Application of Diffusion Models for Robotic Path Planning

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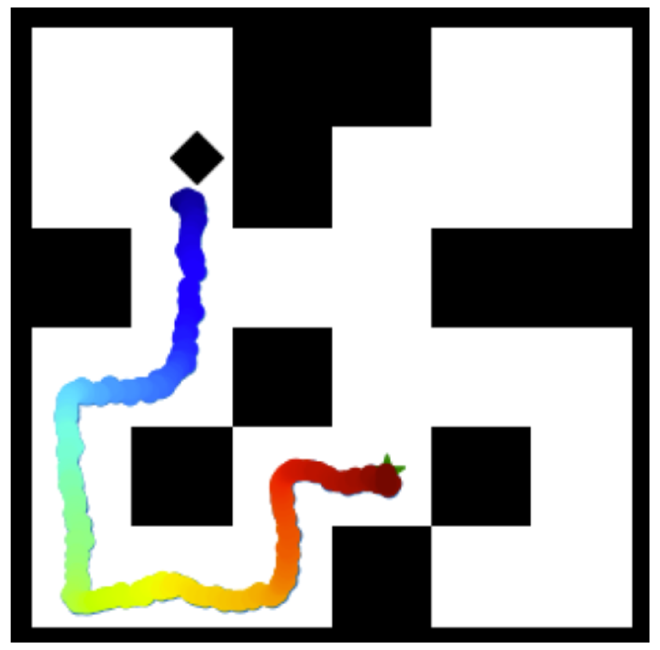
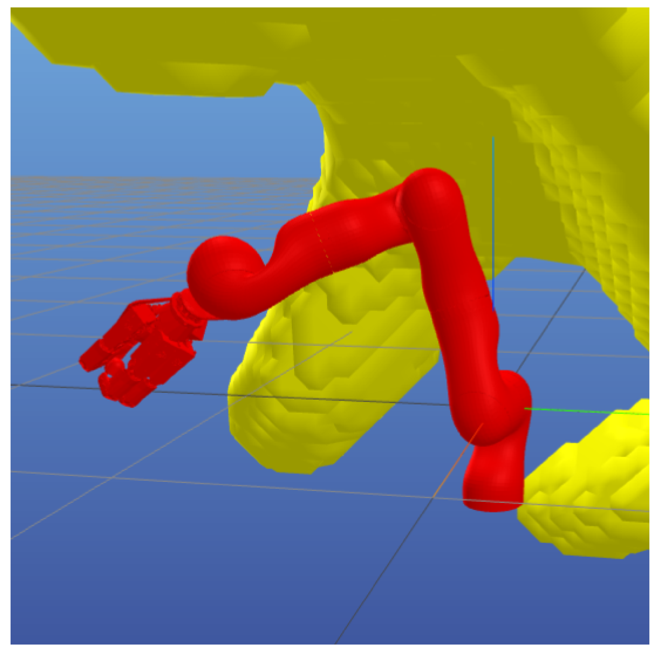
Motivation

Generating trajectories for path planning on the PointMaze Medium and the Kuka Robot Lwr3 (3D) environments using a diffusion model.

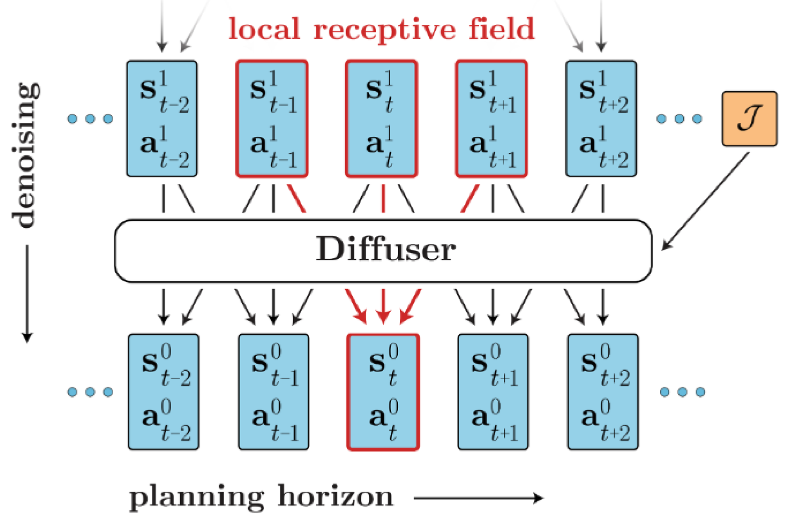
- Could be used as initial guess or warm start for non-learning based methods that can provide safety guarantees
- Is useful for multiple layers of decision-making, from high-level strategic planning to low-level motion control





Background

- The model outputs state-action pairs for the whole planning horizon non-autoregressively
- Integrates trajectory optimization into the modeling process
- Generate globally coherent trajectories by iteratively improving local consistency



Dataset

PointMaze Med. : Trajectories of states-actions in a maze.

- Guided by a PD controller and QIteration
- Same maze configuration with new start-target position per episode

Kuka Robot Lwr3 : 7-DOF robotic arm of Justin

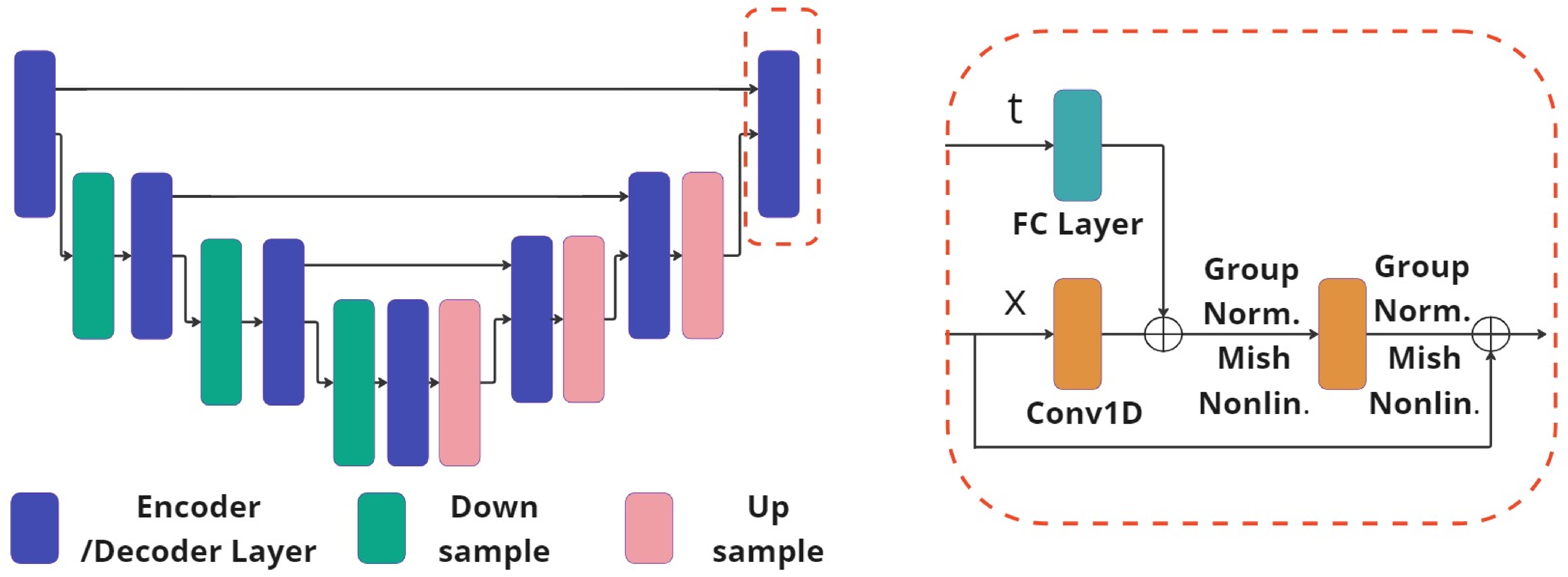
- Contains trajectories that are modeled via the change of each joint's q-value over time
- Unequal distribution of trajectories in cartesian space by an order of magnitude of 3

Environment	Dim.	(State,Action) Dim.	Steps/Episode	Episodes	Num. Envs
PointMaze Medium	2D	(4,2)	209	4778	1
Kuka Robot Lwr3	3D	(7,7)	20	1.5 Mio	12500

Diffusion Model Architecture for Trajectory Generation

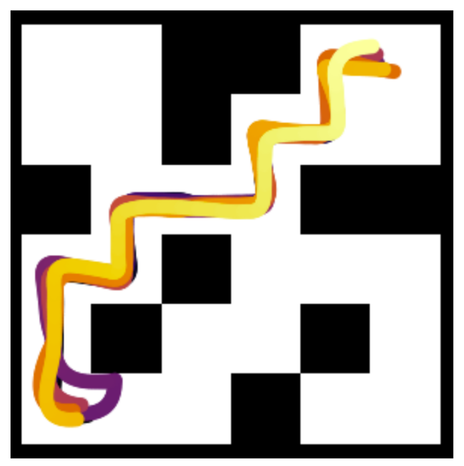
Model the distribution of the state and action trajectories over a horizon τ.

- Generation of τ is an iterative denoising procedure by diffusion probabilistic models
- Forward diffusion process is defined by $q(\tau^i|\tau^{i-1})$, where noise is added at each step i
- To sample a new τ from this distribution, learn how to denoise iteratively $p_\theta(\tau^{i-1}|\tau^i)$ using the model parameters θ
- Total Model parameters: 3.68 million
- Conditioning 2D: Fix start and target positions (x, y)
- Conditioning 3D: Fix start and target q-values (q_i)



Methodology: 2D PointMaze Medium

All dataset trajectories



Dataset trajectories for fixed conditions

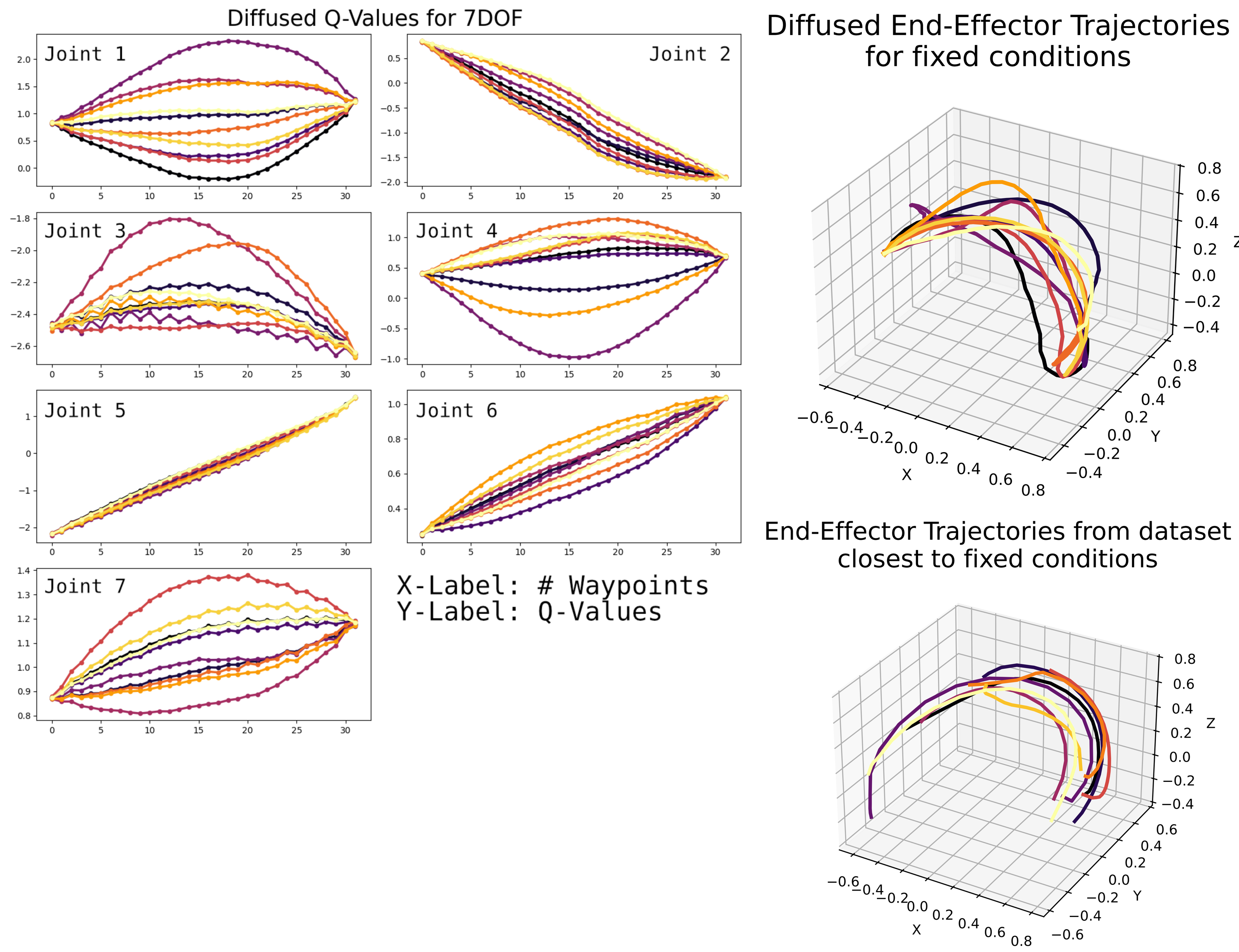
Training specifications:

- Epochs: 100
- Steps per Epoch: 1000
- Training Batch Size: 32
- Learning Rate: 10^{-4}
- Diffusion Steps: 100
- Horizon: 256

Train Step 0 Train Step 50k Train Step 100k

Methodology: 3D 7DOF Kuka Robot Lwr3

Diffusion samples from the validation dataset in comparison to the closest samples from the training dataset given similar start/end conditions.



Training specifications:

- Epochs: 25
- Steps per Epoch: $10,000$
- Training Batch Size: 32
- Learning Rate: 10^{-4}
- Diffusion Steps: 100
- Collision Metric: Aggregation over signed-distance field

Fine Tune:

- Train longer epochs and explore variations of different hyperparameters
- Variation of diffusion timesteps for training

Results & Future Work

Results:

- Applied the diffusion process to a 2D and 3D path planning problem
- Showed the generative power of diffusion models for creating diverse solutions to trajectory generation

Future Work:

- Explore different diffusion architectures
- Condition the diffusion model on the environment