Towards a Methodology for Data-Driven Automatic Analysis of Animal Behavioral Patterns

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ABSTRACT

Measurement of behavior a major challenge in many animal-related disciplines, including ACI. This usually requires choosing specific parameters for measuring, related to the investigated hypothesis. Therefore, a key challenge is determining *a priori* what parameters are informational for a given experiment. The scope of this challenge is raised even further by the emerging computational approaches for animal detection and tracking, as automatizing behavioral measurement makes the possibilities for measuring behavioral parameters practically endless. This paper approaches these challenges by proposing a framework for guiding the decision making of researchers in their future data analysis. The framework is data-driven in the sense that it applies data mining techniques for obtaining insights from experimental data for guiding the choice of certain behavioral parameters. Here, we demonstrate the approach using a concrete example of clustering-based analysis of trajectories which can identify 'prevalent areas of stay' of the animal subjects in the experimental setting.

CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models**; • **Information systems → Data mining**.

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1 INTRODUCTION

Measuring behavior is in the center of many animal-related disciplines, including animal science, ecology, neuroscience, veterinary science, psychology and many more. It is also a cornerstone in ACI, as it provides instruments for understanding the behavior of animals interacting with technologies. Traditionally, behavioral measurements are conducted by direct observation and manual coding of behavioral categories and events. Anderson and Perona discussed in detail that relying on human observation imposes severe limitations on behavioral data acquisition and analysis [4]. 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 tacit knowledge transfer in training. Moreover, human understanding and interpretation of behavior itself is in itself subjective and sometimes inconsistent. The need for the development of tools that promote more objective and quantifiable assessment and measurement of behavior (cf. [14, 22, 24]) has long been acknowledged. Research has recognized the potential of technology to empower the human observer in terms of accuracy and volumes of processed data, and to lead to discoveries of new behavior characteristics inaccessible for human observation.

These considerations give rise to the emerging field of *computational animal behavior analysis* (CABA) [10], which aims to apply techniques from computer science and engineering to facilitate accurate and objective analysis of behavior. One important trend in the context of CABA tools is their *genericity*, i.e., they aim to provide solutions 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 [20], which uses deep neural networks for markerless animal pose estimation. Blyzer [37] similarly uses deep learning for analysis of animal movement patterns. The increasing abilities of CABA approaches and tools mean intelligent systems are getting better at detecting the animal and its movement patterns, generating larger (and more accurate) volumes of movement data. The automatization of animal detection leads a choice problem: if we can measure practically anything, what should we measure? What parameters can be informational for the specific goal of our measurement and study or hypotheses? Thus the new challenge arises of helping researchers use CABA tools more efficiently, and supporting them in data analysis.

In this paper, we discuss the idea of shifting the paradigm of CABA tools from supporting researchers who regularly do manual behavior measurement towards providing insights for improving their decisions with respect to data analysis. More specifically, we address the challenge of identifying behavioral patterns in a collection of videos in a scenario of behavioral testing, i.e., exposing a sample of animal subjects to (semi-)controlled stimuli for testing a certain hypothesis or for investigating behavioral traits of individual animals. One important example of such scenario is dog behavioral testing, which is extensively used, e.g., for evaluating temperamental traits of working dogs [9]. Usually behavioral experiments are recorded, and therefore we assume that we have a collection of videos of the individual experiments $\{v(n_1), \ldots, v(n_k)\}$. This setting can be easily extended to each subject having several experiments/trials.

This paper proposes a data-driven framework, called Data-Driven Behavioral Pattern Analysis (DD-BPA), which aims to incorporate insights mined from experiment data for guiding the choice of behavioral parameters. The framework uses data mining techniques to identify various types of commonalities which we call behavioral patterns in a dataset containing videos of different animal individuals. We demonstrate the approach using a concrete example of clustering-based analysis of trajectories which can identify 'prevalent areas of stay' of the animal individuals in the experiment space.

2 MOTIVATIONAL EXAMPLE

To give a concrete example, we will consider a dataset of video recordings of a two-choice task experiment (see Fig. 1) that was conducted at the Clever Dog Lab (Messerli Research Institute, University of Veterinary Medicine Vienna), aiming to explore a possibility of an attachment-like system in dogs [18]. In the behavioral preference test of this study, dogs were presented screens with dynamic images of two faces: of their owner and of a stranger. The hypothesis of a preference towards their owner was tested.

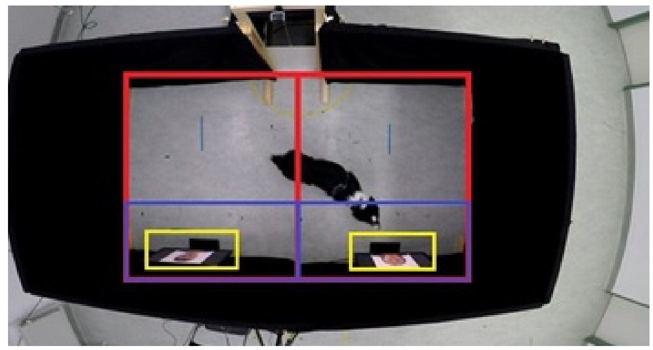

Figure 1: Studying facial preference; data collected in experimental setup

The Blyzer system [37] was applied to measure a possible preference . The crucial question was how to measure such preference, and which parameters to choose as representation of the dog's interest in a particular screen. Figure 1 shows the frame regions considered as possible areas of interest. This highlights the challenges of knowing in advance which of the selected areas would be the most informational ones regarding the experimental setup and research questions. These challenges show the motivation for our data-driven approach: by mining recurrent behavioral patterns more specific decisions can be made with regard to choosing the parameters. For instance, if a pattern of the dog frequently going into the blue area would be apparent, this area could be included in the areas of interest. Conversely, frequently staying in a specific area near the door next to the experimenter could lead to exclusion of this area from analysis as non-informative. It should be noted that meta-data such as where the door is located, where the experimenter is or where the screens are is a crucial part of our framework, as will be explained below.

3 BACKGROUND & RELATED WORK

Human Activity Recognition and Understanding

Human activity recognition and understanding is a very active field of research with many different applications. Several surveys of the methods used in this field are available (see, e.g., [12, 26, 35]). Vishwakarma and Agrawal [35] use a classification of the research efforts in the field into three levels consisting of: (i) low-level methods aiming to classify objects (e.g., humans and things they interact with); (ii) intermediate-level methods, aiming to perform automatic tracking, (iii) high-level methods, aiming to recognize, interpret and understand human activities.

The latter category is the most relevant for our purposes. Approaches for activity recognition are further divided into [35] to non-hierarchical ones, which cover primitive actions and periodic activities (e.g., running, jumping, waving), and hierarchical ones, which refer to complex human activities such as human-object interactions and group activities. The former category includes (i) approaches in which activities are captured using spatio-temporal representations, such as volume, features and trajectories, and (ii) approaches in which activities are represented using a discrete state-based model, such as Hidden Markov Models [36] or Finite State Machines [11]. More details about the mentioned approaches can be found in the comprehensive survey [35].

Automatic Analysis of Animal Behavior

The emergent field of CABA [10], also referred to as 'computational ethology' [4], 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 [4], including, among others, the dimensionality of behavioral analysis, increasing the throughput of behavioral analysis and facilitating real-time analysis of behavior.

Automatic tracking and behavior analyzing systems are increasingly used for different species: wild animals [8], pigs [1, 32], poultry [29], insects [23], and many more. Well-developed systems for automatic behavior of rodents– both commercial [31, 33] and academic [30] 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 of the animals' environment, movement characteristics, behaviors and physiological characteristics. Several works provide reviews of recent advances in the field bio-logging, see, e.g., [27, 28]. 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 (e.g., walk, jump, stop, follow).DeepLabCut is a framework for markerless pose estimation based on transfer learning with deep neural networks [20]. 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 activities.

Despite the fact that dogs are one of the most studied species in animal science, automatic behavior analysis for them is only recently starting to be addressed. Most of the research activity in this direction is inspired by the recent developments in IoT, bringing about the hype of pet wearables. These include a plethora of commercially available canine activity trackers, such as FitBark, Whistle or PetPace. Such devices measure activity and sleep patterns, calorie intake, heart rate and body temperature, etc. Pet wearables have been explored in relation to predicting the success of future guide dogs ([3, 21]), impacting the bonding between dog and owner[2, 39], and supporting the relationship between guide dog centers and puppy raisers ([38]). van der Linden et al. [34] provide a comprehensive overview of the data that commercially available dog trackers capture, as well as discussing their privacy implications. Fair accuracy was achieved for several self-developed sensor-based activity trackers [7, 13, 19], which are limited to a small number of basic positions and postures. It is therefore clear that the class of sensor-based wearables is not sophisticated enough to be used in clinical settings. Video-based approaches are an attractive alternative, due to the huge body of research in computer vision on human activity recognition, which is reviewed above. A few works addressed automatic video-based analysis of dog behavior [21, 25, 25]. However, most of these works use video from 3D Kinect cameras, for which the installation and use is not trivial and quite expensive.

The Blyzer tool [6, 17, 37] is an exception in the sense that it takes as input standard video footage that can be recorded using even low quality web or security cameras. Blyzer 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 [30] which are usually situated in a semi-controlled restricted setting), or camera setting (unlike [5, 21] 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 provides some form of quantification of behavioral parameters. The Blyzer architecture consists of two layers: (i) A computer vision layer which uses dog detection and posture classification models based on neural networks, and (ii) an analysis (sense-making) module, which identifies and measures requested parameters out of the spatio-temporal data obtained from the module. Blyzer has already been used for a variety of scientific projects. One example is the analysis of time budget and sleeping patterns of breeding stock kenneled dogs as welfare indicators [37]. 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 during the night). Blyzer was used to measure parameters such as the total amount of sleep, sleep interval count and sleep interval length.

Another project was the analysis of movement data for the assessment of hyperactive behavior of dogs treated in a behavioral clinic. This data was collected during behavioral consultations of 12 dogs medically treated due to pathological hyperactive 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 hyperactive dogs, such as high speed and frequent re-orientation in room space. A third example is the two-choice task experiment performed at the Clever Dog Lab Vienna already mentioned above. Dogs were presented screens with pictures of different faces, and their potential preference was tested by Blyzer measurement of time spent in different parts of the room, with special interest in the proximity to the screens.

These examples demonstrate the genericity of the Blyzer approach. Moreover, its architecture, separating between computer vision module for low-level dog recognition tasks and a sense-making module for more high-level behavior analysis makes it a suitable basis for our purposes. Our basic assumption, therefore, is that Blyzer can be adapted to the needs of the behavioral representations.

4 A DATA-DRIVEN METHODOLOGY FOR AUTOMATED BEHAVIORAL PATTERN ANALYSIS

As mentioned above, there exist several automatic approaches for supporting data analysis in animal science. However, they focus on supporting the researcher at the level of coding. Replacing manual coding with automatic approaches can save time, prevent human error and allow for processing huge amounts of data quickly. It does not change the traditional processes of data analysis, but rather follows researchers' decisions, coding the categories fixed in advance. The idea of our framework is in taking the role of the computer one step further, so that it can impact decisions made during coding and analysis phases. This is made possible by taking advantage of the *machine-interpretable format* in which behaviors and parameters detected using machine learning are represented. This opens the door to the world of data science, where we can apply a variety of pattern recognition approaches to identify some insights about the data.

For presenting the general framework, we first introduce the following concepts related to analyzing behavioral video data across a collection of video events (usually representing events related to different animal individuals or same individual at different times): *Behavioral representation* (of an individual behavior): a mathematical construction representing behavior extracted from a video footage of a specific individual. An example of such representation can be, e.g., movement trajectory or a behavioral state diagram.

The schematic representation of the approach is presented in Fig. 2 and is structured as follows: (1) We start with raw data (e.g., video or sensor), as well as some contextual information about the experimental setting, e.g., location of objects used in the testing (e.g., screens) and information about these objects (e.g., whether the screen is showing a stranger or the owner), actions performed by human towards the dog, information about the individual (age, breed, sex, etc). (2) Applying CABA tools (such as Blyzer) leads to obtaining machine interpretable abstract representations (e.g, time-series data or finite-state representations). At this stage we are already in the world of Data Science, where pattern recognition approaches such as clustering can be used to mine for common patterns (e.g., most commonly visited place, or common trajectory sequents). (3) At this point we make sense out of the mathematical patterns discovered in the previous step, framing them in the context of the specific experimental setting based on the provided metadata. For example, in the face recognition behavioral preference test described in the motivating example, we may translate trajectories moving towards a specific location as showing preference towards the dynamic image of a stranger.

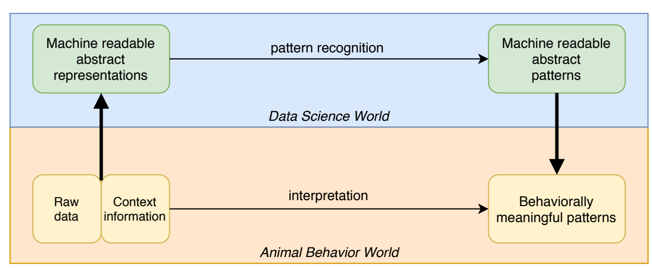

Figure 2: The methodology

5 AN EXAMPLE USE CASE

We now describe one specific use case based the dataset from our motivational example. The basic idea here is to mine specific 'strategic' areas of the room, where most of the tested experiment subjects spent most of their time during the experiment. These areas could then be divided into those closer to stranger or closer to owner and serve as certain areas of interest. We now describe how this idea is implemented, starting by examining how each of the framework components is instantiated:

Extraction of machine readable abstract representations: in the experiment described in [18] in more detail, the behavioral representation used in Blyzer were the movement trajectories of a point on the dog's body in the test arena (the center of mass and the dog's head were used).

Extraction of machine readable abstract patterns: intuitively, a pattern in our context is a point in the experiment space around which many of the participants passed. To detect such points, we use the k-means clustering algorithm [15] which aims to partition the points of trajectories into k clusters (where the optimal k is automatically established, in which each point belongs to the cluster with the nearest mean). The desired points are the clusters' centers. Figures 3 and 4 show the clustering results for nine dogs from trials 1 and 2 of the experiment. It can be seen that three clusters were found, the more intensive color indicates a larger number of points in the cluster.

Behaviorally meaningful patterns: several characteristics of the cluster centers can indicate behavioral insights that can guide the choice of areas of interest in data analysis. First of all, the number of points in the cluster: the larger the number, the more informational the area is. Comparing the clusters can also lead to important insights: e.g., Fig. 3 shows that the left cluster is larger than the right one (it is visualized by more intensive color). In this trial the owner image was exhibited on the left, thus showing a greater interest of the dogs in the left side of the room. Another interesting characteristic are the distances between the cluster centers: the more distant they are, the more indication for their interest in these areas, as the dogs stayed for longer there, and did not stay for long in between them.

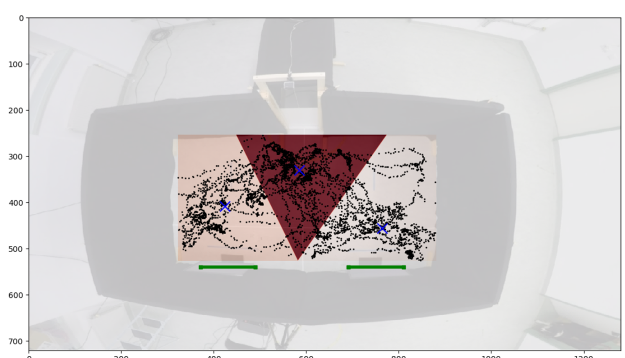

Figure 3: Trial 1; analysis of 9 dogs trajectories; owner on the left, stranger on the right; average distance between the cluster centers: 246 px

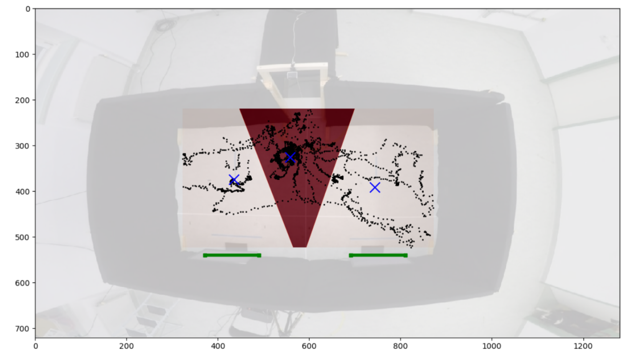

Figure 4: Trial 2; analysis of 9 dogs trajectories; owner on the right, stranger on the left; average distance between the cluster centers: 212 px

6 SUMMARY AND FUTURE WORK

The emergence of CABA tools and the automatization of the processes of animal behavior analysis brings about new challenges in data analysis decision making of researchers. This paper makes the first step towards addressing these challenges by proposing a general framework which maps computational concepts obtained through data mining techniques to behavioral patterns. This may guide the decision on measuring parameters during data analysis. We have demonstrated the utility of the framework on a specific use case of prevalent areas of interest analysis based on clustering. One immediate direction for future work is exploring other instantiations of the framework, looking at different behavioral representations and different behavioral patterns, which will ultimately expand the range of data mining techniques which can be applied in this context. We hope that the paper engages the ACI community to discuss how we can support researchers studying animals in using the plethora of computational tools which continue to emerge in an efficient and effective way. This, of course, is initially a trial-and-error process, and must ultimately support animal researchers at each step of the way.

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