Construct to Understand : Learning through Exploration

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Abstract. Artificial Intelligence (AI) and Animal Cognition (AC) share a common goal: to study learning and causal understanding. However, the perspectives are completely different: while AC studies intelligent systems present in nature, AI tries to to build them almost from scratch. It is proposed here that both visions are complementary and should interact more to better achieve their ends. Nonetheless, before efficient collaboration can take place, a greater mutual understanding of each field is required, beginning with clarifications of their respective terminologies and considering the constraints of the research in each field.

1 INTRODUCTION

A list of advantages and problems within each field is presented. It is proposed that AI and AC can complement each other and help in solving issues that have proved hard to tackle separately within each discipline. For example, within AI it is known how the 'robot brain' was coded and therefore we know what it does and how it does it. In contrast, a wide variety of behaviours can be observed in animals, but they are hard to analyse since there is little direct information about the structures and processes taking place within their brains. The implementation of concrete structures and processes in a computer model, where the robot's behaviour can be compared to an animal's behaviour, opens a new route to propose models for AC that could not be tested in another way.

Before collaboration can take place, a number of problems must be addressed. For instance, AC must overcome its anthropocentric view and clarifications must be made where similar terms are used in AI and AC but have different meanings. Scientists of both fields must keep an open mind towards new techniques and different, unfamiliar views on actually similar questions asked in their own field (Figure 1).

The poster further presents the study of how an individual learns about the deformability of objects as an example to where AI and AC can complement each other. We propose the Three-stage Theory of Exploration (Forming, Testing and Extending & Refining hypotheses), which can be studied from opposing directions by both AC and AI. While AC presents hypotheses about the behaviour that can be observed in New Zealand red-fronted parakeets (*Cyanoramphus novaezelandiae*), AI proposes models that are expected to produce analogous observations in robots[1, 2]. Both views are summarised in parallel boxes where similarities and differences are highlighted.

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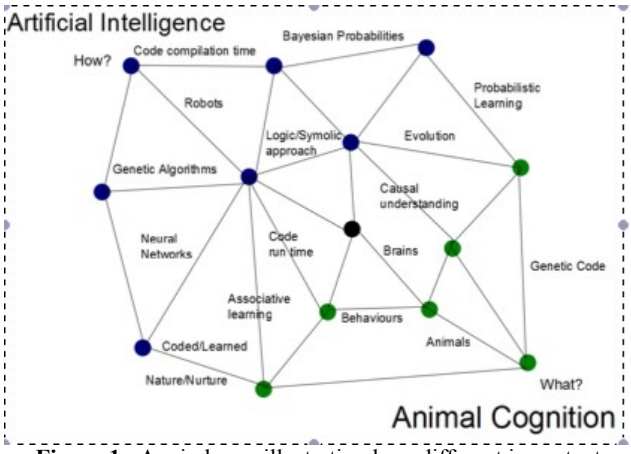

Figure 1. A mind map illustrating how different important concepts and terms in Artificial Intelligence (blue) and Animal Cognition (green) can link to provide a fuller answer to a research question posed by both fields (black)

2 COMMON PROBLEMS & THEIR INTER-DISCIPLINARY ANSWERS

Firstly, both fields are traditionally quite anthropocentric. It is often thought that there is a dichotomy between the cognition of humans and non-humans animals. However, despite each individual and species having unique mechanisms to cope with their unique ecological niche, it is worth investigating competences developed by individuals other than humans. In modelling cognition a single separated type of model is not enough and collaboration between different mechanisms may be required.

Secondly, quite frequently the same terms in each field refer to very different (although analogous) concepts, or similar concepts are called different names. For instance, in AC ' *neural nets'* are connections between neurons in the brain. While in AI they are numerical techniques to approximate an unknown function, inspired by biological systems, but they really do not do the same function and are a lot simpler.

Both fields can help each other if researchers are open to learning and understanding new ideas and terminology proposed by the other field that can seem initially very daunting. While traditional views are always the foundation of any field, techniques, approaches and knowledge are constantly changing and evolving.

There is always more than one way to phrase a question and considering different angles of the situation can provide a more complete answer. This is why collaboration is fruitful and productive. AI & AC are complementary sides of the same coin.

For instance, AC often follows the *top-down* approach when trying to answer a research question (what are the requirements imposed by the environment that results in this particular behaviour?), while AI follows the *bottom-up* approach (let's try to build the system from scratch). At some point, they meet in the middle and provide a complete understanding of the interesting behaviour or learning strategy in question.

3 AN EXAMPLE PROBLEM: HOW DOES AN INDIVIDUAL LEARN ABOUT THE DEFORMABILITY OF OBJECTS?

We have combined our respective expertise in AC and AI to propose a 'Three-stage Theory of Exploration' to explain how individuals learn about the physical properties of their surrounding environment. Specifically, we apply it to a frequent object affordance or property experienced in everyday life – the rigidity or deformability of objects.

Today AI and AC researchers either seem to be focussed on how learning is by simple associative trial-and-error, or probablistic and statistical strategies (e.g. Bayes nets) or by more complex and abstract causal understanding. We propose that it is in fact by a combination of these strategies depending both on the conditions of the environmental situation and the competences of the individual (whatever species). Surprisingly little research has looked at how systematic exploration could support learning strategies.

We believe that exploration is not always random but structured, selective and sensitive to particular features and salient categorical stimuli of the environment. It typically follows through three stages of theory formation specific to particular affordances and processes, but can be generalised to novel situations. Firstly, individuals form internal representations of the world/environment by acting on it in a way that suggests probabilistic reasoning and simple trial-and-error learning is being used. Their exploration further reflects genetic predispositions to particularly salient environmental features, such as edges and corners. Moreover, they perhaps represent and segregate the world into general categories from birth. Secondly, the individual tests these internal hypotheses. They progressively use more complex mechanisms like causal reasoning, so explorative actions become less repetitive and they generally behave more flexibly depending on the situation they are presented with in their environment. Tests internal theories and rules of object relations by performing (initially) certain actions on certain objects. Lastly, individuals extend and refine these hypotheses by analysing their theories and reusing knowledge about the world by combining them in similar but new environmental situations. The individuals can also now fill in gaps in knowledge abstractly by causal inferences, so hypotheses are extended throughout life.

We realise that at this stage, this theory is very general and still has a lot to be expanded upon and considered in more detail. However, it is an example of how apparently different forms of thinking from different research fields can actually be brought together and thus provide plenty more scope for collaboration and further more systematic investigation. It is purposefully designed it this way also to provide a more general framework so that it can be applied to a wide range of behaviours, species and environments. However, we do acknowledge that there are a variety of contributing factors and thus different specific strategies and mechanisms for different contexts. Thus in the next section we briefly explore our specific hypotheses for this context – learning about the deformability of objects in a robotic agentg and parakeets.

4 PROPOSED METHODS & HYPOTHESES

When AC and AI work in parallel the order and priority of their respective hypotheses often becomes altered, yet the methods and results are complimentary. In the case of deformable objects the methods for both can be compared as follows. From the AC perspective, we plan to consecutively present individual parakeets with novel objects of different shapes and deformabilities. Then we will record in detail their actions from a rigid ethogram specific to this behavioural context, backed up by video analysis.

However, from the AI point of view, we have taken a more bottom-up approach and propose a set of candidate mass spring models for every material the individual (i.e. robot) encounters (Figure 2). Subsequently, we will search for the model that best fits the data that the robot acquires through selective interactions with the material. Then we will detect when no model can offer a 'good' representation and evaluate and characterise the search strategies that find the best models and use these results to improve the searching process. Finally, the system will be tested by consecutively presenting the robot with simple solid and deformable novel objects in a similar task design to the parakeets. The quality of the generated models and the number of steps (time) it took to find them will then be evaluated.

It can hence be observed that while AC focuses on the observation of behaviours, AI focuses on the construction of the infrastructure that would produce those behaviours. The hypothesis in each case reflects the opposing goals of both disciplines and the application of the Three-stage Theory of Exploration.

Firstly, in AC we predict that there will be a higher frequency of the parakeets touching the corners and areas of high curvature over the smooth surfaces. Furthermore, they will explore a novel deformability more than a familiar one. Then between trials, the individual begins to explore the most compressible and the most rigid objects more than the other levels of intermediate deformability, but they progressively focus in more detail on these intermediate levels. Lastly, we hypothesise here that the parakeets will eventually reach a point where they have so much experience with the different objects' compressibility and affordances, that they can combine their understanding of the different objects to solve a new task. However, how this will be observed specifically in the behaviour is still to be decided.

On the other hand in AI, we hypothesise that it is possible to generate a geometrical internal representation on top of which a mass spring physical model can be applied [1][2]. The nodes of the mesh will be more likely to be placed at points of high curvature. Secondly, we believe that it is possible to calibrate the parameters of the model by using a random search algorithm. This algorithm samples the space of possible parameters and selects the most suitable ones. Finally, we predict that it is possible to improve learning by providing a clustering algorithm that learns to segment and classify the space of parameters of the physical model, so that the appropriate models for new materials are calibrated faster.

Consequently, from these two sets of hypotheses we can see that in parts they are actually very similar, and where they are not so similar, they can add resolution to each other. For instance, it can be seen that while the first hypothesis of AC looks for evidence of more attention on places with high curvature, the first hypothesis of AI directly establishes that the model will use points of high curvature as pivotal points for the model and expects that the generated model of the behaviour of the deformable object will be good.

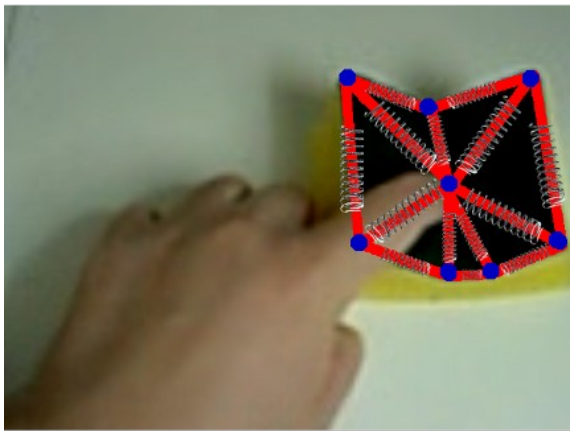

Figure 2. In Artificial Intelligence a generic technique from physics (mass-spring models) is used to generate an internal representation of deformable objects

5 CONCLUSIONS & FUTURE WORK

For AI, the problem of interest is to learn to predict the behaviour of deformable objects based on experience. In order to achieve that, a learning technique is proposed, where the generation and selection of physical models consists of sets of masses connected by springs on top of a mesh of triangles superimposed onto the object of interest. From an AC point of view, it is hypothesised that this learning technique will produce in the robot a behaviour that is analogous (though perhaps simpler) to what can be observed in the parakeets when encountering novel deformable objects. Although parakeets may not directly use a mass-spring model to learn about the deformability of their environment, they may use a similar frequency-based strategy that can be derived from the mass spring model. New hypotheses and experiments could then be designed to further test the applicability of this model and to hopefully extend it.

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