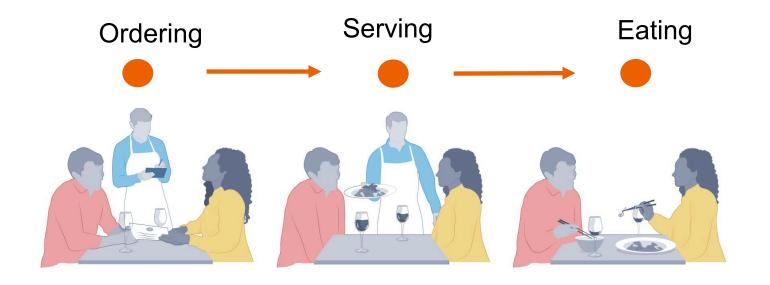
Shaping Sequence Attractor Schema in Recurrent Neural Networks

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Sequence schema

A generalized and reusable abstraction of knowledge enabling flexible intelligence



Generalizing the schema across different scenarios

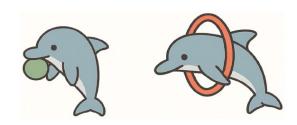




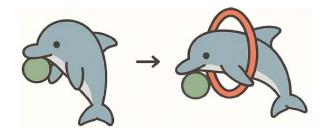


How to learn a complex sequence schema?

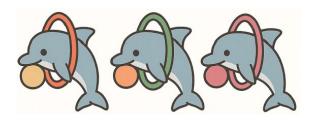
- Many tasks are too complex to be amenable to simple trial and error learning
- Shaping is critical: breaking complex sequence task into simple subtasks learned gradually







Task sequence learning



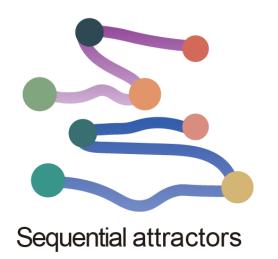
Task schema learning

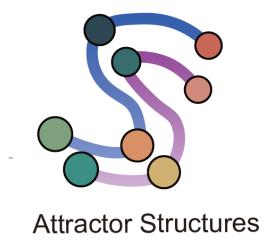
How sequence schemas are learned via shaping?

Hypothesis: Sequence schemas are learned via shaping through sequence attractors. These attractor dynamics emerge gradually through the shaping process.

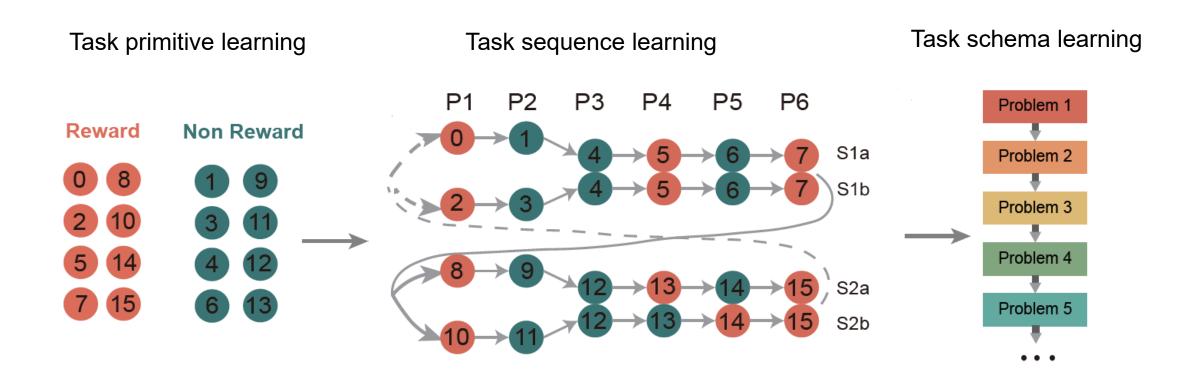
Task primitive learning: Forming basic attractors for simple task parts Task sequence learning: Linking individual attractors into sequence attractors Task schema learning:
Compressing into a compact,
abstract attractor structure



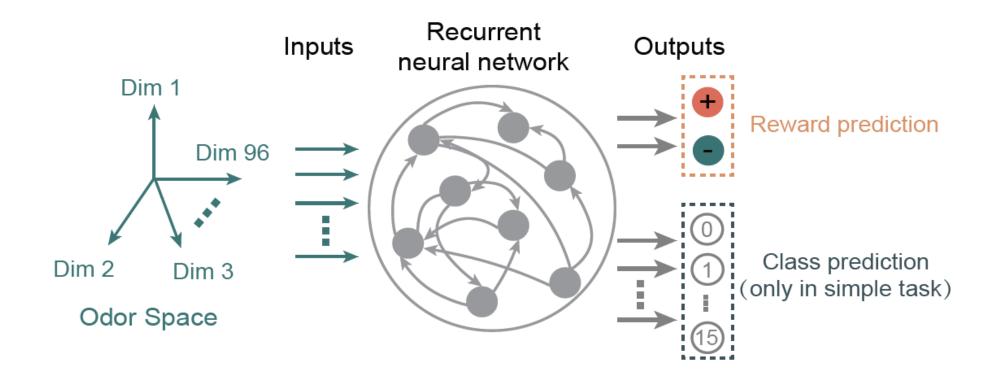




Shaping Paradigm in Animal Training

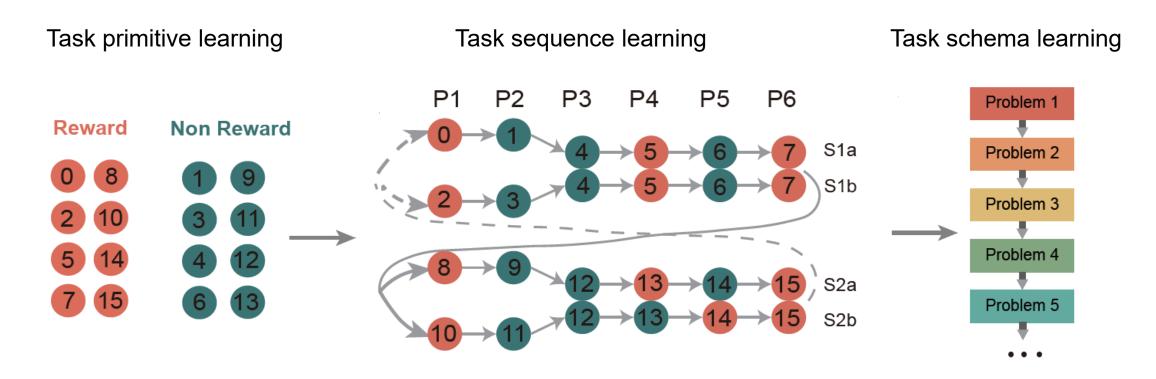


Model architecture



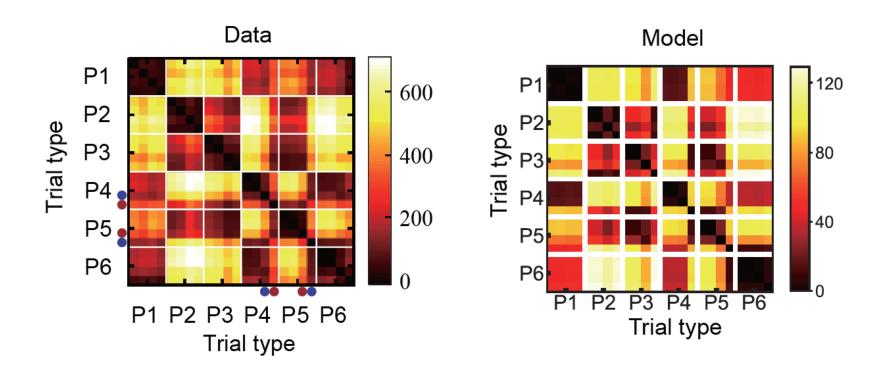
- Input: one-hot vector encoding of the current odour
- Target: predicts reward and/or classifies odours, depending on the training phase

Learning odor-sequence task via shaping



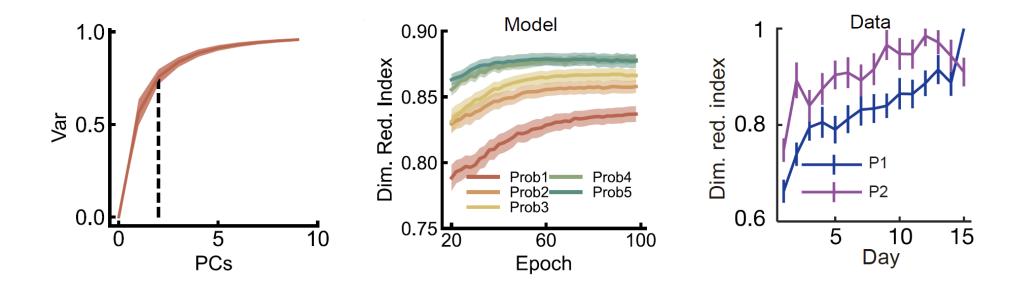
- Task Primitive Learning: RNNs learn to predict rewards based on individual odors.
- Task Sequence Learning: Pretrained RNNs are further trained on odor-sequence tasks.
- Task Schema Learning: The RNN is trained on multiple odor-sequence tasks sharing the same structure.

Reproducing Key Features of OFC Schema Learning: structured task representation geometry

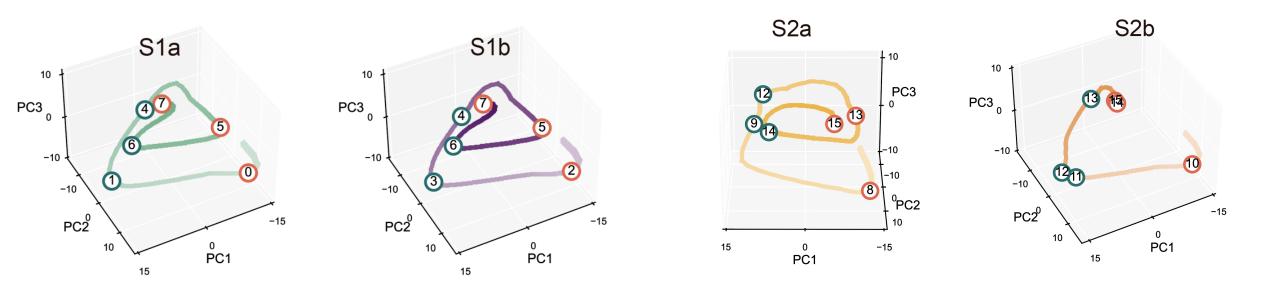


• The RNN's representational dissimilarity matrix (RDM) closely aligns with that observed in rats' orbitofrontal cortex.

Reproducing key features of OFC schema learning: progressive compression of representational dimensionality



 As training progresses, the top 3 principal components (PCs) increasingly explain more variance in neural activity. Four sequences form distinct trajectories with six fixed points each (one per odor position).

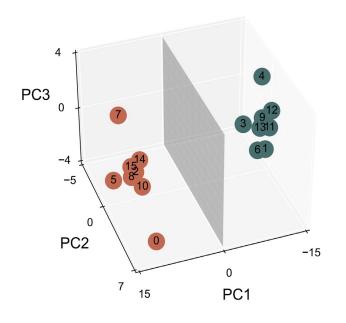


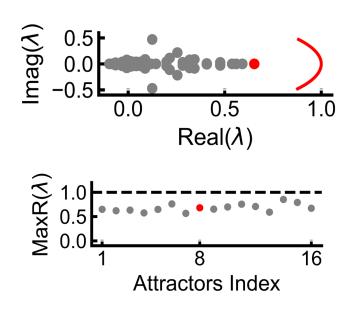
How sequence attractors are learned through shaping protocols?

Task Primitive Learning — Formation of Discrete Attractors

Task Primitive Learning

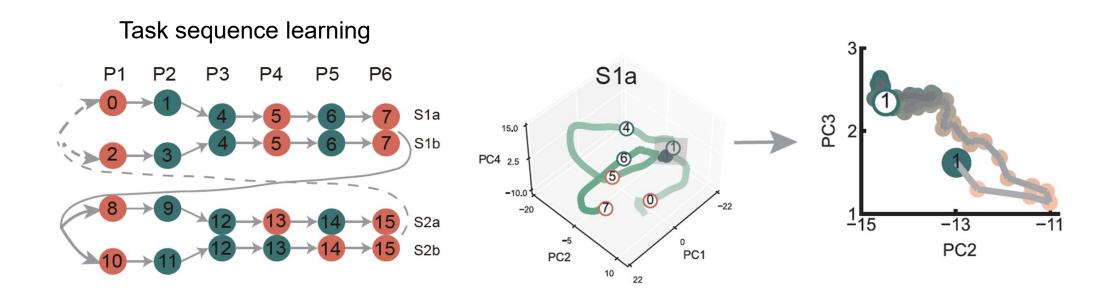






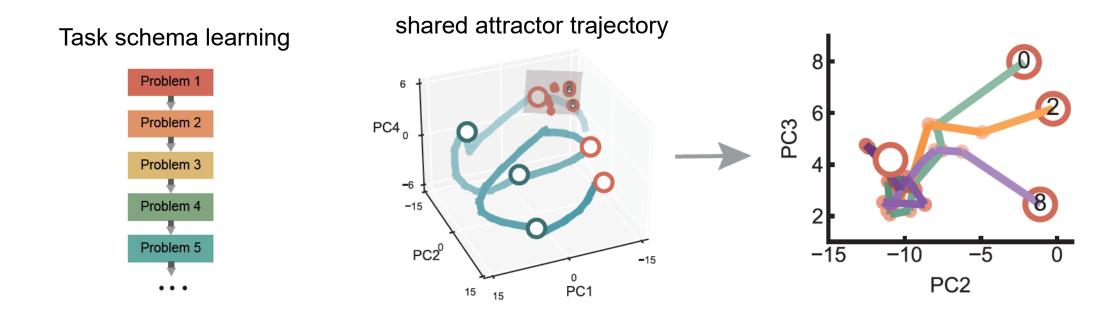
- The network successfully maps odors to rewards.
- Network states form discrete attractors.
- Each odor corresponds to a stable network state.

Task Sequence Learning — Linking discrete attractors to form sequence attractors



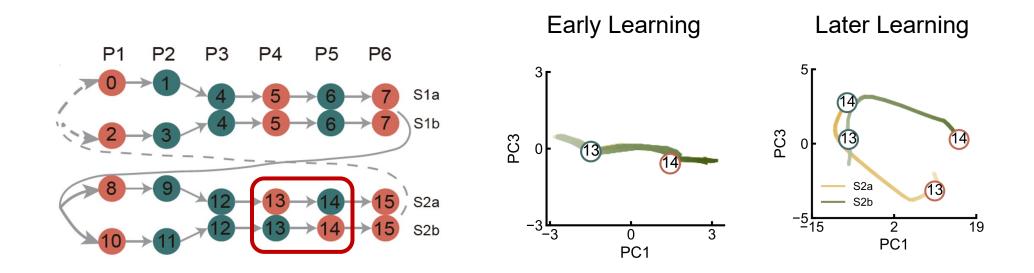
- Prior attractors from primitive learning migrate to form sequence attractors.
- This demonstrates attractors are reused, reorganized, and linked during sequence learning.

Task Schema Learning— Abstraction and Generalization



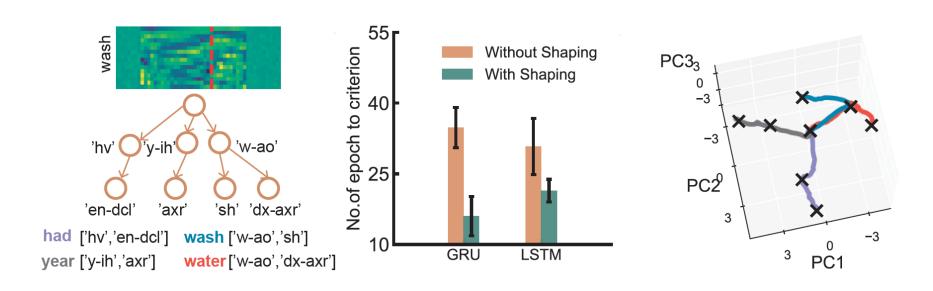
- Trained on tasks with shared structure but different odors
- Network representations shift from odor-specific to abstract, low-dimensional manifolds

Shaped and unshaped RNNs follow divergent learning trajectories



In RNNs lacking shaping, the S2a and S2b attractor trajectories first collapse into
one before separating, which contrasts with shaped RNNs.

Sequence Attractor-Based Shaping Improves Learning Efficiency in Keyword Spotting



- Applied our shaping framework to spoken-word recognition.
- Three-stage training: phoneme primitives \rightarrow word sequences \rightarrow abstract schema.
- Shaping enables faster convergence and interpretable attractor structure.

Conclusion:

- We systematically replicate key behavioral and neural features of schema learning observed in the rat OFC.
- We show that sequence schemas can be encoded as sequence attractors.
- We identify a novel dynamic process of schema formation: from point attractors → sequence attractors → abstract sequence attractors.