Sensitivity to network structures via associate learning in sleeping neonates

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Abstract

Extracting structural patterns is essential for all humans to make sense of the world - particularly so for infants, who must decipher language to acquire it. While it has been shown that infants can learn both low-level statistical regularities and higher-order structures, the neural mechanisms supporting these learning processes remain underexplored. A recent study in adults suggests that a low-level associative mechanism may underlie both types of learning. In this study, we investigated whether a similar mechanism is present in neonates by examining their ability to encode network structures in auditory sequences during sleep. We passively presented them with sequences of tones organised in a community network structure while recording their brain activity using electroencephalography (EEG). The preliminary results of our pilot analysis using multivariate pattern analysis (MVPA) reveal that we can successfully decode the network structure at the individual level. Complementary analysis should confirm these findings at the group level. This study offers insights on the neural mechanisms behind complex structure sensitivity, potentially bridging our understanding of the learning mechanisms at different orders of structure in a unified theoretical framework.

Keywords: network; associative learning; EEG; infant; MVPA.

Introduction

Researchers have long been captivated by the remarkable efficiency and systematicity with which infants acquire language, viewing it as a key case to investigate how the human brain uncovers regularities across multiple levels of structure (Dehaene et al., 2015). Many studies in adults have shown that we are sensitive to different orders of regularities ranging from local statistics between adjacent items to global higher-order regularities such as networks for example (Lynn et al., 2020; Stiso et al., 2022). However, whether tracking regularities across different ranges necessarily involve separate brain processes remains an open question, with a growing body of research arguing that Bayesian models and other statistical frameworks may be sufficient to explain higher-order sensitivity (Frank et al., 2010). Supporting this view, recent work in adults using behavioural and MEG data (Benjamin et al., 2023, 2024) suggests that a low-level associative learning mechanism, consistent with the free energy minimization model (FEMM) (Lynn et al., 2020) - described as a linear combination of transition probabilities across all orders, with an exponential decreasing weight associated with higher orders- could explain both statistical and network learning.

Building on this, and knowing that infants learn statistical regularities not only between adjacent items (Bulf et al., 2011; Saffran et al., 1996), but also non-adjacent items (Fló et al., 2019; Fló, Benjamin, et al., 2022), we wanted to investigate whether sleeping neonates could be sensitive to network structures through a similar associative mechanism.

To do so, we passively presented 40 neonates with sequences of tones generated through a structured random walk within a two-cluster network, while recording their brain activity using EEG. We used MVPA to determine whether they successfully encode the network's underlying structure.

Methods

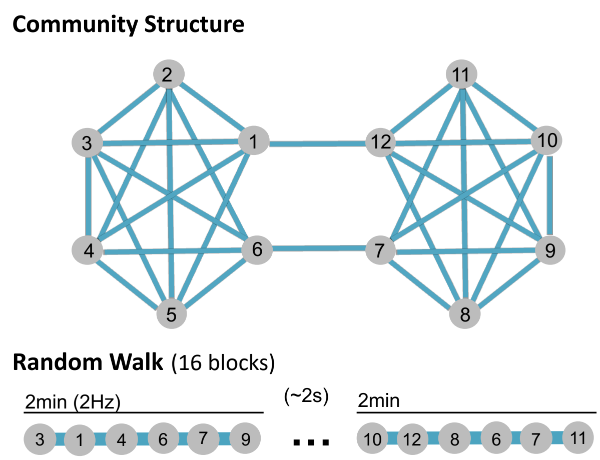

Figure 1: Network community paradigm.

Stimuli

The stimuli are adapted from (Benjamin et al., 2023). We generated twelve tones of 50ms duration, logarithmically distributed from 300 to 1800 Hz. For each participant, the twelve tones were randomly assigned to the twelve nodes of a network (figure 1) composed of two clusters (communities) of six nodes. We created a long sequence of 3840 tones – tones being played every 500ms (2Hz)- by performing a random walk in this network, resulting in a sequence with uniform transition probability (TP) between successive tones (all TP = 1/5).

Participants

3 (out of 40 expected) full-term neonates between days 1 and 3, raised in a French speaking environment at majority were tested. The participants

were recruited on a voluntary basis at the hospital maternity ward. The study was approved by the regional ethical committee for biomedical research, and the parents give their written informed consent for the protocol.

EEG Procedure & Recording

The 128-channel-electroencephalogram (EEG) net was placed on the infant head relative to anatomical marks, with the infant held by the experiment and installed on a cushion in a soundproof and dark room. The auditory sequences were displayed for around one hour. Artifact rejection was performed on the non-epoched continuous recording session using APICE pipeline (Fló, Gennari, et al., 2022).

Decoding methods

We performed time-resolved MVPA by training a logistic regression decoder on short epochs of 700ms ([-0.1, 0.6]), divided into windows of 20ms, and "micro-averaged" (Gennari et al., 2021; Grootswagers et al., 2017). We conducted the decoding analysis generalization across time (GAT) of the decoder to assess the stability of the mental representation. All preliminary results presented here were carried out on a single infant. For the Riemannian decoding, we used the XDawnCov pipeline to compute the covariance estimation of each epoch. We projected them on the space tangent to the Riemannian manifold, and used this projection (instead of the neural data) as input of the logistic regression decoder.

Preliminary results (N=1)

First, we verified that we could decode low-level features in the neural response at the individual level, such as the relative pitch of the tones (high vs low) or the identity of the 12 tones (figure 2, left).To examine whether the brain encoded the community structure as we expect, we then decoded whether the transition that just occurred remained within a community (Within) or switched between communities (Between) (figure 2, right). At the individual level, we found above chance decoding scores, suggesting that the infant brain is indeed sensitive to the network structure.

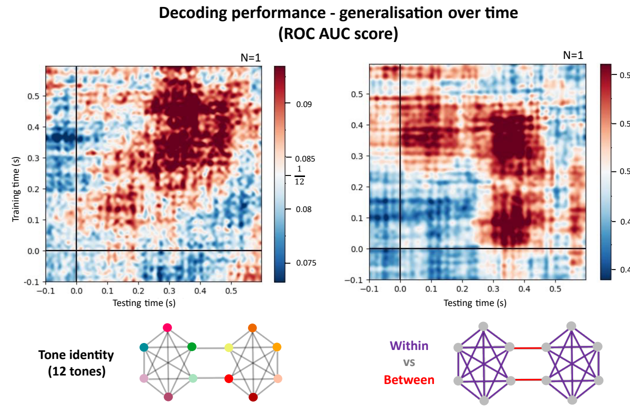

Figure 2: Preliminary decoding results on a single subject: performance (ROC AUC) on classifying the tone identity (left) and within vs between (right).

Expected results (N=40)

Decoding network structure

We will test the sensitivity to the network structure at the group level by performing the same decoding analysis (within/between) and assess the statistical significance of the results.

To eliminate low-level confounds, for example decoding the identity of the tone rather than Within/Between community, we will also run the same decoding analysis by restricting it to only one of the four nodes at the border of the community. Similarly, to control for previous tone identity confound, we will run the analysis on epochs where the transition began with one of these four nodes.

Finally, because of sleeping patterns in neonates, the responses may not be time-locked and therefore may not be captured by time-resolved MVPA. To palliate this problem, we will also use Riemannian geometry classification (Barachant & King, 2017; Simar et al., 2022) to decode Within/Between transitions.

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