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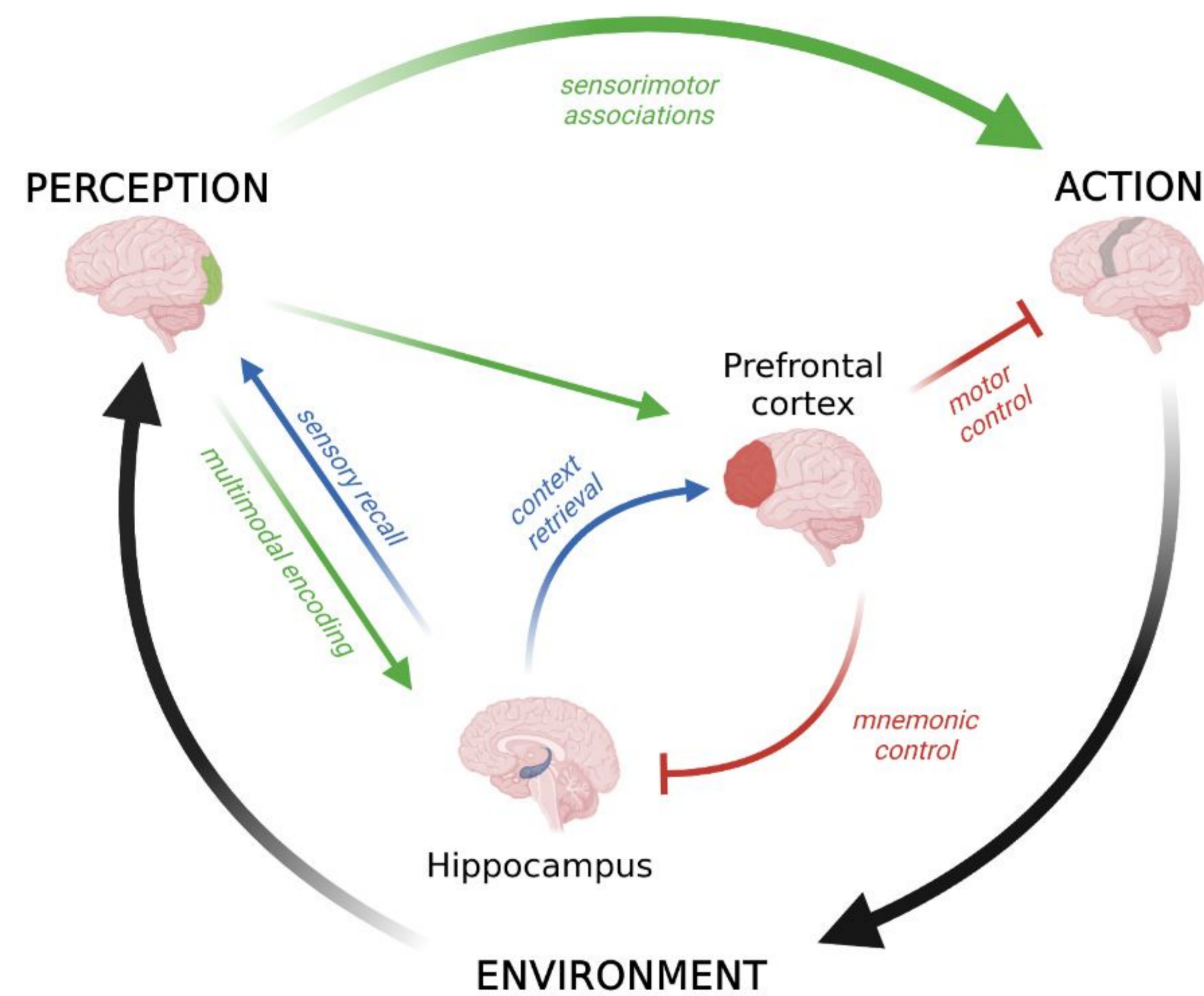
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# Modelling prefrontal-hippocampal interactions for contextual controlled learning using artificial neural networks

Hugo Chateau-Laurent and Frédéric Alexandre

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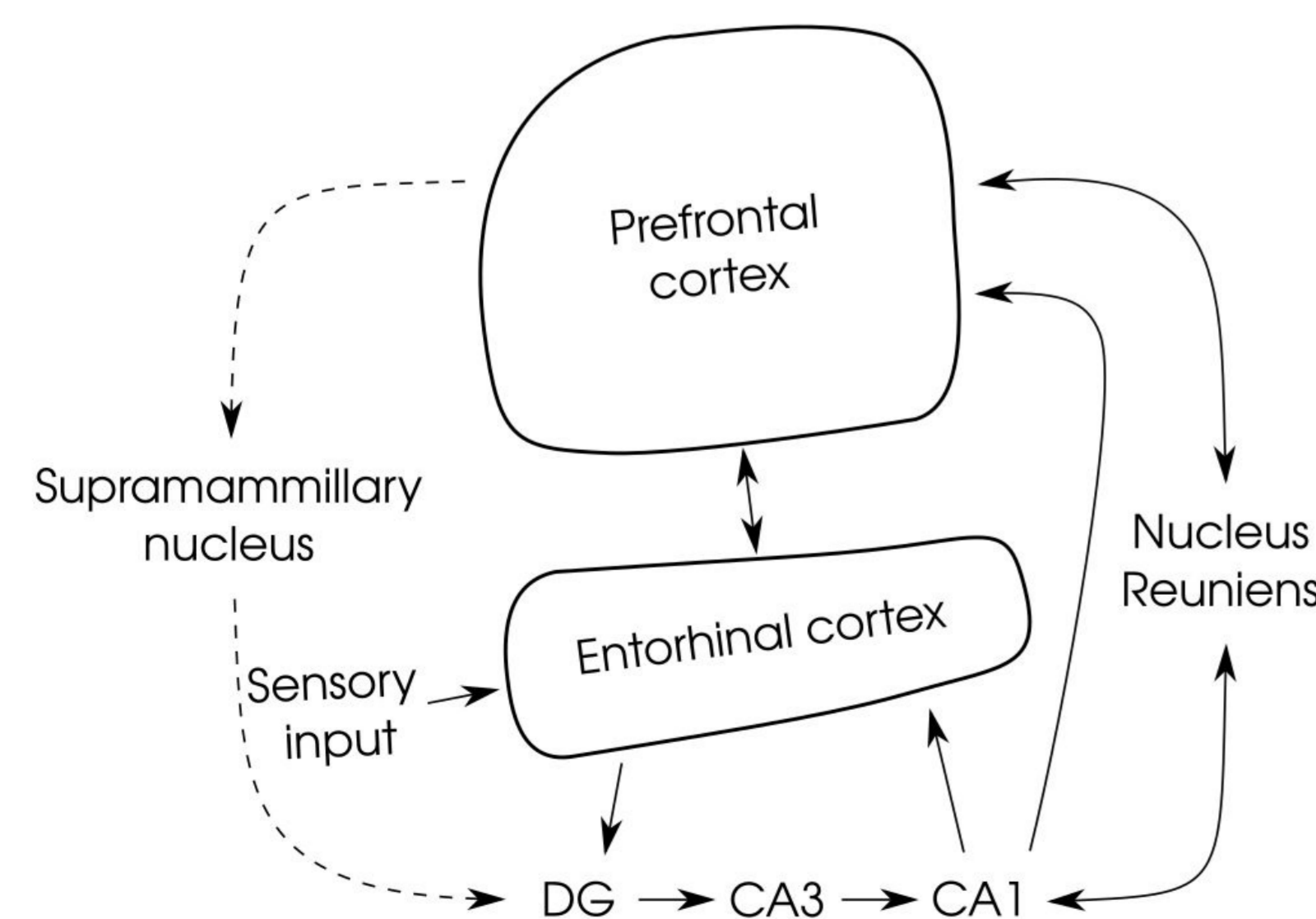
## PFC-HPC interactions



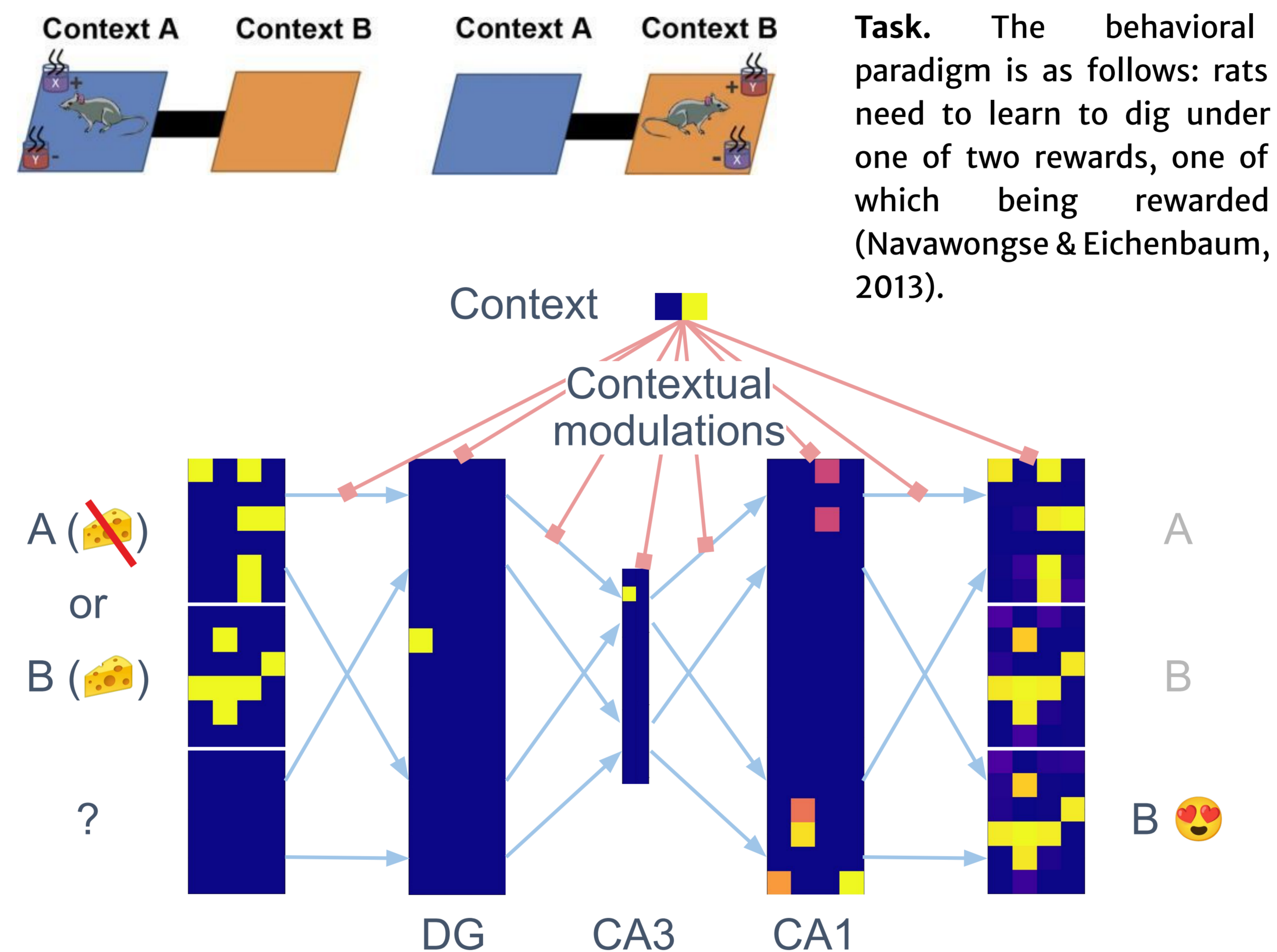
The hippocampus and prefrontal cortex interact bidirectionally through multiple pathways. Their interaction is thought to play an important role in contextual controlled learning. The hippocampus enables rapid learning of multimodal associations. The prefrontal cortex learns to identify contextually relevant information to control decision-making and hippocampal memory recall in a goal-directed manner (Chateau-Laurent & Alexandre, 2021).

## PFC-HPC pathways

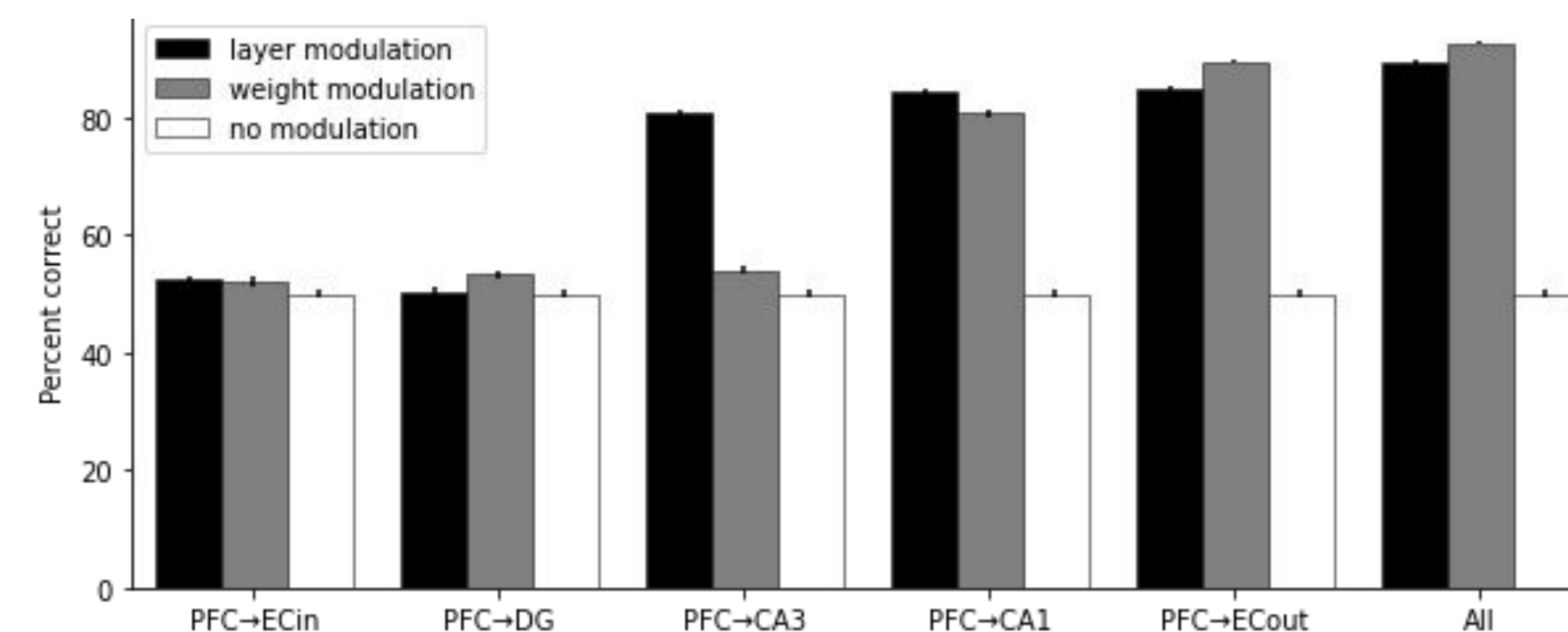
Major PFC-HPC pathways, as reviewed by Eichenbaum (2017), are shown solid arrows. A recent model posits that contextual recall is enabled by the indirect PFC-Supramammillary nucleus-DG connection (dashed arrow; Pilly et al., 2018).



## Contextually-controlled recall

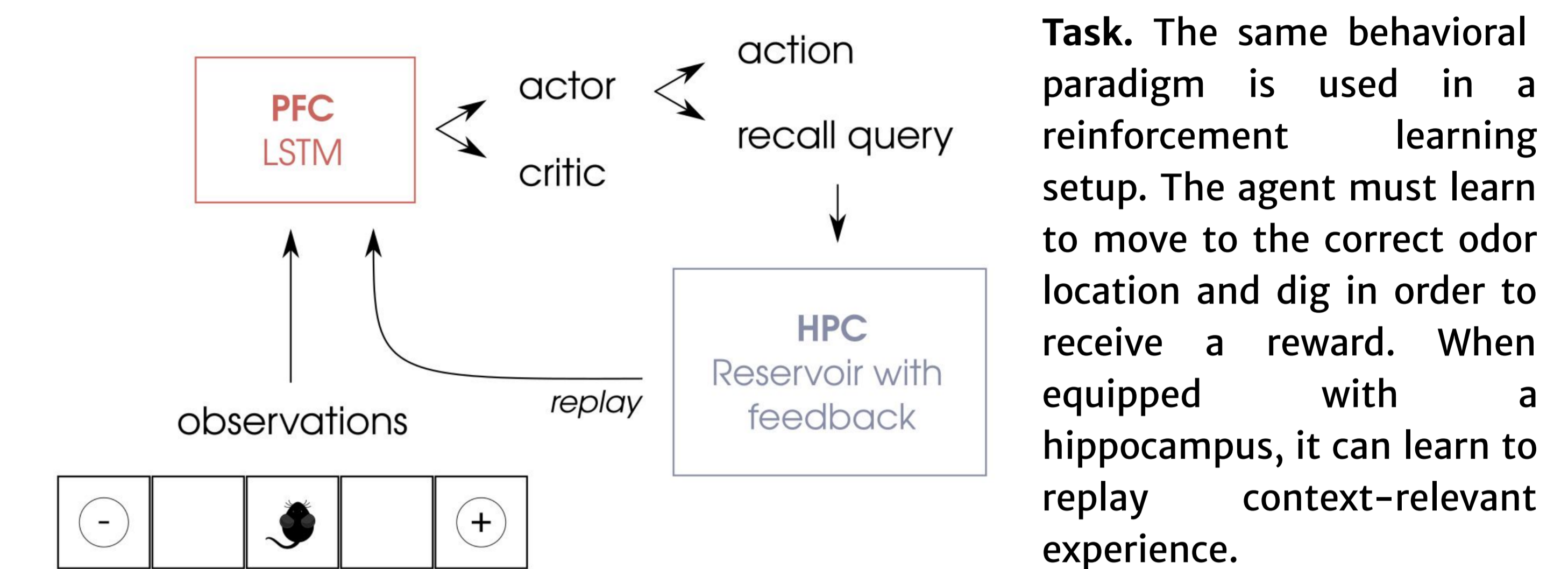


**Methods.** We model the hippocampus with an autoencoder-like network, following an approach similar to Santos-Pata et al. (2021). The input pattern is the concatenation of two odor patterns and an empty pattern. The target output is the concatenation of the input patterns and the pattern associated to the rewarded odor. The relative number of neurons in the entorhinal cortex, dentate gyrus, CA3 and CA1 layers follows the proportion found in biological rats. The contextual layer projects to bias different synaptic weights and layers.



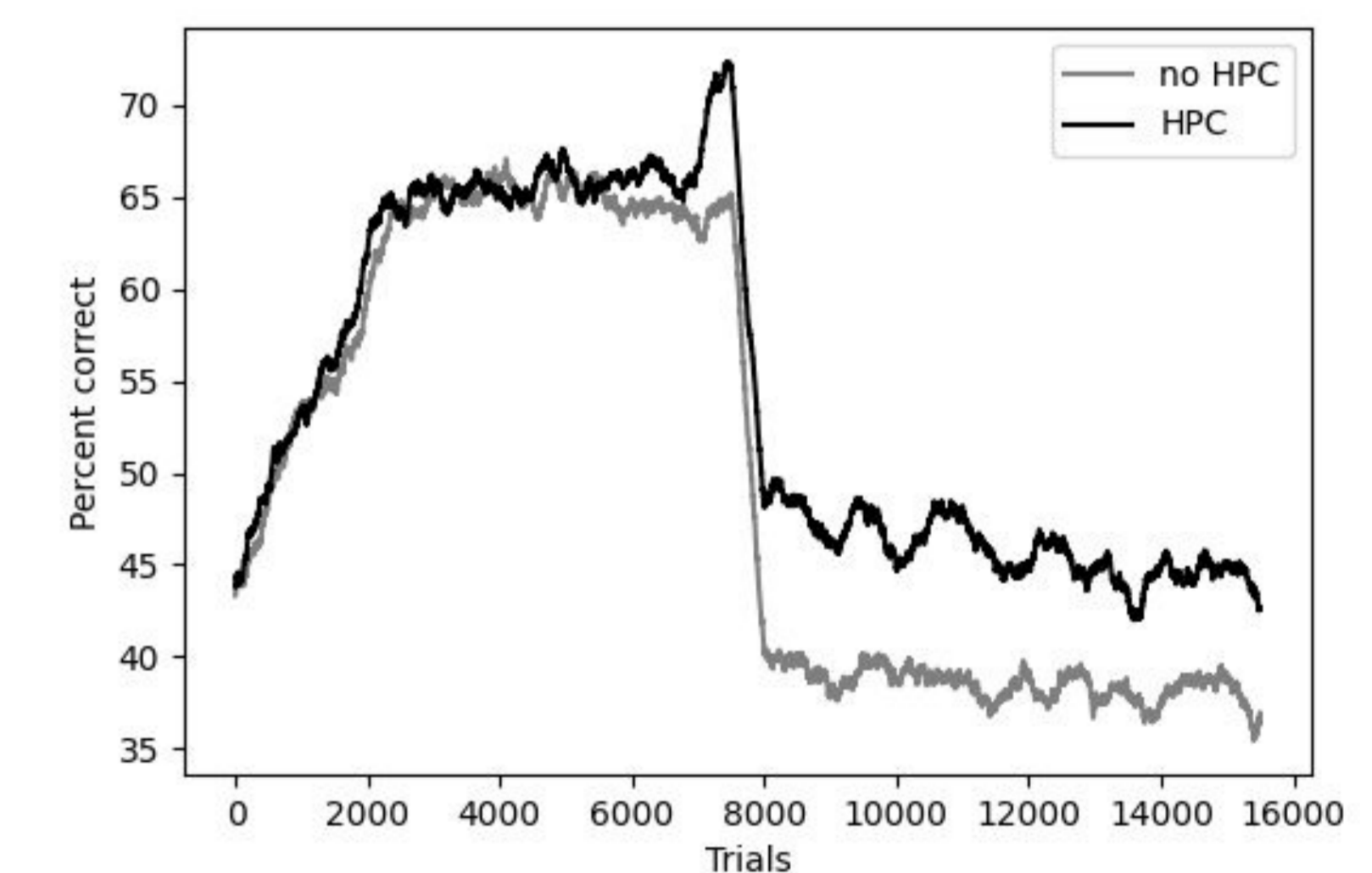
**Results.** Modulation of hippocampal recall through projections from the contextual layer (PFC) enables the model to perform the contextual memory task. The relative efficacy of layer vs. weight modulation is layer-dependent. Furthermore, the PFC→DG connection's ability to modulate recall is weaker than those of downstream modulations

## RL with episodic sequences



**Task.** The same behavioral paradigm is used in a reinforcement learning setup. The agent must learn to move to the correct odor location and dig in order to receive a reward. When equipped with a hippocampus, it can learn to replay context-relevant experience.

**Methods.** We model DG as a sparse layer and CA3 as a reservoir of randomly connected neurons. A readout (hilus) is trained to predict the next DG pattern to be fed back to the reservoir, following the model of Lisman et al. (2005), which allows the hippocampus to learn sequences. Another readout is trained to decode the current pattern and send the content of hippocampal replay to the PFC. The PFC is trained as an actor-critic and is able to send a query for hippocampal replay.



**Preliminary results.** Initial simulations suggest that the model is better able to adapt to reward reversal when the hippocampus module is used. Future studies will assess the ability of the model to perform better using hyperparameter optimization.

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