The presentation provides a roadmap for water utilities and decision makers to assess security risks to drinking water infrastructure and identifies key elements to consider enhancing detection capabilities in order to respond in a timely manner to hostile actions.

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STARLIGHT

Geo-temporal crime forecasting using a Deep Learning attention-based model

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1. Introduction

Predicting crimes is crucial for law enforcement agencies (LEAs) to help them optimally allocate resources with the scope to better respond to criminal activities [1]. In this sense, it is essential to forecast the possible crime hotspots within narrow regions spatially, as general predictions on larger areas, such as the city or district level, do not allow to design and implement strategies to combat crimes effectively [2]. This paper proposes a deep learning-based approach to address this problem by developing a geo-temporal crime forecasting model that can capture crime incidents' spatial and temporal dependencies.

A substantial amount of previous research has been performed on the application of machine learning for the task of crime predictions [3]. This work addresses one of the future works outlined in previous papers, namely the capability of recent models based on Transformer to enhance the accuracy of crime predictions in an urban setting, targeting a daily temporal resolution and a narrow spatial grid.

2. Data and Method

We utilised the public dataset of Crime Incident Reports from the Boston Police Department.[5] This dataset includes information from August 2015 to December 2022 on crime incidents such as larceny, burglary, and robbery. 468208 crimes are reported in the dataset, with an average of 5202 crimes per month. For each crime, the street, district, date, and crime category are annotated among 34 distinct types. We considered predictions on a grid composed of 1km2 cells. The proposed model

5. https://data.boston.gov/dataset/crime-incident-reports-august-2015-to-date-source-new-system

forecasts the daily number of crimes in each cell with a lead time of 7 days (one week), considering as context the crimes that happened during the previous 30 days on the whole grid. The model takes the array of crime occurrences in each cell during the day as input features. The model is based on an Encoder-Decoder Transformer architecture [4] that consists of multiple layers of self-attention and feedforward networks, which allows the model to capture long-term dependencies in the sequential data.

3. Results

We implemented this work on Google Colaboratory Pro+ with Python 3.10.11, using Pytorch 2.0 for the transformer model (i.e., nn.TransformerEncoder and nn.TransformerDecoder) and scikit-learn for the baseline models (i.e., RandomForestRegressor and LinearRegression). We set the Transformer model with a hidden size equal to 64, a dropout equal to 0.1, and a learning rate of 1e-4, while for the Random Forest model, we use 100 trees and a maximum depth of 4. We evaluated the model's performance by measuring the Mean Average Error (MAE) and Mean Squared Error (MSE) of each cell's predicted daily number of crimes. The dataset was split, considering as a training set all the crimes that happened before the 1st of January 2022 and as a test set all the remaining ones. Our experimental results show that the proposed model outperforms traditional machine learning models, such as the linear regression model [5] and random forest [6] for crime forecasting. As it is possible to observe from Table 1, the Transformer model proposed provides a substantial improvement with respect to standard machine learning models. In particular, the model obtains a score of 1.674 in MSE, achieving a reduction of 68% and about 18% compared to the Linear Regression and Random Forest models, respectively.

Table 1. *The obtained MAE and MSE for different models. The baseline models (Linear Regression and Random Forest) are compared with the proposed Transformer model.*

Model	MAE	MSE
Linear Regression	1.319	5.276
Random Forest	0.797	2.041
Transformer	0.791	1.674

4. Conclusions

Accurate crime predictions can assist law enforcement agencies in allocating resources to effectively address crime in specific areas, thereby improving public safety. In this paper, we proposed a deep learning model based on an Encoder-Decoder Transformer architecture for geo-temporal crime forecasting. The model demonstrated its ability to capture crime incidents' spatial and temporal dependencies and forecast crime patterns, improving the prediction accuracy against baseline models proposed in previous studies. In future work, we plan to extend our model by incorporating additional features (e.g., weather forecasts and land use) to make the model spatially agnostic and scalable to different cities.

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