# Probabilistic Learning and Complexity in Phonology 

Robert Staubs<br>University of Massachusetts Amherst

Learnability results offer a window on phonological typology: the frequency of a pattern might be predicted by the difficulty in learning it. Work on artificial language learning demonstrates differences in the learnability of patterns. Such work, however, assumes that the input to a learner is categorical. This contradicts the reality of learning, raising the question: are results in learning experiments robust under noise? I present an experiment replicating some categorical results of Moreton \& Pertsova (2012) in a probabilistic setting. This work suggests that some learning results are preserved when the assumption of categorical input is discarded.

The distinction between probabilistic and categorical learning is important to iterated learning models (e.g. Kirby 1999). One way to view such models is as repeated partial learning: each generation learns only partially, shaping typology as the cycle repeats. Such models rely on learners receiving probabilistic inputs while still adhering to learning biases. It is therefore necessary to confirm that these biases are similar in probabilistic and categorical domains.

A classic result in category learning is Shepard et al. (1961). The authors discuss a taxonomy of the six types of category which can be formed over elements described by three binary features. These are: patterns using only one feature (Type I), only two (Type II), usually two but sometimes three (Types III, IV, V), and three always (Type VI). Subsequent work suggests that relative learnability of types depends on the task (e.g. Love 2002) but work in category learning and phonological artificial language learning yields a partial order: I easier than II, II easier than VI (e.g. Saffran and Thiessen 2003, Pycha et al. 2003).

I adapt the design of Moreton \& Pertsova (2012). Subjects are randomly assigned to a language generated as a Shepard Type I, II, or VI. Words in the language are CVCV. Each segment has two features which may be manipulated to form the types. Subjects listen to and repeat 59 words 4 times. $76 \%$ of these words are in fact from their assigned language, the remaining words are chosen randomly from the space. Subjects perform a forced choice task: one word in the pair is in the target language, one is not. Both words are novel. Subjects choose the word they believe to be in the language learned. 61 subjects were included for analysis.

Summary results are in Table 1. Mean choice of the target language form was $56 \%$ for Types I and II, $53 \%$ for Type VI. This choice was analyzed with a mixed-effects logit model with Helmert coded Type predictors (Table 2). A main effect was found for the distinction between Types I/II and Type VI but not between Type I and Type II. Thus this learning paradigm shows similar, albeit smaller, biases to those observed in categorical conditions.

This experiment provides an instance in which categorical and probabilistic learning results are not contradictory. There is hope that categorical learning results are in general applicable to the more ecologically valid probabilistic setting. Future work will examine the robustness of subtler results in the face of variation.

## Tables

|  | $n$ | Mean Target | SE Target | Mean RT (ms) | SE RT (ms) |
| ---: | ---: | ---: | ---: | ---: | ---: |
| Type I | 21 | 0.575 | 0.063 | 1609.925 | 113.870 |
| Type II | 19 | 0.557 | 0.063 | 1726.185 | 115.593 |
| Type VI | 21 | 0.532 | 0.064 | 1687.638 | 120.205 |

Table 1. Primary experimental results

|  | Estimate | SE | $z$ | $p$ |  |
| ---: | ---: | ---: | ---: | ---: | ---: |
| intercept | 0.019 | 0.063 | 0.306 | 0.760 |  |
| Type I vs. Types II \& VI | -0.055 | 0.055 | -0.999 | 0.318 |  |
| Types I \& II vs. Type VI | -0.070 | 0.033 | -2.108 | 0.035 | $*$ |
| features on same segment | 0.188 | 0.118 | 1.586 | 0.113 |  |
| order of presentation | 0.328 | 0.079 | 4.132 | $3.6 \times 10^{-5}$ | $* * *$ |

Table 2. Regression

## References

Love, B. 2002. Comparing supervised and unsupervised category learning. Psychonomic Bulletin \& Review 2002, 9(4), 829-835.
Kirby, Simon. 1999. Function, selection and innateness: the emergence of language universals. Oxford: Oxford University Press.
Moreton, Elliott, and Katya Pertsova. 2012. Pastry phonotactics: Is phonological learning special? In 43rd Meeting of the North East Linguistics Society (NELS 43).
Pycha, A., P. Nowak, E. Shin, and R. Shosted. 2003. Phonological rule-learning and its implications for a theory of vowel harmony. In Proceedings of the 22nd West Coast Conference on Formal Linguistics (WCCFL 22), ed. M. Tsujimura and G. Garding, 101-114.
Saffran, J., and E. Thiessen. 2003. Pattern induction by infant language learners. Developmental Psychology 39: 484-494.
Shepard, R., C. Hovland, and H. Jenkins. 1961. Learning and memorization of classifications. Psychological Monographs 75(13, Whole No. 517).

