Towards Transparent Crime Prediction: A Random Forest and XAI Approach

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ABSTRACT

KEYWORDS

Educational Machine Learning, Crime Data Prediction, Explainable AI-XAI, SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), Random Forest, Ethical AI

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1 INTRODUCTION

Accurate crime prediction is a crucial aspect of enhancing community safety and efficiently allocating law enforcement resources. Despite advances in technology and data availability, predicting crime remains a complex challenge due to the diverse nature of crimes and their underlying causes. This project aims to develop a robust and explainable crime prediction model using machine learning techniques, with a strong emphasis on Explainable AI (XAI) to ensure transparency and trustworthiness in predictions. Crime is an intricate and multifaceted issue influenced by various social, economic, and environmental factors (Matereke et al. 2021). Traditional crime-solving techniques, though effective to some extent, often fall short in predicting and preventing criminal activities (Dakalbab et al. 2022). As a result, law enforcement agencies are increasingly turning to advanced technologies like data mining and machine learning to address these challenges. By leveraging historical crime data, machine learning algorithms can uncover patterns and trends that are not immediately apparent, enabling proactive measures to prevent future crimes (Rumi et al. 2018).

Data Exploration and Preprocessing: The foundation of our project lies in thorough exploratory data analysis (EDA) (Tukey, 1977). EDA, as described by Tukey, goes beyond simple data cleaning and involves a deep dive into the data's characteristics. Beyond just cleaning the data, EDA involves understanding distributions, correlations, and potential biases within the dataset. This understanding is essential for informed feature engineering and model selection. Our feature selection process is driven by domain knowledge, ensuring that each chosen variable has a justified relevance to crime prediction. Handling missing data is also a critical step, where we explore various imputation strategies (Little & Rubin, 2019) while considering the nature of the missing data. Little and Rubin's work provides a comprehensive framework for dealing with missing data. By splitting the data into training, validation, and test sets prior to preprocessing, we aim to prevent data leakage (Hastie et al., 2009) and maintain the integrity of our model's evaluation. Hastie et al. emphasize the importance of proper data splitting to avoid overly optimistic performance estimates.

Feature Engineering: Leveraging domain knowledge, we engineer features that realistically influence crime occurrences. Time-based features such as the day of the week, time of day, month, and season are considered due to their potential impact on crime patterns. Location-based features, including proximity to points of interest like bars, schools, and parks, as well as neighborhood characteristics like socioeconomic indicators, are also incorporated. Additionally, interaction terms are created to capture the combined effects of existing features. While Principal Component Analysis (PCA) (Jolliffe, 2002) is a common technique for dimensionality reduction, we prioritize real-world interpretability and focus on feature engineering that maintains transparency. Jolliffe's work provides a detailed explanation of PCA, but we choose to avoid it here due to its negative impact on interpretability.

Model Training and Evaluation: We begin with Random Forest (Breiman, 2001) as our baseline model, known for its accuracy and ability to handle high-dimensional data. Breiman's Random Forest algorithm is a powerful and versatile tool. Gradient Boosting algorithms like XGBoost (Chen & Guestrin, 2016) and LightGBM (Ke et al., 2017), along with Neural Networks (Goodfellow et al., 2016), are explored to potentially enhance performance. XGBoost and LightGBM are gradient boosting methods that often provide state-of-the-art performance, while deep learning models like Neural Networks, as discussed by Goodfellow et al., offer the potential to capture highly complex patterns.

Model Selection and Explainability: A core aspect of our project is the explainability of our chosen models. Using SHAP (SHapley Additive exPlanations) (Lundberg & Lee, 2017) and LIME (Local Interpretable Model-agnostic Explanations) (Ribeiro et al., 2016), we thoroughly analyze feature importance and interactions. SHAP and LIME, as developed by Lundberg & Lee and Ribeiro et al., are powerful XAI techniques that provide both global and local explanations. SHAP dependence plots help us understand feature relationships, while LIME provides explanations for individual predictions. This ensures that our models not only perform well but also offer transparent and justifiable predictions. Only models that

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meet both accuracy and explainability criteria are considered for deployment.

By following this comprehensive approach, our project aims to create a more robust and explainable crime prediction system. Emphasizing exploratory data analysis, feature interpretability, and thorough XAI analysis, we seek to build a model that balances accuracy with transparency, ultimately contributing to safer and more informed communities.

The two-fold objectives of this study are (i) to develop a robust and explainable crime prediction model using advanced machine learning and Explainable AI (XAI) techniques, and (ii) to evaluate the effectiveness of these models in enhancing the accuracy and interpretability of crime predictions for law enforcement applications. This study makes the following contributions to support these objectives:

- Comprehensive Data Analysis and Feature Engineering: Conduct thorough Exploratory Data Analysis (EDA) to understand data distributions, correlations, and potential biases.Justify the selection and engineering of features based on domain knowledge, ensuring relevance and interpretability.
- Model Training and Evaluation with Explainable AI: Train and evaluate multiple machine learning models, including Random Forest, Gradient Boosting (XGBoost, LightGBM), and Neural Networks.Utilize Explainable AI techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to ensure model predictions are transparent and understandable.
- IEthical Considerations and Bias Mitigation: Address potential biases in the crime prediction models to ensure fairness and ethical considerations. Implement strategies such as data augmentation and imputation to handle data availability and quality issues, promoting responsible AI use.

Figure 1: LMS Usage Across the Globe (Based on 2019 Data Provided by ClientStat [?])

2 BACKGROUND

3 SYSTEM ARCHITECTURE

3.1 Data Used for the Study

3.2 Overview

3.2.1 Data Collection - Canvas REST API. Student academic data and graded discussion data is gathered from Canvas API [?] [?] using the following three endpoints:

- **List users in a course**

  GET /api/v1/courses/:course_id/students

  Here, the path variable *course_id* is the id of the course and the endpoint returns the paginated list of discussion topics for this course.
- **List Discussion Topics**

  GET /api/v1/courses/:course_id/discussion_topics

  Here, the path variable *course_id* is the id of the course and the endpoint returns the paginated list of students enrolled in this course.
- **Get the detailed Discussion Topic**

  GET /api/v1/courses/:course_id/discussion_topics/:topic_id/view

3.2.2 Data Storage - GrapheneDB.

Rake-PHP-Plus Package
PHP-ML Library
ParallelDots API
Anychart

3.2.4 Front-end. CODA is a PHP-based application developed using the following front end technologies:

- **JQuery** is a JavaScript library that makes HTML document traversal and manipulation, event handling, animation, and Ajax easier to use.
- **Bootstrap** is a CSS framework designed to make responsive web-pages.

3.3 Evaluation Metrics

(1) **Participation in the discussion:**

Figure 2: Selecting Grading Metrics

Figure 3: CODA App on Canvas

REFERENCES