Compression and Decompression in Cognition

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Abstract. This paper proposes that decompression is an important and often overlooked component of cognition in all domains where compressive stimuli reduction is a requirement. We support this claim by comparing two compression representations, co-occurrence probabilities and holographic vectors, and two decompression procedures, top-*n* and Coherencer, on a context generation task from the visual imagination literature. We tentatively conclude that better decompression procedures increase optimality across compression types.

Keywords: decompression, generative cognition, imagination, context, coherence, vector symbolic architectures, cognitive modeling.

1 Introduction

Compression has been implicated in artificial general intelligence and, more broadly, general cognition [1]. In vision, for example, there is massive redundancy in natural images that must be reduced [2]. These reduced representations are then transformed into invariant representations of objects later in the processing stream [3]. Compression of signals from the environment, understood as reducing a stimulus to the details most relevant for survival, is critical to an organism's success [4].

Decompression has received much less attention than compression in the cognitive science and artificial intelligence literatures, but, as we argue, it plays an equally critical role in cognition. Compression is captured by machine learning techniques that move from instances (e.g., pictures of cats) to general regularities (e.g., what a cat looks like), much like inductive inference. Decompression does the reverse: it moves from regularities to instances, much like deductive inference. Decompression allows the agent to apply its general knowledge to its particular circumstances. In vision, visual perception is largely a compression process and visual imagination is a decompression process. In framing the problem in this way, part of our contribution is to demonstrate that decompression, understood as a cognitive process, can be modelled using techniques from artificial intelligence research. We demonstrate this claim by comparing two compression representations and two decompression techniques, and showing the significant and differentiable effect of the latter.

2 Task Description and Implementation

The task is based on the work of [5,6]. In their research, the model must generate

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the content of a coherent, fleshed-out scene (e.g., a "car," "road," and "sky") from a single word input (e.g., "car"). For example, a scene containing "bow," "violin," and "arrow" would be incoherent: it mixes two senses of the word "bow."

The goal of the decompression step is to deduce implicit information in the compressed representation. For the current problem, the model must infer which images contained which labels. For example, the agent knows that "car" co-occurs with "road," in general, but does not know what other labels are in the particular images with "car" and "road."

The task requires the decompression of co-occurrence probabilities and holographic vectors into contextually coherent, 5-label combinations given a query label. The context is judged to have been accurately inferred if at least one of the original images contains the same 5-label combination produced by the agent.

2.1 Compression Representations

The original compression representation outlined by [5,6] used co-occurrence probabilities between pairs of labels: $P(l \mid q) = |I_q \cap I_l| \,/\, |I_q|$, where q is the query label, l is another label and I is the set of images.

We chose to compare the co-occurrence probabilities to a holographic vector or holographic memory representation [7]. Here, each label in the Peekaboom labeled image database is represented by a vector of 1000 dimensions randomly sampled from a normal distribution with a mean of zero and a standard deviation of $1/\sqrt{1000}$. We call these vectors *environment vectors*. Each label is also represented by a second type of vector, termed a *memory vector*: the sum of all environment vectors representing labels that the given label co-occurs with.

The vectors were compared using cosine similarity, which ranges from 1 to -1. The cosine of a memory vector with another memory vector is a measure of second-order association: how often the labels appear in *similar* images. In what follows, we compare task performance for holographic vectors using second-order association to task performance using co-occurrence probabilities.

2.2 Decompression Procedures

We compared two decompression procedures. First, the top-n procedure selects the n labels with the highest probability of co-occurrence with the query label, $P(l \mid q)$, or with the highest cosine similarity to the query label's memory vector.

The second decompression procedure is a model called Coherencer, the visual coherence subsystem of the SOILIE imagination architecture [8,9]. Coherencer is a serial, local hill search algorithm.

Coherencer selects four labels with the highest association with the query—co-occurrence probability or cosine similarity. Then, it calculates the mean association value for each pair of labels. If it passes a threshold (λ), the collection is accepted:

$1/20\ \Sigma^5_{n=1}\Sigma^5_{m=1}A(l_n, l_m) > \lambda$.[1] If it fails to pass the threshold, the label with the lowest row and column averages is discarded without possible reselection. A new label is swapped in and the process repeats until either the pool of labels that co-occur with the query is exhausted or a set passing the threshold is found. If the pool is exhausted, Coherencer returns the best combination found.

3 Method

The entire Peekaboom [10] database was filtered to remove all images with fewer than five labels and any labels that only occurred in those images. A total of 8,372 labels and 23,115 images remained after this filtration. Each of the 8,372 labels was processed by all the algorithms. The top-*n* procedure always yields the same result and was run once. Coherencer has stochastic variation; it was run 71 times on the co-occurrence representation and 9 times on the holographic representation. The results were averaged for each representation. The number of runs conforms to an analytic model run metric [11]. The results for each of the algorithms were assessed with regard to the original images. If at least one of these images contained the five resulting labels, the algorithm scored one point. We compared the total number of points scored by each decompression procedure on each compression representation.

4 Results

Coherencer outperformed the top-*n* model across both compression techniques. Contrary to our original hypothesis, the co-occurrence compression representation outperformed the holographic representation across both decompression procedures. The success rates out of the 8,372 possible query labels for each of the four conditions are: top-*n* and co-occurrence = 4842; top-*n* and holographic = 619; Coherencer and co-occurrence = 5750; Coherencer and holographic = 3259.[2]

A model generated by the logistic regression using three predictors (choice of compression representation, choice of decompression technique, and the interaction between the two) was able to predict success or failure on the basis of those predictors with 69.8% accuracy overall. The predictors as a set reliably distinguished between success and failure of the model, $\chi^2(3, N{=}33218) = 8353.78$, $p < .000$, Negelkerke's $R^2 = .30$. The Wald criterion demonstrated that all three predictors made a significant contribution to the accuracy of the model ($p < .000$).[2]

[1] The diagonal, where $n = m$, is ignored. Thus, the denominator of the average has to be decremented by the cardinality of this diagonal (i.e., by 5). $A(\cdot,\cdot)$ is the association calculation for the given compression representation (either cosine or co-occurrence probability).

[2] The full details are omitted due to space constraints. They can be viewed online, here: `www.theworldmatrix.ca/agi-compression-decompression-stats.pdf`

5 Discussion

The results support the notion that Coherencer is an improvement over the top-*n* control. However, they contradict our expectation that the holographic vector representation would be better able to capture contextual information than co-occurrence probabilities. Future research will explore why.

We take our findings as preliminary evidence of a general property of cognition. Compression is ubiquitous in cognition and the relative optimality of that compression is essential to the success of the agent. This optimality is not given by the compression mechanisms that perform the necessary reductions in information without the additional support of the decompression mechanisms that extract relations implicit in the compressed representations. Our research is a preliminary demonstration that the exclusion of either side of the compression-decompression dyad necessarily gives an incomplete description of the process. Thus, we predict all cognitive domains requiring compression mechanisms will improve with better decompression techniques.

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