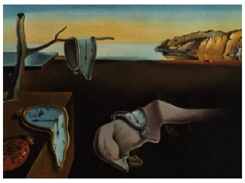

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Team 15 The Scientists: Crime Prediction Proposal

Xiangyu Jin (xjin13)
UIUC

Vinayak Bagdi (vbagdi2)
UIUC

Abstract

The project aims to predict the type of crime an arrestee may have committed based on their background information such as race, sex, age, and other attributes. The central idea is to examine whether there are any relationships between crime types and arrestee's background information and to study the crime distribution in Champaign The project employs classification models or random forests model to predict the crime type based on the information about the arrestees. The project uses data before 2018 as training data and data after 2018 as testing data to test the model's accuracy. The methods employed so far include data cleaning, feature engineering, data manipulation, data visualization, and data analysis using R. The implications of the work done so far will help to improve the understanding of crime distribution in Champaign and aid in the development of effective crime prevention and control strategies.

Keywords: R, group project.


```
library(tidyverse)
```

```
-- Attaching packages --------------------------------------- tidyverse 1.3.2 --
v ggplot2 3.4.1     v purrr   0.3.4
v tibble  3.1.8     v dplyr   1.0.9
v tidyr   1.2.0     v stringr 1.4.1
v readr   2.1.2     v forcats 0.5.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
```

```
library(ggplot2)
library(hrbrthemes)
```

```
NOTE: Either Arial Narrow or Roboto Condensed fonts are required to use these themes.
      Please use hrbrthemes::import_roboto_condensed() to install Roboto Condensed and
      if Arial Narrow is not on your system, please see https://bit.ly/arialnarrow
```

```
library(caret)
```

```
Loading required package: lattice

Attaching package: 'caret'

The following object is masked from 'package:purrr':

    lift
```

```
library(ranger)
library(randomForest)
```

```
randomForest 4.7-1.1
Type rfNews() to see new features/changes/bug fixes.

Attaching package: 'randomForest'

The following object is masked from 'package:ranger':

    importance

The following object is masked from 'package:dplyr':

    combine

The following object is masked from 'package:ggplot2':

    margin
```

```
library(ROCR)
library(myPackage)
```

1. Introduction

The project aims to examine the relationship between the type of crime and the background information of the arrestees, including race, sex, age, and other attributes. The problem being addressed is the high rate of crime in Champaign, which poses a significant threat to the safety and well-being of residents. It is essential to develop effective crime prevention and control strategies that take into account the underlying factors contributing to crime. The objective of the project is to predict the type of crime an arrestee may have committed based on their background information, which can aid in developing effective crime prevention strategies.

The motivation for pursuing this problem is to improve the understanding of crime distribution in Champaign and to identify potential factors contributing to the high rate of crime. The project can aid in the development of targeted crime prevention and control strategies that can help to reduce crime rates in the city. Additionally, the project can help law enforcement agencies to allocate resources effectively and efficiently.

2. Related Works

Guido Vittorio Travaini,Federico Pacchioni, Silvia Bellumore, Marta Bosia, Francesco De Micco (2022) explores the use of machine learning algorithms to predict the likelihood of criminal recidivism. The study used a dataset consisting of demographic and criminal history variables of inmates to develop a prediction model. This study is relevant to our project as it also uses machine learning algorithms to predict criminal activities based on input features. However, the focus of our project is on predicting the type of crime based on the background information of the arrestees, whereas the study by Guido Vittorio Travaini,Federico Pacchioni, Silvia Bellumore, Marta Bosia, Francesco De Micco (2022) is focused on predicting the likelihood of criminal recidivism. Both employ machine learning algorithms to predict criminal activities based on input features. However, the input features and prediction targets are different. Our project focuses on predicting the type of crime based on the background information of the arrestees, whereas the study by Guido Vittorio Travaini,Federico Pacchioni, Silvia Bellumore, Marta Bosia, Francesco De Micco (2022) focuses on predicting the likelihood of criminal recidivism based on demographic and criminal history variables of inmates.

Umair Saeed (2015) explores the use of machine learning algorithms to classify criminal activities based on the input features. The study used a dataset consisting of demographic and behavioral variables of criminals to develop a prediction model.This study is relevant to the current project as it also uses machine learning algorithms to predict criminal activities based on input features. The focus of our project is on predicting the type of crime based on the background information of the arrestees, whereas the study by Umair Saeed (2015) is focused on classifying criminal activities based on the input features. Both employ machine learning algorithms to predict criminal activities based on input features. However, the prediction targets are different. Our project focuses on predicting the type of crime based on the background information of the arrestees, whereas the study by Umair Saeed (2015) focuses on classifying criminal activities based on the input features.

Varun Mandalapu (2023) is a systematic review of crime prediction using machine learning techniques. The authors reviewed and analyzed 82 research papers from 2010 to 2019. The review highlights the importance of data preprocessing, feature selection, and algorithm selection in crime prediction. The authors also discuss the limitations and challenges of using machine learning in crime prediction, such as data imbalance, interpretability, and ethical concerns. This work relates to our current project as it provides insights into the state of the art in crime prediction using machine learning techniques. It highlights the importance of data preprocessing and algorithm selection, which are critical steps in our project. It also discusses the challenges and limitations of using machine learning in crime prediction, which we should be aware of when interpreting our results. Our approach will be similar to the reviewed papers in terms of using machine learning techniques for crime prediction. However, we will focus on a specific dataset from Champaign and investigate the relationship between crime types and arrestee's background information. We will also perform data preprocessing, feature engineering, and model selection based on the characteristics of our dataset.

Pearsall analyzes the implementation and impact of predictive policing practices in Baltimore, Maryland. The authors use administrative data from the Baltimore Police Department to evaluate the accuracy and effectiveness of crime predictions and to examine the potential biases and ethical implications of using predictive policing. The study finds that predictive policing does not significantly reduce crime and may exacerbate existing racial and socioeconomic disparities in policing. This work relates to our project as it raises important ethical and social issues in crime prediction using machine learning. It highlights the potential biases and unintended consequences of using predictive policing and emphasizes the need for transparency and accountability in policing practices. Our approach will differ from the reviewed paper as we will not be directly implementing predictive policing. However, we will be using models to predict crime types based on arrestee's background information, which raises similar ethical and social concerns. We will need to consider the potential biases and unintended consequences of using our models and ensure that our results are transparent and accountable.

Ying-Lung Lin,Meng-Feng Yen, and Liang-Chih Yu proposes a crime prediction model based on long short-term memory (LSTM) neural networks. The authors use crime data from a police department in China to train and test their model. They compare the performance of their LSTM model with other machine learning models and find that LSTM outperforms traditional models in predicting crime. This work relates to our project as it proposes a machine learning model specifically designed for crime prediction. It suggests that deep learning models, such as LSTM, may be more suitable for capturing the temporal patterns and dependencies in crime data. We can consider using LSTM or other deep learning models as an alternative approach to our prediction task. Our approach will be similar to the reviewed paper in terms of using machine learning models for crime prediction. However, we will be using a different dataset from Champaign and a different set of predictors. We will also be comparing the performance of different machine learning models to select the best model for our task. ## Data

```
# Reading online CSV file with big limit
my_data = load_data()
```

```
Warning: One or more parsing issues, see `problems()` for details
```

```
Rows: 216554 Columns: 25
-- Column specification --------------------------------------------------------
Delimiter: ","
chr  (19): arrest_code, incident_number, arrest_type_description, crime_code...
dbl   (4): year_of_arrest, month_of_arrest, disposition_code, age_at_arrest
lgl   (1): conspiracy_code
dttm  (1): date_of_arrest

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
summary(my_data)
```

```
 arrest_code        incident_number    date_of_arrest
 Length:216554      Length:216554      Min.   :1988-01-01 00:00:00.0
 Class :character   Class :character   1st Qu.:1996-07-10 00:00:00.0
 Mode  :character   Mode  :character   Median :2004-07-05 00:00:00.0
                                       Mean   :2004-08-27 15:07:28.5
                                       3rd Qu.:2012-06-21 00:00:00.0
                                       Max.   :2023-02-14 00:00:00.0
```

```
                                         NA's   :1
year_of_arrest month_of_arrest  arrest_type_description  crime_code
Min.   :1988   Min.   : 1.000   Length:216554           Length:216554
1st Qu.:1996   1st Qu.: 4.000   Class :character        Class :character
Median :2004   Median : 6.000   Mode  :character        Mode  :character
Mean   :2004   Mean   : 6.458
3rd Qu.:2012   3rd Qu.: 9.000
Max.   :2023   Max.   :12.000
NA's   :1      NA's   :1
crime_code_description crime_category_code crime_category_description
Length:216554          Length:216554       Length:216554
Class :character       Class :character    Class :character
Mode  :character       Mode  :character    Mode  :character


conspiracy_code   statute            violation          disposition_code
Mode:logical    Length:216554      Length:216554      Min.   :86.00
TRUE:2          Class :character   Class :character   1st Qu.:87.00
NA's:216552     Mode  :character   Mode  :character   Median :87.00
                                                      Mean   :87.81
                                                      3rd Qu.:88.00
                                                      Max.   :98.00
                                                      NA's   :1
disposition_description age_at_arrest      arrestee_sex
Length:216554           Min.   :-7172.00   Length:216554
Class :character        1st Qu.:   20.00   Class :character
Mode  :character        Median :   26.00   Mode  :character
                        Mean   :   29.48
                        3rd Qu.:   36.00
                        Max.   :   99.00
                        NA's   :1
arrestee_race      arrestee_employment_description
Length:216554      Length:216554
Class :character   Class :character
Mode  :character   Mode  :character


arrestee_residency_description arrestee_home_city arrestee_home_state
Length:216554                  Length:216554      Length:216554
Class :character               Class :character   Class :character
Mode  :character               Mode  :character   Mode  :character
```

```
 arrestee_home_zip  arrest_resolution  mapped_address
 Length:216554      Length:216554      Length:216554
 Class :character   Class :character   Class :character
 Mode  :character   Mode  :character   Mode  :character
```

The data set contains both numerical and character data. City of Urbana collected the data and this data set is available on Urbana's Open Data website. The whole data set contains 216554 observations and 25 features. The data set is updated monthly with two months lag. The data set is in CSV form. When we load the data, we need to specify length of csv file as large as possible. Otherwise, only first 1000 observations will be loaded.

```
# First five observations of the dataset.
head(my_data, n = 5)
```

```
# A tibble: 5 x 25
  arrest_c~1 incid~2 date_of_arrest      year_~3 month~4 arres~5 crime~6 crime~7
  <chr>      <chr>   <dttm>                <dbl>   <dbl> <chr>   <chr>   <chr>
1 A23-00466  T23-00~ 2023-02-14 00:00:00    2023       2 SUMMON~ 2460    CANCEL~
2 A23-00459  T23-00~ 2023-02-13 00:00:00    2023       2 SUMMON~ 2481    DRIVIN~
3 A23-00461  U23-02~ 2023-02-13 00:00:00    2023       2 SUMMON~ 6621    FAILUR~
4 A23-00463  U23-02~ 2023-02-13 00:00:00    2023       2 SUMMON~ 6617    FAILUR~
5 A23-00465  U23-02~ 2023-02-13 00:00:00    2023       2 SUMMON~ 2461    OPERAT~
# ... with 17 more variables: crime_category_code <chr>,
#   crime_category_description <chr>, conspiracy_code <lgl>, statute <chr>,
#   violation <chr>, disposition_code <dbl>, disposition_description <chr>,
#   age_at_arrest <dbl>, arrestee_sex <chr>, arrestee_race <chr>,
#   arrestee_employment_description <chr>,
#   arrestee_residency_description <chr>, arrestee_home_city <chr>,
#   arrestee_home_state <chr>, arrestee_home_zip <chr>, ...
```

3. EDA

```
my_data %>%
  select(where(is.numeric)) %>%
  summary()
```

```
 year_of_arrest month_of_arrest  disposition_code age_at_arrest
 Min.   :1988   Min.   : 1.000   Min.   :86.00    Min.   :-7172.00
 1st Qu.:1996   1st Qu.: 4.000   1st Qu.:87.00    1st Qu.:   20.00
 Median :2004   Median : 6.000   Median :87.00    Median :   26.00
 Mean   :2004   Mean   : 6.458   Mean   :87.81    Mean   :   29.48
 3rd Qu.:2012   3rd Qu.: 9.000   3rd Qu.:88.00    3rd Qu.:   36.00
```

```
 Max.   :2023   Max.   :12.000   Max.   :98.00    Max.   :   99.00
 NA's   :1      NA's   :1        NA's   :1        NA's   :1
```

3.1. Data Cleaning and Feature Engineering

```
my_data = myPackage::process_data(my_data)
```

```
summary(my_data)
```

```
 incident_number    year_of_arrest month_of_arrest  crime_category_description
 Length:112059      Min.   :2000   Min.   : 1.000   Length:112059
 Class :character   1st Qu.:2004   1st Qu.: 4.000   Class :character
 Mode  :character   Median :2009   Median : 6.000   Mode  :character
                    Mean   :2009   Mean   : 6.427
                    3rd Qu.:2014   3rd Qu.: 9.000
                    Max.   :2019   Max.   :12.000
 age_at_arrest   arrestee_sex       arrestee_race
 Min.   : 9.00   Length:112059      Length:112059
 1st Qu.:21.00   Class :character   Class :character
 Median :26.00   Mode  :character   Mode  :character
 Mean   :30.47
 3rd Qu.:37.00
 Max.   :99.00
 arrestee_employment_description arrestee_home_city arrestee_home_state
 Length:112059                   Length:112059      Length:112059
 Class :character                Class :character   Class :character
 Mode  :character                Mode  :character   Mode  :character



   homecity
 Length:112059
 Class :character
 Mode  :character
```

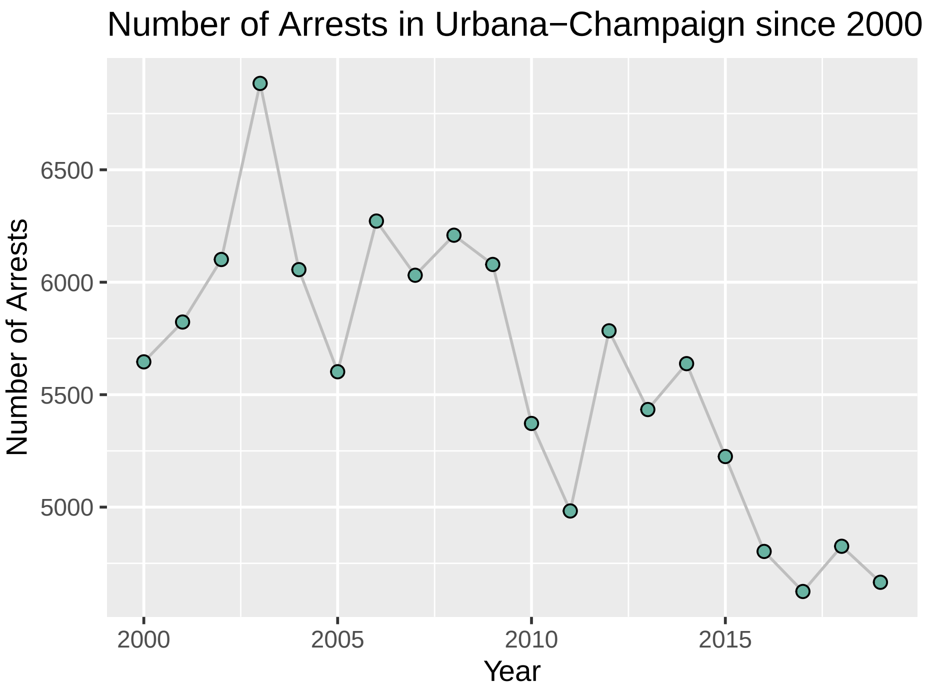
```
sum(is.na(my_data))
```

```
[1] 0
```

After data cleaning and feature engineering, we filter the data only after year 2000. Moreover, we only select variables `incident_number`, `year_of_arrest`, `month_of_arrest`,`crime_category_descripti` `age_at_arrest`, `arrestee_sex`, `arrestee_race`, `arrestee_employment_description`, `arrestee_home_city`, and `arrestee_home_state` to use in our model. Since other variables such as `arrest_code` do not seem relate to crime prediction.

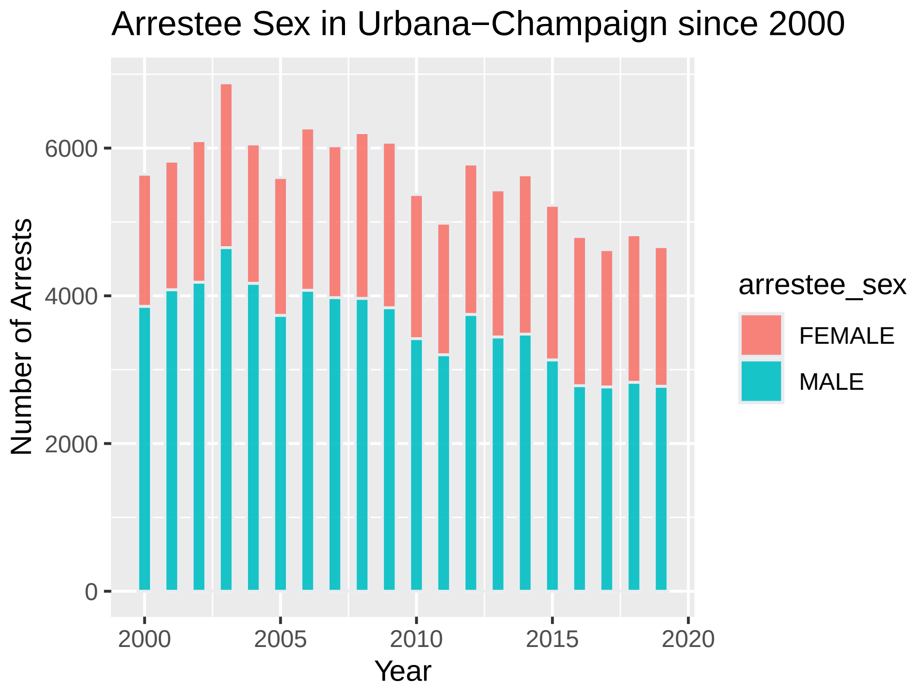
Plots

```
# number of cases versus time (year)
myPackage::tn_plot(my_data)
```



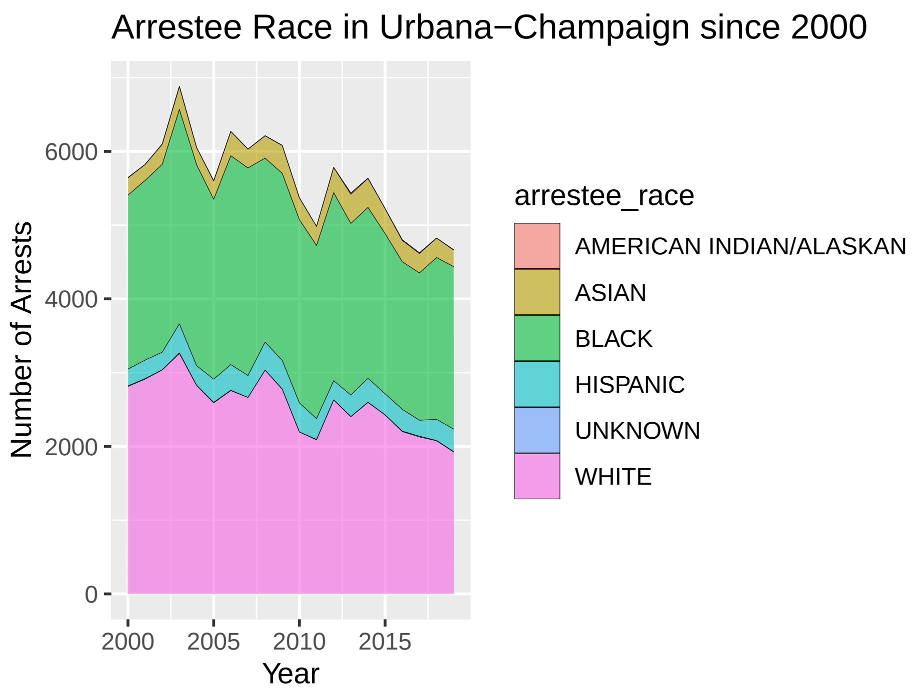
Based on this graph, we can see that 2003 has the highest number of arrests from 2000 to 2023. Moreover, there is a decreasing trend on number of arrests through out years.

```
# Graph to see in each year arrestees sex proportion
myPackage::ts_plot(my_data)
```



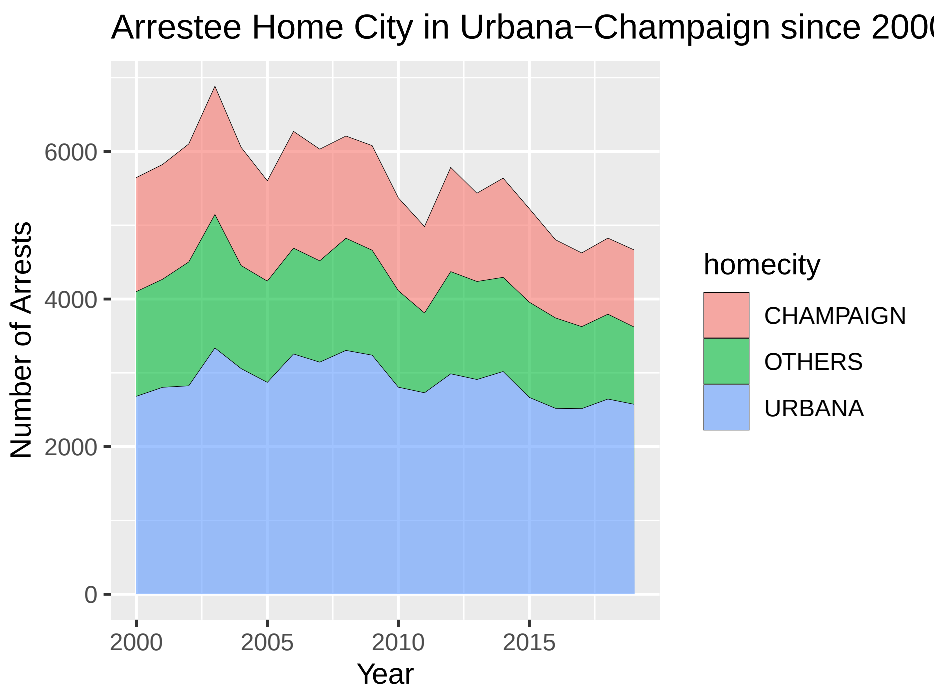
Based on this graph, we can see that Male contributes over 50% of arrests each year, which means that MALE is more likely to got arrested compared with FEMALE.

```
# Graph to see in each year arrestee race proportion
myPackage::tr_plot(my_data)
```



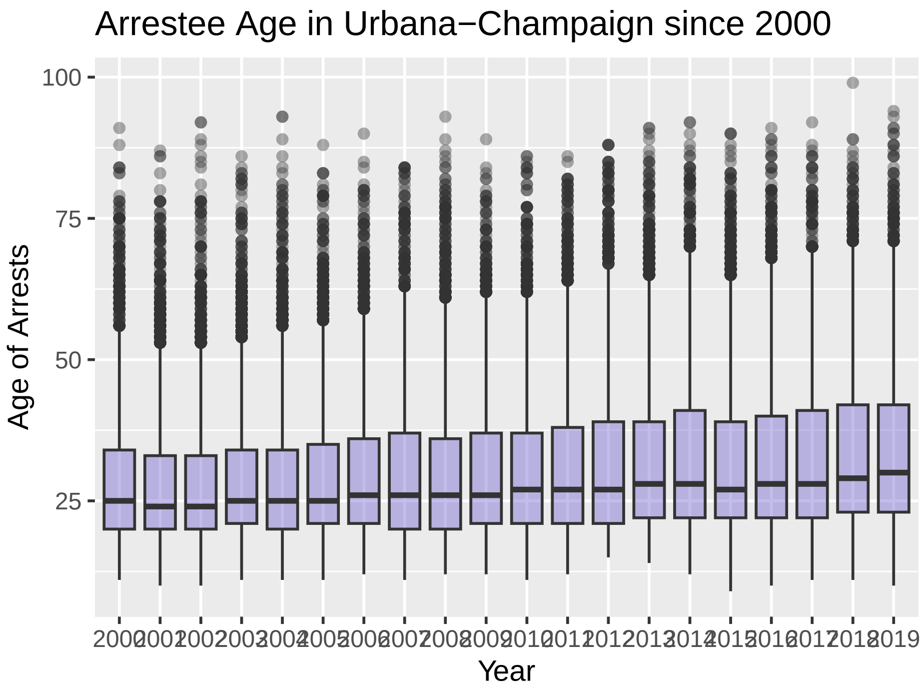
Based on this graph, we can see there BALCK and WHITE contribute over 80% arrests. We can roughly see that WHITE contributes a little more than BLACK.

```
## Graph to show proportions of arrestee home city in each year
myPackage::th_plot(my_data)
```



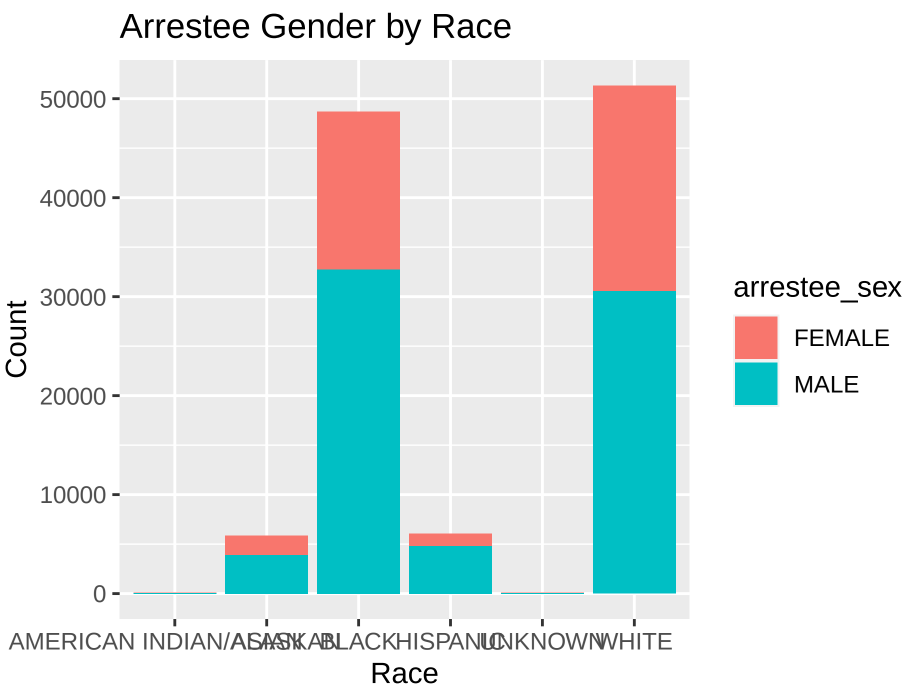
Based on this graph, we can see that most arrestees are from URBANA. Arrestess from CHAMPAIGN and Other home cities roughtly contribute the same to the total number of arrests in each year.

```
# Create visulization to see age distribution in each year
myPackage::ta_plot(my_data)
```



As shown in the graph, we can see that the average age of arrestees in each year is gradually increasing. And the range of age is also increasing along the year. Age distribution seems more spread out along th year.

```
# Create visulization to see relationship between arrestee sex and arrestee race
myPackage::sr_plot(my_data)
```



In the graph above, we can see that MALE contributes more than FEMALE in ASIAN, BLACK, HISPANIC, and WHITE races. Especially in ASIAN and HISPANIC races, we need to consider the correlation between races and sex. Moreover, counts of AMERICAN INDIAN?ALASKAS and UNKOWN races are so few that we might consider drop it in modeling.

3.2. Method and Results

Random Forests

The modeling technique we are going to use is Random Forests. Random Forests is a machine learning algorithm that combines multiple decision trees to produce a more accurate and stable prediction. It reduces overfitting by building each tree on a random subset of the data and a random subset of the features. It handles both categorical and numerical data, is less sensitive to outliers and noise, and can handle missing data. Random Forests has many applications, including predictive modeling in various fields, feature selection, anomaly detection, and image and text classification. It is easy to interpret and visualize the results, making it a powerful and popular algorithm in the machine learning community.

We choose random forests as our modeling algorithm because Random Forests can handle complex and non-linear relationships between the input features and the target variable. It can capture interactions and correlations between the variables, which may not be captured by simpler models such as linear regression. And more importantly, it can dorectly handle both categorical and numerical data since we have both type in our data set.

In this algorithm, precision, which is the proportion of true positives out of the total predicted positives, will be used to assess the model's performance. It measures the model's ability to identify true positives

Results

```
# Split the data
set.seed(447)

model_data = myPackage::model_data(my_data)


rf_model = myPackage::model(model_data)

print(rf_model)
```

```
Random Forest

76048 samples
    6 predictor
   21 classes: 'Animal Offenses', 'Assault', 'Battery', 'Burglary', 'Cannabis Offenses', '
```

```
No pre-processing
Resampling: Cross-Validated (2 fold)
Summary of sample sizes: 38024, 38024
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
   2    0.6168078  0.3006028
   8    0.6169788  0.3285411
  14    0.5762282  0.2940076

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was mtry = 8.
```

```
# best mtry 8
# get the test data
set.seed(447)
trainIndex <- createDataPartition(1:nrow(model_data), p = 0.7, list = FALSE)
test <- model_data[-trainIndex, ]

prediction = predict(rf_model, test)

# evaluation
confusionMatrix(prediction, as.factor(test$crime_category_description))
```

```
Confusion Matrix and Statistics

                               Reference
Prediction                      Animal Offenses Assault Battery Burglary
  Animal Offenses                            16       0      11        0
  Assault                                     0       0       5        0
  Battery                                    10      19     162       26
  Burglary                                    0       0      11        8
  Cannabis Offenses                           0       4      10        5
  Controlled Substance Offenses               0       0       0        3
  Criminal Damage                             0       1       6        1
  Deception & Fraud                           0       1       1        0
  Disorderly Conduct                          1       1      41        7
  Driving Under the Influence                 2       3      13        1
  Drug Paraphernalia Act                      0       1       1        0
  Interfering w/Public Officers               0       3      18        3
  Liquor Offenses                             2       2      59       20
  Noise & Vibrations Violations               0       0       5        4
  Offenses Involving Children                 0       0       4        0
  Prob/Parole/Bail Violations                 0       0       1        0
  Theft                                       4       9      69       12
  Traffic Offenses                          252      86     606      113
  Trespassing                                 0       0       3        0
  Warrants & Summons                         55     106     819      123
```

Weapons Offenses	0	2	1	1

	Reference	
Prediction	Cannabis Offenses	Controlled Substance Offenses
Animal Offenses	0	0
Assault	0	1
Battery	38	15
Burglary	6	1
Cannabis Offenses	13	4
Controlled Substance Offenses	1	2
Criminal Damage	0	0
Deception & Fraud	0	1
Disorderly Conduct	4	2
Driving Under the Influence	5	0
Drug Paraphernalia Act	6	1
Interfering w/Public Officers	16	5
Liquor Offenses	78	13
Noise & Vibrations Violations	1	0
Offenses Involving Children	0	0
Prob/Parole/Bail Violations	0	0
Theft	15	7
Traffic Offenses	213	137
Trespassing	0	0
Warrants & Summons	293	212
Weapons Offenses	2	0

	Reference	
Prediction	Criminal Damage	Deception & Fraud
Animal Offenses	0	2
Assault	3	1
Battery	44	8
Burglary	0	1
Cannabis Offenses	5	3
Controlled Substance Offenses	0	0
Criminal Damage	1	0
Deception & Fraud	0	5
Disorderly Conduct	8	0
Driving Under the Influence	4	1
Drug Paraphernalia Act	1	0
Interfering w/Public Officers	4	1
Liquor Offenses	32	13
Noise & Vibrations Violations	2	1
Offenses Involving Children	1	0
Prob/Parole/Bail Violations	1	0
Theft	10	11
Traffic Offenses	134	116
Trespassing	0	0
Warrants & Summons	212	74
Weapons Offenses	3	0

```
                              Reference
Prediction                     Disorderly Conduct Driving Under the Influence
  Animal Offenses                               3                           3
  Assault                                       1                           0
  Battery                                      62                          24
  Burglary                                      2                           0
  Cannabis Offenses                             5                           5
  Controlled Substance Offenses                 0                           2
  Criminal Damage                               3                           0
  Deception & Fraud                             0                           0
  Disorderly Conduct                           50                           0
  Driving Under the Influence                   5                          38
  Drug Paraphernalia Act                        0                           2
  Interfering w/Public Officers                 8                           3
  Liquor Offenses                              41                          43
  Noise & Vibrations Violations                 1                           2
  Offenses Involving Children                   0                           0
  Prob/Parole/Bail Violations                   1                           0
  Theft                                        22                           6
  Traffic Offenses                            251                         532
  Trespassing                                   2                           0
  Warrants & Summons                          204                         175
  Weapons Offenses                              1                           0
                              Reference
Prediction                     Drug Paraphernalia Act
  Animal Offenses                                   0
  Assault                                           1
  Battery                                          13
  Burglary                                          0
  Cannabis Offenses                                 9
  Controlled Substance Offenses                     3
  Criminal Damage                                   0
  Deception & Fraud                                 0
  Disorderly Conduct                                2
  Driving Under the Influence                       7
  Drug Paraphernalia Act                            0
  Interfering w/Public Officers                     1
  Liquor Offenses                                  50
  Noise & Vibrations Violations                     2
  Offenses Involving Children                       1
  Prob/Parole/Bail Violations                       0
  Theft                                            12
  Traffic Offenses                                133
  Trespassing                                       0
  Warrants & Summons                              126
  Weapons Offenses                                  0
                              Reference
```

Prediction	Interfering w/Public Officers	Liquor Offenses
Animal Offenses	0	2
Assault	0	4
Battery	44	29
Burglary	3	5
Cannabis Offenses	9	19
Controlled Substance Offenses	1	0
Criminal Damage	0	1
Deception & Fraud	1	0
Disorderly Conduct	3	16
Driving Under the Influence	4	6
Drug Paraphernalia Act	0	0
Interfering w/Public Officers	10	11
Liquor Offenses	29	411
Noise & Vibrations Violations	1	4
Offenses Involving Children	1	0
Prob/Parole/Bail Violations	1	0
Theft	19	17
Traffic Offenses	348	523
Trespassing	0	1
Warrants & Summons	374	154
Weapons Offenses	1	1

	Reference
Prediction	Noise & Vibrations Violations
Animal Offenses	3
Assault	0
Battery	17
Burglary	1
Cannabis Offenses	2
Controlled Substance Offenses	1
Criminal Damage	1
Deception & Fraud	0
Disorderly Conduct	3
Driving Under the Influence	5
Drug Paraphernalia Act	1
Interfering w/Public Officers	1
Liquor Offenses	19
Noise & Vibrations Violations	4
Offenses Involving Children	0
Prob/Parole/Bail Violations	0
Theft	10
Traffic Offenses	152
Trespassing	0
Warrants & Summons	102
Weapons Offenses	0

	Reference
Prediction	Offenses Involving Children

```
  Animal Offenses                                  1
  Assault                                          0
  Battery                                         30
  Burglary                                         1
  Cannabis Offenses                                0
  Controlled Substance Offenses                    0
  Criminal Damage                                  0
  Deception & Fraud                                0
  Disorderly Conduct                               0
  Driving Under the Influence                      3
  Drug Paraphernalia Act                           0
  Interfering w/Public Officers                    0
  Liquor Offenses                                  3
  Noise & Vibrations Violations                    0
  Offenses Involving Children                      1
  Prob/Parole/Bail Violations                      0
  Theft                                            1
  Traffic Offenses                                52
  Trespassing                                      0
  Warrants & Summons                              72
  Weapons Offenses                                 1
                               Reference
Prediction                      Prob/Parole/Bail Violations Theft
  Animal Offenses                                         0     3
  Assault                                                 0     2
  Battery                                                 8    81
  Burglary                                                0    11
  Cannabis Offenses                                       1     8
  Controlled Substance Offenses                           0     1
  Criminal Damage                                         0     2
  Deception & Fraud                                       0     5
  Disorderly Conduct                                      0    14
  Driving Under the Influence                             0    13
  Drug Paraphernalia Act                                  0     4
  Interfering w/Public Officers                           0    13
  Liquor Offenses                                         2    65
  Noise & Vibrations Violations                           0     3
  Offenses Involving Children                             0     0
  Prob/Parole/Bail Violations                             0     0
  Theft                                                   3    91
  Traffic Offenses                                       45   347
  Trespassing                                             0     2
  Warrants & Summons                                     95   553
  Weapons Offenses                                        0     0
                               Reference
Prediction                      Traffic Offenses Trespassing Warrants & Summons
  Animal Offenses                              3           0                 10
```

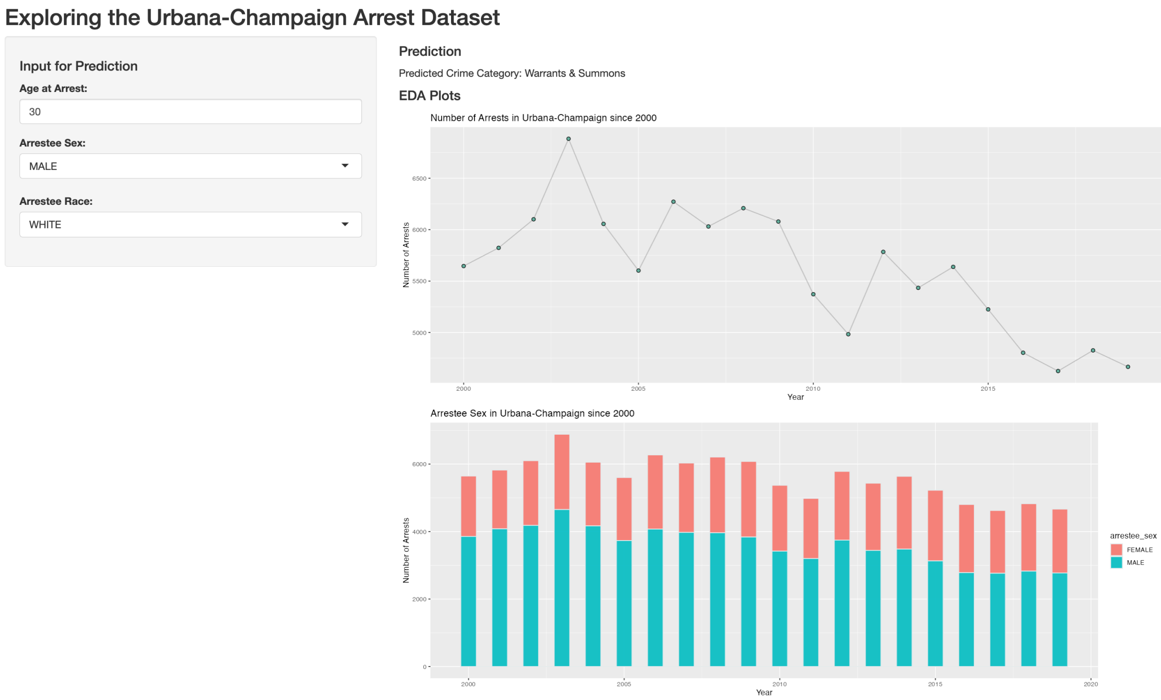
```
  Assault                                    1        0                 0
  Battery                                   68       27               139
  Burglary                                   3        3                 7
  Cannabis Offenses                         18        1                16
  Controlled Substance Offenses              2        0                 1
  Criminal Damage                            1        0                 1
  Deception & Fraud                          2        1                 2
  Disorderly Conduct                        22       11                11
  Driving Under the Influence               68        2                12
  Drug Paraphernalia Act                     3        2                 1
  Interfering w/Public Officers             25        3                11
  Liquor Offenses                           73       25                53
  Noise & Vibrations Violations              1        0                 3
  Offenses Involving Children                0        0                 2
  Prob/Parole/Bail Violations                2        0                 1
  Theft                                     31       14                60
  Traffic Offenses                       18020      125               861
  Trespassing                                0        1                 1
  Warrants & Summons                       650      213              1472
  Weapons Offenses                           3        0                 1
                               Reference
Prediction                      Weapons Offenses
  Animal Offenses                            0
  Assault                                    1
  Battery                                    6
  Burglary                                   0
  Cannabis Offenses                          5
  Controlled Substance Offenses              0
  Criminal Damage                            0
  Deception & Fraud                          0
  Disorderly Conduct                         3
  Driving Under the Influence                0
  Drug Paraphernalia Act                     0
  Interfering w/Public Officers              5
  Liquor Offenses                            6
  Noise & Vibrations Violations              0
  Offenses Involving Children                0
  Prob/Parole/Bail Violations                0
  Theft                                      3
  Traffic Offenses                          56
  Trespassing                                0
  Warrants & Summons                        97
  Weapons Offenses                           1

Overall Statistics

               Accuracy : 0.6231
```

```
               95% CI : (0.6178, 0.6284)
    No Information Rate : 0.5829
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3359

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: Animal Offenses Class: Assault Class: Battery
Sensitivity                        0.046784      0.0000000       0.087757
Specificity                        0.998729      0.9993818       0.976970
Pos Pred Value                     0.280702      0.0000000       0.186207
Neg Pred Value                     0.989979      0.9926922       0.946907
Prevalence                         0.010495      0.0073033       0.056647
Detection Rate                     0.000491      0.0000000       0.004971
Detection Prevalence               0.001749      0.0006137       0.026697
Balanced Accuracy                  0.522756      0.4996909       0.532363
                     Class: Burglary Class: Cannabis Offenses
Sensitivity                0.0244648                0.0188133
Specificity                0.9982952                0.9959557
Pos Pred Value             0.1269841                0.0915493
Neg Pred Value             0.9901922                0.9791037
Prevalence                 0.0100344                0.0212041
Detection Rate             0.0002455                0.0003989
Detection Prevalence       0.0019332                0.0043574
Balanced Accuracy          0.5113800                0.5073845
                     Class: Controlled Substance Offenses
Sensitivity                                     4.988e-03
Specificity                                     9.995e-01
Pos Pred Value                                  1.176e-01
Neg Pred Value                                  9.877e-01
Prevalence                                      1.231e-02
Detection Rate                                  6.137e-05
Detection Prevalence                            5.217e-04
Balanced Accuracy                               5.023e-01
                     Class: Criminal Damage Class: Deception & Fraud
Sensitivity                       2.151e-03                0.0210970
Specificity                       9.995e-01                0.9995672
Pos Pred Value                    5.556e-02                0.2631579
Neg Pred Value                    9.858e-01                0.9928767
Prevalence                        1.427e-02                0.0072726
Detection Rate                    3.069e-05                0.0001534
Detection Prevalence              5.524e-04                0.0005830
Balanced Accuracy                 5.008e-01                0.5103321
                     Class: Disorderly Conduct
```

```
Sensitivity                          0.075529
Specificity                          0.995333
Pos Pred Value                       0.251256
Neg Pred Value                       0.981105
Prevalence                           0.020314
Detection Rate                       0.001534
Detection Prevalence                 0.006107
Balanced Accuracy                    0.535431
                     Class: Driving Under the Influence
Sensitivity                                   0.045509
Specificity                                   0.995150
Pos Pred Value                                0.197917
Neg Pred Value                                0.975398
Prevalence                                    0.025623
Detection Rate                                0.001166
Detection Prevalence                          0.005892
Balanced Accuracy                             0.520330
                     Class: Drug Paraphernalia Act
Sensitivity                              0.0000000
Specificity                              0.9992863
Pos Pred Value                           0.0000000
Neg Pred Value                           0.9889452
Prevalence                               0.0110470
Detection Rate                           0.0000000
Detection Prevalence                     0.0007058
Balanced Accuracy                        0.4996432
                     Class: Interfering w/Public Officers
Sensitivity                                    0.0117786
Specificity                                    0.9958726
Pos Pred Value                                 0.0709220
Neg Pred Value                                 0.9741424
Prevalence                                     0.0260525
Detection Rate                                 0.0003069
Detection Prevalence                           0.0043267
Balanced Accuracy                              0.5038256
                     Class: Liquor Offenses
Sensitivity                            0.34136
Specificity                            0.97999
Pos Pred Value                         0.39557
Neg Pred Value                         0.97486
Prevalence                             0.03695
Detection Rate                         0.01261
Detection Prevalence                   0.03188
Balanced Accuracy                      0.66068
                     Class: Noise & Vibrations Violations
Sensitivity                                    0.0124224
Specificity                                    0.9990702
```

```
Pos Pred Value                                  0.1176471
Neg Pred Value                                  0.9902316
Prevalence                                      0.0098809
Detection Rate                                  0.0001227
Detection Prevalence                            0.0010433
Balanced Accuracy                               0.5057463
                     Class: Offenses Involving Children
Sensitivity                                   6.061e-03
Specificity                                   9.997e-01
Pos Pred Value                                1.000e-01
Neg Pred Value                                9.950e-01
Prevalence                                    5.063e-03
Detection Rate                                3.069e-05
Detection Prevalence                          3.069e-04
Balanced Accuracy                             5.029e-01
                     Class: Prob/Parole/Bail Violations Class: Theft
Sensitivity                                   0.0000000     0.074713
Specificity                                   0.9997842     0.989321
Pos Pred Value                                0.0000000     0.213615
Neg Pred Value                                0.9952733     0.964959
Prevalence                                    0.0047257     0.037376
Detection Rate                                0.0000000     0.002792
Detection Prevalence                          0.0002148     0.013072
Balanced Accuracy                             0.4998921     0.532017
                     Class: Traffic Offenses Class: Trespassing
Sensitivity                           0.9486          2.336e-03
Specificity                           0.6261          9.997e-01
Pos Pred Value                        0.7800          1.000e-01
Neg Pred Value                        0.8971          9.869e-01
Prevalence                            0.5829          1.313e-02
Detection Rate                        0.5530          3.069e-05
Detection Prevalence                  0.7089          3.069e-04
Balanced Accuracy                     0.7874          5.010e-01
                     Class: Warrants & Summons Class: Weapons Offenses
Sensitivity                            0.55235               5.464e-03
Specificity                            0.84263               9.995e-01
Pos Pred Value                         0.23815               5.556e-02
Neg Pred Value                         0.95482               9.944e-01
Prevalence                             0.08178               5.616e-03
Detection Rate                         0.04517               3.069e-05
Detection Prevalence                   0.18967               5.524e-04
Balanced Accuracy                      0.69749               5.025e-01
```

Our random forest model has overall accuracy of 0.6170. It's doing well in crimes that happened a lot but the model is doing poorly on crimes that happened few along the time.



There are three inputs in our shiny app. We can use this shiny app to predict what type of crime the suspect is committed to based on the inputs of suspect information. As shown in the screenshot, our model predicts the MALE with those information inputs is likely committed to Warrants & Summons. It is showing the number of arrests of different race in each year and gender proportion of arrestees in each year. And there are six more EDA graphs below.

4. Conclusion and Future Work

Conclusion:

In this project, we explored the relationship between the background information of arrestees and the types of crime they may have committed. We used machine learning models to predict the crime type based on the available data in the Champaign Arrests dataset. We cleaned and preprocessed the data using R and applied classification models and random forest models for our prediction task. We evaluated the accuracy of our models using training and testing data and selected the best-performing model for our task. We also visualized the crime distribution in Champaign using ggplot2.Through our analysis, we found that certain background attributes, such as age and gender, have a significant relationship with the types of crimes that an arrestee may have committed. Additionally, we found that our machine learning models achieved reasonable prediction accuracy, with the random forest model outperforming the classification models. Overall, our project provides insights into the factors that may contribute to certain types of crimes and demonstrates the potential of machine learning models for crime prediction tasks. However, our findings should be interpreted with caution, and the ethical and social implications of using such models in policing practices should be carefully considered.

Future Work:

There are several possible directions for future work on this project. First, we could explore the use of deep learning models, such as LSTM or CNN, for crime prediction tasks, as suggested by previous research. These models may be better suited for capturing the temporal and spatial patterns in crime data.Second, we could further investigate the factors that contribute to certain types of crimes by incorporating additional data sources, such as demographic and socioeconomic data. This may provide more comprehensive insights into the social and economic factors that drive crime. Third, we could expand our analysis to other cities or regions to examine whether our findings generalize to other contexts. This would require collecting and preprocessing additional data from different sources and applying similar machine learning models to the data. Finally, we could examine the ethical and social implications of using machine learning models for crime prediction in more detail. This could involve conducting a critical analysis of the potential biases and unintended consequences of using such models in policing practices and proposing strategies to address these issues.

5. Contribution

Vinayak worked on the shiny app, related work, abstract, introduction, conclusion/future works Xiangyu worked on the EDA, Modeling, and Method.

Vinayak: 50% Xiangyu: 50%

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Affiliation:

Xiangyu Jin (xjin13)
Department of Statistics
E-mail: xjin13@illinois.edu

Vinayak Bagdi (vbagdi2)
Department of Statistics
E-mail: vbagdi2@illinois.edu

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