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Automatic Animal Behavior Analysis: Opportunities for Combining Knowledge Representation with Machine Learning

Anna Zamansky[a], Aleksandr Sinitca[b], Dirk van der Linden[c], Dmitry Kaplun[b,*]

[a]*University of Haifa, Abba Khoushy Ave 199, Haifa 3498838, Israel*
[b]*Saint Petersburg Electrotechnical University "LETI", 5 Professor Popov street, St. Petersburg 197376, Russia*
[c]*Northumbria University, 2 Sandyford Rd, Newcastle upon Tyne NE1 8QH, UK*

Abstract

Computational animal behavior analysis (CABA) is an emerging field which aims to apply AI techniques to support animal behavior analysis. The need for computational approaches which facilitate 'objectivization' and quantification of behavioral characteristics of animals is widely acknowledged within several animal-related scientific disciplines. State-of-the-art CABA approaches mainly apply machine learning (ML) techniques, combining it with approaches from computer vision and IoT. In this paper we highlight the potential applications of integrating knowledge representation approaches in the context of ML-based CABA systems, demonstrating the ideas using insights from an ongoing CABA project.

Keywords: Animal Behaviour; Computational Analysis; Machine Learning; Artificial Intelligence; Computer Vision; Spatio-temporal Data Processing

1. Introduction

Measuring behavior is in the center of many animal-related disciplines, including animal science, ecology, neuroscience, veterinary science, psychology and many more. Traditionally, it is done through direct observation and manual coding of behavioral categories. Anderson and Perona discussed in detail that relying on human observation imposes severe limitations on behavioral data acquisition and analysis [3]. First and foremost, it is a laborious and tedious task, thus seriously limiting the volumes of processed data, as well as the number of analyzed behaviors or behavioral variables. But even more importantly, human analysis of behavior is prone to *subjectivity*. Behavior measurement strongly depends on human perceptual abilities, leaving lots of room for human error and making efficient

* Corresponding author. Tel.: +7-921-655-0470.
E-mail address: dikaplun@etu.ru

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tacit knowledge transfer in training. Moreover, human understanding and interpretation of behavior is in itself subjective and sometimes inconsistent. In fact, there is still no agreement among biologists on the definition of 'behavior'.

The need for the development of tools that promote more objective and quantifiable assessment and measurement of behavior (cf. [23, 14, 20]) has long been acknowledged, recognizing the potential of technology not only to empower the human observer in terms of accuracy and volumes of processed data, but also to lead to discoveries of new characteristics of behavior which are inaccessible for human observation. One example is the use of modern videography which has led to the discover of unknown motor sequences in the songbird [32].

These considerations give rise to the emerging field of *computational animal behavior analysis* (CABA) [12], which aims to apply techniques from computer science and engineering to facilitate accurate and objective analysis of behavior. So far advances in this field have mainly been data-driven and based on machine learning (ML) techniques. Several state-of-the art CABA tools are *generic*, i.e., providing ML tools for a variety of species and environments. One example is the JAABA system [16], which allows users who are not experienced with machine learning to create behavioral classifiers by annotating a small set of video frames. Another generic framework is DeepLabCut [18], which uses deep neural networks for markerless animal pose estimation. Blyzer [34] similarly uses deep learning for analysis of animal movement patterns.

The increasing genericity of CABA approaches and tools means that we can identify numerous behaviors, measure numerous parameters and quantify numerous behavioral patterns–but which patterns do we want? This challenge leads to the need for creating specification languages which could be used by animal scientists to ask the questions they are interested in. In addition to specific questions, hypotheses or queries posed by scientists, the data-driven nature of CABA techniques open the door for new exciting possibilities of mining novel behavioral patterns. However, the results need to be formulated in comprehensible terms, reiterating the need for formalisms of knowledge representation.

In this paper we discuss the potential of integrating knowledge representation approaches in the field of CABA. This is demonstrated using several case studies in which the Blyzer tool has been applied.

The rest of the paper is structured as follows. Section 2 surveys the current state of the field of CABA, focusing specifically on generic data driven state-of-the-art approaches. Section 3 discusses the concept of behavior, and a structured language for its representation. Section 4 presents our ongoing Blyzer project and discusses the challenges and opportunities in integrating a knowledge representation layer into it. Section 5 presents a summary and a discussion of future research directions.

2. Computational Animal Behavior Analysis

The emergent field of CABA [12], also referred to as 'computational ethology' [3], aims to apply techniques from computer science and engineering to facilitate automatic quantification of behavior and its characteristics and has been predicted to be a game changer for animal-related disciplines. Several aspects in which such approach has already shown significant impact on behavior analysis have been identified [3], including, among others, the dimensionality of behavioral analysis, increasing the throughput of behavioral analysis, facilitating real-time analysis of behavior.

Automatic tracking and behavior analyzing systems are increasingly used for different species: wild animals [8], pigs [1, 31], poultry [27], insects [22], and many more. Well-developed systems for automatic behavior of rodents–both commercial [33, 30] and academic [28] are widely used in behavioral research.

Automatic analysis can be performed on different types of data. One type of animal behavioral data is obtained from animal-attached wearable devices or bio-logging tags that collect data on the animals' environment, movement characteristics, behaviors and physiological characteristics. Several works provide reviews of recent advances in the field bio-logging, see, e.g., [25, 26]. Another prevalent type of data, on which we henceforth focus due to its wide popularity in animal science is *video footage*.

A recent trend in CABA research is *genericity*: the ability of a tool or framework to address a large variety of species and environments. The JAABA system [16] allows users not experienced with machine learning to create behavior classifiers by annotating a small set of video frames. The system has been used to create several classifiers for simple behaviors of mice and Drosophila, both individual (e.g., walk, jump, stop), and social (e.g., follow).

DeepLabCut is a framework for for markerless pose estimation based on transfer learning with deep neural networks [18]. Its utility has already been demonstrated on mice and Drosophila, but there is no inherent limitation of this framework, meaning it can also be used for other species.

Blyzer [2, 17] is another framework based on deep learning neural networks for analyzing movement parameters of an animal video footage. It currently focuses on dog behavior analysis, and its underlying models have already been trained on multiple datasets collected in veterinary clinics and dog behavioral testing experiments (cf. [34, 7, 17]).

3. Representation of Behavior

As animal-related disciplines become more quantitative and computational, mathematical models have emerged that attempt to account for behavioral phenomena instead of more traditional qualitative verbal descriptions. Phenomenological description, i.e. a description that accounts for the form of the behavioral phenomenon as one of the most basic types of descriptions [3]. For example, a phenomenological description of a "chase," whether it is carried out by a fly or a mouse, consists of walking fast for a short distance behind another individual for at least a certain amount of time. As behavioral phenomena take place at multiple scales of resolution in time and space, there is a *hierarchy* of different elements needed to describe their phenomenology. This hierarchy is due to the different *logical* structure of these phenomena. Some examples of the phenomenological elements of a "language for representing behavior", as suggested by literature [3] are discussed below:

moveme: These are short behavioral phenomena, described by a relation on the set of objects, intuitively associated with a verb in natural language, applying to either the whole body or its element. *Moveme* is analogous to phoneme in natural languages. Examples are "step", "turn", "extend wing"–basic units which cannot be further decomposed.

action: A composition of movemes that always occur always in the same stereotypical sequence is termed an *action*. Examples are "walk" (step + step + step), "sing" (extend wing + hold wing out + retract wing) [29], and "lunge" (stop + raise on hind legs + lunge forward + stop) [15].

activity: More complex sequences of movemes and actions, in which there is also place for variability (at different times and among individuals) are termed *activities*. Examples are "courtship", "fighting" [10].

ethogram: These are representations of the different actions that occur during an activity or activities, which indicate the frequency or probability with which each action is followed by another action (either the same or a different one). Ethograms are one of the most important tools in ethology, and have traditionally been computed manually, by generating a "transition matrix" composed of all the actions that are observed and the number of times each action is followed by another, given action, averaged over an observation period.

Figure 2 hints at the possibility of developing symbolic formalisms for describing behavior, which in its turn opens the door for new exciting opportunities for integrating knowledge representation approaches into CABA systems such as Blyzer, to represent and reason about behavior.

The next section presents details on one concrete idea related to using a symbolic specification language in a CABA system called Blyzer. Section 5 discusses further some promosing general directions for integrating knowledge representation (KR) approaches in ML-based CABA systems.

4. A Specification Language for Blyzer

In this section we describe how KR methods are applied in our ongoing project of developing the Blyzer system. We start by describing the system and its applications in further details. We then describe our vision for opportunities to apply KR techniques in the context of CABA.

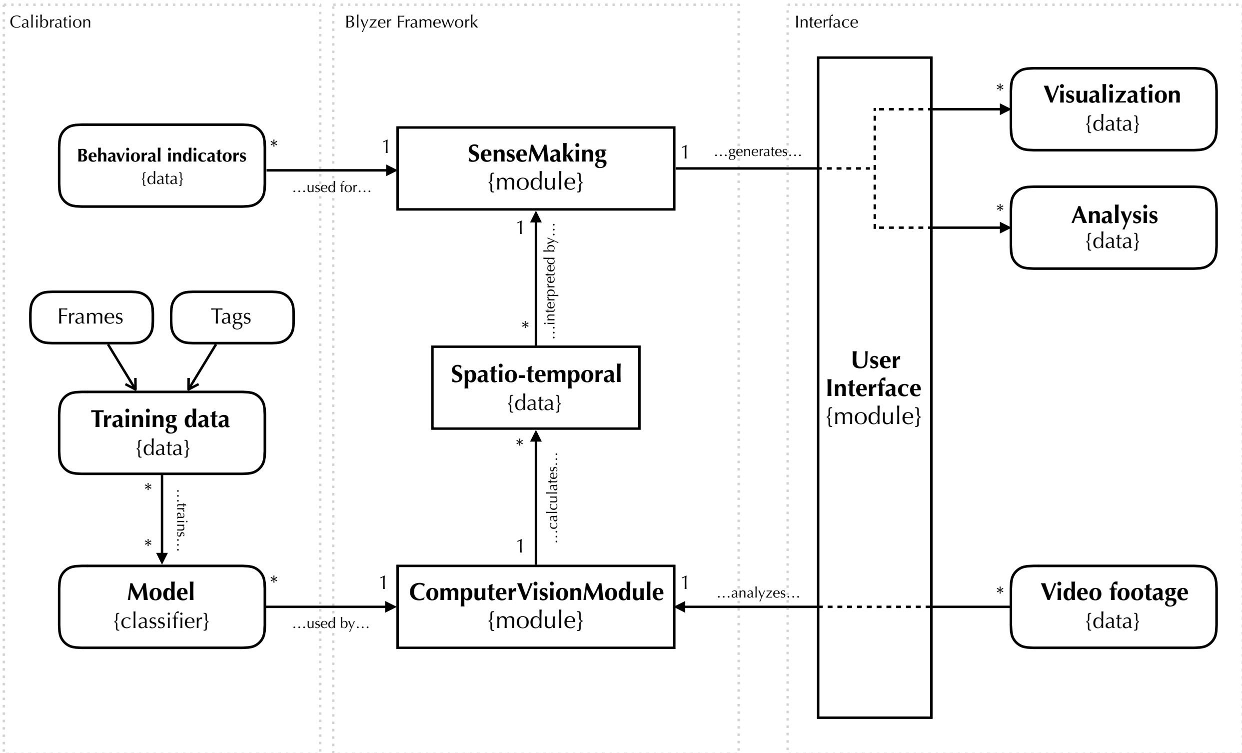

Fig. 1: Blyzer architecture.

4.1. Blyzer and its applications

The Blyzer system [17, 34, 7] aims to provide automatic analysis of animal behavior with minimal restrictions on the animal's environment (unlike tracking systems designed for rodents, e.g. in [28] which are usually situated in a semi-controlled restricted setting), or camera setting (unlike [19, 4] where a 3D Kinect camera is used).

Blyzer's input is video footage of a dog freely moving in a room and possibly interacting with objects, humans or other animals. Its output includes measurements of specific parameters specified by the user, which then provide some form of quantification of behavioral parameters. The Blyzer architecture is presented in Figure 1. It consists of two layers: (i) computer vision layers which uses dog detection and posture classification models based on neural networks, and (ii) analysis (sensemaking) module, which identifies and measures requested parameters out of the spatio-temporal data obtained from module (i). Blyzer has already been used for a variety of scientific projects; some concrete examples are discussed below:

- Analysis of time budget and sleeping patterns of breeding stock kenneled dogs as welfare indicators (see Fig. 4. The dogs, bred and maintained by the Animal Science Center in Brazil, were observed for eight consecutive months using simple security cameras installed in their kennels (using night vision at night). Blyzer was used to measure parameters such as total amount of sleep, sleep interval count and sleep interval length [34].
- Analysis of movement data for assessment of ADHD-like behavior of dogs treated in a behavioral clinic (see Fig 3. This data was collected during behavioral consultations of 12 dogs medically treated due to ADHD-like behavior, and compared to a control group of 12 dogs with no reported behavioral problems. Blyzer was configured to measure more than 20 different movement-related parameters, several of which led to the identification of dimensions of characteristic movement patterns of dogs with ADHD-like behaviors(summary for this task is presented in Fig. 6), such as high speed and frequent re-orientation in room space [7].

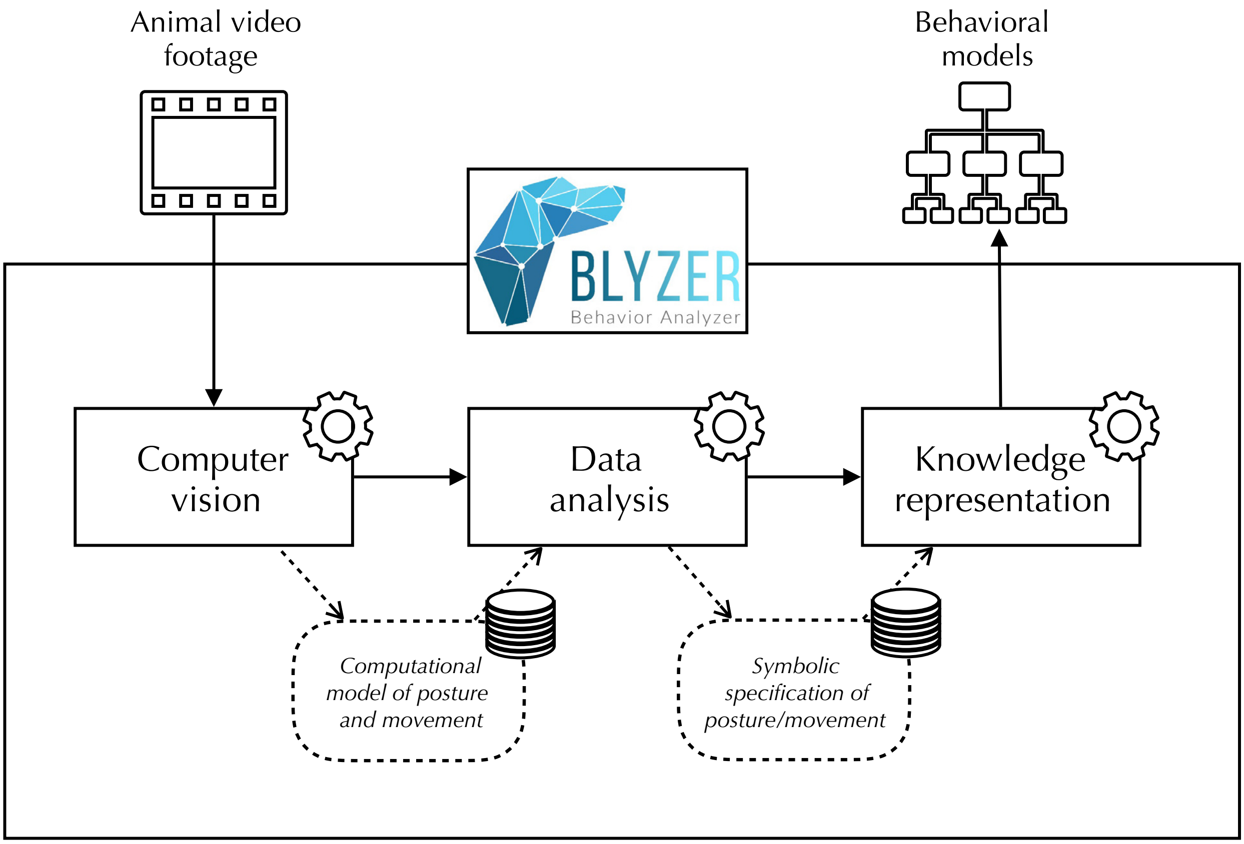

Fig. 2: Adding a KR layer.

Fig. 3: Studying ADHD-like behavior; data collected in behavioral vet clinics.

- Analysis of data collected in a two-choice task experiment performed at Messerli Research Institute in Vienna (see Fig. 5. Dogs were presented screens with pictures of different faces, and preference was tested by measuring time spent in different parts of the room, with special interest in the proximity to the screens.

These examples demonstrate the diversity of behavioral parameters of interest to Blyzer's users. To adapt Blyzer to these scenarios, we created different versions of the tool. However, using KR techniques can promote reusability

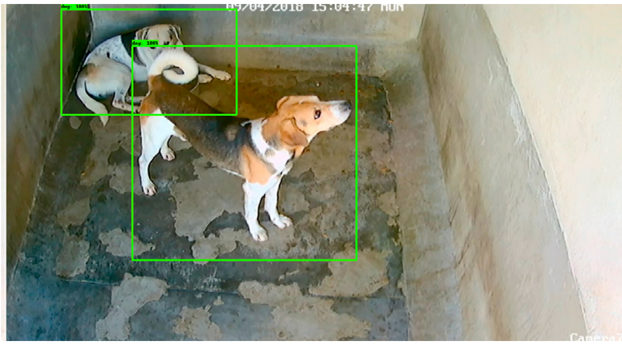

Fig. 4: Studying sleeping patterns as welfare indicators; data collected in breeding stock kennels.

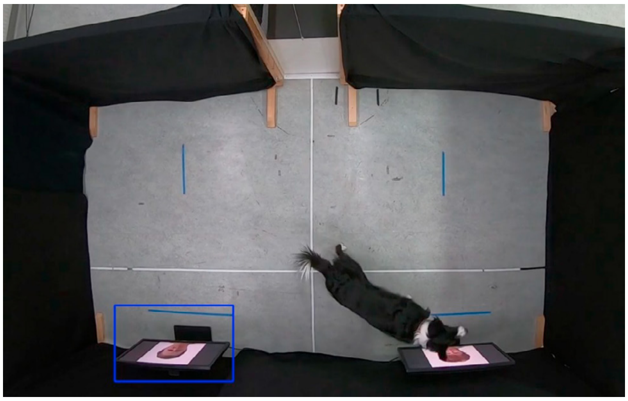

Fig. 5: Studying facial preference; data collected in experimental setup.

and make Blyzer configurable to the different needs of its users by introducing a third new layer for knowledge representation, as shown in Fig. 2. In this layer the user can specify the parameters and patterns of interest using a domain-specific logical specification language. It can also let the user provide context on the experiment/study, and in the future we plan to extend it with automatic reasoning capabilities.

Our starting point is a specification formalism is a Z-notation-style language [24]. The constructs of the language are used to describe the situation in a given frame. It has some built-in types of basic spatial constructs such as points (e.g., $\mathsf{point}(\mathsf{x}_1, \mathsf{x}_2)$), or geometric shapes of interest (e.g., $\mathsf{Rectangle}(\mathsf{p}_1, \mathsf{p}_2, \mathsf{p}_3, \mathsf{p}_4)$), where p_i are points. It also has dog-related primitives, which represent dog body parts which are currently detected by the system (e.g., nose, head, end of tail, etc). Thus we can express with respect to a single frame f information such as 'the nose of dog d_1 is within rectangle r_1' denoted by $[Within(d_1, r_1)]_f$. We can then consider sequences of frames, expressing things such as 'dog d was interested in screen 1' as 'the dog's nose was within a specified rectangle around Screen 1 in at least 20 consecutive frames'.

5. Discussion and Future Research

In this paper we have highlighted the exciting opportunities for the KR community to engage with the emerging new field of ML-based computational animal behavior analysis. We have demonstrated a concrete proposal of using a specification language for the description of parameters of interest in the Blyzer system. This leads to intriguing research questions and challenges concerning the expressibility of such domain-specific languages relating to spatio-temporal concepts enriched with species-specific elements (e.g., different body parts), as well as contextual information about the animal's environment. Moreover, our vision is to make such languages machine-interpretable, allowing for an automatic configuration of the system, which is another challenge for future research.

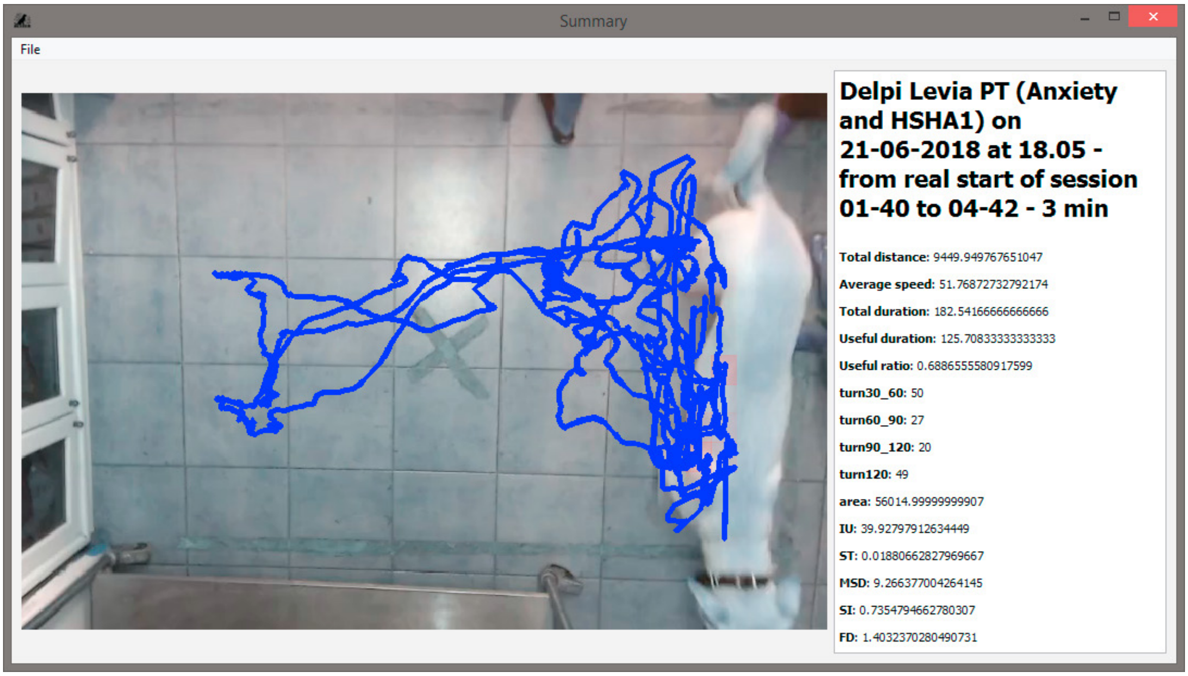

Fig. 6: Blyzers' application in ADHD task.

There are also other opportunities for integrating KR approaches in the context of ML-based CABA systems. Some promising directions include:

- *Computational models of animal behavior.* Different types of complex systems such as biological and cyber-physical systems have benefited greatly from formal approaches applied in the domain of computer science, such as formal analysis, model checking, static analysis, and runtime verification [6]. Behavioral data, which typically forms the output of CABA systems, and can be represented in the form of spatio-temporal data, can be transformed to behavioral computational models to which temporal reasoning could be applied both for formulating and testing specific behavioral hypotheses (e.g., using model checking and verification anlogously to biological systems [11], and for mining new insights applying mining techniques such as [13, 5].
- *Context-awareness.* Spatio-temporal data of a moving animals may suffice for automatic detection of movemes and actions, but to identify more complex behavioral elements, such as activities, *contextual information* of the animal is needed in addition to its movement patterns. For example, aggression or play involves more than one animal, while manipulating an object may have a purpose that is only explainable based on environmental context. This leads to the challenge of developing systematic ways of context representation, which can be adapted to behavioral data for different species and environments. Similar ideas have already been explored in human activity recognition, and specifically in automatic video-surveillance and anomaly detection, see, e.g., [9, 21]. Ontology and description logic may hold a promising way forward.

So far KR approaches have not been explored in the context of CABA systems. It is our hope that this paper stimulates a discussion and cross-fertilization between these communities and leads to new collaborations working on the types of challenges presented here.

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