Languages evolve as they pass through generations of learners’ minds (Kirby, 2001) and adapt to selection pressures exerted by our cognitive architecture and learning biases. An important feature of human languages is their striking regularity (Chambers et. al., 2003). Language learners exhibit a strong regularization bias which can be observed naturally in language contact situations (Bickerton, 1984), and in the laboratory with artificial language learning experiments (Reali & Griffiths, 2009). The nature of this linguistic regularization bias has been heavily debated: some argue for domain-general causes such as memory limitations (Hudson Kam & Chang, 2009) and others argue for domain-specific biases regarding linguistic stimuli (Bickerton, 1984).

Across four experimental conditions, we quantify the contribution of domain-general factors (due to different frequency learning demands) and domain-specific factors (due to a linguistic and non-linguistic framing of the task) to adult learners’ linguistic regularization bias. 512 participants took part in a basic frequency learning task over the internet, where they either observed two different marbles being drawn from a container in a particular ratio, or two different words being used to name an object in a particular ratio. This constituted the domain manipulation.

For the demand manipulation, participants in the low-demand condition observed 10 marble draws/naming events for one container/object. Then in a testing phase, they were asked to produce some more representative marble draws/naming events. 10 responses were collected. In the high-demand condition, each participant observed 10 events per 6 different container/objects. Each container/object was associated with a unique ratio: 0:10, 1:9, 2:8, 3:7, 4:6, 5:5. During testing, participants produced some more representative marble draws/naming events per container/object. A total of 60 responses were collected: 10 per container/object. In the low-demand condition, each participant was randomly assigned one of the ratios above. Training and testing ratios are compared per participant and the difference in entropy of these two ratios is computed. Regularization behavior is
defined by a drop in testing ratio entropy.

Condition 1 (low demand, non-linguistic) elicited clear probability matching behavior. Condition 2 (high demand, non-linguistic) and 3 (low demand, linguistic) elicited similar, moderate amounts of regularization. Condition 4 (high-demand, linguistic) elicited strong regularization, constituting the full linguistic regularization bias typical of matched artificial language learning tasks (Reali & Griffiths, 2009). All differences between the amount of regularization per condition were significant to \( p < .001 \) (with the Wilcoxon rank sum test), except for the difference in regularity between conditions 2 and 3.

A mixed effects linear regression analysis showed a significant effect of domain on entropy scores, \( t(7) = -7.118, p < .001 \), demand on entropy scores, \( t(7) = -9.276, p < .001 \), and no significant interaction between domain and demand. This means that domain and demand independently contribute to learners’ full linguistic regularization bias. Furthermore, neither one of these factors were significantly better predictors of entropy scores in condition 4.

These results suggest that domain-general cognitive constraints on frequency learning and production, and domain-specific expectations about the regularity of linguistic stimuli, are of equal importance to the origin of regularity in language. In addition to being a traditional psychology experiment, this experiment was also designed so that the data collected would constitute an empirical transition matrix for each condition. Such matrices allow us to extrapolate a population of learner’s behavior forward in evolutionary time and obtain more information about the effects of these learning biases on regularization behavior. For example, the average convergence time (measured in generations of learners) to the equilibrium level of regularity per condition is much faster for demand-elicited regularization behavior. Such analyses have strong practical implications for experimental design in the iterated learning paradigm and we welcome discussion on these methods.

References


