Prediction of Homicides in Urban Centers: A Machine Learning Approach

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Abstract—Relevant research has been standing out in the computing community aiming to develop computational models capable of predicting occurrence of crimes, analyzing contexts of crimes, extracting profiles of individuals linked to crimes, and analyzing crimes according to time. This, due to the social impact and also the complex origin of the data, thus showing itself as an interesting computational challenge. This research presents a computational model for the prediction of homicide crimes, based on tabular data of crimes registered in the city of Belém - Pará, Brazil. Statistical tests were performed with 8 different classification methods, both Random Forest, Logistic Regression, and Neural Network presented best results, AUC ~ 0.8. Results considered as a baseline for the proposed problem.

Keywords — Prediction, Homicide, Crime, Tabular, Classification.

I. INTRODUCTION

The term Computational Model is used in computer science to refer to specific molds, definitions, standards, or procedures that must be performed to achieve the solution of a problem. Usually, these models are represented by one or more specific computational algorithms based on mathematical functions that represent the relationship between the context to be worked and the objective to be achieved [1].

The definitions of data preprocessing and algorithms to be used in a model, are directly linked to the characteristics of the problem to be solved as well as the natural characteristics of the data complexity [2].

Problems in the area of criminology, such as identifying a criminal profile, exploring the context of crime, and predicting crimes, have shown interesting challenges for the computing area. These challenges have enabled the development of research focused on these themes, through different forms and perspectives [3][4][5][6][7].

Data in a context that lead an individual to commit a crime are of high dimensions, as they have considerable numbers of variables that, directly or indirectly, are related to a specific crime [8].

Criminological data sources, such as data from social networks, open databases on the internet, data from demographic surveys, socioeconomic data from a region and records from public safety institutions, for example, have relevant information that can be exploited and correlated with each other, enabling an in-depth study of the nature of one or more specific crimes, most of them depending on the time and space that occurred.

Crimes Against the Person, for example, are motivated by several factors of human nature, the environment that surrounds it, the time that occurred and also social issues [9].

The relationship between the occurrence of Crimes Against the Person, and the context to which the individual was placed, are usually analyzed by research aimed at developing tools to predict, understand and prevent the occurrence of crimes [3].

The diverse possibilities of aggregating information directly or indirectly related to specific crimes, has motivated analyzes of criminological data by a considerable part of the computing community in the world, mainly in machine learning research [4][5].

This research explores 8 different computational models created from lazy, eager, and ensemble learning algorithms, seeking to identify which is the best computational model to carry out the process of predicting the occurrence of homicide in the city of Belém - Pará, taking as a database of police reports. Thus creating a baseline of reference for other Brazilian cities and also other cities in the world.

II. RELATED WORK

Analysis of databases related to crimes brings together problems that can be worked on using computational artificial intelligence techniques. However, considering the high number of variables that are related to the proposed context, problems such as prediction of crimes and identification of criminal profiles, for example, have shown computational problems of considerable complexity [3].
In this sense, machine learning surveys using crime data are important both for the computing community and for society in general. With this, research such as:

- “San Francisco Crime Classification”. Description: Proposal of classificatory computational models capable of predicting the type of crime that may occur in the city of San Francisco in the United States, from the time and place of the crime in question. The tested algorithms are: Logistic Regression, Naive Bayes and Random Forest [10].

- “Addressing Crime Situation Forecasting Task with Temporal Graph Convolutional Neural Network Approach”. Description: Article on a proposed computational model based on Graph Convolutional Neural Network and Recurrent Neural Network to capture the spatial and temporal dynamics of crime statistics recorded in the city of San Francisco - California, USA, from 2003 to 2018 [7].

- “Crime Data Analysis and Prediction of Perpetrator Identity Using Machine Learning Approach”. Description: A complete article on analyzing and predicting the profile of perpetrators of crimes using machine learning. In this study, homicide data from the city of San Francisco (United States) from 1981 to 2014 were used [11];

- “Crime Pattern Detection, Analysis & Prediction ”. Description: A complete article on analyzing crime data by detecting patterns and predictions. The data used in this research refer to six different categories of crimes registered in the interval of 14 years (2001-2014), referring to the city of Thane (India) [6];

- “Predictive Policing Software - PredPol ”. Description: Software for police use, focused on the monitoring and analysis of several variables in a micro-region, enabling the prediction of the probability of occurrence of specific crimes with a location and time suggested by the tool. This tool is a success story of the application of intelligent algorithms to criminology data, as it is currently used by security institutions in countries such as the United States of America. Details about the data analyzed by this tool to make predictions are omitted by the developers. [12];

- “A review: Crime analysis using data mining techniques and algorithms”. Description: A literature review on the main computational techniques based on data mining applied to the analysis of crime data. This work lists six main intelligent tools developed to analyze different crime data. The algorithms present in the tools presented by the work are: ID3, Z-CrimeTool, Classifiers based on Naive Bayes, Apriori, among others [13];

- “An overview on crime prediction methods”. Description: A literature review on the main computational methods applied to crime predictions. This study mentions methods such as Support Vector Machine (SVM), Fuzzy Theory, Artificial Neural Network, and Multivariate Time Series [14];

From reading the works cited above, there are different approaches applied to problems in the area of criminology, highlighting methodological strategies based on algorithms for prediction, time series analysis, use of spatial data as input of the model, non-use personal data of individuals and use of data from police reports from different cities around the world.

Note, it is important to highlight that in all studies cited, computational models, directly or indirectly, use information from crimes related to time and also to space, as well as the research described here.

In this way, this research focuses on presenting a computational model focused on the prediction of homicides that occurred in specific neighborhoods in the city of Belém – Pará, Brazil, which can also be replicated for other urban locations.

III. MACHINE LEARNING APPROACH

A. The data

The data used in this research were provided by the Assistant Secretariat of Intelligence and Criminal Analysis - SIAC of the state of Pará, Brazil. Such data refer to the police reports registered during the years 2016 to 2018 in the city of Belém - Pará.

The raw data can be characterized as transactional tabular data containing information such as id, crime’s date, registration’s date, crime’s time, registration’s time, crime’s type, crime’s description, crime’s cite, crime’s neighborhood, unit from the register, and others 31 administrative context attributes.

In terms of size, the database has 41 attributes per 507,065 instances. Where each instance represents a police report registered in the city. Only 5 of the 41 attributes mentioned above were used to create the new database, the main reason being related to the lack of filling in of the other data, as well as the non-direct relationship with the crime context. The 5 attributes in question are: crime’s date, crime’s time, crime’s type, crime’s neighborhood, and others.

The database has records related to more than 500 different types of crimes. Highlighting the crimes of theft, damage in traffic, threat, other atypical facts, bodily injury, embezzlement, and injury, as the eight most common crimes in the base, nomenclatures defined by the Civil and Criminal codes of Brazil [15][16].

The use of this database makes it possible to analyze how different crimes are dynamically related to homicides in the city of study. Because the occurrence of specific crimes is related to a context of the conflict between individuals and one crime may influence another [9].

B. Pre-processing

The pre-processing procedures applied in the database of the proposed model are presented in the following topics:

- Exclusion of 9 sparse attributes (with unregistered data) and id;
• Exclusion of 21 attributes not directly related to the crime context;
• Exclusion of 2 attributes related to personal data of registered individuals;
• Exclusion of 2 attributes related to the location of the crime that occurred due to inconsistency;
• Exclusion of 2 attributes of crime’s georeferencing (latitude and longitude), due to inconsistency;
• Removing special characters (such as: @#$% &*áöüç?!™$®±ç£™);
• Consolidation of neighborhoods in the city of study;
• Exclusion of records related to occurrences in neighborhoods located on islands or in rural areas due to high inconsistency;
• Exclusion of police reports instances considered non-crimes;
• Exclusion of duplicate occurrence records (since a crime can be registered in more than one police report, in this case by different people);
• General transformation of the database from tabular transactional to tabular based in time and space.

In this pre-processing and cleaning, there was a decrease from 507,065 instances to 493,932. Attributing such data loss to higher quality and consolidation.

Among the pre-processing procedures listed above, more characteristics of the transformation of the tabular transactional database to a tabular based in time and space database, was inspired in Online Analytical Processing – OLAP [17] and multidimensional temporal database [18].

This transformation was necessary because the objective model needed to perform the prediction of crimes according to time, but specifically crimes of homicide. In this way, the tabular transactional database was transformed into a new tabular database, considering the year of the crime, the month of the crime, and the neighborhood of the crime concerning the numbers of each of the registered crimes, Table 1.

**TABLE 1. ILLUSTRATION OF NEW TABULAR DATASET**

| year | month | neighborhood | count threat | count theft | count homicide | -- | Class |
|------|-------|--------------|--------------|-------------|----------------|----|-------|
| 2016 | 1     | 1            | 3            | 5           | 5              | 1  |       |
| 2016 | 2     | 1            | 2            | 5           | 7              | 0  |       |
| 2017 | 1     | 3            | 4            | 3           | 2              | 1  |       |
|      |       |              |              |             |                |    |       |
| 2016 | 2     | 1            | 5            | 40          | 5              | 1  |       |

Note in Table 1, the Class attribute (with values between 0 and 1) defines whether or not homicide occurred in the month following the date of crime instance, taking into account the year, month and neighborhood of the instance.

As above, temporal attributes were used to group the data (year and month), as well as a spatial attribute (neighborhood) as an extra dimension for the base. The other data, except for the class, refer to the counts of specific crimes according to time and space.

To better explain the treatment, follow the example: in Table 1, line 1 shows a record of the year 2016, month 1 (one), neighborhood 1 (one) and count threat 3 (three), count theft 5 (five), count homicide 5 (five) and Class 1 (one). The Class had a value 1 (one), as there was a homicide in the month after (month 2) of this record, in the same neighborhood 1 (one), as can be seen in the same figure but in the penultimate line, specifically in the column count homicide 5 (five). If this last cited column had a value of 0 (zero), the class in question would be 0 (zero). Thus, the class only presented a value equal to 1 (one) since the count homicide was greater than 0 (zero).

The new tabular database class was processed to become binary, now showing values of 0 (zero) or 1 (one). Being 0 (zero) the absence of homicide and 1 (one) the existence of homicide, taking into account a specific year, month, and neighborhood. The balance between classes in the dataset was: 1,231 instances for class 0 (non-homicide) and 1,034 for class 1 (homicide).

Importantly, the need to have the class of the problem and the granularity of the new tabular dataset in months is due to the need presented by agents of security institutions. Because, as observed through dialogues with security experts from the state of the city of study, there is a real need to plan monthly surveillance actions and strategies to combat crime.

However, the new database suffered a significant reduction in dimensionality, with 2,265 instances, 45 attributes (42 quantitative of different crimes, 3 ordinal attributes referring to the year and month, and neighborhood) plus 1 binary class (0 and 1).

Detail, all attributes of crime numbers went through minmax normalization, obtaining values between 0 and 1 [19]. The year attribute presents the numeric values 2016, 2017 and 2018. The month attribute has been converted to an entire numeric ranging from 1 to 12 (equivalent to each year’s month). The neighborhood, on the other hand, was treated as ordinal from the ordering of their names in an increasing manner (with values from 0 to 81), limited to the neighborhoods of interest in this analysis (66 in total).

This research did not carry out any process of reducing the dimensionality by automatic methods such as feature selection, considering it unnecessary at this moment, since it is desired to obtain the maximum information from a crime context, considering space and time. In this way, all the data from the new tabular dataset were used by different models, leaving each one to perform automatic attribute selection processes.

More details about the dataset and analysis of this study Git: >>> https://github.com/josesousaribeiro/Pred2Town.

C. Analyzed algorithms

From the database, cleaned, consolidated, pre-processed, transformed and with dimensionality reduction previously presented, this research carried out a series of tests with algorithms of different potentials: lazy learners (represented by
KNN [20]), eager learners (represented by SVM [21], Decision Tree [22], Neural Network [23], Naive Bayes [24], Logistic Regression [25]) and ensemble learners (represented by Adaboost [26] and Random Forest [27]), all this from Orange Platform version 3.26 [28].

As seen above, the idea is to carry out the process of creating computational models not only using robust algorithms such as the cases of ensemble learners, but also simpler and faster learning algorithms, as is the case with lazy and eager learners. This, seeking to evaluate which of the algorithms can better exploit the database.

The tuning process of each algorithm was carried out individually, varying parameter values for each model as shown in Table II, and considering the smallest errors in the model’s outputs.

### TABLE II. TUNING PROCESS DESCRIPTION

| Model          | Variation of parameters                                                                 | Best configuration found                                                                 |
|----------------|-----------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| Adaboost       | Base: Tree; Number of Trees: 10 to 100; Learning Rate: 0,1999992 to 0,9999992; Classification Alg.: SAMME and SAMMER; Loss Function: Linear; Square and Exponential; | Base: Tree; Number of Trees: 100; Learning Rate: 0,5999992; Classification Alg.: SAMMER; Loss Function: Linear; |
| Decision Tree  | Induce Binary Tree: True; Min. number of instances in leaves: 2 to 200;                  | Induce Binary Tree: False; Min. number of instances in leaves: 90;                        |
| KNN            | Number of Neighbors: 2 to 100; Metric: Euclidian, Manhattan, Chebyshen, and Mahalanobis; Weight: Uniform and Distance; | Number of Neighbors: 40; Metric: Manhattan; Weight: Uniform;                              |
| Logistic Regression | Regularization Type: Lasso and Ridge; Strength: 0.001 to 100;                        | Regularization Type: Lasso; Strength: 0.8;                                               |
| Naive Bayes    | Without changing parameters                                                              | Without changing parameters                                                              |
| Neural Network | Neurons in hidden layer: 1 to 20; Activation: Identify, Logistic, Than and Relu; Solver: Adam, Sed, L-BFGS-B; Regularization: 0.0001 to 4.00; Max. number of iterations: 50 to 500; Replicable: True and False; | Neurons in hidden layer: 2; Activation: Than; Solver: Adam; Regularization: 0.07; Max. number of iterations: 100; Replicable: True; |
| Random Forest  | Number of Trees: 10 to 500; Replicable Train: True and False; Grow Control: True and False; | Number of Trees: 300; Replicable Train: True; Grow Control: False;                       |
| SVM            | Type: SVM and v-SVM; Cost: 0.2 to 0.9; Kernel: Linear, Polynomial, RBF, and Sigmoid; Numerical Tolerance: 0.01 to 1.0; | Type: SVM; Cost: 0.6; Kernel: RBF; Numerical Tolerance: 0.9;                               |

All the best configurations found and presented in Table II, refer to the lowest values of Area Under ROC - AUC found in the model outputs (in cross-validation [29] with 5 folds). We chose to use this evaluation metric because it takes into account the successes and errors identified in both classes (1 and 0) of the problem in question. Thus, the AUC measures both successes and errors of homicides and non-homicides that occurred, a characteristic that is desirable in view of the nature of the problem — Since predicting a homicide is just as important as predicting a non-homicide.

### IV. DISCUSSION

Tests were carried out with the eight algorithms mentioned above, based on stratified cross-validation [29] with folds = 100, random sampling stratified with 70% of set size for train, and evaluation metric AUC, Table III.

### TABLE III. ALGORITHMS FROM AUC

| Algorithm     | AUC from 100 folds | Algorithm     | AUC from 100 folds |
|---------------|-------------------|---------------|-------------------|
| Random Forest | 0.868             | Naive Bayes   | 0.842             |
| Logistic Regression | 0.868   | Tree       | 0.842             |
| Neural Network | 0.864             | KNN          | 0.823             |
| SVM           | 0.854             | Adaboost     | 0.703             |

Table III shows the results of the base tests with each of the listed algorithms (ordered by AUC). This research chose AUC as the base metric to measure the performance of each algorithm since it is invariant in scale and works with classifications precision instead of its absolute values. The AUC also measures the quality of the model's predictions, regardless of the classification threshold, important for the proposed model.

Considering the values presented in table III, related to Area Under Roc, it can be verified that the three best-tested algorithms were Random Forest, Logistic Regression, and Neural Network.

Taking as a basis the confusion matrices obtained from the results of Random Forest, Logistic Regression, and Neural Network, Table IV, it can be verified that the algorithm that most hits class 1 (homicide occurrence) is the Logistic Regression, with 79.2% correct.

### TABLE IV. COMPARISON OF CONFUSION MATRICES

|          | Random Forest | Logistic Regression | Neural Network |
|----------|---------------|---------------------|---------------|
|          | 0    | 1            | 0    | 1            | 0    | 1            | 0    | 1            | 0    | 1            | 0    | 1            | Σ    |
| 0        | 80.6%| 24.2%        | 76.8%| 20.8%        | 79.4%| 23.1%        | 37000|
| 1        | 19.4%| 75.8%        | 23.2%| 20.6%        | 76.9%| 23.1%        | 31000|
| Σ        | 68000|               |       |               |       |               |       |

Referring to Table IV, it can be verified that the algorithm that most hits class 0 (zero, no homicide occurrence) is the Random Forest, with 80.6% of correct answers.

This research analyzed the errors found in the outputs of the algorithms, arranging them in general in a confusion matrix format. Obtaining in the best models an average error of 21.9% (for the two objective classes). These errors can mean loss of information or noise, refer to random crimes occurring in specific neighborhoods or even inconsistent information in the act of creation the occurrence record.

However, to enable a better distinction about which algorithm is better among the 8 tested, a statistical analysis was performed based on the tests performed above, analyzing the variances of the executions, density of results and comparison of pairs of models.

Based on the AUC value found in each of the 100 executions, the following boxplot graph was obtained, Figure 1.
It is possible to notice again the considerable performance of the Random Forest, Neural Network, and Logistic Regression, closely followed by the SVM.

Again concerning Figure 1, it is noticed too others algorithms with lower performances. Highlight for Adaboost that even being an ensemble got the worst performance.

For better it presents the difference in performance between the best classifier identified so far (Random Forest) and the worst (Adaboost), in figure 2 it is presented the density graph from the same test of Figure 1.

Fig. 1. Rank according to average values (left to right), generated from the from cross-validation (folds=100) for the AUC Score. Note, values nearby between Random Forest, Neural Network and Logistic Regression near. The orange line represents the median, while the blue dot represents the average.

Fig. 2. Density of the AUC values for 100 tests of the Random Forest (Blue line), Adaboost (orange line). Highlight for the relevant existence of difference in performances between the two classifiers, since their lines almost never overlap.

To better identify the differences presented by the all models analyzed, the Friedman test [30] was performed. It is important to highlight that the p-values were calculated based on the AUC score of each algorithm for the tests previously mentioned, Figure 3.

From the inspection of figure 1, it is understood that the results obtained by the Random Forest algorithm are the best presented among the other algorithms. However, when looking at Figure 3, it is noted that there is no statistically significant difference between the results of this algorithm and the results of Neural Network (p-value=0.9) and Logistic Regression (p-value=0.9). There is a significant difference to the others.

The algorithms Naive Bayes and kNN had similar results, but it should be noted that they are considered intermediate results for the proposed classification.

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It can be noted a significant difference in performance of the Random Forest, Neural Network, and Logistic Regression, when compared with SVM, Decision Tree Naïve Bayes KNN and Adaboost, Figura 3.

V. CONCLUSION

As presented in this article, this research creates a baseline for the problem of prediction of homicide crimes through the data obtained in the city of Belém do Pará, Brazil. Thus enabling new research, analysis and questions to arise from this starting point.

We have evidenced that the need for standardization and better consistency in the database related to records of police reports in the state of Pará, as it was noted that many data were discarded due to inconsistency. Even so, all data pre-processing and transformations presented in this study proved to be effective regarding the creation of a tabular dataset based on time and space of crimes with minimum granularity of month and neighborhood.

In view of the tested models, this research presented three main models with the best performances: Random Forest, Neural Network and Logistic Regression.
This research understands how desirable a computational model aimed at predicting the crime of homicide that is explainable, for this reason it suggests in a more comprehensive way the use of logistic regression since it can have its weights analyzed. Emphasizing that, regardless of the model used, the final decision to execute or plan the final action to combat criminology will always be the responsibility of the end user, human security manager, supported by computational models such as those described in this work.

VI. FUTURE WORKS

It is intended to incorporate, in future works, data of different natures to the model, such as socioeconomic and structural aspects of the city of study, in order to verify how such data are related to crimes.

We intend to carry out an in-depth study of the computational models proposed here, with the objective of analyzing through techniques of Explainable Artificial Intelligence - XAI, how and what the number of homicide crimes, used as inputs to the proposed model, influence the prediction of homicides, thus explaining which crimes the algorithm is based on to predict homicide.

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