Brain-like replay for continual learning with artificial neural networks

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Bridging AI and Cognitive Science workshop (ICLR 2020)

Catastrophic forgetting in neural networks

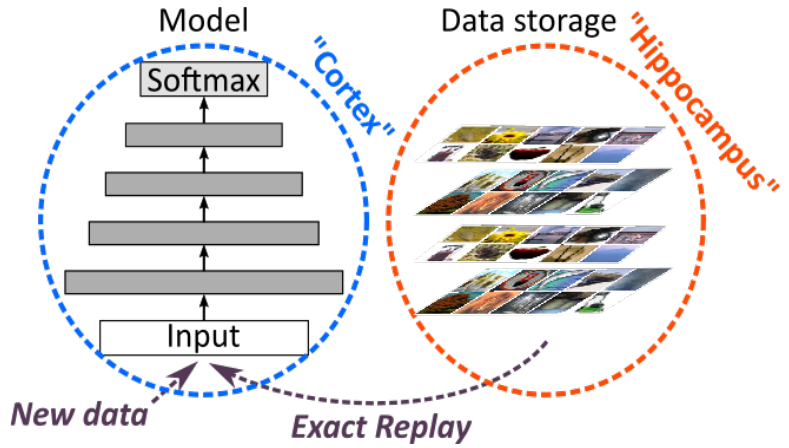
- When a neural network is trained on something new, it rapidly forgets what was learned before [McCloskey & Cohen, 1989 *Psych Learn Motiv*; Ratcliff, 1990 *Psych Rev*]

- Humans continually accumulate information throughout their lifetime
- A brain mechanism thought to underlie this ability is the replay of neuronal activity patterns that represent previous experiences
  - replay is orchestrated by the hippocampus, but also observed in cortex [Wilson & McNaughton, 1994 *Science;* O'Neill et al., 2010 *TINS*]

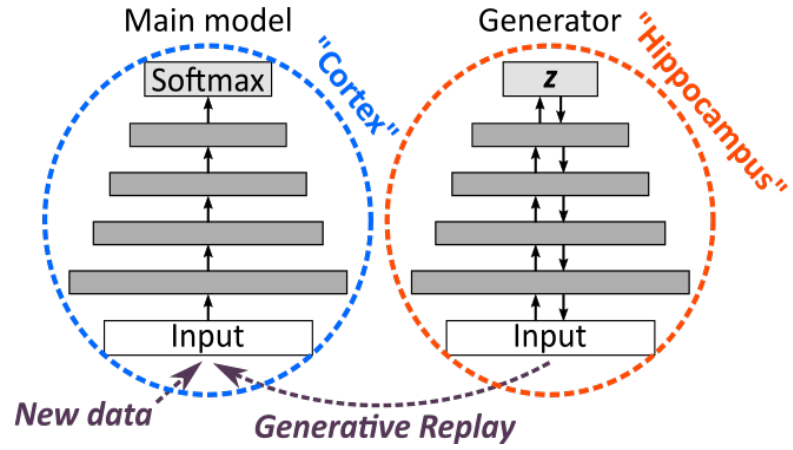
→ Could adding replay to artificial neural networks help protect them from catastrophic forgetting?

How to add replay to artificial neural networks

- Store data and interleave – *"exact"* or *"experience replay"*
  - *Initial argument for role of replay in memory consolidation* [McClelland et al., 1995 *Psych Rev*]
  - *Unclear how the brain could do directly store data*
  - Not always possible (e.g., privacy concerns, limited storage)
  - Problematic when scaling up to true lifelong learning



- Use a generative model – *"generative replay"*
  - *More realistic from neuroscience point of view*
  - *Views hippocampus as a generative neural network and replay as a generative process; see also* [Liu et al., 2018 *Neuron*; Liu et al., 2019 *Cell*]
  - Learning a generative model as a more scalable, privacy-preserving way of remembering previous seen data



Does generative replay work?

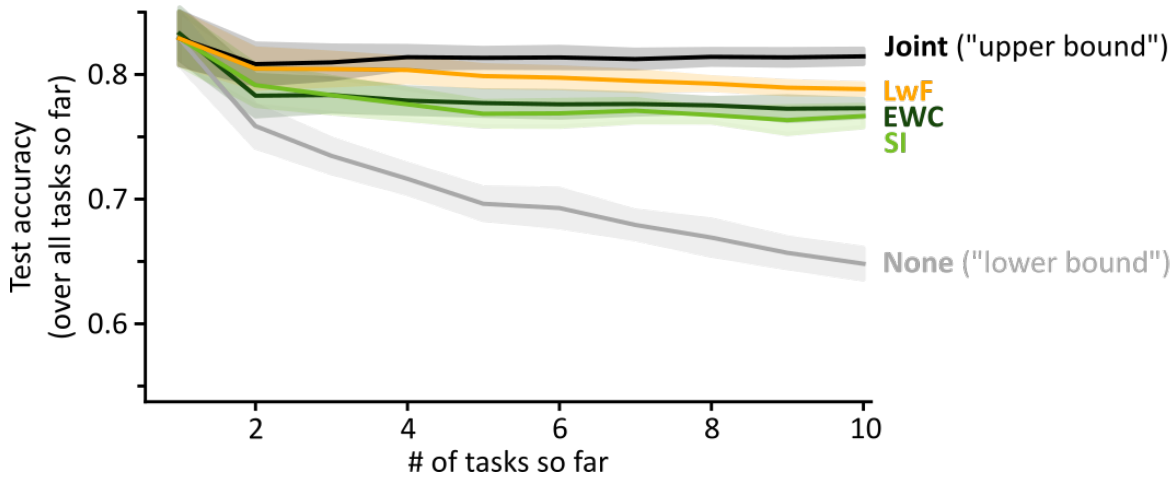
- Generative replay works very well for MNIST-based continual learning problems [Shin et al., 2017 *NeurIPS*; van de Ven et al., 2018 *arXiv*]
  - For class-incremental learning, generative replay is currently the only method capable of performing well without relying on stored data (even for MNIST!)
- Generative replay is reported to break down with more complex inputs (e.g., natural images) [Lesort et al., 2019 *IJCNN*; Aljundi et al., 2019 *NeurIPS*]

→ Two problems to be addressed:

- This raises doubt as to whether or how replay could be used by the brain
- Class-incremental learning with complex inputs (e.g., natural images) remains an unsolved problem in machine learning

Generative replay on natural images

Task-Incremental Learning
Choice only between classes within given task



Class-Incremental Learning
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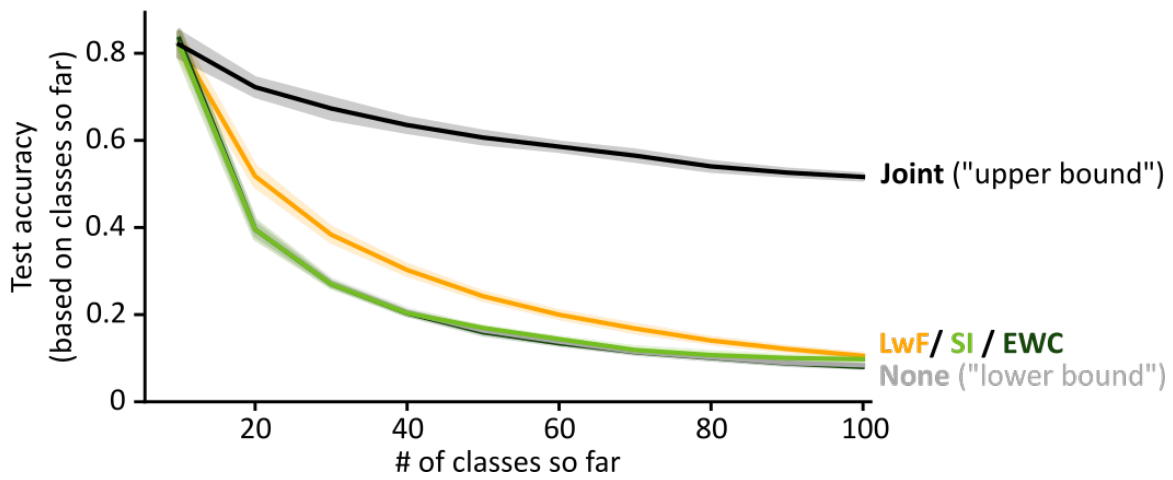

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(all methods use pre-trained convolutional layers)

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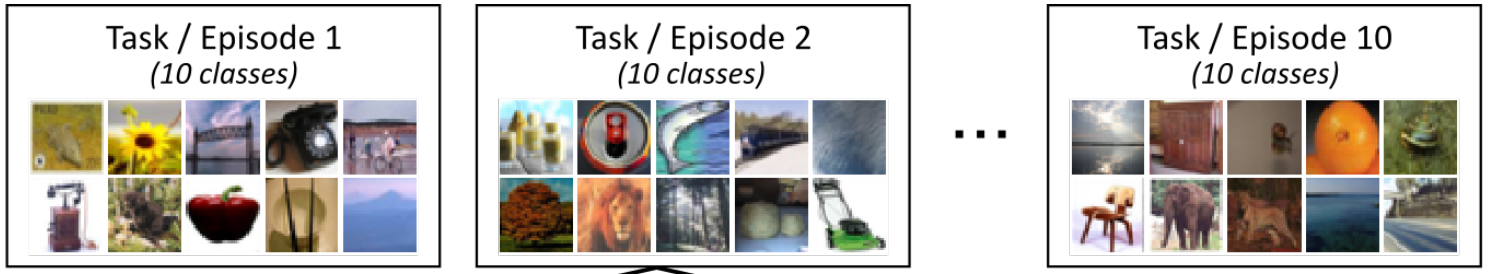

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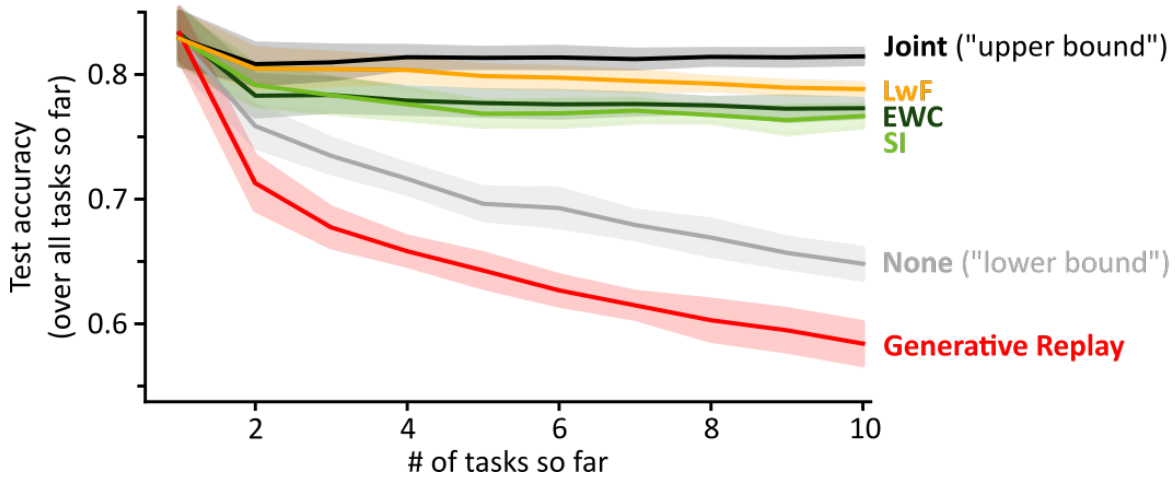

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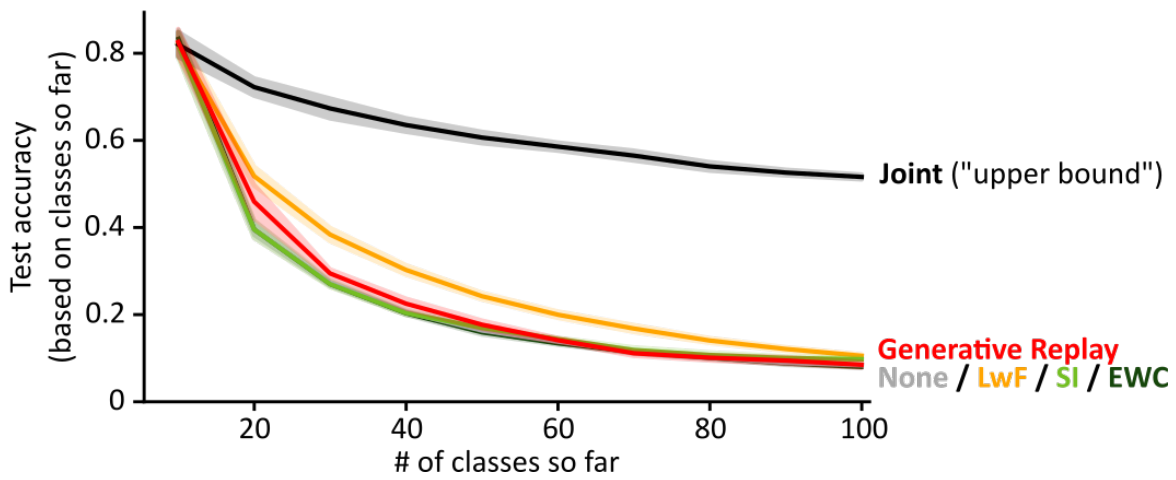

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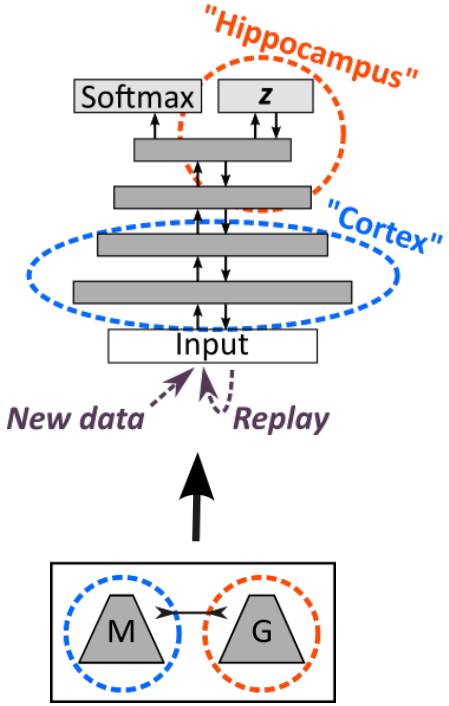
Brain-inspired Modifications to Generative Replay



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Inspired by brain anatomy

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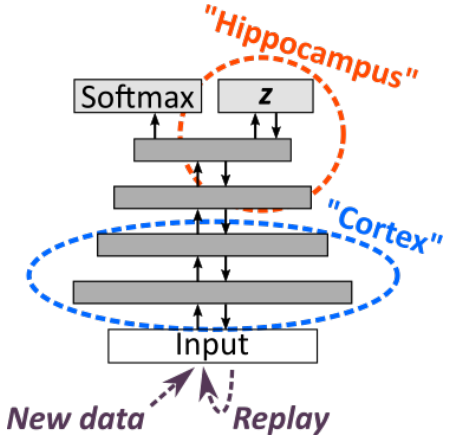

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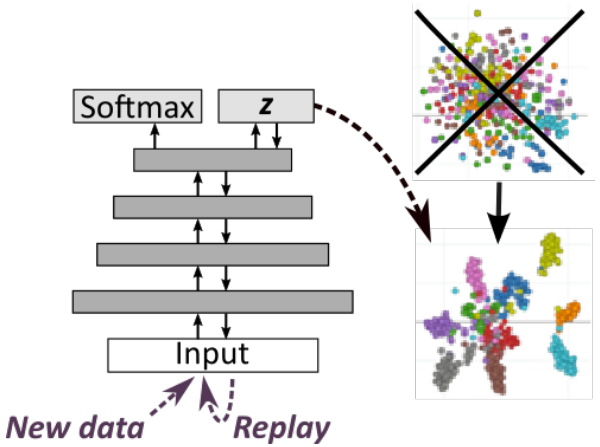
- ***Conditional Replay:*** Enable model to generate specific classes, by replacing the standard normal prior by a Gaussian mixture with a separate mode for each class

Inspired by introspection



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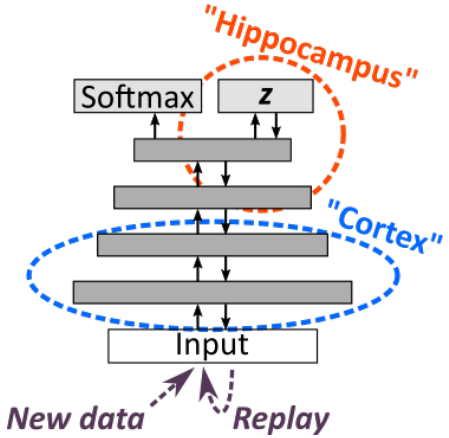

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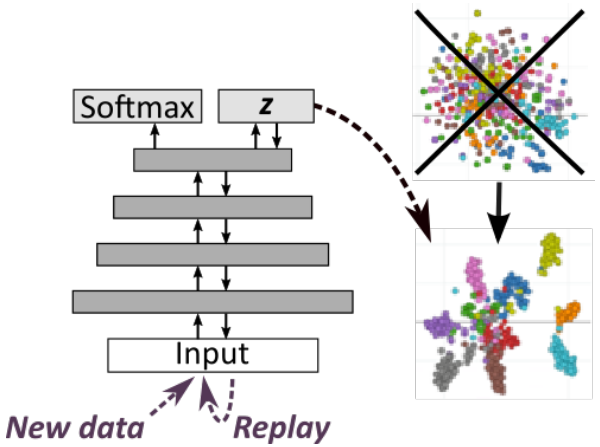

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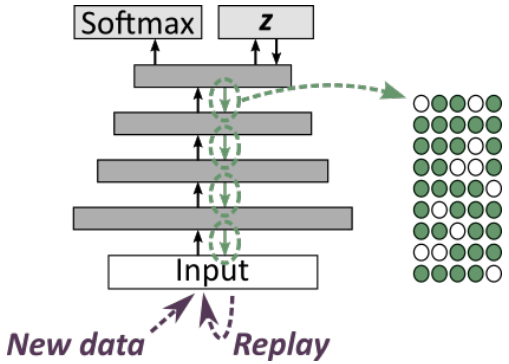

- ***Gating based on Internal Context:*** For each class, inhibit (or gate) a different subset of neurons during the generative backward pass

Inspired by inhibition & context-dependent processing

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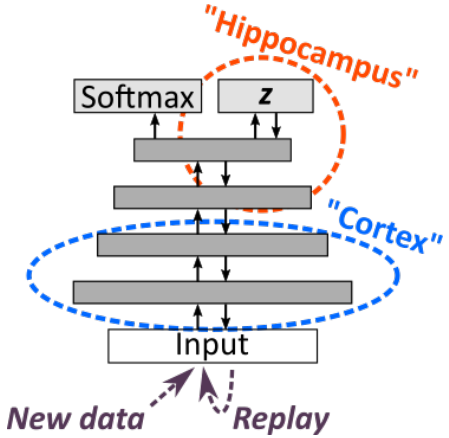

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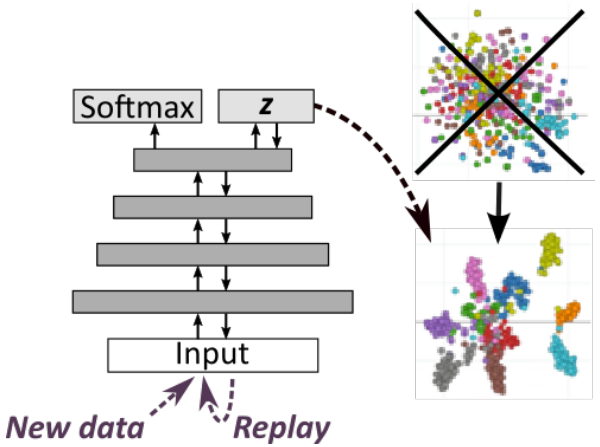

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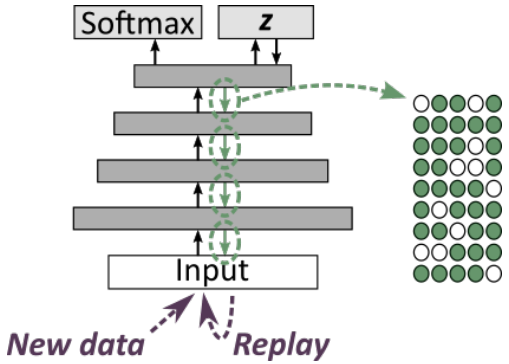

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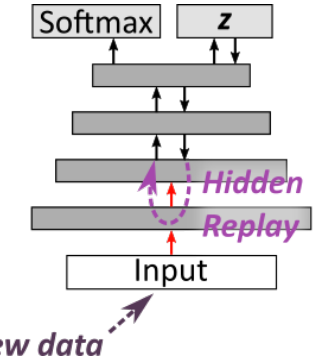
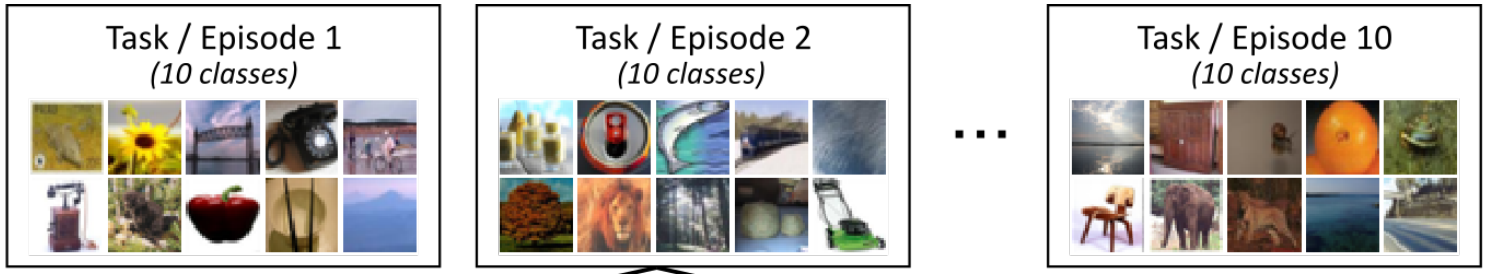


- ***Internal Replay:*** Replay internal or hidden representations, instead of at the input level (e.g., pixel level)

Inspired by developmental plasticity

Brain-Inspired Replay on natural images



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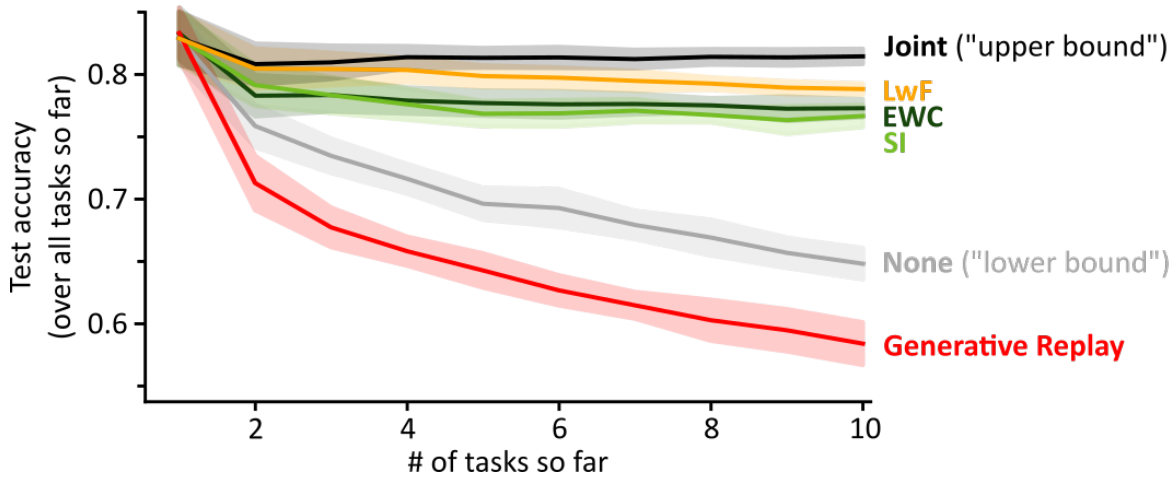

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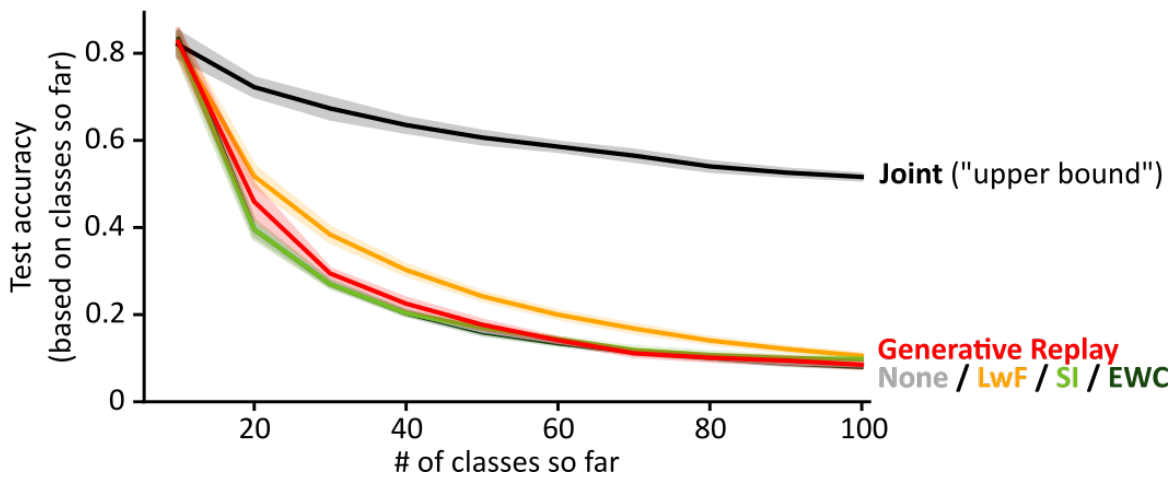

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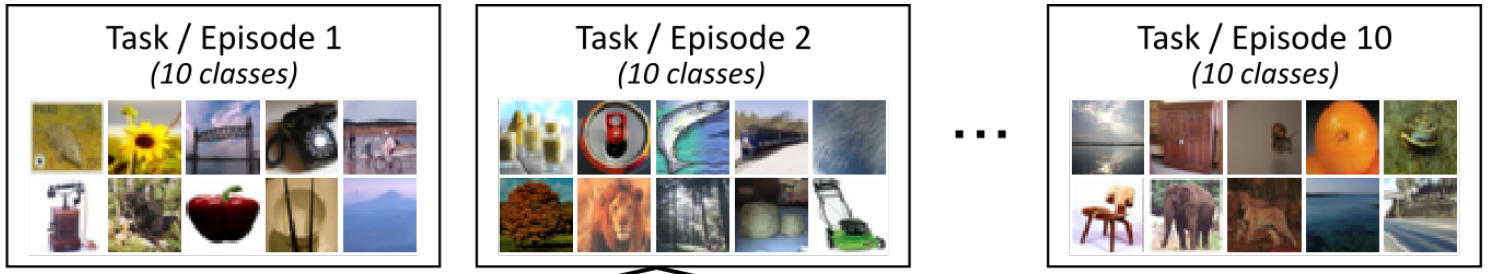

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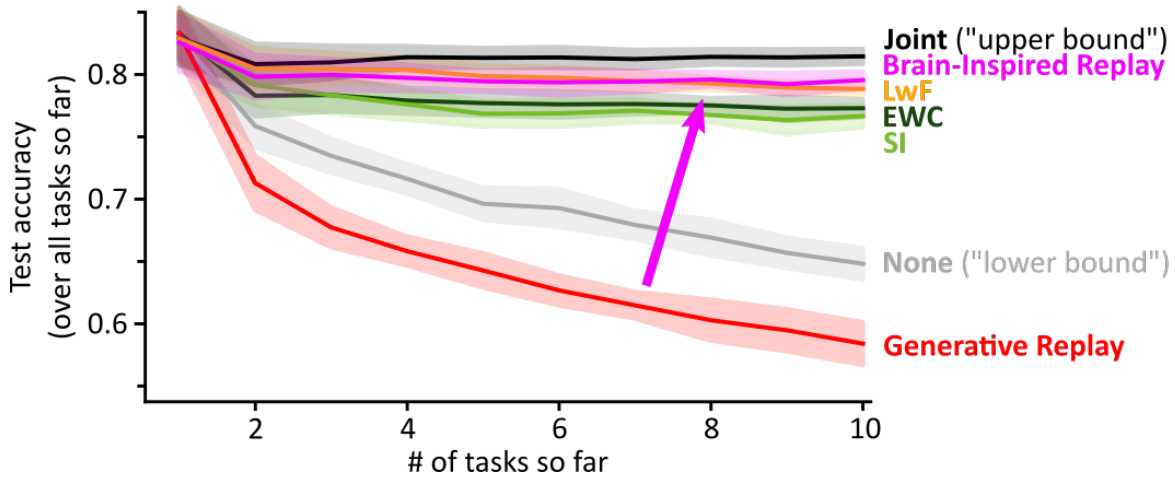

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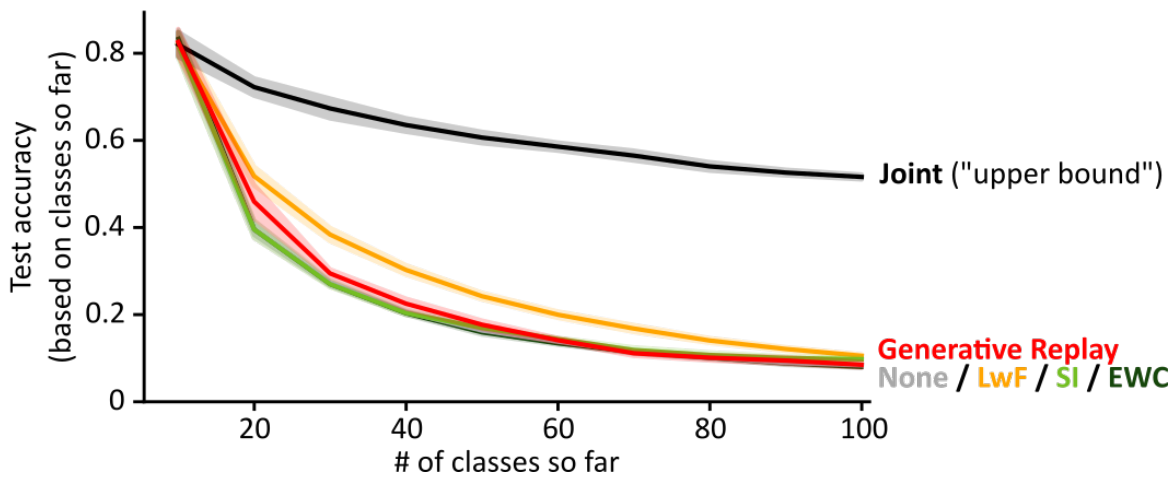

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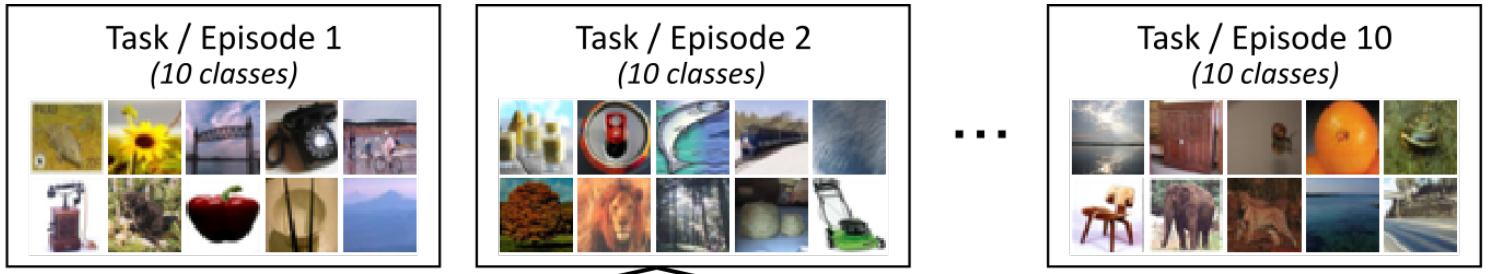

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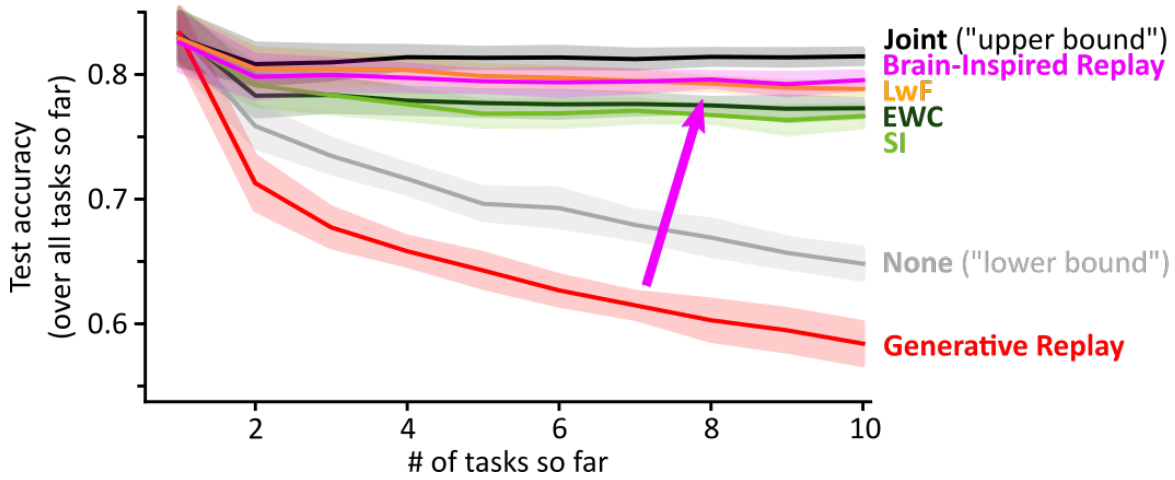

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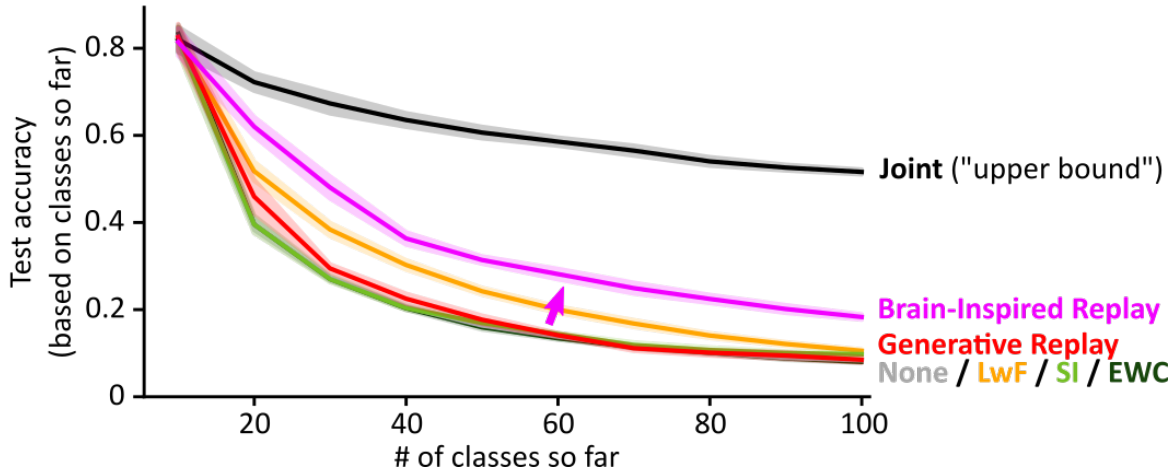

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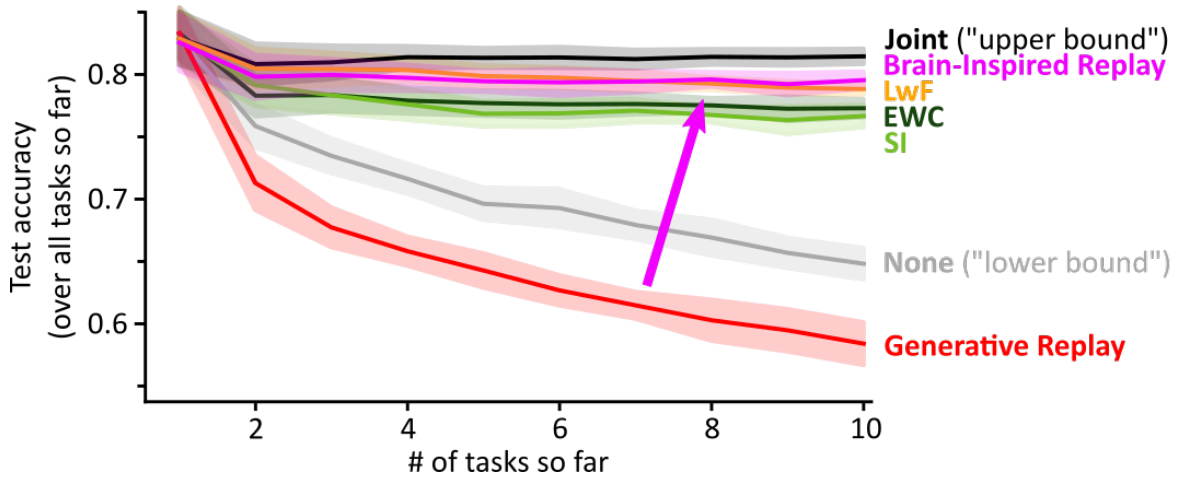

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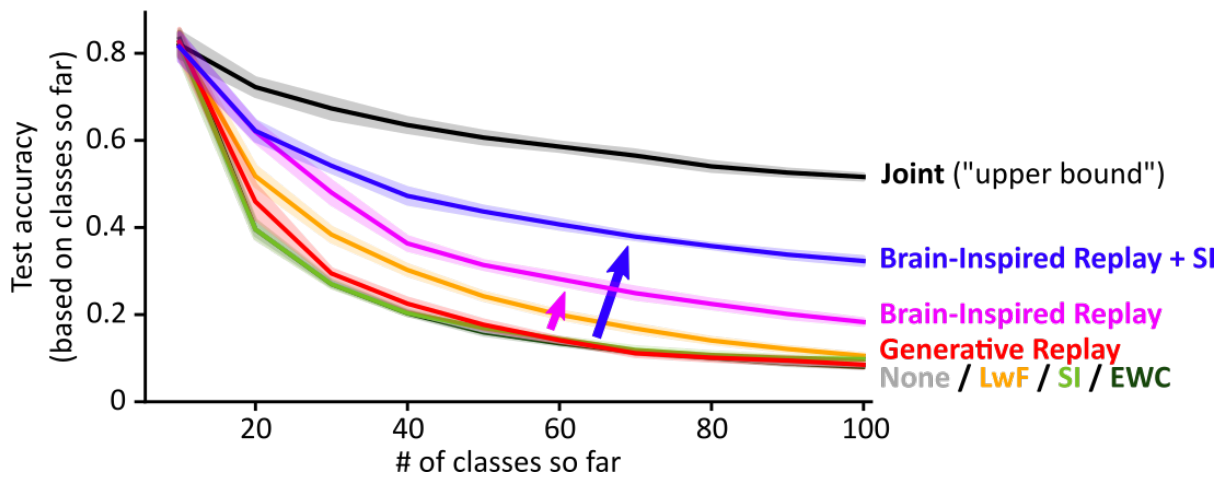

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Summary

- We proposed a new, brain-inspired variant of generative replay in which internal or hidden representations are replayed that are generated by the network's own, context-modulated feedback connections

Machine Learning contribution

Our method is the first to perform well on the challenging problem of class-incremental learning with natural images without relying on stored data

Cognitive Science contribution

Our method provides evidence that replay could indeed be feasible way for the brain to combat catastrophic forgetting

I'm available to answer questions during Virtual Poster Session #2 (9-10pm GMT)

Acknowledgements

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