4th International Conference on Computational Systems and Information Technology for Sustainable Solution

# Identification of Criminal Activity Hotspots using Machine Learning to aid in Effective Utilization of Police Patrolling in Cities with High Crime Rates

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Presented by Ramshankar Yadhunath

# AGENDA

## RELEVANCE AND NEED FOR THE RESEARCH

What and Why is this research important?

## PREDICTIVE MODELLING - HOW DOES IT HELP OUR PROBLEM STATEMENT?

A Machine Learning based approach

## THE RESEARCH METHODOLOGY

How did we go about our idea?

## RESEARCH OUTCOME AND RESULTS

How did our models perform? What was the novelty in our work?

## CONCLUSION

Wrapping it Up!

# RELEVANCE AND NEED FOR THE RESEARCH

## What and Why is this research important ?

# AN OVERLOOKED PROBLEM

"There can be no sustainable development without peace and no peace without sustainable development"

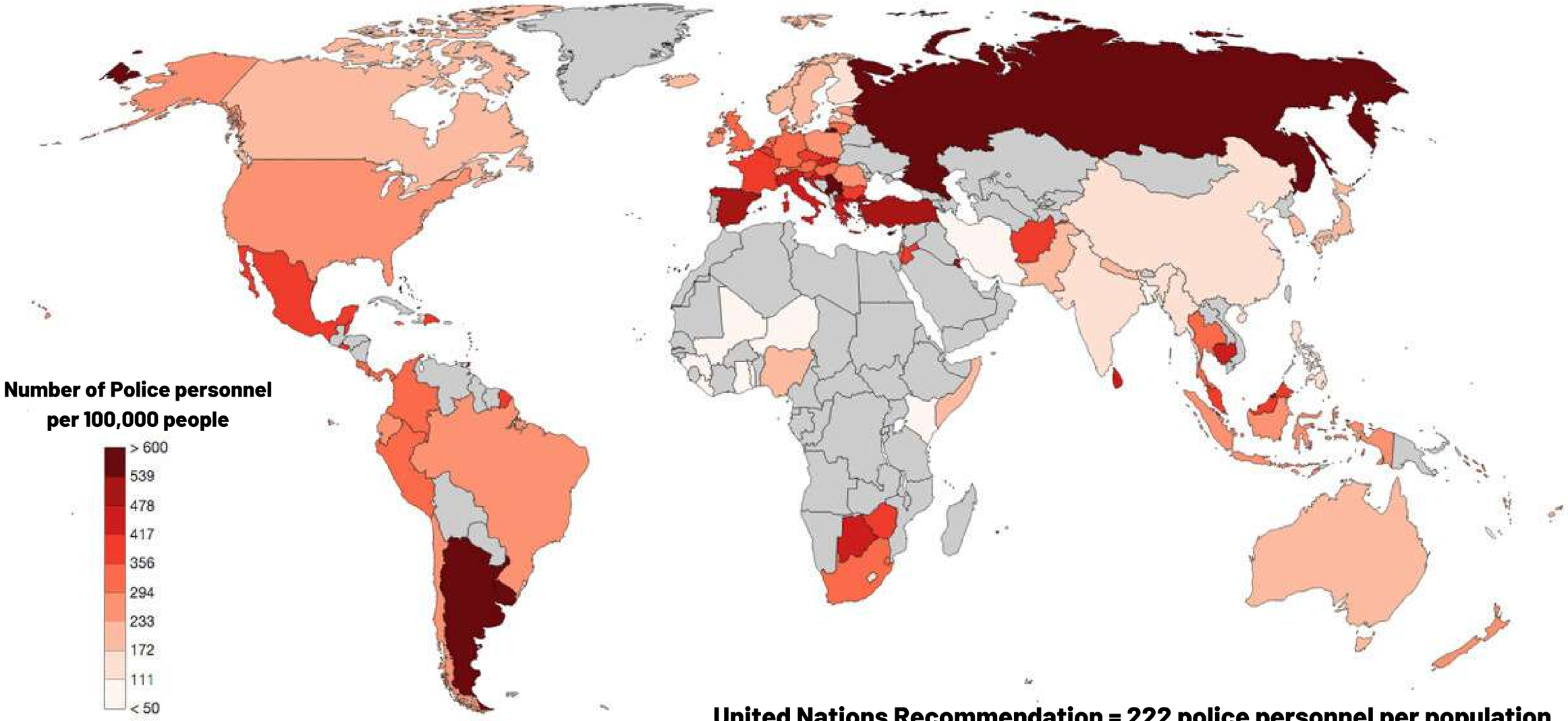
- United Nations 2030 Agenda for Sustainable Development

- Crime is a major deterrent to a peaceful world
- Several organizations are taking steps to reduce crime and its effects

BUT, WHAT IF THERE IS A FACTOR HIDDEN TO THESE ORGANIZATIONS?

"THE PROBLEM OF POOR POLICE-POPULATION RATIOS"

# WORLD (POLICE:POPULATION) RATIOS




**United Nations Recommendation = 222 police personnel per population**

# THE PROBLEM STATEMENT

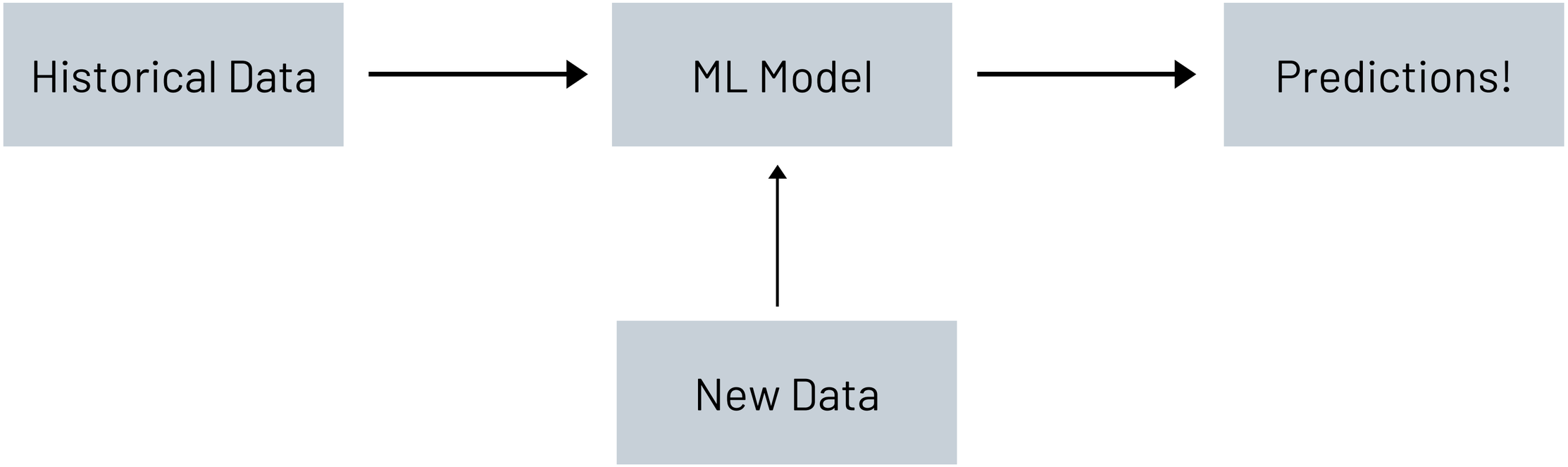
## The Problem Statement

To facilitate effective distribution of police forces in a city among multiple districts based on the extent to which each district is prone to crime at a given hour, in a given day, for a given month.

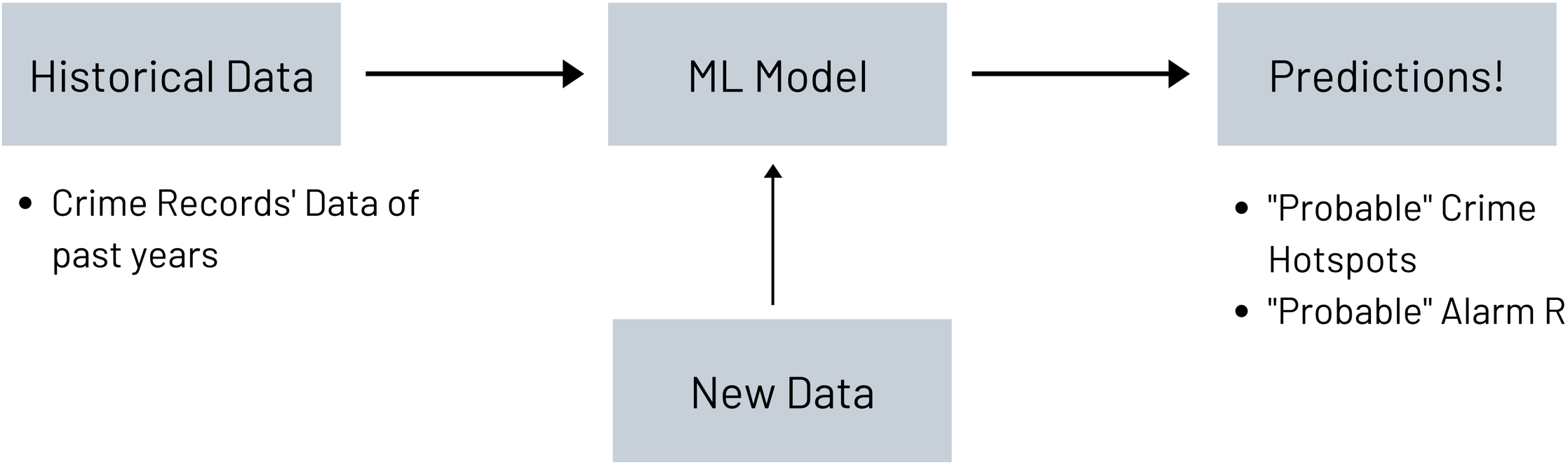
# PREDICTIVE MODELLING

## A Machine Learning Based Approach

# PREDICTIVE MODELLING IN A NUTSHELL



# USING PREDICTIVE MODELLING FOR OUR WORK



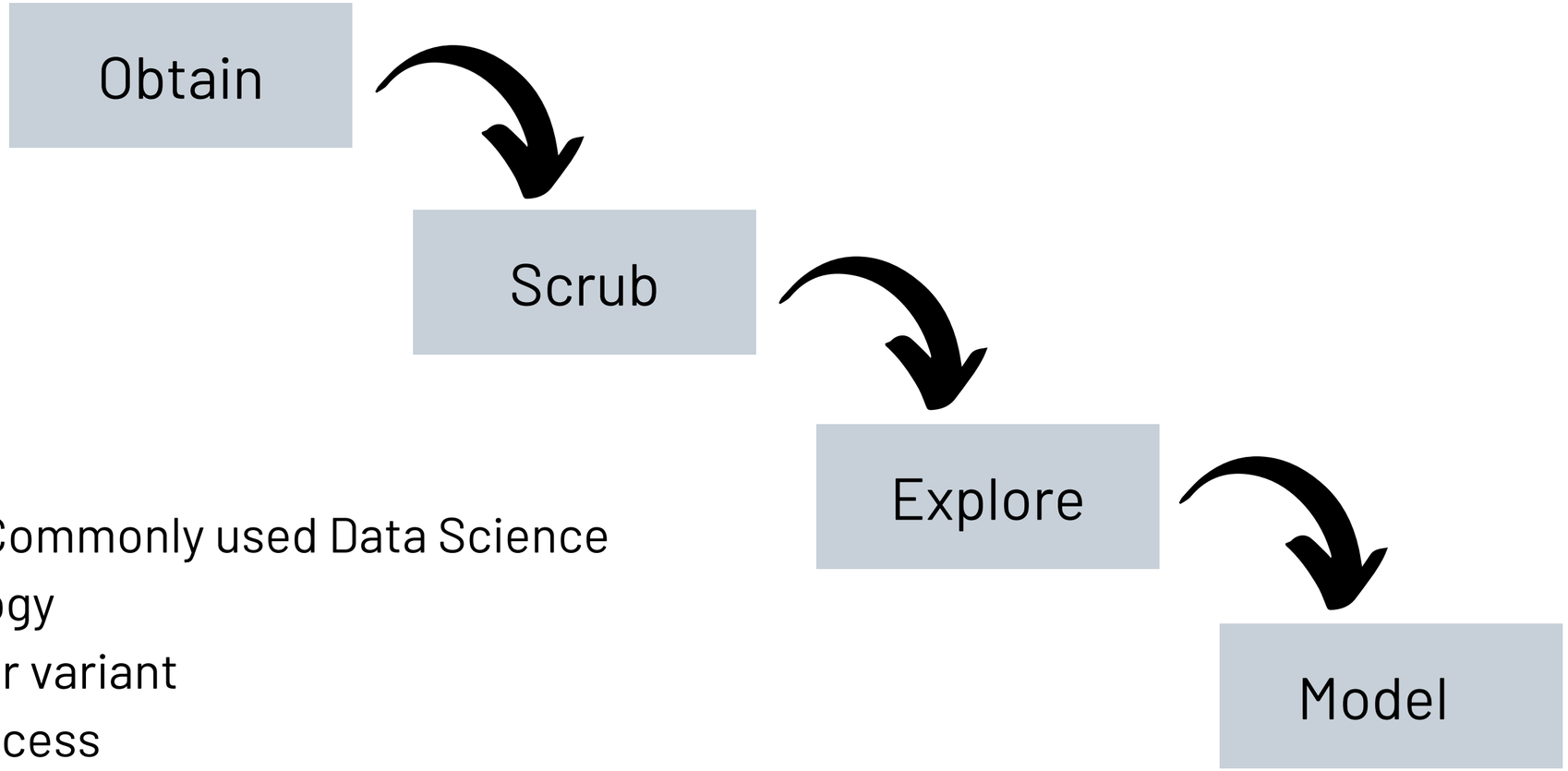

- Crime Records' Data of past years

- "Probable" Crime Hotspots
- "Probable" Alarm Rates

# THE RESEARCH METHODOLOGY

## How did we go about our idea ?

# AN OVERVIEW OF THE METHODOLOGY



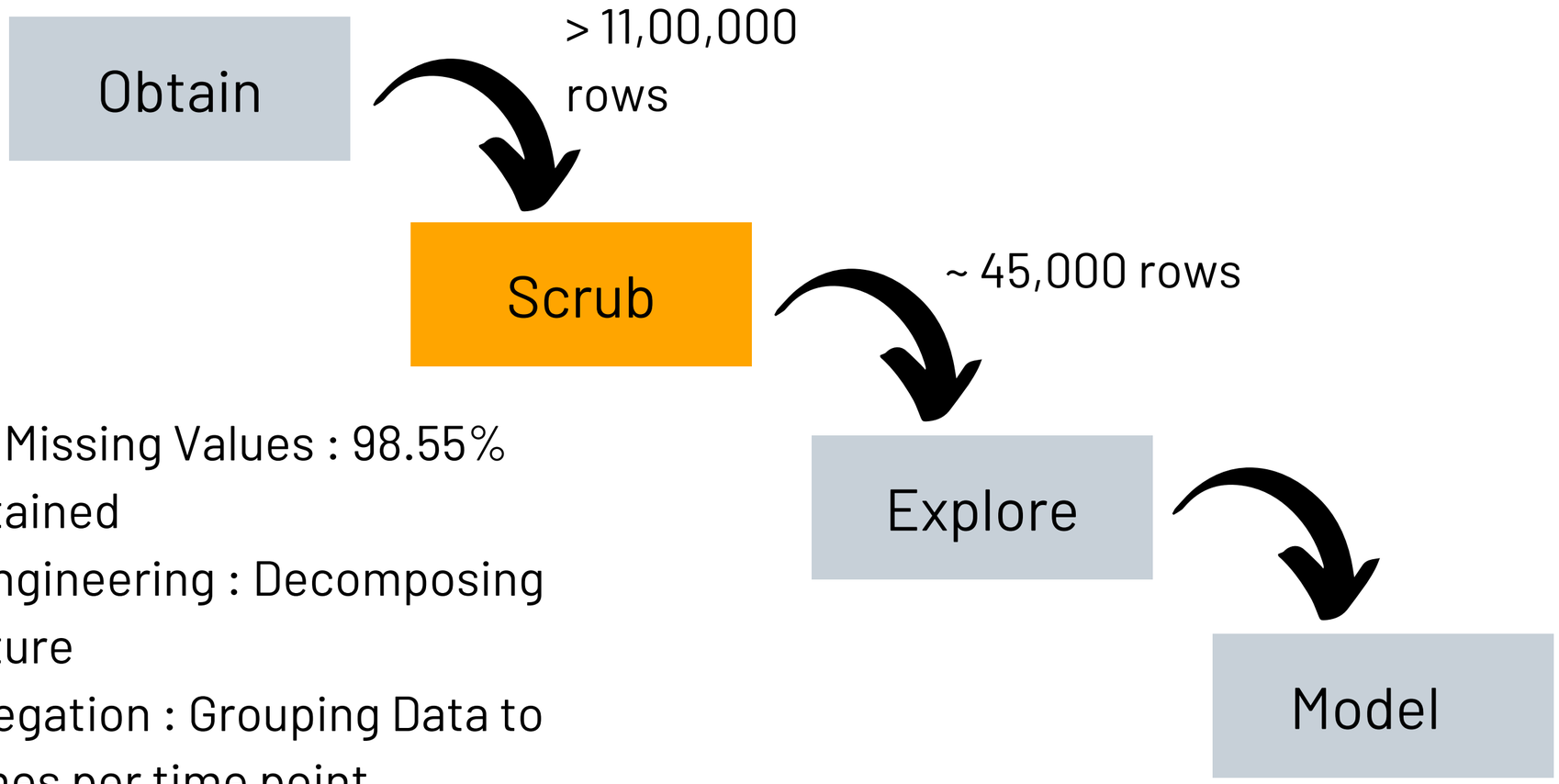

- OSEMN - Commonly used Data Science Methodology
- OSEM - Our variant
- Linear Process

# OBTAIN DATA

Obtain → Scrub → Explore → Model

- City of Chicago Data Portal
- Training Sample : Data from 2015 - 2019 (May)
- Test Sample : Data from 2012 - 2014
- Over 11 lakh entries

# SCRUB (PRE-PROCESS) DATA




- Removing Missing Values : 98.55% entries retained
- Feature Engineering : Decomposing "Date" feature
- Data Aggregation : Grouping Data to count crimes per time point

# EXPLORE DATA

Obtain → Scrub → Explore → Model

- Create a "Target" feature
- Label based on "Normal Distribution" and IQR

TABLE I
FIRST 5 ROWS OF *crimeDat*

| Month | Day | Hour | District | CrimeCount |
|---|---|---|---|---|
| 5 | 2 | 9 | 31 | 1 |
| 1 | 3 | 10 | 31 | 1 |
| 4 | 2 | 10 | 31 | 1 |
| 1 | 2 | 16 | 31 | 1 |
| 1 | 2 | 13 | 31 | 1 |

# EXPLORE DATA

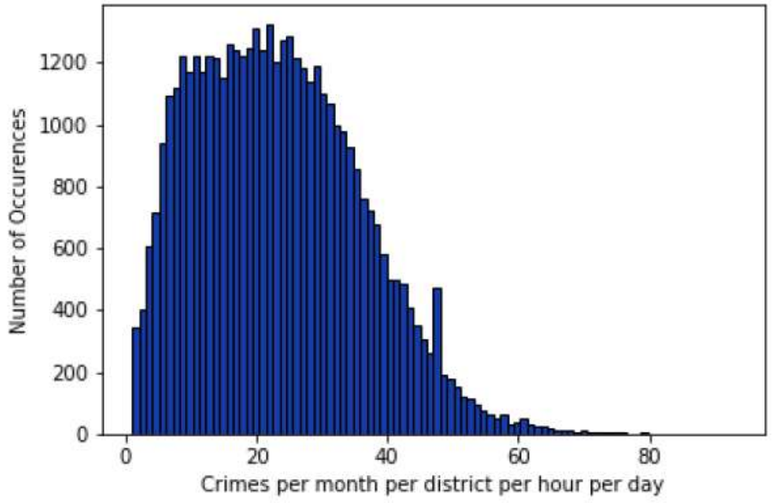
Obtain

Scrub

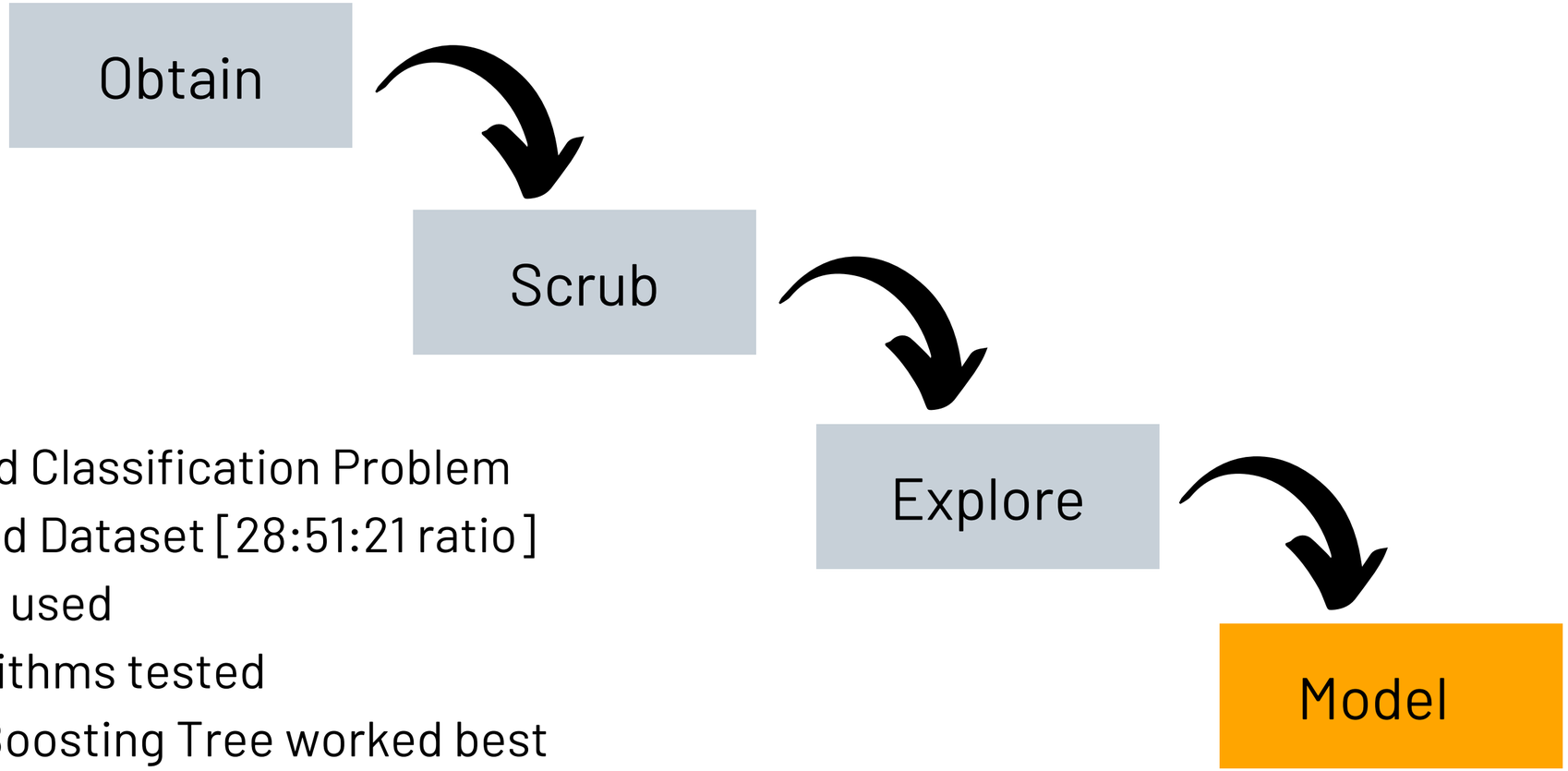
Explore

Model

- Create a "Target" feature
- Label based on "Normal Distribution" and IQR



# MODEL THE DATA




- Supervised Classification Problem
- Imbalanced Dataset [28:51:21 ratio]
- 3 Samples used
- 7 ML algorithms tested
- Gradient Boosting Tree worked best

# RESEARCH OUTCOME AND INNOVATION

## How did our model perform? What was the novelty in our work?

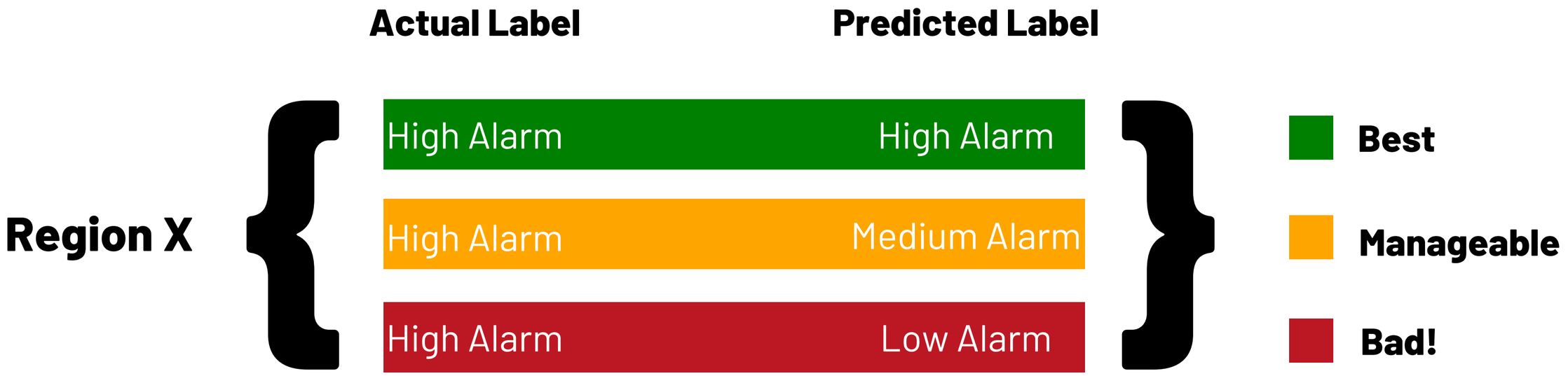
# MODEL EVALUATION METRICS

We have evaluated our models based on the following metrics that are common to most ML problems :

- Accuracy
- Precision
- Recall
- F1 Score
- Unweighted Average Recall

But, we also need a "PROBLEM-SPECIFIC" metric to improve the robustness of our work.

# A NOVEL METRIC FOR OUR PURPOSE




- We must have a model that "minimizes" the ■ scenario
- Problem-specific metric : Percentage of misclassifications of "high alarm" regions as "low alarm" regions
- Let's call this metric "HL-mis" in the further slides

# KEY CONSIDERATIONS WHILE CHOOSING A MODEL

## Key Considerations while choosing a Model :

- High Accuracy
- High F1 score
- Low HL-mis

## Testing Samples :

- Sample 1 : 25% of crimeDat (With class imbalance)
- Sample 2 : 25% of crimeDat (Without class imbalance - Achieved by oversampling)
- Sample 3 : All crime records from 2012-2014

# MODEL COMPARISONS - TRADITIONAL METRICS

TABLE II
COMPARING MODEL PERFORMANCES

| Machine Learning Model | Performance | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Sample 1 | | | Sample 2 | | | Sample 3 | | |
| | Accuracy | F1 Score | UAR | Accuracy | F1 Score | UAR | Accuracy | F1 Score | UAR |
| Gradient Boosting Tree | 80.50 | 80 | 78.59 | 81.32 | 81 | 81.47 | 67.48 | 64 | 73.16 |
| Random Forest | 78.35 | 77 | 76.70 | 88.65 | 88 | 88.65 | 66.25 | 62 | 67.39 |
| Decision Tree | 71.73 | 71 | 71.20 | 86.40 | 86 | 86.39 | 65.39 | 61 | 66.39 |
| K Nearest Neighbour | 75.89 | 75 | 73.77 | 80.1 | 79 | 80.10 | 69.68 | 64 | 67.85 |
| Support Vector Machine | 58.32 | 43 | - | 59.25 | 57 | 59.27 | 49.23 | 46 | 56.61 |
| Naive Bayes | 58.51 | 47 | 48.93 | 59.84 | 56 | 59.84 | 47.01 | 44 | 56.98 |
| Logistic Regression | 56.13 | 44 | 46.06 | 58.88 | 57 | 58.89 | 49.63 | 47 | 55.78 |

# MODEL COMPARISONS - OUR METRIC

TABLE III
MISCLASSIFYING "HIGH ALARM" AS "LOW ALARM"

| Machine Learning Model | Percentage of samples that are 2, but wrongly classified as 0 | | |
|---|---|---|---|
| | Sample 1 | Sample 2 | Sample 3 |
| Gradient Boosting Tree | 0.04 | 0.02 | 0 |
| Random Forest | 0 | 0 | 0.11 |
| Decision Tree | 0.04 | 0 | 0.16 |
| K Nearest Neighbour | 0.56 | 0.77 | 0.23 |
| Support Vector Machine | 6.21 | 10.49 | 10.75 |
| Naive Bayes | 6.08 | 11.37 | 11.58 |
| Logistic Regression | 5.91 | 9.53 | 9.69 |

# CONCLUSION

## Wrapping it Up!

# OUR CONTRIBUTIONS

- Our work looks at predictive policing from the angle of "Optimizing low police force" to control crime even in those cities with very high crime rates
- This work can also be incorporated on a state-level or county-level basis and can be the foundation to more complex police force allocation mechanisms
- Our paper is based along the notion of using "Data science as a means of promoting social good"
- The new problem specific metric is an effective way to evaluate the robustness of a model that can predict the alarm rate of a region

# A FEW IMPORTANT REFERENCES


[1] nancy.cao, "Sustainable development goals," Available at https://www.unodc.org/unodc/en/about-unodc/sustainable-development-goals/sdgs-index.html (2019/07/19).

[3] M.-J. Lin, "More police, less crime: Evidence from us state data," *International Review of Law and Economics*, vol. 29, pp. 73–80, 06 2009.

[4] V. P. Sriharsha Devulapalli, "Indias police force among the worlds weakest," Available at https://www.livemint.com/news/india/india-s-police-force-among-the-world-s-weakest-1560925355383.html (2019/07/19).

# A FEW IMPORTANT REFERENCES


[9] T. Almanie, R. Mirza, and E. Lor, "Crime prediction based on crime types and using spatial and temporal criminal hotspots," *arXiv preprint arXiv:1508.02050*, 2015.

[10] S. Das and M. R. Choudhury, "A geo-statistical approach for crime hot spot prediction," *International Journal of Criminology and Sociological Theory*, vol. 9, no. 1, 2016.

[13] "Crimes - 2001 to present — city of chicago — data portal," Available at https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2/data (2019/05/11).

# THANK YOU