A framework for modeling human-like driving behaviors for autonomous vehicles in driving simulators

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A Framework for Modeling Human-like Driving Behaviors For Autonomous Vehicles in Driving Simulators

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ABSTRACT

A framework for modeling driver behavior within driving simulators is described in this paper. This framework serves as a basis for building human-like driving behavior models for autonomous vehicles operating within the virtual environment of a driving simulator. The framework consists of four units, the Perception Unit, the Emotions Unit, the Decision-making Unit (DMU), and the Decision-implementation Unit (DIU). The Perception Unit defines how the model perceives its environment in local and global terms. The Emotions Unit defines how the model responds emotionally to its environment. The DMU investigates the environment for possible actions that might potentially serve the model's emotional demands. And finally the DIU tries to implement these decisions when a traffic condition, perceived as safe enough for such an implementation, emerges. Each of these units has its own set of fuzzy variables and fuzzy if-then rules. Any driving model, that is based on this framework, should provide membership function parameters for these fuzzy variables in accordance with the category of human driving behavior this model is targeting. Our framework addresses decision making and implementation at the maneuvering and operational levels of the driving task. Decisions at the planning level are addressed through a script-based traffic controller. The present model is limited to simulating human behaviors when driving in a two-lane rural environment.

Keywords

Models of emotion and personality, Driver behavior modeling, Autonomous vehicles.

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1. INTRODUCTION

Autonomous vehicles are commonly used to simulate traffic in driving simulators. Drivers on real roads demonstrate naturalistic behaviors that make the driving task very rich in terms of possible scenarios and outcomes. It is important to present this kind of behavior through autonomous vehicles in driving simulators because that would result in a more immerse virtual environment to which subjects may react more realistically. Providing an implementation of different human-like driving behaviors within a driving simulator may have a considerable impact on the validity of such a simulator and on the credibility of driving studies performed on it.

Considerable effort has been allocated toward developing intelligent behavioral models for autonomous vehicles in driving simulators during the last decade [1, 12, 14]. Almost all studies have used the hierarchical control structure model for simulating driving behavior. The hierarchical control structure [5] divides the driving task into three levels of control: 1) a strategic level that primarily addresses route planning in addition to other general considerations, 2) a maneuvering level that addresses maneuver control, and 3) an operational level that addresses the direct low-level control of the vehicle. Script languages are commonly used within driving simulators to control autonomous vehicles and to address driving decisions at the planning level [6, 13]. Driving behavior at the maneuvering and control levels has been generally modeled in one or more of three approaches: 1) rule-based models [12], 2) state machines models [1], and 3) probabilistic models [14]. Rule-based models rely on knowledge bases, composed of rules, in making driving decisions. Each rule, or set of rules, indicates a certain action under certain conditions. State machines encode driving behavior into states that represent low-level driving sub-tasks. Higher level driving actions, e.g. making turns, are executed through performing a set of these states in a certain order. Hierarchical concurrent state machines (HCSM) add the concepts of hierarchy and concurrency to state machines in addition to providing communication capabilities between different states [2]. Probabilistic models base their decisions on empirical data that characterize different kinds of real driving behavior. Probabilistic models are very effective in introducing randomness to virtual driving environments.

The objective of this paper is to present a framework for building driver behavior models that are associated with autonomous vehicles. When these autonomous vehicles are deployed in a driving simulator, they would perform in a human-like manner. The framework consists of four units that collaborate together to make driving decisions at the maneuvering level, and then implements these decisions at the operational level of the driving task. Each unit corresponds to a group of driving characteristics and driving sub-tasks that constitute a major area of difference between different categories of observed human driving behavior such as aggressive driving, drunk driving, etc. This provides high flexibility when generating different kinds of naturalistic and realistic driving behaviors using the framework by tuning its units in accordance with the targeted category of driving behavior. We use the term "framework" or "driving framework" to refer to the abstract specification of the driving task. The term "driving models" is used to refer to a concrete implementation, based on the driving framework, of a specific category of human driving behavior.

Driving models are assigned to autonomous vehicles which are controlled by a script-based traffic controller whose responsibility is to handle decisions at the planing level of driving. The deployment of these autonomous vehicles within a driving simulator would transform its virtual environment into a more realistic and less predictable environment that could increase the credibility of experiments performed on that simulator.

2. DRIVING BEHAVIOR MODELING AND RELATED WORK

A thorough and an extensive review of driver behavior models and their evolution can be found in [8]. Prior to the 1960s, the field was dominated by skill-based driving models, which implied that the driving task could be explained in terms of drivers' skills. Motivational driving models started to appear in the 1960s as alternatives to skill-based models. Motivational models consider drivers' emotional state and their willingness to take risks as primary factors in modeling driver behavior. Motivational models are generally classified into risk-threshold models [7], risk-compensation models [11], and risk-avoidance models [3]. Risk-compensation models suggest that drivers always adjust their level of accepted risk in accordance with safety aspects of the environment. Risk-threshold models suggest that drivers always perform in relation to their perceived level of risk, which should be zero in most cases. Risk-threshold models generally apply risk-compensation mechanisms if the threshold of risk is exceeded. Risk-avoidance models are built around the concept that efficiency (getting to a destination in an acceptable time) and safety (avoiding dangerous situations) are the predominant concerns of drivers. It explains the driving task based on the conflict between efficiency and safety. Although these theories have succeeded in emphasizing very important elements of their models, they didn't explain how these elements would be transformed into cognitive functions [5].

Michon [5] introduced a hierarchical control structure for the driving task and suggested this structure as basis for a comprehensive driving behavior model. This structure, as explained in the previous section, divides driving into three levels of control: 1) a strategic level that addresses route planning in addition to other general considerations, 2) a maneuvering level that addresses maneuver control, and 3) an operational level that addresses the direct low-level control of the vehicle. Since its emergence, this structure has influenced most studies in the field of driver behavior modeling.

Fuzzy Logic has proven to be a very effective tool for handling imprecision and uncertainty, which are both very important characteristics of driving environments. This makes fuzzy logic a powerful candidate tool in most traffic engineering studies [4]. Data describing characteristics of driving environments are not generally available to drivers in precise numerical format. Instead drivers perceive and describe the environment in imprecise terms such as 'high speed' or 'enough space to change lanes'. An important outcome of imprecision is the possibility of assigning more than one symbolic value at the same time to the same variable with different degrees of truth in each of these values. Because of Fuzzy Logic's ability to handle these cases, it has been successfully used in modeling human behavior in general and driver behavior in particular [10].

In general, driver behavior models should be independent from applications that choose to adopt them. However, as driving simulators become the targeted application for a driver behavior model, emphasis expectedly shifts toward emulating or approximating driving behavior rather than explaining it. This feature comes in support of using Fuzzy Logic for modeling driver behavior within driving simulators since Fuzzy Logic has proven successful wherever approximation is desired or required

3. A FRAMEWORK FOR MODELING HUMAN-LIKE DRIVING BEHAVIORS FOR AUTONOMOUS VEHICLES IN DRIVING SIMULATORS

The framework we developed is a microscopic driver behavior framework that operates within driving simulators through autonomous vehicles. This framework contains abstractions that can be extended into concrete implementations of recognized categories of driver behavior. The framework is composed of four units, each unit corresponds to a group of driving characteristics and driving sub-tasks of human driver behavior that partially indicates a certain category of behavior. The four units of the framework are the Perception Unit, the Emotion Unit, the Decision-making Unit (DMU), and the Decision-implementation Unit (DIU). Each of these units uses one or more Fuzzy Logic techniques to transform data and to make or implement decisions. Figure 1 shows the architecture of the driving framework and the relationship between our framework and the simulator's environment.

The Perception Unit transforms the environmental data into fuzzy input and determines the values of other fuzzy variables within this unit. These values are used by the Emotions Unit to determine how the model would respond emotionally to the environment. Decisions are then made by the Decision-making Unit in response to the current data of the environment and the current emotional status of the model. The Decision-making unit makes decisions at the maneuvering level with respect to Michon's hierarchical control structure. After a decision is made, the Decision-implementation Unit starts trying to implement the decision. The Decision-implementation Unit makes decisions at the tactical and operational levels of the hierarchical control structure. The lifetime of a particular driving model is the same as the lifetime of the autonomous vehicle it is associated with. A script-based traffic controller, manages the entering and leaving of autonomous vehicles in the virtual driving environment of the simulator. The traffic controller is responsible for making decisions at the planning level of the driving task. The internal structure and the functionality of each of the driving framework units are explained in more details in the following sub-sections.

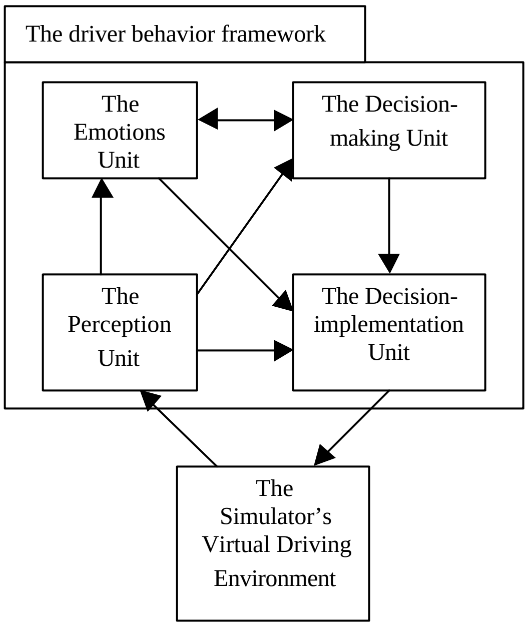

Figure 1. Architecture of the driver behavior framework

3.1 The Perception Unit

The Perception Unit plays a very important role in defining how a driving model perceives its environment and in shaping most of its later actions. Examples from the real world are that the same space that looks enough to change lanes to a skilled driver, might look not enough to a novice one, and a vehicle speed that is unsatisfactory to an aggressive driver might be high or even dangerous to a conservative driver. Different pieces of information about the environment are passed to this unit in numerical format. The job of the Perception Unit is to use these data to find the values of its fuzzy variables and the degree of truth for each of these values. This will allow different models, derived from the framework, to see the same world through different eyes and to conclude different results from the same set of data based on different perceptual styles. The perceptual style was found to be a major contributor to driving errors in a driving model [9]. Thus, the Perception Unit helps in addressing a driving model's imperfections through fuzzifying its environment in a way that is consistent with that model's limitations.

The Perception Unit consists of a set of fuzzy variables with different symbolic values. Driving models that are based on our framework are required to define the possibility distributions for all of the fuzzy variables. This defines how a model would describe each relevant entity in the world around it, and the degree of truth in each of these descriptions. In addition to data needed to describe the environment locally to the autonomous vehicle, like speeds of neighboring vehicles, the Perception Unit has access to data that enable it to describe the environment in more global terms, like the average speed of vehicles in the other lane, the average speed of vehicles in the same lane ahead of the model's vehicle, etc.

After obtaining all the information it needs, the Perception Unit uses the data to find the fuzzy values for its own set of fuzzy variables. The main fuzzy variables of the Perception Unit are the fuzzy speed, the fuzzy passing speed and fuzzy leading and tailgating distances in the same lane and in the neighboring lane. The same fuzzy speed definition, i.e. the membership functions of the different values of fuzzy speed, is applied to the model's vehicle and to other vehicles in the environment. Fuzzy speed is defined as a function of the current speed and the desired speed. The desired speed in turn is a function of the speed limit and of the model itself. The fuzzy passing speed is a relative speed that describes the relation between the speed of the model's vehicle and the average speed in the other lane. The fuzzy leading and tailgating distances define the distance in connection with the speeds of the involved vehicles, i.e. the same physical distance might be described as far if the speeds of the involved vehicles are low or might be considered close if those speeds are high.

If the current local environment conditions, as perceived by the Perception Unit, constitute a dangerous situation, control is passed immediately to the Decision-implementation Unit to make and implement a decision to avoid such a situation. Otherwise, control is passed to the Emotions Unit to continue the normal driving process. Driving models, based on our framework, are required to address this part of the Perception Unit and to extend the mechanism of detecting dangerous situations in accordance with the category of driving behavior they are trying to present.

The fuzzy membership functions of the fuzzy variables of a driving model derived from our framework are defined based on observed and collected data from the category of driving behavior that the model is trying to emulate. This means that although the driving models derived from the framework will have the same variables with the same values, the membership functions for each value will be different from one model to another. Thus, the same driving environment will be perceived differently by different autonomous vehicles. Comparing an aggressive driving model and a conservative driving model (both are derived from our framework), what is perceived as low speed by the first might be perceived as normal speed by the second and what is perceived as enough distance for the first might be perceived as too close to the second. These two vehicles, in addition to other vehicles in the environment, are going to react differently to the environment. Each of them would make decisions and implement them based on how each sees the world. This shows the importance of the Perception Unit to the framework and the role that it plays in rendering its actions.

3.2 The Emotions Unit

The Emotions Unit tries to capture the emotional response of the model to the driving environment as it is perceived through the Perception unit. Because of the Emotions Unit, a driving model does not implement driving actions based simply on current traffic conditions. Instead, the model is more concerned about satisfying its emotional variables. In that sense, the decision-making process is going to be motivated by the emotional needs of the model rather than by the current environment conditions. The Emotions Unit thus plays an important role in defining the driving task as a reflective rather than reactive task. It also makes the model an active player in the environment rather than being a passive one that only does what the environment directly allows.

In addition to capturing the emotional status of a driving model under different traffic conditions, the Emotions Unit would also indicate the urge of the model to improve that status. The desire of the model to improve its emotional status would determine how much the model is willing to take risks in making decisions and in implementing these decisions.

The Emotion Unit adopts the theory proposed by risk-avoidance models [13]. It makes the driving task balanced around the two often contradicting factors of safety and efficiency. It describes the emotional status of the model in terms of the model's satisfaction with its performance, mainly speed, and in terms of the model's discomfort with the surrounding traffic conditions, and the distances between the model's vehicle and other vehicles around it, mainly the following vehicle in the same lane. Low satisfaction generally triggers decisions that would potentially increase the speed, e.g. changing to a faster lane or, if in the fast lane, tailgating the leading vehicle to force it to speed up or leave the lane. High discomfort, on the other side, triggers decisions that would potentially lead to a safer situation, e.g. going to a slower lane if the model was forced to drive at a speed that is perceived as unsafe or if it was tailgated by the following vehicle.

The Emotions Unit doesn't propose any direct decisions to improve the emotional status. Rather, it just describes this status and indicates the model's desire to improve it. The desire of a driving model to improve its emotional status depends on that emotional status itself, i.e., the emotions history of the model, and on a non-circumstantial factor called the model's demeanor that describes this driving model outside the context of the driving task. The higher the demeanor, the more anxious the model to achieve a certain emotional level of satisfaction. The model's demeanor provides the capability of defining different variations among the same category of driving behavior, e.g. a conservative older driver model vs. an aggressive older driver model. It has to be stated that the Emotions Unit, even with the demeanor factor, stops short of capturing the complicated emotional state of an individual human driver. Instead, it tries to capture a general emotional state of a categorical driving model, which is exactly what it is intended to do at this stage of our work.

Once the emotional status of a driving model and its desire to improve it are determined by that model's Emotions Unit, the Decision-making Unit starts investigating the current traffic condition for actions that would serve the model's emotional demands. If an action is found in that respect, the model's Decision-implementation Unit starts trying to implement it, if the current traffic condition allows it, or waits for a more suitable condition. The desire to improve the model's emotional status, either toward increasing satisfaction or decreasing discomfort, is very important in determining the amount of risk that the model might take in making and implementing its decisions. If the desire to increase satisfaction is low, the model might refrain from changing lanes if the speeds and distances of the involved vehicles are not perceived as safe enough for changing lanes. However, if the model's satisfaction is low and the desire to increase it is very high, the model might take the risk and change lanes in that same traffic condition

3.3 The Decision-making Unit (DMU)

The Decision-making Unit, DMU, is responsible for making decisions at the maneuvering level of the hierarchical control structure. However, the DMU is not responsible for implementing its decisions. This is left for the Decision-implementation Unit whose job is to wait for an appropriate traffic situation to start implementing an already-made decision. The DMU's ultimate goal is to find an action, by looking through all possible avenues, that might potentially improve the emotional status through increasing satisfaction or through decreasing discomfort, whichever is more urgent to the model.

As mentioned in a previous section, control in dangerous situations is passed immediately from the Perception Unit to the Decision-implementation Unit. So the DMU operates only in normal driving situations. The DMU goes on with its job of improving the emotional status of the model. In the case of low satisfaction, which is generally caused by low speed, the DMU uses its collection of fuzzy if-then rules in evaluating the driving environment for actions that would increase the speed.

If a driving model is uncomfortable with the current traffic condition, the DMU, backed with information from the Emotions Unit about the reason behind the discomfort, analyzes the surrounding environment for possible ways to decrease the discomfort. That could result in slowing down to a speed that is perceived as safe by the model, or speeding up temporarily to avoid a close tailgating distance by the following vehicle, etc.

The history of the emotional status of a driving model is taken into account by the DMU as it makes its decisions. If the model spends more time in a low satisfaction status, it is expected that it would make more aggressive decisions as it is running out of patience. This relationship between emotions' history and decisions is demonstrated in different places in the collection of the fuzzy if-then rules that define the DMU. Models derived from our framework should address this relationship in accordance with the category of driving behavior they represent.

Since the rules that compose the DMU are fuzzy rules with fuzzy output, more than one set of rules could be satisfied while evaluating the current conditions of the model and of traffic. This will result in more than one decision, each with a different weight, being proposed by the DMU as appropriate candidates. These decisions are evaluated and the decision with the highest weight is chosen and passed to the Decision-implementation Unit to carry it out when possible. The separation between making a decision and actually implementing it comes from the fact that real drivers do not normally implement decisions as they make them. An obvious example is that a driver might decide that he wants to change lanes even if it is not appropriate to do so at the moment the decision was made. With that decision in mind the driver would wait for an appropriate condition to implement the decision or he might even participate in creating such an appropriate condition by adjusting his speed. The DMU investigates the driving environment globally for actions that would serve emotional needs, be it efficiency, safety, etc., and then the Decision-implementation unit investigates the driving environment locally to see when it is best to carry out these decisions.

3.4 The Decision-Implementation Unit (DIU)

The Decision-implementation Unit, DIU, is responsible for completing the DMU decisions at the maneuvering level and for making decisions at the operational level of the driving task. Decisions made by the DMU at the maneuvering level need to be approved and get scheduled by the DIU. The DIU, upon approval, performs the operational part in carrying out the scheduled decision once conditions allow its implementation with a sufficient degree of believe in the safety of such an implementation. However, this decision may be replaced with another decision in response to changes in the environment during the waiting time.

The DIU works in accordance with the dynamic model of the vehicle that is associated with the behavioral model. Instead of determining the speed and direction of the vehicle directly, the DIU sends signals to the dynamic model that result in the desired speed and orientation. The DIU interfaces with the dynamic model through three input signals, gas, brake, and change in steering angle, and receives two output signals from the dynamic model, speed and vehicle orientation. Other data is provided to the dynamic model through the driver model only once, e.g. the vehicle's mass or maximum acceleration, and through the simulator's environment, e.g. road conditions. Having the behavioral model control the vehicle through input signals rather than by inputting desired speed and orientation, provides more flexibility in modeling the driving task at the operational level. In addition to the signals passed to the dynamic model, the DIU sends left turn and right turn signals that update the status of the vehicle and inform other vehicles on the road about its intention to change lanes or make turns. These signals don't go to the dynamic model since they don't interfere with the vehicle control. Instead they go to the simulator to make them available to other vehicles. The relationship between the DIU, the vehicle dynamic model, and the simulator's virtual environment is shown in Figure 2.

Driving models derived from the framework are required to provide a steering factor, a reaction time factor, and an alertness factor. These factors partially determine the degree of driving skills in the driver behavior model. They also play an important role in models that are required to demonstrate impaired conditions like drunk driving. The steering factor introduces a human error to the model's ability to steer in a perfect manner. The driving model has to continuously control the steering wheel in order to follow the desired path while changing lanes, making turns, driving on curves, or even maintaining its lane position on straight roads. An ideal model would be able to send the exact steering signal to the vehicle's dynamic model required to achieve a desired vehicle orientation. The steering factor shapes the model's ability and skills in controlling the vehicle's orientation. The reaction time factor introduces a delay to the model's ability to react immediately in situations perceived as dangerous by the model. In the event of dangerous situations, indicated by the Perception Unit, the DIU needs to react immediately to avoid such a situation. The reaction time would be increased to allow demonstrating classes of driving behavior with a physical impaired status such as alcohol-in-blood or insomnia. Finally, the alertness factor alters the model's ability to consider all requirements before implementing a decision. If the alertness factor of the model is low, it is more probable that one or more important requirements, chosen randomly, for implementing a decision are not going to be considered by the model before it starts implementing that decision. The reaction time factor and alertness factor partially determine the model's ability to avoid accidents and render a specific condition as a safe condition or an accident prone one based on the values of these two factors.

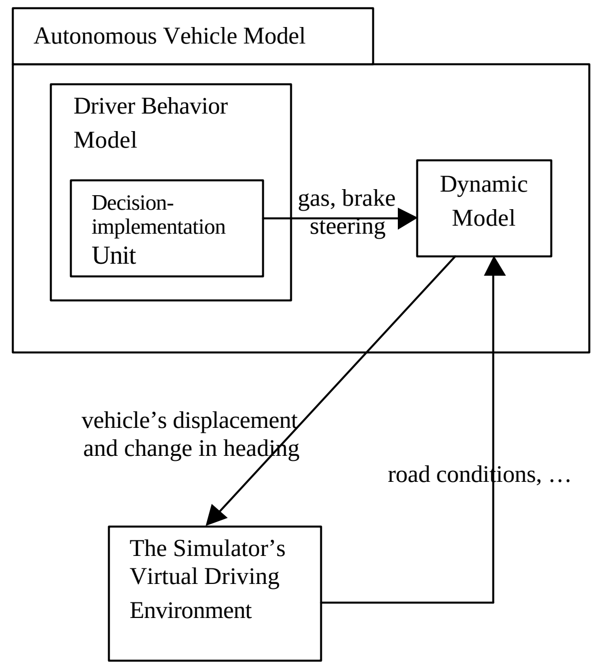

Figure 2. Relationship between the Decision-implementation Unit, the vehicle dynamic model, and the simulator's virtual environment

In the event of a dangerous situation, the DIU immediately makes and implements a decision to avoid such a condition. However, in normal situations, the DIU starts by determining if the current traffic condition would allow implementing the decision made by the DMU. If the accompanying traffic condition is not perceived as safe enough to implement that decision, the DIU waits for a better condition in terms of safety. In some cases, the DIU might orchestrate the accompanying traffic condition to make it safer for implementation by adjusting its speed. An example would be to slow down or to speed up to get a space in the next lane that is safe enough for a driving model to change lanes.

The DIU uses fuzzy values of speeds and distances when evaluating a traffic situation for safety in connection with implementing a pre-made decision. Driving models derived from our framework need to address this part of the DIU and to define the safety concerns of the model through altering the membership functions and the rules involved in evaluating conditions for safety. These models need also to address the relationship between the emotional status history and the risk that a model might be willing to take either through tolerating some safety concerns or through lowering the threshold of risk before implementing decisions. The failure of the DIU in finding a suitable condition for implementing a decision for a long duration would increase the model's frustration and would make it more likely that the model is going to implement the decision in situations that are perceived as more difficult or less safe.

4. CONCLUSIONS AND FUTURE WORK

The presented framework of driving behavior allows modeling different kinds of human driving behavior for autonomous vehicles within a driving simulator. The deployment of autonomous vehicles with their human-like driving characteristics would make the simulator's virtual driving environment more realistic and less predictable. This could increase the validity of the simulator and the credibility of studies performed on it since subjects may react more realistically. The presented driving behavior framework dictates that each model to be derived from it has to provide certain parameters to the membership functions of its fuzzy variables. It also requires that these models should address decision-making issues through different sets of fuzzy if-then rules. Finally, driving models based on this framework have to provide values for non-circumstantial factors that describe the model within and without the context of the driving task. The four units of the framework, the Perception Unit, The Emotions Unit, the Decision-making Unit, and the Decision-implementation Unit, provide high flexibility in building concrete human-like driver behavior models and in creating variations within the same class of driving behavior like an aggressive older driver model versus a conservative older driver model or drunk older driver model. Our framework is currently under development for two-lane highway driving, but can be easily extended for driving on multi-lane highways. Future work will also include building a specialized collision avoidance unit.

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