Computational Model Supplemental Material

The model we developed has a variable determining the probability of producing a speech-related vocalization vs. a non-speech-related vocalization, $P(sp)$. $P(nsp)$ is the probability of producing a non-speech-related vocalization and $P(sp)$ and $P(nsp)$ sum to 1. A fixed number of vocalizations are produced per day, N_d. Each time it vocalizes, the vocalization is chosen at random to either be speech-related or not-speech-related; the probability of randomly being chosen to be speech-related is the model's current $P(sp)$. If the vocalization is speech-related, whether or not it receives a response is also determined probabilistically, based on the constant value, $P(r|sp)$; if the vocalization is not speech-related, the response probability is $P(r|nsp)$. If a vocalization is speech-related and receives a response then $P(sp)$ is incremented by a fixed small amount (.000003 is added to $P(sp)$, then $P(sp)$ and $P(nsp)$ are normalized). If a vocalization is not speech-related and receives a response then $P(sp)$ is decremented by a fixed small amount (.000003 is subtracted from $P(sp)$, then $P(sp)$ and $P(nsp)$ are normalized). If a vocalization does not receive a response, then no change is made to $P(sp)$.

We set N_d, $P(r|sp)$ and $P(r|nsp)$ according to the mean values actually observed in for the TD and ASD groups in the matched subsample recordings: for TD, $N_d = 2592$, $P(r|sp) = .209$, and $P(r|nsp) = .144$; for ASD, $N_d = 2123$, $P(r|sp) = .197$, and $P(r|nsp) = .148$. The learning rate parameter, .000003, was selected by trial and error until an approximate match to the human children's $P(sp)$ at about 4 years of age was achieved. Model code and data can be found by unzipping the *Computational Model Code and Data Supplemental Material* or by contacting the first author.

100 simulations of each version of the model were each run for three years' worth of vocalization experiences. $P(sp)$ was initially set to .5. At the end of the three years, the TD version of the simulation had a mean $P(sp)$ of .826 (95% confidence interval = [.825,.828]). The ASD version had a mean $P(sp)$ of .730 (95% confidence interval = [.728,.731]). Comparing these to the values in Fig. 3, these differences are of the same order of magnitude as the actual differences we observed between the TD and ASD groups at about four years old in their proportions of vocalizations that were speech-related.

Versions of the model with TD child vocalization rate and ASD adult response probabilities and vice versa were also run in order to determine the effects of each factor independently. The simulations with ASD N_d and TD response probabilities exhibited an average final $P(sp)$ of .782 (95% confidence interval = [.780,.784]), which was intermediate between the full ASD and full TD versions of the model. The simulations with TD N_d and ASD response probabilities also exhibited intermediate final outcome, $P(sp)$ = .769 (95% confidence interval = [.767,.771]). This suggests that child vocalization rate and adult response contingency both play a role in the effectiveness of the feedback loop.

Interestingly, if the learning rate was increased, we were able to obtain statistically significant contingencies of the model's vocalization type on whether the previous speech-related vocalization received a response, similar to what we found in the daylong child recordings. However, for this contingency to become apparent, the learning rate had to be so fast that the model increased its rate of speech-related vocalization much faster than the human children did. This suggests the model is not a perfect fit to the way children learn; in reality children's learning process may have both a fast short-term component and a slower long-term consolidation component; this would be an interesting topic for future study.

Our computational model was inspired by the Rescorla-Wagner model (Rescorla & Wagner, 1972; Ramscar, Yarlett, Dye, Denny, & Thorpe, 2010; Ramscar, Dye, & Klein, 2013; Ramscar, Dye, Gustafson, & Klein, 2013) and by the Q-learning reinforcement learning method (Sutton & Barto, 1998). The Rescorla-Wagner model has previously been shown to be a good fit to data from children and adults performing word learning, specifically feature-label mapping, tasks (Ramscar et al., 2010; Ramscar, Dye, & Klein, 2013). However, when we adapted it to operant learning using adult response contingencies from our daylong recordings, the model converged on matching of speech-related vocalization probability to the adult response rates. This didn't fit the pattern we observed for children's vocalizations, which are more heavily biased toward being speech related. On the other hand, Q-learning converged almost immediately on always producing speech-related vocalizations, which also did not match the pattern we observed for child data. The model we ended up developing, described above, falls between these two extremes.

References

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