Literature Review on categorization in avian species

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Abstract

This literature review is dedicated to categorization ability in birds and models that implement categorization.

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1 Introduction

The question of how our cognition functions has been puzzling the humanity probably for as long as it has existed. By the beginning of the 19th century people discovered that brain is essential for sensations and movement and that it communicates with the rest of the body by the means of neurons. Since then numerous approaches emerged from molecular level studies determining what kind of hormones are responsible for functions to cellular to behavioral and finally cognitive, which aspires to explain higher level mental activity in human brain [2].

One of the essential functions of a brain is considered to be categorization – ability to attribute different stimuli to different classes and respond accordingly. This term is sometimes distinguished from concept. As claimed in [3] this difference is rather a spectrum than a binary distinction. It can be illustrated through the following: there's a category of a letter any letter can be written, read, folded, wrapped in an envelope, stamped. However the concept of a letter may involve not a physical letter but rather an electronic one, so whilst the idea is the same the implementation is different enough so the reactions triggered

by electronic letter do not fully resemble actions that can be performed with an ordinary paper letter.

Categorization is believed to be crucial for living beings since they continuously need to interact with the environment and categorize the stimuli to be able to respond appropriately in order to survive. Interestingly enough, we never get the same stimuli even from the same object every sensory experience is rather different [6], for example even the most simple objects observed from different angles provide different picture or same sounds pronounced twice provide two different frequency patterns.

Birds are incredibly convenient organisms to study categorization. To justify that I should point out that it is believed that avian and mammalian brains portray an amazing example of parallel evolution: despite avian and mammalian cortex having different structure, they actually are capable of providing the same functionality. Birds as well as the majority of mammals receive most of the information about the world through vision and structure of visual pathways in avian brain resembles one in mammalian though they seem quite different anatomically [3].

Originally, ability for categorization was believed to be inseparable from language and thus bound solely to human cognition [3]. That was until the release of [4] in 1964 by Herrnstein and Loveland. They performed behavioral experiments on pigeons training them to identify humans on photographs: initially pigeons were trained to eat from the feeding device then to trigger it then to trigger it once it was illuminated and, finally, to check for the ability to categorize plates were illuminated with projections of photographs half of those photographs contained humans. Pigeons demonstrated rather good results which supported the notion that categorization is not exclusively inherent to humans but to all the mammalians as well. Though there might have been issues concerning the fact that pigeons could base their judgement not on the presence of human on the picture but rather on the surroundings this still is an evidence of avian categorization ability. After that many papers on the matter emerged [5] further strengthening this notion as well as replicating the results achieved by the pioneers.

Statement of a problem

The master's thesis is dedicated to the problem of biologically plausible mechanisms for feature selection and categorization.

The goal of this work is to provide a review of existing categorization models as well as invoke the question of feature selection for categorization.

2 Literature review

Models for categorization are often based on the following notion: stimuli can be represented as a collection of individually activated representational elements the more elements two stimuli have in common the more likely is their affiliation to the same category. As stated in [6] the idea must have been applied for explanation of animal behavior from the late 1940. Problem of such models is that they might be able to explain categorization they fail to explain the ability to identify each stimulus. The work [9] by Rescorla and Wagner proposed a solution for this issue involving an error-driven learning rule:

$$\Delta V_{ij} = \alpha_i \beta_j (\lambda_j - V_{ij}),$$

where V_{ij} is the associative strength between i-th stimulus and j-th outcome on a trial, α_i and β_j – parameters for learning rate, λ_j – maximal amount of associative strength supported by j-th outcome. This error-driven learning rule minimizes disparity between maximal associative strength of the outcome and associative strength presented on the trial. It is worth noting that common elements rule combined with error-driven learning rule proved to be successful in explaining categorization of objects as well as identification of those.

An interesting model was provided in [6]: as stated earlier, common elements model though provides great explanation for categorization fails to explain the ability to identify stimuli. In this work authors suggest probabilistic approach. Suppose exemplars for each category are provided, observation of any stimuli activates representational elements some of them are ubiquitous to all the examples some elements are common in the category and some are personal characteristic of a particular stimulus. Based on this idea, authors even suggest diagnosticity of an element – measure of how useful this element is for categorization. What is rather peculiar about this paper is that authors claim that even without explicit knowledge about similarity relations inside of a particular category, it is possible to categorize elements solely on premise that stimuli in the same category share more elements than stimuli in different categories. In the provided model stimuli are represented as a collection of elements that either activate or not activate in the presence of stimulus whilst categories are assigned rather arbitrary distributions for elements' activations with the only condition that they are significantly different from one another. The underlying premise here is that stimuli from the same category are more likely to activate similar elements so would be categorized into the same group. For training they used Rescorla-Wagner's rule and the choice rule – probability of attributing the particular stimulus to a category:

$$P(R_j|S) = \frac{\mathbf{e}^{\theta V_{Sj}}}{\sum_j \mathbf{e}^{\theta V_{Sj}} + \mathbf{e}^{\theta V_0}},$$

where $P(R_j|S)$ – probability of response R_j in presence of stimulus S, V_0 – unknown incentive value of the test subject doing nothing because this is still an available response.

Though researchers believe that attention is important to categorization for avian species its mechanisms can still vary greatly from what humans portray. In [8] authors raise the question of whether the success of birds in categorization is achieved through executive functions akin to human abilities or it is based on associative model. They decided to check pigeons abilities in tasks involving rule-based (RB) – which is more typical in humans – and information integration (II) abilities – which they presume to be used by pigeons. As they claim, prior research has shown that whilst there is a time gap in human learning RB and II tasks former taking longer for pigeons such gap is not observed. The authors used an instance of a model provided in [7] to model pigeons studying dynamics and concluded that for modeling categorization in pigeons it is sufficient to use a model of associative learning, which generally means remembering categorized stimuli and basing new decisions on how close the provided stimulus is to the one remembered, since the observed on actual pigeons lack of the gap was present for the model as well.

In [7] the authors author proposed a unified framework for two learning dynamics: associative and strength-based learning. The associative learning is practically basing the decision of a category on presented instances and how close the studied stimulus is to them, the decision is made with the following probability:

$$A_{t,c} = \frac{\sum_{i \in c} a_{t,i}}{\sum_j a_{t,j}}$$

here $a_{t,j}$ – is a function of distance between j – representational point – and stimulus provided on take t, naturally $a_{t,j} \sim \exp(-\delta d_{j,t})$ and δ is a slope parameter.

Whilst strength-based resembles actually developing a rule for categorization. So the author tried to unify the two into a model in which associative and rule-based learning approaches are extremes and varying constants one could get an integration of the two. This article is interesting since it provides detailed explanation of plausible categorization models and can serve as foundation for creating more advanced categorization models. Practically, the learning rule would be:

$$P_{t+1} = SP_t + \alpha[K(X_t|e_t, \delta)\mathbf{1}_{(1\times C)}] \cdot [f_t \mathbf{1}_{1\times N_t} - \omega P_t],$$

where

$$K(X_t|e_t, \delta) = \exp(-(\delta|X_t - e_t|)$$

is a similarity kernel between X_t – stored representational data points, and e_t – stimulus provided on trial t, f_t – correct category assignment – they choose

one-hot-encoding for categories. S is interactions matrix which is diagonal unless states of the category representations can directly affect one another. ω is a parameter used to switch between strength representational model $\omega = 0$ and similarity infused Rescorla-Wagner model when $\omega = 1$. This model seems interesting to examine as a candidate for further research on feature selection.

As for the feature selection itself it seems prominent to start with the convolutional networks since this is not only a generally great way to process visual information that is biologically plausible and inspired but also as stated in [1] integrating cognitively motivated constraints on the model results in better performance of CNNs so it seems that biologically plausible categorization layer could be finely complemented by the feature selection trough convolution images viewed.

3 Conclusion

Categorization is a vital part of mental activity which is not bound to speech and presents itself in avian species as well as in mammalian. Birds are generally great model organisms for studying this ability since not only do they present with great vision but also their brain is an outstanding example of parallel evolution. Great part of all categorization models are based on common elements theory which states that stimuli that can be placed in the same category must present greater number of common elements compared to those from different categories. The provided articles serve as a great introductory point for studying categorization and supply with detailed explanations of already existing models which can be implemented for further research on feature selection in categorization or serve as a base for other models.

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