EDGI: Equivariant Diffusion for Planning with Embodied Agents

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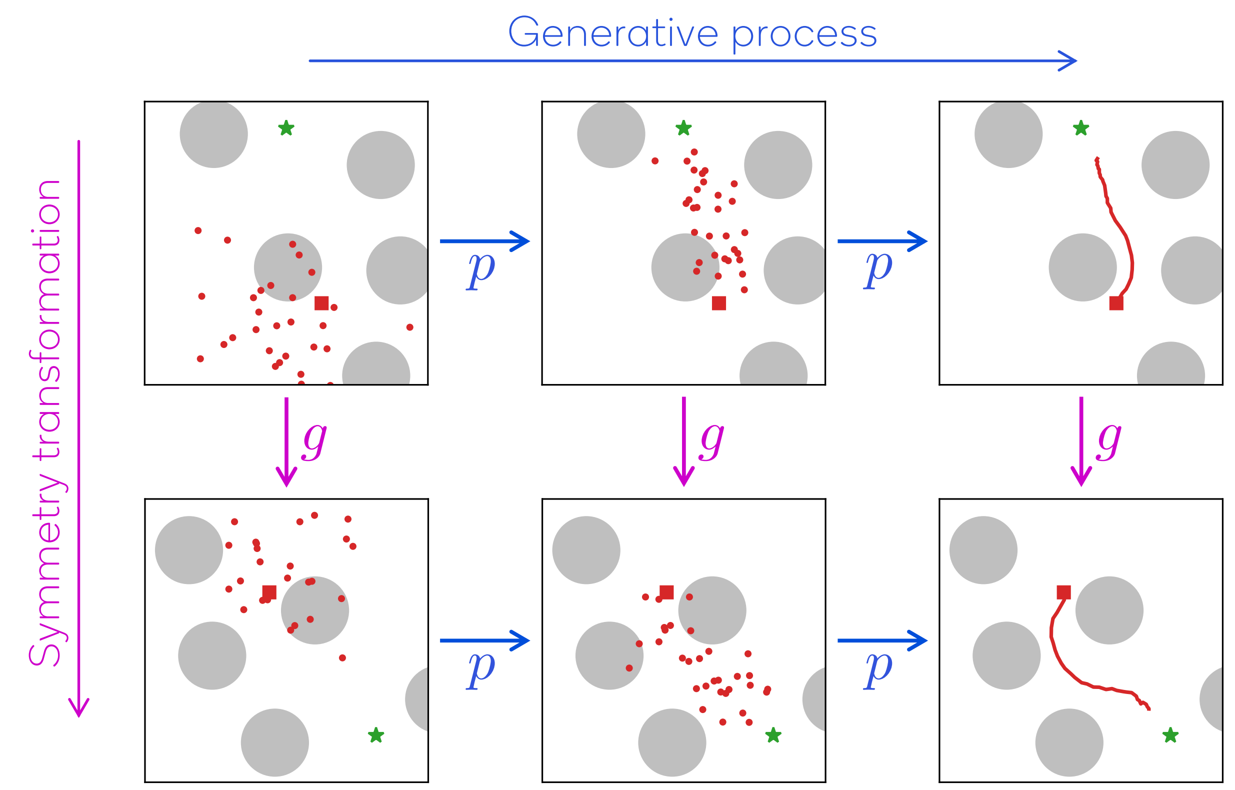
Idea: Embodied AI is full of symmetries

- Embodied agents face a structured world with spatial, temporal, and permutation symmetries
- We introduce EDGI, a planning algorithm that takes these symmetries into account
- Based on the Diffuser approach [1], EDGI treats planning as an **equivariant generative modelling** problem [2-3]



- It solves this through a new SE(3) × ℤ × S_n-equivariant denoising network + soft symmetry breaking at test time

Background: Planning as diffusion

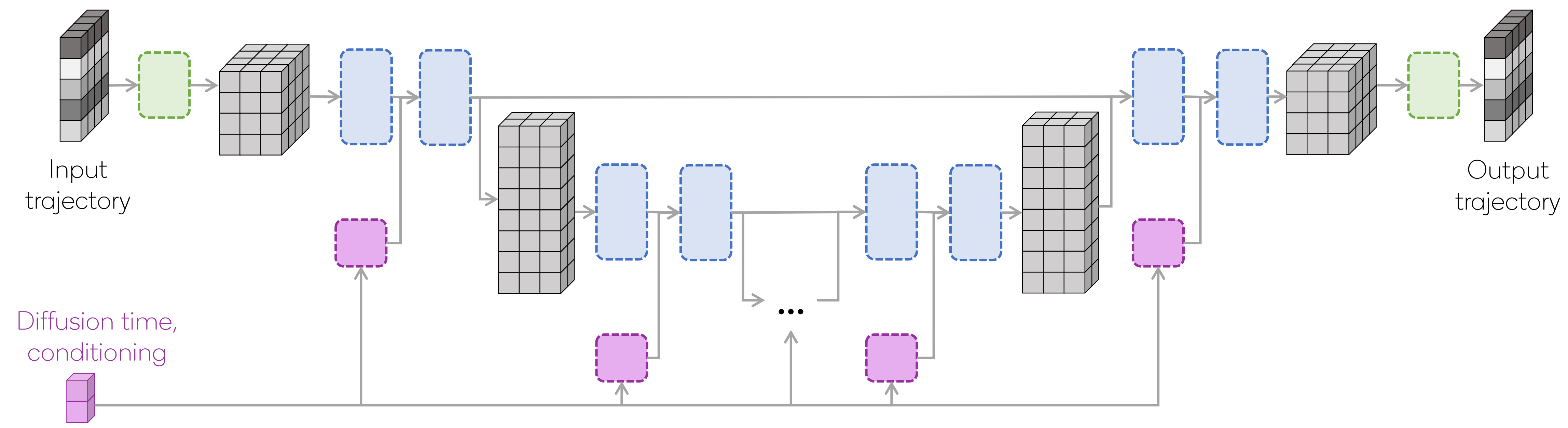
- Diffuser [1] unifies learning a world model and a policy into a generative modelling problem over state-action trajectories

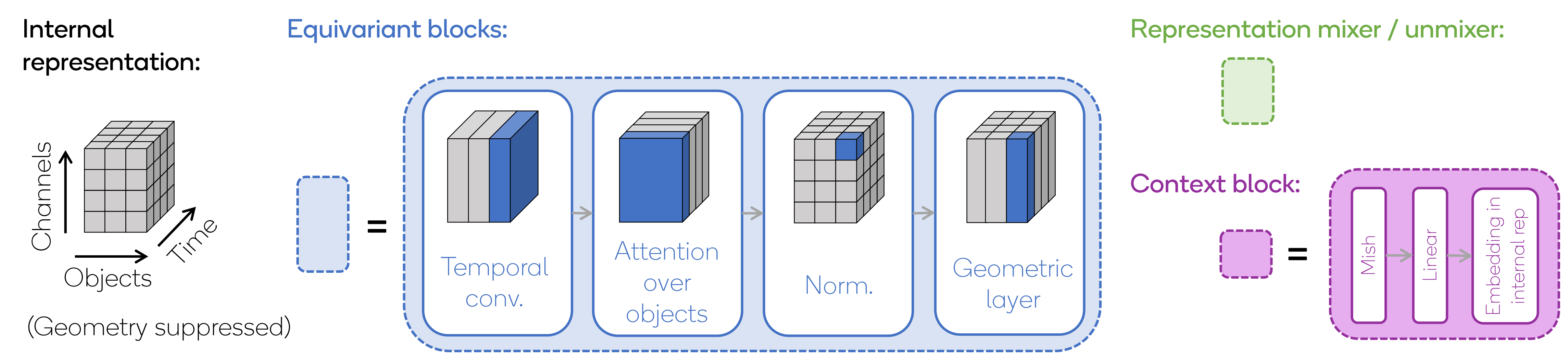
$$\tau = \begin{bmatrix} s_0 & s_1 & \dots & s_T \\ a_0 & a_1 & \dots & a_T \end{bmatrix}$$

- A diffusion model trained on such trajectories can later be conditioned on the current state, goal states, and guided by reward models, sampling from

$$\tilde{p}_\theta(\tau) \propto p_\theta(\tau) h(\tau)$$

Method: SE(3) × ℤ × S_n-equivariant denoising network





- Unify state-action trajectories into internal representation

$$w_{toc} = \begin{pmatrix} s_{toc} \\ v_{toc} \end{pmatrix} \rightarrow w'_{toc} = \begin{pmatrix} \rho_0(g) s_{toc} \\ \rho_1(g) v_{toc} \end{pmatrix}$$

time objects channels scalar quantities vector quantities

- New equivariant layers along each symmetry axis:
  - **Temporal layers**: convolutions over time
  - **Geometric layers**: fully expressive mixing between vectors and scalars [4]

$$S_{to} = \{s_{toc}\}_c \cup \{v_{toc} \cdot v_{toc'}\}_{c,c'} \qquad w'_{toc} = \left(\phi(S_{to})_c, \sum_{c'} \psi(S_{to})_{cc'} v_{toc'} \right)$$

  - **Permutation layers**: self-attention over objects

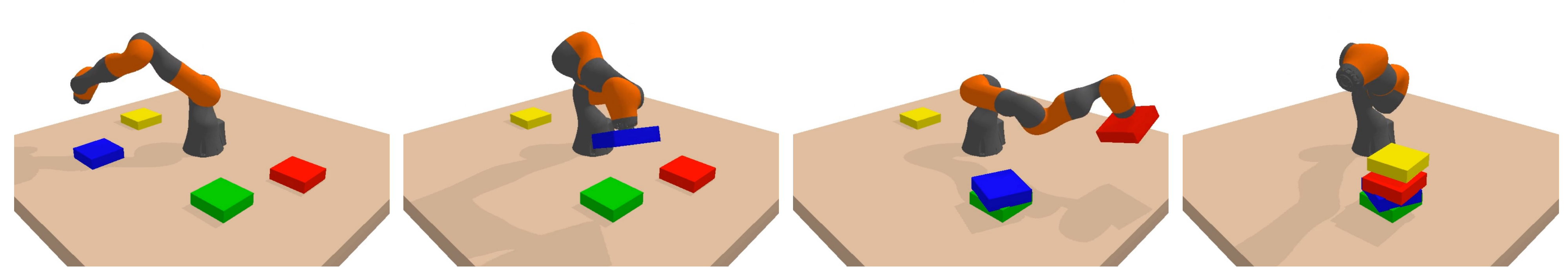
$$\mathbf{K}_{toc} = \sum_{c'} \mathbf{W}^K_{cc'} w_{toc} \, , \mathbf{Q}_{toc} = \sum_{c'} \mathbf{W}^Q_{cc'} w_{toc} \, , \mathbf{V}_{toc} = \sum_{c'} \mathbf{W}^V_{cc'} w_{toc}$$

$$w'_{toc} \propto \sum_{o'} \mathrm{softmax}_{o'} \left(\frac{\mathbf{Q}_{to} \cdot \mathbf{K}_{to'}}{\sqrt{d}} \right) \mathbf{V}_{to'c}$$

- Train on expert demonstrations with standard diffusion loss
- At test time, plug into (open or closed) **planning loop**
  - Conditioning on current state and reward guidance **softly break symmetries**

Experiments: EDGI improves data efficiency and robustness

- We test EDGI in two environments:
  - Goal-conditioned navigation with obstacles
  - Three different block stacking tasks with a Kuka robotic arm [1]

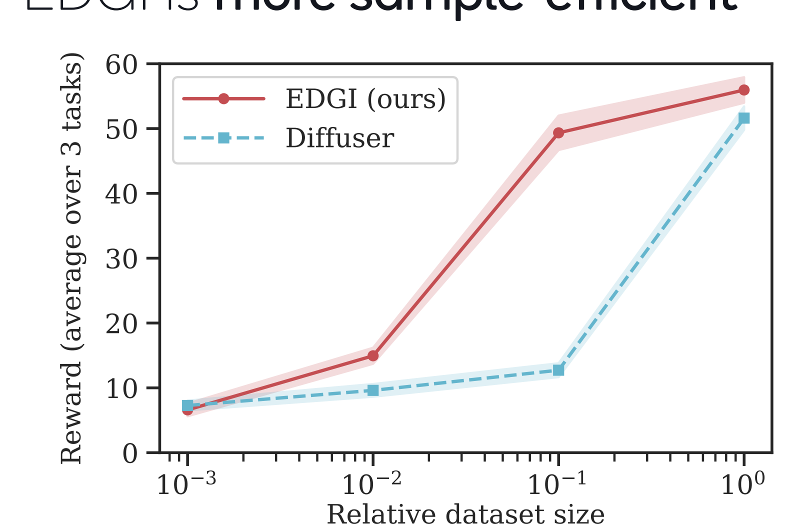


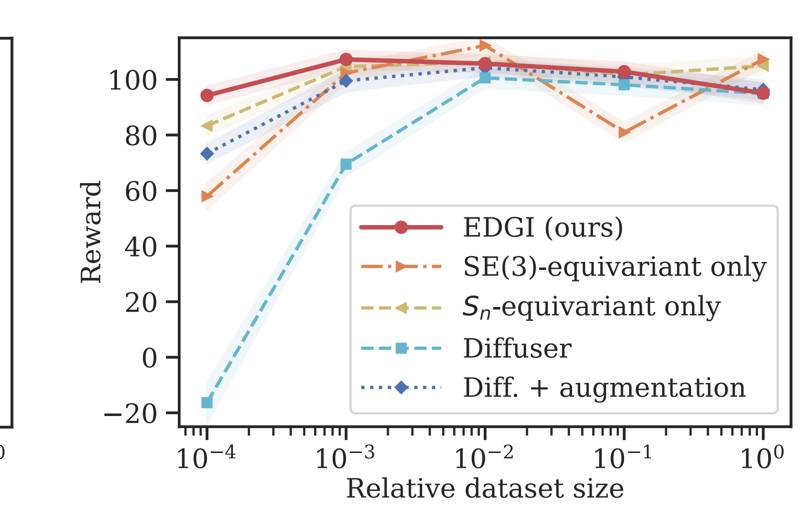
- We learn behaviours from expert demonstrations, assuming access to the true state (positions and orientations of objects)

- EDGI **generalizes across the symmetry group**

Environment	Standard setting BCQ	CQL	Diffuser	EDGI (ours)	SO(3) generalization Diffuser	EDGI (ours)
Navigation	–	–	**94.9** $_{\pm 3.9}$	**95.1** $_{\pm 3.4}$	5.6 $_{\pm 4.4}$	**83.3** $_{\pm 3.5}$
Unconditional	0.0	24.4	59.7 $_{\pm 2.6}$	**68.7** $_{\pm 2.5}$	38.7 $_{\pm 2.3}$	**69.0** $_{\pm 2.7}$
Conditional	0.0	0.0	46.0 $_{\pm 3.4}$	**52.0** $_{\pm 3.6}$	16.7 $_{\pm 2.0}$	**35.9** $_{\pm 3.5}$
Rearrangement	0.0	0.0	**49.2** $_{\pm 3.3}$	**47.2** $_{\pm 3.9}$	17.8 $_{\pm 2.3}$	**45.0** $_{\pm 3.6}$
Average	0.0	8.1	51.6 $_{\pm 1.8}$	**56.0** $_{\pm 2.0}$	24.4 $_{\pm 1.3}$	**50.0** $_{\pm 1.9}$

- EDGI is **more sample-efficient**





Qualcomm AI Research is an initiative of Qualcomm Technologies, Inc.

[1] M. Janner et al, "Planning with Diffusion for Flexible Behavior Synthesis", ICML 2022
[2] J. Köhler et al, "Equivariant flows: Exact likelihood generative learning for symmetric densities", ICML 2020
[3] J. Bose et al, "Equivariant Finite Normalizing Flows", arXiv:2110.08649
[4] S. Villar et al, "Scalars are universal: Equivariant machine learning, structured like classical physics", NeurIPS 2021