Does size matter? Regularization in different inventory sizes: experimental and typological evidence

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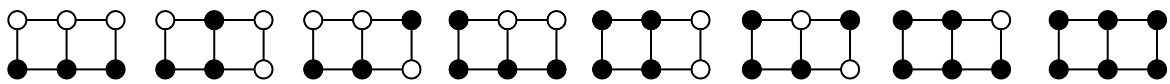
Over recent years, much attention has been devoted to the role that learnability plays in linguistic typology. Kirby et al. [1], for instance, argue that languages have evolved to be both expressive and compressible. This latter term is intimately related to the notion of regularity, i.e. the degree to which a certain system behaves predictably: the fewer exceptions a system has, the more compressible it is. Experimental work suggests that human learners have a regularity bias, and that they eliminate unpredictable variation [2, 3]; this preference is indeed attested in natural language [4, 5], although typology is obviously subject to more pressures than only learnability. In phonology, the idea that learning and typology are intertwined is hinted at by a.o. Martinet [6], but experimental and typological evidence has only begun to accrue much more recently [7, 8, 9].

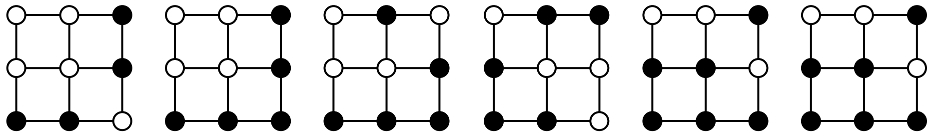
In an earlier study, we investigated the learnability of sound systems based on cross-linguistically frequent plosive inventories: these systems could be defined with one ternary contrast (such as place, e.g. labial vs. coronal vs. dorsal) and one binary contrast (such as voice, e.g. voiceless vs. voiced). Assuming that a language has at least three out of the six possible combinations, eight structurally different inventories or 'types' are possible, as shown in the figure below. Black circles indicate categories, i.e. feature combinations, that are present in the type; white circles indicate categories that are absent. Type (1a), for instance, has no voicing contrast, i.e. it represents inventories such as /p t k/ or /b d g/; type (1e) lacks one place of articulation, such as a language with /p t k g/. For each of the eight types, a complexity measure can be established to indicate its compressibility [10], as shown in the figure. A regular inventory is one that does not have exceptions or gaps, i.e. types (1aeh); regular systems are maximally compressible, yielding a complexity index of 1.



	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)	(1h)
cpx.	1	2	5	2	1	5	3	1

We conducted an implicit-learning experiment in which each participant ($n = 96$) acquired one of the types above, then performed a categorization task. In order to emulate *de novo* acquisition, and to avoid any interference from learners' phonological knowledge, we did not use speech categories as stimuli, but created an artificial sign language with identical structure: its categories could be defined as combinations of a ternary handshape contrast and a binary thumb opposition contrast. We established a negative correlation between complexity and correct categorization ($\rho = -.304$, $p = .003$), and found that learners significantly reduced the complexity of their inputs ($t = -3.135$, 95% CI -0.51 – -0.11, $p = .002$). Out of the 96 participants, 14 did not categorize their input correctly; all these 14 learners added unseen categories. Nine participants regularized their input, i.e. they filled all gaps. These results seem to support Kirby et al.'s hypothesis that the reduction of complexity happens in the learning process.

In order to explore the robustness of learners' regularizing behavior, we conducted a follow-up experiment in which we expanded the language by adding an extra feature value to the thumb opposition contrast, resulting in two ternary contrasts. Again assuming that a language has at least three categories, a total of 14 types can be drawn from this 3×3 space, in addition to the ones shown above. Of these 14, we selected the six types shown in the next figure: types (2aef) are equally complex, and types (2bcd) have the same number of categories.



	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)
cpx.	6	2	5	8	6	6

As in the first experiment, after a phase of implicit learning, participants (n = 72) performed a categorization task. Again, learners reduced the complexity of their inputs (t = -2.837, 95% CI = -0.87 – -0.15, p = .006), and while most miscategorizations again involved the introduction of unseen categories rather than the omission of seen categories, none of the learners regularized their input. It seems that in both experiments, learners reduced the complexity of their input by adding new categories; however, the apparent regularization in the first experiment may have been an artefact of the size of the search space — after all, regularity is much easier to achieve in a 3×2 space than it is in a 3×3 space.

We tested this hypothesis in a third experiment, in which participants (n = 40) were shown three irregular types, namely (1b), (1c) and (2a) from the figures above: the first occupies a 2×2 space, the second a 3×2 space, and the third a 3×3 space. For each type, learners saw the signs of that inventory plus two other signs, one of which would increase the complexity of the type when added, the other decrease it. Participants were asked to select the sign that they thought fit the language best. We found an effect of search space size on proportion of selected complexity-reducing signs, suggesting that learners are better at reducing complexity in smaller search spaces. This would readily explain why in [3], with its 2×2 design, regularization occurred easily, while irregularity does not seem to be rare in the sound systems of spoken languages, most of which are bigger than the inventories from our experiments. (It should again be noted that other pressures than learnability operate on the typology of sound systems: these tend to strike an optimal balance between auditory distinctiveness and articulatory ease [6, 11, 12].) We are currently testing the prediction that larger phoneme inventories are less likely to be regular than smaller inventories, by doing a typological survey in UPSID.

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