

# Towards Practical Multi-object Manipulation using Relational Reinforcement Learning

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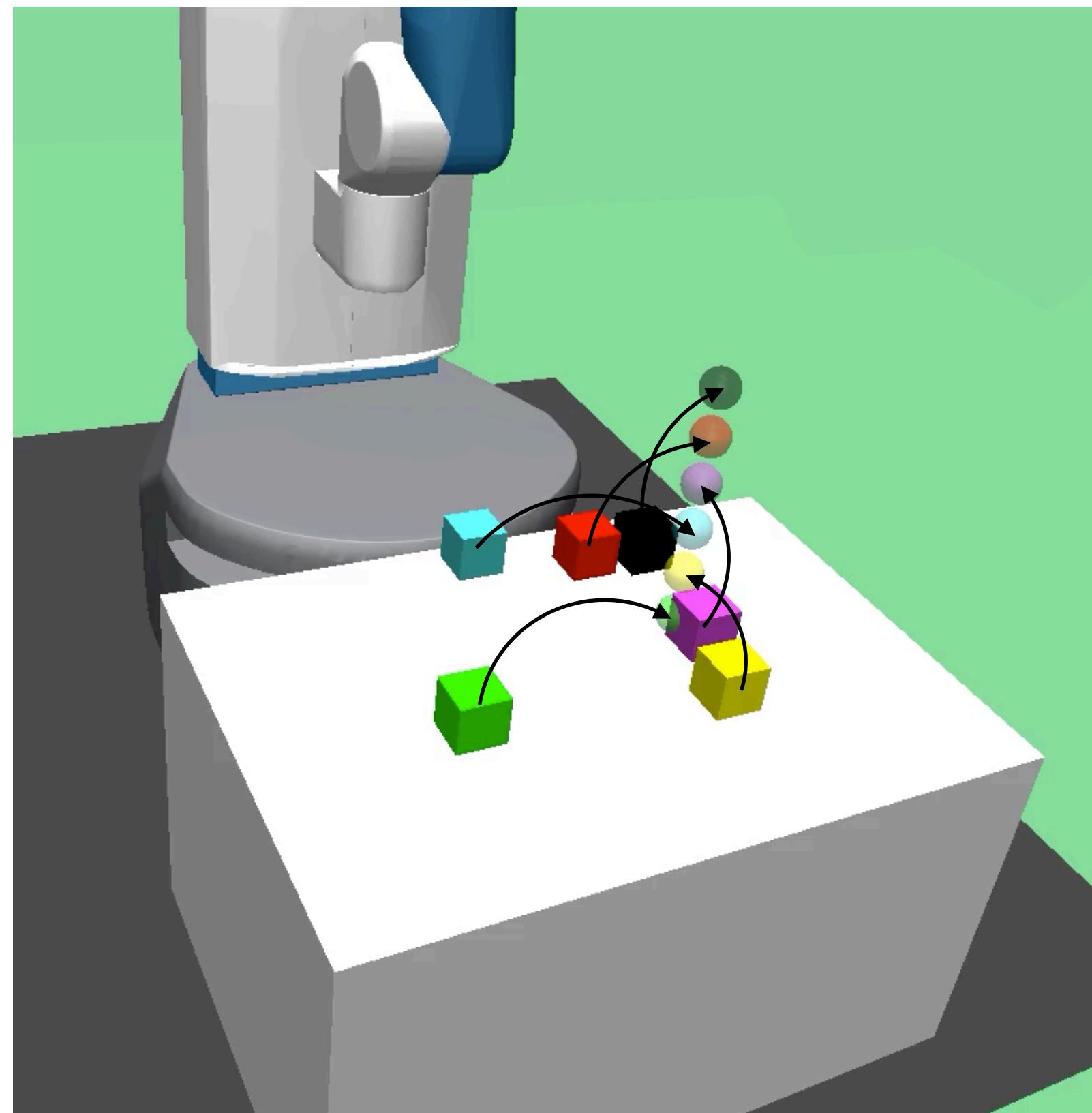
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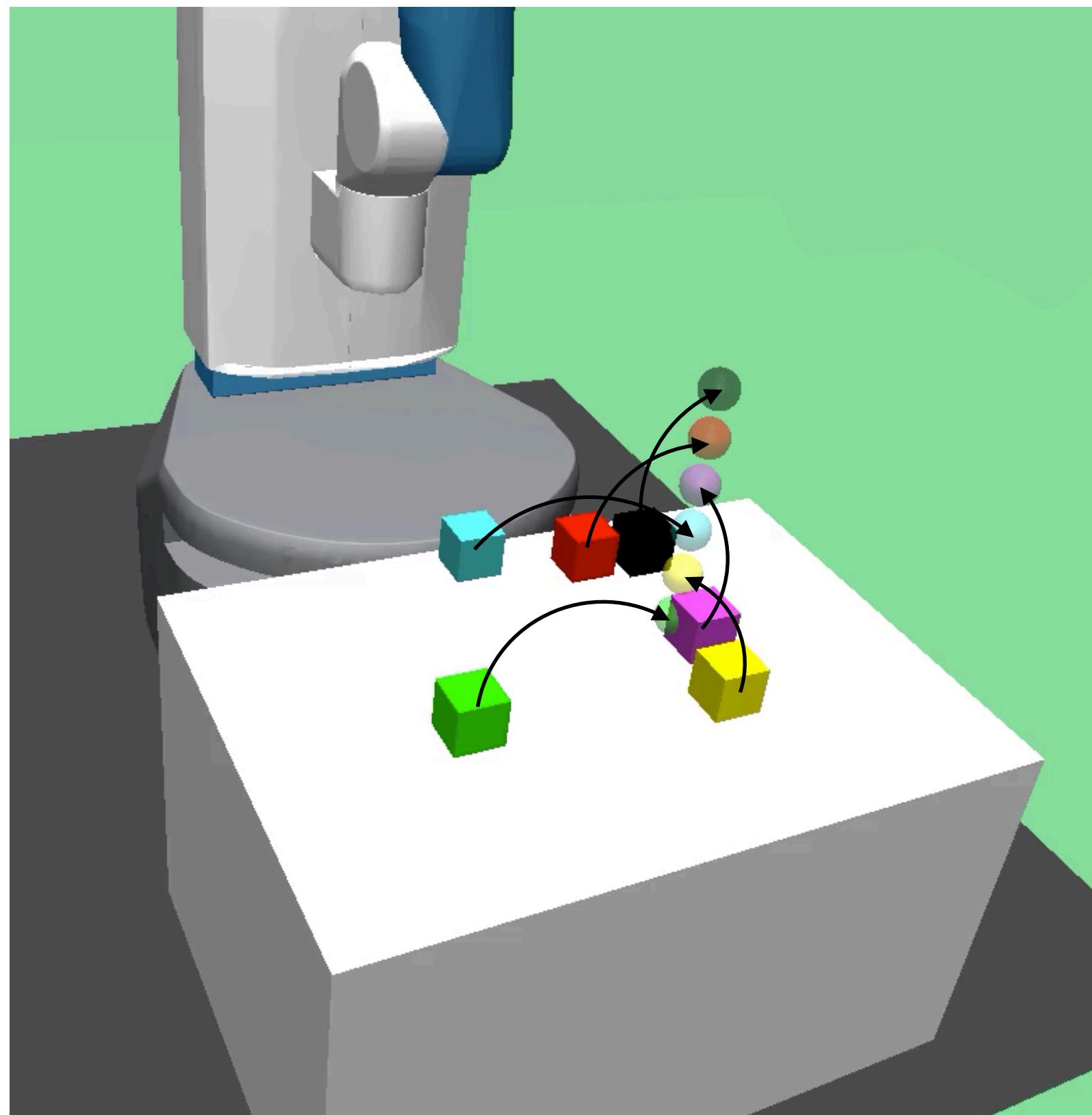
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# Block stacking task in reinforcement learning



+1 reward per block close to goal

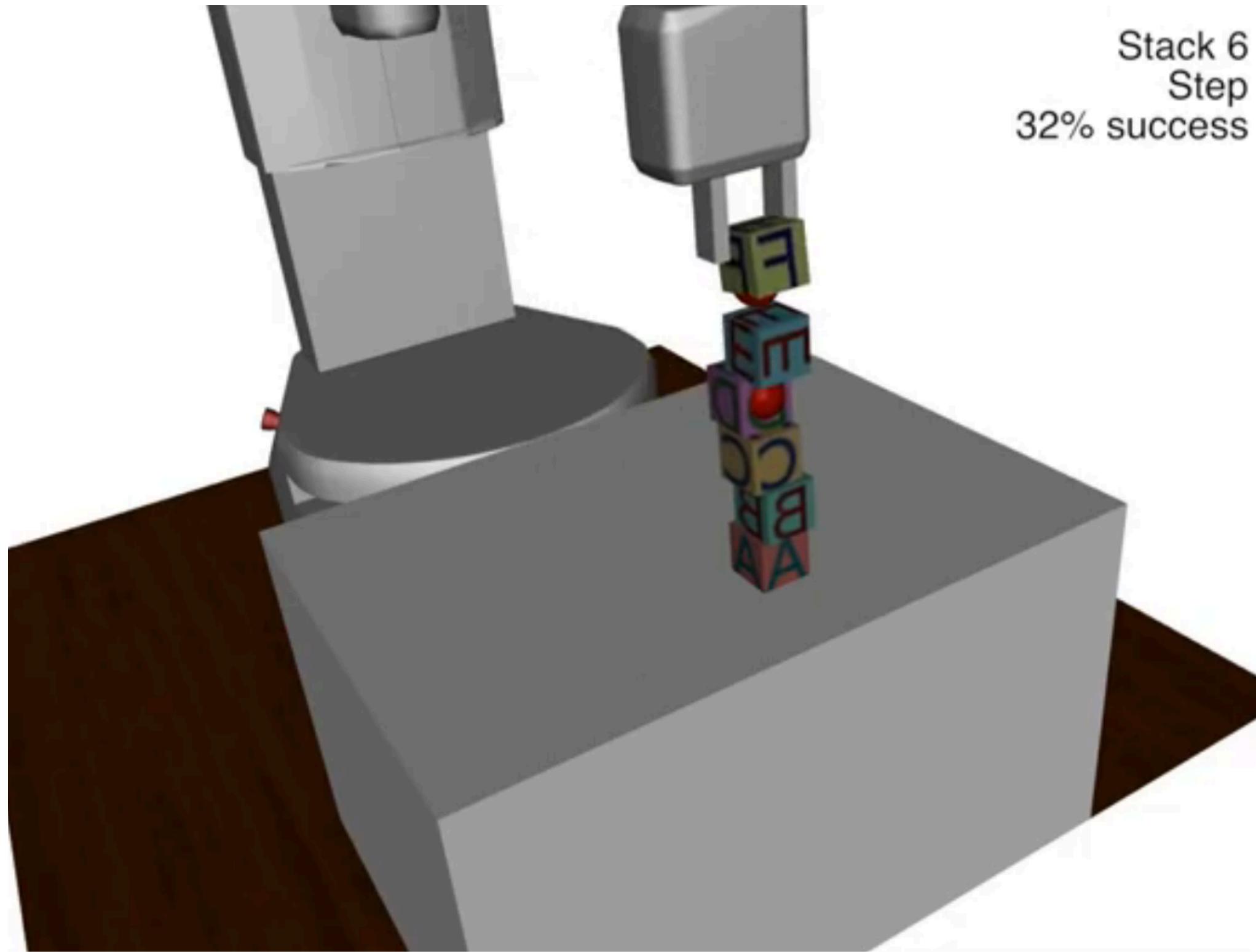
# Block stacking task in reinforcement learning



- Difficult exploration
  - Sparse reward
  - Long horizon
  - Multiple objects

+1 reward per block close to goal

# Demonstration-guided RL



Stack 6  
Step  
32% success

- Behavioral cloning loss

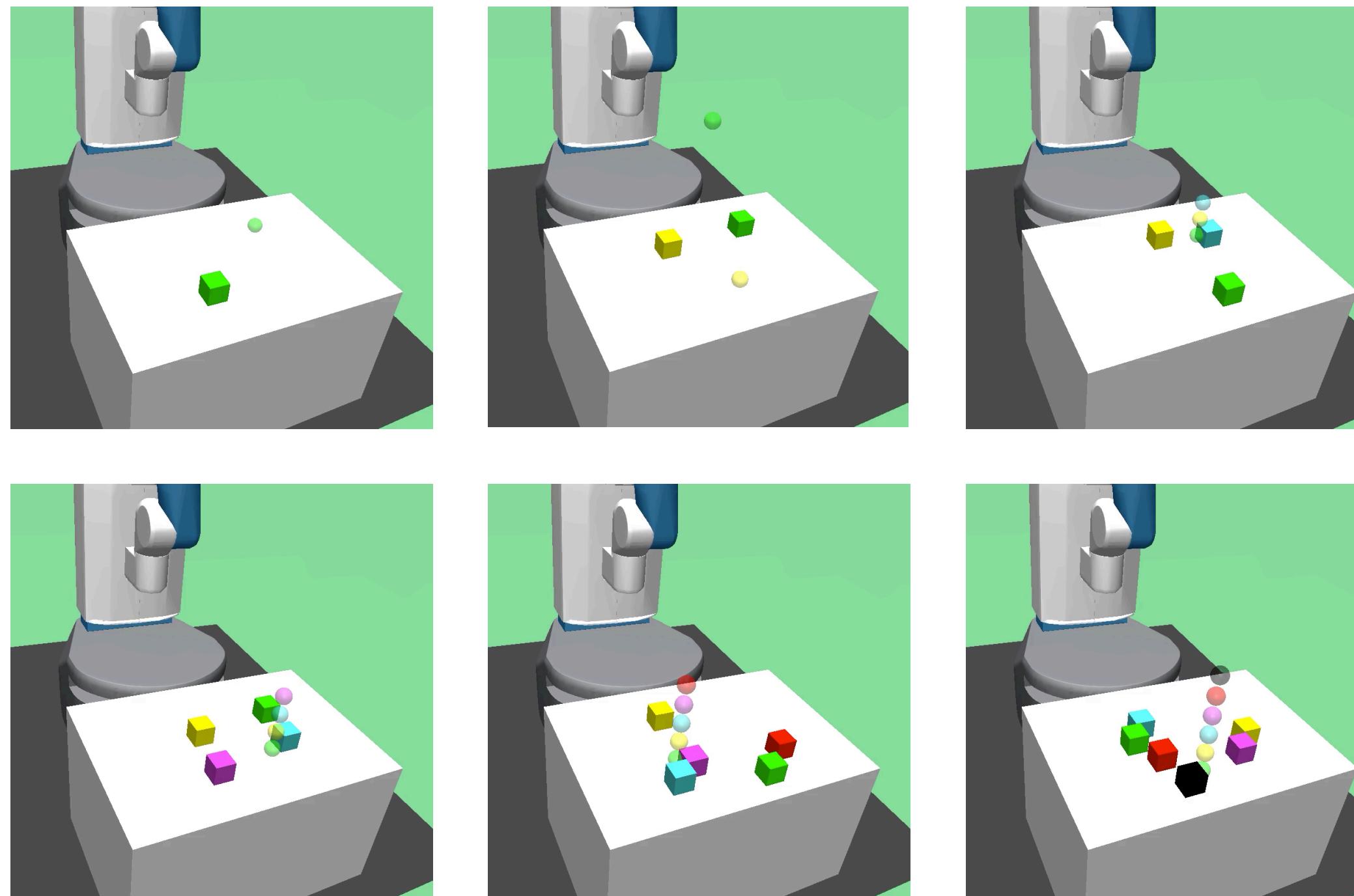
Nair '18

# Comparison of results

## Stacking 6 Blocks

	Nair '18 (SOTA)	Ours
Success rate	32%	<b>75% (↑43%)</b>
Environment steps	2300M	<b>30M (↓77x)</b>

# Curriculum over object cardinality

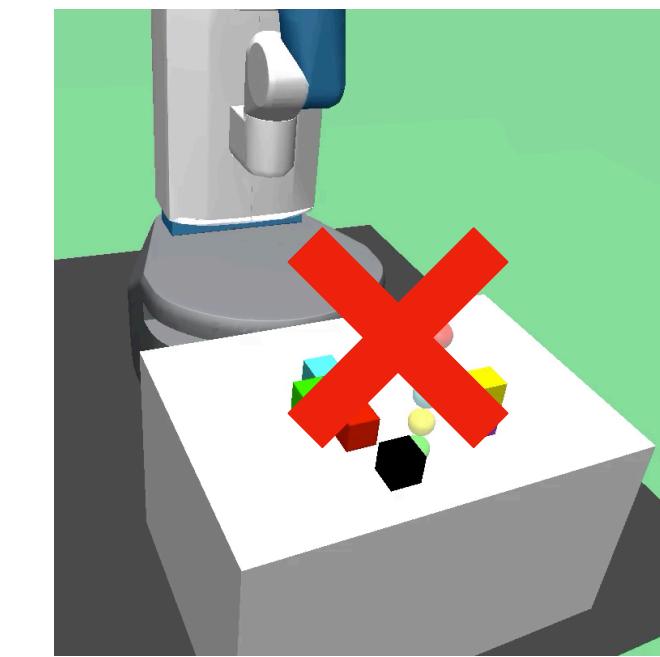
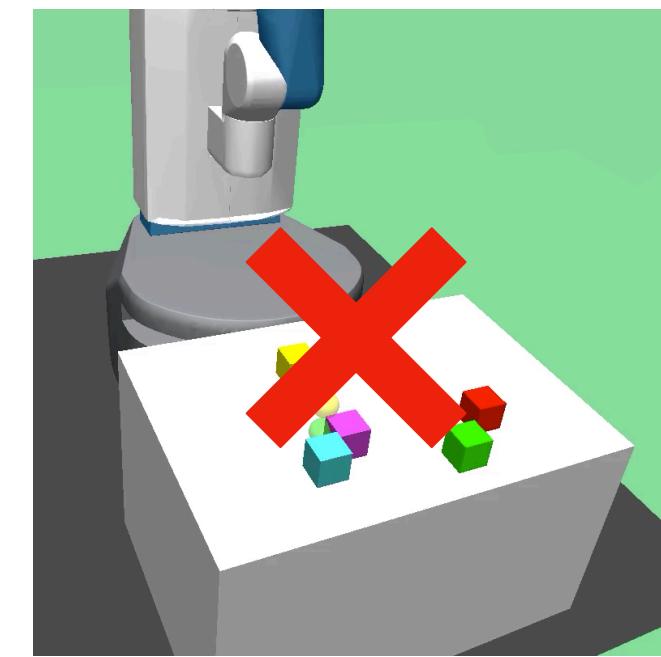
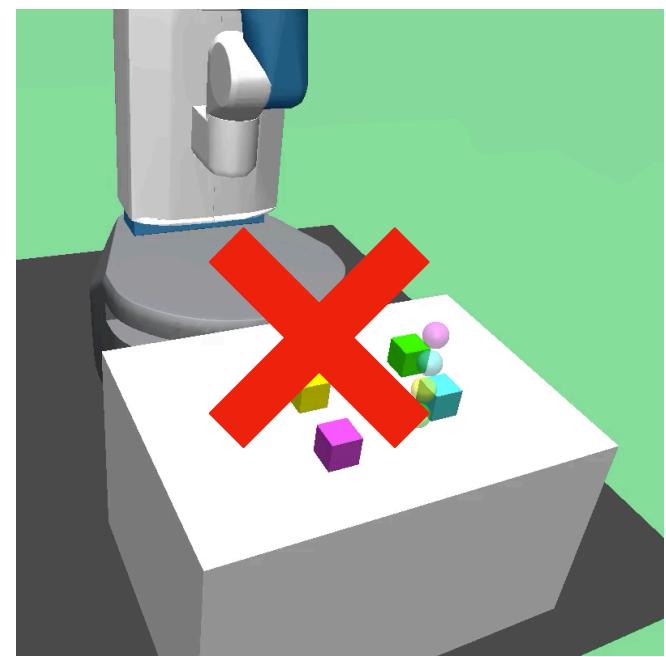
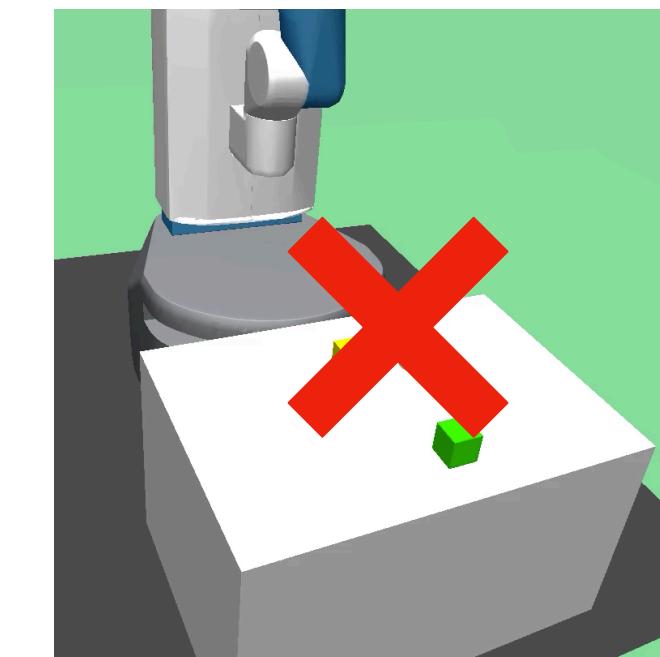
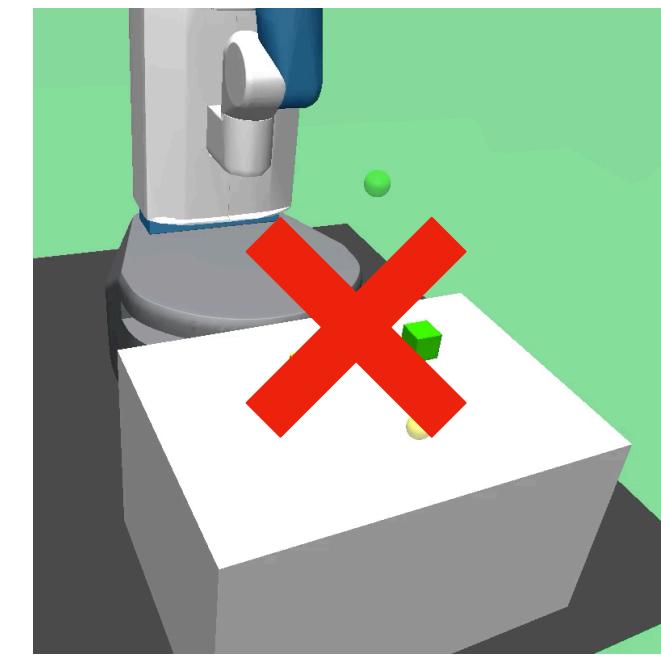
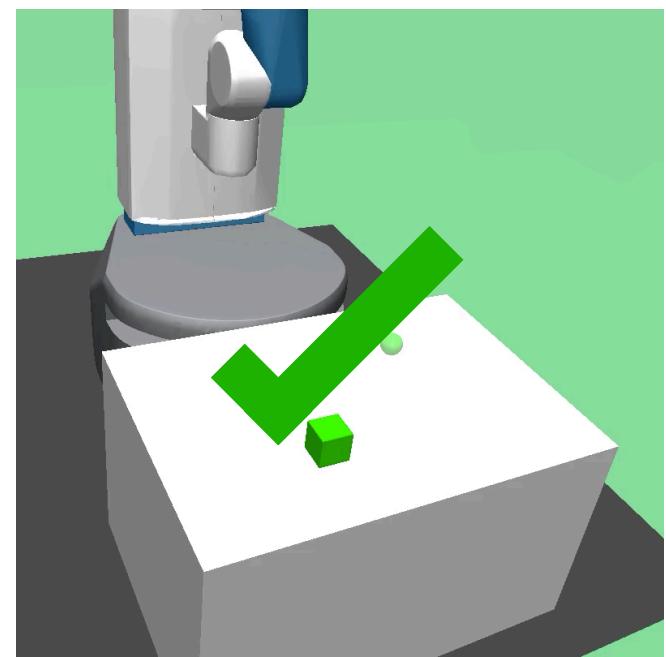


- Start with 1 block, sequentially transfer to harder tasks
- Soft Actor Critic + Hindsight Experience Replay

NerveNet (Wang '18)

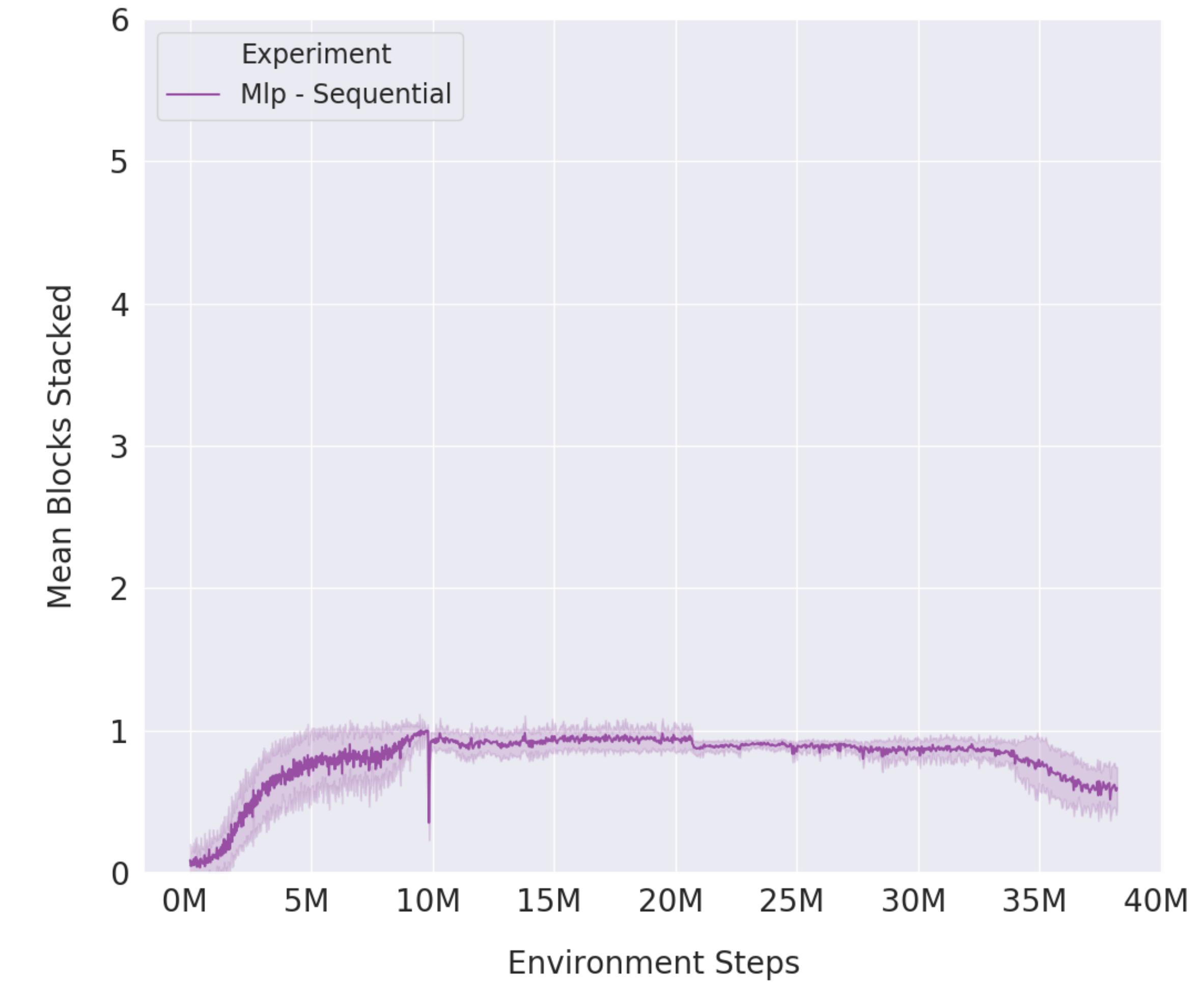
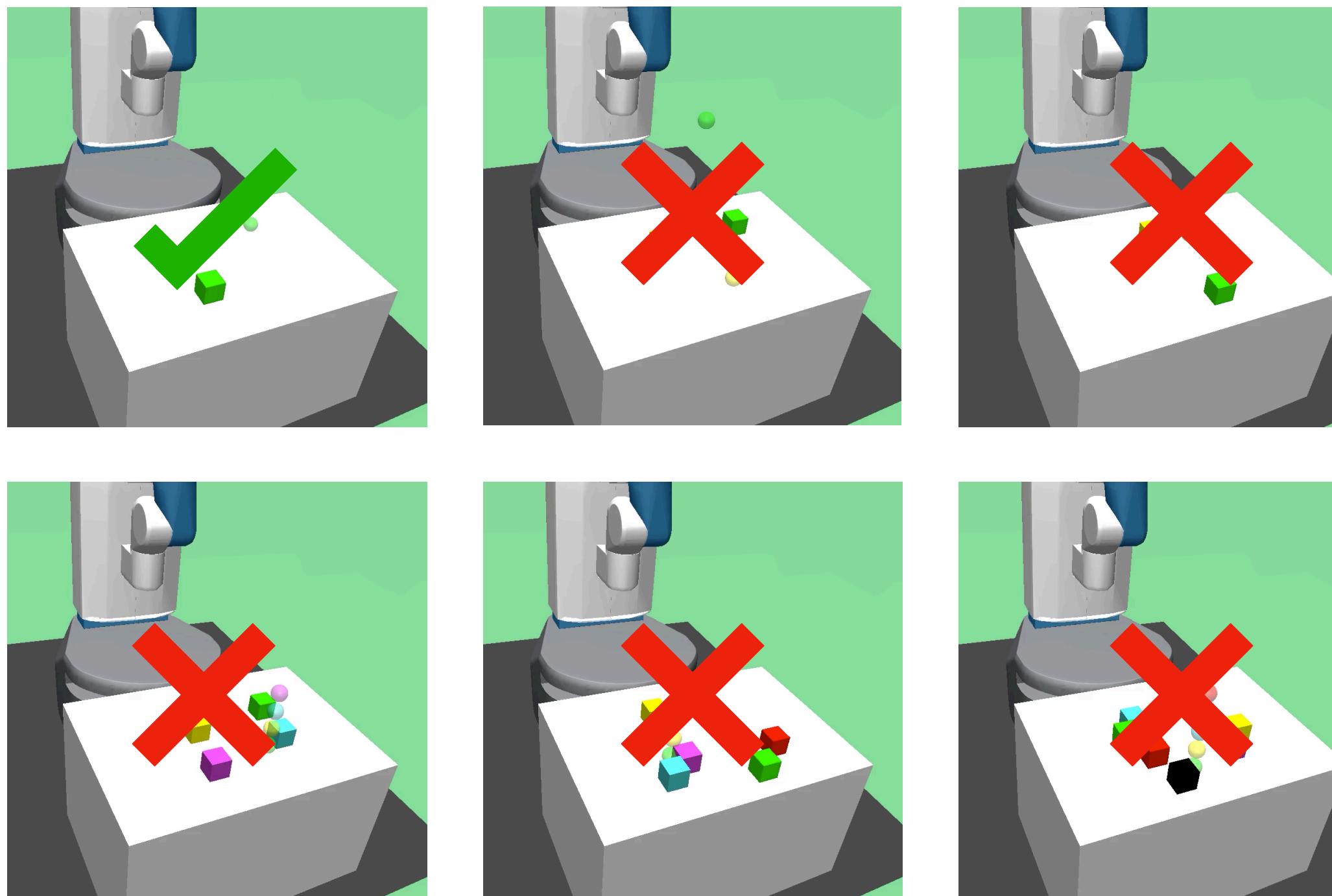
Self-Assembling Morphologies (Pathak '19)

# Curriculum with Multi-layer Perceptron (MLP)



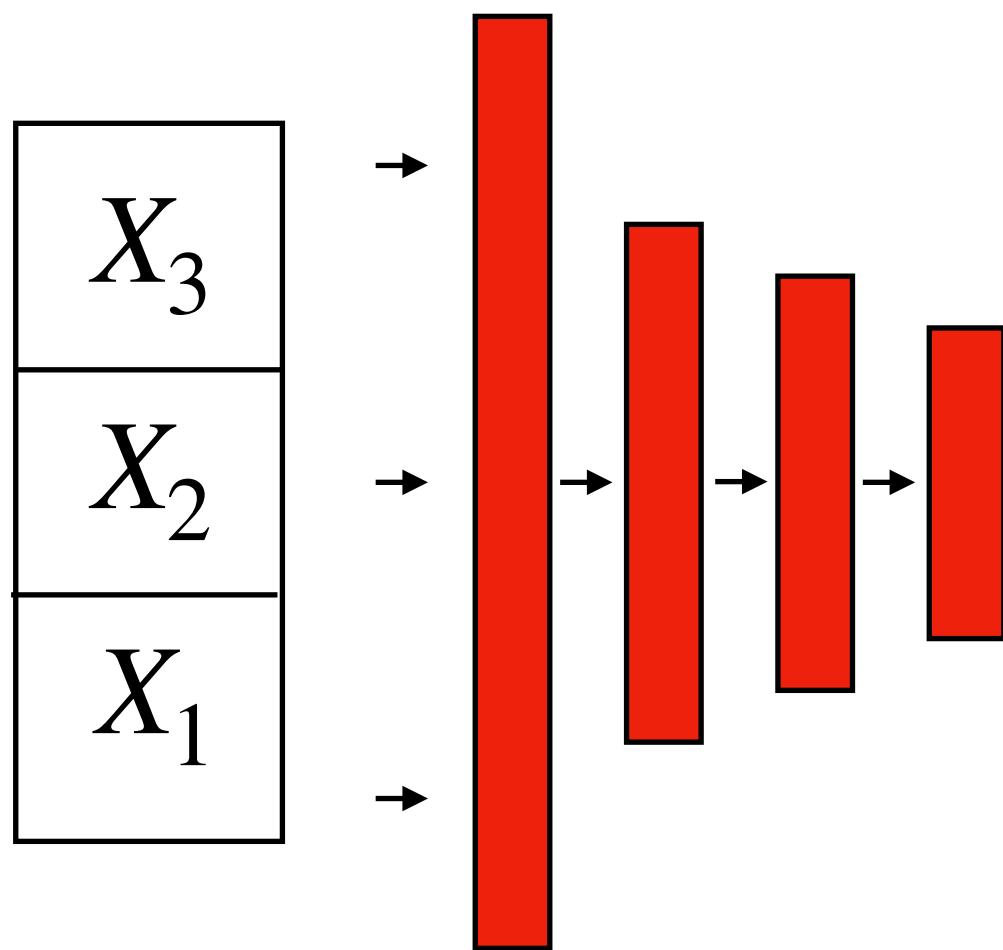
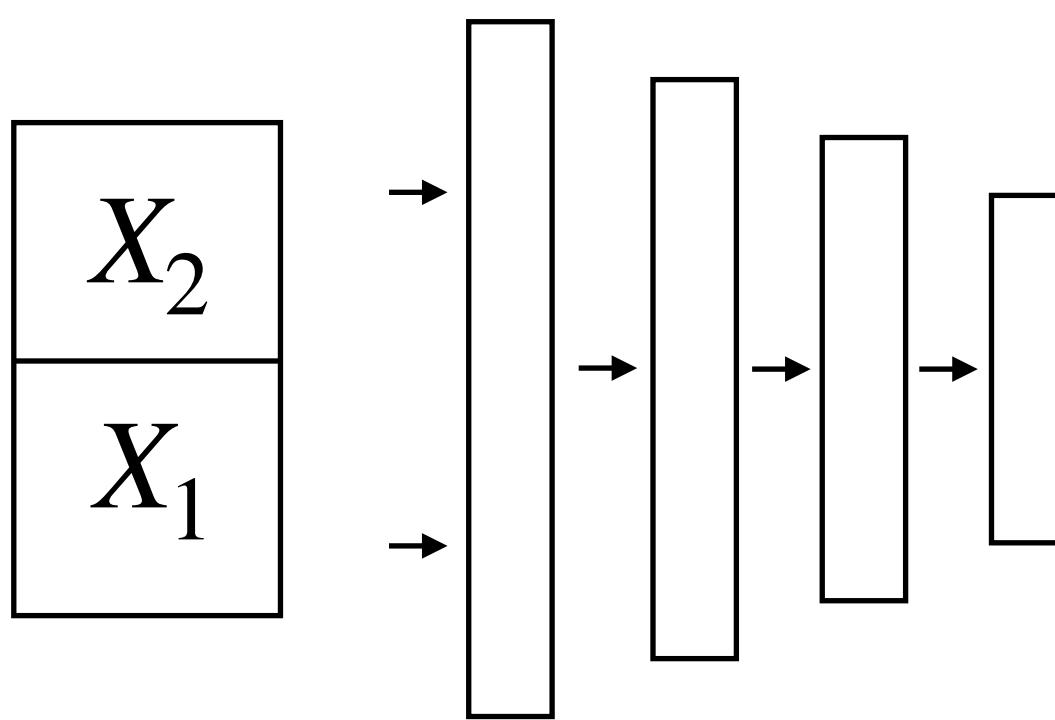
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# Curriculum with Multi-layer Perceptron (MLP)

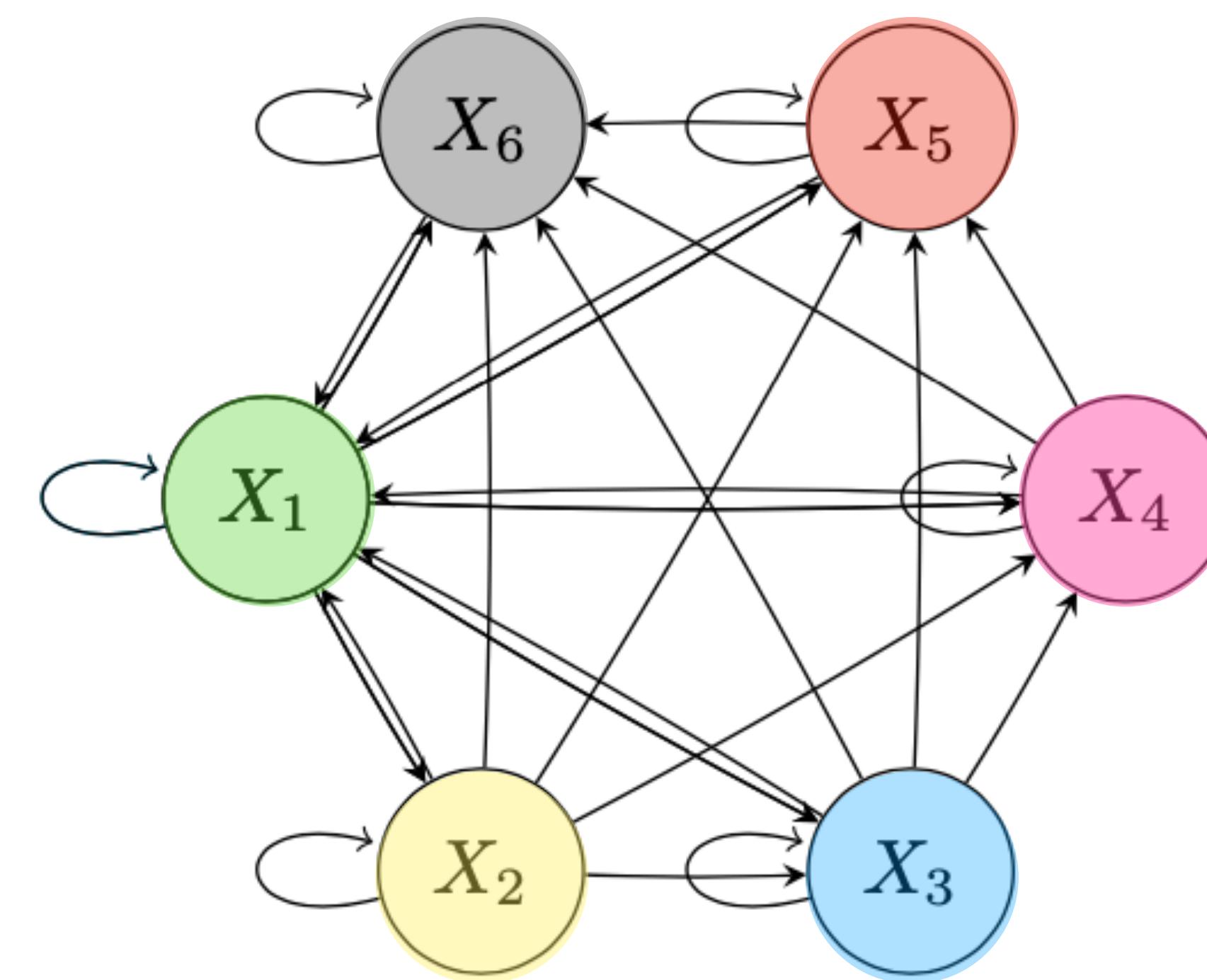
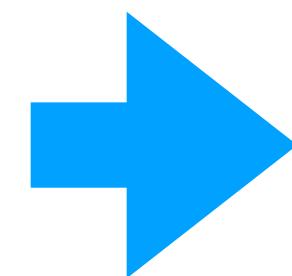
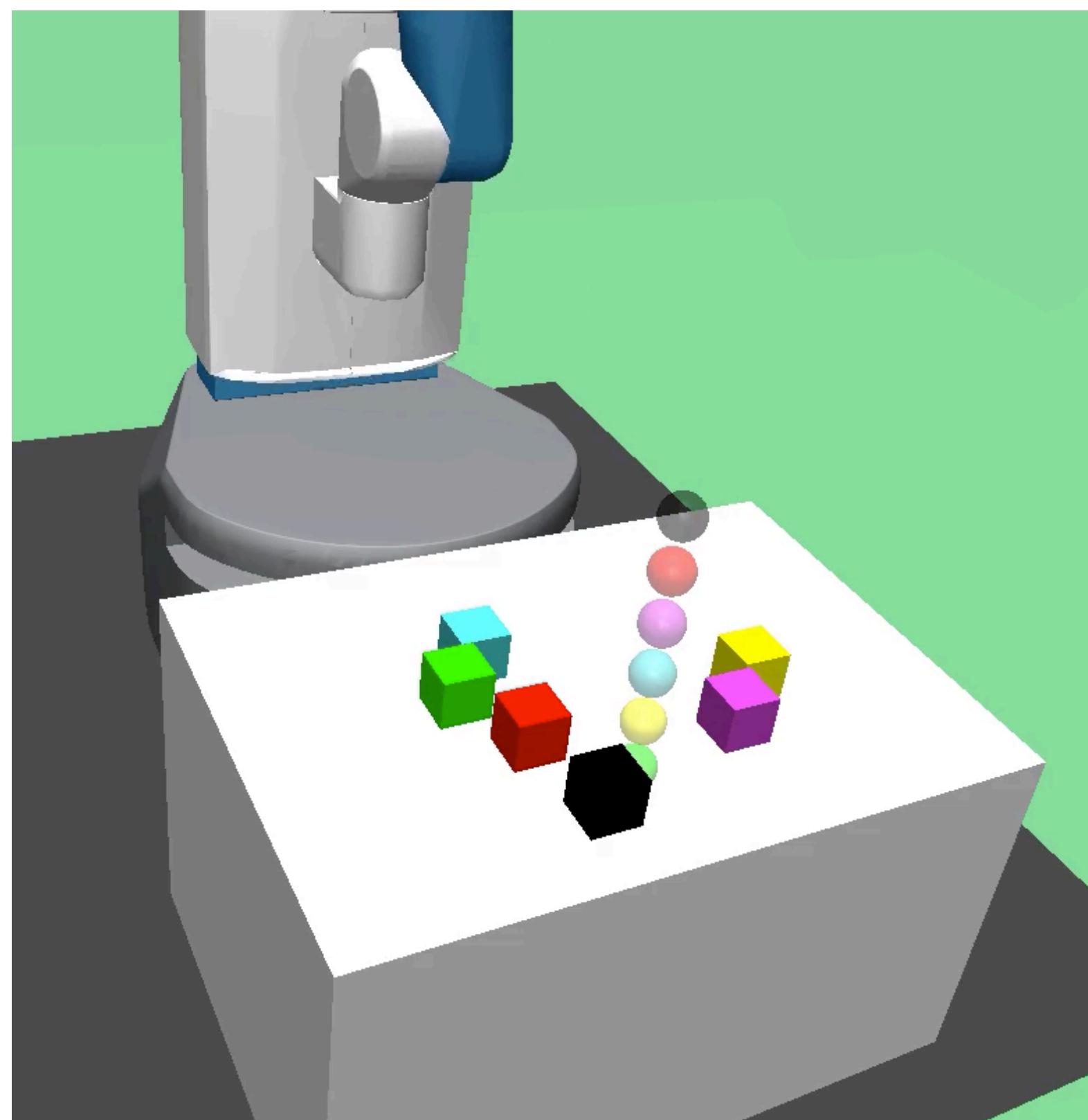


# Problem: Discrete domain shift

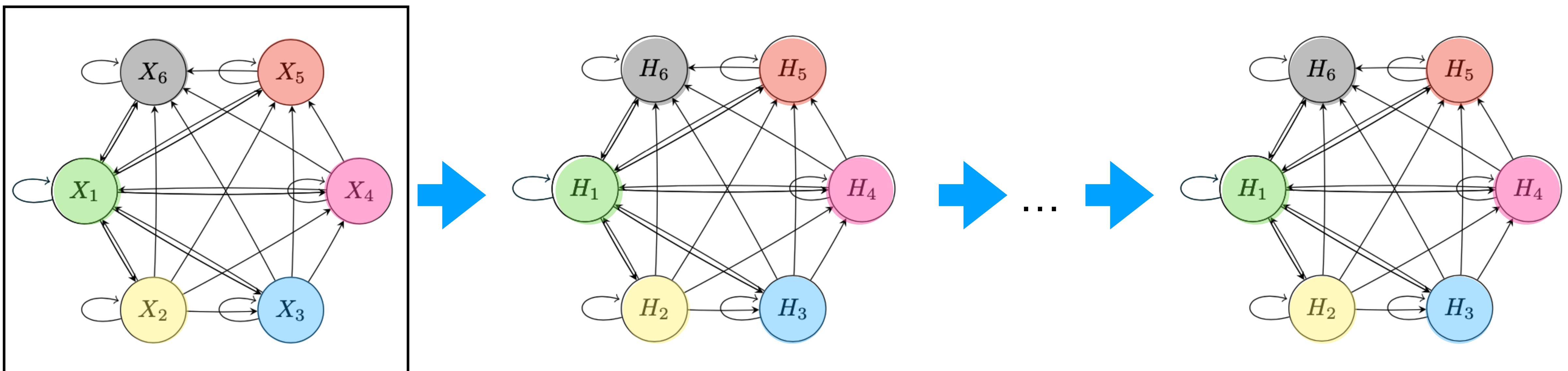
2 blocks  $\rightarrow$  3 blocks



# Swap MLP for Graph Neural Network (GNN)



# Attention-based GNN



$q_i$ : query

$k_i$ : key

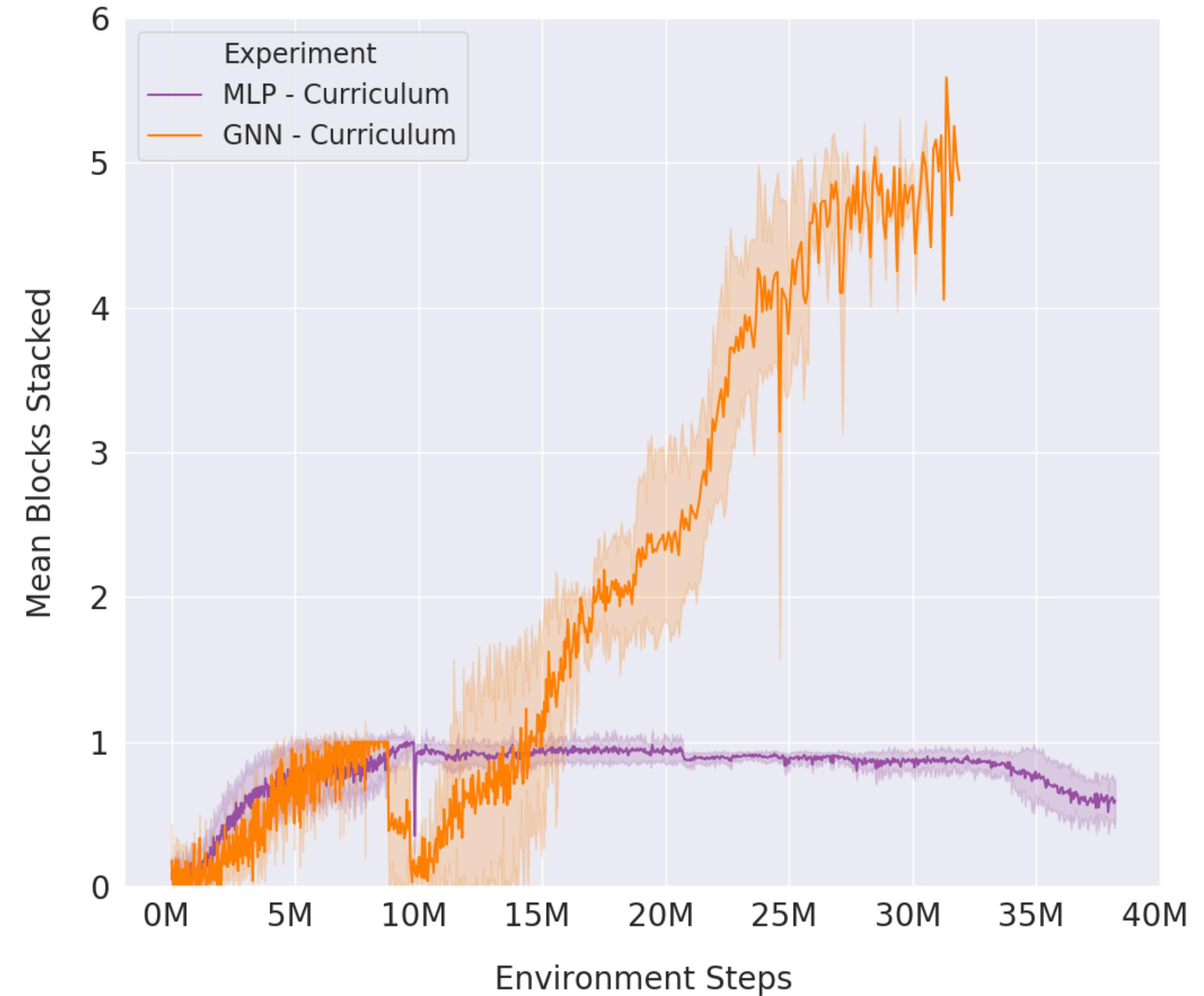
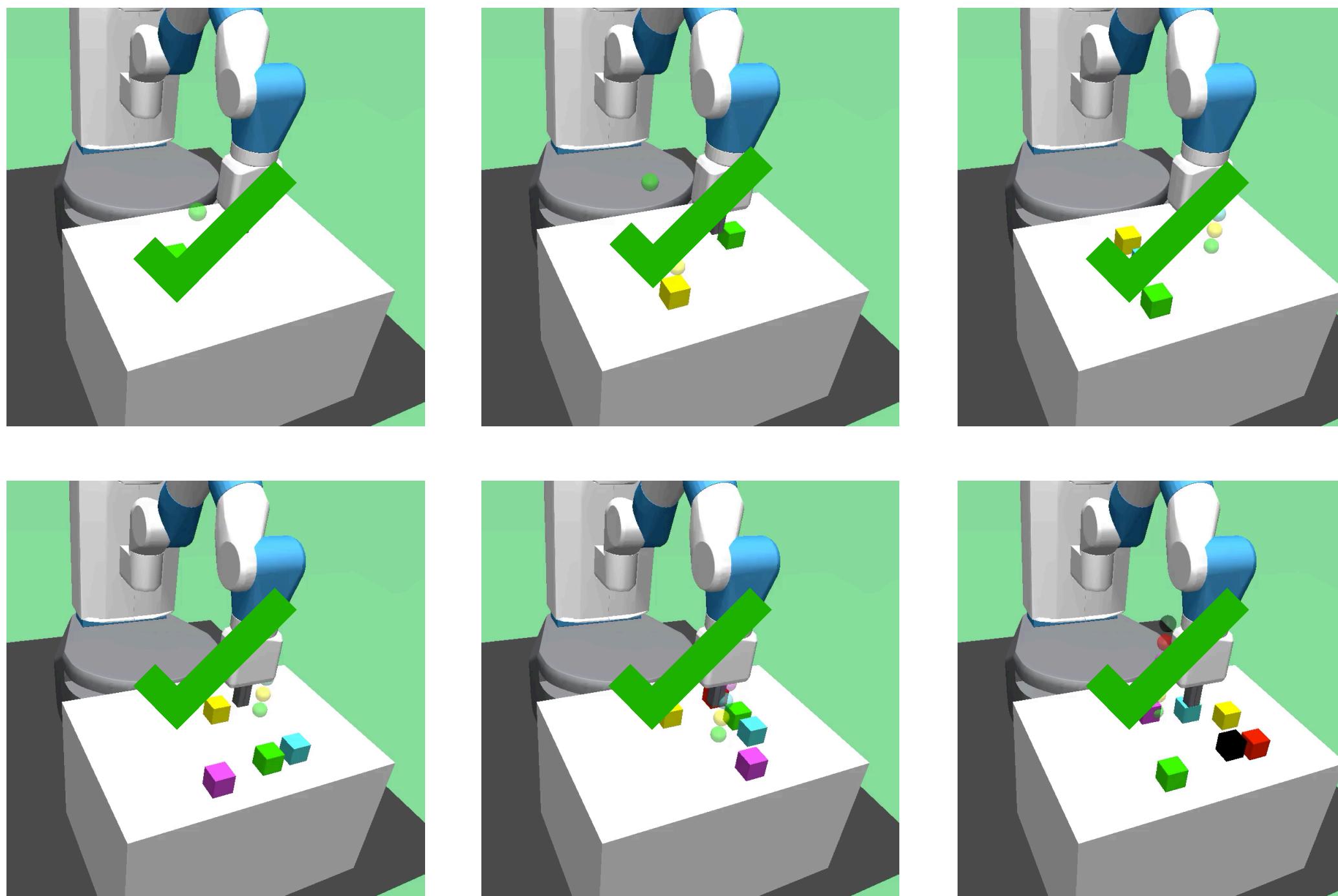
$m_i$ : message / value

MHDPA/Self-attention (Vaswani '17)

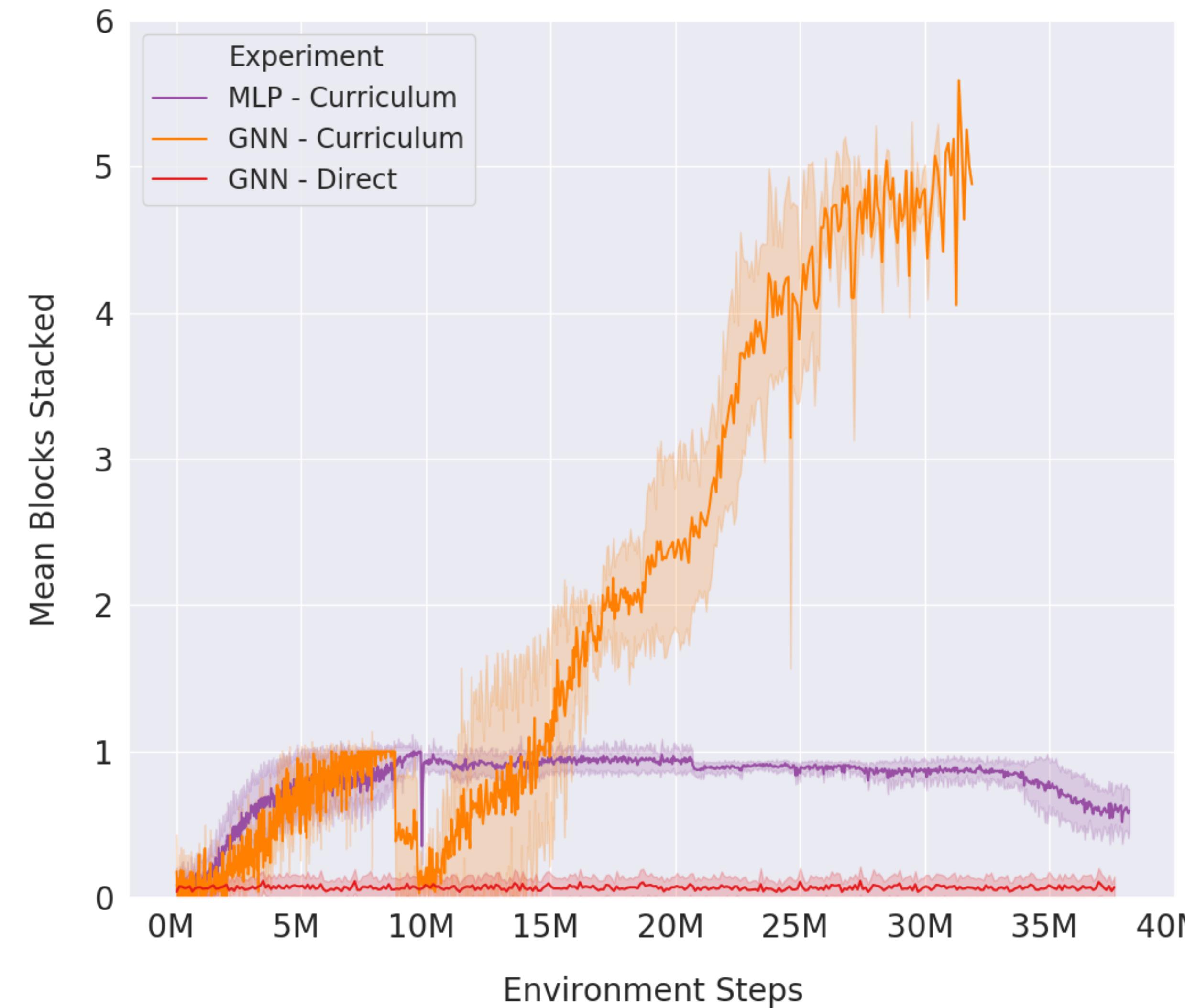
Relational Deep RL (Zambaldi '19)

# Curriculum with attention-based GNN

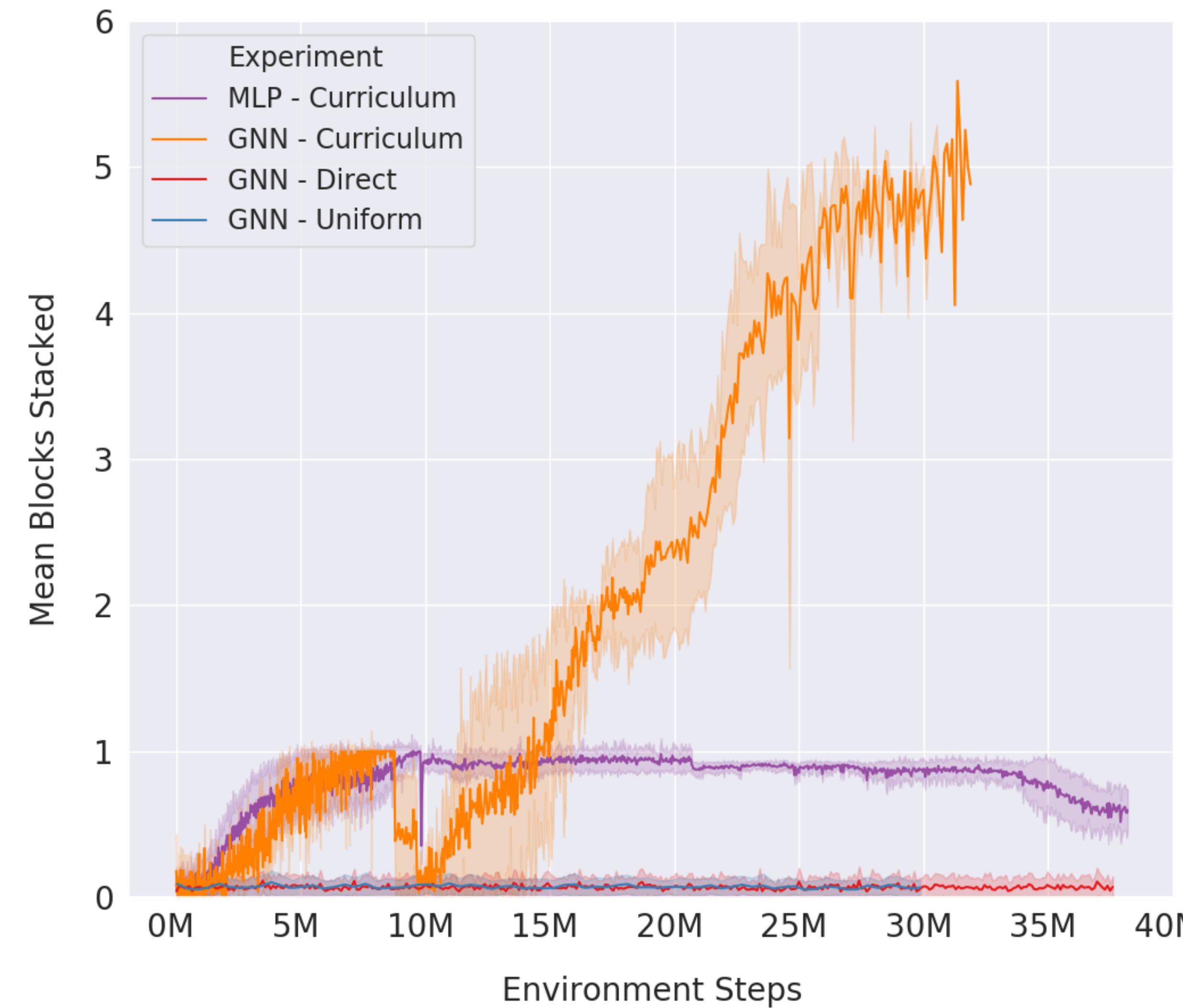
(Our method)



# Comparison of GNN with/without Curriculum



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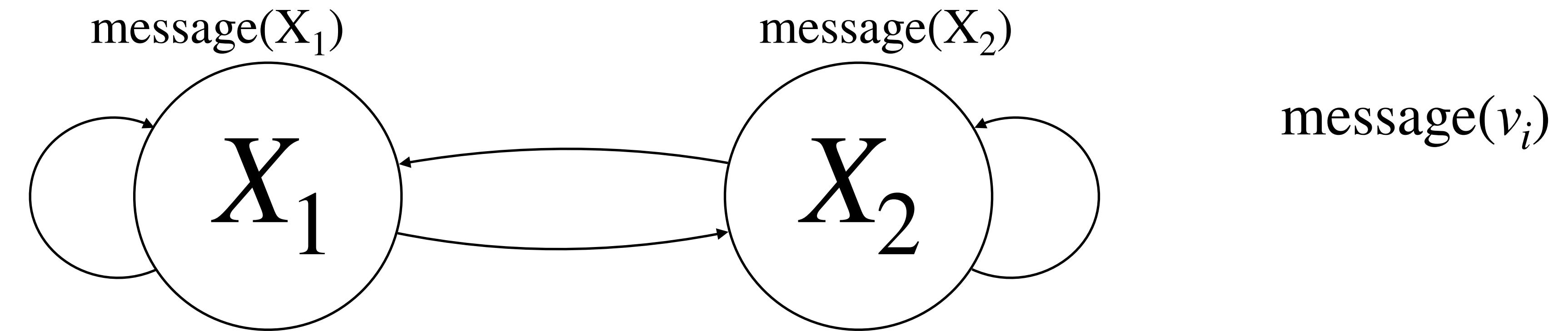


# Why does the GNN transfer to more objects?

Local functions can be applied inductively to arbitrary # of nodes

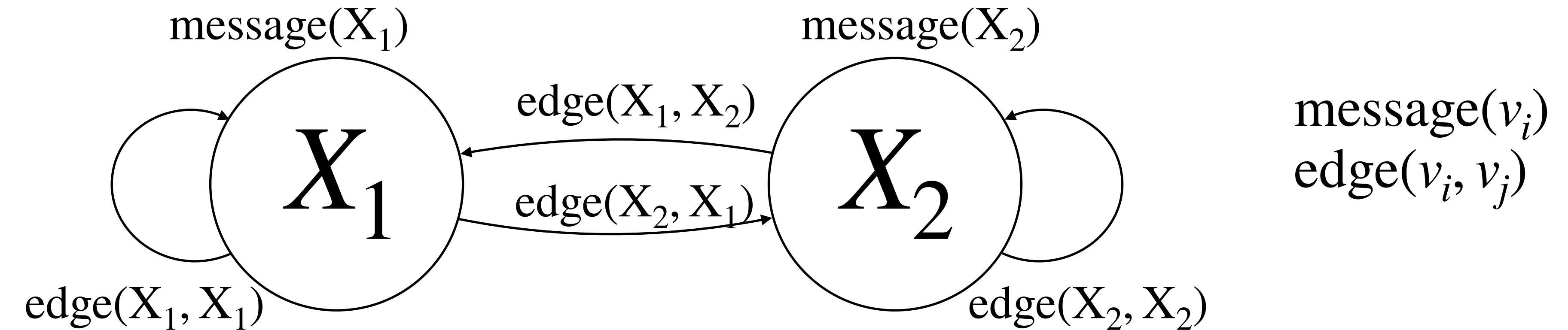
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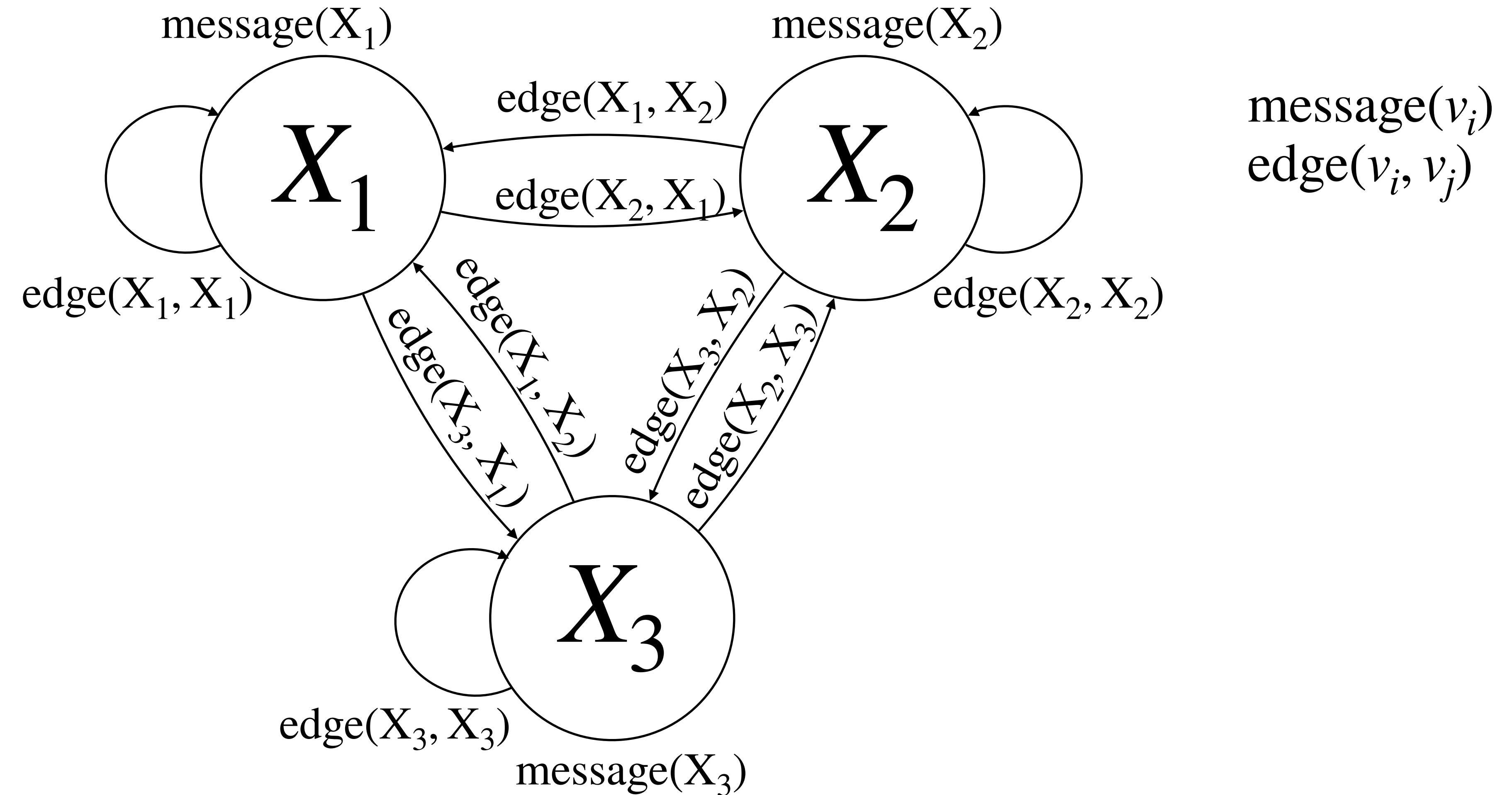
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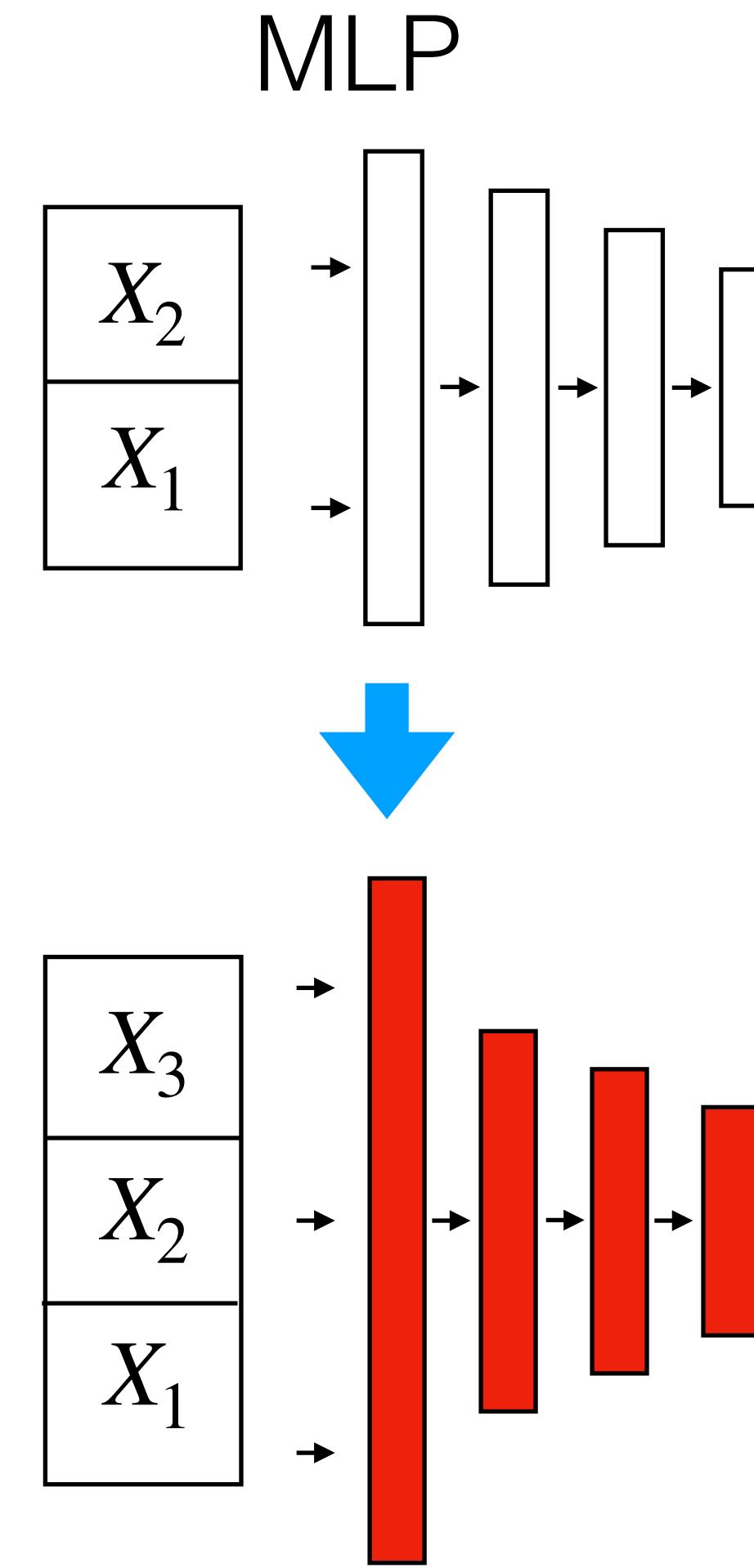
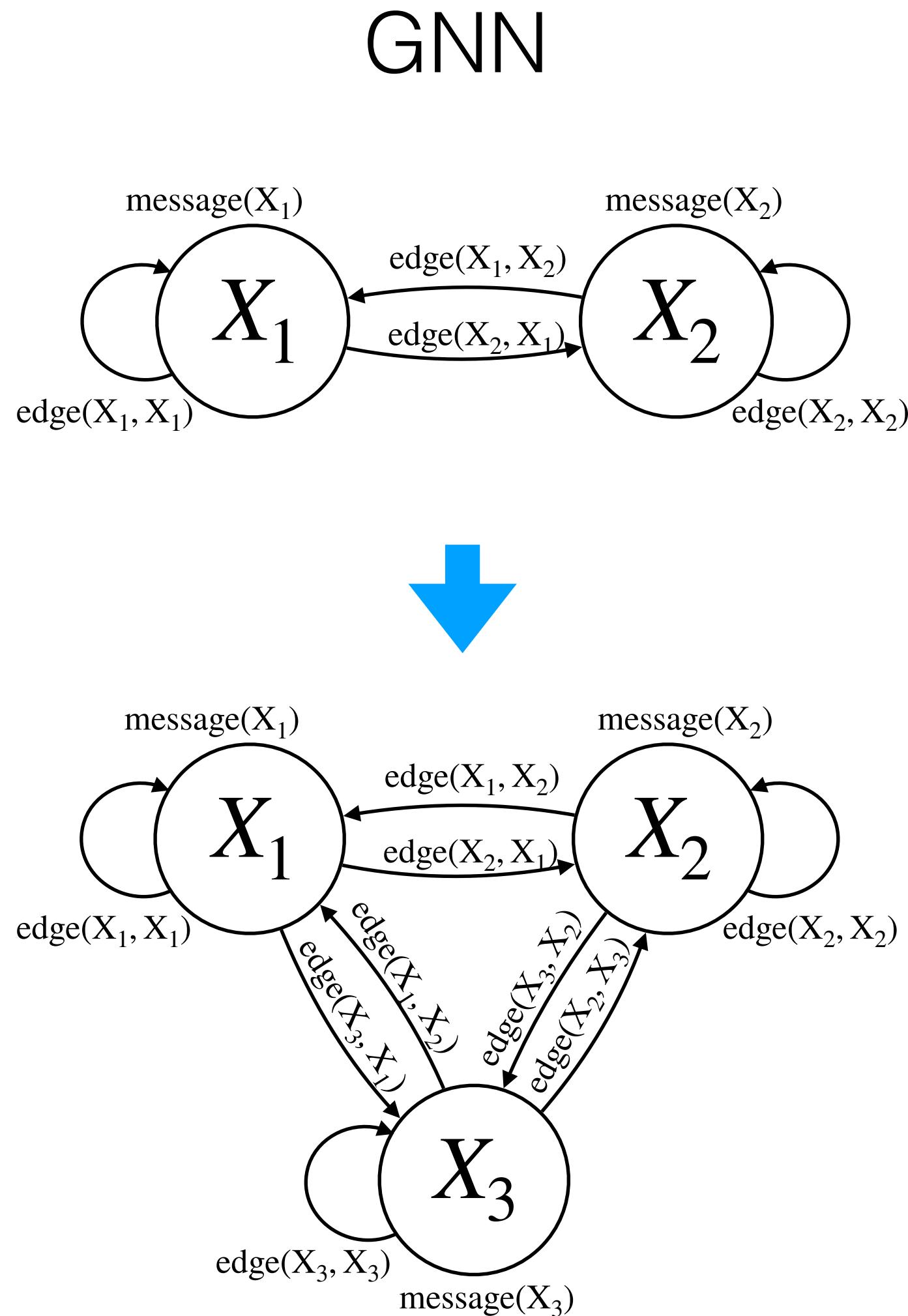
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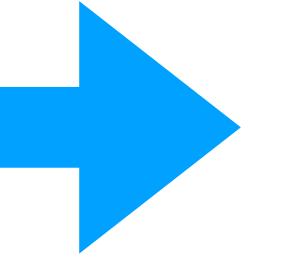
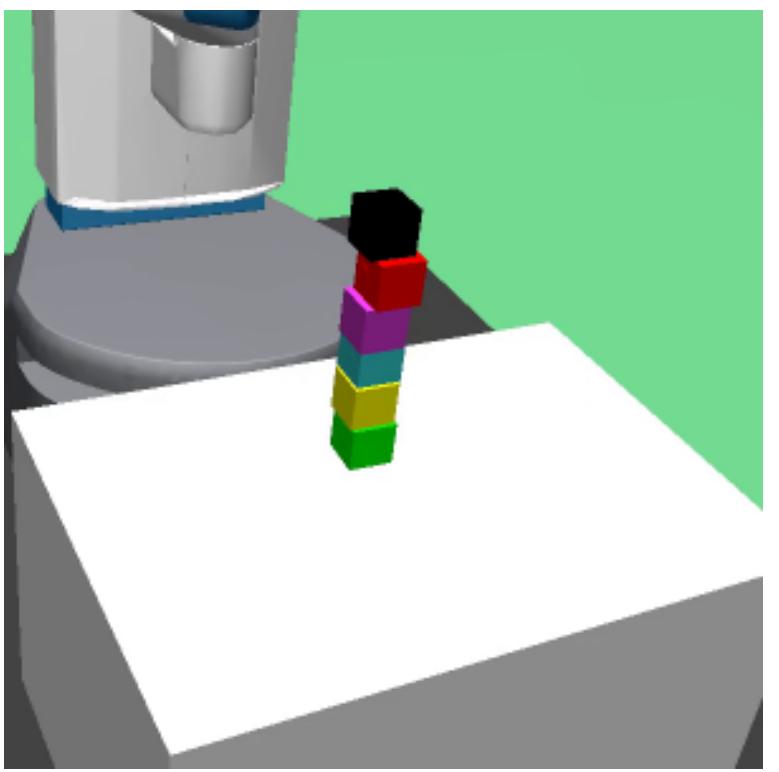


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# Zero-shot generalization



training  
single tower 6

# Emergent strategies

# Failure modes

# Conclusions

- Curriculum learning + graph architecture = drastic improvement in sample efficiency!
- Generalization to novel goals
- Learn efficient strategies that are hard to manually design