Sparse distributed memory constraints drive representational change as a function of temporal learning sequence

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Abstract

Prior work suggests that different learning sequences—blocking (spacing out overlapping information) vs. interleaving (intermixing related content)—bias memory representations toward integration or separation (e.g., overlapping or distinct representations) to support different functions. However, findings on how sequences influence memory representations remain inconsistent. We propose that individual differences in memory capacity, encoding style, and their interaction govern the balance between memory integration and separation. Using feedforward neural networks, we modeled inference performance while varying memory capacity and encoding sparsity versus distributedness. We find that blocked training promotes integration when memory capacity is low, while interleaved training enhances integration when capacity is high. Sparse representations benefit from blocked schedules by orthogonalizing related information, whereas distributed representations favor interleaved schedules that promote overlap and integration. These results highlight the critical role of individual differences in memory capacity and encoding constraints in shaping the effects of training sequences on memory representations.

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