Smart Is A Matter of Context

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Abstract. Smart cities involve, in a large scale, a wide array of interconnected components and agents, giving birth to large and heterogeneous data flows. They are inherently cross-disciplinary, provide interesting challenges, and constitute a very promising field for future urban developments, such as smart grids, eco-feedback, intelligent traffic control, and so on. We advocate that the key to these challenges is the proper modelling and exploitation of context. However, said context is highly dynamic and mainly unpredictable. Improved AI and machine learning techniques are required. Starting from some of the main smart cities features, this paper highlights the key challenges, explains why handling context is crucial to them, and gives some insights to address them, notably with multi-agent systems.

Key words: smart cities, multi-agent systems, complexity

1 Introduction

The term "Smart City" regroups various problematics and features stemming from the use of new information and communication technologies (ICTs) in order to build a better living for every citizen. This includes many different fields such as governance, city planning, health, mobility, housing, energy, and so forth, making smart cities an active cross-disciplinary research ground.

The various features of smart cities share a common trait, that may seem trivial: they are all context-dependent. Accessing or forecasting contextual data, and extracting relevant information from it, is always the key to push forward the efficiency of smart cities features. However, context in smart cities is complex. The wide array of interconnected components, their dynamics, their heterogeneity, and reliability issues of real-world problems make smart cities' contextual data very difficult to handle, even for automated systems. This often requires advanced artificial intelligence and machine learning techniques. Such complexity can only be dealt with bottom-up approaches. Thanks to their self-* properties and their "built-in" notion of environment, Multi-Agent Systems (MASs) are a good candidate for designing context handlers for smart cities features.

Figure 2 proposes a graphical abstract of this paper. Section 2 presents definitions of smart cities from litterature, while section 3 goes deeper with common features of smart cities. Section 4 explains the main challenges that arises when

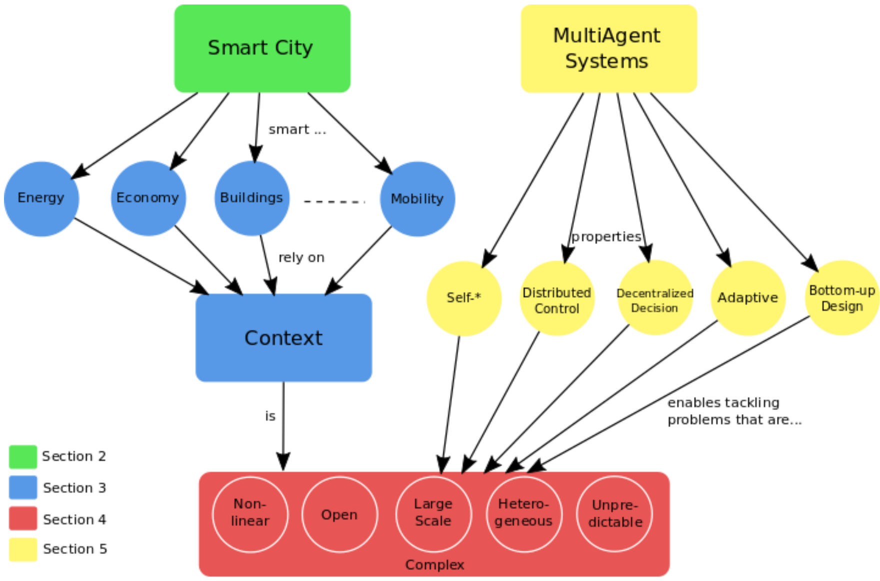

Fig. 1. Graphical Abstract

dealing with context in smart cities. Finally, section 5 presents multi-agent systems and explains why they are suitable for these challenges, before we conclude with perspectives in section 6.

2 Smart Cities

Being a transdisciplinary subject, it is difficult to have an accurate and consensual definition of what a smart city is. Depending on its focus, each author proposes a different definition, and sometimes relative words are used to emphasise a specific dimension of smart city (like "Intelligent City", "Creative City", etc) [22]. However, most of the time, the use of information and communication technologies is an important part of the design of a smart city. In this paper, we consider that three characteristics (proposed by Harrison all [12]) are common to all smart cities: instrumented, interconnected and intelligent. *Instrumented* means that the city can use a large set of data-acquisition systems in order to produce data from the real world. *Interconnected* means that these data can be used across different services and users in the city, and finally *intelligent* emphasises the ability to analyse and use efficiently these data.

3 Smart Cities Features

It is almost impossible to provide an exhaustive list of all possible features of a smart city, due to the large number of way to think smart cities. In this section are presented various features selected to illustrate the importance of taking into account the context in the management of the smart city. The different application areas are inspired by Neirotti et al. [23].

3.1 Natural Resources and Energy

With the growing threat of resource scarcity, the improvement of resource and energy management in cities becomes a major issue.

Smart Grids In the classic way to distribute energy, electricity is in a centralised way, then it is distributed to all the customers. The energy flow is unidirectional, from the producer to the customer. In a smart-grid, the energy flow is bidirectional, allowing greater flexibility in the management of energy [11]. This kind of technology is very interesting for smart cities, because it allows to easily add decentralised energy production units in the energy grid, like wind turbine or solar panel. These green power sources are a promising way to make smart cities self-sufficient in energy and to reduce their natural resources consumption. But, these energy sources are intermittent. So, currently, energy grids can't rely only on these energy sources. If energy demand reaches a peak, or if energy coming for intermittent sources decreases, thermal power plants must provide energy to meet the demand in order to avoid a blackout. But thermal power plants can't be activated instantaneously. In order to efficiently use smart grids in smart cities, we must be able to anticipate the need for additional power sources.

It is in this anticipation requirement that lies the need for proper context understanding. Indeed, the variation of production and the variation of consumption must be taken into account. The first one depends on the weather, but also on the facilities conditions, and the second one is affected by pretty much all the events that affect the city (season, hour, weather, events, etc). All this contextual information must be efficiently used in order to provide good forecasting.

3.2 Transport and Mobility

Smart cities, by concentrating a large number of people, must deal with traffic congestion. The presence of numerous sensors offer interesting opportunities for transport management [30].

Traffic Control One of the most significant use case is about automatic control of traffic lights. Indeed, an efficient management of these traffic lights can have a great impact on traffic congestion. In a smart city, sensors (cameras) could be used to measure the number of cars at many points in the city, and so traffic congestion could be measured in real time. But these data are not the only thing that affect the traffic in the city. To efficiently manage traffic lights, contextual data must be considered. For instance, these data could be considered: current day and hour, people and car localisation, weather, price of fuel, etc... In fact, because of the complexity of an urban network, a huge array of data could be interesting to consider. It's at this point that efficient context management become essential. Choosing the most relevant data in a large sensor panel, and using them to determine the best behaviour for traffic control is a complex task.

3.3 Buildings

At a more local scale, smart cities rely on smart buildings to improve quality of life and optimise energy consumption. Smart buildings are designed for energy efficiency. Equipped with ICT, they can monitor and control their own devices while also communicating with other buildings [19].

Anomaly detection Smart buildings, using a large array of sensors, are able to provide an overview of energy consumption and production of a building. It's an useful tool to improve management of energy. But it should be possible to get even more interesting results. In fact, using these data, it is possible to identify anomalies[31] (by analysing the behavior of sensors data). The automated detection of such situations opens up many possibilities in terms of predictive maintenance: identifying flawed sensors, broken effectors, leaks, mechanical failures, and so on. It becomes possible to improve the time reaction to repair, thus improving the management of the building, and optimising energy consumption.

Eco-feedback The human aspect is an important concern in many definitions of the smart city. So the mechanisms which allow to influence the behavior of citizens naturally have a role to play in smart cities. An example of such mechanism is *eco-feedback*. The goal of eco-feedback technology is to provide feedback to people on their behaviour in order to optimise environmental impact[9]. Making such eco-feedback is complex, because each individual potentially reacts differently to a specific feedback in a specific context. So, an automatic system trying to produce an eco-feedback must take in account who is the recipient[26], which medium is used, where the action takes place, in order to deliver a meaningful information. Once again, context is a key to this problem.

3.4 Governance

In a smart city, institutions interact dynamically with multiple stakeholders (communities, citizens and businesses) [22]. In such a system, a decision maker can't rely on data specific to its own department. Data coming from other stakeholders are essential to efficiently manage the city. For instance, the construction of a new shopping mall is affected by many different contextual data coming from different stakeholders: cadastre from the public administration, different services offered from close providers, habits from citizens. Each stakeholder is involved. This is also true for "classic" cities, but the need for efficiency of smarts cities combined with an increased access to data makes it both necessary and possible to optimise decision making thanks to contextual data.

3.5 Economy and People

Cultural heritage The development and valorization of the cultural heritage of a smart city are an important issue, either from an economic perspective (tourism) or from a societal perspective[1]. One of the tracks laid down by smart cities is that of augmented reality[28]. Here, augmented reality is designed to provide additional background information to allow the user to benefit the most from the wealth of monuments, art, and more generally speaking culture of the city. To this end, it is necessary to use at best all available data, in order to provide information that is relevant to the user. This data can be: the position of the user, what he has seen, the time of day, his current attendance, and so on.

3.6 Contextual features

In all of these features, the intelligent management of the environment is of primary importance. Given the complexity of a system such as a smart city, it becomes mostly impossible for human operators to effectively use and understand the flow of dynamic data produced by the smart city. In fact, today the majority of methods focus on computational approaches to manage these data effectively, with the goals of controlling, monitoring, and providing decision support. However, the particularities of complex systems in general, and smart city in particular, create some problems which need to be addressed in order to successfully manage context in such approaches.

4 Challenges for Context Management in Smart Cities

The previous section stated that a proper context handling is crucial for many smart city applications. Here, context handling means extracting relevant information from data and being able to forecast and anticipate their occurrence (learning predictive relationships).

However, cities are complex systems [2, 23]. Hence, applications in smart cities are plunged into a complex context. Along with the social challenges that go with new technologies, such as acceptability or ethical dilemma, the complexity of context adds (among others) non-linearity, openness, heterogeneity, and large-scale data to the challenges that context management systems have to face.

4.1 Non-linearity

When a small change on the input of a system may result in a big change on its output, the system is said non-linear. Controlling such a system is a difficult task. Unfortunately, voltage in smart grids, heating in buildings and housing, traffic, and many smart cities systems we seek to control are non-linear.

In a linear system, the distribution of data is such that it can be exactly abstracted using only simple mathematical functions. On the contrary, machine learning algorithms have to be sophisticated and fine-tuned to be able to learn non-linear patterns and perform with contextual data from smart cities [34].

4.2 Openness

A system is said open when parts may dynamically enter and exit the system. With the Internet of Things, smart cities are inherently open [13]. New devices, new sources of contextual data, are continually added, and some old ones are deleted, or suffer fatal failures. An intelligent algorithm designed to handle contextual data in a smart city should be able to easily incorporate new sources and delete old ones. For instance, a new room is built in a smart building and equipped with various sensors and effectors that add their data to the contextual data flows of the energy management system. This system had learnt the optimal behaviours to balance energy consumption and comfort. Now, it has to seamlessly incorporate these new data sources to its decision making process. Otherwise, administrators would have to reset and restart the whole learning process. It would be very time costly. Such openness can prove really difficult to achieve for many types of machine learning algorithms, particularly artificial neural networks and evolutionary algorithms.

4.3 Large-scale

Smart city are deemed to generate huge masses of data. For instance, a traffic light control system managing all the crossroads of a city would have to deal with all the various sensors of all the roads and crossroads to take simultaneously multiple decisions about which light to turn on and off. All these decisions are so interdependent that distributed control should be favoured over a central decision making process [7]. The solution has to rely on autonomous unit taking local decisions.

4.4 Heterogeneity

Contextual data in smart cities include a large variety of data types, whether they are numerical or not, continuous or discrete, multidimensional or not. Not all algorithms are able to deal with such heterogeneity. While numerical data are usually easily handled by current algorithms, modelling and treating ontologies and abstract concepts is a whole field of research. If some algorithms work very well with continuous numerical data, they are utterly unable to deal with data like the colour of an object, the smell of an animal, or more abstract concepts like the emotion of people. Sophisticated methods have to be employed to process together heterogeneous data in a single algorithm. For instance, Lewis et al. use kernel methods, but it does not answer the problem of modelling abstract concepts [15]. Moreover, heterogeneity also appears in time scales. Fore some data and tasks, it is relevant to make measurements every millisecond. For other it is days, weeks, or months. Algorithms are usually suited for a given timescale, but struggle to manage several at once.

4.5 Unpredictable Dynamics

Contextual data in smart cities are always dynamic. Weather changes, density of population changes, traffic changes, and so on. This is a quite obvious fact to state. There would be very little interest to gather constant data. Current algorithms can easily find predictive relationships in smooth linear and complete data set. However, in the real world, the way data change is difficult to handle, and often unpredictable. The dynamics you have learnt at a given moment may not be true some times later. This stems from several factors such as non-linearity, partial perception (there is not always a sensor for every relevant data), unreliable or missing data, failures, openness, and so on. This pressures the machine learning algorithms to perpetually self-adapt to the ever-changing data. Offline learning [25] is out of the question if we do not wish to regularly perform a new costly training.

4.6 Privacy

Smart cities are able to collect and gather large amounts of information, and this could harm the privacy of citizens [17]. But whatever the services brought by new connected technologies, nobody should have to give up its privacy. Data should not be used outside of what the considered services need. A good alternative to enforce this would be for the data to be processed physically close to its source, and not being transferred and stored when it is not necessary.

To answer these difficult challenges, the ideal context handler would have to be decentralised, adaptive, open, and modular. The next section describes the Multi-Agent Systems approach which, done right, could exhibit all of these properties.

5 Multi-Agent Systems and Smart Cities

The challenges listed in the previous section are not restricted to Smart Cities. In fact, they are at the very heart of **complex systems**. Smart Cities are representative of complex systems, notably by merging problematics coming from several domains, like politics, urban planning, health or ecology, each domain coming with its own requirements. Thereby, the "Smart" component of tomorrow cities is not just deploying state-of-the-art information and communication technologies, but doing it intelligently. To play well its role, ICTs, and especially artificial intelligence, must adopt methodologies that enable to face the problematics of those complex systems but also ensure its massive deployment and sustainability. *Ad hoc* solutions, aiming to develop for each problematic its own new solution, are clearly not answering those needs. On the contrary, abstraction and re-usability of solutions must be taken into account. In this section, we argue that the Multi-Agent approach is not only suitable for the challenges of smart city, but that the agent paradigm includes *de facto* the notion of context.

5.1 The Multi-Agent Paradigm

Multi-Agent Systems (MAS) are systems composed of multiple interacting and autonomous entities, the agents, within a common environment. MASs offer a methodological way to model and study complex systems with a bottom-up approach. In computer science, the MAS paradigm focus on the design of agents and their collective behaviours leading to the realisation of a particular task. However, the MAS paradigm is not restricted to computer science as it allows to express a large variety of problems focusing on the entities composing it and their interactions. Thus, it is used in areas such as sociology, cognitive science, geography, or ethology, each of those domains use the MAS paradigm to model, study or even simulate complex phenomenon. The natural distribution of tasks inside the different agents composing a MAS, and the possibility to decentralise control and decision, makes them highly suitable to overcome a greater complexity than conventional methods and tackle the Smart City challenges (see section 4).

A classic definition of an agent given by Ferber is that "*an agent can be a physical or virtual entity that can act, perceive its environment (in a partial way) and communicate with others, is autonomous and has skills to achieve its goals and tendencies.*" [8].

This definition highlights the fundamental properties of an agent:

- An agent is **autonomous**, which means the agent is the only one to control its own behaviour. This implies that the choice to act or not is only driven by the agent's own behaviour. The agent's capacity to say "no" (to choose not to act) makes a concrete differentiation between an agent and a sub-program.
- An agent evolves in an **environment** (physical or virtual) on which it is able to locally perceive information and locally act. This environment is everything that is external to the agent and which can be perceived by the agent, including the other agents. This environment acts as the interaction medium.
- An agent is able to **interact** and **communicate** with other agents either directly or through the environment. The other agents are then part of the social component of the agent's environment.
- An agent possesses a **partial** knowledge of this environment.
- An agent possesses its own **resources** and **skills**.

The notion of environment is crucial in MASs. Indeed, the environment is not only a source of information, but also the medium through which those agents act and interact. Agents are coupled with their environment, the activity of one constantly influencing the activity of the others. They are designed to extract information from their environment and to reason based on this information. In many aspects, the notion of environment is very similar to the notion of context.

The most common way to model the behaviour of an agent in its environment is to adopt a three steps looping lifecycle of *Perception-Decision-Action*:

- 1: **Perception** is the process during which the agent acquires information from its environment and updates its internal representations.

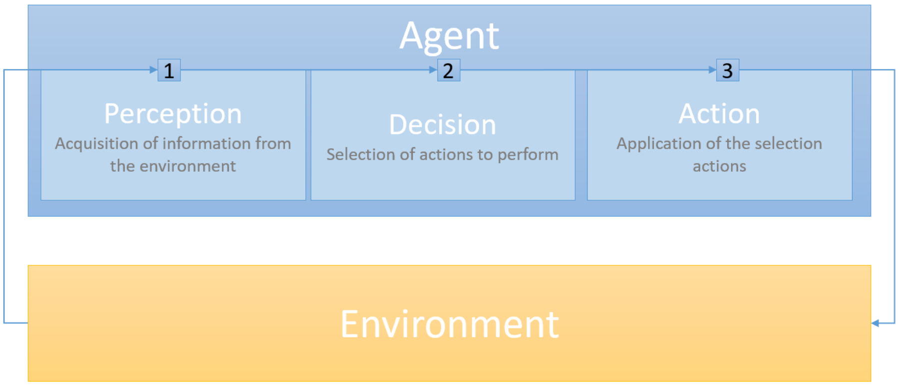

Fig. 2. The Lifecycle of an Agent [33].

– 2: **Decision** is the process during which the agent decides of actions to perform. This decision is based on its local perceptions, its internal knowledge and its own objectives.
– 3: **Action** is the process during which the agent applies the actions.

5.2 Multi-Agent Properties Addressing Complexity

Multi-Agent Software Engineering (also called Agent-Oriented Software Engineering) is gathering a rather long practice of systems development. It focuses on enabling designers to have precise ideas on which Multi-Agent System properties can address the features of complex systems.

Bottom-up Design Bottom-up design starts by adding interaction and decision skills to entities from the application domain in order to "transform" them into agents. Even if the application domain is a complex system with heterogeneous parts, it still can easily be represented in terms of agents. Focusing on the entities and their interactions at a local level makes it easier to deal with complexity.

Distributed Control In almost every multi-agent system, there is no predifined hierarchical organisation. Combined with the autonomy of agent, this drives the designer towards architectures where control is distributed, with no Master-Slaves nor Client-Server patterns. Hence, with every agent being aware of its environment, deciding on its own what to do when this environment changes, being able to adapt to these changes, multi-agent systems are naturally open and can easily handle the openness of a complex system to which it is coupled.

Decentralised Decision Since every decision is made at the agent level, the structure of a multi-agent system decentralises the decision making process. This decentralisation eases the addition of new agents in the system (openness) and also eases the scaling of the whole system by avoiding unnecessary combinatory computing.

Adaptive Multi-agent systems usually have interesting capabilities in terms of adaptivity. Indeed, agents can change their own behaviour and their relationship with other agents and with their environment, and the whole MAS can remove or add new agents. This flexibility of MASs make them efficient for solving problems in unpredictable environments.

Self-* MASs are composed of autonomous entities and are usually designed to be themselves autonomous. The trend go towards less human intervention to maintain certain properties or activities of the system when its environment changes. These systems are called "self-maintaining", "self-healing", or "self-organizing" depending on their level of autonomy. This enables MAS to efficiently deal with non-linearity, openness and unpredictable dynamics of complex systems such as smart cities.

5.3 Multi-Agents Usage in Smart Cities

As a matter of fact, the paradigm is more and more used in the context of Smart Cities [27]. Those usage can be categorised in three categories:

- **Modelling**: By focusing on the agents and their interactions, the MAS paradigm eases the design of complex systems. The design of a MAS take into account of the heterogeneity of the entities involved in the problem to model, their distributed nature (with may be physically distributed and/or logically distributed) and the openness. It is notably used to "*offer a decentralised and collaborative architecture with requirements of autonomy, pro-activity, decentralisation, inter-operability, easiness of deployment, and ability to seamlessly incorporate future evolutions*" [4]. But the benefits of agent based modelling may also be found in the fact that the egocentric approach to design an agent enables to model natural and social structures such as human organisations [29], and to "*allow solving problems in a distributed manner by taking advantage of social behaviours as well as the individual behaviour of the agents*" [6].
- **Simulation**: Another usage of the MAS paradigm in Smart Cities is the simulation of complex phenomenons. For example, Gueriau et al. [10] use a multi-agent simulation to study the impact of cooperative traffic management strategies. Here, the MAS paradigm enables to address the problematic of traffic management both in a behavioural way, by modelling the cooperative strategies, and a topological way, with the characterisation of the environment on which the different car-agents drives. Another example of simulation with a MAS is the work of [20] who proposed a framework for the study of the impact of a specific natural disaster organisational structure and its related management policies on natural disaster response performance. Here, the MAS paradigm enables to study how the organisation of a set of agents may affect a

decision process. Another example of MAS usage in the context of Smart City is the work of Vaubourg et al. [32] that shows how the multi-agent paradigm can be successfully applied for smart grids multi-model simulation.

– **Problem solving**: The MAS paradigm partly emerged from the community working on distributed problem solving. Its popularity is growing when it comes to face complex problem coming from real world, notably by using its natural distribution of tasks among the system. Scientific literature is filled with examples of problem solving with multi-agent systems [16]. We propose to illustrate these usages with some examples coming from Smart City challenges. One of these example, which is applied to Smart Cities, is the work of Cerquides et al. [5] who proposed a multi-agent approach for the design of marketplaces for the trading and distribution of energy in the Smart Grid. They face the challenge to design markets for producers and consumers in smart grids that consider distribution grid constraints. In their model, the local producers of electricity are modelled as agents, which can trade electricity within their neighbourhood. Through message-parsing, the agents manage to trade electricity while satisfying the constraints of the grid in a decentralised way. Another example is the work of Mazac et al. [18] which proposes to detect recurrent patterns at the interaction between a system and its environment. In this approach, inspired by the constructivist theory [21], three populations of agents interact with each other, guided by a feedback from the global system activity in order to construct relevant patterns and provide a model of the environment dynamic. This work is applied to ambient systems. The last example is the work of Nigon et al. [24], which designed a generic multi-agent system to model, by observation, the dynamics of a system. In this approach, the agents which are dynamically created by the system intend to model the consequences of the application of a particular action in a particular context. At the opposite of the approach from Mazac et al., the different agents cooperate to build a model of the system. This approach is deployed and tested with real world applications such as smart-building monitoring, energy efficiency and user satisfaction in ambient systems.

All these applications truly depend on their context: context of deployment when we focus on architectural design, topological or structural context when we focus on simulation, or decision context when we deal with problem solving. Each of these applications is designed, thanks to the focus set by the MAS approach on the locality of agents decisions, to model, simulate or take decisions based on the context of the entities involved in the problem to study. Moreover, MASs are naturally good to deal with context, and have been used to explicitly learn actions from contextual observations [3].

6 Conclusion

Smart city is a research field full of promises. From efficient natural resources management to transport and mobility, ICTs may be able to significantly improve the living conditions in cities. For many of smart cities applications, context is the cornerstone around which great progress can be made. However, the complex nature of smart cities raises challenges that have to be tackled, especially dealing with unpredictable dynamics, openness and heterogeneity in large-scale environments. The large amount of sensors is not by itself a sufficient answer to this complexity and, in a seemingly paradoxical way, the integration of additional technology to make the city smarter adds even more complexity to it [14]. An efficient way to automatically manage the complexity of the context is the next big step forward in many aspects of the smart city.

Furthermore, an interesting parallel can be drawn between the requirements expected to handle such complex systems and the properties of a well known paradigm in science: multi-agent systems. Indeed, the adaptive and self-* properties, the decentralised decisions, the ability to be easily distributed, and their bottom-up design philosophy offer interesting perspectives to handle complexity in smart cities. In this approach, the context (similar to the notion of environment in multi-agent systems) is a first-class citizen, and offers different ways to think about interactions between agents and environment. In the case of smart cities, MASs can be used to model, simulate and solve problems, and answer a lot of needs. This paper advocates for their usage for context handling in complex environments such as smart cities, and aims at triggering discussion among different fields in order to better understand their cross-disciplinary needs.

Acknowledgements

This work is partially funded by the Midi-Pyrénées region for the neOCampus initiative (www.irit.fr/neocampus/) and supported by the University of Toulouse.

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