NEURAL INFORMATION PROCESSING SYSTEMS

DEL: Discrete Element Learner for Learning 3D Particle Dynamics with Neural Rendering

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Motivation

- Learning-based particle dynamics simulator requires **3D particle correspondence** to train the model.
- Directly training simulators with 2D images via differentiable rendering is inefficient due to **2D-to-3D uncertainty**.
- Existing GNN-based simulators are black box and **physically uninterpretable**, are not followed and integrated with <u>physics prior knowledge</u>.

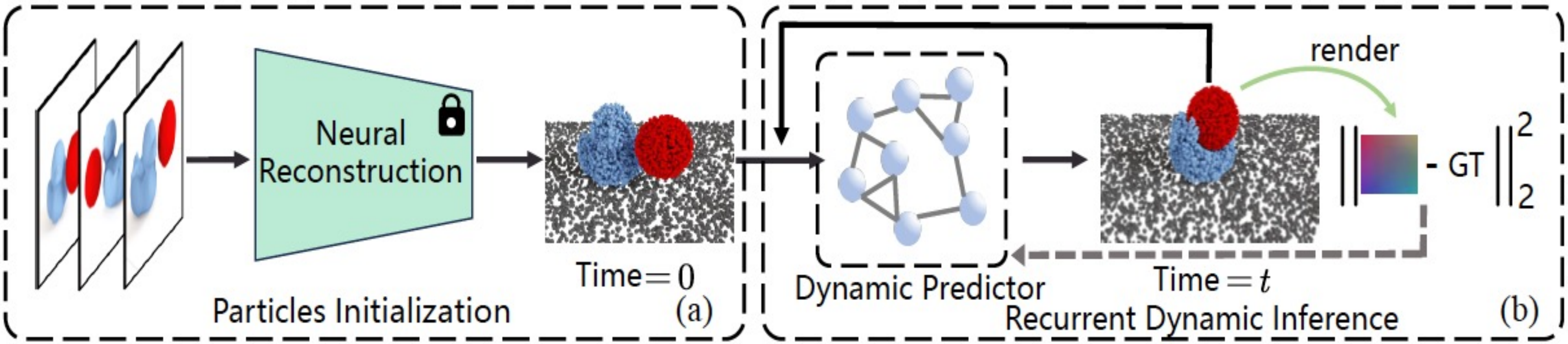
Contribution

- a novel physics-integrated neural simulation system which learns 3D dynamics from 2D images and alleviate 2D-3D uncertainty by physics-priors.

- A physics-integrated GNN architecture, called DEL, which is designed under the guidance of particle level Newtonian mechanics and Discrete Element Method framework, make the classic and neural parts benefits mutually.

- The presented approach can be used to simulate various materials including elasticity, plasticity, rigidity, granular, liquid, with complex initial shapes

Methodology



(a) Particles Initialization Process. The scene is initialized as particles.
(b) Recurrent Dynamic Inference Process.
The generated particle set is fed into a dynamic predictor to infer the next state iteratively.

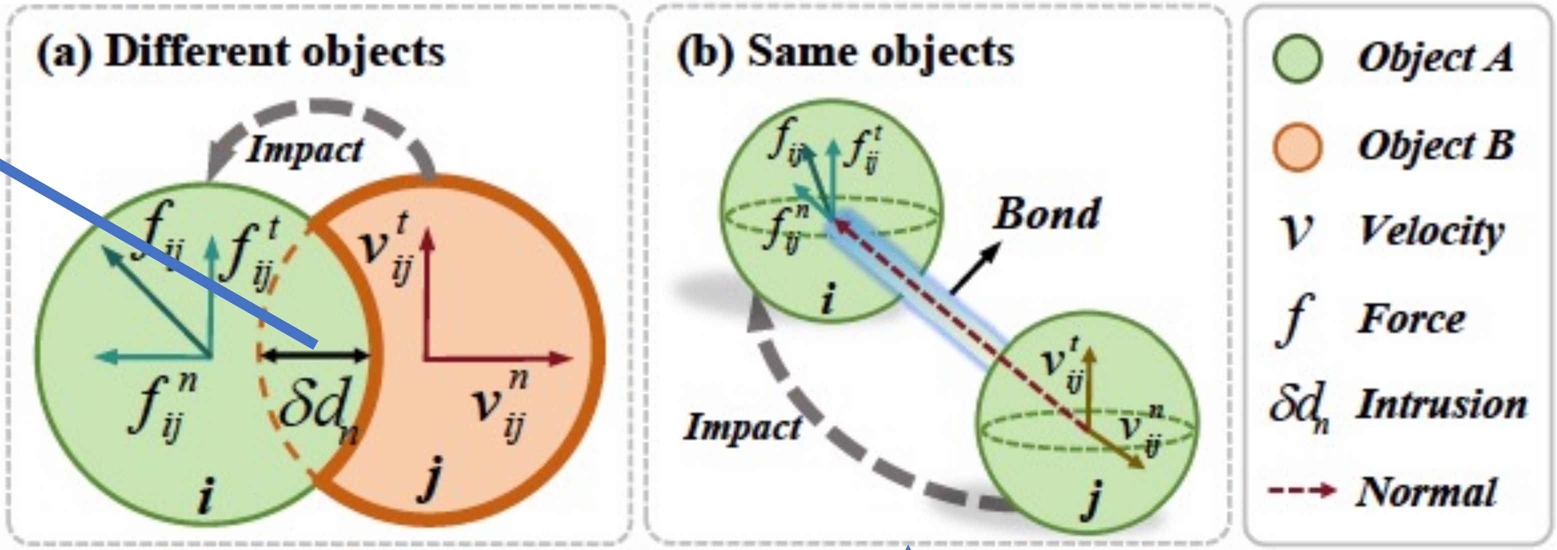
Methodology

$$m_i \frac{d^2\mathbf{u}}{dt^2} = \sum_{j=1}^{N} (\mathbf{F}_{ij}^{pn} + \mathbf{F}_{ij}^{vn}) + \sum_{j=1}^{N} (\mathbf{F}_{ij}^{pt} + \mathbf{F}_{ij}^{vt})$$

Force decomposition

normal **tangential**

$$\delta d_n = (r_i + r_j) - \|\mathbf{x_i} - \mathbf{x_j}\|_2$$



Normal force $$\mathbf{f}_{ij}^{n} = \begin{cases} (\mathcal{F}_c^n(\delta d_n, A_{ij}) + \mathcal{F}_b^n(\delta d_n, A_{ij}))\mathbf{n} & i,j \in \mathcal{O}_k, \\ \mathcal{F}_c^n(\delta d_n, A_{ij})\mathbf{n} & i,j \notin \mathcal{O}_k. \end{cases}$$

Tangential force $$\mathbf{f}_{ij}^{t\,\prime} = \mathcal{F}_c^t(\delta d_t, A_{ij}, ||\mathbf{f}_{ij}^n||)\mathbf{t} + \mathcal{F}_b^n(\delta d_t, A_{ij}, ||\mathbf{f}_{ij}^n||)\mathbf{t} \qquad \breve{\delta} d_t = ||\mathbf{v}_{ij}^t \Delta t||_2$$

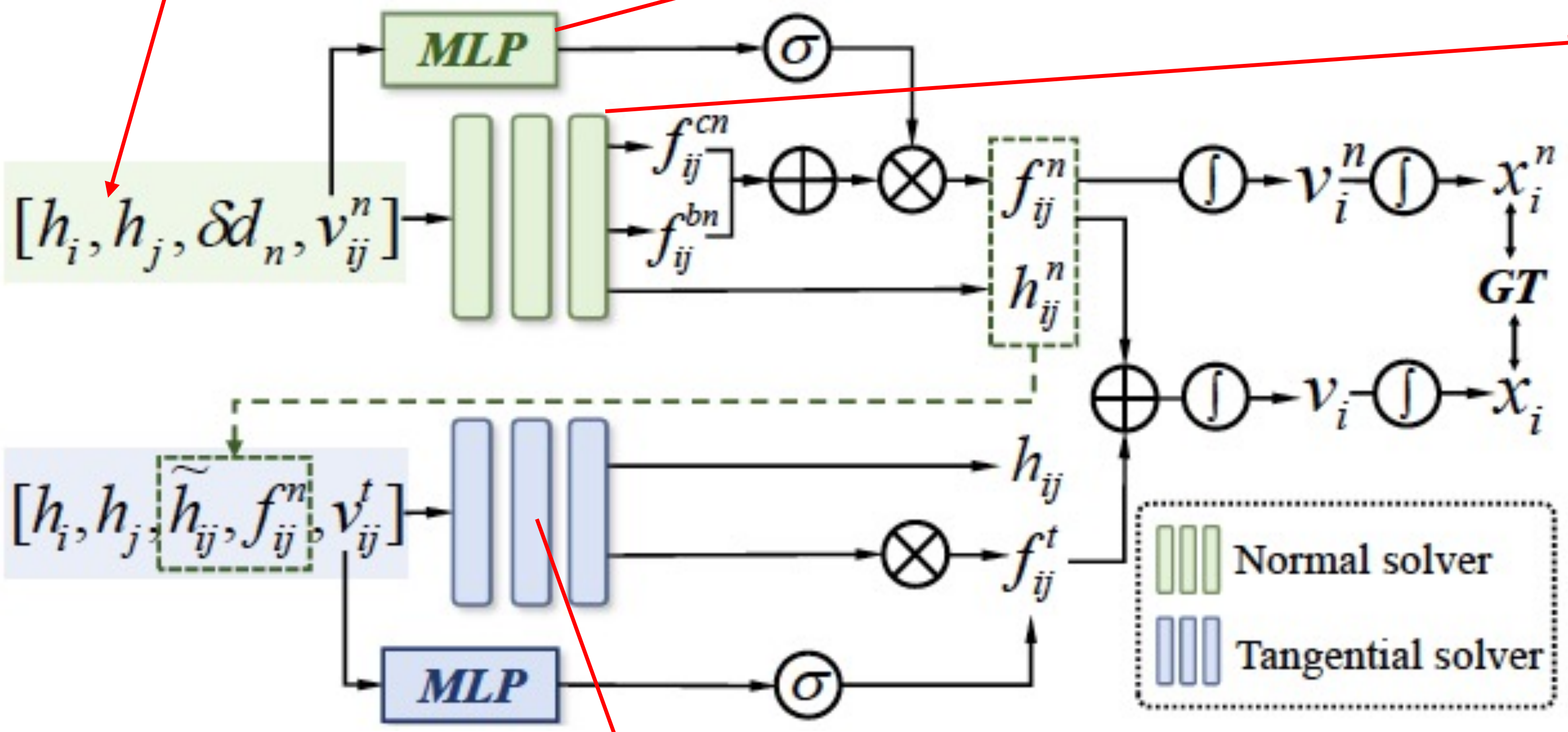
Energy dissipation $$F_{vis} = -\eta \cdot c_{crit} \cdot v_{rel}$$

Methodology

Particle Attributes : material type, etc.

$$\mathbf{f}_{ij}^{n} = \boxed{\sigma(\phi^{n}(\|v_{ij}^{n}\|_2, e_{ij}))} f_{ij}^{n'} \mathbf{n}$$

$$h_i = Norm(\mathrm{MLP}(A_i))$$



$$\boxed{\begin{gathered} n_i, n_j, e_{ij} = \Phi^{n}(\delta d_n, h_i, h_j) \\ f_{ij}^{cn} = \mathrm{ReLU}(\mathcal{H}_c(n_i, n_j, e_{ij})) \\ f_{ij}^{bn} = \mathcal{H}_b(n_i, n_j, e_{ij}) \\ f_{ij}^{n'} = f_{ij}^{cn} + f_{ij}^{bn} \end{gathered}}$$

$$f_{ij}^{t'}, e_{ij} = \Phi^{t}(\|v_{ij}^{t}\|_2, f_{ij}^{n'}, e_{ij}, n_i, n_j)$$

Results

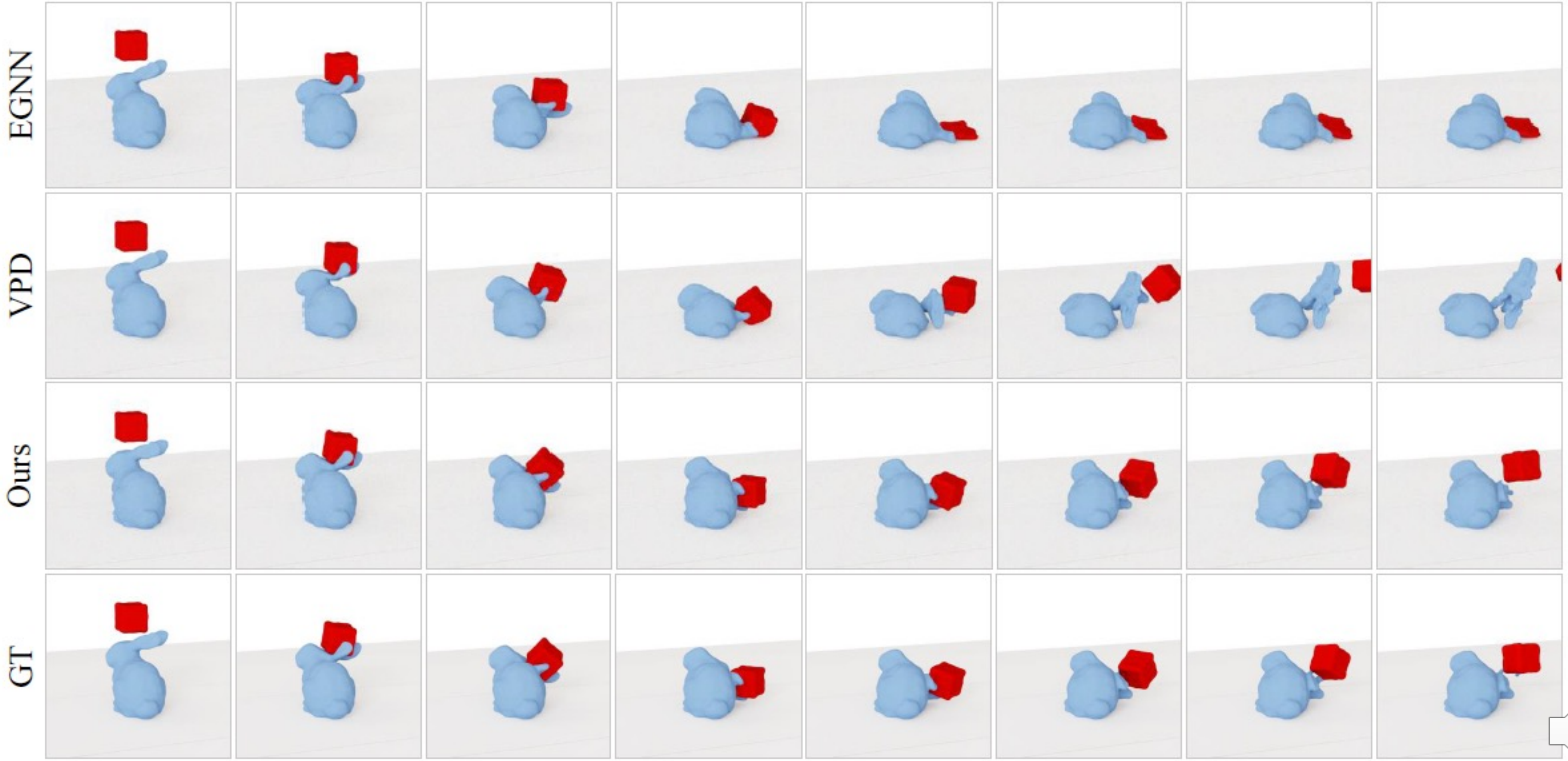
Table 1: Quantitative Comparisons between ours and benchmarks on five scenarios in render views.

	Plasticine			SandFall			Multi-Objs			FLuidR			Bear		
Method	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
SGNN* [9]	25.27	0.925	0.143	23.61	0.886	0.216	24.76	0.909	0.166	28.88	0.935	0.168	27.61	0.949	0.132
NeRF-dy [5]	21.09	0.893	0.225	22.58	0.879	0.216	19.61	0.826	0.318	25.79	0.925	0.270	22.83	0.873	0.232
EGNN* [17]	26.27	0.944	0.119	25.17	0.918	0.178	26.38	0.928	0.144	30.28	**0.951**	0.123	29.13	0.953	0.117
VPD [39]	27.06	0.941	0.101	24.61	0.926	0.127	25.62	0.921	0.136	30.06	0.947	0.126	**30.52**	**0.964**	**0.102**
Ours	**28.09**	**0.959**	**0.091**	**26.65**	**0.945**	**0.113**	**27.06**	**0.939**	**0.128**	**30.53**	0.944	**0.122**	30.08	**0.964**	0.105

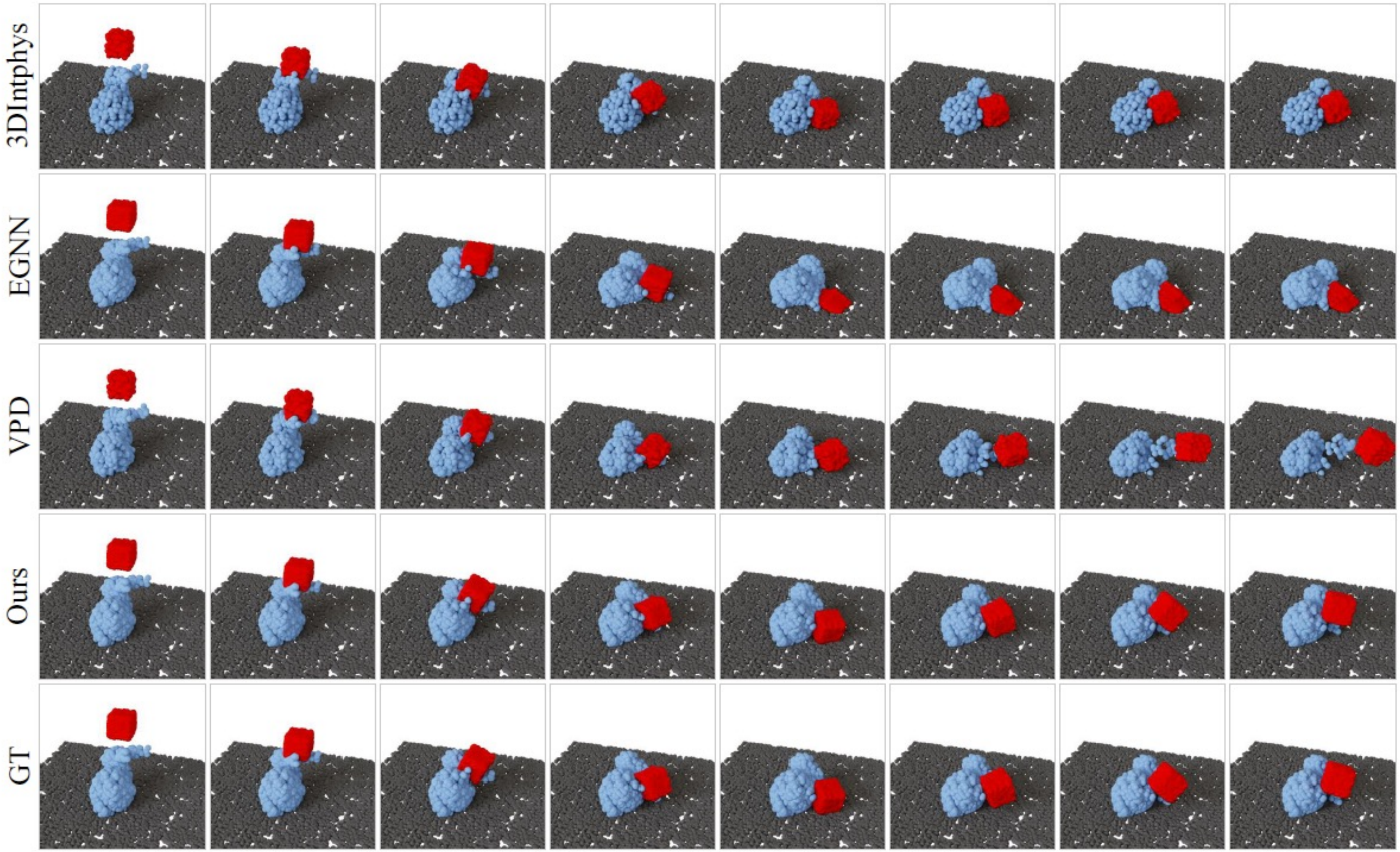
Table 2: Quantitative comparisons between ours and baselines on five scenarios in particle views.

	Plasticine		SandFall		Multi-Objs		FluidR		Bear	
Method	CD↓	EMD↓	CD↓	EMD↓	CD↓	EMD↓	CD↓	EMD↓	CD↓	EMD↓
SGNN* [9]	35.91	26.4	2.47	2.69	20.3	26.9	3.98	5.02	4.69	5.01
3DIntphys [11]	26.99	22.61	3.17	3.35	16.55	17.61	6.92	8.01	6.69	6.01
EGNN* [17]	16.20	14.61	2.13	2.56	13.21	13.77	2.58	3.01	3.95	4.16
VPD [39]	16.96	12.77	1.99	2.35	14.26	14.57	3.22	2.94	**3.41**	3.71
Ours	**7.54**	**7.10**	**1.73**	**1.90**	**8.48**	**9.13**	**1.72**	**1.88**	3.54	**3.33**

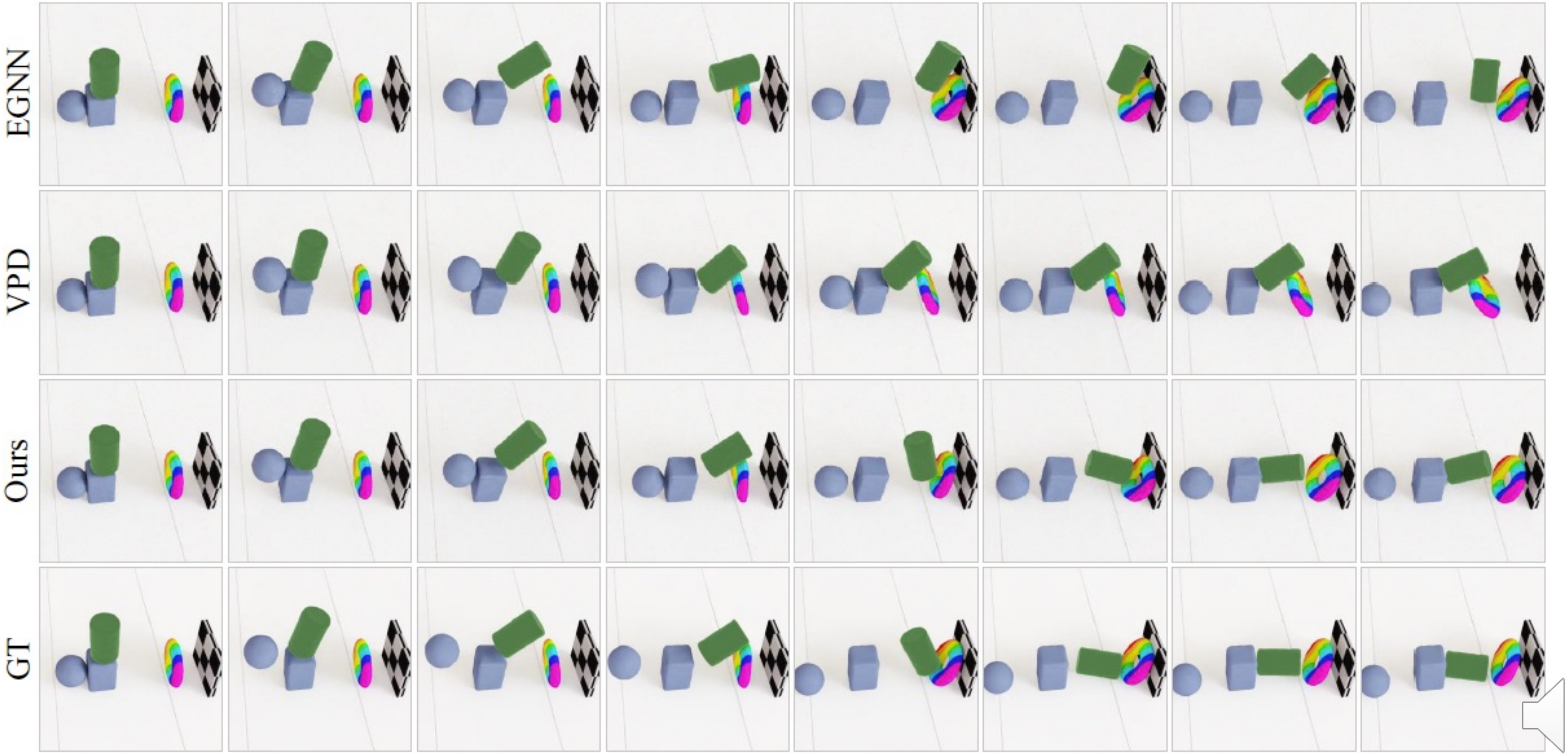
Results



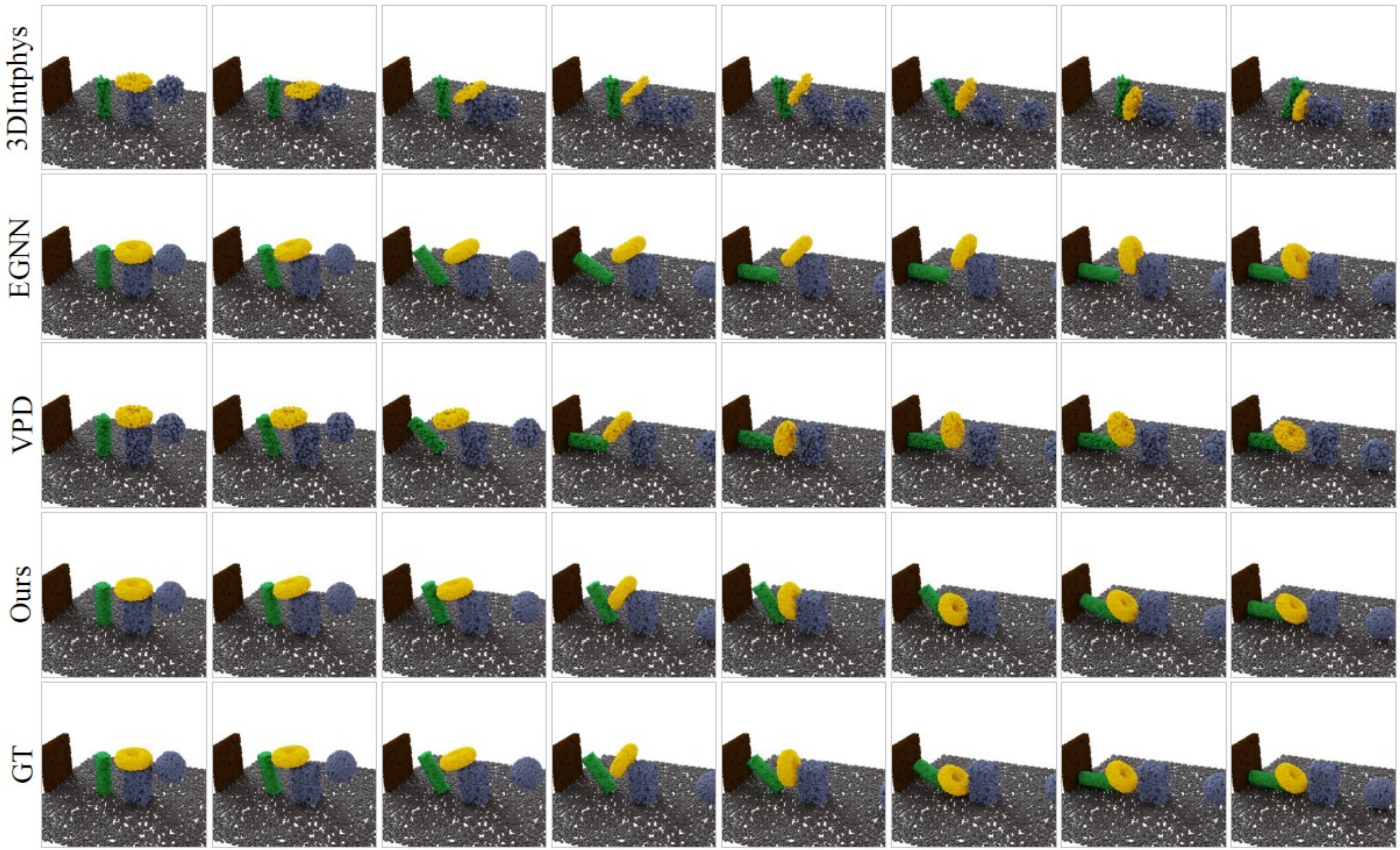
Results



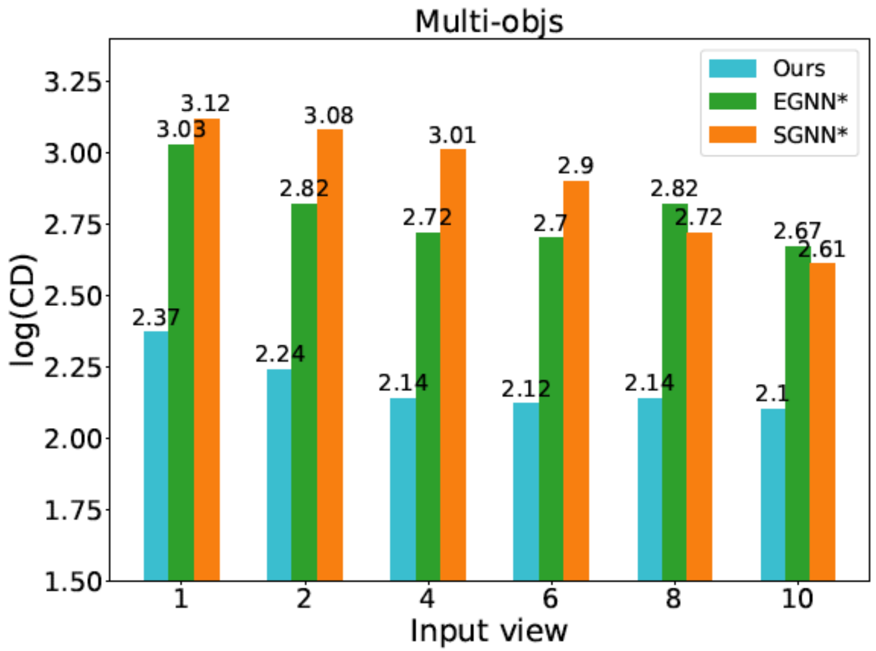
Results

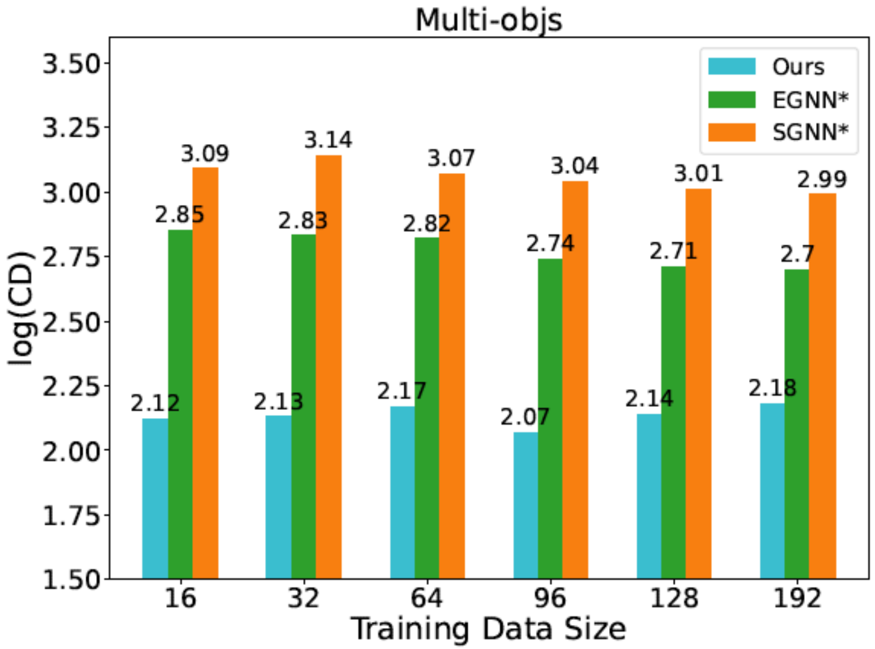


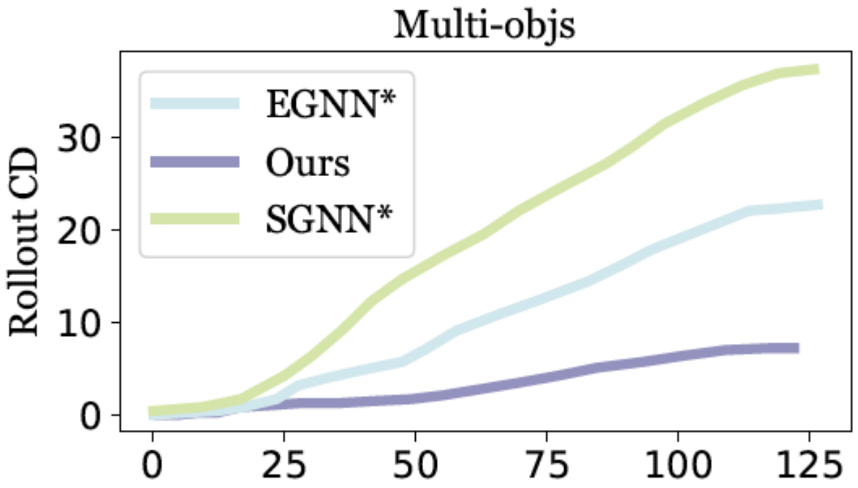
Results

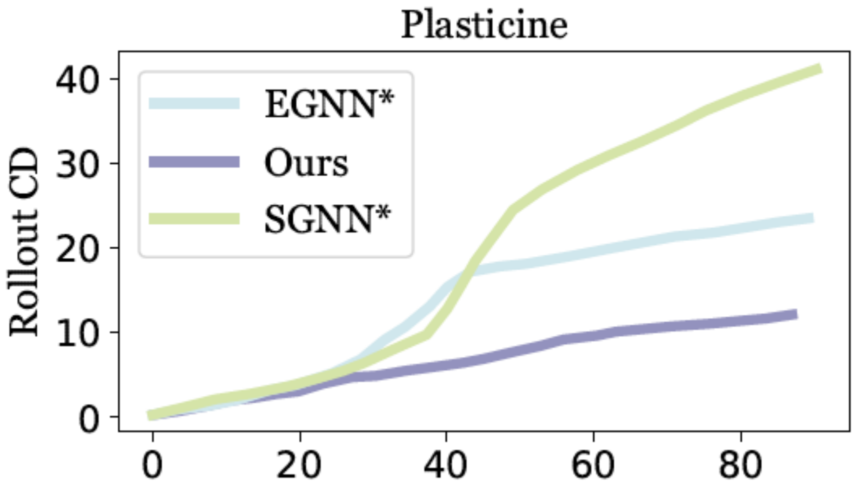


Results Ablation studies and long term dynamics



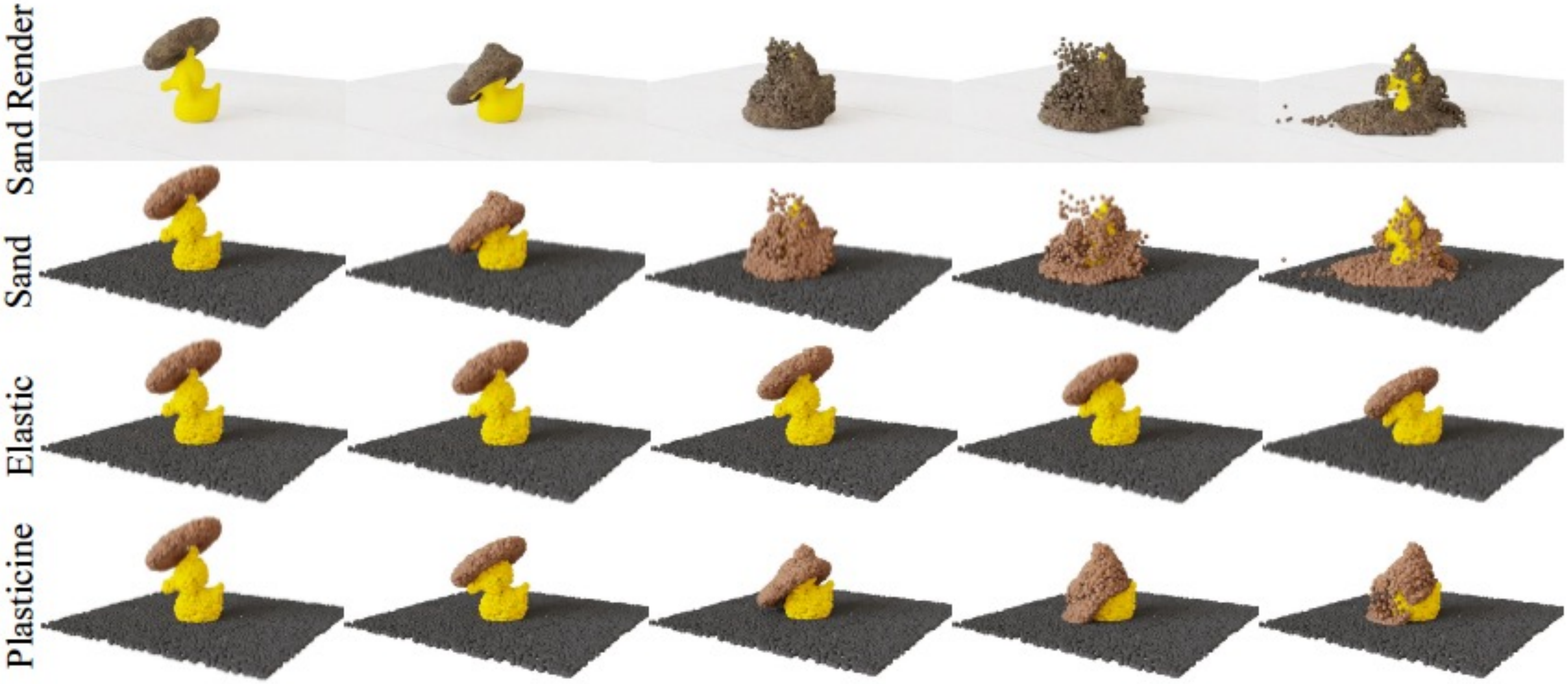






Results

Examples about material swapping on SandFall



Results

Visualization of the learned constitutive mapping.