Monkey See, Monkey Know: A Probabilistic Model of Cognition in Tufted Capuchins (*Cebus apella*)

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Abstract

Causal learning, or the process by which we learn the relationship between cause and effect, is critical for human cognition. However, humans are not uniquely capable of causal learning, as many non-human primates are able to successfully complete causal learning tasks. One such task, the blicket detector task, measures participants' abilities to reason whether or not an object caused a machine to turn on. While humans and non-human primates, such as capuchins (*Cebus apella*) can perform this task, capuchins, unlike humans, fail to successfully complete the task in the absence of a food reward. While human causal learning can be explained via Bayesian data analysis, capuchin causal learning can best be understood via a mixture model approach which assumes an unbounded number of latent causes, and categorization of observations based on reinforcement, cue, and context. Such modeling demonstrates that causal learning is not bound to a single analytic approach, but rather that discrete probabilistic models of causal learning can be applied to human and non-human primates.

Keywords: causal learning; primate cognition; mixture model; human cognition; capuchins; monkeys; Bayesian data analysis

Introduction

One way of understanding human cognition is by exploring causal learning. Detecting spacio-temporal associations in one's environment and altering behavior based on those findings is a hallmark of intelligence. In the blicket task, various distinct objects are placed on a machine, known as the blicket detector (Gopnik and Sobel, 2000). The subject then observes the blicket detector activating or remaining off. At the end of the task, the participant is asked to decide which objects are blickets. Such data is key for developing probabilistic modeling of causal learning and helping us to better understand our own intelligence and how we think.

However, we also know that humans brains are not the only "thing that thinks," as Descartes phrased it. Non-human primates, such as capuchins (*Cebus apella*), chimpanzees (*Pan troglodytes*), bonobos (*Pan paniscus*), orangutans (*Pongo abelii*), and gorillas (*Gorilla gorilla*) can also perform causal learning tasks, such as the blicket detector task (Edwards et al. 2014, Völter, Sentís, and Call 2016). However, results on non-human primates' causal learning abilities are mixed, especially in the capuchin subject population (Edwards et al. 2014). While capuchins are able to accurately determine which objects are blickets in the presence of a food reward, they fail to do so in the absence of a reward.

Background

Indeed, the traditional approach of modeling the blicket task in humans, using Bayesian data analysis, fails to explain capuchin behavior in relation to causal learning. One potential explanation for the failure of the traditional model is simply that capuchins, in a strict sense, are unable to perform the blicket task and engage in causal learning. By this argument, capuchins are not truly engaging in causal learning, since they miscategorize blickets as non-blickets under certain conditions. However, one other possibility is that the cognitive mechanism by which capuchins reason about causal learning differs from the mechanism in humans, though both are able to engage in causal learning. A probabilistic model of such data would provide key insights into our understanding of cognition and how models of cognition differ across primate species, including our own.

Based on the findings from Gopnik and Sobel (2000) and Edwards et al. (2014), we want to know whether humans and non-human primates adopt different models of causal learning. Specifically, we want to know whether humans and capuchins adopt a different model of causal learning on the blicket detector task, and if so, how those models differ.

Related Research

One potential avenue to describe causal learning and its relation to reinforcement comes from the study of mice. In the canonical example of reinforcement learning, mice learn to fear a tone when it is paired with a shock. Eventually, the mice learn to fear the tone even when not paired with a shock. In a latent cause model (Courville, 2006; Courville, Daw, Gordon, & Touretzky, 2004; Courville, Daw, & Touretzky, 2002), both the stimuli and reinforcement can be attributed to causes that are hidden from observation. Redish et al. (2007) posits a theory of reinforcement and extinction learning whereby actors, such as mice, use "state classification" to categorize observations when the number of categories is unknown.

Building on these models, Gershman, Blei, and Niv (2010) proposed a revised model of context, learning, and extinction. In this model, the animal must combine its prior beliefs with the full set of evidence from its observations, eventually inferring a causal structure in their environment. Such a model has three key components.

First, it is a generative model that allows for an unknown and unbounded number of latent causes. At the outset, animals do not know how many categories their observations will fall into. They typically prefer a small number of cases, but can, at any point, update their causal structure to allow for a new latent cause given a new set of observations that do not match to previously inferred latent causes.

Second, the trials reflect the animal sampling from a potential cause via a mixing distribution, and sampling features of the observation conditioned on the cause from an observation distribution. The authors argue that the animals are, in essence, using a mixture model approach to reason about latent causes.

Third, animals partition groups of information into clusters based on their properties. In the case of classical conditioning in mice, the animals parse the observations into three key components - reinforcement, cue, and context. Reinforcement typically refers to the presence or absence of a shock. Cue in this sense typically refers to a tone accompanying the shock, and context refers to the environmental factors present during the observation, such as the location or appearance of the cage.

While this model is framed in the context of classical conditioning in mice, the manner in which it reasons about latent cause theory and causal learning has direct applications to the study of causal learning in capuchins. Specifically, the proposed model can be applied to any animal tasked with identifying the latent causes of its observations and from that and predicting reinforcement via clusters of observations.

Methods

While human causal learning can be modeled by Bayesian statistical techniques, we hypothesize that capuchin learning is best described via a mixture model approach which assumes an unbounded number of latent causes. In the present study, we apply data from the blicket task as performed by capuchin monkeys (Edwards et al. 2014) to a latent cause mixture model and assess its ability to explain capuchin behavior in terms of causal learning. Such a model, if successful, should predict: first, that capuchins are able to correctly reason about causal structure in the presence of reinforcement; second, that capuchins do not predict objects paired with reinforcement and objects not paired with reinforcement to have the same latent cause, and third, the latent cause theory for a specific set of observations is maintained for those observations if no new information is given.

Experimental Design

Six capuchin monkeys (Cebus apella) were tested on the blicket detector task mirroring the task presented by Gopnik and Sobel (2000). In this present task (Edwards et al. 2014), subject monkeys observed or were allowed to test a series of objects, known as "blickets," as they were placed on a machine, known as the "blicket detector." Some blickets activated the machine, resulting in a flashing light and squeaking noise from the machine. In certain scenarios, the blicket detector released a grape in the presence of a blicket. Other objects were not blickets, and so placing them on the machine did not change the machine's state, nor did it cause a grape to be released.

In experiment 1, monkeys watched as a series of blickets were placed on the machine by an experimenter. The stimuli presented were four novel objects, noted as A, B, C, and D, each with a distinct color and shape. In the one-cause condition, monkeys observed that object A activated the machine and object B did not activate the machine. The monkeys also observed objects A and B being placed on the machine simultaneously, which activated the blicket detector. In the two-cause condition, monkeys observed object C activated the machine. They also observed that object D did not activate the machine. However, during a separate observation, object D did activate the machine. Thus, object C activated the machine with a higher probability than did object D. Importantly, for all observations, when the machine was activated, the monkeys received a grape reward. In both the one-cause and two-cause condition, the experiment began with a two sessions of ten training phases, during which the monkey observed the objects being placed on the machine, followed by two test phases, during which time the monkey could select which blicket (A or B; C or D) to place on the machine using a single-choice paradigm. Correctly placing a blicket on the blicket detector resulted in a grape reward.

In experiment 2, subjects were presented with two familiar objects, A and B, and two novel objects, E and F. The training phase consisted of ten trials, five for the familiar objects and five for the unfamiliar objects. During this time, the subject could place the objects on the machine and observe the results. Importantly, no grape reward was given during these observations. As in experiment 1, object A activated the machine, while object B did not. Similarly, novel object E activated the machine, while novel object F did not. During the two test trials, the monkey could select which blicket (A or B; E or F) to place on the machine using a single-choice paradigm. For the test trials only, a grape dispenser was attached to the machine such that the monkeys would receive a grape for a correctly placed blicket.

Model Design

Extending the work of Gershman, Blei, and Niv (2010) and Gershman and Niv (2012), we developed a latent cause infinite-capacity mixture model of causal learning in capuchin monkeys. We have implemented this model in WebPPL, a probabilistic programming language (Goodman & Stuhlmuller, electronic), and runnable code for the model and associated data visualization is available online at https://github.com/sophialsanchez/cs428. The model centers on the idea that animals partition groups of information into clusters based on their properties. Thus, each observation is comprised of three key components - reinforcement, cue, and context. Reinforcement in this context refers to the presence or absence of the grape reward during the observation. The cue, similar to a Pavlovian bell cue, refers to the state of the blicket detector when the object is placed on it. That is, the blicket detector is either activated (on) or not (off). Lastly, the context refers to the specific configuration of objects placed on the machine, such as A and B, only D, etc.

Second, we posit that the multinomial parameters come from a Dirichlet distribution. Intuitively, the animal has no prior predictions about the experiment or potential outcomes before the first observation. Thus, the Dirichlet distribution, which gives equal probability to all possible multinomial parameters under the prior, reflects this intuition.

Additionally, the model assumes an unbounded number of latent causes. In other words, the model assumes that the monkeys prefer a small number of potential latent causes, but, at any time, can establish a new latent cause given a new set of information that does not fit into any previously created category of information. Thus, in contrast to Bayesian data analysis approach to the blicket detector task, whereby objects are either grouped as blickets or not blickets, here observations are grouped into an unbounded number of clusters. Importantly, this model predicts that an observation for object A, in which reinforcement was present and the blicket detector was activated, would fall into a different cluster than an observation for object E, in which the grape reinforcement was absent but the blicket detector was activated.

Results

The results from experiment 1 show that monkeys chose object A (blicket) over object B (non-blicket) in the one-cause condition (Mean = 98% of trials, $p<0.0001$) (Figure 1). Likewise, the monkeys chose object C over object D in the two-cause condition (Mean = 97% of trials, $p<0.0001$). The results from experiment 2 show that monkeys continued to chose familiar object A (blicket) over familiar object B (non-blicket) (Mean=100%). However, they placed novel object E (blicket) on the machine in only 12.5% of test trials (Figure 2). In the remaining 87.5% of test trials, neither object E nor object F (non-blicket) were placed on the machine, despite the fact that the monkeys observed the state of the machine when either object was placed on it during the training phase.

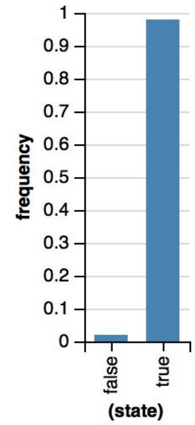

Figure 1. Results from experiment 1 indicating the relative number of trials blicket A was correctly selected (true).

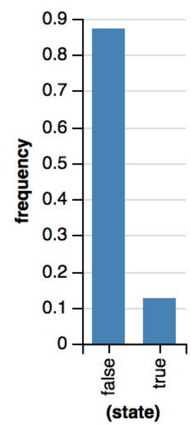

Figure 2. Results from experiment 2 indicating the relative number of trials blicket E was correctly selected (true).

While the data for experiment 1 correspond well to the predictions generated via Bayesian data analysis, the data for experiment 2 are not in line with the Bayesian data analysis predictions. According to this analysis, the posterior prediction for object A, which is a blicket, is 0.8608. In other words, the Bayesian data analysis model aligns with the experimental data (Figure 1), as both suggest that object A is a blicket. Similarly, the Bayesian model prediction indicates that blicket A and nonblicket B do not have the same probability of being a blicket (posterior prediction = .8135). This is also in agreement with with experimental data, whereby blicket A was preferentially selected over nonblicket B (Figure 1).

Importantly, however, the test data and Bayesian model results do not align for experiment 2. The Bayesian data analysis result indicates that A and E have the same probability distribution, meaning that both are blickets (posterior prediction = 0.7604). However, as Figure 2 shows, the capuchins did not consider object E to be a blicket, even though it caused the blicket detector to activate.

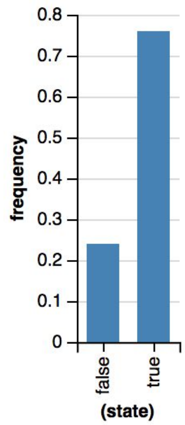

Figure 3. Results from Bayesian data analysis indicating that blicket A and blicket E have the same probability distribution (i.e. that both are blickets).

In contrast, the results from the mixture model more closely mirror the observed behavior. Just as with the Bayesian data analysis approach, the mixture model suggests that objects A and B, where A is a blicket and B is not a blicket, are not in the same cluster (Figure 4). Likewise, the model predicts that objects A and C, which are both blickets, are in the same cluster (Figure 5). As anticipated, the model predicts that object C, which is consistently a blicket (reinforcement=true, cue=true), is in the same cluster as object D, which is a blicket in 50% of trials (Figure 6). However, while C and D are likely in the same cluster, the probability that they are in the same cluster (Figure 6) is lower than for two objects that are both consistently blickets, such as A and C (Figure 5).

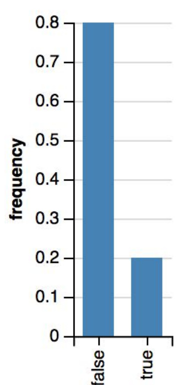

Figure 4. Mixture model visualization of the probability that blicket A and nonblicket B are in the same cluster.

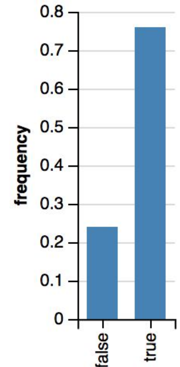

Figure 5. Mixture model visualization of the probability that blicket A and blicket C are in the same cluster.

Figure 7 represents the mixture model visualization comparing blicket A with blicket E. During the observations for blicket A, the monkey both received a grape (reinforcement = true) and observed the machine activate (cue = true). Since blicket E was presented in experiment 2, the monkey did not receive a grape (reinforcement = false) and observed the machine activate (cue = true). Objects A and E, though they are both blickets, are most likely not in the same cluster according to the mixture model. As such, the mixture model predictions for objects A and E (Figure 7) are more closely aligned with the experimental results than was the Bayesian data analysis approach; namely, capuchins consider object A to be a blicket and object E to be a non-blicket (Figure 1, Figure 2).

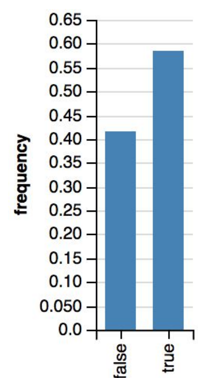

Figure 6. Mixture model visualization of the probability that high-frequency blicket C and low-frequency blicket D are in the same cluster.

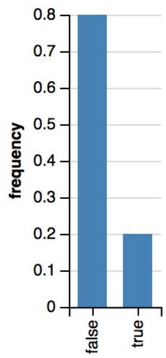

Figure 7: Mixture model visualization of the probability that blicket A and blicket E are in the same cluster.

Discussion

In the real-world experiment, the monkey correctly placed blicket A on the machine in order to receive a grape, but did not place blicket E on the machine, even though doing so would have resulted in a reward. In contrast, the Bayesian data analysis model predicted that if capuchins are able to engage in causal learning, then they should consider both A and E to be blickets. One hypothesis is that the monkeys simply cannot reason about causal structures in the absence of immediate reinforcement during observations. Another hypothesis, which is indicated by the mixture model, is that unlike humans, monkeys reason about causal structures using clustering. In other words, while to a human, a blicket is a blicket regardless of whether reinforcement is present, to a monkey, an object that both makes the machine go off and is associated with a grape being delivered is in a different category from an object that makes the machine go off but is not associated with a grape.

Indeed, this categorization of objects based on a rich set of observations, is consistent with the data. The mixture model predicts that objects A and E are not in the same cluster. One potential critique of the mixture model explanation is that perhaps the data are the product of a lack of curiosity, rather than clustering. In other words, perhaps the monkeys are simply not curious when there is no grape to hold their attention, and thus they do not truly observe and process the information from the blicket detector. However, several factors make this explanation unlikely. First, in the second iteration of the capuchin experiment, the subject capuchins directly handed the objects over to an experimenter, who when placed the object on the blicket detector (Edwards et al. 2014). This ego-centric approach means that the action was not passive, decreasing the likelihood of the "lack of interest" explanation. Second, in the experiment 2 test trials, the monkeys tended to place neither object on the blicket detector, rather than guess randomly. This behavior indicates that the monkeys reasoned that neither object was a blicket, as a correct random guess would have resulted in a food reward.

Overall, the mixture model predictions are much more closely aligned with the experimental data than are the original Bayesian data analysis predictions. These results make intuitive sense, as by the classification logic, an observation in which the blicket detector activates and a grape is dispensed is not the same as an observation in which the blicket detector activates and a grape is not dispensed. There is strong evidence that capuchins employ a latent cause infinite-capacity mixture model of causal learning.

These findings have important ramifications for future models of causal learning in non-human animals. Specifically, the "one-size-fits-all" model of cognition is not a scientifically rigorous approach. One should not assume that the internal model humans use to evaluate causal structures is identical to the internal model that non-human animals employ, and that the lack of concordance between the human model's predictions and the experimental data in animals suggests a lack of understanding. The model presented here demonstrates that causal learning is not bound to a single analytic approach, but rather that discrete probabilistic models of causal learning can be applied to human and non-human primates. Indeed, the analysis of all measures of cognition should be evaluated in light of the idea that different approaches can address the same cognitive problem, whether in causal learning or intelligence more broadly.

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