Behaviour Modelling of Social Animals via Causal Structure Discovery and Graph Neural Networks

Extended Abstract

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ABSTRACT

Better understanding the natural world is a crucial task with a wide range of applications. In environments with close proximity between humans and animals, such as zoos, it is essential to better understand the causes behind animal behaviour to predict unusual changes, mitigate their detrimental effects and increase the well-being of animals. However, the complex social behaviours of mammalian groups remain largely unexplored. In this work, we propose a method to build behavioural models using causal structure discovery and graph neural networks for time series. We apply this method to a mob of meerkats in a zoo environment and study its ability to predict future actions and model the behaviour distribution at an individual-level and at a group level. We show that our method can match and outperform standard deep learning architectures and generate more realistic data, while using fewer parameters and providing increased interpretability.

KEYWORDS

Causal Inference; Graph Neural Networks; Animal Behaviour

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1 INTRODUCTION

(a) Carrying a pup. **(b) Digging.** **(c) Interacting with object.** **(d) Playfighting.**

Figure 1: Examples of meerkat behaviours in the Meerkat Behaviour Recognition Dataset [17].

Understanding non-human animal behaviour is a fundamental task in ecological research, with wide applications ranging from unusual behaviour detection [2], population dynamics [14], habitat selection analysis [28], and disease spread modelling [5]. One particular application of behaviour modelling is to monitor the well-being of animals in zoo environments [18, 22, 23]. The advent of machine learning has opened up the possibility of simultaneously considering multiple factors when investigating complex correlations in animal behaviours [16, 24, 27]. However, learning correlations without recovering the cause and effect knowledge cannot provide a full understanding of the studied phenomenon [21]. While existing research has largely concentrated on the interplay between behaviour and environmental factors [27], the cause-and-effect relationships among behaviours have been less explored. Causal relationships among behaviours are particularly prominent in social mammals, like meerkats and chimpanzees [4, 8, 31] and are often interrelated in complex ways. In zoo populations, human intervention adds an additional layer of complexity. Consequently, determining the causal relationships between behaviours that evolve over time can be challenging. Causality theory for time series aims to recover the causal dependencies between variables that evolve over time [6, 7, 13, 15, 26]. An existing body of work recovers the causal structure of animal behaviours but only focuses on insect swarms [12] or bird flocks [3] and does not attempt to model the complex social interactions of individuals. In this work, we propose an approach based on Causal Structure Discovery [7] and Neural-Causal Inference [33] to (1) automatically discover the causal relationships between the behaviours of individuals in a social group and (2) model and predict the behaviours of individuals over time. We apply the proposed method to simulate the behaviours of a mob of meerkats in an enclosure of the Wellington Zoo. Figure 1 illustrates some examples of the observed behaviours. Our code is available at: https://github.com/Strong-AI-Lab/behavior-causal-discovery.

2 CAUSAL BEHAVIOUR MODELLING

We propose an approach based on Causal Structure Discovery and Causal Inference, summarised in Figure 2. We build a causal model from time-series with categorical data containing the behaviours to be learned and contextual information. We model the transition functions between the behaviours and the causal dependencies between them (what nodes cause the transition from one behaviour to the next). The method is divided into two modules: a *Causal Structure Discovery* module that recovers the dependencies and structure of the causal graph, and a *Causal Inference* module that learns the transition functions given the data and graph structure. We use the PCMCI algorithm [19] to discover the causal structure of the behaviour model. We use a Graph Neural Network (GNN) [10, 20] for the Causal Inference module to take advantage of the causal structure generated by the Causal Discovery module. The choice of a GNN is motivated by its ability to represent causal mechanisms under the Structural Causal Model [32, 33].

3 APPLICATION TO BEHAVIOUR PREDICTION

we apply our method to the problem of modelling the behaviour of social animals in Table 1. We study meerkats due to the complex social behaviours they demonstrate and the availability of behavioural data. We use the Meerkat Behaviour Recognition Dataset [17], a collection of annotated videos of a mob of meerkats in the Wellington Zoo from static cameras. We simulate individual behaviours evolving over time using the proposed method and investigate how accurate the generated series is, compared to the ground truth. We use several GNN architectures: GCN [10], GAT [30] and GATv2 [1] with a single GNN layer to represent causal paths only [34]. We compare our model against a Long Short-Term Memory (LSTM) [9] and a Transformer [29]. To quantify the difference between the ground truth and the simulated behaviours, we train a LSTM discriminator model to classify true and counterfeit data.

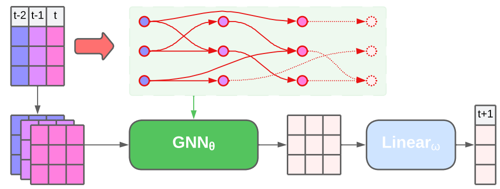

Figure 2: Neural-Causal Model based on Graph Neural Networks. The causal graph is built using the Causal Structure Discovery module (on top, in red) and provided to the GNN (at the bottom, in green). The GNN aggregates the features following the causal dependencies and generates a probability vector for the next timestep (on the right, in blue).

Table 1: Performance of the model. *Acc.* is the accuracy on next-step prediction task. *Mutual I.* is the associated Mutual Information [11, 25] between the prediction and the ground truth. The higher the better. The *LTSM-Discriminator* is tasked to distinguish real samples from simulated samples, the lower acc. the better (as we aim to fool the discriminator).

	Acc.	Mutual I.	LSTM-Discr.
PCMCI$_\mathcal{G}$	0.287 ±0.000	0.004 ±0.000	0.873 ±0.005
+GCN$_\mathcal{G}$	**0.588 ±0.008**	0.143 ±0.025	*0.866 ±0.002*
+GAT$_\mathcal{G}$	0.482 ±0.015	0.111 ±0.009	**0.865 ±0.002**
+GATv2$_\mathcal{G}$	*0.567 ±0.012*	0.116 ±0.004	*0.866 ±0.001*
LSTM	0.565 ±0.007	**0.190 ±0.009**	0.888 ±0.002
Transformer	0.343 ±0.068	*0.145 ±0.011*	0.887 ±0.001

4 DISCUSSION AND CONCLUSION

We tackle the problem of modelling the behaviours of a group of meerkats interacting together in a zoo environment using causality theory and graph neural networks to build an interpretable prediction and generation engine. Our method can compete with and outperform standard deep learning models with a higher number of parameters, making more accurate predictions and generating more realistic simulation data than the baselines. This paper uncovers some limitations of the proposed and current models, such as the lack of Information (in Shannon's definition [11, 25]) learned by the models. We highlight a discrepancy between accuracy performance at the statistical level, and accurate modelling of the inner mechanisms of the agents.

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