Syntax and Hierarchy in Animal Behavioral Structure

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Introduction

Neuroscientists and computer scientists, alike, have long attempted to explain how the brain gives rise to behavior. But doing so requires a careful dissection of behavioral structure so that neuroscientists can align descriptions of neural data alongside behavioral observations.

Objective

Our goal is to capture behavioral structure and gain insight into the syntax that is associated with behavior. We are especially interested in decomposing behavior into separable modules that form a behavioral hierarchy.

Method

Six mice were exposed to an open-field for one hour. Using B-SOiD, an open-source unsupervised algorithm for behavioral identification, we label videos of mice using eleven distinct behaviors. We use these labels to study behavioral structure through a Markov model and formal language.

Results

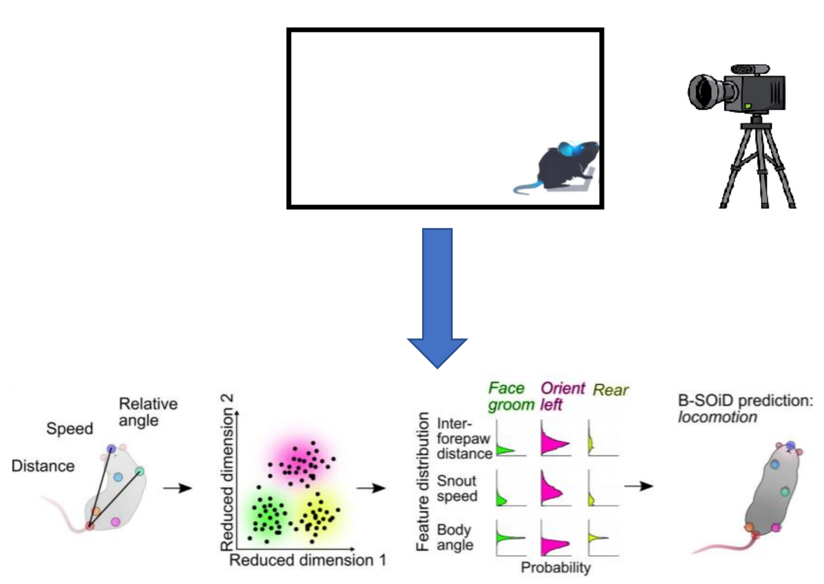
Using a Markov Model, we are able to capture of syntax and repetitive structure in behavior. Moreover, we design an algorithmic procedure using grammar inference to derive a set of behavioral motifs. These motifs are candidates for the separable modules that make up a behavioral hierarchy. We show that the set of motifs that best captures behavioral variation are both infrequent and correlated.

1. Experimental Procedure

Open Field Task

Six C57BL/6 mice were introduced to a novel 15 by 12 inch rectangular arena. Video recordings were captured at 60 Hz with a 1280x720 video camera.

Behavioral Labelling using B-SOiD



Source: Hsu & Yttri, 2021

Letter/Number	Behavior
a/1	Pause
b/2	Nose Poke
c/3	Rear
d/4	Wall Rear
e/5	Body Lick
f/6	Head Groom
g/7	Face Groom
h/8	Paw Groom
i/9	Orient Left
j/10	Orient Right
k/11	Locomote

Post-Processing Steps:
(1) Remove Self-Transitions
(2) Linear Smoothing

2. Markovian Model of Behavior

Let X_t be a discrete-time Markov Chain with states given by B-SOiD labels, irreducible transition matrix P. The hitting time for a state i is a random variable given by

$$\tau_i = \inf\{t \geq 1 \mid X_t = i\}$$

We then further define a matrix Q and A

$$Q_{ij} = \Pr_i(\tau_j < \tau_i)$$

$$A_{ij} = \begin{cases} \sqrt{Q_{ij} Q_{ji}}, & i \neq j \\ 1, & i = j \end{cases}$$

Our distance metric (Boyd et al., 2021) is then:

$$d(i,j) = -\log(A_{ij})$$

2. Markovian Model of Behavior (cont.)

A small distance between two fixed states i, j indicates that sequences of the form:

$$i \to a \to j \to b \to i$$
$$j \to a \to i \to b \to j$$

are probable where a, b are arbitrary sequences of states. Figure 1 depicts how behavioral states relate to each other.

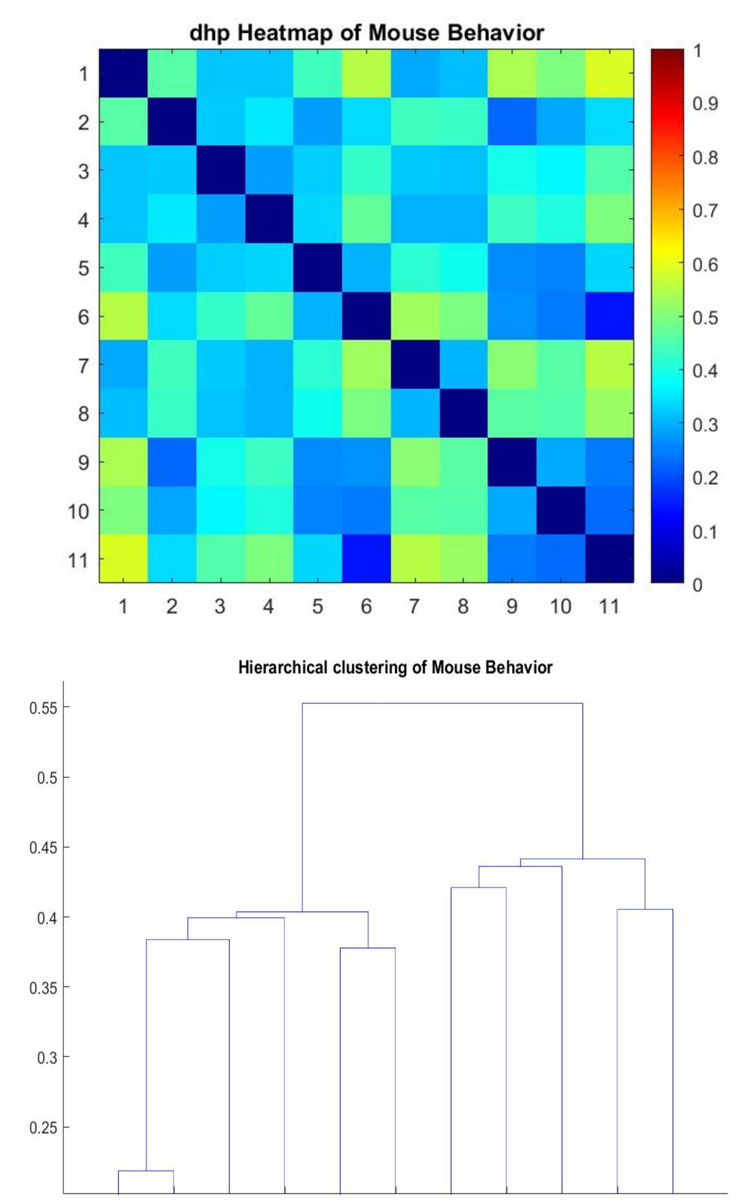


Figure 1: (Top) Pairwise distances between behavioral states (Bottom) Hierarchal Clustering of Behavioral States

3. A Behavioral Language

We treat behavioral sequences as strings by letting B-SOiD's labels be an alphabet. Using an n-gram language model we find that mouse behavior is highly repetitive (see Figure 2).

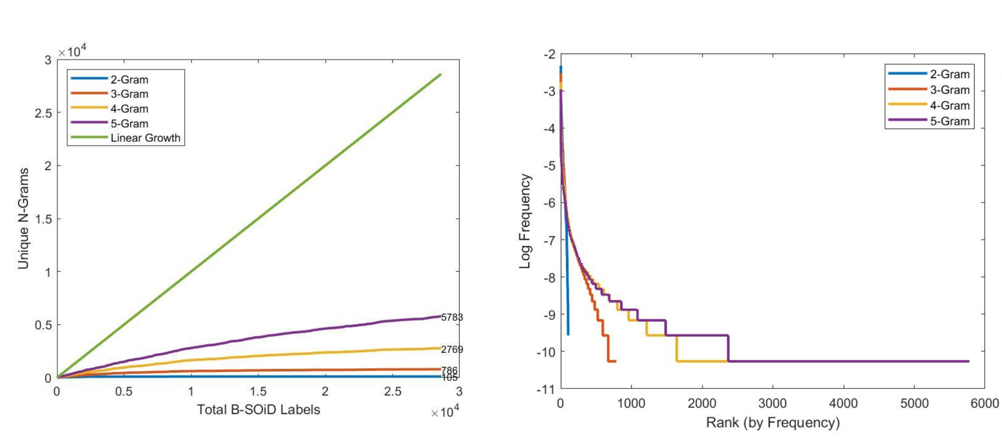
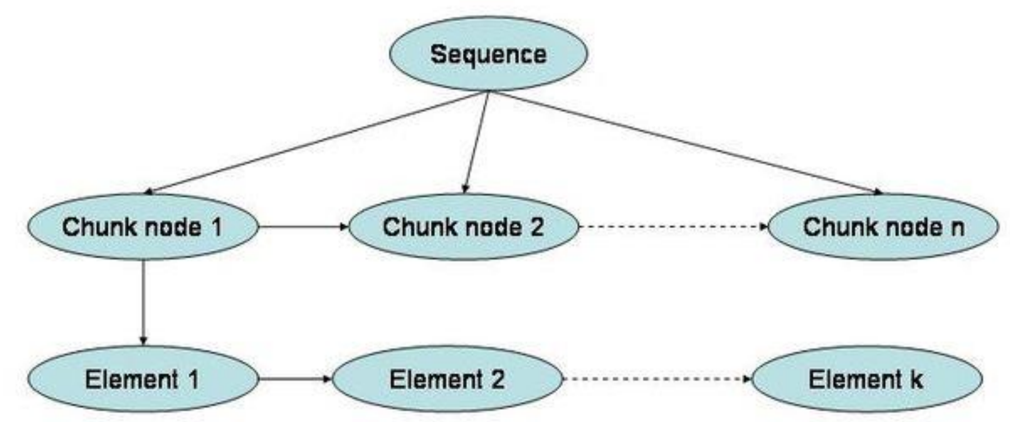


Figure 2: (Left) Unique N-Gram growth grows sub-linearly with respect to input indicating n-grams are repetitive (Right) Frequent N-Grams are characterized by a small subset of N-Grams

4. A Behavioral Hierarchy

Behavior has a hierarchal structure where units of behavior are composed of nested sub-units that are stereotyped and correlated with each other.



5. The Search for Behavioral Motifs

Repeated and correlated patterns of behavior, or motifs, make great candidates for being the separable modules in behavior.

Multivariate Generalization of Mutual Information

We quantify the degree of correlation shared by a set of random variables: $x_1, x_2, \ldots, x_n$ with an adjusted version of specific correlation that corrects bias for low frequency events:

$$SI(x_1, \ldots, x_n) = \log\left(\frac{p(x_1, x_2, \ldots, x_n)}{\prod_{i=1}^{n} p(x_i)}\right) + p(x_1, x_2, \ldots, x_n)$$

Our Algorithmic Approach to Finding Motifs

We adapt the use of *Sequitur*, a linear-time algorithm that infers a context-free grammar to find approximate variable length behavioral motifs. We take a grammatical approach because production rules can represent sequences of variable length, enabling variable length motif discovery. Additionally, grammar more easily reveals hierarchal structure (Li & Lin, 2010)

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Algorithm 1 Finding Behavioral Motifs
  Input: Labels - Sequence of Discrete Behavioral Labels
  Output: Motifs - Set of Behavioral Motifs
Rules ← Sequitur(labels)
Rules ← FilterFrequency(Rules)              ▷ Remove Infrequent Motifs
Rules ← FilterLength(Rules)                 ▷ Remove Long Motifs
Threshold ← [T1, T2, ..., T100]
RandLabels ← Randomly Shuffle Labels
for k < 100 do
    From RandLabels, create distribution of correlation metric for k-length
subsequences
    Threshold[k] ← value at 99.9% percentile of distribution
end for
Motifs ← FilterCorrelation(Rules, Threshold)    ▷ Remove Motifs Below
Threshold
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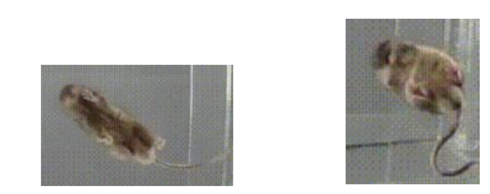
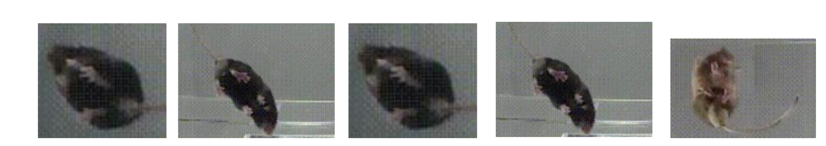
5. The Search for Behavioral Motifs (cont.)

Example Frequent Motif



Example Correlated Motif



Motifs Reveal Natural Variation in Behavior

A set of rare but correlated behavioral sequences best capture variation in behavior (see Figure 3).

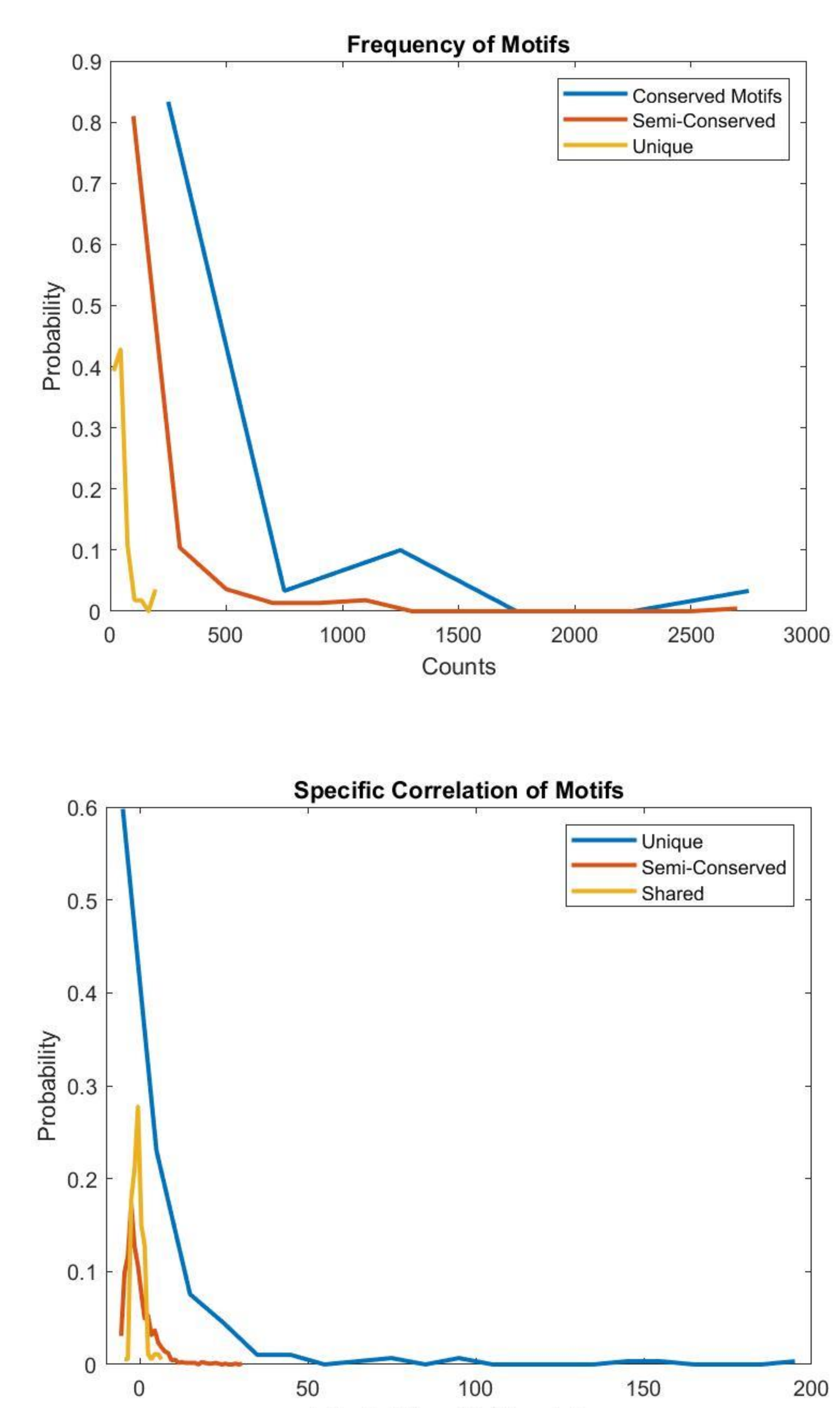
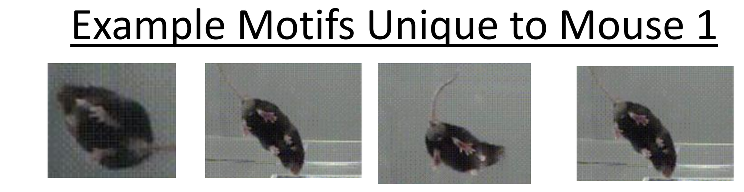


Figure 3: (Top) Frequency Distributions of Motifs. (Bottom) Distribution of adjusted specific correlation of Motifs. Here, conserved motifs are shared among all animals, semi-conserved motifs are shared among at least two animals but not all, and unique motifs are specific to one animal.

5. The Search for Behavioral Motifs (cont.)

Example Motif Shared Among Mice

Example Motifs Unique to Mouse 1



6. Future Work

Combining Behavioral with Neural Data

Integrating our behavioral work with neural recordings taken during the open-field task will enable analysis into how neural activity gives rise to behavioral structure. Such studies can also answer whether or not behavioral motifs are **neurologically** meaningful as we have no ground truth for which to compare these sequences to.

Characterizing Disease's Effects on Behavior

With a means to capture behavioral structure, we can look to understand how behavior changes with respect to disease. For example, we can better understand the effects that OCD, Parkinson's, and other disorders have in shaping behavior.

7. Acknowledgements

I would like to thank my advisors: Dr. Leila Wehbe and Dr. Eric Yttri as well as Alex Hsu and Alex Hodge from the Yttri Lab for their assistance throughout this project. Additionally, I would like to thank CMU URO for providing me funding for my project over the years.

8. References

Boyd, Z. M., Fraiman, N., Marzuola, J., Mucha, P. J., Osting, B., & Weare, J. (2021). A metric on directed graphs and Markov chains based on hitting probabilities. *SIAM Journal on Mathematics of Data Science*, *3*(2), 467-493.

Hsu, A. I., & Yttri, E. A. (2021). B-SOiD, an open-source unsupervised algorithm for identification and fast prediction of behaviors. *Nature communications*, *12*(1), 1-13.

Li, Y., & Lin, J. (2010, July). Approximate variable-length time series motif discovery using grammar inference. In *Proceedings of the Tenth International Workshop on Multimedia Data Mining* (pp. 1-9).