Compression without compromise

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Abstract:

Dubova and Sloman's framework assumes that representations trade fidelity for complexity. However, a species of representation prevalent in both minds and machines — lossless compression — enables perfect recovery while taking on a minimal structure with rich symbols. This form of representation crosscuts the proposed capacity regimes, reveals a challenge of reverse inference, and highlights a missing piece of the capacity puzzle.

Main text:

Try to remember the pattern in Figure 1A. This is trivially easy. Why? In theory, the image contains lots of raw information, yet we have no issue recalling or recreating the pattern perfectly.

Dubova and Sloman's (D&S) insightful taxonomy takes inspiration from computer science and denotes distinct learning regimes which might help us understand how this happens. *Constrained capacity* systems lack expressivity and thus "compress these experiences, effectively discarding details"; *sufficient capacity* systems offer just enough expressivity to perfectly memorize past experiences; and *excess capacity* systems deploy more representational resources than needed for memorization. D&S analyze signatures of these different regimes and arrive at a thought-provoking and surprising conclusion: Excess capacity systems capture many aspects of human cognition.

However, D&S overlook a type of representation prevalent in both minds and machines: lossless compression. These representations encode information both minimally and perfectly. Lossless compression algorithms find repeating primitives in data and then replace redundancies with compact codes (as in common ZIP algorithms in computers). For example, an algorithm of this kind might encode the string of characters '12345123451234512345' as '[12345] REPEAT 4'.

At first, lossless compression might seem like an idealization from computer science, but cognition engages in lossless compression in a variety of domains — e.g., concept learning (Feldman, 2000), similarity judgments (Hahn et al., 2003), and so on. Working memory research offers a particularly prominent example: A 'chunk' in working memory is a losslessly compressed unit (e.g., [12345] above, a sequence of motor actions in a dance, a series of steps in a recipe, etc.), and is often defined as such (Mathy & Feldman, 2012; see also Planton et al., 2021). Opportunities for chunking (and lossless compression more generally) present themselves whenever regularities occur in the environment, and the ability to create chunks emerges without formal instruction or explicit metamemorial strategies, as even infants chunk items in memory (Feigenson & Halberda, 2008; Moher et al., 2012; Rosenberg & Feigenson, 2013).

Now, consider the algorithms in Figure 1B, which offer compressed representations of the image in Figure 1A. Which of D&S's capacity regimes captures these algorithms? The answer seems to be "none of them" — but it might just as well be "any of them". Either way, this reveals a structural problem for D&S's framework. If the 'size' or complexity of a representation determines its capacity regime, then these representations fall under *constrained capacity* (as they encode less data than the stimulus itself). If the fidelity of a representation determines its capacity regime, then these representations fall under *sufficient capacity* (as they allow for perfect recovery). Finally, if the 'richness' of a representation determines its capacity regime, then these representations fall under *excess capacity* (as they "impose structure on the patterns implied by these representations", a signature that D&S assign to excess capacity systems). The underlying problem is that D&S's framework conflates representational complexity and representational fidelity: It assumes that compression (i.e., decreasing complexity or 'size') entails "discarding details deemed irrelevant" (i.e., decreasing fidelity or ability to fully recover an experience). Lossless compression, however, crosscuts the proposed regimes and offers a distinct mode of representation where a constrained representation facilitates perfect recovery through its use of rich, structured symbols. This conflation also creates an interpretive challenge for D&S's capacity regimes. If a single mode of representation arguably falls under any of the three capacity regimes, then it is difficult to diagnose a system's capacity regime by observing its behavior. In other words, a reverse inference problem emerges.

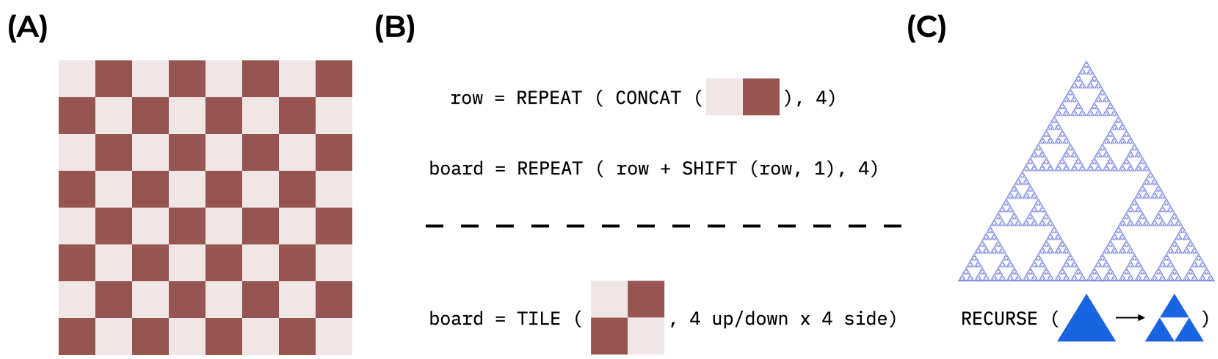

Figure 1. Efficient representation with lossless compression. (A) This pattern contains lots of raw 'information', but it is trivially easy to encode and remember. (B) Lossless compression offers one path to efficient representation of this image: The pattern contains substantial regularities and can thus be captured with a combination of simple primitives and operators. (C) Certain stimuli such as fractals (here, the Sierpinski triangle) may be quite difficult or even impossible to perfectly encode without a compression-like algorithm.

The issue of reverse inference recurs in many of the findings D&S cite as evidence for excess capacity. For example, when asked to judge whether a given three-sided polygon is a triangle (Lupyan, 2013), participants "relied on unnecessary cues like the relative lengths of the sides of the triangle, to the detriment of their accuracy and speed". D&S take this as evidence for excess capacity because participants incorporate "unnecessary cues" (i.e., overparameterize). But triangles that differ in side length or angle also differ in their compressed representations (as two lines differing in length cannot be represented merely as direct copies of one another), making scalene triangles harder to identify as such than equilateral triangles. Perhaps more pressingly, D&S cite the massive capacity of long-term memory (Brady et al., 2008) as evidence that "people store nearly all their past experiences" (a contested premise in itself; Cunningham et al., 2015). For them, this implies excess capacity. But high-fidelity representation in such tasks need not require excess capacity. Instead, efficient compositional feature codes (e.g., of object identity, category, pose, state, etc.) mimic the performance of excess capacity without requiring raw item-wise storage. In other words, "massive capacity" by no means implies "excess capacity". As with the examples in Figure 1, a compression-based story might explain this result by appealing to all three capacity regimes. First, given that the compositional feature codes 'discard' information about the stimulus, they operate under constrained capacity. Second, given that the representations facilitate successful recovery of the experience in ways that help distinguish two similar stimuli stored in memory, they operate under sufficient capacity. Finally, given that the representations contain 'parameters' beyond what exists in the raw images themselves (like object state or pose), they operate under excess capacity.

How might D&S's framework approach this reverse inference problem? A potential repair centers around representational format. Lossless compression takes on a different format from (say) rote memorization (a difference that carries important consequences; Figure 1C), even though both systems facilitate perfect recovery. In the current framework, both might be lumped together as instances of sufficient capacity. However, by uncovering the format of these representations — a well-characterized problem in cognitive science — we might find an additional axis that separates lossless compression (and other language-like formats; e.g., Dehaene et al., 2022; Quilty-Dunn et al., 2023) from rote memorization. Thus, to circumvent the challenge of reverse inference, theories of capacity must consider not only a system's "expressivity" but also its format.

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