offenders. A solution to this issue (which would guarantee unique identification,) would be to use offender social security number, which is most likely only available to the CT judicial system internally.

The recidivism calculator falls short in two aspects. The calculator takes into account offenders that were re-sentenced within five years after their initial arrest. Due to the small time frame of the dataset offered by the CT judicial system (past 10 years of arrest data,) many of the later offenders were unable to be followed up with because five-years of time hadn't elapsed since their arrest. A potential solution to this issue is to check if the offender already exists in the database when new arrest data is automatically ingested into the system (discussed in a few paragraphs.) The initial idea for the recidivism calculator came from The United States Bureau of Justice Statistics (BJS); BJS used prisoner data from 2005 to create a "prisoner recidivism analysis tool" to estimate recidivism rates based on factors such as gender, race, type of crime, and prior arrests [5]. Due to time restrictions, I was unable to calculate a recidivism score for each offender in the dataset, and then run those scores through a linear regression model to obtain statistical support for my calculator.

When looking for correlations between crimes, I based the correlating factors on successful correlations found in previous studies. The Bureau of Justice Statistics reported that 24% of drug offenders were charged with possession of a weapon during their arrest [6]. In my study, there was not a visible correlation between drug and weapon charges. I believe that the reason why my correlation results did not reflect the BJS's findings was because the BJS's study consisted of federal inmates, who tend to be more dangerous (more likely to be in possession of weapons) than offenders arrested at the state-level.

In addition to the cases utilized in my research, the CT judicial website also offers information about pending cases (<http://www.jud2.ct.gov/crdockets/parm1.aspx>.) An automated process could be created to scrape and ingest new court records from this pending case database into my local MySQL database. Having this automatic ingestion process would allow real-time trend analysis on a day-by-day (daily) time granularity.

Another idea I had - but was unable to implement due to time restrictions - was to split the dataset into a training and testing set by arrest year. I would try to train a model with the first six years of criminal records to calculate recidivism rates for each offender, and then test the calculated recidivism rate against the testing set (cases following the first six years) to see how accurate the recidivism calculator is, based on offenders that were rearrested in the testing set years.

There were other factors that were not examined during this projects due to time restrictions and lack of data offered by the CT judicial website, such as gender. BJS analyzed criminals in parole programs and found that 48% of the female parolee's successfully completed their parole program, while only 39% of males completed their parole program [7]. In 2015, 59% of female federal prisoners and 49% of male federal prisoners were serving sentences for drug charges [8]. If we wanted to analyze Connecticut crimes based on gender, an additional field would be added to the database; gender. This field would hold characters 'M' for male or 'F' for female, which would be obtained by determining offender gender based on their first name. The main issue with finding gender based on a first name is unisex names; if CT judicial provided this in their database, gender could have easily been incorporated into this project.



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