A Compositional Object-Based Approach to Learning Physical Dynamics
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1 Vision
Vision: In order to rapidly learn new tasks and flexibly adapt to changes in inputs and goals, an agent needs a prior on physics that allows it to naturally generalize reasoning to novel scenes.

2 Steps
Combining the advantages of symbolic and neural models
How to incorporate inductive biases that are not only strong enough to generalize across scenes, but also flexible enough to learn from and adapt to different inputs?

3 Neural Physics Engine (NPE)
Scenario
Model Architecture
Predict the velocity of each object in turn, given the pairwise interactions with its neighborhood context objects.

4a Generalization: different numbers of objects
Ingredients useful for generalization
What are the primitives, means of combination, and means of abstraction that underlie the training and testing distributions, such that generalization comes for free?

4b Generalization: different scene configurations
Ingredients useful for generalization
By combining the expressiveness of physics engines and the adaptability of neural networks in a compositional architecture that naturally generalizes in fundamental aspects of physical reasoning, the Neural Physics Engine is an important step towards lifting an agent's ability to think at a level of abstraction where the concept of physics is primitive.