

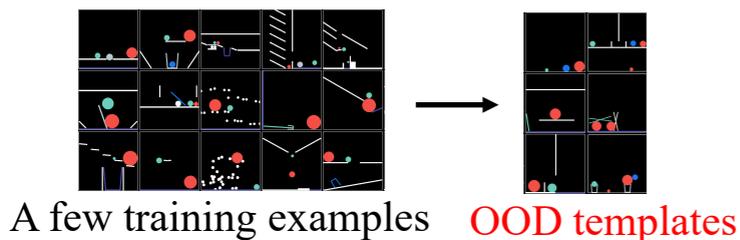
Background

Human intuitive physics vs. AI models

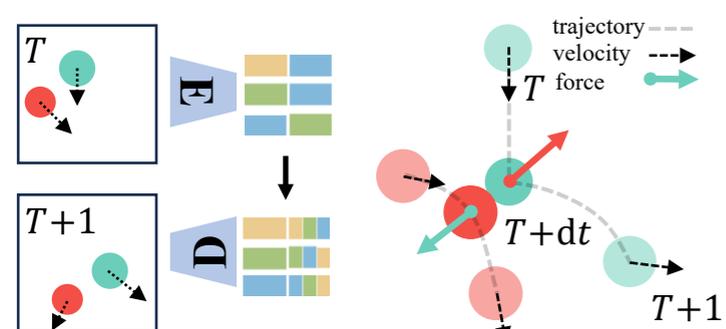
- From infancy, humans develop robust intuitive physics understandings.
- AI models struggle to achieve human-level few-shot learning and generalization ability in physical reasoning.



Goal: Achieve human-like few-shot learning and generalization in physical reasoning



Comparison of transition

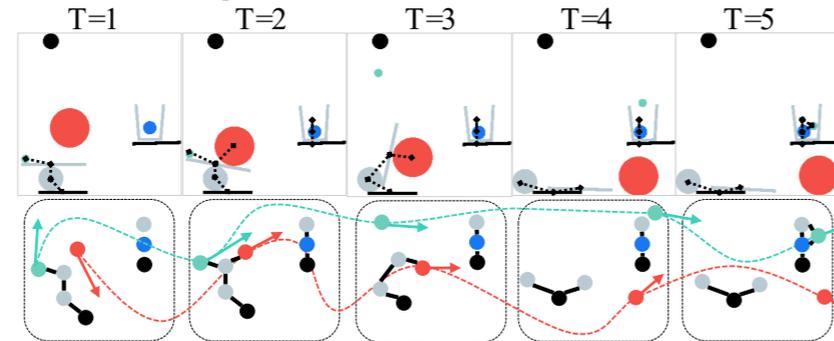


Discrete prediction vs. NNODE continuous transition.

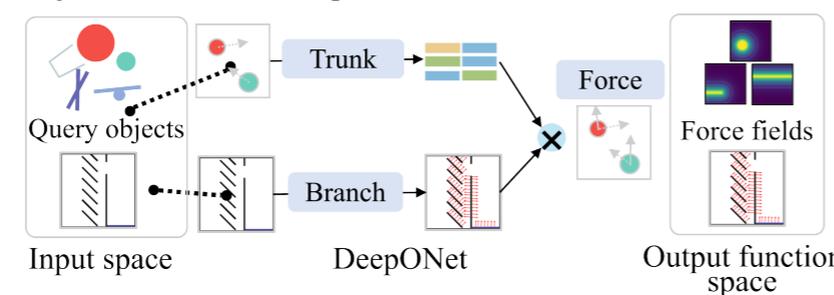
Neural Force Field

a neural function map from objects to forces for efficient interactive learning and reasoning.

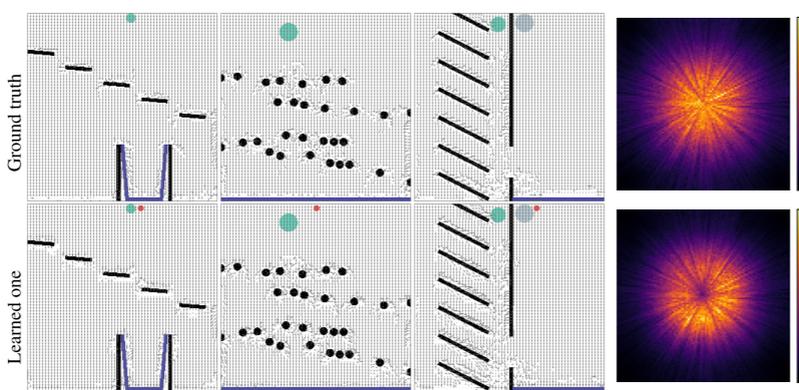
(a) NFF models complex physical interactions by constructing dynamic interaction graphs from scenes and performing continuous integration on force fields.



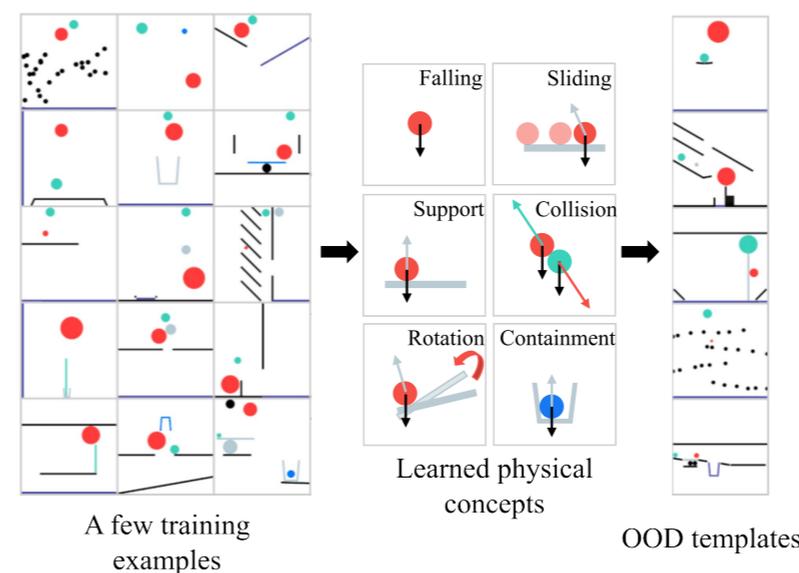
(b) The force fields are inferred by a neural operator that takes object interactions as input.



Learned force fields



Invert underlying force fields using back-propagation.

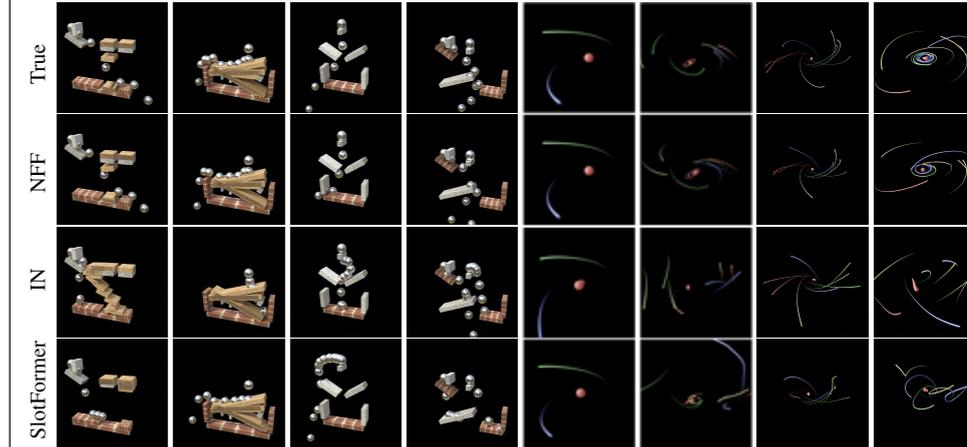
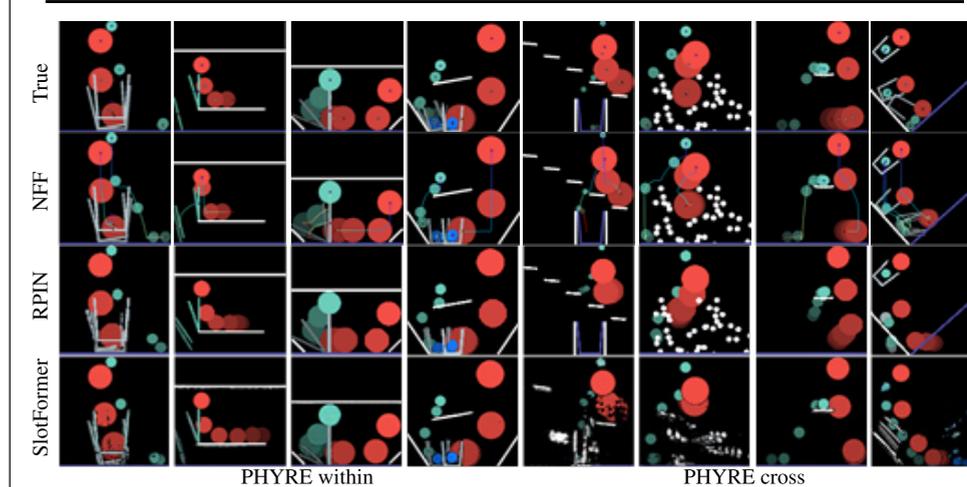


(c) After learning from a few examples, NFF can capture various physical concepts such as sliding, support and collision represented by force fields and generalize to unseen OOD scenarios.

Prediction results

Superior OOD generalization.

Metric	Model	I-PHYRE		N-body		
		Within	Cross	Within [0,T]	Within [0,3T]	Cross [0,3T]
RMSE ↓	IN	0.12	0.19	0.20	0.75	6.94
	Slotformer	0.07	0.21	0.21	1.09	2.53
	SEGNO	0.20	0.31	0.08	0.69	2.76
	NFF	0.05	0.13	0.10	0.53	1.23



Contact



Planning results

Few-shot planning with minimal data.

Method	Refine	Round 1	Round 2	Round 3	Round 4	Round 5
Random	-	0.24	0.37	0.45	0.51	0.56
IN	×	0.25	0.33	0.39	0.42	0.45
IN	✓	0.25	0.39	0.48	0.57	0.63
SlotFormer	×	0.30	0.36	0.39	0.41	0.43
SlotFormer	✓	0.30	0.42	0.49	0.55	0.60
NFF	×	0.51	0.55	0.58	0.60	0.62
NFF	✓	0.51	0.62	0.69	0.74	0.77
Human	-	0.52	0.70	0.79	0.83	0.86

Metric	DQN	RPIN	SlotFormer	NFF
Sample (M)	200.00	3.20	0.12	0.01
AUCCESS	30.96	36.58	21.04	49.22