Estimating Future Crime Rates in Los Angeles Based on Crime Data from 2023 to Present

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Introduction

This project aims to forecast future crime rates in Los Angeles by analyzing crime data from 2023 to the present. The goal is to explore how factors such as socio-economic changes, mobility patterns, and land-use influence crime dynamics and to use machine learning models to predict future trends. The study will help identify areas of concern, allowing law enforcement to allocate resources more effectively.

Motivations:

- **Post-Pandemic Crime Evolution:** The COVID-19 pandemic changed crime trends in cities. Lockdowns, reduced mobility, and economic stress led to fewer property crimes but an increase in domestic violence and cybercrime. This shift provides a chance to study how crises affect criminal behavior and how law enforcement can prepare for future changes.

  Localized Crime Hotspots: In a large city like Los Angeles, crime isn't spread evenly. Factors like population density, land use, and socio-economic conditions create crime hotspots. Knowing these patterns is key for law enforcement to use resources wisely and stop crimes before they grow. This study aims to offer targeted insights to improve urban safety.

  Mobility and Criminal Opportunities: Los Angeles, with its high mobility and frequent visitors, sees crime rates shift based on movement patterns. Areas with heavy foot traffic often have more crime opportunities, partly due to visitor anonymity. This project explores the link between urban mobility and crime to better understand how movement shapes criminal chances.

Goal of the Project:

The main goal of this project is to predict crime rates in Los Angeles based on data from 2023-2024 and to forecast crime trends for the year 2025. By analyzing historical data, this study aims to provide insights that help law enforcement agencies prepare for and address emerging crime patterns. Several key questions will guide this research:

Impact of Post-Pandemic Socio-Economic Changes: How have the socio-economic factors in 2023-2024, such as unemployment rates, population density, and mobility patterns, influenced different types of crime in Los Angeles? Are there observable shifts in criminal behavior that need targeted intervention?

Spatial and Temporal Crime Dynamics: Which neighborhoods and times of day are most prone to criminal activities? How do urban characteristics, such as mixed land use and foot traffic, affect crime rates in these areas? Understanding these dynamics will allow for better allocation of law enforcement resources.

Predictive Modeling: Can machine learning models accurately forecast crime trends for 2025 based on historical and real-time data? Which methods and models provide the best accuracy for predicting crime rates and identifying emerging hotspots?

Illustration / Figure

Omissions and Context

This project aims to fill these gaps by integrating diverse and dynamic data sources, like real-time mobility patterns and socio-economic indicators, to improve the accuracy of crime predictions. By advancing traditional methods and adopting machine learning techniques, the project recognizes the need for continuous model updates and the inclusion of new data to better predict crime trends in an ever-evolving urban landscape.

Related Work

1. Socio-economic, built environment, and mobility conditions associated with crime: A study of multiple cities

   13 Apr 2020 De Nadai Marco, Xu Yanyan, Letouzé Emmanuel, González Marta C., Lepri Bruno

   https://cs.paperswithcode.com/paper/socio-economic-built-environment-and-mobility

2. Crime Prediction Based On Crime Types And Using Spatial And Temporal Criminal Hotspots

   9 Aug 2015 **Tahani Almanie**, **Rsha Mirza**, **Elizabeth Lor**

   https://paperswithcode.com/paper/crime-prediction-based-on-crime-types-and

3. Changes in Crime Rates During the COVID-19 Pandemic

   19 May 2021 - Mikaela Meyer, Ahmed Hassafy, Gina Lewis, Prasun Shrestha, Amelia M. Haviland, Daniel S. Nagin ·

   https://stat.paperswithcode.com/paper/changes-in-crime-rates-during-the-covid-19

Data Processing

```
packages <- c(
"tibble",
"dplyr",
"readr",
"readxl",
"miceadds",
"aods3",
"carDat",
"gridExtra",
"tidyr",
```

```r
"purrr",
"broom",
"magrittr",
"corrplot",
"caret",
"rpart",
"rpart.plot",
"e1071",
"torch",
"luz"
)
# renv::install(packages)
sapply(packages, require, character.only=T)
```

```
Loading required package: tibble

Loading required package: dplyr


Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union

Loading required package: readr

Warning: package 'readr' was built under R version 4.4.2

Loading required package: readxl

Warning: package 'readxl' was built under R version 4.4.2

Loading required package: miceadds
```

```
Warning: package 'miceadds' was built under R version 4.4.2

Loading required package: mice

Warning: package 'mice' was built under R version 4.4.2


Attaching package: 'mice'

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

    filter

The following objects are masked from 'package:base':

    cbind, rbind

* miceadds 3.17-44 (2024-01-08 19:08:24)

Loading required package: aods3

Warning: package 'aods3' was built under R version 4.4.2

Loading required package: carDat

Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
logical.return = TRUE, : there is no package called 'carDat'

Loading required package: gridExtra

Warning: package 'gridExtra' was built under R version 4.4.2


Attaching package: 'gridExtra'

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

    combine
```

```
Loading required package: tidyr

Loading required package: purrr

Loading required package: broom

Loading required package: magrittr


Attaching package: 'magrittr'

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

    set_names

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

    extract

Loading required package: corrplot

Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
logical.return = TRUE, : there is no package called 'corrplot'

Loading required package: caret

Loading required package: ggplot2

Loading required package: lattice


Attaching package: 'caret'

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

    lift

Loading required package: rpart
```

```
Loading required package: rpart.plot

Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
logical.return = TRUE, : there is no package called 'rpart.plot'

Loading required package: e1071

Loading required package: torch

Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
logical.return = TRUE, : there is no package called 'torch'

Loading required package: luz

Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
logical.return = TRUE, : there is no package called 'luz'

    tibble      dplyr      readr     readxl   miceadds      aods3     carDat
      TRUE       TRUE       TRUE       TRUE       TRUE       TRUE      FALSE
 gridExtra      tidyr      purrr      broom   magrittr   corrplot      caret
      TRUE       TRUE       TRUE       TRUE       TRUE      FALSE       TRUE
     rpart rpart.plot      e1071      torch        luz
      TRUE      FALSE       TRUE      FALSE      FALSE
```

```r
library(e1071)
library(caret)
```

```r
library(lubridate)
```

```
Attaching package: 'lubridate'

The following objects are masked from 'package:base':

    date, intersect, setdiff, union
```

```r
library(dplyr)

# Read the CSV files
crime_data <- read.csv("Crime_Data_from_2023_to_Present.csv", header = TRUE)
```

```r
head(crime_data)
```

```
      DR_NO      Date.Rptd       DATE.OCC TIME.OCC AREA   AREA.NAME Rpt.Dist.No
1 231000510 1/5/2023 0:00 1/5/2023 0:00     2050   10 West Valley        1067
2 231404137 1/5/2023 0:00 1/4/2023 0:00     1400   14     Pacific        1441
3 232104453 1/5/2023 0:00 1/3/2023 0:00      249   21     Topanga        2126
4 231604110 1/5/2023 0:00 1/4/2023 0:00     1200   16    Foothill        1672
5 230704222 1/5/2023 0:00 1/5/2023 0:00     2200    7    Wilshire         736
6 230900519 1/5/2023 0:00 1/4/2023 0:00     1005    9    Van Nuys         994
  Part.1.2 Crm.Cd                    Crm.Cd.Desc             Mocodes Vict.Age
1        1    330           BURGLARY FROM VEHICLE 1822 0344 1300 1402       24
2        1    510                VEHICLE - STOLEN                            0
3        2    354               THEFT OF IDENTITY                 930       37
4        1    510                VEHICLE - STOLEN                            0
5        2    901 VIOLATION OF RESTRAINING ORDER      2038 2004 1218       51
6        2    623         BATTERY POLICE (SIMPLE)           1212 0417        0
  Vict.Sex Vict.Descent Premis.Cd            Premis.Desc Weapon.Used.Cd
1        M            B       101                 STREET            500
2                             101                 STREET             NA
3        F            H       501 SINGLE FAMILY DWELLING             NA
4                             101                 STREET             NA
5        F            W       710          OTHER PREMISE             NA
6        X            X       101                 STREET            400
                                     Weapon.Desc Status  Status.Desc Crm.Cd.1
1                  UNKNOWN WEAPON/OTHER WEAPON      AA Adult Arrest      330
2                                                   IC  Invest Cont      510
3                                                   IC  Invest Cont      354
4                                                   IC  Invest Cont      510
5                                                   IC  Invest Cont      901
6 STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)     AA Adult Arrest      623
  Crm.Cd.2 Crm.Cd.3 Crm.Cd.4                                LOCATION
1      998       NA       NA 17400    VENTURA                      BL
2       NA       NA       NA          WESTMINSTER                  AV
3       NA       NA       NA 20900    SATICOY                      ST
4       NA       NA       NA 11900    ART                          ST
5       NA       NA       NA  5700 W  3RD                          ST
6       NA       NA       NA  3600    BEVERLY GLEN                 BL
                      Cross.Street     LAT       LON
1                                  34.1660 -118.5095
2 E  MAIN                       ST 33.9843 -118.4643
3                                  34.2136 -118.5912
4                                  34.2337 -118.3915
```

```
5                                     34.0689 -118.3440
6                                     34.1360 -118.4527
```

```r
sapply(crime_data, function(x) sum(is.na(x)))
```

```
         DR_NO       Date.Rptd        DATE.OCC        TIME.OCC            AREA 
             0               0               0               0               0 
     AREA.NAME     Rpt.Dist.No        Part.1.2          Crm.Cd     Crm.Cd.Desc 
             0               0               0               0               0 
       Mocodes        Vict.Age        Vict.Sex    Vict.Descent       Premis.Cd 
             0               0               0               0               6 
   Premis.Desc  Weapon.Used.Cd     Weapon.Desc          Status     Status.Desc 
             0          233338               0               0               0 
      Crm.Cd.1        Crm.Cd.2        Crm.Cd.3        Crm.Cd.4        LOCATION 
             4          314787          334512          335164               0 
  Cross.Street             LAT             LON 
             0               0               0 
```

```r
crime_data <- crime_data %>%
  select(-Crm.Cd.2, -Crm.Cd.3, -Crm.Cd.4,-Weapon.Used.Cd)
```

```r
crime_data$Vict.Age[is.na(crime_data$Vict.Age)] <- median(crime_data$Vict.Age, na.rm = TRUE)
```

```r
crime_data$DATE.OCC <- as.Date(crime_data$DATE.OCC, format = "%m/%d/%Y")
crime_data$Date.Rptd <- as.Date(crime_data$Date.Rptd, format = "%m/%d/%Y")
```

```r
# Step 1.4: Extract day of the week, month, and time of day from date and time columns
crime_data$Day_of_Week <- weekdays(crime_data$DATE.OCC)
crime_data$Month <- month(crime_data$DATE.OCC, label = TRUE)

# Step 1.5: Create additional relevant features based on data insights (e.g., categorize cri
crime_data$Time_of_Day <- case_when(
  crime_data$TIME.OCC >= 0 & crime_data$TIME.OCC < 600 ~ "Night",
  crime_data$TIME.OCC >= 600 & crime_data$TIME.OCC < 1200 ~ "Morning",
  crime_data$TIME.OCC >= 1200 & crime_data$TIME.OCC < 1800 ~ "Afternoon",
  TRUE ~ "Evening"
)


crime_data$AREA.NAME <- as.factor(crime_data$AREA.NAME)
crime_data$Crm.Cd.Desc <- as.factor(crime_data$Crm.Cd.Desc)
crime_data$Vict.Sex <- as.factor(crime_data$Vict.Sex)
```

```r
single_class_rows <- crime_data %>%
  group_by(Crm.Cd.Desc) %>%
  filter(n() == 1)

# Remove these from the main dataset and create a train-test split without them
main_data <- anti_join(crime_data, single_class_rows)
```

```
Joining with `by = join_by(DR_NO, Date.Rptd, DATE.OCC, TIME.OCC, AREA,
AREA.NAME, Rpt.Dist.No, Part.1.2, Crm.Cd, Crm.Cd.Desc, Mocodes, Vict.Age,
Vict.Sex, Vict.Descent, Premis.Cd, Premis.Desc, Weapon.Desc, Status,
Status.Desc, Crm.Cd.1, LOCATION, Cross.Street, LAT, LON, Day_of_Week, Month,
Time_of_Day)`
```

```r
head(main_data)
```

```
      DR_NO  Date.Rptd   DATE.OCC TIME.OCC AREA   AREA.NAME Rpt.Dist.No
1 231000510 2023-01-05 2023-01-05     2050   10 West Valley        1067
2 231404137 2023-01-05 2023-01-04     1400   14     Pacific        1441
3 232104453 2023-01-05 2023-01-03      249   21     Topanga        2126
4 231604110 2023-01-05 2023-01-04     1200   16    Foothill        1672
5 230704222 2023-01-05 2023-01-05     2200    7    Wilshire         736
6 230900519 2023-01-05 2023-01-04     1005    9    Van Nuys         994
  Part.1.2 Crm.Cd                    Crm.Cd.Desc             Mocodes Vict.Age
1        1    330         BURGLARY FROM VEHICLE 1822 0344 1300 1402       24
2        1    510               VEHICLE - STOLEN                           0
3        2    354              THEFT OF IDENTITY                 930       37
4        1    510               VEHICLE - STOLEN                           0
5        2    901 VIOLATION OF RESTRAINING ORDER      2038 2004 1218       51
6        2    623        BATTERY POLICE (SIMPLE)           1212 0417        0
  Vict.Sex Vict.Descent Premis.Cd            Premis.Desc
1        M            B       101                 STREET
2                             101                 STREET
3        F            H       501 SINGLE FAMILY DWELLING
4                             101                 STREET
5        F            W       710          OTHER PREMISE
6        X            X       101                 STREET
                                     Weapon.Desc Status  Status.Desc Crm.Cd.1
1                    UNKNOWN WEAPON/OTHER WEAPON     AA Adult Arrest      330
2                                                    IC  Invest Cont      510
3                                                    IC  Invest Cont      354
4                                                    IC  Invest Cont      510
```

```
5                                                      IC  Invest Cont      901
6 STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)       AA Adult Arrest      623
                                   LOCATION                        Cross.Street
1 17400    VENTURA                       BL
2          WESTMINSTER                   AV E  MAIN                          ST
3 20900    SATICOY                       ST
4 11900    ART                           ST
5  5700 W  3RD                           ST
6  3600    BEVERLY GLEN                  BL
      LAT       LON Day_of_Week Month Time_of_Day
1 34.1660 -118.5095    Thursday   Jan     Evening
2 33.9843 -118.4643   Wednesday   Jan   Afternoon
3 34.2136 -118.5912     Tuesday   Jan       Night
4 34.2337 -118.3915   Wednesday   Jan   Afternoon
5 34.0689 -118.3440    Thursday   Jan     Evening
6 34.1360 -118.4527   Wednesday   Jan     Morning
```

Decision Tree Model building

```
set.seed(123)
trainIndex <- createDataPartition(main_data$Crm.Cd.Desc, p = 0.7, list = FALSE)
```

```
Warning in createDataPartition(main_data$Crm.Cd.Desc, p = 0.7, list = FALSE):
Some classes have no records ( BRIBERY, FIREARMS EMERGENCY PROTECTIVE ORDER
(FIREARMS EPO), MANSLAUGHTER, NEGLIGENT, PETTY THEFT - AUTO REPAIR, THEFT, COIN
MACHINE - ATTEMPT, TRAIN WRECKING ) and these will be ignored
```

```
train_data <- main_data[trainIndex, ]
test_data <- main_data[-trainIndex, ]

train_data <- bind_rows(train_data, single_class_rows)
```

```
# Train the model using relevant features
tree_model <- rpart(Crm.Cd.Desc ~ AREA.NAME + Vict.Age + Day_of_Week + Month + Time_of_Day, d

# View the model's summary
summary(tree_model)
```

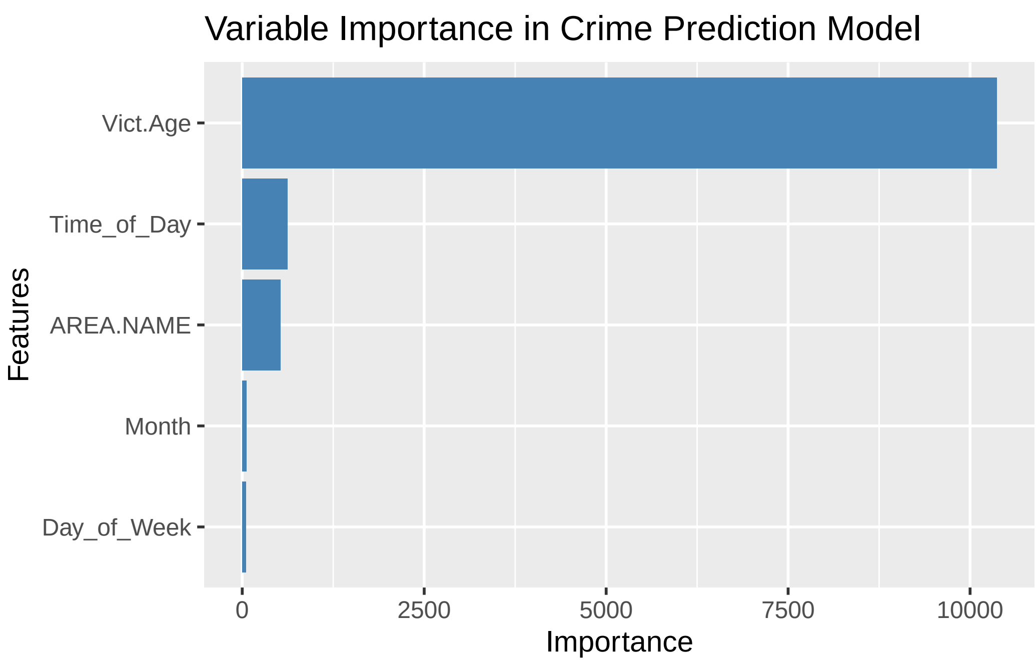
```
Call:
```

```
rpart(formula = Crm.Cd.Desc ~ AREA.NAME + Vict.Age + Day_of_Week +
    Month + Time_of_Day, data = train_data, method = "class")
  n= 234685

          CP nsplit rel error    xerror         xstd
1 0.07998278      0 1.0000000 1.0000000 0.0007598157
2 0.01000000      1 0.9200172 0.9200172 0.0009190726

Variable importance
Vict.Age
     100

Node number 1: 234685 observations,    complexity param=0.07998278
  predicted class=VEHICLE - STOLEN          expected loss=0.8806784  P(node) =1
    class counts:   507   155 11298   973 16838    61   515   928     3     3  1313     2
   probabilities: 0.002 0.001 0.048 0.004 0.072 0.000 0.002 0.004 0.000 0.000 0.006 0.000 0.0
  left son=2 (163724 obs) right son=3 (70961 obs)
  Primary splits:
      Vict.Age    < 1 to the right, improve=10366.38000, (0 missing)
      Time_of_Day splits as  RLRL, improve=  623.09260, (0 missing)
      AREA.NAME   splits as  RLLRRRLRLRLLLLRRLLLLL, improve=  527.51970, (0 missing)
      Month       splits as  LLLRRRRRRRRR, improve=   57.36366, (0 missing)
      Day_of_Week splits as  RRLLRRR, improve=   48.30511, (0 missing)

Node number 2: 163724 observations
  predicted class=BATTERY - SIMPLE ASSAULT  expected loss=0.8984572  P(node) =0.697633
    class counts:   294    36 10876   834 16625    43   136   921     2     2  1282     2
   probabilities: 0.002 0.000 0.066 0.005 0.102 0.000 0.001 0.006 0.000 0.000 0.008 0.000 0.0

Node number 3: 70961 observations
  predicted class=VEHICLE - STOLEN          expected loss=0.6066995  P(node) =0.302367
    class counts:   213   119   422   139   213    18   379     7     1     1    31     0
   probabilities: 0.003 0.002 0.006 0.002 0.003 0.000 0.005 0.000 0.000 0.000 0.000 0.000 0.0
```

```r
tree_predictions <- predict(tree_model, test_data, type = "class")
```

```r
importance <- varImp(tree_model, scale = FALSE)

# Plot the variable importance using ggplot2
ggplot2::ggplot(importance, aes(x = reorder(rownames(importance), Overall), y = Overall)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
```

```
  labs(title = "Variable Importance in Crime Prediction Model", x = "Features", y = "Importar
```



Describe a simple, baseline model that you will compare your neural network against. This can be a simple model that you build.

random forest

```
library(randomForest)
```

```
randomForest 4.7-1.2

Type rfNews() to see new features/changes/bug fixes.


Attaching package: 'randomForest'

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

    margin
```

```
The following object is masked from 'package:gridExtra':

    combine


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

    combine
```

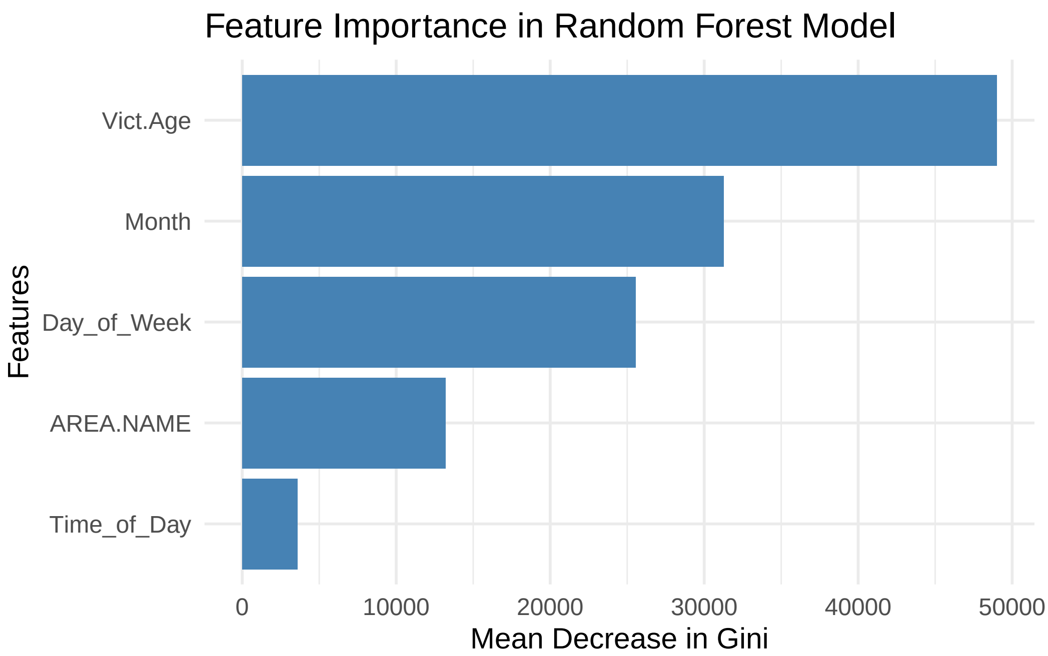
```
rf_model <- randomForest(
  Crm.Cd.Desc ~ AREA.NAME + Vict.Age + Day_of_Week + Month + Time_of_Day,
  data = train_data,
  ntree = 10,
  mtry = 3
)
# print(rf_model)
```

```
# Extract feature importance
importance_matrix <- as.data.frame(importance(rf_model))

# Check the structure of importance_matrix
print(importance_matrix)
```

```
            MeanDecreaseGini
AREA.NAME          13195.714
Vict.Age           48996.840
Day_of_Week        25539.617
Month              31253.791
Time_of_Day         3582.961
```

```
# Ensure feature names are in a separate column
importance_matrix <- importance_matrix %>%
  tibble::rownames_to_column(var = "Feature") %>%  # Create a column for feature names
  select(Feature, MeanDecreaseGini)  # Select only the needed columns

# Remove duplicates (if any)
importance_matrix <- importance_matrix %>% distinct()
```

```
ggplot(importance_matrix, aes(x = reorder(Feature, MeanDecreaseGini), y = MeanDecreaseGini))
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(
    title = "Feature Importance in Random Forest Model",
    x = "Features",
    y = "Mean Decrease in Gini"
  ) +
  theme_minimal()
```



Linear regression

```
train_data$Crm.Cd.Desc <- as.numeric(as.factor(train_data$Crm.Cd.Desc))
test_data$Crm.Cd.Desc <- as.numeric(as.factor(test_data$Crm.Cd.Desc))
```

```
linear_model <- lm(Crm.Cd.Desc ~ AREA.NAME + Vict.Age + Day_of_Week + Month + Time_of_Day, da

# View the model's summary
summary(linear_model)
```

```
Call:
lm(formula = Crm.Cd.Desc ~ AREA.NAME + Vict.Age + Day_of_Week +
    Month + Time_of_Day, data = train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-106.50  -48.91   14.74   36.21  101.12

Coefficients:
                      Estimate Std. Error  t value Pr(>|t|)
(Intercept)          96.256436   0.491304  195.921  < 2e-16 ***
AREA.NAMECentral     -1.751432   0.528318   -3.315 0.000916 ***
AREA.NAMEDevonshire   3.933988   0.601855    6.536 6.31e-11 ***
AREA.NAMEFoothill     3.917887   0.664667    5.895 3.76e-09 ***
AREA.NAMEHarbor       4.252710   0.618364    6.877 6.11e-12 ***
AREA.NAMEHollenbeck   4.881561   0.649598    7.515 5.72e-14 ***
AREA.NAMEHollywood    1.285844   0.584665    2.199 0.027859 *
AREA.NAMEMission      7.326728   0.619333   11.830  < 2e-16 ***
AREA.NAMEN Hollywood  4.553032   0.574212    7.929 2.22e-15 ***
AREA.NAMENewton       1.090900   0.585687    1.863 0.062520 .
AREA.NAMENortheast    6.758596   0.614149   11.005  < 2e-16 ***
AREA.NAMEOlympic      0.597179   0.585606    1.020 0.307842
AREA.NAMEPacific      7.712638   0.556676   13.855  < 2e-16 ***
AREA.NAMERampart      1.128036   0.591557    1.907 0.056536 .
AREA.NAMESoutheast    0.917106   0.590434    1.553 0.120359
AREA.NAMESouthwest    4.916404   0.558704    8.800  < 2e-16 ***
AREA.NAMETopanga      7.115082   0.607045   11.721  < 2e-16 ***
AREA.NAMEVan Nuys     6.779135   0.605194   11.202  < 2e-16 ***
AREA.NAMEWest LA      7.440596   0.599978   12.401  < 2e-16 ***
AREA.NAMEWest Valley  1.515298   0.607575    2.494 0.012632 *
AREA.NAMEWilshire     4.475829   0.581545    7.696 1.40e-14 ***
Vict.Age             -0.626168   0.004295 -145.785  < 2e-16 ***
Day_of_WeekMonday    -0.087498   0.354305   -0.247 0.804942
Day_of_WeekSaturday  -1.107258   0.349062   -3.172 0.001514 **
Day_of_WeekSunday    -1.764344   0.355352   -4.965 6.87e-07 ***
Day_of_WeekThursday  -0.244242   0.352330   -0.693 0.488173
Day_of_WeekTuesday    0.302009   0.355211    0.850 0.395202
Day_of_WeekWednesday  0.051237   0.351962    0.146 0.884256
Month.L              -2.294808   0.340373   -6.742 1.57e-11 ***
Month.Q              -5.541935   0.335569  -16.515  < 2e-16 ***
Month.C               1.990900   0.339765    5.860 4.64e-09 ***
Month^4               5.502383   0.338867   16.238  < 2e-16 ***
```

```
Month^5              0.384131   0.340328    1.129 0.259022
Month^6             -3.102570   0.344716   -9.000  < 2e-16 ***
Month^7             -0.980031   0.339508   -2.887 0.003894 **
Month^8              0.418739   0.340388    1.230 0.218631
Month^9              1.026789   0.344701    2.979 0.002894 **
Month^10             0.978032   0.338989    2.885 0.003913 **
Month^11             0.725443   0.333434    2.176 0.029581 *
Time_of_DayEvening  -2.289210   0.239017   -9.578  < 2e-16 ***
Time_of_DayMorning   2.144749   0.266704    8.042 8.90e-16 ***
Time_of_DayNight    -4.862291   0.300919  -16.158  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 46.3 on 234643 degrees of freedom
Multiple R-squared:  0.0909,    Adjusted R-squared:  0.09074
F-statistic: 572.2 on 41 and 234643 DF,  p-value: < 2.2e-16
```

```r
predictions <- predict(linear_model, test_data)
# Calculate Mean Squared Error (MSE)
mse <- mean((predictions - test_data$Crm.Cd.Desc)^2)
cat("Mean Squared Error (MSE):", mse, "\n")
```

```
Mean Squared Error (MSE): 2149.225
```

```r
comparison <- data.frame(Actual = test_data$Crm.Cd.Desc, Predicted = predictions)
```

```r
comparison <- data.frame(
  Category = c(rep("Actual", length(test_data$Crm.Cd.Desc)), rep("Predicted", length(predict
  Values = c(as.numeric(test_data$Crm.Cd.Desc), as.numeric(predictions))
)
```

```r
ggplot(comparison, aes(x = Values, fill = Category)) +
  geom_density(alpha = 0.5) +
  labs(
    title = "Linear Regression: Actual vs Predicted Crime Codes",
    x = "Crime Codes",
    y = "Density"
  ) +
  scale_fill_manual(values = c("Actual" = "blue", "Predicted" = "green")) +
  theme_minimal()
```

XGBoost Model

```
library(xgboost)
```

```
Warning: package 'xgboost' was built under R version 4.4.2


Attaching package: 'xgboost'

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

    slice
```

```
target_variable <- "Crm.Cd.Desc"
train_matrix <- model.matrix(~ AREA.NAME + Vict.Age + Day_of_Week + Month + Time_of_Day - 1,
test_matrix <- model.matrix(~ AREA.NAME + Vict.Age + Day_of_Week + Month + Time_of_Day - 1, d

xgb_train <- xgb.DMatrix(data = train_matrix, label = as.numeric(train_data[[target_variable]
xgb_test <- xgb.DMatrix(data = test_matrix, label = as.numeric(test_data[[target_variable]])
```

```r
xgb_params <- list(
  objective = "multi:softmax",                # Multiclass classification
  num_class = length(unique(train_data[[target_variable]])), # Number of classes
  eval_metric = "merror",                    # Error evaluation metric
  max_depth = 6,                             # Maximum depth of trees
  eta = 0.3,                                 # Learning rate
  gamma = 0,                                 # Minimum loss reduction
  subsample = 0.8,                           # Subsample ratio of the training set
  colsample_bytree = 0.8                     # Subsample ratio of columns
)

# Train the XGBoost model
xgb_model <- xgb.train(
  params = xgb_params,
  data = xgb_train,
  nrounds = 100
)
```

```r
# Ensure the target variable in test_data is a factor
test_data[[target_variable]] <- factor(test_data[[target_variable]])
xgb_predictions <- predict(xgb_model, xgb_test)
# Convert predictions to a factor and align levels with the target variable
predicted_classes <- factor(
  xgb_predictions + 1,
  levels = levels(test_data[[target_variable]])
)

# Evaluate performance using the confusion matrix
library(caret)
xgb_confusion <- confusionMatrix(
  predicted_classes,
  test_data[[target_variable]]
)

# Print confusion matrix and accuracy
print(xgb_confusion)
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   2   3   4   5   6   7   8  11  13  14  15  17
        1    0   0   0   0   0   0   0   0   0   0   0   0   0
```

2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	9	2	449	34	675	4	10	40	35	0	2	116	5
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	14	0	646	60	999	1	7	60	46	0	2	163	6
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	18	2	279	29	475	3	17	18	36	0	4	71	3
21	7	1	482	29	723	2	5	30	70	0	1	127	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
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32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	6	5	187	13	271	0	0	18	21	0	0	55	2
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0

49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	10	1	389	30	535	1	5	18	44	0	0	120	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	9	4	270	19	379	0	17	31	27	0	2	61	0
99	0	0	0	0	0	0	0	0	0	0	0	0	0

100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	14	6	77	12	126	3	21	9	18	1	6	27	0
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	9	0	242	18	382	2	10	21	43	1	3	69	4
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	17	0	346	33	457	1	4	28	32	0	3	82	2
113	20	6	113	19	152	0	16	7	9	3	7	35	0
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	10	0	411	29	694	5	4	32	62	0	2	131	6
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	12	3	373	26	599	1	11	40	71	0	3	131	1
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	5	4	79	11	131	1	10	4	10	1	3	36	0
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	14	5	410	36	567	1	12	37	36	3	2	117	0
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	42	27	88	19	50	1	71	4	2	8	11	18	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	43	15	268	463	3	18	0	8	47	11	23	3	4
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	76	23	445	636	8	36	0	8	73	28	19	6	5
6	0	0	0	0	0	0	0	0	0	0	0	0	0

7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	78	9	615	369	5	44	0	5	22	4	8	1	3
21	47	10	376	855	8	20	0	1	5	4	2	1	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	18	8	133	198	2	9	0	4	28	5	2	1	1
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
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45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
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49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0

55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
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59	0	0	0	0	0	0	0	0	0	0	0	0	0
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61	0	0	0	0	0	0	0	0	0	0	0	0	0
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65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	29	16	249	455	9	20	0	1	8	9	2	1	6
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	27	6	172	291	7	14	0	5	42	13	9	3	1
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	27	10	224	149	2	12	1	1	26	4	15	0	3

105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	42	11	339	341	4	33	0	0	15	5	5	3	3
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	43	11	328	431	1	14	0	1	5	1	0	0	2
113	15	4	234	156	0	18	0	1	5	0	1	1	0
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	109	19	447	501	4	33	1	2	8	4	2	5	1
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	60	21	404	506	7	29	0	5	23	8	7	0	7
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	18	5	123	110	1	9	0	2	5	2	1	1	0
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	38	11	442	535	5	22	0	4	27	2	9	1	5
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	14	2	814	94	0	58	0	6	20	3	11	3	4
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	31	32	33	34	35	36	37	38	39	40	41	42	43
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	24	0	0	0	0	17	172	23	2	1	0	10
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	21	1	0	0	1	22	231	28	1	0	2	5
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0

15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	1	17	0	1	0	0	11	109	12	1	4	2	17
21	0	21	0	0	0	1	13	146	2	3	1	0	9
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	8	0	1	0	0	0	77	8	1	1	0	1
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0

60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	20	0	0	0	0	11	140	5	0	0	0	2
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	11	1	0	0	1	7	78	19	0	1	0	10
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	1	2	0	2	0	0	1	37	12	0	3	1	16
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	13	0	1	1	2	5	110	5	3	0	0	10

111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	13	1	0	1	0	5	118	4	0	1	1	6
113	0	8	1	2	0	1	4	49	1	4	2	0	19
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	0	30	0	0	1	0	6	174	9	3	0	0	3
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	1	19	1	0	0	1	12	144	12	2	3	0	7
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	0	6	0	0	2	0	1	31	3	4	2	0	6
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	0	16	0	1	0	0	11	158	14	1	1	0	23
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	2	0	0	2	0	1	26	7	4	13	1	105
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	44	45	46	47	48	49	50	51	52	54	55	56	57
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	14	24	0	1	1	0	3	0	22
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	1	0	14	29	0	0	0	0	4	1	36
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	11	45	0	1	2	0	34	1	14

21	0	0	0	0	17	21	0	0	1	1	10	1	19
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	6	7	0	0	1	0	3	0	9
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0

66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	0	0	0	12	17	0	0	1	0	6	0	9
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	0	0	0	5	8	0	0	1	0	16	1	15
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	0	0	0	2	19	0	0	1	0	75	2	5
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	1	0	0	4	23	1	1	0	0	18	3	11
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	1	0	0	0	7	16	0	0	0	0	16	0	14
113	0	0	0	0	6	11	0	2	1	0	55	3	9
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	1	0	0	0	19	45	0	3	0	0	12	0	27

116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	0	0	0	0	13	28	1	0	2	1	22	1	19
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	0	0	0	1	0	12	0	0	0	2	20	1	5
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	0	0	0	0	10	26	0	0	3	1	14	4	14
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	2	0	0	6	40	0	0	3	0	157	3	5
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	58	59	60	61	63	64	65	66	67	69	70	71	72
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	4	2	1	0	1	6	2	0	1	12	98	360
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	5	5	2	0	0	10	1	0	0	23	127	459
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	20	2	2	0	1	0	0	0	0	5	71	257
21	0	2	5	1	0	0	0	0	0	0	9	118	462
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0

26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	5	0	0	0	0	2	1	0	0	6	38	150
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0

72	0	4	3	1	0	0	1	1	0	0	9	127	448
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	8	0	0	0	0	12	2	0	0	1	59	216
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	7	1	5	0	0	2	0	0	0	3	12	101
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	10	3	0	0	0	2	0	0	0	5	52	222
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	4	3	0	0	0	3	0	1	0	4	91	262
113	1	16	1	0	0	0	0	0	1	0	2	37	76
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	0	3	5	0	0	0	3	1	0	0	11	107	404
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	0	11	1	1	1	0	2	3	0	0	10	79	308
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0

122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	0	5	1	1	0	0	0	0	0	5	2	19	63
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	0	23	2	3	0	0	2	1	0	0	7	100	375
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	0	77	0	5	0	0	0	0	2	0	2	4	20
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	73	74	75	76	77	78	81	82	83	84	85	87	88
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	5	2	64	3	2	0	9	33	37	0	1	64	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	14	7	116	9	3	0	11	44	55	1	4	73	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	3	2	63	8	1	0	3	21	50	1	2	37	0
21	5	0	84	9	0	0	8	39	54	1	3	105	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0

31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	2	0	27	2	0	0	2	9	22	0	3	12	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	5	1	57	3	0	0	6	28	28	0	1	58	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0

77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	3	2	44	4	3	0	7	11	26	1	2	37	0
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	10	0	15	3	0	0	3	8	40	2	0	10	0
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	5	0	59	3	0	0	3	27	34	0	0	31	1
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	2	1	45	4	0	0	3	25	28	1	3	27	0
113	2	0	35	2	0	1	0	6	39	1	4	14	0
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	3	1	104	7	0	0	4	41	49	3	6	33	0
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	9	1	89	6	0	0	3	28	45	0	2	40	0
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	1	0	19	2	0	0	1	5	20	1	2	15	0

128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	4	2	60	6	0	0	4	32	44	1	3	51	0
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	4	2	12	0	0	1	1	5	100	4	1	3	0
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	89	90	91	93	94	95	97	98	99	100	101	102	103
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	3	1	0	48	0	6	230	1	14	14	19	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	3	1	4	45	0	1	302	1	34	19	26	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	1	1	0	2	16	2	9	179	6	6	6	43	1
21	1	2	2	6	32	1	2	235	0	0	11	26	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0

36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	1	1	1	15	0	3	80	1	8	6	8	1
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	2	0	3	28	0	1	194	0	6	7	16	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0

84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	1	1	2	25	1	2	172	3	14	10	40	0
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	0	0	0	5	4	9	134	16	0	2	176	4
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	0	0	3	17	0	5	153	3	8	6	53	0
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	3	2	0	2	22	1	5	134	2	3	4	13	0
113	0	0	0	0	15	3	13	129	14	5	4	78	1
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	2	1	0	2	24	0	1	216	4	3	12	32	0
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	0	1	3	1	27	0	7	192	2	6	8	39	0
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	0	1	0	0	8	0	4	85	11	2	2	40	0
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	1	2	0	2	28	2	3	236	6	1	8	46	2
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	1	0	0	0	1	17	39	296	26	2	1	249	2

133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference												
Prediction	104	105	106	107	108	110	111	112	113	114	115	116	117
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	92	11	2	4	5	235	2	301	111	1	417	4	363
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	166	12	2	6	8	332	1	410	133	2	620	1	528
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	284	9	2	1	6	283	2	292	238	0	446	2	331
21	142	14	4	5	7	320	7	370	134	1	544	1	496
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	72	4	1	0	2	109	0	136	41	0	221	2	211
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0

41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	74	9	5	8	9	202	4	288	84	1	433	2	302
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0

90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	188	8	0	3	5	144	5	135	130	0	227	0	222
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	1028	1	0	1	0	225	0	76	450	0	113	4	213
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	255	7	3	5	2	257	4	220	197	0	323	2	344
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	71	4	3	3	8	204	3	363	96	0	397	2	293
113	452	2	2	1	0	193	0	115	411	0	144	1	173
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	138	7	4	3	7	311	4	387	123	1	937	4	523
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	256	7	1	3	5	353	0	326	157	0	553	2	489
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	236	1	1	0	1	107	1	73	165	0	98	1	126
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	272	15	3	3	5	281	5	354	241	1	468	3	403
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	1183	9	3	1	0	413	1	59	1300	0	61	9	251
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

Prediction	119	120	121	122	123	124	125	127	128	129	130	131	132
	Reference												
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	37	3	3	0	1	74	3	348	133	33	97
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	42	2	9	0	0	85	8	500	186	84	49
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	28	3	3	0	0	163	3	444	140	45	800
21	0	0	34	7	4	0	1	96	5	480	162	45	81
22	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	10	1	2	0	0	36	0	143	62	23	39
39	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0

46	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	0	24	2	5	1	0	55	1	350	110	46	28
73	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0

97	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	0	23	1	3	0	0	91	2	235	81	28	371
99	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	0	12	2	3	1	0	291	4	255	78	5	1348
105	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	0	25	1	2	0	0	119	0	320	89	33	537
111	0	0	0	0	0	0	0	0	0	0	0	0	0
112	0	0	23	1	5	0	0	44	3	368	106	48	52
113	0	1	4	0	3	0	0	181	1	240	77	16	1337
114	0	0	0	0	0	0	0	0	0	0	0	0	0
115	0	0	39	3	5	0	0	95	4	424	150	46	46
116	0	0	0	0	0	0	0	0	0	0	0	0	0
117	0	0	31	4	9	0	0	130	0	417	147	67	235
119	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	0	0	0	0	0	0	0	0	0	0
121	0	0	0	0	0	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	0	0	0	0	0	0
123	0	0	0	0	0	0	0	0	0	0	0	0	0
124	0	0	0	0	0	0	0	0	0	0	0	0	0
125	0	0	0	0	0	0	0	0	0	0	0	0	0
127	0	0	7	1	4	0	0	476	0	193	58	13	492
128	0	0	0	0	0	0	0	0	0	0	0	0	0
129	0	0	30	4	7	0	0	159	6	489	180	58	592
130	0	0	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	0	0	0	0	0	0	0	0	0
132	1	0	5	1	1	0	0	512	2	563	169	14	5896
133	0	0	0	0	0	0	0	0	0	0	0	0	0
134	0	0	0	0	0	0	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0
136	0	0	0	0	0	0	0	0	0	0	0	0	0
137	0	0	0	0	0	0	0	0	0	0	0	0	0

	Reference				
Prediction	133	134	135	136	137
1	0	0	0	0	0
2	0	0	0	0	0
3	1	70	78	7	0

4	0	0	0	0	0
5	0	70	136	11	0
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0	0	0	0
11	0	0	0	0	0
13	0	0	0	0	0
14	0	0	0	0	0
15	0	0	0	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	15	40	82	5	0
21	1	48	83	11	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	0	0	0
26	0	0	0	0	0
27	0	0	0	0	0
28	0	0	0	0	0
29	0	0	0	0	0
30	0	0	0	0	0
31	0	0	0	0	0
32	0	0	0	0	0
33	0	0	0	0	0
34	0	0	0	0	0
35	0	0	0	0	0
36	0	0	0	0	0
37	0	0	0	0	0
38	0	25	51	3	1
39	0	0	0	0	0
40	0	0	0	0	0
41	0	0	0	0	0
42	0	0	0	0	0
43	0	0	0	0	0
44	0	0	0	0	0
45	0	0	0	0	0
46	0	0	0	0	0
47	0	0	0	0	0
48	0	0	0	0	0
49	0	0	0	0	0
50	0	0	0	0	0

51	0	0	0	0	0
52	0	0	0	0	0
54	0	0	0	0	0
55	0	0	0	0	0
56	0	0	0	0	0
57	0	0	0	0	0
58	0	0	0	0	0
59	0	0	0	0	0
60	0	0	0	0	0
61	0	0	0	0	0
63	0	0	0	0	0
64	0	0	0	0	0
65	0	0	0	0	0
66	0	0	0	0	0
67	0	0	0	0	0
69	0	0	0	0	0
70	0	0	0	0	0
71	0	0	0	0	0
72	3	38	76	7	0
73	0	0	0	0	0
74	0	0	0	0	0
75	0	0	0	0	0
76	0	0	0	0	0
77	0	0	0	0	0
78	0	0	0	0	0
81	0	0	0	0	0
82	0	0	0	0	0
83	0	0	0	0	0
84	0	0	0	0	0
85	0	0	0	0	0
87	0	0	0	0	0
88	0	0	0	0	0
89	0	0	0	0	0
90	0	0	0	0	0
91	0	0	0	0	0
93	0	0	0	0	0
94	0	0	0	0	0
95	0	0	0	0	0
97	0	0	0	0	0
98	12	17	44	3	0
99	0	0	0	0	0
100	0	0	0	0	0
101	0	0	0	0	0

102	0	0	0	0	0
103	0	0	0	0	0
104	68	7	14	4	0
105	0	0	0	0	0
106	0	0	0	0	0
107	0	0	0	0	0
108	0	0	0	0	0
110	14	31	55	4	1
111	0	0	0	0	0
112	3	43	85	7	0
113	44	15	24	1	0
114	0	0	0	0	0
115	3	59	114	7	1
116	0	0	0	0	0
117	20	45	102	9	0
119	0	0	0	0	0
120	0	0	0	0	0
121	0	0	0	0	0
122	0	0	0	0	0
123	0	0	0	0	0
124	0	0	0	0	0
125	0	0	0	0	0
127	26	7	11	3	0
128	0	0	0	0	0
129	22	47	87	10	0
130	0	0	0	0	0
131	0	0	0	0	0
132	218	7	11	0	1
133	0	0	0	0	0
134	0	0	0	0	0
135	0	0	0	0	0
136	0	0	0	0	0
137	0	0	0	0	0

```
Overall Statistics

               Accuracy : 0.1389
                 95% CI : (0.1368, 0.1411)
    No Information Rate : 0.1194
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.085
```

```
 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: 1  Class: 2 Class: 3 Class: 4 Class: 5  Class: 6
Sensitivity          0.000000 0.0000000 0.092749 0.000000 0.138462 0.0000000
Specificity          1.000000 1.0000000 0.941121 1.000000 0.918814 1.0000000
Pos Pred Value            NaN       NaN 0.073837      NaN 0.116542       NaN
Neg Pred Value       0.997851 0.9993433 0.953481 0.995851 0.932378 0.9997413
Prevalence           0.002149 0.0006567 0.048172 0.004149 0.071795 0.0002587
Detection Rate       0.000000 0.0000000 0.004468 0.000000 0.009941 0.0000000
Detection Prevalence 0.000000 0.0000000 0.060510 0.000000 0.085298 0.0000000
Balanced Accuracy    0.500000 0.5000000 0.516935 0.500000 0.528638 0.5000000
                     Class: 7 Class: 8 Class: 11 Class: 13 Class: 14 Class: 15
Sensitivity          0.000000  0.00000  0.000000 0.0000000 0.0000000   0.00000
Specificity          1.000000  1.00000  1.000000 1.0000000 1.0000000   1.00000
Pos Pred Value            NaN      NaN       NaN       NaN       NaN       NaN
Neg Pred Value       0.997811  0.99605  0.994408 0.9998308 0.9994925   0.98648
Prevalence           0.002189  0.00395  0.005592 0.0001692 0.0005075   0.01352
Detection Rate       0.000000  0.00000  0.000000 0.0000000 0.0000000   0.00000
Detection Prevalence 0.000000  0.00000  0.000000 0.0000000 0.0000000   0.00000
Balanced Accuracy    0.500000  0.50000  0.500000 0.5000000 0.5000000   0.50000
                     Class: 17 Class: 18 Class: 19 Class: 20 Class: 21
Sensitivity          0.0000000  0.000000  0.000000   0.10957  0.140394
Specificity          1.0000000  1.000000  1.000000   0.93388  0.930692
Pos Pred Value             NaN       NaN       NaN   0.08927  0.115572
Neg Pred Value       0.9997114  0.993194  0.998199   0.94661  0.943768
Prevalence           0.0002886  0.006806  0.001801   0.05585  0.060600
Detection Rate       0.0000000  0.000000  0.000000   0.00612  0.008508
Detection Prevalence 0.0000000  0.000000  0.000000   0.06855  0.073616
Balanced Accuracy    0.5000000  0.500000  0.500000   0.52172  0.535543
                     Class: 22 Class: 23 Class: 24 Class: 25 Class: 26
Sensitivity          0.0000000  0.000000  0.00e+00 0.0000000  0.000000
Specificity          1.0000000  1.000000  1.00e+00 1.0000000  1.000000
Pos Pred Value             NaN       NaN       NaN       NaN       NaN
Neg Pred Value       0.9993433  0.996129  1.00e+00 0.9994627  0.996428
Prevalence           0.0006567  0.003871  1.99e-05 0.0005373  0.003572
Detection Rate       0.0000000  0.000000  0.00e+00 0.0000000  0.000000
Detection Prevalence 0.0000000  0.000000  0.00e+00 0.0000000  0.000000
Balanced Accuracy    0.5000000  0.500000  5.00e-01 0.5000000  0.500000
                     Class: 27 Class: 28 Class: 29 Class: 30 Class: 31
Sensitivity           0.000000  0.000000 0.0000000 0.0000000 0.000e+00
Specificity           1.000000  1.000000 1.0000000 1.0000000 1.000e+00
```

```
Pos Pred Value              NaN        NaN       NaN       NaN       NaN
Neg Pred Value         0.998975   0.998846 0.9997015 0.9995522 1.000e+00
Prevalence             0.001025   0.001154 0.0002985 0.0004478 2.985e-05
Detection Rate         0.000000   0.000000 0.0000000 0.0000000 0.000e+00
Detection Prevalence   0.000000   0.000000 0.0000000 0.0000000 0.000e+00
Balanced Accuracy      0.500000   0.500000 0.5000000 0.5000000 5.000e-01
                      Class: 32 Class: 33 Class: 34 Class: 35 Class: 36
Sensitivity            0.000000 0.000e+00 0.000e+00 0.000e+00 0.000e+00
Specificity            1.000000 1.000e+00 1.000e+00 1.000e+00 1.000e+00
Pos Pred Value              NaN       NaN       NaN       NaN       NaN
Neg Pred Value         0.997701 1.000e+00 9.999e-01 9.999e-01 9.999e-01
Prevalence             0.002299 4.975e-05 7.961e-05 6.966e-05 6.966e-05
Detection Rate         0.000000 0.000e+00 0.000e+00 0.000e+00 0.000e+00
Detection Prevalence   0.000000 0.000e+00 0.000e+00 0.000e+00 0.000e+00
Balanced Accuracy      0.500000 5.000e-01 5.000e-01 5.000e-01 5.000e-01
                      Class: 37 Class: 38 Class: 39 Class: 40 Class: 41
Sensitivity            0.000000 0.0427778  0.000000 0.0000000 0.0000000
Specificity            1.000000 0.9733117  1.000000 1.0000000 1.0000000
Pos Pred Value              NaN 0.0284028       NaN       NaN       NaN
Neg Pred Value         0.998736 0.9823795  0.998368 0.9997114 0.9996716
Prevalence             0.001264 0.0179113  0.001632 0.0002886 0.0003284
Detection Rate         0.000000 0.0007662  0.000000 0.0000000 0.0000000
Detection Prevalence   0.000000 0.0269765  0.000000 0.0000000 0.0000000
Balanced Accuracy      0.500000 0.5080447  0.500000 0.5000000 0.5000000
                      Class: 42 Class: 43 Class: 44 Class: 45 Class: 46
Sensitivity           0.000e+00  0.000000  0.00e+00 0.000e+00 0.000e+00
Specificity           1.000e+00  1.000000  1.00e+00 1.000e+00 1.000e+00
Pos Pred Value              NaN       NaN       NaN       NaN       NaN
Neg Pred Value        9.999e-01  0.997522  1.00e+00 1.000e+00 1.000e+00
Prevalence            6.966e-05  0.002478  1.99e-05 2.985e-05 9.951e-06
Detection Rate        0.000e+00  0.000000  0.00e+00 0.000e+00 0.000e+00
Detection Prevalence  0.000e+00  0.000000  0.00e+00 0.000e+00 0.000e+00
Balanced Accuracy     5.000e-01  0.500000  5.00e-01 5.000e-01 5.000e-01
                      Class: 47 Class: 48 Class: 49 Class: 50 Class: 51
Sensitivity           0.000e+00  0.000000  0.000000  0.00e+00 0.000e+00
Specificity           1.000e+00  1.000000  1.000000  1.00e+00 1.000e+00
Pos Pred Value              NaN       NaN       NaN       NaN       NaN
Neg Pred Value        1.000e+00  0.998547  0.996308  1.00e+00 9.999e-01
Prevalence            9.951e-06  0.001453  0.003692  1.99e-05 7.961e-05
Detection Rate        0.000e+00  0.000000  0.000000  0.00e+00 0.000e+00
Detection Prevalence  0.000e+00  0.000000  0.000000  0.00e+00 0.000e+00
Balanced Accuracy     5.000e-01  0.500000  0.500000  5.00e-01 5.000e-01
                      Class: 52 Class: 54 Class: 55 Class: 56 Class: 57
```

Sensitivity	0.0000000	0.000e+00	0.000000	0.000000	0.000000
Specificity	1.0000000	1.000e+00	1.000000	1.000000	1.000000
Pos Pred Value	NaN	NaN	NaN	NaN	NaN
Neg Pred Value	0.9998308	1.000e+00	0.995373	0.999791	0.997681
Prevalence	0.0001692	4.975e-05	0.004627	0.000209	0.002319
Detection Rate	0.0000000	0.000e+00	0.000000	0.000000	0.000000
Detection Prevalence	0.0000000	0.000e+00	0.000000	0.000000	0.000000
Balanced Accuracy	0.5000000	5.000e-01	0.500000	0.500000	0.500000

	Class: 58	Class: 59	Class: 60	Class: 61	Class: 63
Sensitivity	0.000e+00	0.00000	0.0000000	0.0000000	0.000e+00
Specificity	1.000e+00	1.00000	1.0000000	1.0000000	1.000e+00
Pos Pred Value	NaN	NaN	NaN	NaN	NaN
Neg Pred Value	1.000e+00	0.99797	0.9996617	0.9997811	1.000e+00
Prevalence	9.951e-06	0.00203	0.0003383	0.0002189	9.951e-06
Detection Rate	0.000e+00	0.00000	0.0000000	0.0000000	0.000e+00
Detection Prevalence	0.000e+00	0.00000	0.0000000	0.0000000	0.000e+00
Balanced Accuracy	5.000e-01	0.50000	0.5000000	0.5000000	5.000e-01

	Class: 64	Class: 65	Class: 66	Class: 67	Class: 69
Sensitivity	0.00e+00	0.0000000	0.0000000	0.00e+00	0.0000000
Specificity	1.00e+00	1.0000000	1.0000000	1.00e+00	1.0000000
Pos Pred Value	NaN	NaN	NaN	NaN	NaN
Neg Pred Value	1.00e+00	0.9995522	0.9998806	1.00e+00	0.9999403
Prevalence	1.99e-05	0.0004478	0.0001194	3.98e-05	0.0000597
Detection Rate	0.00e+00	0.0000000	0.0000000	0.00e+00	0.0000000
Detection Prevalence	0.00e+00	0.0000000	0.0000000	0.00e+00	0.0000000
Balanced Accuracy	5.00e-01	0.5000000	0.5000000	5.00e-01	0.5000000

	Class: 70	Class: 71	Class: 72	Class: 73	Class: 74
Sensitivity	0.000000	0.00000	0.107100	0.0000000	0.000000
Specificity	1.000000	1.00000	0.948729	1.0000000	1.000000
Pos Pred Value	NaN	NaN	0.083179	NaN	NaN
Neg Pred Value	0.998895	0.98867	0.960729	0.9992338	0.999791
Prevalence	0.001105	0.01133	0.041624	0.0007662	0.000209
Detection Rate	0.000000	0.00000	0.004458	0.0000000	0.000000
Detection Prevalence	0.000000	0.00000	0.053595	0.0000000	0.000000
Balanced Accuracy	0.500000	0.50000	0.527915	0.5000000	0.500000

	Class: 75	Class: 76	Class: 77	Class: 78	Class: 81
Sensitivity	0.000000	0.0000000	0.000e+00	0.00e+00	0.0000000
Specificity	1.000000	1.0000000	1.000e+00	1.00e+00	1.0000000
Pos Pred Value	NaN	NaN	NaN	NaN	NaN
Neg Pred Value	0.991114	0.9992935	9.999e-01	1.00e+00	0.9993233
Prevalence	0.008886	0.0007065	8.956e-05	1.99e-05	0.0006767
Detection Rate	0.000000	0.0000000	0.000e+00	0.00e+00	0.0000000
Detection Prevalence	0.000000	0.0000000	0.000e+00	0.00e+00	0.0000000

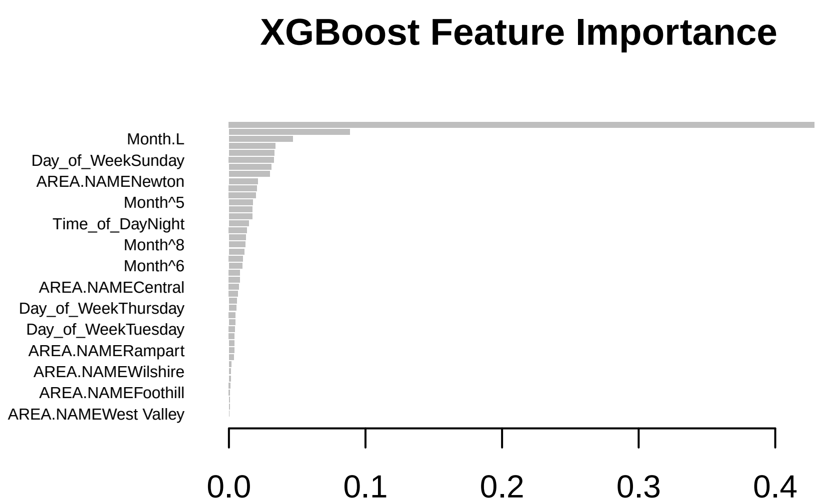
```
Balanced Accuracy     0.500000 0.5000000 5.000e-01  5.00e-01 0.5000000
                     Class: 82 Class: 83 Class: 84 Class: 85 Class: 87
Sensitivity           0.000000  0.000000 0.0000000 0.0000000   0.00000
Specificity           1.000000  1.000000 1.0000000 1.0000000   1.00000
Pos Pred Value             NaN       NaN       NaN       NaN       NaN
Neg Pred Value        0.996398  0.993323 0.9998308 0.9996318   0.99393
Prevalence            0.003602  0.006677 0.0001692 0.0003682   0.00607
Detection Rate        0.000000  0.000000 0.0000000 0.0000000   0.00000
Detection Prevalence  0.000000  0.000000 0.0000000 0.0000000   0.00000
Balanced Accuracy     0.500000  0.500000 0.5000000 0.5000000   0.50000
                     Class: 88 Class: 89 Class: 90 Class: 91 Class: 93
Sensitivity          0.000e+00 0.000e+00  0.000000 0.000e+00 0.0000000
Specificity          1.000e+00 1.000e+00  1.000000 1.000e+00 1.0000000
Pos Pred Value             NaN       NaN       NaN       NaN       NaN
Neg Pred Value       1.000e+00 9.999e-01  0.999801 9.999e-01 0.9997214
Prevalence           9.951e-06 9.951e-05  0.000199 8.956e-05 0.0002786
Detection Rate       0.000e+00 0.000e+00  0.000000 0.000e+00 0.0000000
Detection Prevalence 0.000e+00 0.000e+00  0.000000 0.000e+00 0.0000000
Balanced Accuracy    5.000e-01 5.000e-01  0.500000 5.000e-01 0.5000000
                     Class: 94 Class: 95 Class: 97 Class: 98 Class: 99
Sensitivity           0.000000 0.0000000  0.000000  0.057971 0.0000000
Specificity           1.000000 1.0000000  1.000000  0.957981 1.0000000
Pos Pred Value             NaN       NaN       NaN  0.040281       NaN
Neg Pred Value        0.996458 0.9996915  0.998905  0.970953 0.9990447
Prevalence            0.003542 0.0003085  0.001095  0.029524 0.0009553
Detection Rate        0.000000 0.0000000  0.000000  0.001712 0.0000000
Detection Prevalence  0.000000 0.0000000  0.000000  0.042490 0.0000000
Balanced Accuracy     0.500000 0.5000000  0.500000  0.507976 0.5000000
                     Class: 100 Class: 101 Class: 102 Class: 103 Class: 104
Sensitivity            0.000000   0.000000   0.000000  0.0000000    0.20941
Specificity            1.000000   1.000000   1.000000  1.0000000    0.95062
Pos Pred Value              NaN        NaN        NaN        NaN    0.17884
Neg Pred Value         0.998886   0.998806   0.991005  0.9998905    0.95904
Prevalence             0.001114   0.001194   0.008995  0.0001095    0.04885
Detection Rate         0.000000   0.000000   0.000000  0.0000000    0.01023
Detection Prevalence   0.000000   0.000000   0.000000  0.0000000    0.05720
Balanced Accuracy      0.500000   0.500000   0.500000  0.5000000    0.58002
                     Class: 105 Class: 106 Class: 107 Class: 108 Class: 110
Sensitivity            0.000000  0.0000000  0.0000000  0.0000000   0.064752
Specificity            1.000000  1.0000000  1.0000000  1.0000000   0.947009
Pos Pred Value              NaN        NaN        NaN        NaN   0.047841
Neg Pred Value         0.998806  0.9996418  0.9995323  0.9993034   0.960977
Prevalence             0.001194  0.0003582  0.0004677  0.0006966   0.039495
```

```
Detection Rate        0.000000  0.0000000 0.0000000 0.0000000  0.002557
Detection Prevalence  0.000000  0.0000000 0.0000000 0.0000000  0.053455
Balanced Accuracy     0.500000  0.5000000 0.5000000 0.5000000  0.505880
                     Class: 111 Class: 112 Class: 113 Class: 114 Class: 115
Sensitivity           0.0000000   0.092958    0.10247  0.000e+00   0.156115
Specificity           1.0000000   0.952210    0.95308  1.000e+00   0.931794
Pos Pred Value              NaN   0.072906    0.08323        NaN   0.126930
Neg Pred Value        0.9996119   0.962917    0.96233  9.999e-01   0.945604
Prevalence            0.0003881   0.038858    0.03991  6.966e-05   0.059724
Detection Rate        0.0000000   0.003612    0.00409  0.000e+00   0.009324
Detection Prevalence  0.0000000   0.049545    0.04914  0.000e+00   0.073456
Balanced Accuracy     0.5000000   0.522584    0.52777  5.000e-01   0.543954
                     Class: 116 Class: 117 Class: 119 Class: 120 Class: 121
Sensitivity            0.000000   0.092825  0.000e+00  0.000e+00   0.000000
Specificity            1.000000   0.932362  1.000e+00  1.000e+00   1.000000
Pos Pred Value              NaN   0.070563        NaN        NaN        NaN
Neg Pred Value         0.999602   0.948923  1.000e+00  1.000e+00   0.996278
Prevalence             0.000398   0.052421  9.951e-06  9.951e-06   0.003722
Detection Rate         0.000000   0.004866  0.000e+00  0.000e+00   0.000000
Detection Prevalence   0.000000   0.068959  0.000e+00  0.000e+00   0.000000
Balanced Accuracy      0.500000   0.512593  5.000e-01  5.000e-01   0.500000
                     Class: 122 Class: 123 Class: 124 Class: 125 Class: 127
Sensitivity           0.0000000  0.0000000   0.00e+00   0.00e+00   0.182585
Specificity           1.0000000  1.0000000   1.00e+00   1.00e+00   0.973357
Pos Pred Value              NaN        NaN        NaN        NaN   0.154345
Neg Pred Value        0.9996418  0.9993233   1.00e+00   1.00e+00   0.978124
Prevalence            0.0003582  0.0006767   1.99e-05   1.99e-05   0.025942
Detection Rate        0.0000000  0.0000000   0.00e+00   0.00e+00   0.004737
Detection Prevalence  0.0000000  0.0000000   0.00e+00   0.00e+00   0.030688
Balanced Accuracy     0.5000000  0.5000000   5.00e-01   5.00e-01   0.577971
                     Class: 128 Class: 129 Class: 130 Class: 131 Class: 132
Sensitivity           0.0000000   0.084763    0.00000    0.00000    0.49133
Specificity           1.0000000   0.926620    1.00000    1.00000    0.91616
Pos Pred Value              NaN   0.065726        NaN        NaN    0.44281
Neg Pred Value        0.9995821   0.943259    0.98081    0.99399    0.92998
Prevalence            0.0004179   0.057406    0.01919    0.00601    0.11941
Detection Rate        0.0000000   0.004866    0.00000    0.00000    0.05867
Detection Prevalence  0.0000000   0.074034    0.00000    0.00000    0.13249
Balanced Accuracy     0.5000000   0.505692    0.50000    0.50000    0.70375
                     Class: 133 Class: 134 Class: 135 Class: 136 Class: 137
Sensitivity            0.000000   0.000000    0.00000  0.0000000   0.00e+00
Specificity            1.000000   1.000000    1.00000  1.0000000   1.00e+00
Pos Pred Value              NaN        NaN        NaN        NaN        NaN
```

```
Neg Pred Value         0.995522   0.994338    0.98952  0.9990845    1.00e+00
Prevalence             0.004478   0.005662    0.01048  0.0009155    3.98e-05
Detection Rate         0.000000   0.000000    0.00000  0.0000000    0.00e+00
Detection Prevalence   0.000000   0.000000    0.00000  0.0000000    0.00e+00
Balanced Accuracy      0.500000   0.500000    0.50000  0.5000000    5.00e-01
```

```
xgb_importance <- xgb.importance(feature_names = colnames(train_matrix), model = xgb_model)

# Plot feature importance
xgb.plot.importance(xgb_importance, main = "XGBoost Feature Importance")
```



Qualitative Results

```
# Define a results table to store metrics
results <- data.frame(Model = character(), Accuracy = numeric(), stringsAsFactors = FALSE)
```

```
tree_model <- rpart(Crm.Cd.Desc ~ AREA.NAME + Vict.Age + Day_of_Week + Month + Time_of_Day,
                    data = train_data, method = "class")

# Predict and calculate accuracy
```

```r
tree_predictions <- predict(tree_model, test_data, type = "class")
levels(train_data$Crm.Cd.Desc) <- union(levels(train_data$Crm.Cd.Desc), levels(test_data$Crm
levels(test_data$Crm.Cd.Desc) <- levels(train_data$Crm.Cd.Desc)
tree_predictions <- factor(tree_predictions, levels = levels(test_data$Crm.Cd.Desc))
tree_accuracy <- sum(tree_predictions == test_data$Crm.Cd.Desc) / nrow(test_data)
results <- rbind(results, data.frame(Model = "Decision Tree", Accuracy = tree_accuracy))
```

```r
train_data$Crm.Cd.Desc <- as.numeric(as.factor(train_data$Crm.Cd.Desc))
test_data$Crm.Cd.Desc <- as.numeric(as.factor(test_data$Crm.Cd.Desc))
linear_predictions <- predict(linear_model, test_data)
linear_accuracy <- 1 - mean((linear_predictions - test_data$Crm.Cd.Desc)^2) / var(test_data$C
results <- rbind(results, data.frame(Model = "Linear Regression", Accuracy = linear_accuracy)
```

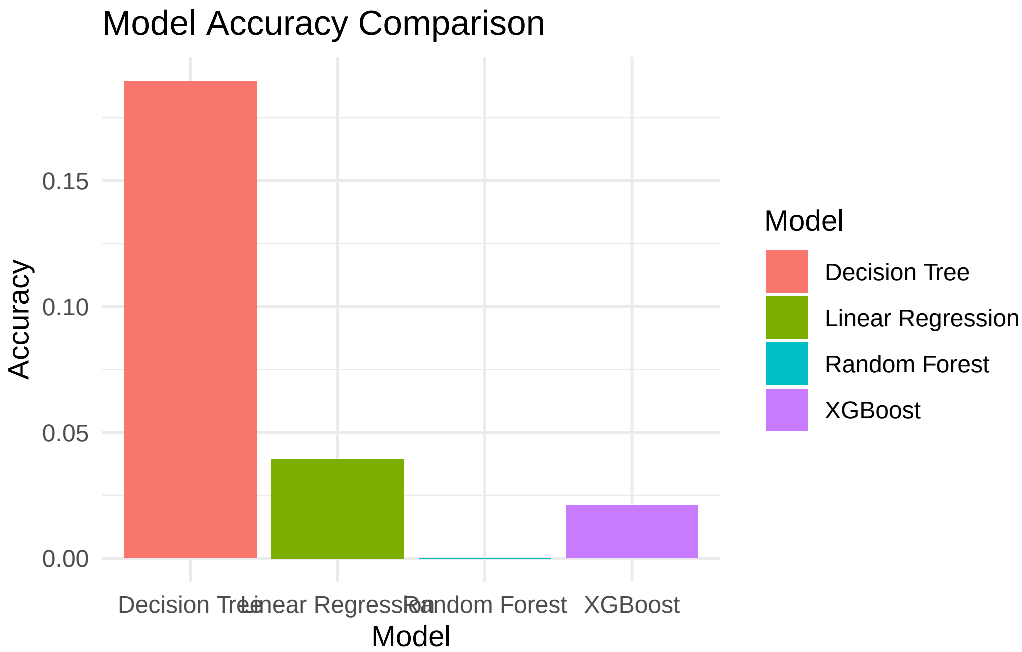
```r
xgb_predictions <- predict(xgb_model, xgb_test)
xgb_accuracy <- sum(xgb_predictions == test_data$Crm.Cd.Desc - 1) / nrow(test_data)
results <- rbind(results, data.frame(Model = "XGBoost", Accuracy = xgb_accuracy))
```

```r
# Predict and calculate accuracy
rf_predictions <- predict(rf_model, test_data)
rf_accuracy <- sum(rf_predictions == test_data$Crm.Cd.Desc) / nrow(test_data)
results <- rbind(results, data.frame(Model = "Random Forest", Accuracy = rf_accuracy))
```

```r
print(results)
```

```
              Model   Accuracy
1     Decision Tree 0.18962137
2 Linear Regression 0.03954005
3           XGBoost 0.02092641
4     Random Forest 0.00000000
```

```r
ggplot(results, aes(x = Model, y = Accuracy, fill = Model)) +
  geom_bar(stat = "identity") +
  labs(title = "Model Accuracy Comparison", x = "Model", y = "Accuracy") +
  theme_minimal()
```



Include some sample outputs of your model, to help your readers better understand what your model can do. The qualitative results should also put your quantitative results into context (e.g. Why did your model perform well? Is there a type of input that the model does not do well on?)

Discussion

Discuss your results. Do you think your model is performing well? Why or why not? What is unusual, surprising, or interesting about your results? What did you learn?

Ethical Considerations

Description of a use of the system that could give rise to ethical issues. Are there limitations of your model? Your training data?

(Note that the expectations are higher here than in the project proposal.)

Conclusion(Optional)

Summarize the whole report.