Feedback-driven trial-by-trial learning in autism spectrum disorders

Marjorie Solomon, Ph.D.[1,2,3]; Michael J. Frank, Ph.D.[4]; J. Daniel Ragland, Ph.D.[1,3]; Anne C. Smith, Ph.D.[5]; Tara A. Niendam, Ph.D.[1,3]; Tyler A. Lesh, Ph.D.[1,3]; David Grayson, B.S.[2,6]; Jonathan S. Beck, B.S.[1,2]; John C. Matter, B.S. [1,2]; Cameron S. Carter, M.D.[1,3]

[1]University of California, Davis, Department of Psychiatry & Behavioral Sciences, [2]MIND Institute, [3] U. C. Davis Imaging Research Center, [4]Brown University, Cognitive, Linguistic, & Psychological Sciences [5]University of Arizona, [6]University of California, Davis, Center for Neuroscience.

Supplemental Data

Analysis of Behavioral Data

Raw data

Raw binary response data for each subject of each group for each of the three tasks is shown in Figure A1 (a correct response is green and an incorrect response is red).

We wish to estimate how learning differs between groups.

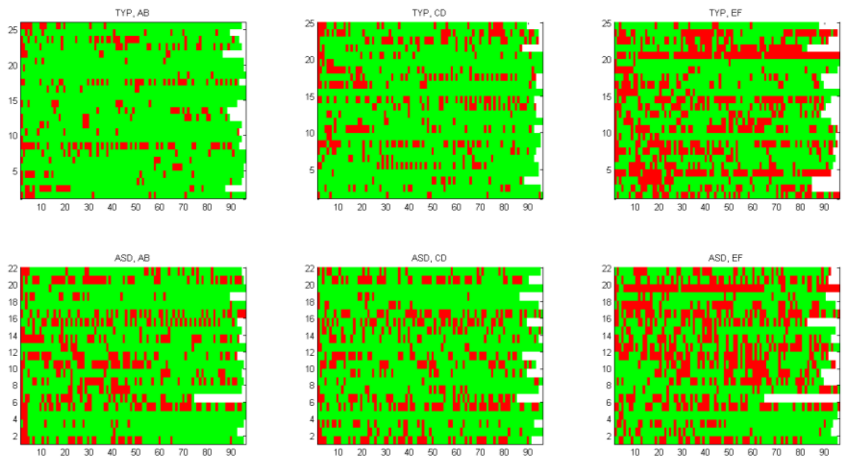

Figure S1. Raw learning data for all subjects across trials. Red squares indicate incorrect responses and green squares indicate correct. Top row are TYP subjects and bottom row are ASD subjects.

Visual inspection of the results for TYP and ASD for the AB task indicates poorer performance for the ASD group (top figure vs. bottom figure in left column, Figure A1).

Learning Model

The between group comparison in Figure 2 was computed with the state-space model approach described in detail in Smith et al. (2004) and using the Bayesian estimation methods described in Smith et al. (2007) (software available from http://www.neurostat.mit.edu/behaviorallearning).

State-space models work under the assumption that trial-by-trial observations of task performance are a noisy approximation of an underlying smooth cognitive state. They consider trial-by-trial performance within the context of the entire task, provide a more accurate means of determining whether learning has occurred than other methods, and have become a widely accepted way to conceptualize animal and human learning, where they have been used as parametric modulators in fMRI analyses to illuminate brain regions associated with the probability of having learned because they provide trial by trial learning estimates and model situations when learning is very rapid when the “light goes on” and the learning curve becomes asymptotic, and/or when performance drops due to inattention.

The state-space model can be represented by a state equation and an observation equation (Kitagawa & Gersch, 1996). The state equation defines the temporal evolution of task learning and is assumed to follow a Gaussian random walk. The observation equation relates the state to the observations using a binomial probability distribution. It is referred to as an ideal observer approach because it computes the learning curve fit to all the data over all time, in contrast to a causal filter approach. The model is estimated using Markov chain Monte Carlo methods (A. C. Smith, Wirth, Suzuki, & Brown, 2007).

Specifically, the observation for each group at trial $k = 1, \ldots, K$ is the number of correct responses n_k out of m_k trial outcomes from the whole group. The observation model is

$$\Pr(n_k \mid p_k, m_k) = \binom{m_k}{n_k} p_k^{\,m_k} (1 - p_k)^{m_k - n_k}$$

where p_k is the probability of a correct response at trial k. We relate p_k to the state, x_k, at trial k using the logistic equation

$$p_k = \frac{\exp(x_k)}{1 + \exp(x_k)}$$

and assume the state follows a random walk

$$x_k = x_{k-1} + \varepsilon_k$$

where ε_k is Gaussian noise with mean 0 and precision (=inverse variance) τ. We assume priors on the initial state $x_0 \sim \mathrm{N}(0, \tau)$ and on the precision $\tau \sim \mathrm{dgamma}(5, 1)$. The distribution of p_k is estimated for each group using the free software WinBUGS (Lunn et al., 2000) which uses MCMC methods to estimate samples from the posterior distribution. To compare groups, we compare samples from these two distributions.

References

Lunn DJ, Thomas A, Best N, Spiegelhalter D. WinBUGS - A Bayesian modelling framework: Concepts, structure, and extensibility. Stat Comput. 2000;10(4):325-37.

Smith AC, Frank LM, Wirth S, Yanike M, Hu D, Kubota Y, Graybiel AM, Suzuki WA, Brown EN. Dynamic analysis of learning in behavioral experiments. Journal of Neuroscience 2004; 24(2): 447-461.

Smith AC, Wirth S, Suzuki WA, Brown EN. Bayesian analysis of interleaved learning and response bias in behavioral experiments. Journal of Neurophysiology, 2007, 97(3): 2516-24.