Toward Generalized Application of the Motion Planning Diffusion

Mid-term Project Presentation

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Contents

Motivation

- Most existing planners assume static, simplified environments.

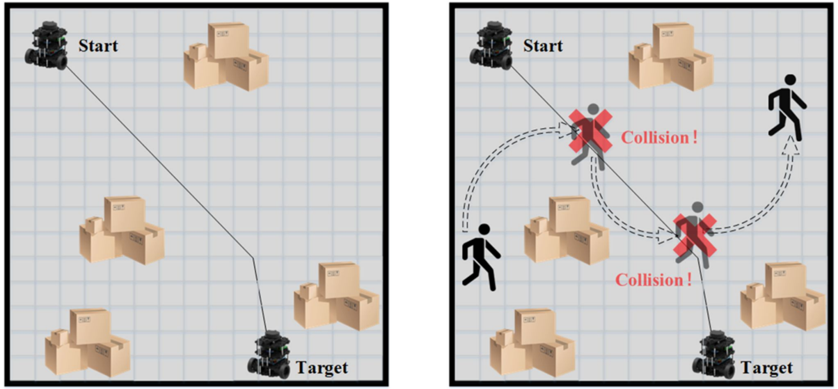
- Real-world robots face **dynamic obstacles**, **uncertainty**, and **unknown events**.

- Motion/path planning should be applicable in **more general, realistic environments**.

Problem Statement: Two Key Challenges

1. Planning in Dynamic Environments

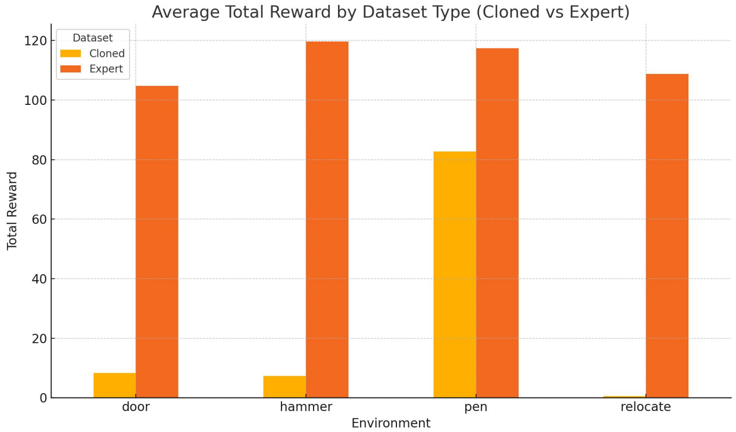
: Most benchmarks assume static, synthetic scenes.



(a) Static Environment (b) Dynamic Environment

2. Diverse diffusion-planner datasets

: *Performance differs per dataset* ⇒ need **quantitative evaluation**



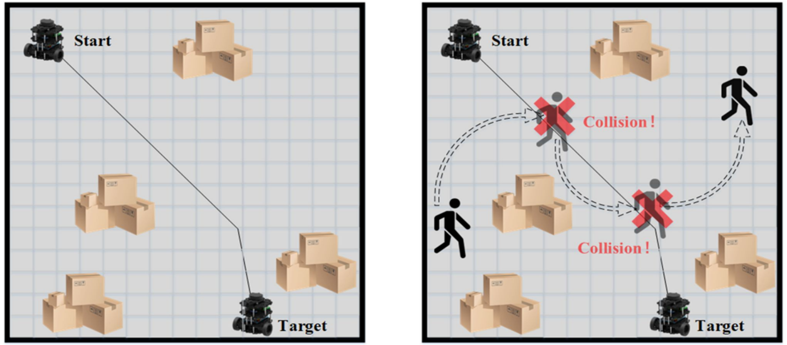
Lu, Haofei, et al. "What Makes a Good Diffusion Planner for Decision Making?." *The Thirteenth International Conference on Learning Representations*. 2025.

https://www.mdpi.com/1424-8220/23/7/3521

Related Work – Problem ①: Dynamic Environments

CoBL-Diffusion (IROS 2024)

- **Objective**
  - Enable **safe and goal-reaching** motion planning in **dynamic multi-agent environments**
  - Combine the strengths of **data-driven trajectory generation** and **control-theoretic safety**



(a) Static Environment (b) Dynamic Environment

- **Method**
  - A diffusion planner guided by **Control Barrier Functions (CBFs)** and **Control Lyapunov Functions (CLFs)**
  - Conditions the reverse diffusion process using **gradient-based rewards** derived from CBF/CLF

Mizuta, Kazuki, and Karen Leung. "CoBL-Diffusion: Diffusion-based conditional robot planning in dynamic environments using control barrier and lyapunov functions." IROS 2024

Related Work – Problem ①: Dynamic Environments

- **Control Barrier Functions (CBFs) - Ensuring Safety**

❖ **Purpose**

➢ To keep the robot inside a predefined **safe set** at all times

➢ Prevents collisions with **dynamic obstacles** by enforcing state constraints

❖ **Barrier condition** (avoid obstacle q):

$$h_{\text{cbf}}(\mathbf{X}_q) = (x - x_q)^2 + (y - y_q)^2 - r^2$$

❖ **Interpretation**

➢ $h\_cbf > 0 \rightarrow$ distance to obstacle > r (safe)

➢ Gradient of h_cbf supplies a **repulsive push** during denoising

➢ No heavy math shown; focus on the concept of “stay outside a radius r”

Related Work – Problem ①: Dynamic Environments

- **Control Lyapunov Functions (CLFs) - Ensuring Goal Reaching**

❖ **Purpose**

➢ To **stabilize** the system toward a **goal state**

➢ Guarantees that the robot **progresses** toward the goal over time

❖ **Goal attraction** encoded by:

$$h_{\text{clf}}(\mathbf{x}) = ||\mathbf{x} - \mathbf{x}_g||^2$$

❖ **Interpretation**

➢ Lower value ⇒ closer to goal x_g

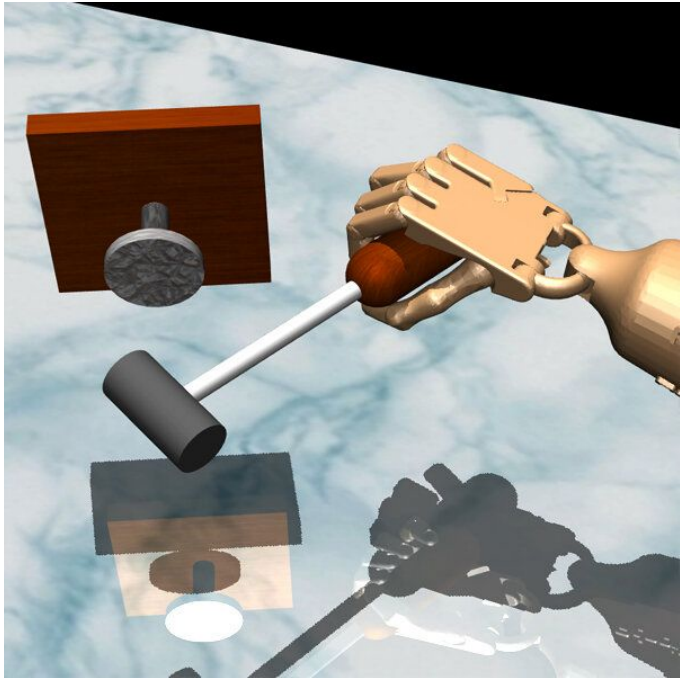
➢ Gradient of h_clf injects a **pull toward the goal** at every reverse step

➢ Together with CBF, yields "**avoid obstacles, attract goal**" behavior

Related Work – Problem ②: Data Quality vs Performance

WHAT MAKES A GOOD DIFFUSION PLANNER FOR DECISION MAKING? (ICLR 2025)

- **Tasks (Adroit Hand)**
  - 4 tasks: Door, Hammer, Pen, Relocate
  - 30-DOF robotic hand



- **Metric**
  - Normalized Episodic Return
  - Task success per episode
  - To quantitatively compare performance

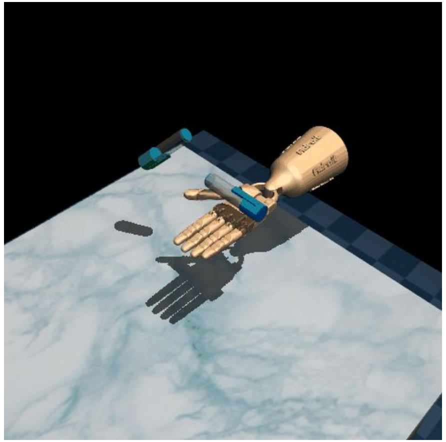
https://www.researchgate.net/figure/ADROIT-manipulation-suite-consisting-of-complex-dexterous-manipulation-tasks-involving_fig2_353066551

Related Work – Problem ②: Data Quality vs Performance

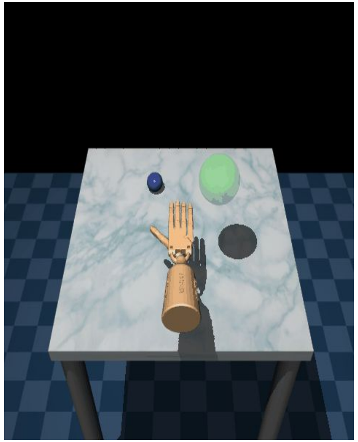
- **Tasks (Adroit Hand)**

Door

Hammer



Pen



Relocate

https://www.researchgate.net/figure/ADROIT-manipulation-suite-consisting-of-complex-dexterous-manipulation-tasks-involving_fig2_353066551

Related Work – Problem ②: Data Quality vs Performance

- **Dataset Construction**
  - **Cloned Dataset (Sub-optimal)**

5k cloned dataset

25 Human demos $\xrightarrow{\text{x100 Duplication}}$ 2.5k Human demos $\xrightarrow{\text{Behavior cloning}}$ 2.5k BC rollouts

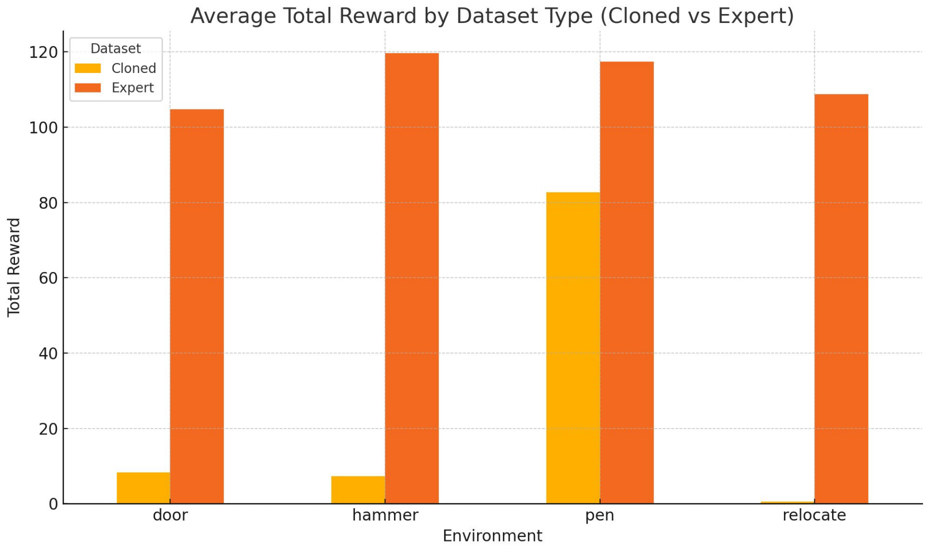
  - **Expert Dataset (Optimal)**

Expert Policy $\xrightarrow{\text{sampled expert trajectories}}$ 5k Expert dataset

≥ 99% success

Related Work – Problem ②: Data Quality vs Performance

- **Results**



➔ Expert dataset >> Cloned dataset

- ➢ Valuable insights gained from this comparison
- ➢ We plan to **apply similar evaluation** in our project
- ➢ Train **same models on different datasets**
- ➢ **Quantitatively compare** dataset impact on performance

Baselines Overview : Safe RL

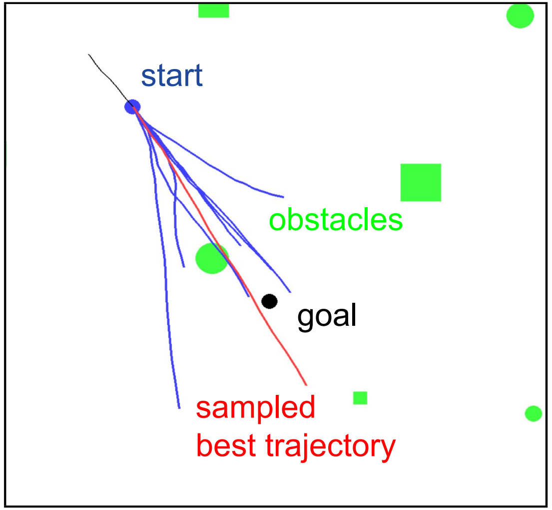
Safe Offline Reinforcement Learning using Trajectory-Level Diffusion Models (ICRA workshop 2024)

- **Dataset**
  - Offline roll-outs in simulators using **random exploration**
  - Mix of **successful** trajectories **and collision / failure** episodes

    → plentiful safety-violation labels

- **Algorithm / Planning pipeline**
  - **Trajectory-level diffusion** model
  - At every denoise step, apply a **hard projection**
  - Theoretical zero-collision guarantee if projection is feasible
  - **Receding-horizon loop** (short time window, warm-starts next window)

    → **react to dynamic obstacles**



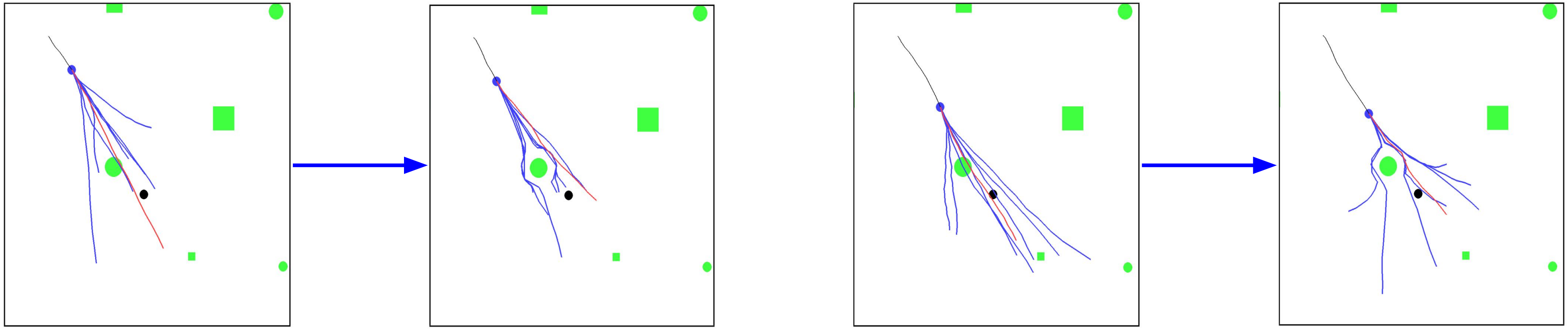
Evaluated 2d environment example

Römer, Ralf, et al. "Safe Offline Reinforcement Learning using Trajectory-Level Diffusion Models." ICRA 2024 Workshop

Baselines Overview : Safe RL

Safe Offline Reinforcement Learning using Trajectory-Level Diffusion Models (ICRA 2024)

- **Hard projection**
  - Ensure that **each state and action** in a trajectory remains in the **safe set** during denoising.
  - After each reverse diffusion step, perform **projection onto the safe set**
  - If projection is successful, the resulting trajectory is **constraint-satisfying** at every time step.

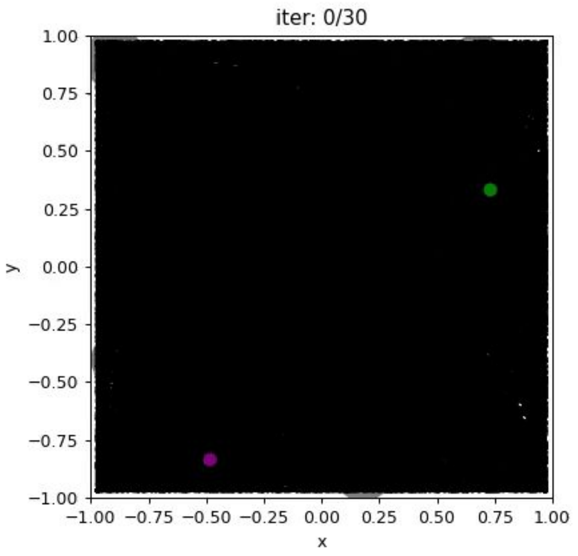


Baselines Overview : MPD

Motion Planning Diffusion : Learning and planning of robot motions with diffusion models. (IROS 2023)

- **Dataset**
  - Generate **expert collision-free paths** once: RRT-Connect search → B-spline smoothing
  - Only **success-fulfilling, smooth** trajectories; ⇒ no collisions retained

- **Algorithm / Planning pipeline**
  - Diffusion over **B-spline control points**
  - Inference uses **cost-guided posterior sampling** (collision, joint-limit, smoothness terms)
  - No projection; relies on **soft cost penalties** to discourage violations



Motion Planning Diffusion Inference example

Carvalho, Joao, et al. "Motion planning diffusion: Learning and planning of robot motions with diffusion models." 2023 IEEE/RSJ IROS 2023.

Baselines Overview : MPD

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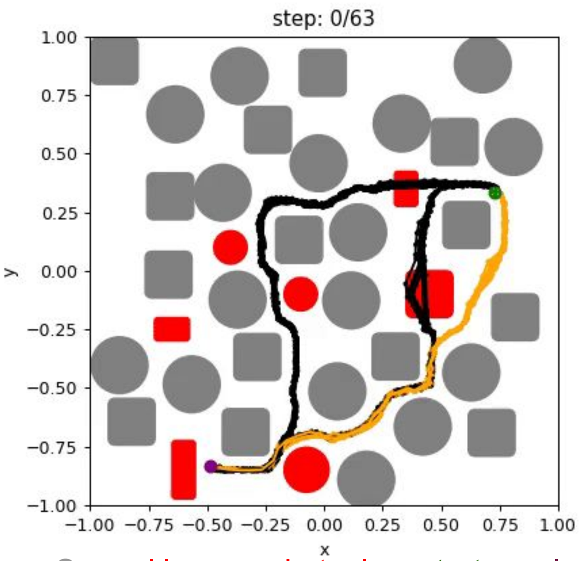
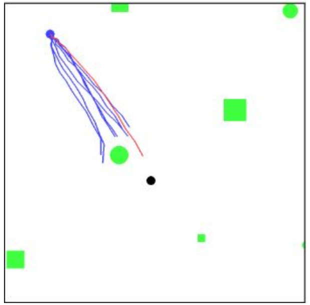
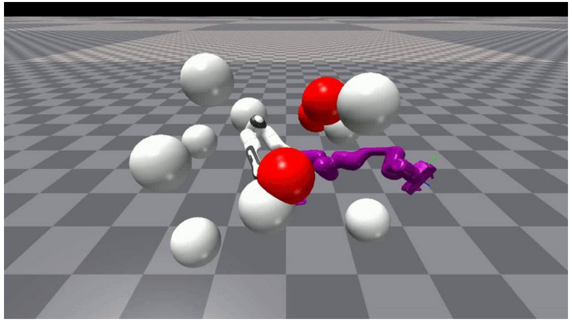


Seen, Unseen obstacles, start, goal
Collision free path (multi-modal)
Unsuccessful samples

Carvalho, Joao, et al. "Motion planning diffusion: Learning and planning of robot motions with diffusion models." 2023 IEEE/RSJ IROS 2023.

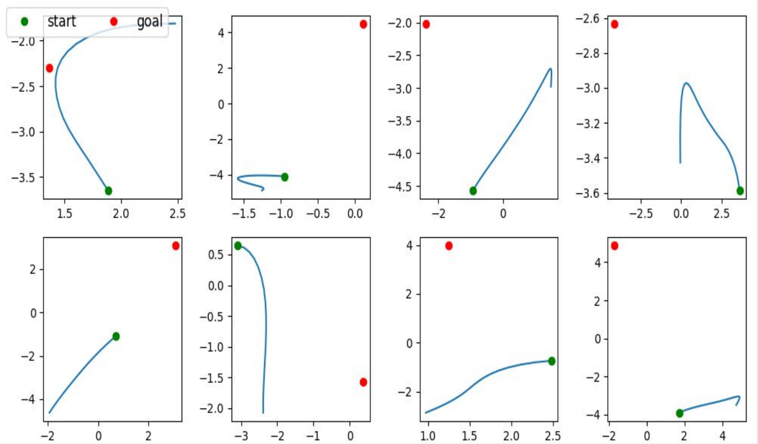
Baseline Comparisons : Safe RL vs MPD

Method	Römer, et al (2024). in short, **Safe RL**	Carvalho, et al (2023). in short, **MPD**
Environments	**2D unseen dynamic obstacles**  2d pointrobot (simple control) 2d quadrotor (complex control)	**2D/3D dense, unseen static obstacles** 
Dataset Generation	Randomly uniformly selected action → **sub-optimal dataset**	Only collision-free smooth trajectories → **high quality expert dataset**
Diffusion Guidance	Initial and terminal state fixed to the given start, goal position	
	Hard projection on safe state region	Minimization of weighted cost functions

Limitations

- **Safe RL**

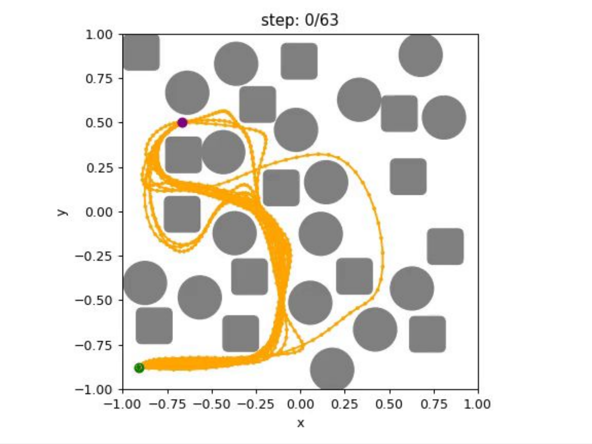
1. Low training dataset quality
2. Only evaluated in simple 2D dynamic envs.
3. Hard projections is computationally heavy



Safe RL training dataset: random, low quality

- **MPD**

1. Only trained on high quality expert dataset
2. Didn’t consider dynamic envs.
3. Expected to fail on the Safe RL setup



MPD training dataset: refined, high quality

Project Objective : **1. Evaluate MPD, training with datasets of different optimalities.**
2. Extend MPD, so it can be applied for dynamic environment.

Project Proposal: Objective 1. Impact of the training dataset quality

- Apply MPD into the 2D **static** environments introduced in Safe RL paper, Römer, et al (2024).
  ⇒ Adapt environment setting, dataset generation method from the Safe RL paper.

- 1-1. Train MPD with dataset generated using the Safe RL method. **(low quality dataset)**

  1-2. Train MPD with dataset generated using the MPD method. **(high quality dataset)**

- Compare with the evaluation results with the original paper
  ⇒ Inverse Dynamics (ID) is also applied in MPD, so compare results using ID.

	Mobile Robot		Quadrotor	
	Success rate ↑	Timesteps ↓	Success rate ↑	Timesteps ↓
w/ ID	**0.99** / 0.89	20.4 / **31.8**	**0.90** / 0.63	**71.5** / 105.6
w/o ID	0.99 / 0.79	**18.4** / 36.6	0.87 / 0.61	71.0 / 114.0

Results from the Static environments

Project Proposal: Objective 2. Applying in the dynamic environments

- Extend MPD so it can be applied to the 2D **dynamic** environments
  ⇒ Need to improve dataset generation method of MPD (RRT Connect can not be applied)
  ⇒ **Proposed method : Global planning with RRT + Local planning with Collision Avoidance (tentative)**

- 2-1. Inference MPD in the dynamic environment,
  where diffusion model was originally trained in the static environment **(Naive application)**

  2-2. Train MPD with expert dataset generated using the **proposed method**. **(Novelty)**

- Apply it to 3D environment: create new 3D dynamic environment (As time allows)

- Compare evaluation results with the original paper

	Mobile Robot		Quadrotor	
	Success rate ↑	Timesteps ↓	Success rate ↑	Timesteps ↓
w/ ID	0.99 / $\boxed{0.89}$	20.4 / $\boxed{31.8}$	0.90 / $\boxed{0.63}$	71.5 / $\boxed{105.6}$
w/o ID	0.99 / 0.79	18.4 / 36.6	0.87 / 0.61	71.0 / 114.0

Results from the Dynamic environments

Summary

- Motion Planning Diffusion(MPD) is an effective diffusion-based trajectory planner
  Applicable to dense 2D, complex 3D environments with unseen obstacles.

- However, 1) It is trained with refined high quality training dataset
  2) Didn't consider environment with dynamic obstacles (Not well studied yet)

- For the generalized application of MPD in more realistic scenarios with sub-optimal dataset,
  Our project aims to evaluate and extend capabilities of MPD
  on the experiment setup introduced in Safe RL, Römer, et al (2024).

  Objective 1. Evaluation on the low quality training dataset.
  Objective 2. Extend MPD to be applicable to the 2D dynamic environment.

Schedule & Roles

- Student lecture : JeongWoo
- Paper presentation : JiHwan
- Midterm, Final Project Proposal
  - Related works, baseline : JiHwan
  - Project details, implementation : JeongWoo

- **TODO** :
  - Qualitative comparison of generated training dataset optimality (Safe RL, MPD method)
  - Adapting MPD on Safe RL setup.
  - Implementation of generating expert dataset on dynamic environment
  - Applying same method to 3D dynamic environments (As time allows)