3D-IntPhys: Towards More Generalized 3D-grounded Visual Intuitive Physics under Challenging Scenes

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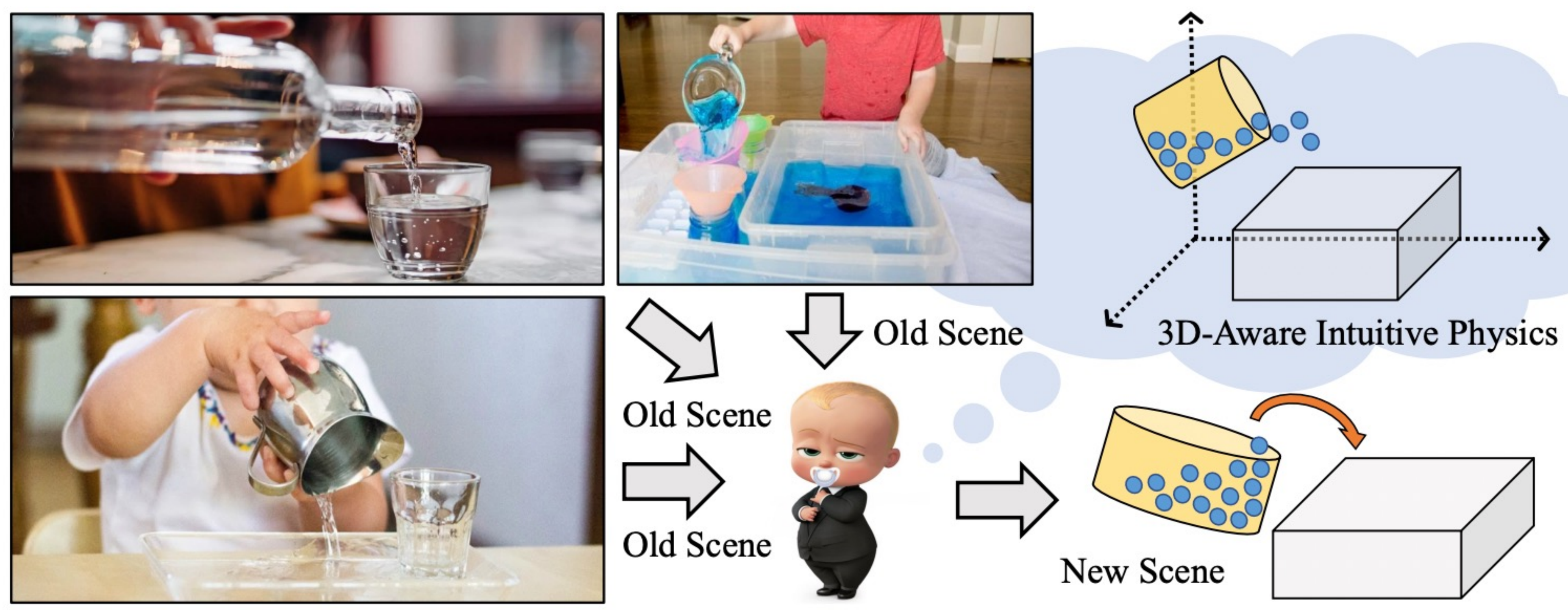
NEURAL INFORMATION PROCESSING SYSTEMS

Background: Intuitive Physics

- Humans have ability to gain **strong intuition** about the **physical world** around them, we can predict the movement of **complex dynamics** in 3D space without knowing the underlying dynamics:



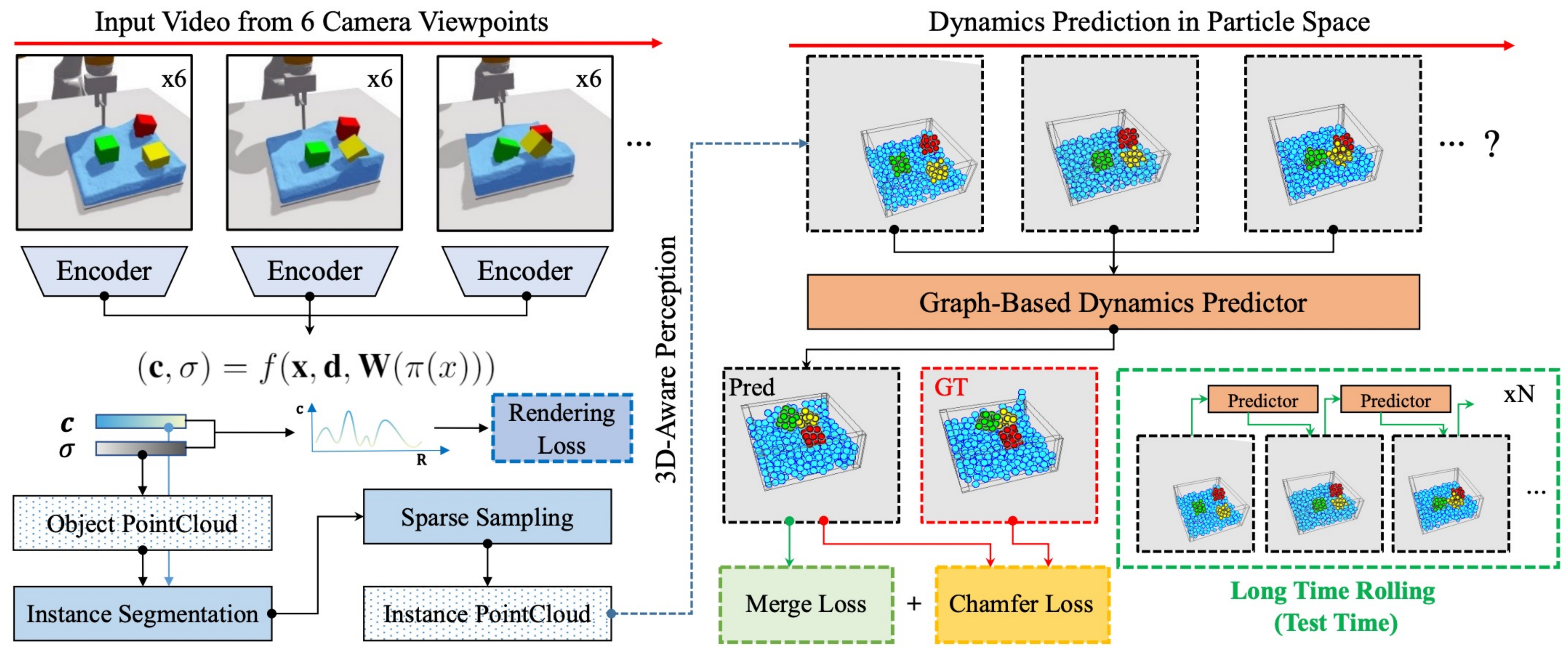
- Learning from visual inputs of old scenes, humans can generalize the acquired **3D-aware intuition** to new scenes.

Motivation: Learning 3D-IntPhys from Video

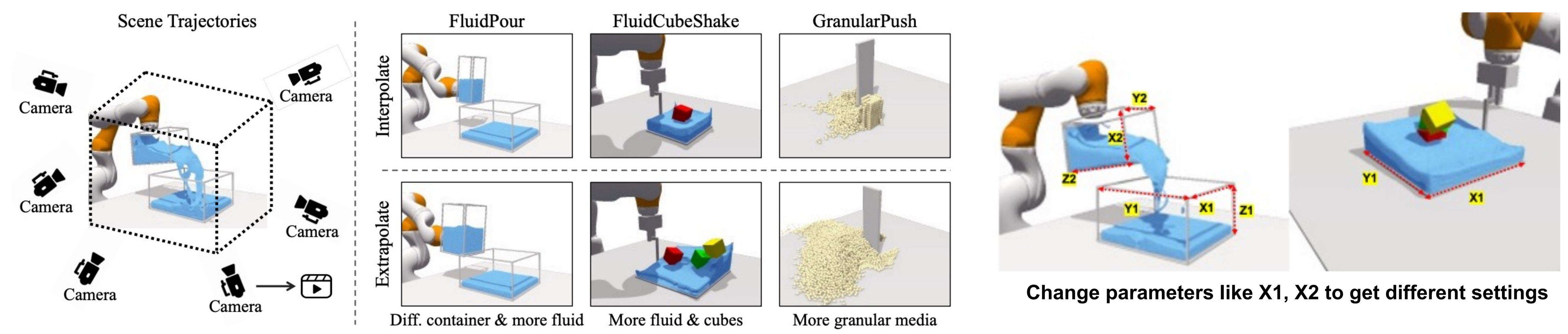
- We want a framework to **enable machine** to learn such kind of **3D-aware intuitive physics** from solely **visual inputs**.
- We want to impose strong **inductive bias**, to make it possible to learn reasonable intuitive physics from visual inputs with **a strong generalization ability** to unseen settings.

Our Approach: 3D-IntPhys

Key Idea: learn explicit 3D-based representation to model dynamics from visual inputs, which can be well-generalized to unseen scenes.

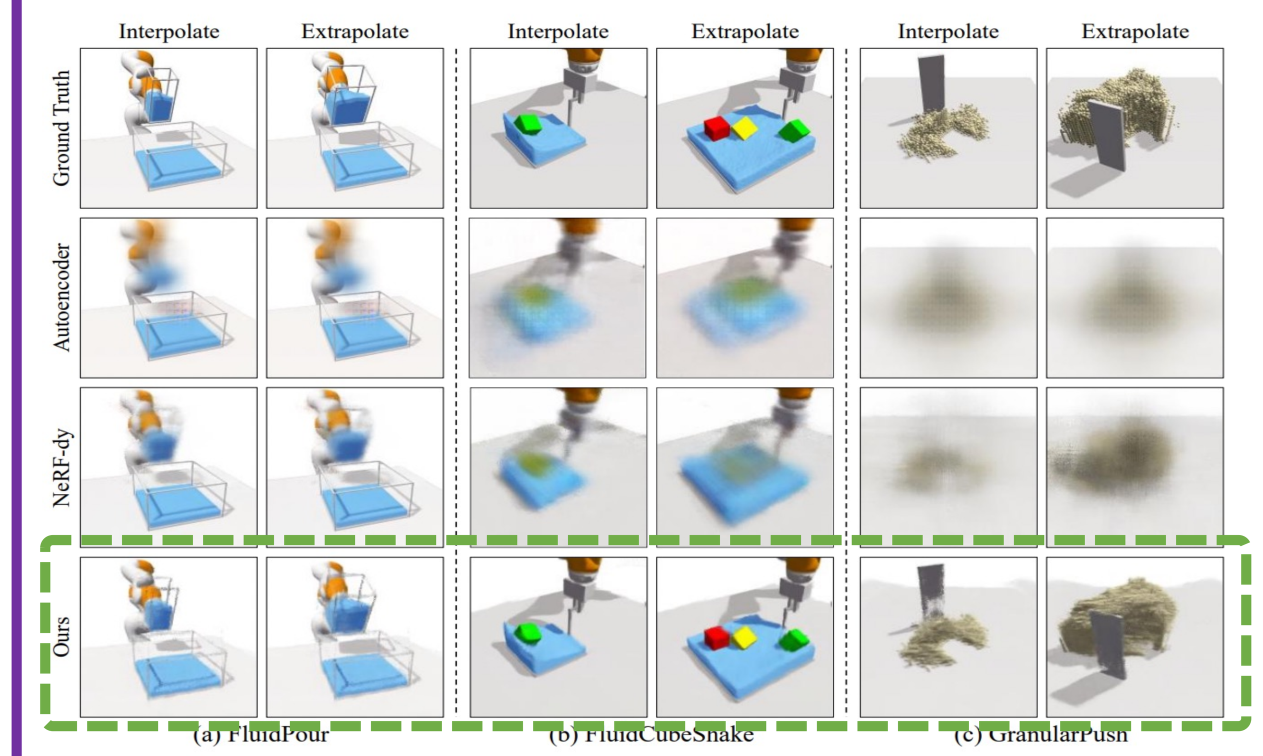


- Our method is composed of a **conditional NeRF**-style visual frontend and a **3D point-based dynamics** prediction backend, **imposing strong structural inductive bias**.
- We first train **conditional NeRF** to reconstruct explicit 3D representation, then we learn explicit 3D dynamics with **Chamfer Loss** and Merge Loss.
- We generate **multi-view dataset for interpolate and extrapolate settings:**

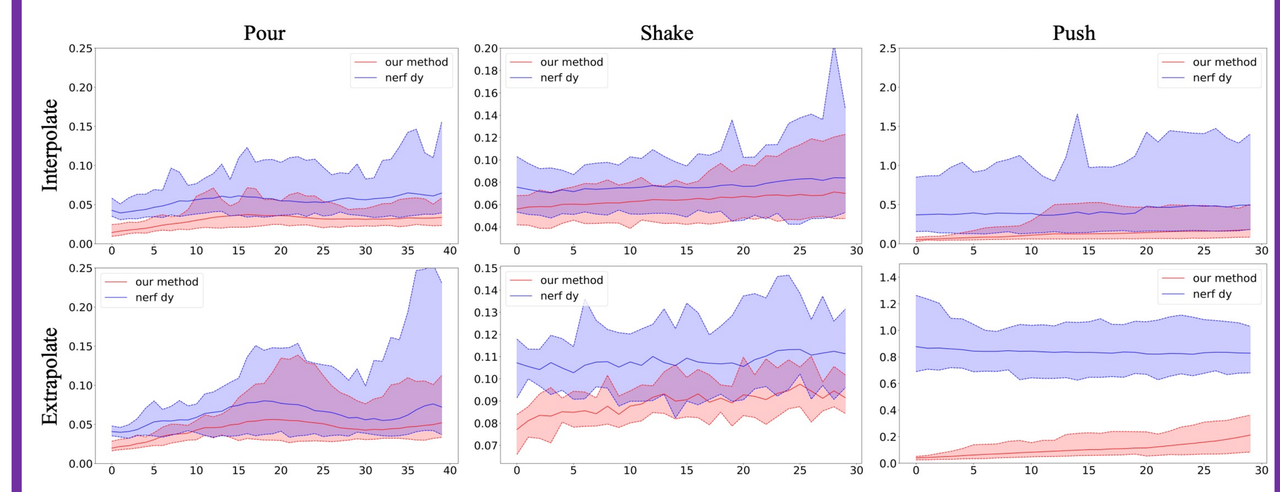


Results

Visual-head Reconstruction: 3D-IntPhys has a more generalized visual head:



Long-term Rollout Prediction: the error of 3D-IntPhys vs Baseline:



More video about the dataset and rollout prediction can be found by scanning the QR code:

More video results can be found here 👉