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Functional brain networks for learning predictive statistics

Joseph Giorgio ^a, Vasilis M. Karlaftis ^a, Rui Wang ^{a,b}, Yuan Shen ^{c,d}, Peter Tino ^d, Andrew Welchman ^a and Zoe Kourtzi ^{a,*}

^a Department of Psychology, University of Cambridge, Cambridge, UK

^b Key Laboratory of Mental Health, Institute of Psychology, Chinese Academy of Sciences, Beijing, China

^c Department of Mathematical Sciences, Xi'an Jiaotong-Liverpool University, Suzhou, China

^d School of Computer Science, University of Birmingham, Birmingham, UK

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ABSTRACT

Making predictions about future events relies on interpreting streams of information that may initially appear incomprehensible. This skill relies on extracting regular patterns in space and time by mere exposure to the environment (i.e., without explicit feedback). Yet, we know little about the functional brain networks that mediate this type of statistical learning. Here, we test whether changes in the processing and connectivity of functional brain networks due to training relate to our ability to learn temporal regularities. By combining behavioral training and functional brain connectivity analysis, we demonstrate that individuals adapt to the environment's statistics as they change over time from simple repetition to probabilistic combinations. Further, we show that individual learning of temporal structures relates to decision strategy. Our fMRI results demonstrate that learning-dependent changes in fMRI activation within and functional connectivity between brain networks relate to individual variability in strategy. In particular, extracting the exact sequence statistics (i.e., matching) relates to changes in brain networks known to be involved in memory and stimulus-response associations, while selecting the most probable outcomes in a given context (i.e., maximizing) relates to changes in frontal and striatal networks. Thus, our findings provide evidence that dissociable brain networks mediate individual ability in learning behaviorally-relevant statistics.

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1. Introduction

Successful interactions in a new environment entail interpreting initially incomprehensible streams of information and making predictions about upcoming events. The brain is

thought to succeed in this challenge by finding regular patterns and meaningful structures that help us to predict and prepare for future actions. This skill is thought to rely on our ability to extract spatial and temporal regularities, often with minimal explicit feedback (Aslin & Newport, 2012; Perruchet & Pacton, 2006). For example, previous behavioral studies have

* Corresponding author. Department of Psychology, University of Cambridge, Cambridge, UK.

E-mail address: zk240@cam.ac.uk (Z. Kourtzi).

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shown that structured patterns become familiar after simple exposure to items (shapes, tones or syllables) that co-occur spatially or follow in a temporal sequence (Chun, 2000; Fiser & Aslin, 2002; Saffran, Aslin, & Newport, 1996; Saffran, Johnson, Aslin, & Newport, 1999; Turk-Browne, Junge, & Scholl, 2005).

Functional imaging studies have identified key brain regions involved in the learning of statistical regularities. In particular, striatal and hippocampal regions have been implicated in the learning of temporal sequences (Aizenstein et al., 2004; Gheysen, Van Opstal, Roggeman, Van Waelvelde, & Fias, 2011; Hsieh, Gruber, Jenkins, & Ranganath, 2014; Rauch et al., 1997; Rose, Haider, Salari, & Buchel, 2011; Schendan, Searl, Melrose, & Stern, 2003). Further, the medial temporal cortex has been implicated in learning of probabilistic associations (Schapiro, Kustner, & Turk-Browne, 2012; Turk-Browne, Scholl, Johnson, & Chun, 2010). However, we know little about the functional brain networks and their interactions that mediate statistical learning of temporal structures.

Recent functional connectivity studies provide accumulating evidence for learning-dependent changes in human brain networks due to training in a range of tasks including visual perceptual learning (Baldassarre et al., 2012; Lewis, Baldassarre, Committeri, Romani, & Corbetta, 2009), motor learning (Bassett et al., 2011; Ma, Narayana, Robin, Fox, & Xiong, 2011; Sun, Miller, Rao, & D'Esposito, 2007), auditory learning (Ventura-Campos et al., 2013) and language learning

(Veroude, Norris, Shumskaya, Gullberg, & Indefrey, 2010). These studies typically involve prolonged training with feedback. Here we ask whether mere exposure to streams of information (i.e., without trial-by-trial feedback) changes processing in functional brain networks that mediate our ability to extract statistical regularities.

We combine behavioral measurements and multi-session fMRI (before and after training) to investigate processing in functional brain networks that mediate statistical learning of temporal structures. Event structures in the natural environment typically contain regularities at different scales from simple repetition to probabilistic combinations. To investigate the brain networks involved in extracting such structures unencumbered by past experience, we generated temporal sequences based on Markov models of different orders (i.e., context lengths of 0 or 1 previous item) (Fig. 1). We exposed participants to sequences of unfamiliar symbols and varied the sequence structure unbeknownst to the participants by increasing the context length. To facilitate learning, sequences were first determined by frequency statistics (i.e., occurrence probability per symbol), and then by context-based statistics (i.e., the probability of a given symbol appearing depends on the preceding symbol). Participants performed a prediction task, indicating which symbol they expected to appear next in the sequence. Following previous statistical learning paradigms, participants were exposed to the sequences without trial-by-trial feedback. We tested for improvement in the prediction

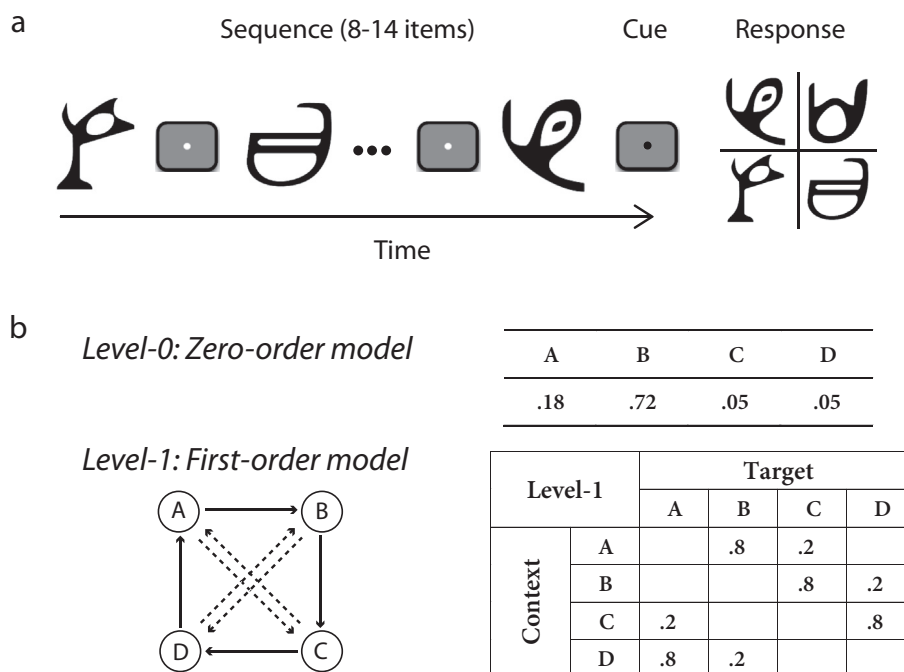


Fig. 1 – Trial and sequence design. (a) The trial design: 8–14 symbols were presented sequentially followed by a cue and the test display. (b) Sequence design: Markov models of the two context-length levels. For the zero-order model (level-0): different states (A, B, C, D) are assigned to four symbols with different probabilities. For the first-order model (level-1), diagrams indicate states (circles) and conditional probabilities (solid arrows: high probability; dashed arrows: low probability). Transitional probabilities are shown in a four-by-four (level-1) conditional probability matrix, where rows indicate the context and columns the corresponding target.

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