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A Predictive Policing Application to Support Patrol Planning in Smart Cities

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***Abstract*—Recently, patrol planning and other predictive policing strategies were improved for Smart Cities applications. In such public safety context, some police departments have been recording crime events in their databases to compose better strategies to understand and predict crime incidence. This work presents the ROTA-Analytics, a web-based application which aims to provide crime incidence forecasting as outputs. This crime incident forecasting helps patrol supervisors to elaborate the list of predefined locations (points) and staying time at which each police vehicle must patrol. ROTA-Analytics supports multiple machine and statistical learning methods selection to create an environment of crime prediction in different areas of the city. All the phases from time series creation to the automatic machine selection are discussed and exemplified with real data from Natal City in Brazil. Finally, we evaluated our architecture by using two regression strategies for different spatial granularity levels.**

***Keywords*—smart cities, crime forecasting, patrol planning, software architecture.**

I. Introduction

According to [1], approximately 70% of the worlds population will soon live in urban areas. As cities grow, so increases the complexity and management challenges for government authorities in dealing with the various urban problems that arise as a result of this high population density. Cities have a vital role in looking for ways to achieve a more efficient management of infrastructures and address challenges of development, sustainability, and inclusion [2].

Some cities are addressing these challenges by initiating Smart City initiatives. These initiatives focus on how cities can transform themselves in different policy areas such as the use of alternative or renewable energy, use and management of resources, crime reduction, etc [3].

For instance, the Natal City Council, in partnership with both public and private sectors, defined a plan to transform Natal into a smart city [4]. The purpose of the Natal Smart City approach is to allow for and speed up the delivery of outcomes across various sectors through a truly integrated approach. Many actions have been implemented to realize this plan [4]–[8]. Public safety is a key area in this plan. In fact, crimes statistics for 2015 reflect high levels of crimes in the city of Natal in the categories of robbery and the homicide rates rose fulled by growing local drug market.

To tackle such public safety issues, Natal Smart City initiative developed the ROTA platform [5], [6] . ROTA is a smart city platform aimed to improve public safety by integrating several information systems from different law enforcement agencies. ROTA provides a set of mobile applications that enhance information sharing aiming at providing actionable, timely intelligence, as well as to support police operations. Despite the platform's benefits, ROTA does not support the detection of spatial and temporal patterns of criminal activity. In fact, modeling the spatial and temporal patterns of criminal activity can allow police departments to deploy their task forces where and when they are most needed, allowing them to be present in certain geographical areas in certain times of the day where specific crime categories are most probable, proactively combating crime in a *data-driven* manner. Naturally, police departments have a *good sense* and experience where to deploy their forces, but several aspects can change the trend in crime surges, and this is the where machine learning can play a big role by detecting and reacting to such trend shifts.

Hence, this paper fulfills this gap by describing a new module for the ROTA platform [5], [6], named ROTA-Analytics. ROTA-Analytics is a web-based application which aims to provide crime incidence forecasting as outputs. This crime incident forecasting is integrated to the ROTA platform and helps the patrol supervisor to elaborate the list of predefined locations (points) and staying time at which each police vehicle must patrol. The remainder of this paper is organized as follows. Section II briefly presents the Natal Smart City initiative. Section III presents the background on predictive and spatial time series regression. Section IV describes the ROTA-Analytics architecture and main components. Section V presents the prediction methodology and discusses some preliminary results. Section VI describes related works and Section VII contains concluding remarks.

II. The Smart City Initiative in Natal

Natal, a city of Northeastern Brazil, has joined the IEEE Smart City initiative as an affiliated city. This initiative aims to transform Natal into a smart city through the development of systems and applications to bolster the use of IT as means

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Fig. 1. Program Card in the ROTA PVM mobile application.

of contributing to improve the life quality of its citizens. Many actions have been implemented [4]–[10].

For instance, one of the solutions developed under the Natal Smart City initiative is ROTA [5], [6], a smart city platform aimed to improve public safety by collecting, integrating, analyzing, and share information about occurrences and patrol vehicles. ROTA provides some modules such as: *Patrol Supervisor Module* (ROTA-PSM) [5] and *Patrol Vehicle Module* (ROTA-PVM) [6]. ROTA-PSM is a mobile application used by patrol supervisors to display the real-time position of all patrol vehicles and occurrences. ROTA-PVM is an Android mobile application deployed in the patrol vehicles. The main purpose of ROTA-PVM is to support patrol in its operations, thus making occurrence handling easier and faster.

By adopting ROTA-PVM, the occurrence handling flow no longer requires using radio communication, except when strictly necessary. When an occurrence is registered, a notification appears on the screen of the patrol vehicles tablet. Upon confirming that the received notification was seen, the policeman is provided with all relevant data regarding the occurrence, such as location, type, suspects characteristics, and the transcription of the call made by the citizen. During the operation, the patrol officer can notify any change regarding the occurrence, e.g., his/her arrival on scene, the need of an additional displacement, finishing occurrence, and occurrence reports. Another functionalities of the ROTA-PVM is the program card. A program card is a practical policing methodology used by Police to distribute staff in a given area. It consists of a list containing predefined locations (haven, ambush, and crime-prone areas), patrol teams, route plan and staying time at which each police vehicle must patrol as shown in Figure 1. Hence, Patrol officers use patrol vehicles equipped with ROTA-PVM to patrol the assigned beats defined by the program card.

Despite the existence of ROTA-PVM, program card elaboration still happens manually, i.e., there is no tool to support the detection of spatial and temporal patterns of criminal activity. Patrol supervisors need to use their knowledge to define the program card for each patrol team that is under their supervision. Hence, detecting spatial and temporal patterns are essential for the definition of the program card. Next section describes how some predictive policing approach can be used to support the definition of program cards and section IV describes the proposed approach used to integrate predictive policing algorithms with the ROTA-PVM module.

In order to detect this spatiotemporal pattern of crime incidence, police department provide their dataset of occurrences registered by the dispatch central. These occurrences are stored as tuples of crime name, category, latitude, longitude and a timestamp. All analysis here presented use these dataset to build statistics and predictions.

III. Background

A. *Predictive Policing*

Predictive policing is defined by Perry et al. [11] as the application of quantitative techniques to improve police intervention and to prevent crime by statistical predictions. Distributed in space and time, crime has its randomness associated with various characteristics of our cities, and some of these are measured by police with the purpose of detect patterns in such events. Hence, when aggregated in time, crimes associated with a neighborhood could be used to keep helping police efforts to effectively improve better resources allocation [12].

In fact, several different predictive methods are described in literature. Perry et al. [11] establishes a taxonomy for these methods in order to categorize different approaches.

- Methods for predicting crimes:
  Approaches to forecast places and times with an increased risk of crime.
- Methods for predicting offenders:
  Approaches that identify individuals at risk of offending in the future.
- Methods for predicting perpetrators' identities
  These techniques are used to create profiles that accurately match likely offenders with specific past crimes.
- Methods for predicting victims of crimes
  Similar to offenders, these approaches focus to identify groups or individuals who are likely to become a victim of crime.

Although predictive methods are a strategic way to improve police resource allocation, they are not the unique task to achieve crime incidence reduction. According to Perry et al. [11], "making predictions is only half of prediction-led policing; the other half is carrying out interventions". In this context, police departments need to get these useful statistics into visual environments to interact with all those analytics, in order to keep its decision supported by an application easy to extract insights.

B. *Spatial vs Time Series Regression*

Given that crimes in a city are distributed in space and time dimensions, regression methods are the basic tools to predict crimes in such time (and spatial) series. Considering the frequency of these events, grouped in a time granularity level

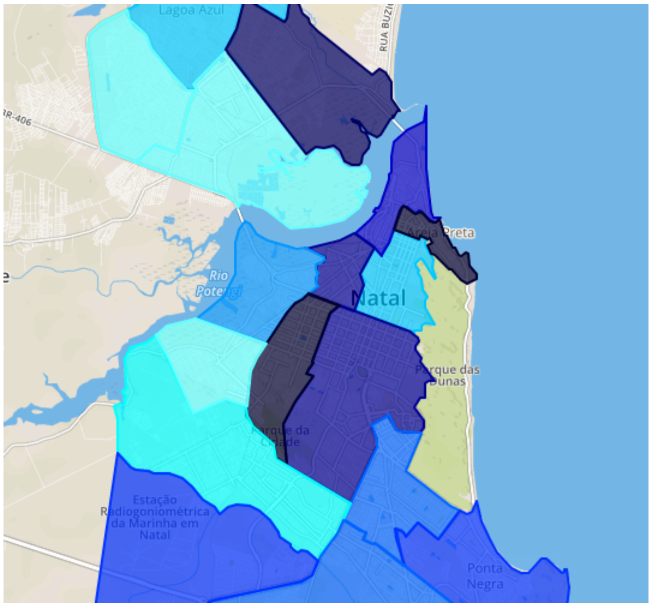

Fig. 2. Choropleth map for regions divided by Natal's police department.

(daily, weekly or monthly), it is possible to measure crime distribution over the periods. However, to include spatiality, the city must be divided into subregions and crimes be labeled with this property and these are the spatial granularity level. There are different methods to divide the city into those regions. An approach is to use a rectangular grid where its cells cover a regular area of the city. Other is to use a division defined by cities' departments and institutions, as neighborhoods. As an alternative, [13] proposes a K-Means approach that could be used to create convex hull polygons based on crimes attributes, called K-Grid. All these methods creates spatial objects that have to be joined into crime datasets to label them, and the spatial granularity level will have considerable influence in model's quality [14].

After this localization step, time series are generated for each subregion based on a time granularity. This time series creation is an important step of analysis before the application of any forecasting methods. Some authors [14], [15] suggests that as higher these granularity levels is, including both temporal and spatial division, as poor is the results in terms of prediction quality. This happens because in high granularity levels, as in daily series in small rectangular grid, there are few amount or no incidence of data, most likely not representative and not sufficient to allow the construction of good predictive models. This will be discussed in Sec. V.

Then, forecasting methods have to be applied to these time series, completing the whole spatio-temporal prediction of crime incidence. Thinking it as a regression task, time series features are necessary to be used in such quantitative techniques to extract next period estimative. In this work, as we are investigating such task, we only use autoregressive components as features to predict crime incidence for each spatial cell with two regression machines.

To evaluate alternative approaches, we choose one linear and one non-linear strategy providing initial results. The first one is the *AutoRegressive Integrated Moving Average* (ARIMA), which is a classical strategy for time series analysis, proposed by Box and Jenkins [16]. With this one, the purpose is to select the number of autoregressive terms (lags), differentiations and moving average terms and fit its coefficients, concerning to get better accuracy in Y_{n+1} estimation. The second approach is a neural network strategy; we use *MultiLayer Perceptron* (MLP) architecture, which uses non-linear layers of activation and weights are optimised to create a continuous estimation based on lags of crime incidence variable. We evaluate our proposed architecture using both approaches in Section V.

IV. ROTA-Analytics

One of the challenges of a smart city is to enhance technological solutions within the needs of society. This paper proposes the ROTA-Analytics, a web-based new module of the ROTA platform which aims to provide crime incidence forecasting as outputs. This crime incident forecasting is integrated to the ROTA-PVM and helps the patrol supervisor to elaborate the list of predefined locations (points) and staying time at which each police vehicle must patrol. Another important functionality of the ROTA-Analytics is to show a thematic map (heat-map or choropleth map) for different spatial scales to be chosen by the user, as neighborhoods polygons or with a rectangular grid, for instance. In the case of Natal, the police department has its own city's districts as described in Figure 2. The polygons are police districts called AISPs (Integrated Area of Public Safety). Each district is colored according to a specified metric, such as the crime forecasting, prediction error, criminal occurrences density per area, school density, and other important crime features. Other important functionality of the ROTA-Analytics is its support to historical analysis of crime incidence in order to help decision-making. Histograms for day-of-week crime distribution and pie chart showing crime distribution by hour are some descriptive tools which provide better insight to elaborate the program card with alternative time's granularity level.

A. Architecture

The ROTA-Analytics architecture is depicted in Figure 3 and comprises five components: *Spatial Model*, *Data Handler*, *Prediction Handler*, *Controller* and *User Interface*. The *Spatial Model* is responsible for storing spatial objects that represents the city such as the police district and criminal occurrences. Moreover, the *Spatial Model* keeps the predictive model's hyperparameters (results of training steps) and the prediction results itself to be processed. *Data Handler* abstracts the access to the *Spatial Model* by implementing time series creation from occurrences records, performing spatial objects conversion to GeoJSON format, and calculating descriptive statistics. One of the main design goals of the ROTA-Analytics architecture is to support different predictive methods. As consequence, the *Prediction Handler* is the main component of the architecture. It is responsible for (i) fitting a selected regression

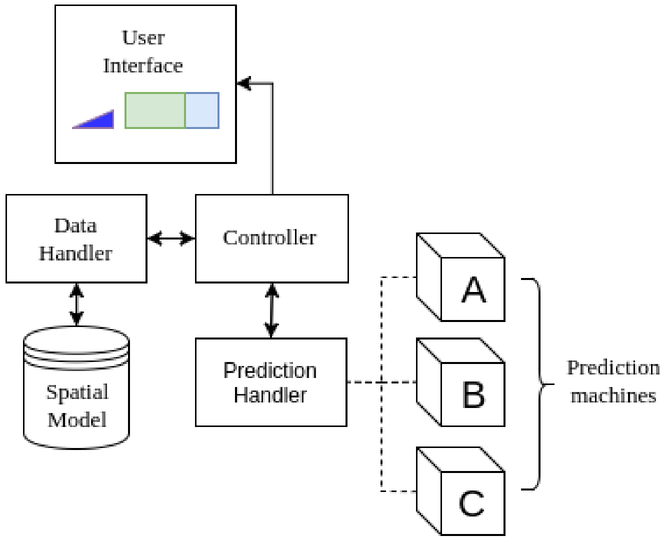

Fig. 3. Architecture of ROTA-Analytics

model with one time series for each spatial object, (ii) storing the hyperparameters of fitted models and quality metrics, and (iii) estimating and storing next period crime incidence with these hyperparameters. The *Controller* component integrates the *User Interface*(UI) with the *Data Handler* and *Prediction Handler*. UI may requests the following information to the *Controller*: map layer (GeoJSON of spatial objects), layer values (JSON of colour map arrangement) and descriptive statistics. The *Controller* abstracts the access to *Data Handler* in order to process all queries from UI. Also, the prediction must be scheduled to be processed by the Controller, depending on time granularity setting. Finally, the UI implementation is illustrated in Figure 4. It is possible to see a map with thematic layers and charts for descriptive statistics to create the visual environment to provide better decision-making in patrol planning.

V. Prediction Methodology and Evaluation

As described in the ROTA-Analytics architecture, the *Prediction Handler* component may support the utilization of a set of alternative predictor machines. In order to select the most accurate predictor for each time series, an automatic selection scheme is used to identify and auto adjust the scheme. The adjustable scheme must be capable not only to follow up the performance of each prediction machine belonging to the prediction core but also to start new training sections and parameters adjustment whenever a loss of accuracy is detected.

The auto adjustment of the prediction machines is fundamental, once the behavior of crime and its statistics, most likely, will suffer constantly changes in response to the ROTA system and the preventive actions taken by the police. In order to evaluate and select the most accurate predictors among a set of them, the *Prediction Handler* module needs (i) to store a reasonably large time window of the original series as well as the respective predictions made by each predictor for each region in the spatial grid and (ii) use one or more quality metrics to quantify and compare the accuracy of all predictors available. The most qualified machine is used inside the prediction core. Besides, a grid prediction quality metric for the spatial grid is also important to ensure low accuracy monitoring.

To do so, besides using the two well-known metrics used in regression problems, (i) Mean Squared Error (MSE) and (ii) residuals behavior analysis through Ljung-Box test, we created two new metrics named *Regression Accuracy Score* (RAS) and *Regression Precision Score* (RPS) to carry prediction quality evaluation. Before define them, it's important to consider a *success* definition as in Equation 1, where V_i represents the test sample value, P_i the predict sample value and T_i is a fraction (threshold) of training sample variance, recommended to be 10%, meaning a window of success around V_i. Then, the metrics are defined in Equations 2 and 3, where RAS represents the amount (percentage) of success in predicting sample and RPS the precision of this success, measuring the MSE of success samples normalized by the variance of training sample. As RAS is close to 1, more accurate is the prediction and as RPS is close to 0, it becomes more precise.

$$S_i = \begin{cases} 1, & \text{if } |V_i - P_i| \leq T_i \sigma_T \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$RAS = \frac{\sum_{i=0}^{N-1} S_i}{N} \tag{2}$$

$$RPS = \frac{MSE_{RAS}}{\sigma_T^2} \tag{3}$$

To illustrate machine selection and exemplify the previous presented metrics, we evaluate our approach using the Natal's dataset with 10 years (2006-2016) of crime records. Table I shows the performance in AISP configuration for three spatial objects using only autoregressive (lags) terms as machine's input. In AISP #1, ARMA model overpass MLP in all criteria, with less MSE, greater RAS, less RPS and greater Ljung-Box p-value. As AS is the major quality metric chosen by our approach, in AISP #3, ARMA model is preferred as well. Finally, in AISP #2, MLP was selected with greater AS but it almost was reproved in Ljung-Box test for no autocorrelation in residuals behavior.

TABLE I
Machine Selection Result for Three Spatial Objects

AISP	**Machine**	**MSE**	**RAS**	**RPS**	**Ljung-Box**
#1	MLP	207.63	0.4864	0.0107	0.2233
	ARMA	195.11	0.4872	0.0017	0.4495
#2	**MLP**	270.19	0.5789	0.0809	0.0579
	ARMA	312.66	0.3846	0.0368	0.6198
#3	MLP	269.12	0.4864	0.0856	0.0144
	ARMA	148.43	0.4359	0.1252	0.7865

To evaluate spatial granularity level and check for model obsolescence, another metric should be used, which must

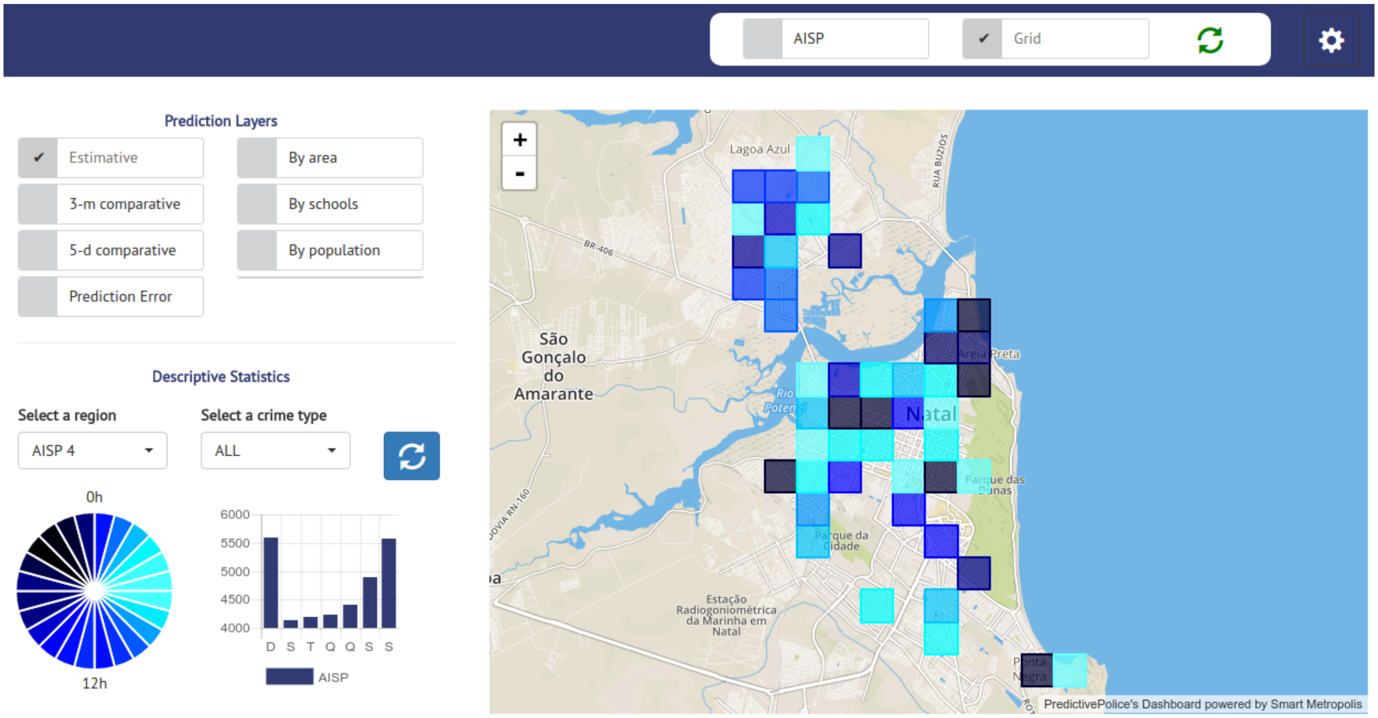

Fig. 4. ROTA-Analytics interface. Top-left options allows user to change the colormap layer. Down-left are displayed descriptive statistics of crime distribution by hour (left) and by week (right). Dark colors always represents high incidence.

consider a spatial feature (area, for instance). Based on Density Weighted Grid Prediction Error (DWGPE) defined by Ziehr [13], we adapt it to use with MSE. It consists of pondering error by each spatial object's density of occurrences, representing the performance of the whole grid. Equations 4 and 5 defines its use, where c_i represents number of crimes and a_i the area of region i. To exemplify its use, Table II illustrates performance of AISP versus rectangular grid configuration, and we conclude that AISP outperforms the rectangular grid in both machines.

$$DWPGE = \frac{\sum_{i=1}^{k}(d_i MSE_i)}{\sum_{i=1}^{k} MSE_i} \tag{4}$$

$$d_i = \frac{c_i}{a_i} \tag{5}$$

TABLE II
DWGPE COMPARISON FOR SPATIAL GRANULARITY LEVELS FOR MLP AND ARMA MODELS

	AISP	**rectGrid**
MLP	0.0048	0.0078
ARMA	0.0052	0.0075

Iustrated by the correlogram in Figure 5, the conclusion about the spatial granularity level to be used is that as spacial object becomes bigger, it aggregates a more representative dataset what allows the construction of more accurate prediction machines. According to the correlogram, area is inversely

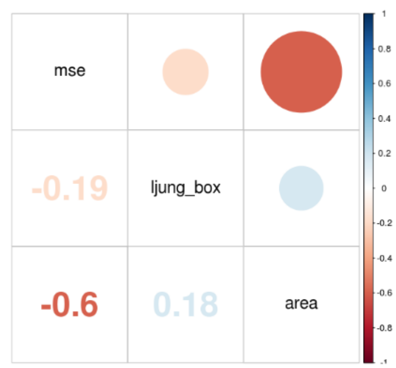

Fig. 5. Correlogram of prediction quality and spatial object's area.

proportional to MSE and does not correlate with Ljung-Box statistic. Then the trade-off between a fine-gran spatial configuration and the prediction error must be considered in real cases in order to patrol a smaller area with more confidence.

VI. Related Works

In literature, the topics discussed in this work are spread in different scopes and knowledge domains. GIS Applications, for instance, are very discussed in geoscience's topics. Griffith and Chun [17] discuss how this application concept is synergistic to spatial statistical/econometrics analysis. Nara [18] suggests to call GIS softwares that incorporates temporal dimension to its conventional framework of Space-Time GIS (ST-GIS), which fits ROTA-Analytics purposes.

In Predictive Policing domain, crime data analysis has been explored for many researches . Malik et al. [14] explore the use of Seasonal and Trend decomposition by loess (STL) and Kernel Density Estimation (KDE) to predict crimes along spatial cells of the city, treating parts of the dataset with no incidence of crimes, enriching input features of the models. Ziehr [13] uses city' spatial features for different machine learning models and apply them to the same Natal's dataset, and creates a novel spatial grid using K-Means algorithm, extracting convex hull polygons as spatial cells. In ROTA-Analytics, we don't use this, so called, *K-Grid* approach because AISP grid configuration was a requisite from local police department. Other authors as Wang et al. [19] have complemented their models with social media text analysis to enrich their performance through topic-modeling strategies. In terms of predictive policing application, Camacho-Collados and Liberatore [20] innovated developing a Decision Support System (DSS) for spanish police corps, but they do not explore prediction system modularity to consider an ensemble of predictors and other possible spatial grid configuration.

VII. Conclusion

In this work we discussed concepts and methods from Predictive Policing studies to provide better resource allocation in smart cities and public safety context. In particular, we proposed a new module for the ROTA platform [5], [6], named ROTA-Analytics. This new module uses a modular data analysis component that maintain its prediction approach easy to be replaced in case of obsolescence. The adoption of ROTA modules in the police activities has produced impressive strategical and operational results. In both cases, computational technologies are promoting changes in the modus operandi of law enforcement agencies. From the strategical point of view, the ROTA-Analytics has brought an innovative proposal for obtaining information to optimize police resources management, which proposes new ways towards a better planning of police resource distribution through city streets. Consequently, the technology becomes part of the officers' daily activities. For instance, supervisors could save time since they are able to easily elaborate program cards and police commanders have now a new information source to plan police activities.

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References

[1] "Oecd, environmental outlook to 2050: The consequences of inaction," http://www.oecd.org/env/indicators-modelling-outlooks/oecd-environmental-outlook-1999155x.htm, (Accessed on 07/05/2017).

[2] N. Komninos, P. Tsarchopoulos, and C. Kakderi, "New services design for smart cities: A planning roadmap for user-driven innovation," in *Proceedings of the 2014 ACM International Workshop on Wireless and Mobile Technologies for Smart Cities*, ser. WiMobCity '14. New York, NY, USA: ACM, 2014, pp. 29–38. [Online]. Available: http://doi.acm.org/10.1145/2633661.2633664

[3] "Designing Next Generation Smart City Initiatives - Harnessing Findings And Lessons From A Study Of Ten Smart City Programs," in *22nd European Conference on Information Systems (ECIS 2014)*, 2014. [Online]. Available: http://www.edwardcurry.org/publications/SmartCityDesign_ECIS.pdf

[4] N. Cacho, F. Lopes, E. Cavalcante, and I. Santos, "A smart city initiative: The case of natal," in *2016 IEEE International Smart Cities Conference (ISC2)*, Sept 2016, pp. 1–7.

[5] J. C. et al, "ROTA: A smart city platform to improve public safety," in *New Advances in Information Systems and Technologies - Volume 1 [WorldCIST'16, Recife, Pernambuco, Brazil, March 22-24, 2016].*, 2016, pp. 787–796.

[6] M. M. et al, "Improving public safety at fingertips: A smart city experience," in *2016 IEEE International Smart Cities Conference (ISC2)*, Sept 2016, pp. 1–6.

[7] A. Cacho et al, *Social Smart Destination: A Platform to Analyze User Generated Content in Smart Tourism Destinations*. Cham: Springer International Publishing, 2016, pp. 817–826. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-31232-3_77

[8] A. Cacho et al., "Mobile tourist guide supporting a smart city initiative: a brazilian case study," *International Journal of Tourism Cities*, vol. 2, no. 2, pp. 164–183, 2016. [Online]. Available: http://dx.doi.org/10.1108/IJTC-12-2015-0030

[9] B. Moreira, N. Cacho, F. Lopes, and E. Cavalcante, "Towards civic engagement in smart public safety," in *2017 IEEE International Smart Cities Conference (ISC2)*, Sept 2017.

[10] A. Souza, J. Pereira, J. Oliveira, C. Trindade, E. Cavalcante, N. Cacho, T. Batista, and F. Lopes, "A data integration approach for smart cities: The case of natal," in *2017 IEEE International Smart Cities Conference (ISC2)*, Sept 2017.

[11] W. L. Perry, *Predictive policing: The role of crime forecasting in law enforcement operations*. Rand Corporation, 2013.

[12] D. E. Brown and R. B. Oxford, "Data mining time series with applications to crime analysis," vol. 3, pp. 1453–1458, 2001.

[13] D. Ziehr, "Leveraging Spatio-Temporal Features for Improving Predictive Policing," Master's thesis, Karlsruhe Intitute of Technology, Germany, 2017.

[14] A. Malik, R. Maciejewski, S. Towers, S. McCullough, and D. S. Ebert, "Proactive spatiotemporal resource allocation and predictive visual analytics for community policing and law enforcement," *Visualization and Computer Graphics, IEEE Transactions on*, vol. 20, no. 12, pp. 1863–1872, 2014.

[15] P. Chen, H. Yuan, and X. Shu, "Forecasting crime using the arima model," in *Fuzzy Systems and Knowledge Discovery, 2008. FSKD'08. Fifth International Conference on*, vol. 5. IEEE, 2008, pp. 627–630.

[16] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

[17] D. A. Griffith and Y. Chun, "Gis and spatial statistics/econometrics: An overview," *Reference Module in Earth Systems and Environmental Sciences*, vol. 75, pp. 25–37, 2017.

[18] A. Nara, "Space-time gis and its evolution," *Reference Module in Earth Systems and Environmental Sciences*, vol. 75, pp. 25–37, 2017.

[19] X. Wang, D. E. Brown, and M. S. Gerber, "Spatio-temporal modeling of criminal incidents using geographic, demographic, and twitter-derived information," in *Intelligence and Security Informatics (ISI), 2012 IEEE International Conference on*. IEEE, 2012, pp. 36–41.

[20] M. Camacho-Collados and F. Liberatore, "A decision support system for predictive police patrolling," *Decision Support Systems*, vol. 75, pp. 25–37, 2015.

[1] http://smartmetropolis.imd.ufrn.br