# TD-MPC


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2023-2024
PANDROIDE

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# CONTENT

# INTRODUCTION OF THE PROJECT

Integration of "**Temporal Difference Learning for Model Predictive Control**" algorithm by Nicklas Hansen, Xiaolong Wang and Hao Su into **BBRL** library.

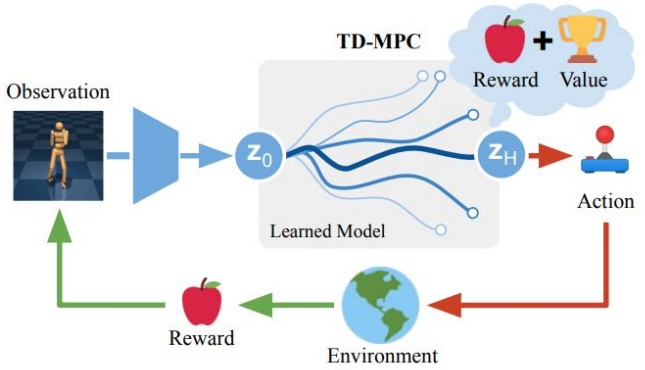
# SUMMARY OF THE PAPER

## Temporal Difference Learning for Model Predictive Control

Nicklas Hansen [1] Xiaolong Wang [*1] Hao Su [*1]


### Abstract

Data-driven model predictive control has two key advantages over model-free methods: a potential for improved sample efficiency through model learning, and better performance as computational budget for planning increases. However, it is both costly to plan over long horizons and challenging to obtain an accurate model of the environment. In this work, we combine the strengths of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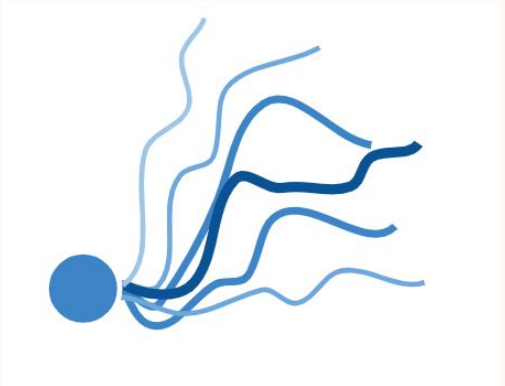
- TD-MPC is a novel framework in RL that integrates the strengths of **model-free** and **model-based** approaches for data-driven model predictive control.

- It leverages a learned task-oriented latent dynamics (TOLD) model for short-term trajectory optimization and a learned terminal value function for long-term return estimation, both optimized *jointly* through temporal difference learning.

# MODEL PREDICTIVE CONTROL

- Model-based algorithm
- Planning is done using a learned model of the environment
- It models everything in the environment

Downside?



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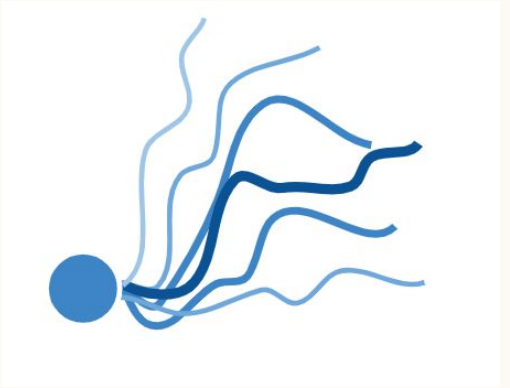


Downside?

How to resolve ?

Total return of a sampled trajectory :

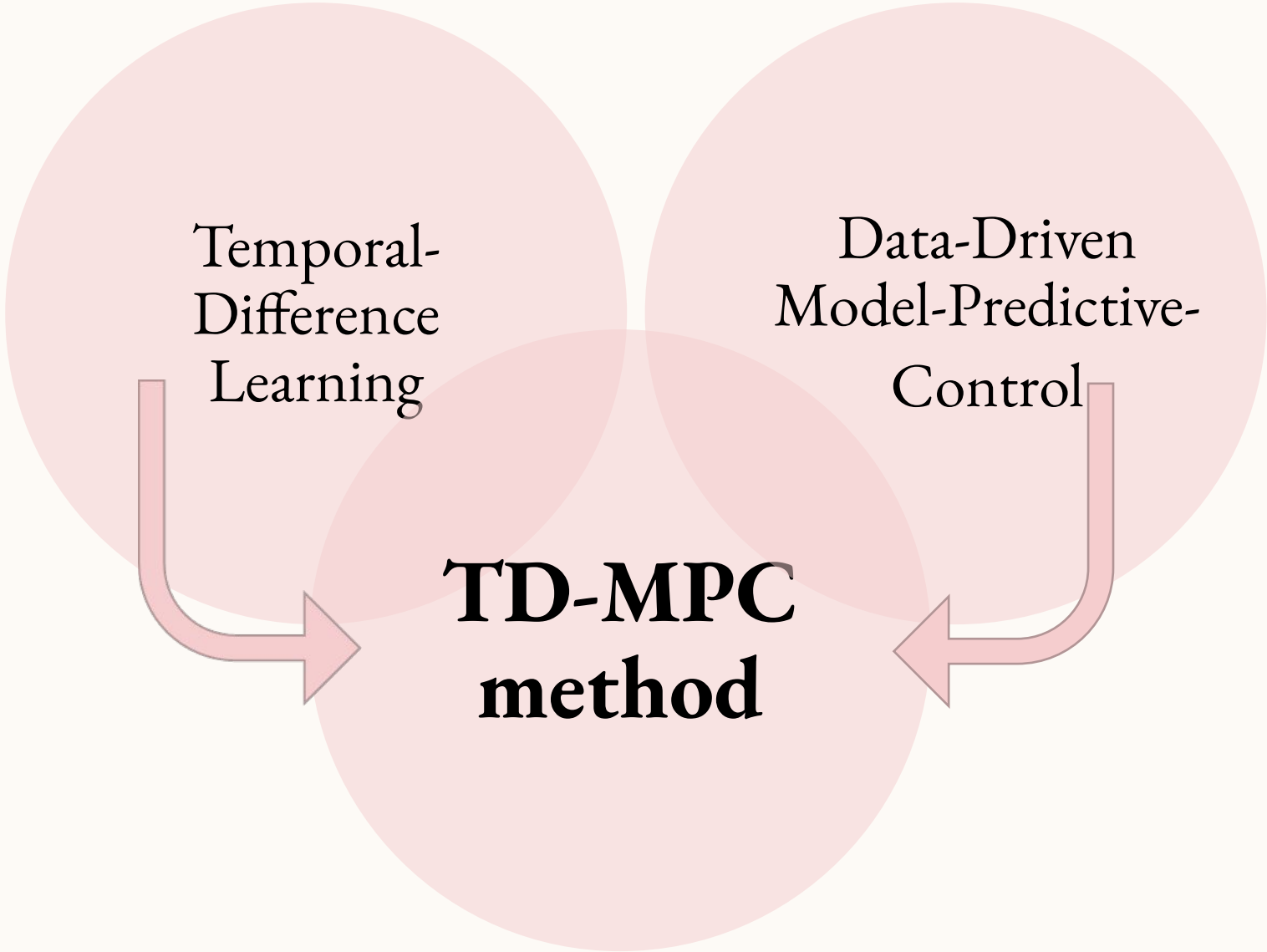
$$\phi_\Gamma \triangleq \mathbb{E}_\Gamma \left[ \gamma^H Q_\theta(\mathbf{z}_H, \mathbf{a}_H) + \sum_{t=0}^{H-1} \gamma^t R_\theta(\mathbf{z}_t, \mathbf{a}_t) \right]$$

# TD LEARNING

- Model-free algorithm
- Learning by bootstrapping from the current estimate of value function through samples from the environment

Downside?

Can TD-Learning mitigate challenges of MPC?

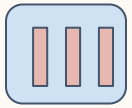
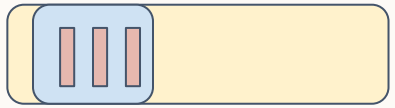

Temporal-
Difference
Learning
Data-Driven
Model-Predictive-
Control
TD-MPC
method

# DELVING DEEP INTO THE MODEL/CODES OF THE PAPER

# Task-Oriented Latent Dynamics Model

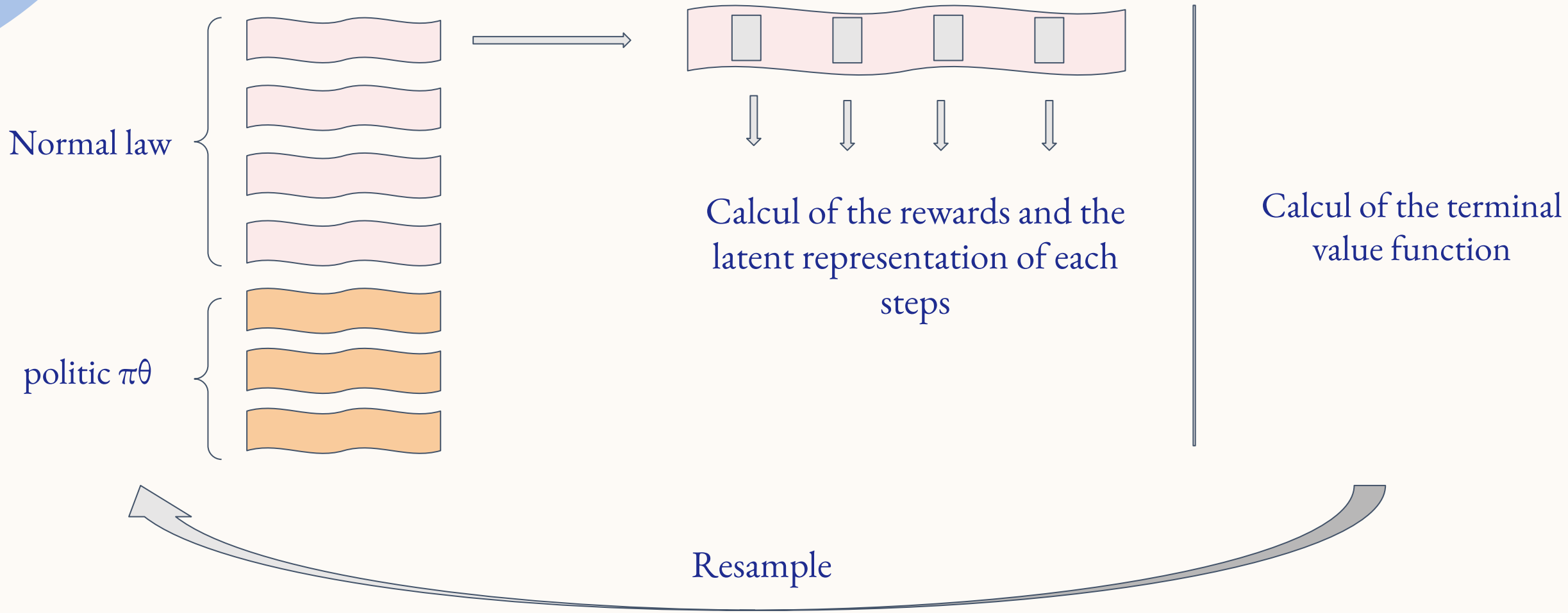
| | | | |
|---|---|---|---|
| ▪ Latent Representation | Encoder → | ▪ Observation | ▪ $z_t = h_\theta(st)$ |
| ▪ Latent Dynamics Model | MLP → | ▪ Current latent state + action = predicts the next latent state | ▪ $z_{t+1} = d_\theta(z_t, a_t)$ |
| ▪ Reward Model | MLP → | ▪ Current latent state + action = estimates the immediate reward | ▪ $\hat{r}_t = R_\theta(z_t, a_t)$ |
| ▪ Policy Model | MLP → | ▪ Current latent state = suggests the next action | ▪ $\hat{a}_t \sim \pi_\theta(z_t)$ |
| ▪ Double Q-learning | Q-Function MLP → | ▪ Given latent states + actions = estimate the state-action values | ▪ $\hat{q}_t = Q_\theta(z_t, a_t)$ |

# Overview

1. Initialization of a replay buffer 
2. Initialization of an episode 
3. **Collect trajectory** 
4. Add the full episode to the replay buffer 
5. **Update the model** with the buffer
6. Go to step 2

# Planning

Use of Cross Entropy Method



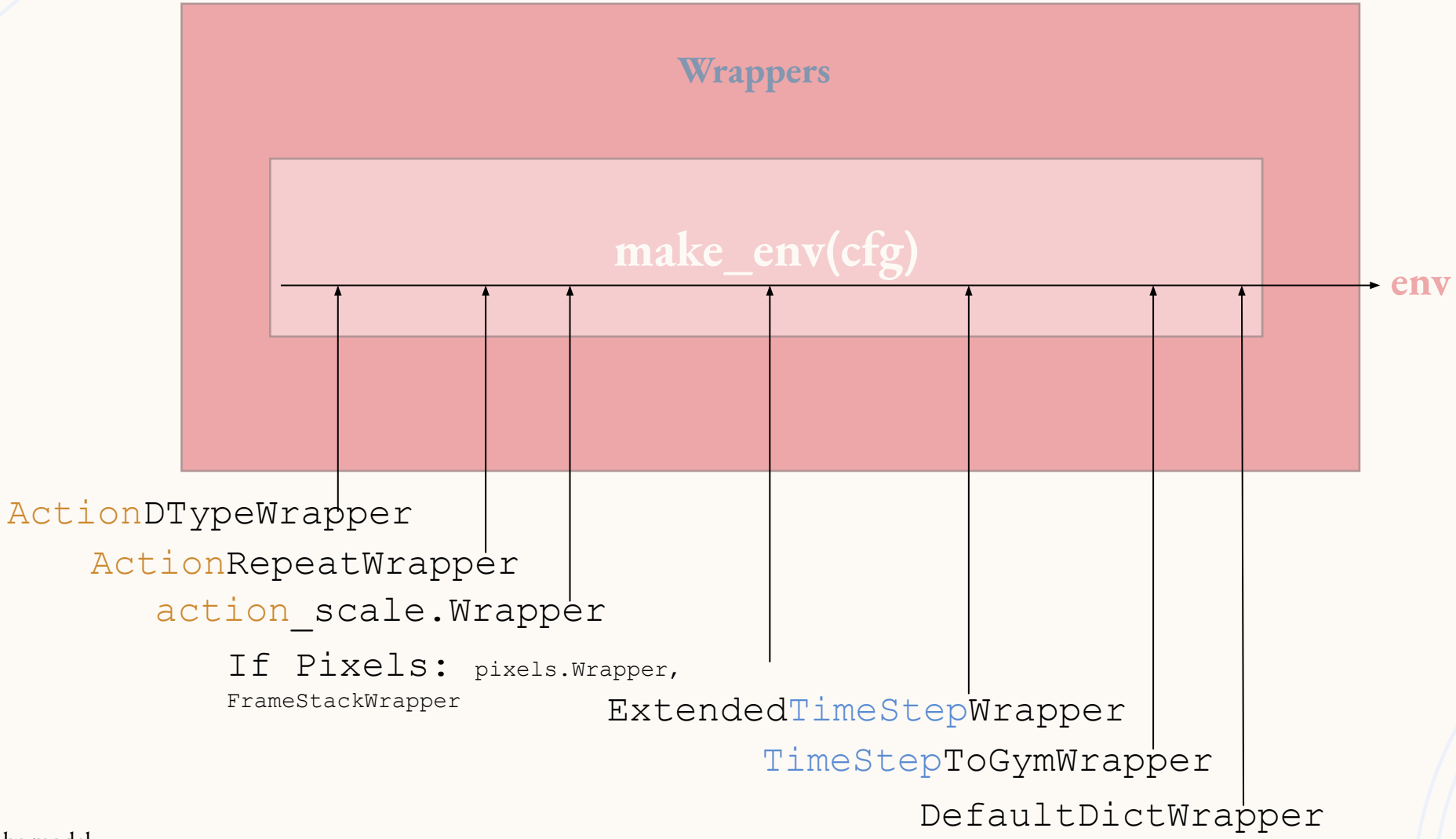
# Update of the model

Temporal Difference Error

- Use the predicted rewards to make the difference with the actual rewards

- Use the loss to optimize the model

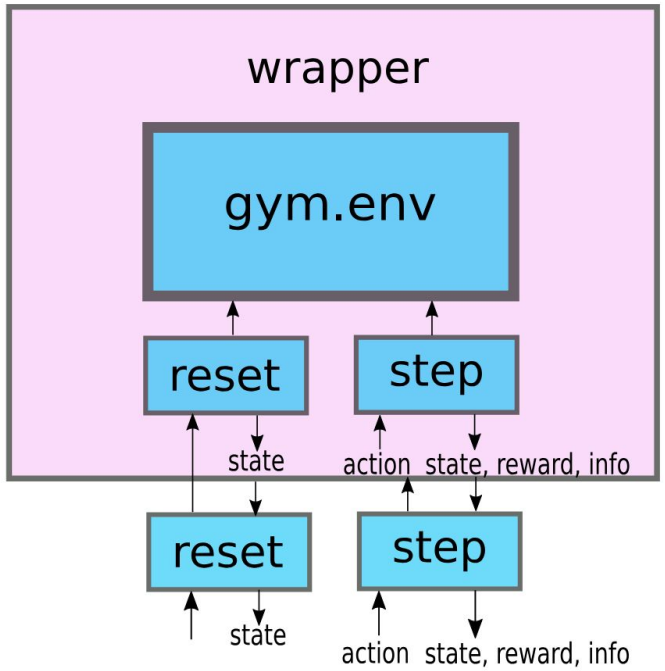
# Environment Architecture (env.py)



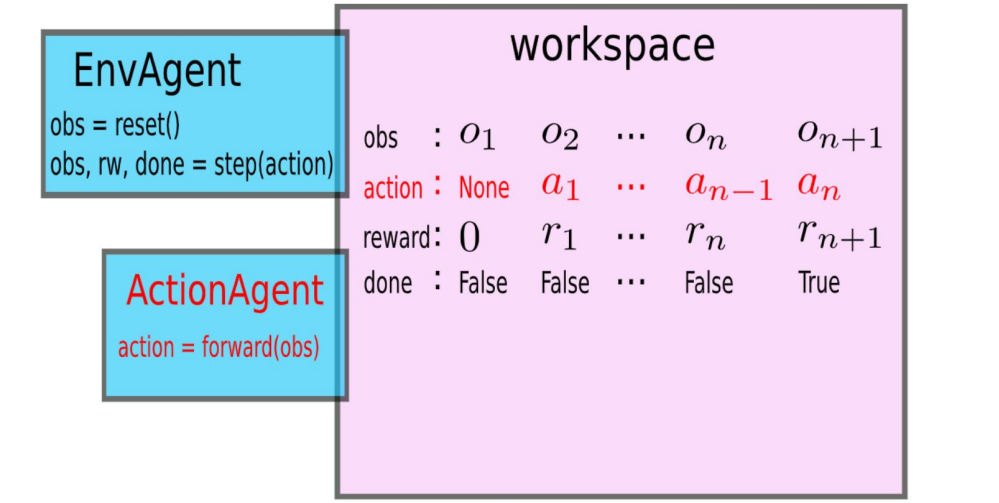
# PRESENTING BBRL LIBRARY

- **BBRL** (BlackBoard RL) Library is a derivation from **SaLinA** Library but limited to RL algorithms.

# WRAPPERS


wrapper
gym.env
reset
step
state
action
state, reward, info
reset
step
state
action
state, reward, info

BBRL Structure




- **BBRL** consists of Workspace and Agents
- Workspace is a blackboard where all agents read and write temporal data, everything else is agent
- Agents are **PyTorch** *nn.Modules*

# WORKSPACE AND REPLAYBUFFER IN THE BBRL LIBRARY

- Workspace is a collection of tensors (*SlicedTemporalTensor*, *CompactTemporalTensor* or *CompactSharedTensor*) organized in a dictionary-like structure. It is designed to manage the state and data during learning processes.

Workspace

| | | | | | |
|---|---|---|---|---|---|
| state : | $s_0$ | $s_1$ | $\cdots$ | $s_n$ | $s_{n+1}$ |
| action : | $a_0$ | $a_1$ | $\cdots$ | $a_n$ | $a_{n+1}$ |
| reward: | 0 | $r_1$ | $\cdots$ | $r_n$ | $r_{n+1}$ |
| done : | False | False | $\cdots$ | False | True |

- ReplayBuffer utilizes the Workspace class to manage the storage and retrieval of experiences efficiently during learning

# AGENTS IN THE BBRL LIBRARY

- *Everything except Workspace in the BBRL Library is structured into agents.*

Environment Agents

*Agent(nn.Modules)*

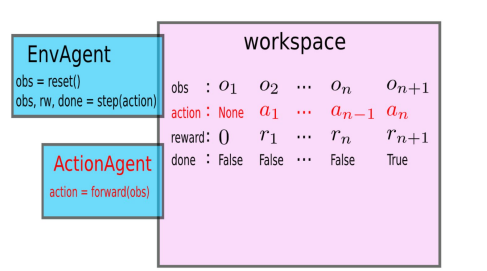
*Agents(Agent)*
*TemporalAgent(Agent)*
*TimeAgent(Agent)*
*SerializableAgent(Agent)*

*GymAgent(TimeAgent, SeedableAgent, SerializableAgent)*

*ParallelGymAgent(GymAgent)*

RL Agents

...



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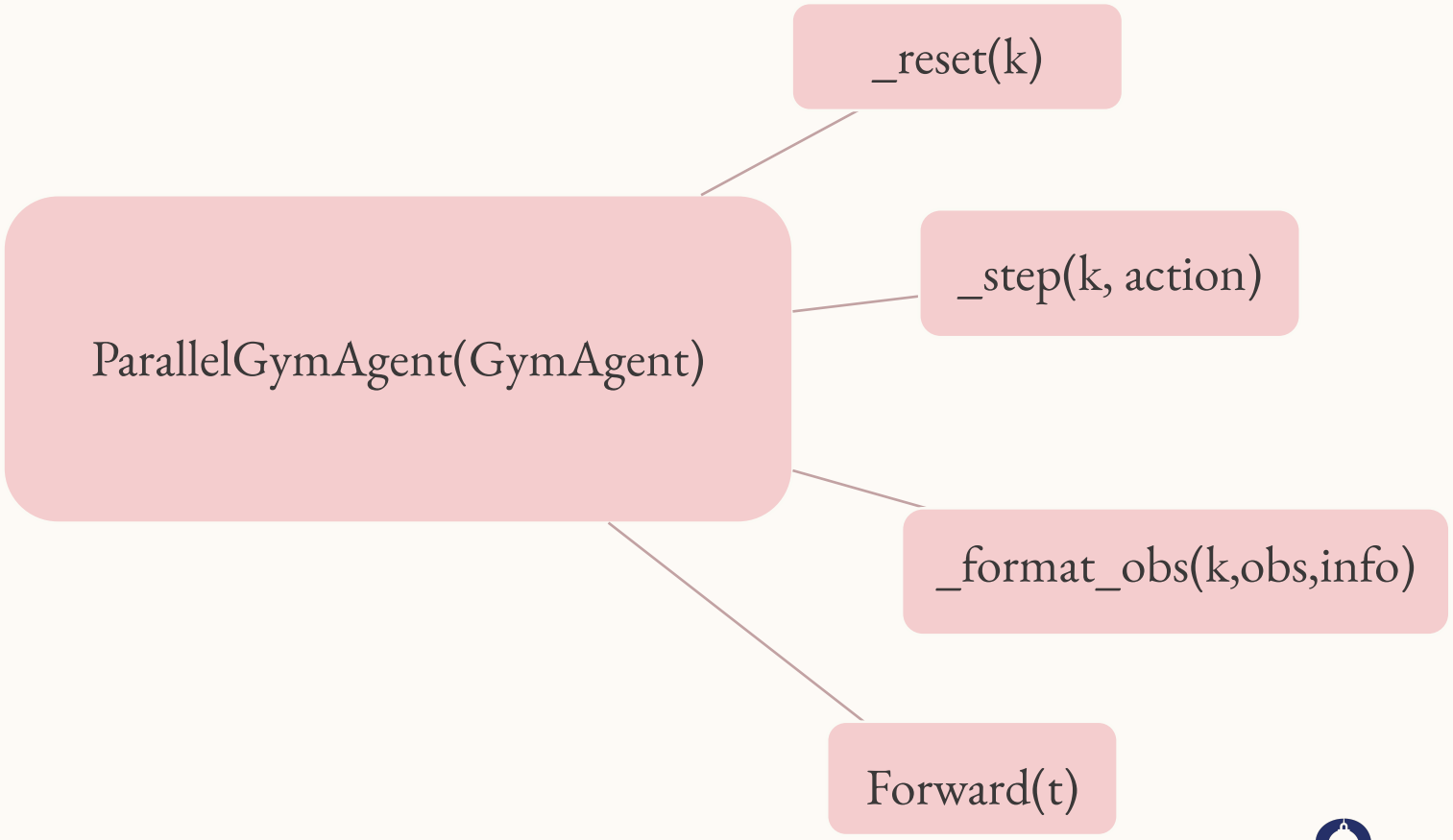
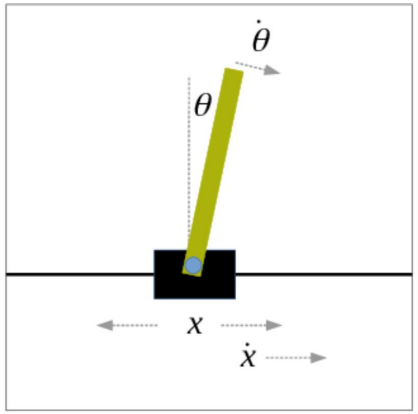
# PARALLELGYMAGENT(GYMAGENT)

- For creating an Agent from a gymnasium environment

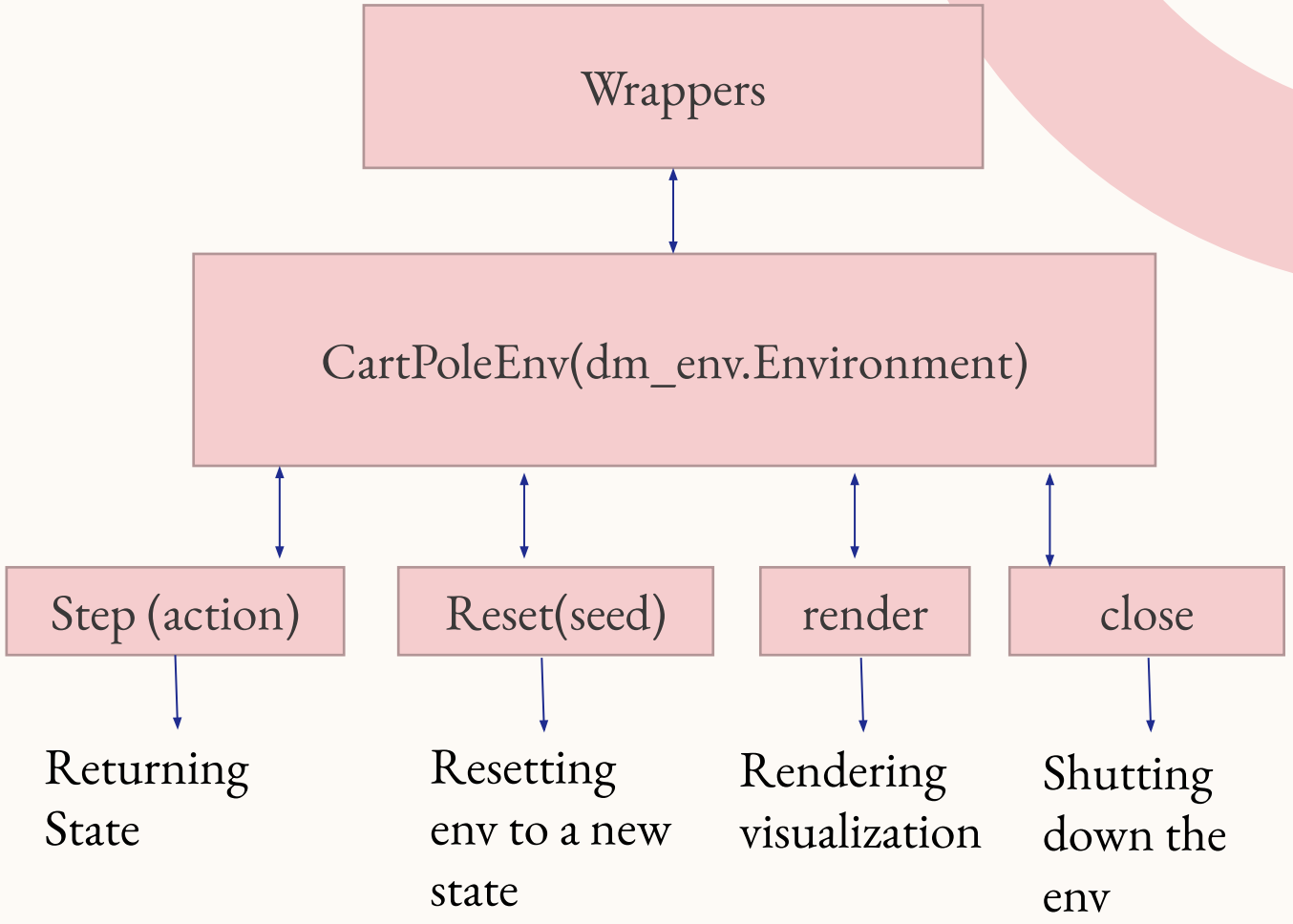


# INTEGRATION OF TDMPC INTO BBRL LIBRARY

# PREPROCESSING OF TD-MPC (CARTPOLE EXAMPLE TASK)




States: Position, Velocity, Angle, Angular Velocity
Actions: Left, Right



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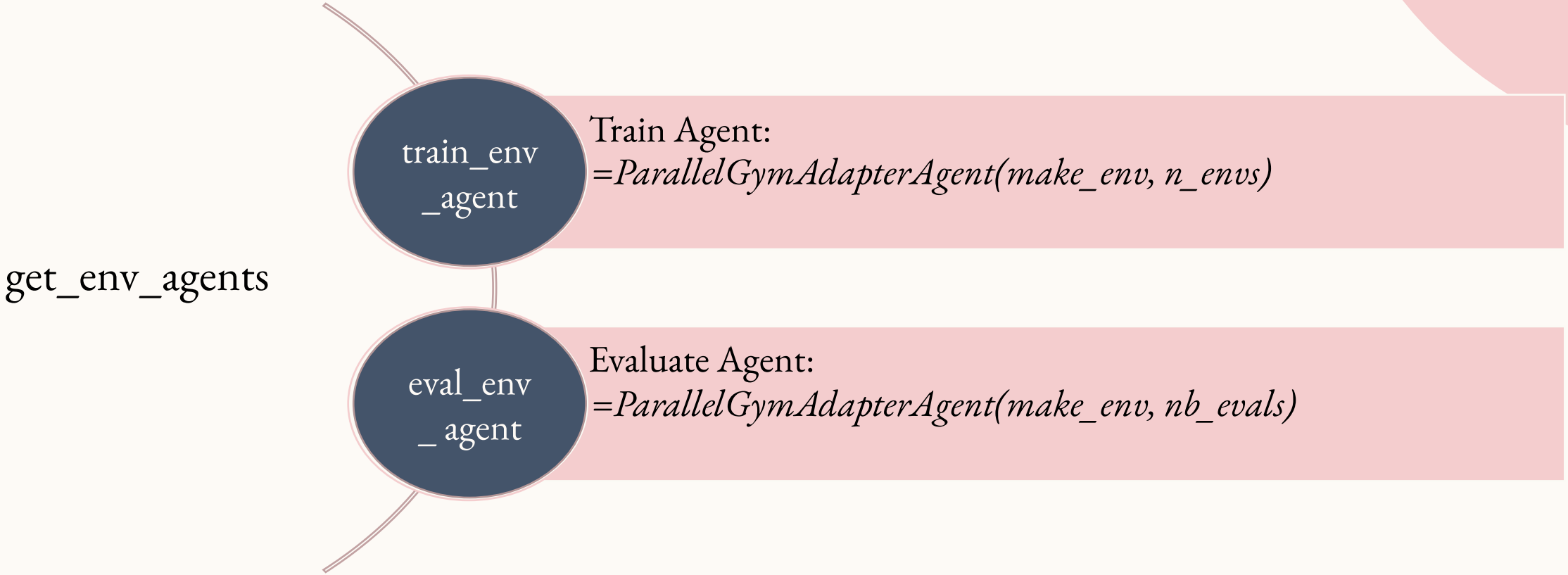
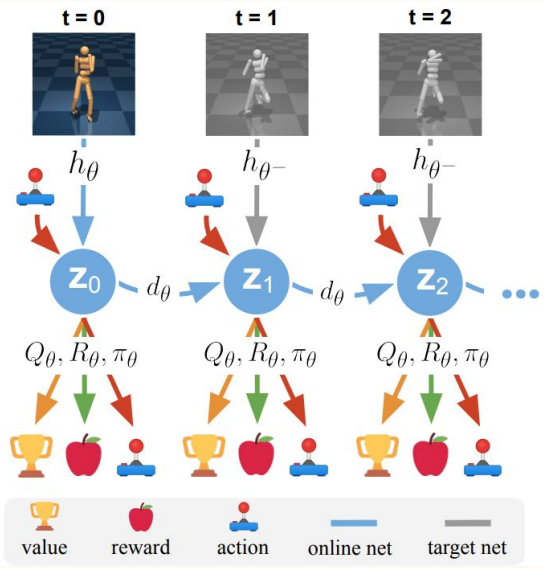
# ENVIRONMENT AGENTS OF TD-MPC

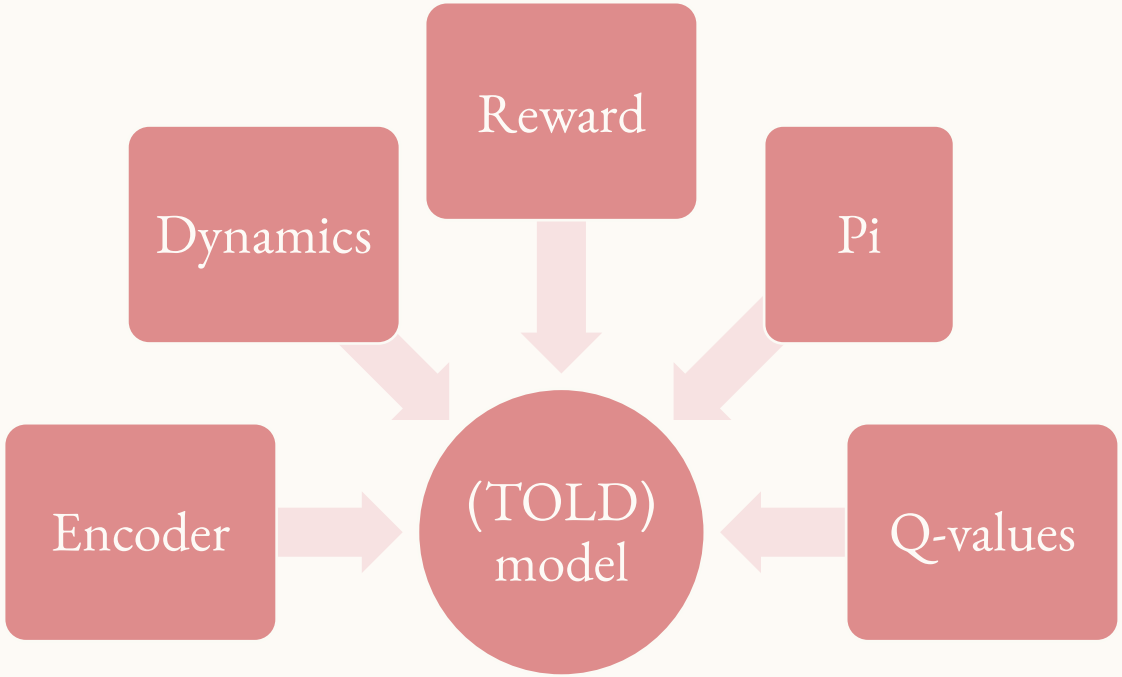


# TDMPC AGENTS: TOLD MODEL

- Referring to “TOLD Structure” explained in the slide number 12




Elements of TOLD model



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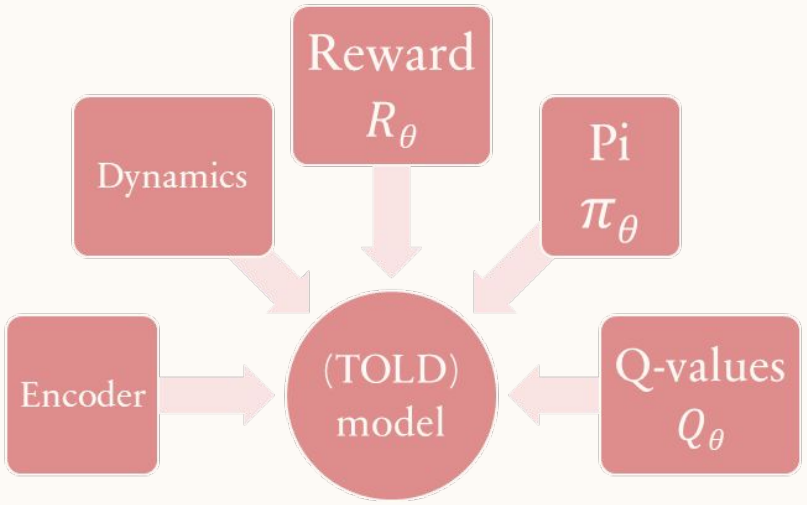
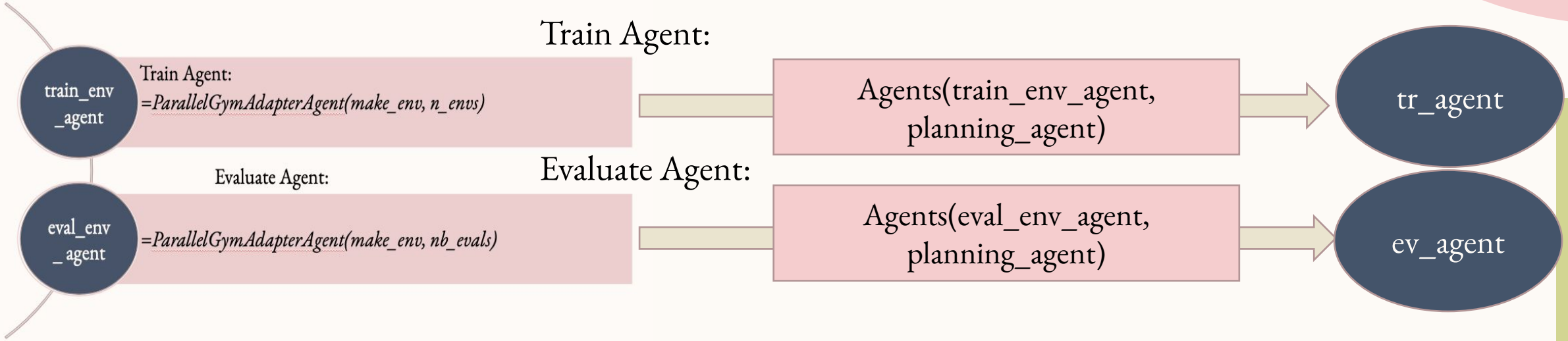
# TDMPC AGENTS: TOLD AGENTS



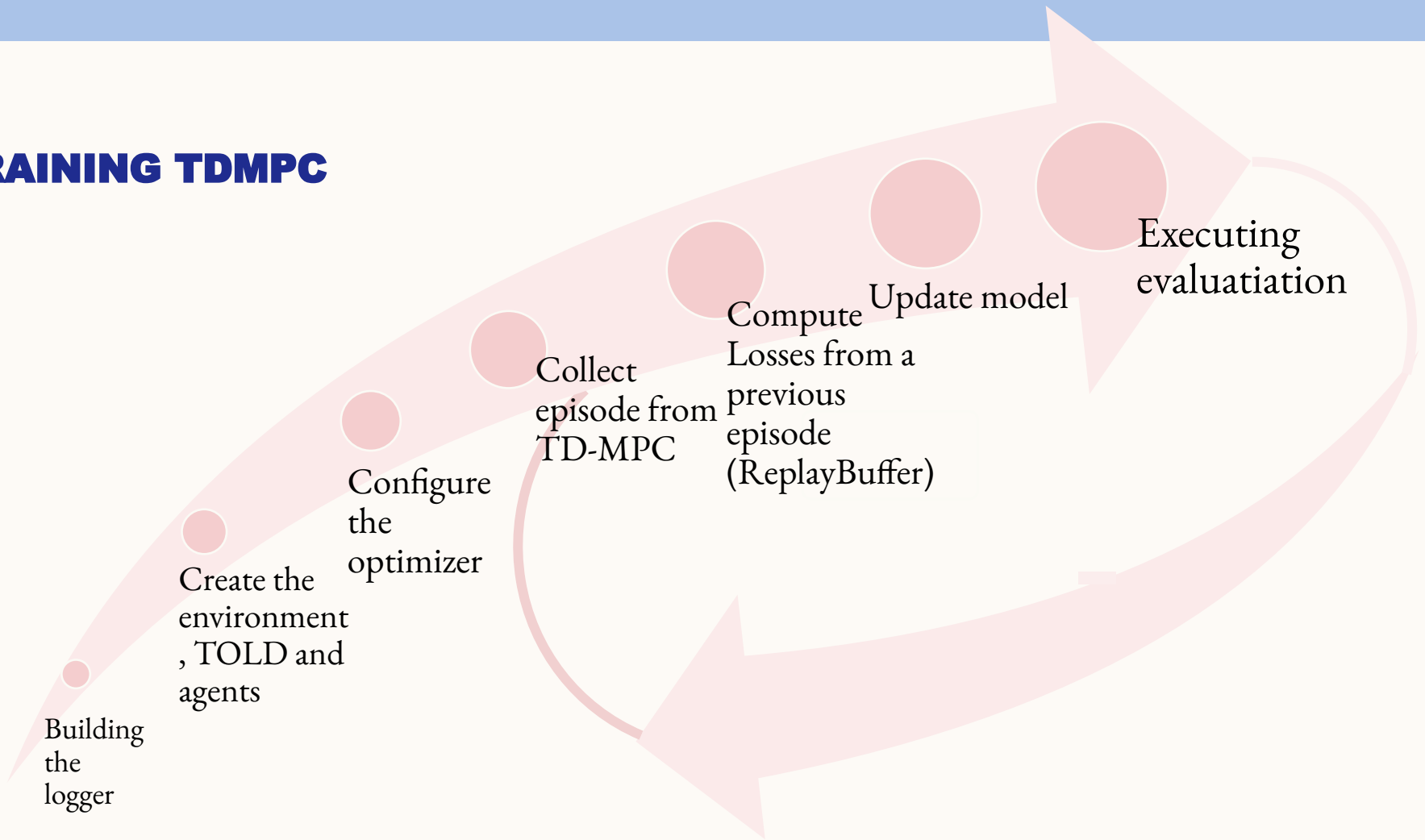

| | |
|---|---|
| encoder | =*RepresentationAgent(Agent)* |
| dynamics | =*LatentDynamicAgent(Agent)* |
| reward | =*RewardAgent(Agent)* |
| Pi | =*PolicyAgent(Agent)* |
| Qvalues | =*ValueAgent(Agent)* |

# ENVIRONMENT AGENTS OF TD-MPC

- train and evaluate agents are then combined with encoder, pi, reward and dynamics agents

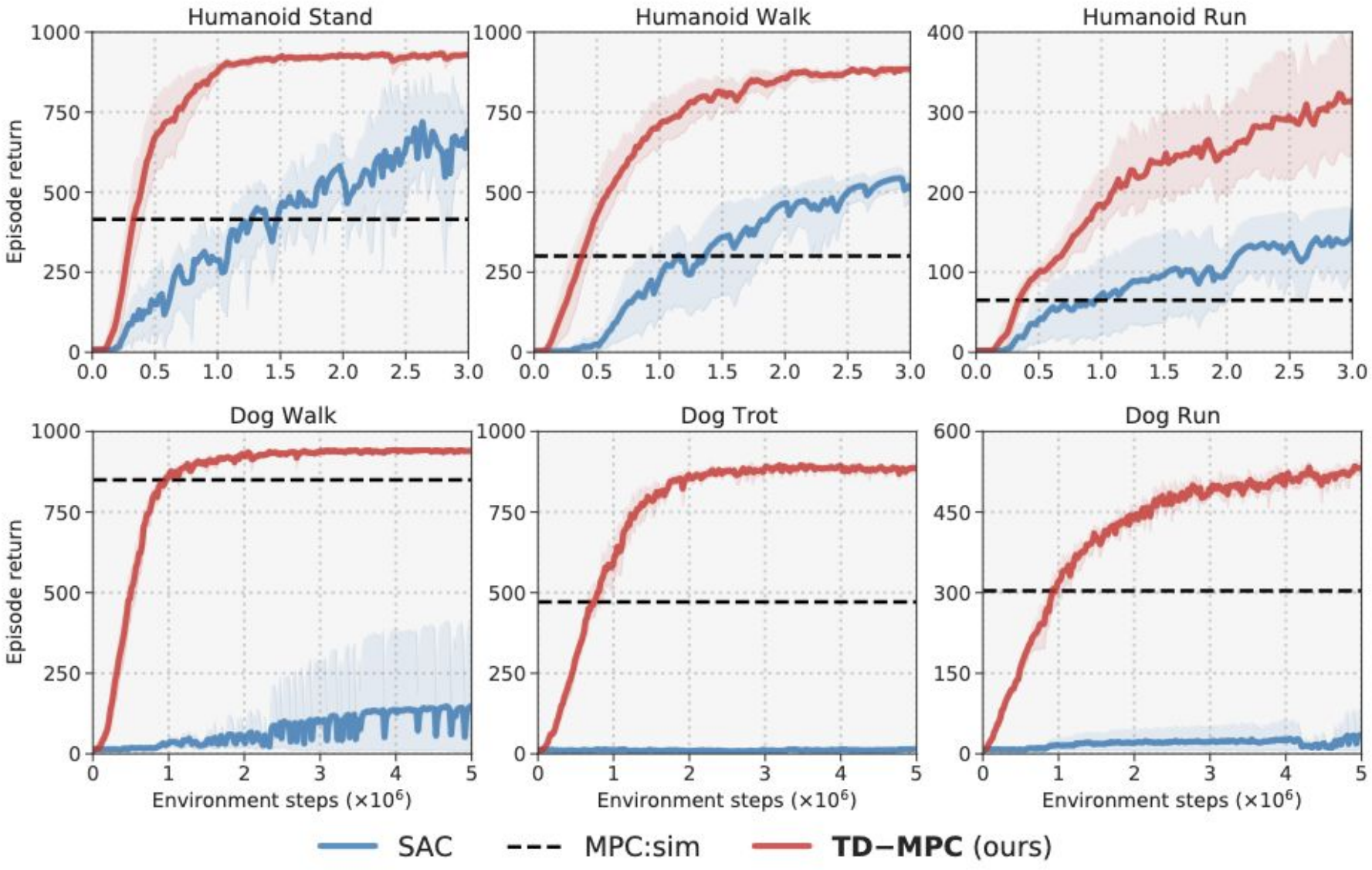


# TRAINING TDMPC



# Results

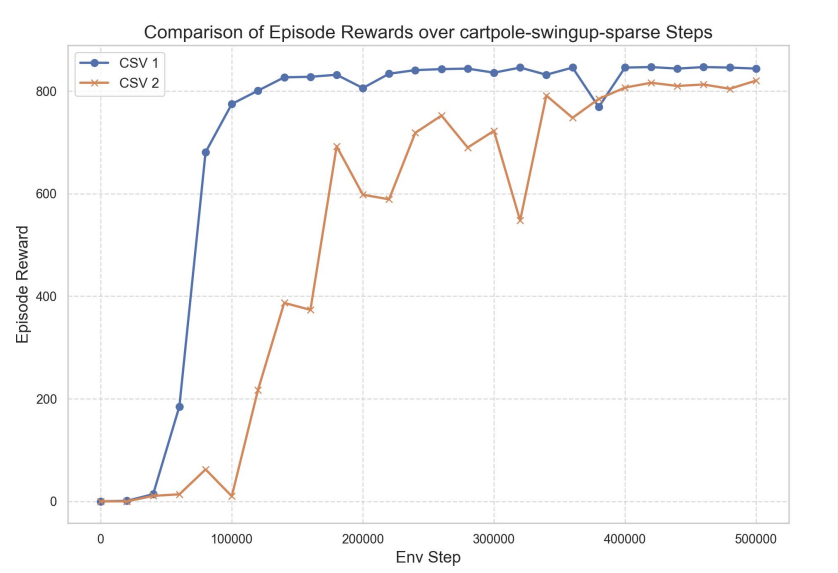


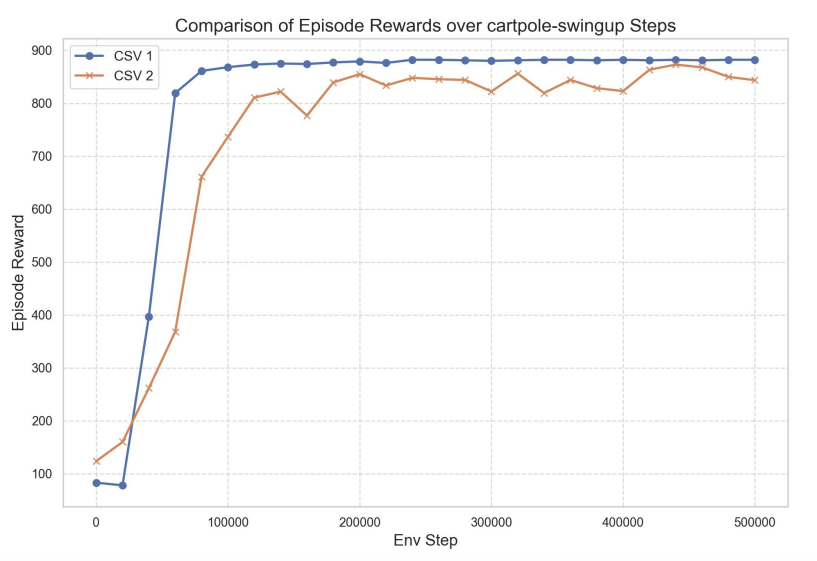

Humanoid Stand
Humanoid Walk
Humanoid Run
Dog Walk
Dog Trot
Dog Run
Episode return
Environment steps (×10^6)
SAC
MPC:sim
TD−MPC (ours)

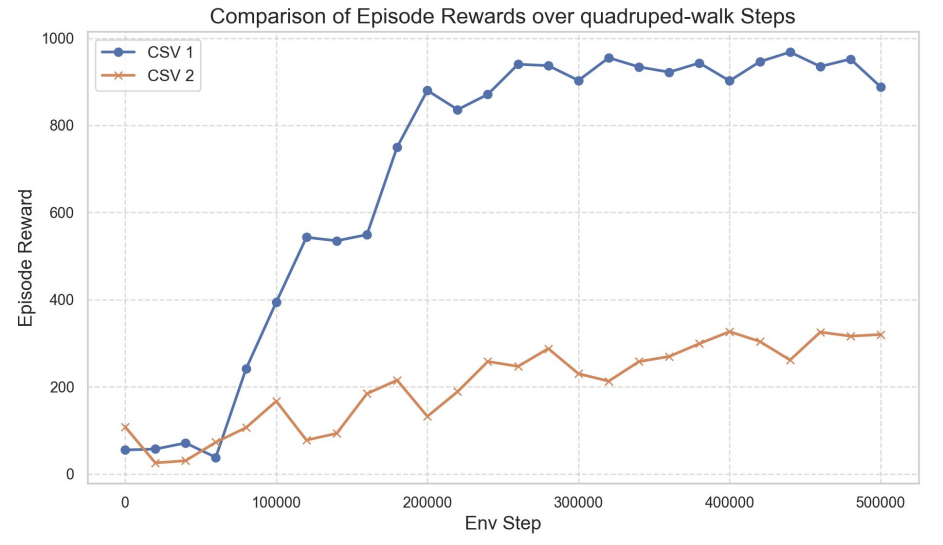
# Results

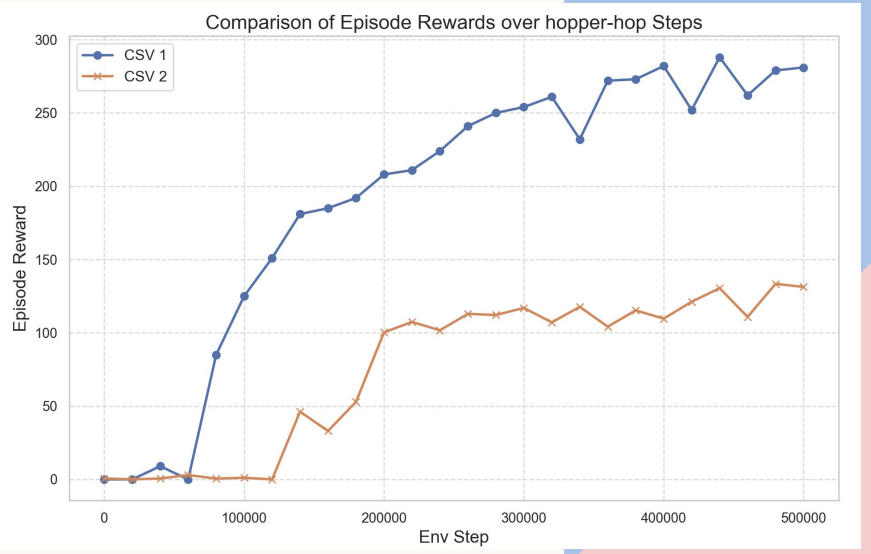


Blue for the Article's code, Orange for our implementation

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