COGNITIVE CITIES AN ARCHITECTURAL FRAMEWORK FOR THE CITIES OF THE FUTURE

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ABSTRACT

Digital transformation has changed management models in cities. The use of tools supported by information and communication technologies has facilitated the planning and control of the urban space allowing a rapprochement between the city and the citizens. This proximity is exponentiated with the advent of the Internet of things becoming possible to permanently know the state of the city and to act on the different infrastructures in a dynamic way. This paper proposes the use of Machine Learning techniques to enhance city management by predicting behaviours and automatically adapt rules mechanisms in order to mitigate city problems contributing to the improvement of lives living or visiting municipalities.

KEYWORDS

Architecture, Learning City, Smart Cities, Machine Learning, Big Data

1. INTRODUCTION

Demographic evolution mirrors the changes felt in cities: on one hand, large cities are receiving more and more people; on the other, small cities tend to be empty of people becoming increasingly isolated and aged. But regardless of the city's demographics, they all share the same ambitions: to evolve by protecting natural resources, optimizing infrastructure and equipment utilization, improving the day-to-day processes and offering more and better digital services leading all to a better way of life in the urban space.

Cities are becoming more and more digital supported by new communication and information technologies and many cities try to be Smart Cities and obtain their benefits [12]. The advent of Internet of Things (IoT) is another step taken towards the automation of internal flows contributing greatly to the city's operational efficiency and cost reduction. The information gathered by sensors is used to know the state of the city and to act on the different infrastructures, contributing to the improvement of the city in all its dimensions [13][14]. But the increasing complexity brought by the addition of more and heterogeneous data sources makes it difficult to configure rules in city analysis systems.

Thus, the logic of the city must be supported by learning mechanisms based on the construction of appropriated prediction models, enabling almost instantaneous answers to the city requests.

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This article presents an architecture that uses Machine Learning techniques to predict the occurrence of situations and to introduce contextual recommendations that help to improve the city management. This architecture foresees to change models whenever the dynamics of urban space will require, enhancing the adaptation of the city to the real needs of the citizen.

2. MOTIVATION

The main motivation of this work is the definition of an architecture enabling the management and automation of a city. An urban platform integrating intelligence will allow the city to adapt to current and future needs of the population. Through Machine Learning techniques it is possible to predict behaviors and automate rules mechanisms in order to improve the quality of life of the population in cities.

In this work it will be proposed a future-proof architecture for future cities, combining Smart Cities, IoT and Machine Learning.

3. STATE OF ART

3.1. Smart Cities

Smart City is an expression that is widely used nowadays but its meaning can be analyzed from different perspectives and as so multiple definitions. Despite this diversity, it is generally understood that a Smart City is a city where efficiency and optimization of resources, infrastructures and services are enhanced by the use of technology. The city, according to Sotiris Zygiaris, can be broken down into different pillars: economy, mobility, environment, life and government [1].

Also, [2] defines and establishes methodologies for a set of indicators enabling to measure city services performance and by that, the quality of life of citizens, that are defined in ISO 37120:2018. In [2] are defined 17 themes - Economy; Education; Energy; Environment; Finance; Governance; Health; Recreation; Safety; Shelter; Solid Waste; Telecommunications; Transportation; Urban Planning; Wastewater; Water & Sanitation and finally Fire & Emergency; Response – that are accountable for city quality of life.

Looking to all above domains, the task to improve urban performance is huge. It is essential that city transformation is supported by intelligence and to do so, the city must use all the necessary data from all available of sources together to monitor, analyze and act over the urban space, increasing the collaboration between different economic agents and encourage innovative business models, both in private and public sectors, with the ultimate goal of improving the living standards of the citizen [3].

3.2. Internet of Things

IoT (Internet of Things) "extends" the Internet to objects and leverage a myriad of new services. It will impact on innovation, create new businesses and revolutionize the way we live in society. But IoT is also a new technological paradigm characterized by the availability of a network of machines that are able to communicate with each other [4], bringing things, with computational and communication capabilities to the Internet. In this context, it is necessary to invest efforts in doing the appropriate planning, so that current and future cities are prepared for the necessary development in a robust, creative and sustainable way for the improvement of the society quality of life. IoT is definitely the most important tool to consider in the city transformation [5]. This concept is also a major challenge, not only at conceptual and technological level, because there are several different technologies in the ecosystem, but also at social and political level [6].

In [9], the authors refers that "*the IoT Application scenarios extend to personal health monitoring, home control, smart grid, smart traffic & transportation management, smart environmental monitoring and more. The applications of IoT and M2M communications in the context of smart cities are the particular interest*". The authors also emphasize the integration into oneM2M standard architecture by IoT framework for mobile crowd sensing. Also, in [11] is mentioned that "*for smart traffic solutions, crowdsourcing could offer real time traffic update enabling drivers to change the route to destination if necessary"* based in M2M devices.

M2M facilitate the creation of new use cases in different industrial sectors [15] and the deployment of M2M technologies is increasing in urban environments [16].

3.3. Machine Learning

Machine Learning is an Artificial Intelligence branch that gives systems the ability to learn automatically. Its application focuses on the development of models envisaged to learn with data that has been previously collected and processed [7].

All smart cities are digital cities, but not all digital cities are smart cities. While digital cities are enable the provision of services through digital channels, in intelligent cities it is possible to go further by planning, operating and performing all over the urban space in an orchestrated and autonomous way [8].

Learning is a fundamental part of cities' evolution and the big data help this learning [12]. As more forecasting capabilities are in place as more events can be anticipated and mitigated ensuring the safety and quality of life of citizens. Allowing cities to learn, using the historical data provided by the urban ecosystem makes it possible to speed up the resolution of various problems and improve processes and procedures. Besides historical data, the use of real-time data to feed city brain will enable just in time decision making and autonomous actuation.

4. ARCHITECTURE

This article aims at describing the key functionalities of the proposed architecture in order to facilitate the everyday life in cities. The architecture of cognitive cities encompasses two distinct functional blocks that complement each other. The first one, the city learning model, includes all the necessary components for the construction of the model of Machine Learning to be adopted by the city as well as the permanent evaluation of the deployed one. The second block, the city runtime, is constituted by the necessary elements for the daily management of the city, allowing to know and to act in the infrastructures and equipments taking into account the context of the urban space. Both functional entities resort to a data management platform to store and persist the raw and analyzed city data. Figure 1 presents the cognitive framework for the cities of the future.

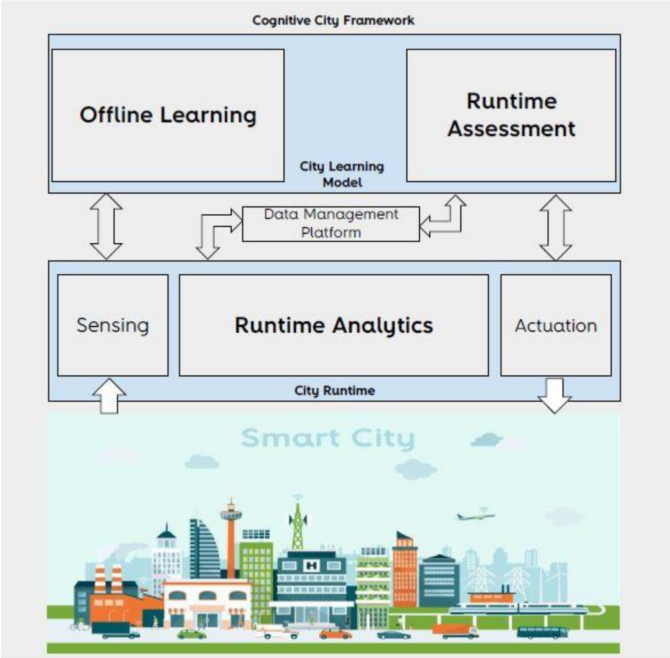

Figure 1. Generic Cognitive City Framework Architecture

4.1. City Learning Model

The city model has the objective of managing the life cycle of the models to be applied in cities. It encompasses the whole learning process, the deploy component in the city's systems, as well as its evaluation taking into account new entries collected by existing urban systems. City model encompasses two major blocks: **offline learning** and **runtime evaluation**. Figure 2 presents the city learning model module.

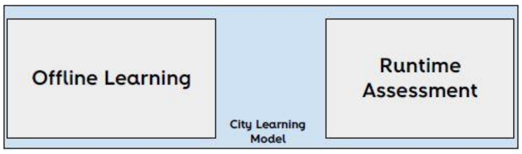

Figure 2. City Learning Model

4.1.1. Offline Learning

The offline learning functional entity includes the key tasks for providing cities with learning capabilities. It is an offline component encompassing all the stages for training the model based on the available dataset of the problem domain. It assumes a data preparation stage where the data preprocessing takes place to arrange the dataset for the Machine Learning algorithms, including checking missing values, dealing with outliers, correcting duplicates, standardizing or splitting data for training and testing. Also, the offline learning includes the proper processes for models creation based on a set of Machine Learning algorithms(Figure 3). The training data is used as input for kNN, Naïve Bayes, Decision Trees, Random Forest, SVM and Neural Networks algorithms resulting in different models able to be applied for prediction.

Each model is evaluated using confusion matrix aiming at determining the performance of the classification models created.

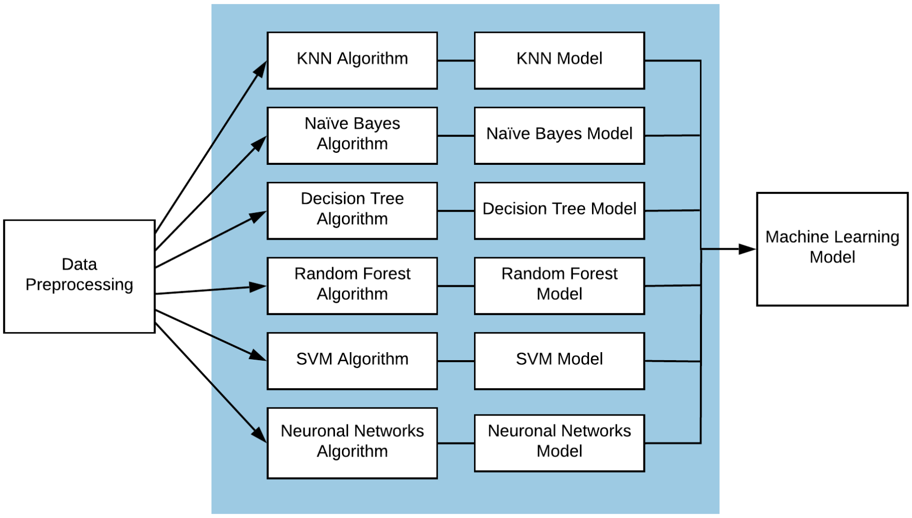

Figure 3. Processes for model creation

Finally, the most appropriate model is selected and deployed in the runtime environment making possible to predict city critical situations and to anticipate mitigation actions. Figure 4 presents the offline learning module.

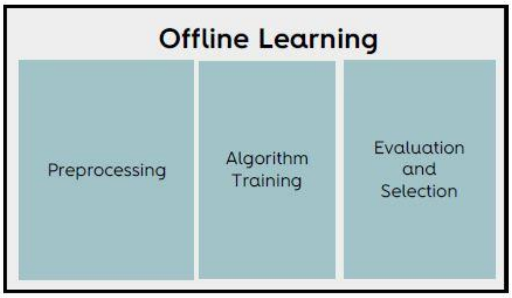

Figure 4. Offline Learning

4.1.2. Runtime Assessment

The runtime assessment aims to ensure that the deployed model remains adapted to the dynamics of the city. For this, it uses the **verification** module to complement the forecast made with the actual result, that is, it verifies whether the forecast done was correct or not. Moreover, it runs the **evaluation** module to verify the model accuracy levels. When the accuracy begins to decrease it is necessary to redo the model taking into account all the new data gathered. Figure 5 presents the runtime assessment module.

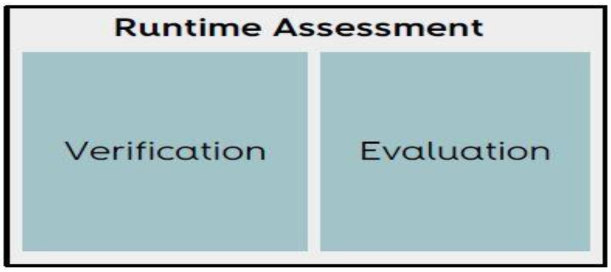

Figure 5. Runtime Assessment

4.2. City Runtime

The city runtime aims at managing the city infrastructure in "real time" in order to make life in cities easier. This module uses the model developed in offline mode to manage occurrences in the city. The data are collected through sensors scattered in the urban space and analyzed in order to obtain a prediction of a certain occurrence. According to the expected result will be made a recommendation of action that will trigger a change in the infrastructures of the city.

The City Runtime encompasses the following components: sensing, runtime analytics and actuation. Figure 6 presents the city runtime module.

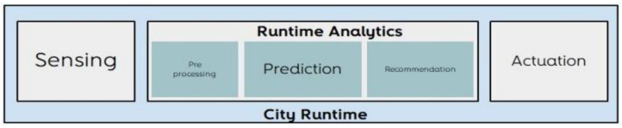

Figure 6. City Runtime

4.2.1. Sensing

Sensing is the entity in charge of collecting physical measurements related with city infrastructure. It resorts to a set of sensors that collect raw data related with different city assets, such as noise, traffic, temperature among others, and transmit it towards the data management platform for storage and further analysis.

4.2.2. Runtime Analytics

The Runtime Analytics is the "brain" of the runtime system. It gets the information sensed and prepares it for the Machine Learning module. The cleaned data sample is used to predict a specific event; it enters in the prediction entity, which runs the Machine Learning model deployed in the city system, allowing getting the classification or regression result. Depending on the prediction outcome, a specific recommendation is set in order to update the city infrastructure status. Figure 7 presents the runtime analytics module.

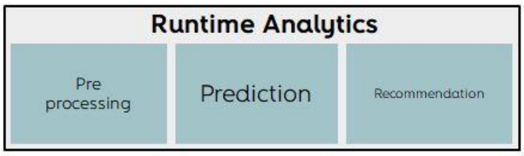

Figure 7. Runtime Analytics

4.2.3. Actuation

The Actuation entity is responsible for the enforcement of the recommendations provided. It closes the loop by sending appropriate commands towards the infrastructure in order to adapt it to the instantaneous city needs.

4.3. City Data Management Platform

The key functionality of the City Data Management Platform is to make data mediation between different system entities. It is a cloud-based open API platform able to upkeep different technologies and protocols facilitating the end-to-end system integration. It supports both request & response and publish & subscribe message exchange patterns. The City Data Management

Platform allows linking different city domains by enabling the storage and the share of city data, solving the typically city information silos issues. All the city data lifecycle is here managed in order to make it permanently available for authorized entities.

4.4. Global Architecture Framework for Cognitive Cities

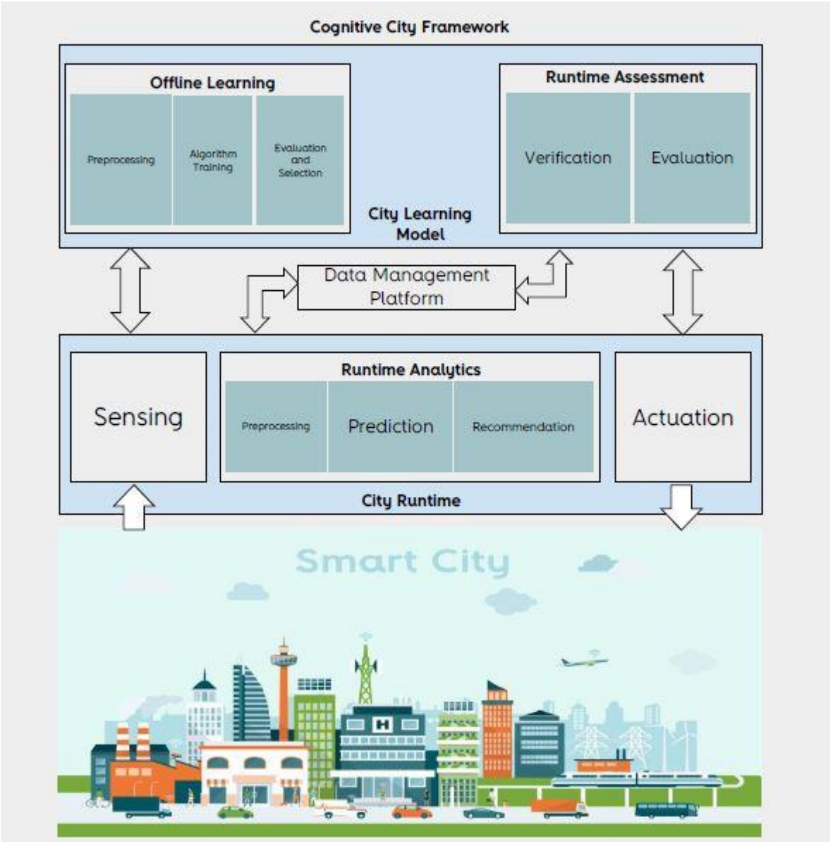

Figure 8. Global Architecture Framework for Cognitive Cities

5. CITY ACCIDENT SCENARIO – AN EXAMPLE

Usually there aren't enough resources for victims' rescue in road accidents. When there are several occurrences at the same period of time, it may be required to manage priorities, enabling to first aid to the most seriously injured. However, it is not always easy, given the huge number of involved factors, to realize quickly which the most severe occurrence was.

António is a citizen of a city that already uses the Cognitive City Framework. Unfortunately, on the way to work on a rainy day, he had an accident. Although slight, medical resources were needed and therefore people who saw the accident called the first aid.

On a road parallel to Maria, she also had an accident, and this was a serious accident and it was urgent that rescue be provided as soon as possible. However, the resources of relief were not many, and there was only one ambulance available. From the information given through the calls, it was not possible to perceive, because of the nervousness of those who spoke, that Antonio's accident despite needing help was not serious. Through various features it is possible to make this prediction and first to rescue Maria.

By applying a Machine Learning model to the attributes that make this prediction possible, it will be possible to prioritize events more effectively.

6. DATA FLOW

6.1. Learning Phase

This phase encompasses all steps required to create a model appropriate to predict specific situations in the city. The City Learning Model block uses the data stored in the Data Management Platform for the modelling process (step 1). Within the Offline Learning entity, the collected data is cleaned in the preprocessing stage resulting in a prepared dataset for model creation (step 2). As can be seen in Figure 8, the dataset works as input for different Machine Learning algorithms, such as, Naïve Bayes, Random Forest, neural networks, among others. For each algorithm, a model is created becoming ready for assessment (step 3). Each model is tested and evaluated, based on performance, and the selected one is deployed in the City Runtime block for runtime usage (step 4).

6.1. Runtime Phase

The Runtime Phase controls the city infrastructure in a dynamic way. It impacts the citizens' daily life by adapting in anticipation the urban space to the city needs. It resorts to the Machine Learning model built to predict city situations and mitigate them in advance.

The sensors spread in the city are periodically making available city data. This data is collected and set into a common information model (step 5), being then sent to the Data management Platform (step 6), which stores and persists the information. The Data Management Platform notifies the Preprocessing module in the Runtime Analytics (step 7), which cleans the data making it ready for the Prediction module. The Prediction runs the model deployed; based on the input it labels the class allowing anticipating critical situations. The prediction done is published in the Data Management Analytics (step 8), which, by its turn, notifies the Recommendation module (step 9). Based on the prediction received, the Recommendation sets the actions required to mitigate the issue and sends it to the Actuation module (step 10). Finally, the Actuation changes the infrastructure state (step 11) adapting the city to the dynamics of daily life.

6.1. Evaluation Phase

This module is responsible for the verification of the veracity of the prediction as well as for the evaluation of the deployed model. In a supervised way, it is checked if the prediction done was correct or not (step 12), being the result stored in the Data Management Platform. Periodically, the Evaluation module gathers all the information (step 13) and compares the prediction with the verified values in order to check the model accuracy. This result is published in the platform (step 14), which notifies the Offline Learning about the new results (step 15). Depending on the system policies, the result of the model evaluation can trigger the creation of a new model to be deployed in the city fitting the citizens' needs.

Depending on the scenario, we need evaluate metrics as accuracy, precision, recall and confusion matrix. If in the scenario is important eliminate false negatives so the most important metric is recall. This metric indicates how well the model identifies positive cases correctly [10]. For example, in sick patient detection, the cost associated with false negative can be very high to the patient. It's important analyze the confusion matrix too. If in the scenario are important predict the most cases correctly so it's important analyze accuracy and precision. The better results are when metrics are close to 1.

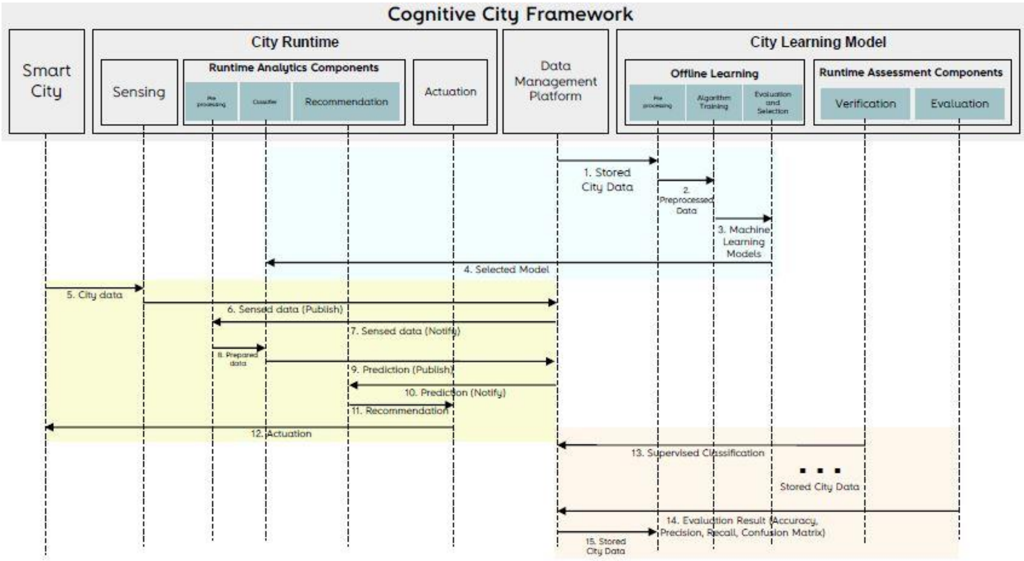

Figure 9. Cognitive City Framework Data Flow

7. CONCLUSIONS

The future of smart cities goes through the Machine Learning applied to them.

The relationship between smart cites, IoT and Machine Learning is quite close and thus they all complement themselves.

By establishing a connection between technology and the majority of people, smart cities may become a way to accomplish a balance on the life quality of the population [4]. The Learning City Framework seeks to facilitate the introduction of Machine Learning in the already existent smart cities.

In the future we will apply the Learning City Framework to the scenario in order to obtain results that prove the quality of this.

ACKNOWLEDGEMENTS

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