PPO×Family

第二讲：解构复杂动作空间

主办 中国计算机学会 CCF

承办 上海人工智能实验室 Shanghai Artificial Intelligence Laboratory

协办 GAIAA 北京大学人工智能研究院 INSTITUTE FOR ARTIFICIAL INTELLIGENCE, PEKING UNIVERSITY 浙江大学上海高等研究院 SHANGHAI INSTITUTE FOR ADVANCED STUDY ZHEJIANG UNIVERSITY 商汤 sensetime

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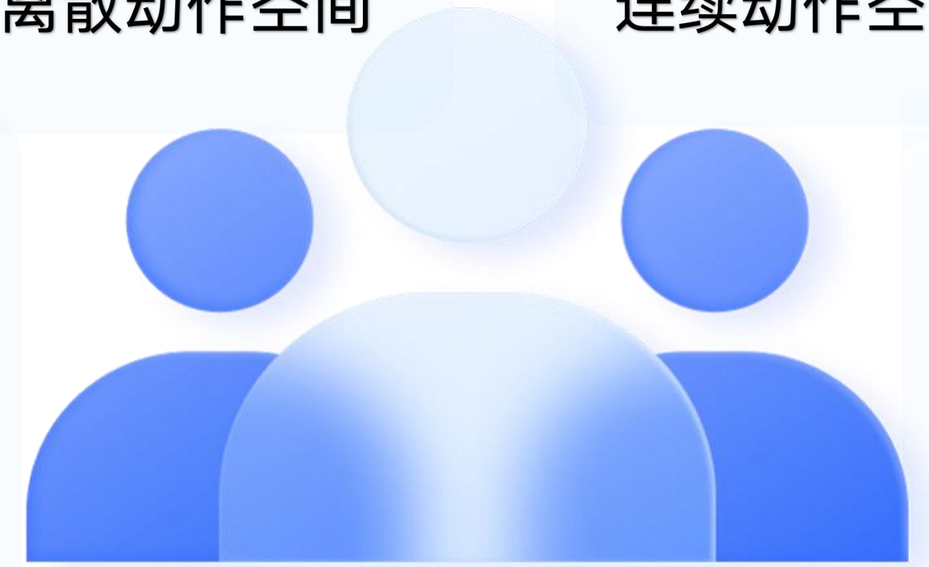
动作空间四重奏

01

离散动作空间

02

连续动作空间



03

多维离散动作空间

04

混合动作空间

Action Space Overview

动作空间概述

https://en.wikipedia.org/wiki/Keyboard_layout

动作空间的分类

特点：

- 不同的动作空间常需要不同的算法
- 标准的 RL 算法常需要对特定动作进行适配和定制化
- 同一个环境可以用不同的动作空间

Action Shaping

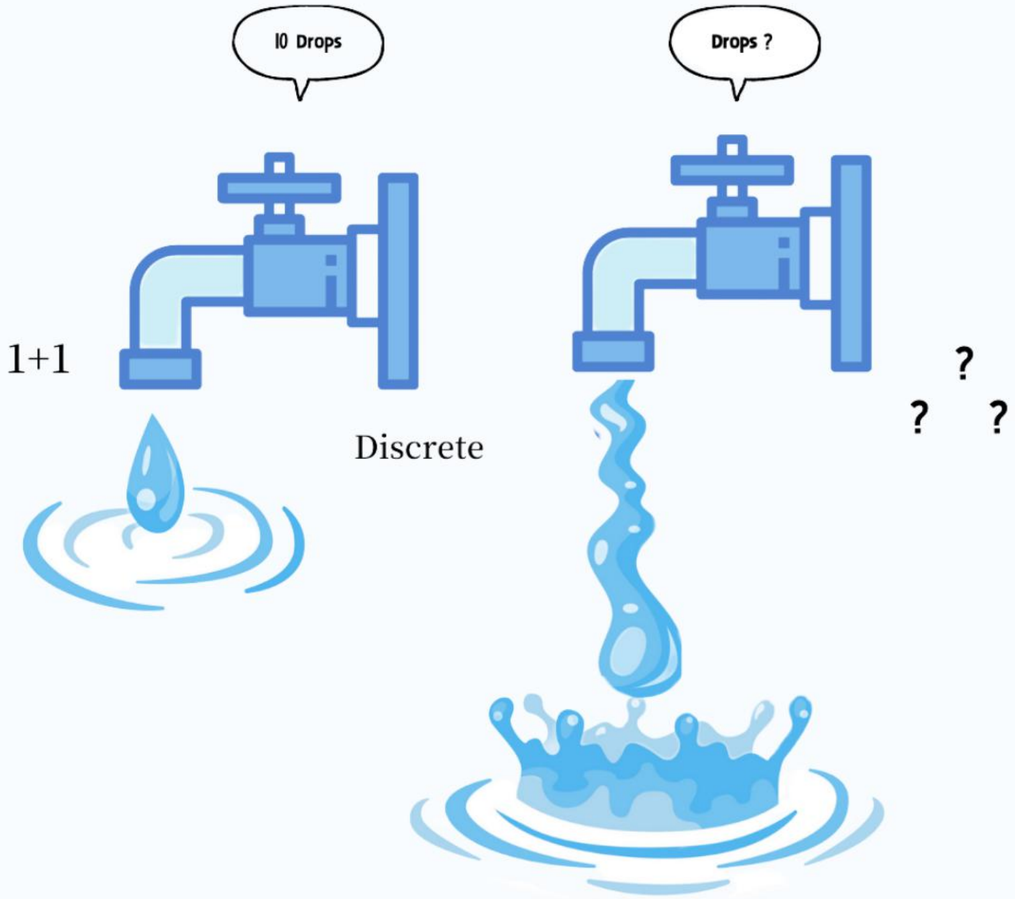
动作塑形

Environment Name	Original action space	Transform	Transformed action space	Performance
MineRL	Multi-discrete(2, 2, 2, 2, 2, 2, 2, 2, 7, 8, 5, 8, 3), Continuous(2)	DC RA CMD	Discrete(36)	
		DC RA CMD	Discrete(10)	1st place
		DC RA CMD	Discrete(216)	2nd place
		DC RA	Multi-discrete(2, 2, 3, 3, 7, 8, 5, 8, 3, 40)	3rd place
		DC RA	Multi-discrete(2, 2, 2, 5, 8, 3, 8, 7, 3, 3)	5th place
Unity Obstacle Tower Challenge	Multi-discrete(3, 3, 2, 3)	RA CMD	Discrete(12)	1st place
		RA	Discrete(6)	2nd place
VizDoom (Doom)	38 binary buttons, 5 continuous	RA CMD	Discrete(256)	1st place (Track 2)
		RA	Discrete(6)	1st place (Track 1)
Atari	Discrete(18)	RA	Discrete(4 - 18)	
StarCraft II	Multi-discrete	DC RA	Multi-discrete	
Dota 2	Multi-discrete	DC RA	Multi-discrete	
GTA V (car driving only)	Multi-discrete	RA CMD	Discrete(3)	
Torcs	Multi-discrete	RA CMD	Discrete(3)	
DMLab (Quake 3)	Multi-discrete(3, 3, 2, 2, 2), Continuous(2)	RA CMD	Discrete(9)	
Honor of Kings (MOBA)	Multi-Discrete, Continuous	RA CMD	Multi-discrete, Continous	
Little Fighter 2 (lf2gym)	Multi-Discrete(2,2,2,2,2,2,2)	CMD	Discrete(8)	

Action Space Shaping in Deep Reinforcement Learning: https://ieeexplore.ieee.org/document/9231687

Discrete

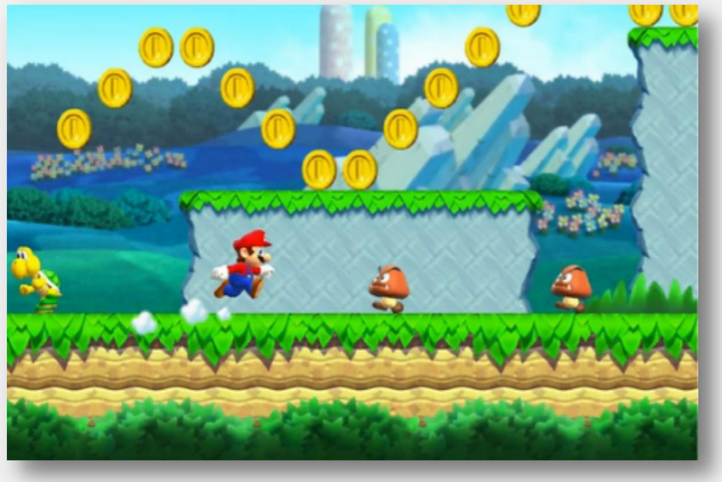
离散动作空间



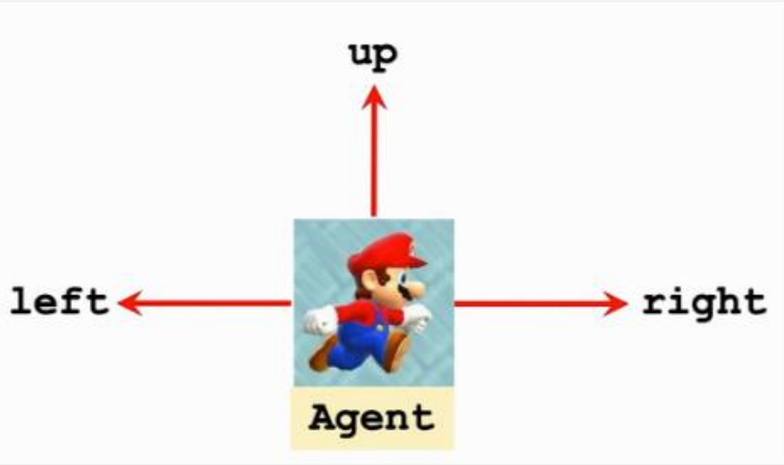
https://www.cuemath.com/data/discrete-data/

Discrete

理论：PPO+离散动作 定义



图片观察状态s



离散动作a

示例：随机性策略

$\pi(a_t|s_t)$

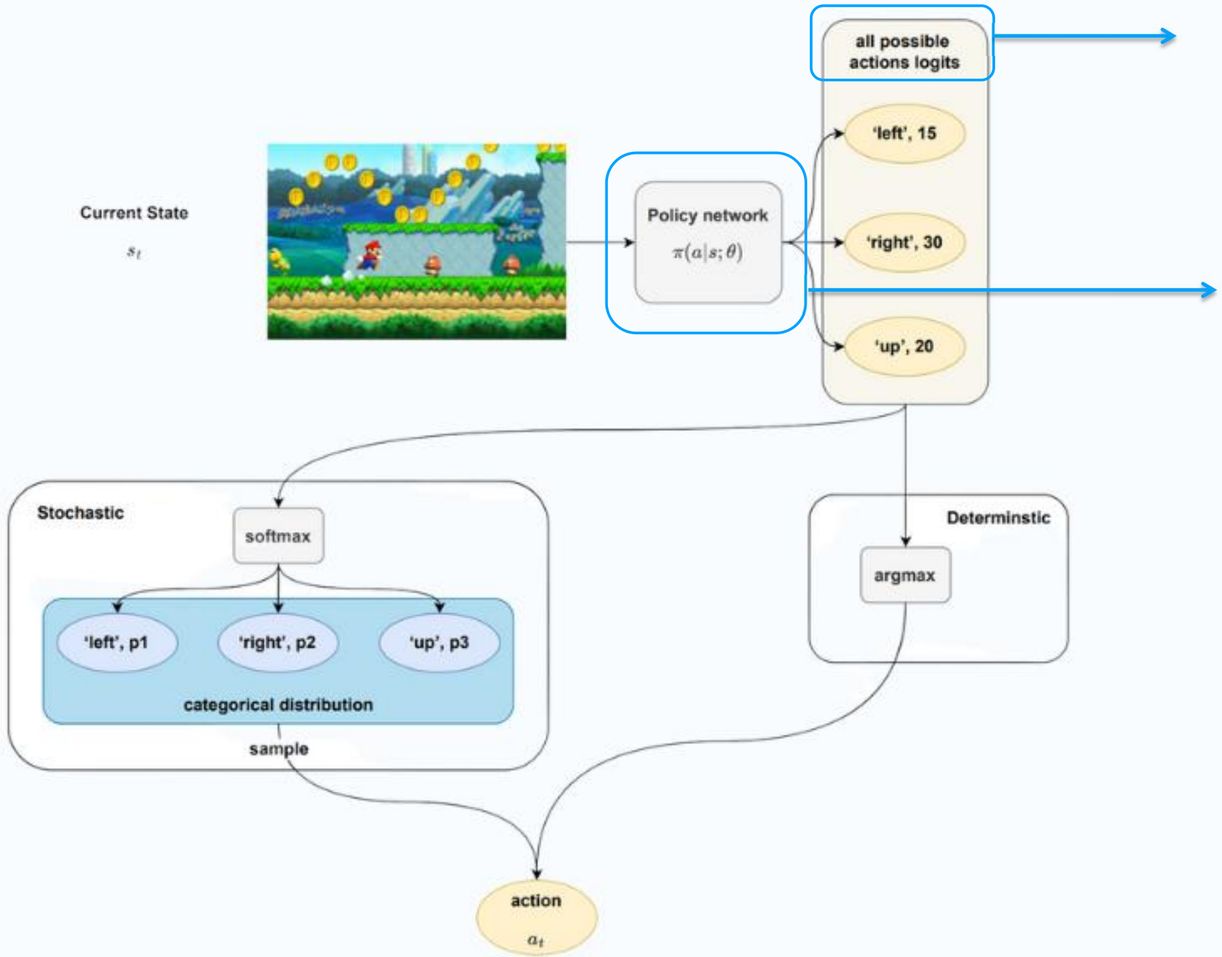
$\pi(\text{left}|s_t) = 0.2$

$\pi(\text{right}|s_t) = 0.7$

$\pi(\text{up}|s_t) = 0.1$

Discrete

理论：PPO+离散动作 计算图

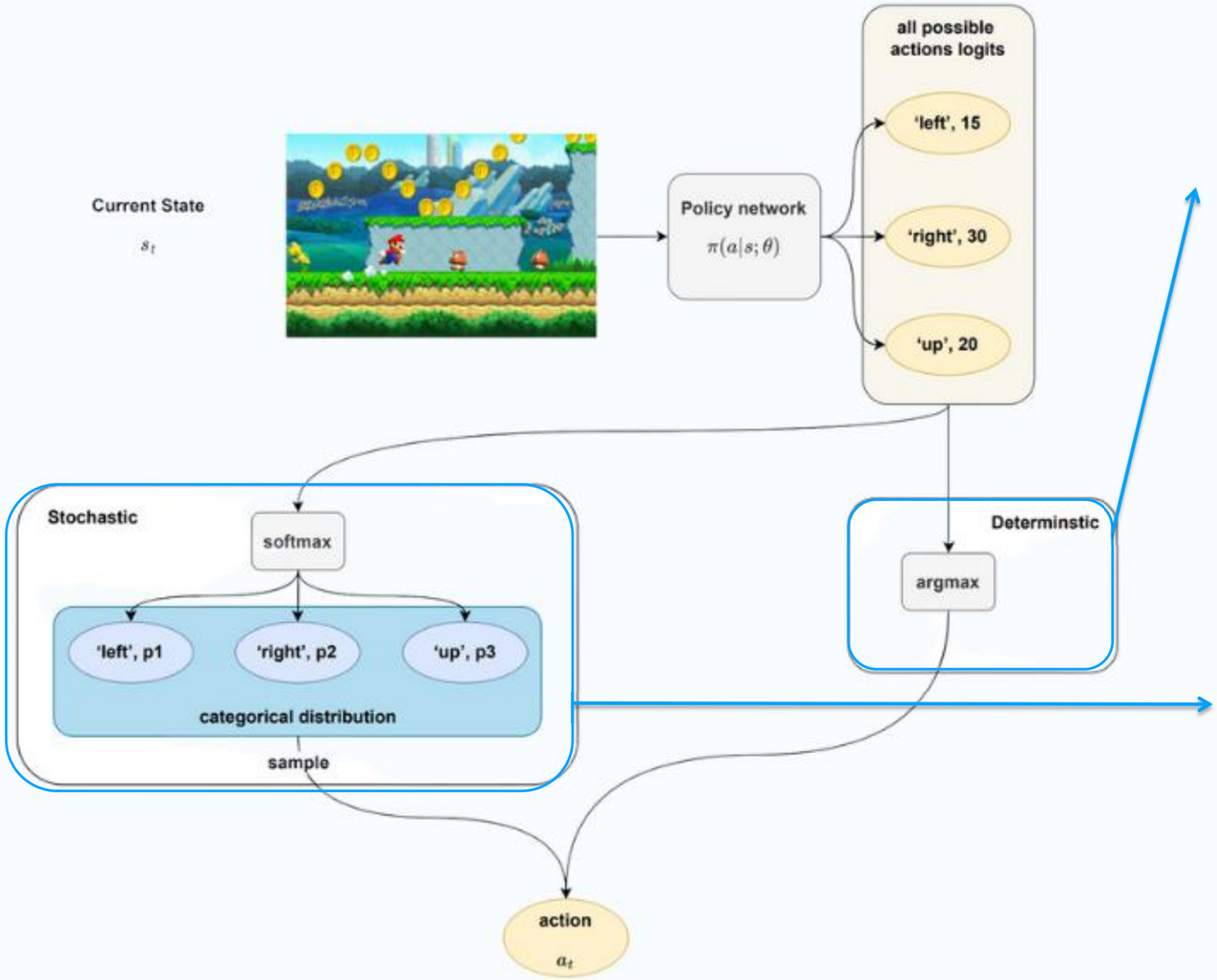


logit：策略神经网络的原始输出，比如最后一层全连接层的输出，不加激活函数

用神经网络来实现参数化的随机性策略，策略网络输出 logit，构建选择动作的 Categorical Distribution

Discrete

理论：PPO+离散动作采样



确定性决策：直接贪心选择 logit 最大的那一维动作（确定性评测时使用）

随机性决策：根据概率构建玻尔兹曼分布进行采样（随机性评测+收集数据使用）

Discrete

代码：PPO如何实现离散动作

PyTorch demo of PPO algorithm in discrete action space.

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View code on GitHub

Overview
The computation graph of discrete action policy network used in PPO.

```python
def forward(self, x: torch.Tensor) -> torch.Tensor:
```

Transform original state into embedding vector (i.e. (B, *) -> (B, N)).

```python
        x = self.encoder(x)
```

Calculate logit for each possible discrete action dimension (i.e. (B, action_shape)).

$$\pi_\theta(a|s)$$

```python
        logit = self.head(x)
        return logit


```

Overview
The function of sampling discrete action, input shape = (B, action_shape), output shape = (B,).
In this example, batch_shape = (B,), event_shape = (), sample_shape = ().

```python
def sample_action(logit: torch.Tensor) -> torch.Tensor:
```

Transform logit (raw output of policy network, e.g. last fully connected layer) into probability.

```python
    prob = torch.softmax(logit, dim=-1)
```

Construct categorical distribution.
Related Link

```python
    dist = torch.distributions.Categorical(probs=prob)
```

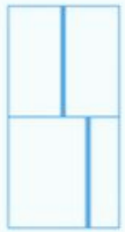
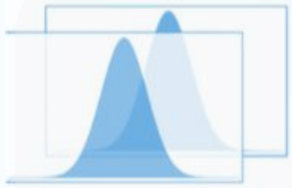
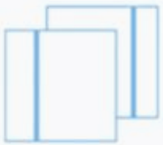
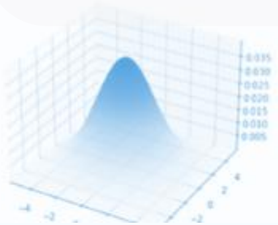
Sample one discrete action per sample and return it.

```python
    return dist.sample()

```

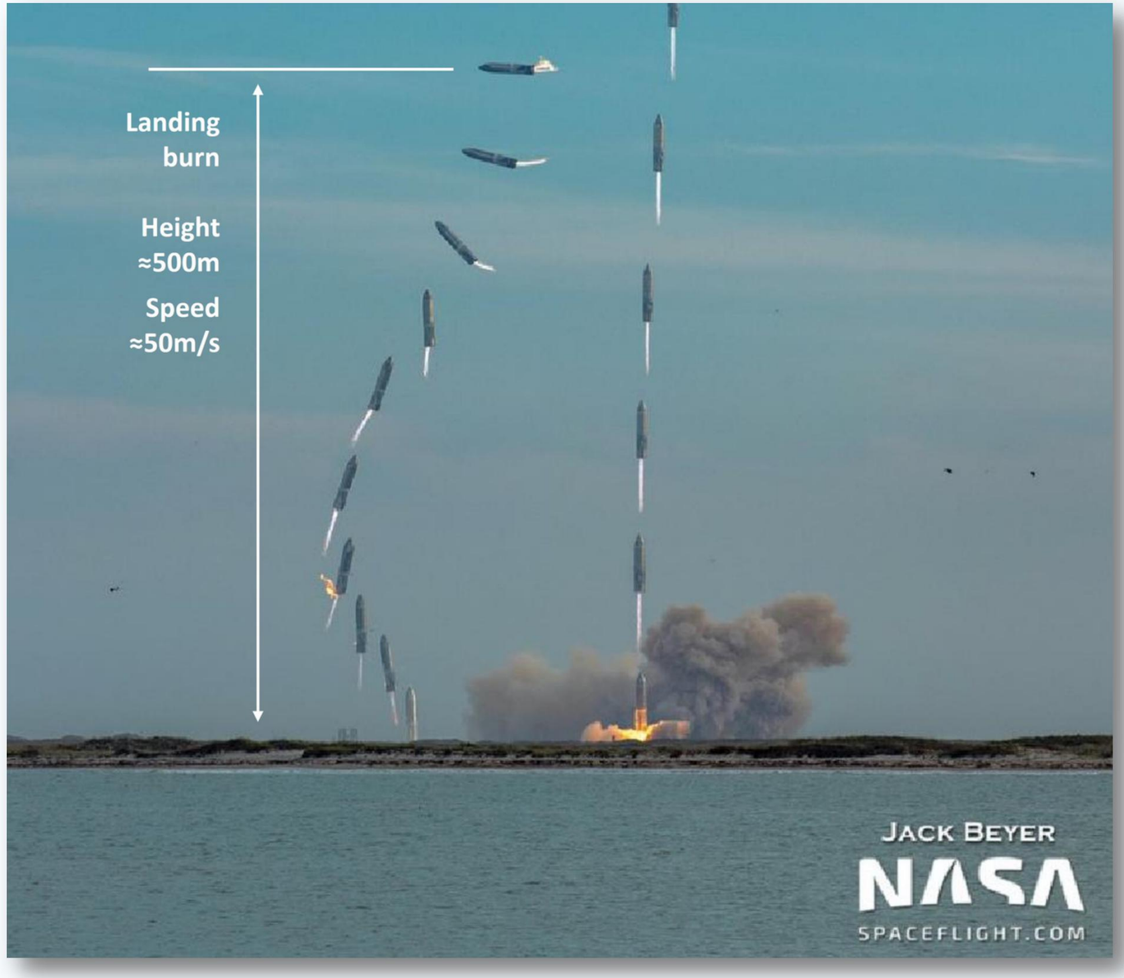
完整示例：https://opendilab.github.io/PPOxFamily/

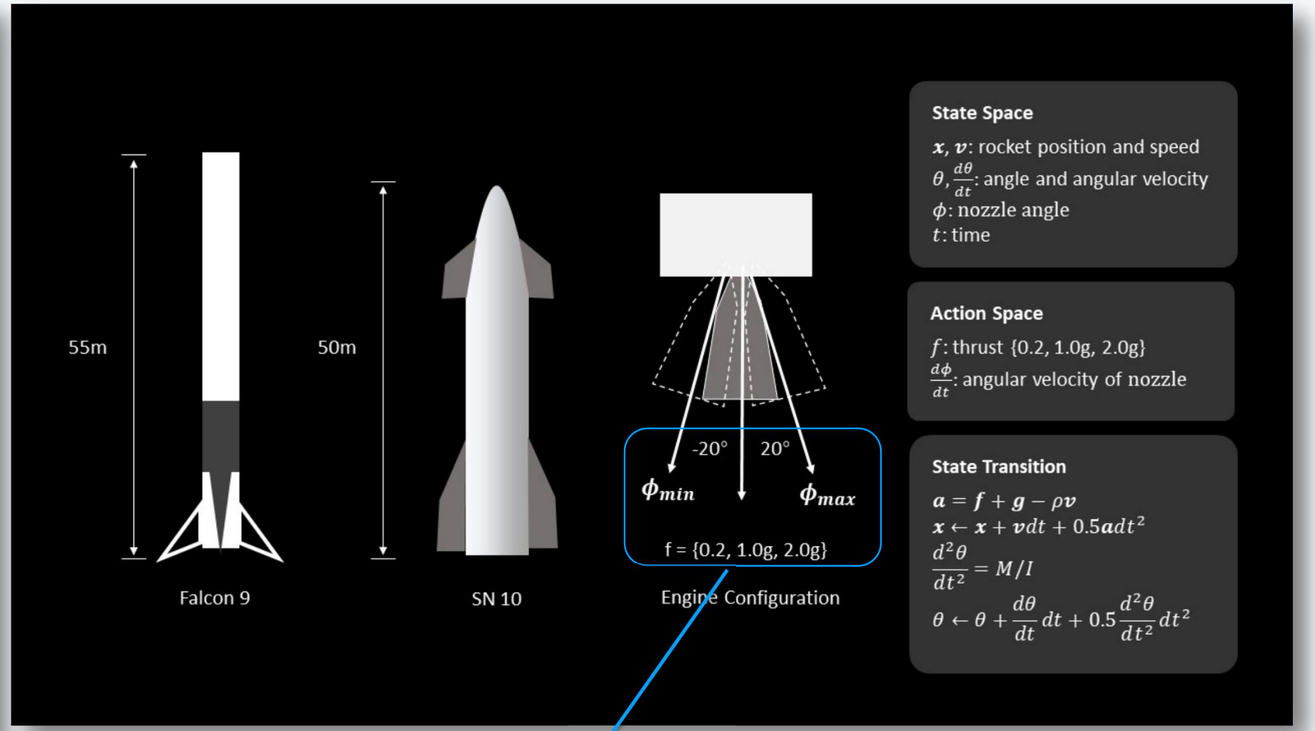
代码：PPO如何实现动作采样

分布	抽样	Event Shape	Batch Shape	Sample Shape	解释	
		()	()	(2,)	对1个1元正态分布进行2次抽样	独立同分布地多次采样
		()	(2,)	()	对2个1元正态分布进行1次抽样	从多个独立分布中采样
		(2,)	()	()	对1个2元正态分布进行1次抽样	对一个多维事件采样

TensorFlow Distributions: https://arxiv.org/abs/1711.10604

实践：PPO+火箭回收

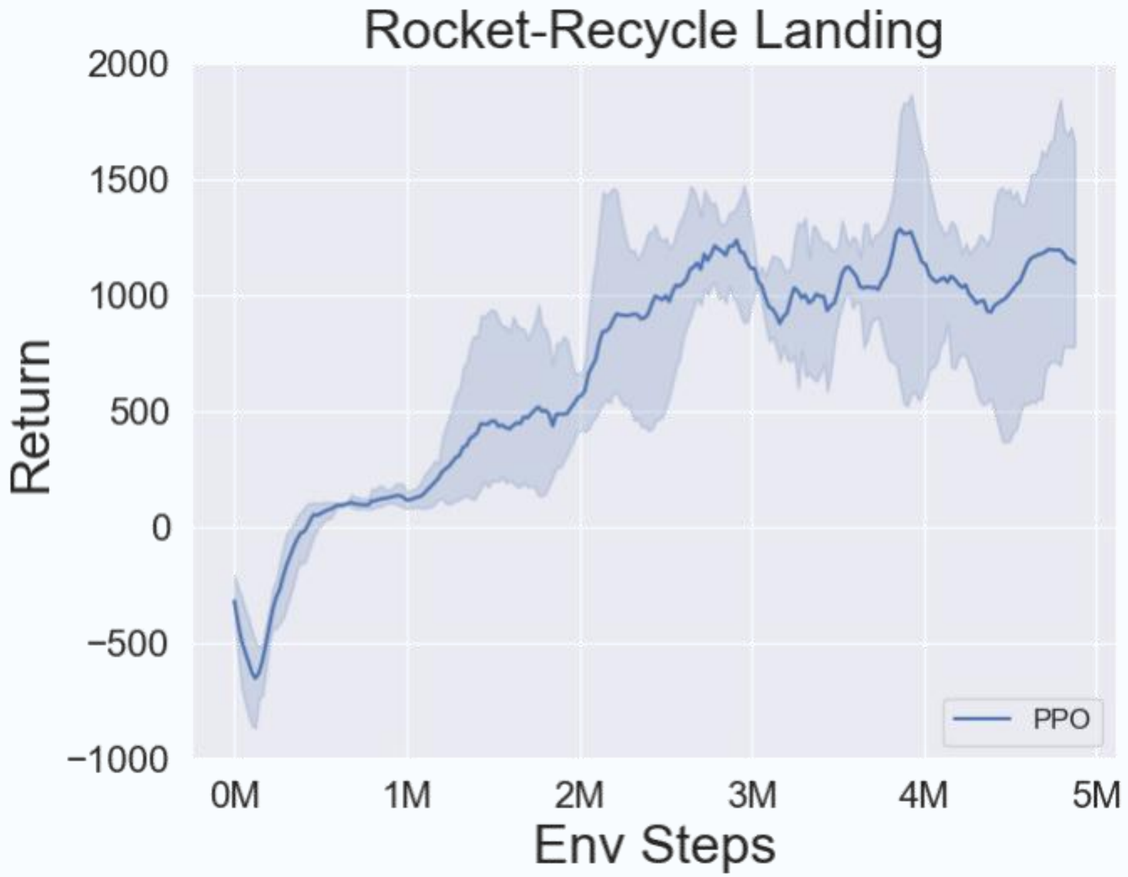




离散化为3个角度 x 3种推力共9维离散动作

Rocket Recycle Landing: https://github.com/jiupinjia/rocket-recycling

实践：PPO+火箭回收



奖励空间：与着陆目标的距离 + 姿态控制

1. 乱喷气直接坠落（0–100k）
2. 学会半空悬停（200k–500k）
3. 学习控制落点大趋势（600k–1M）
4. 学会落地减速（1M–2M）
5. 探索较短的轨迹，反复横跳（2M–3M）
6. 学习落地保持稳定（3M–5M）

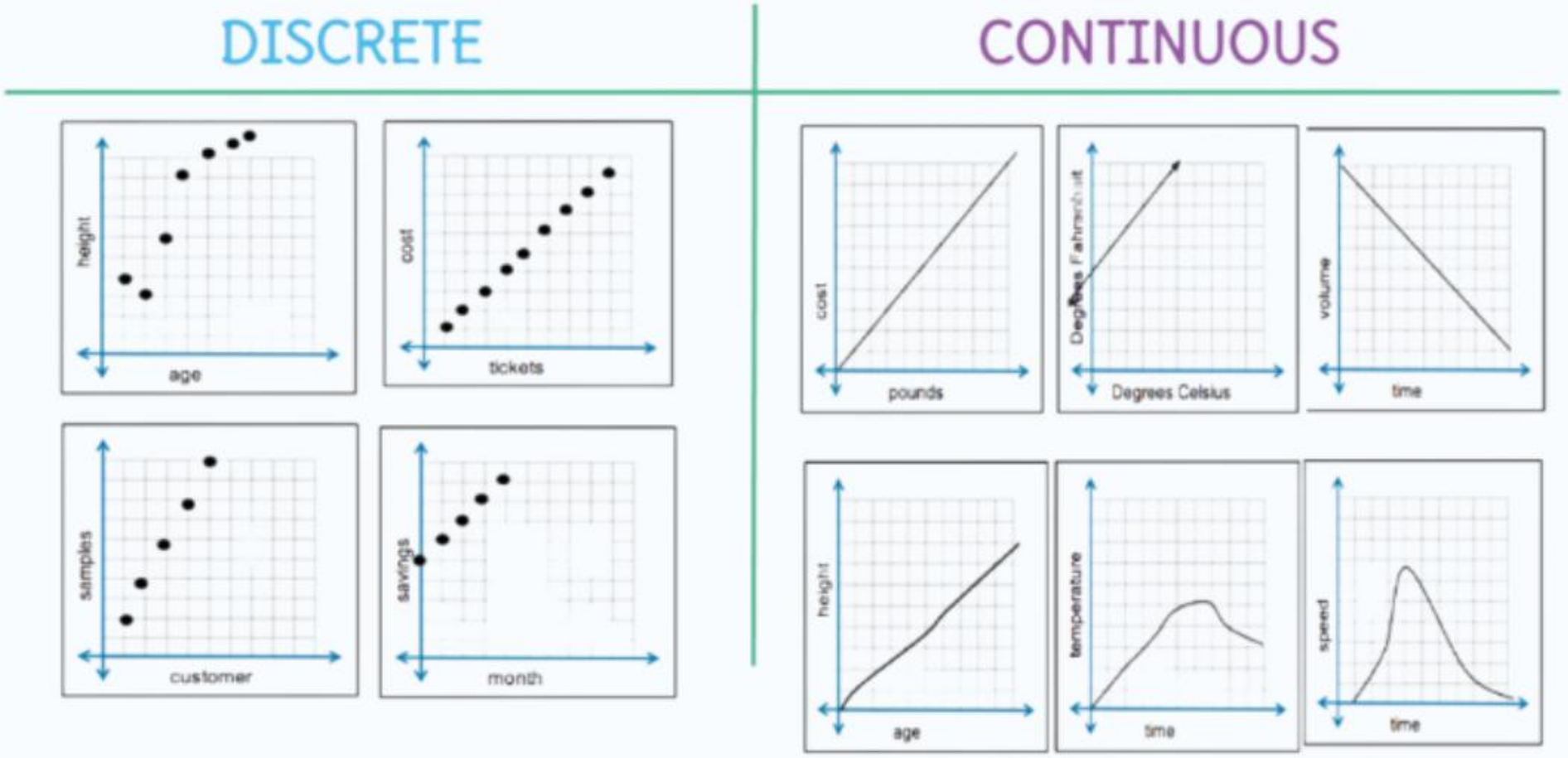
实验细节：https://github.com/opendilab/PPOxFamily/issues/4

实践：PPO+火箭回收

视频样例：https://github.com/opendilab/PPOxFamily/issues/4

Continuous

连续动作空间



https://learnzillion.com

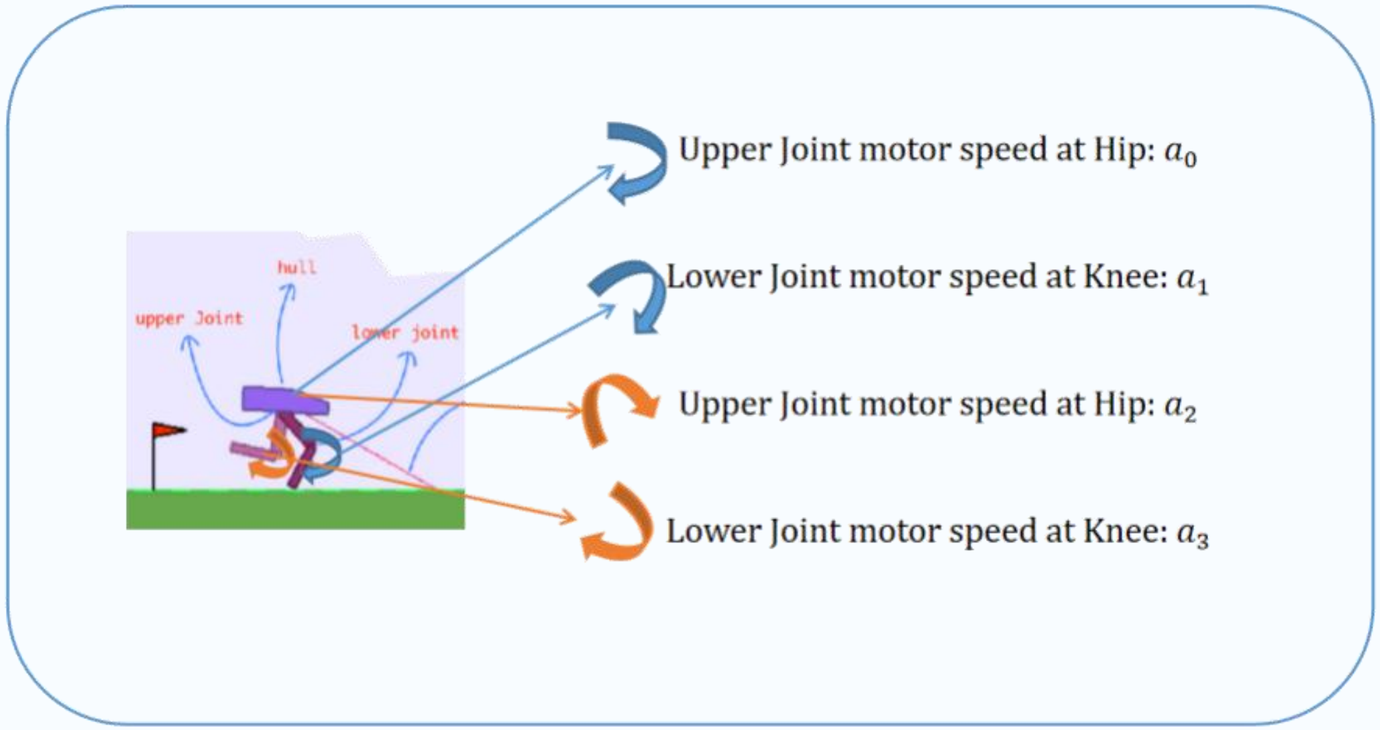
离散

Discrete

连续

Continuous

理论：PPO+连续动作 定义

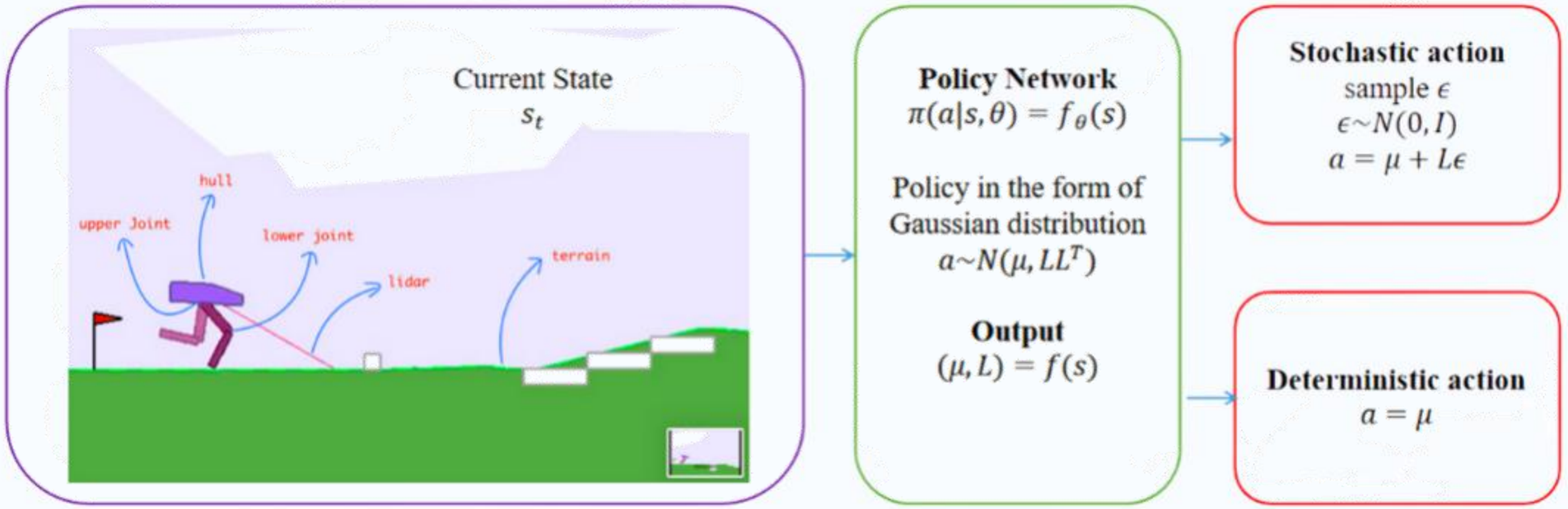


特点：

- 连续的，稠密的，不可数个动作元素组成的连续区间（类似回归问题）
- 可以根据具体取值来衡量数值大小和远近关系
- 可以直接回归，也可重参数化

Bipedal Walker: https://di-engine-docs.readthedocs.io/zh_CN/latest/13_envs/bipedalwalker_zh.html

理论：PPO+连续动作 计算图

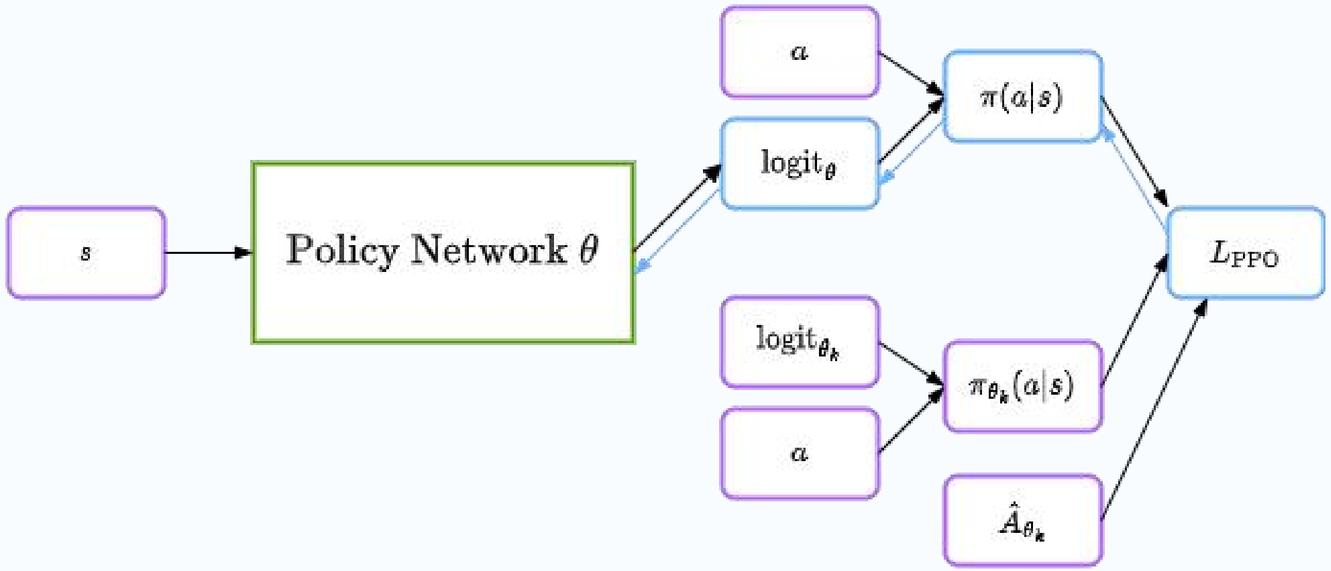


运动状态（24维） -> 策略神经网络 -> 分布参数 -> 连续动作（4维）

理论：PPO+连续动作 梯度流

Data: $< s, a, \hat{A}_{\theta_k}, \text{logit}_{\theta_k}, \cdots >$

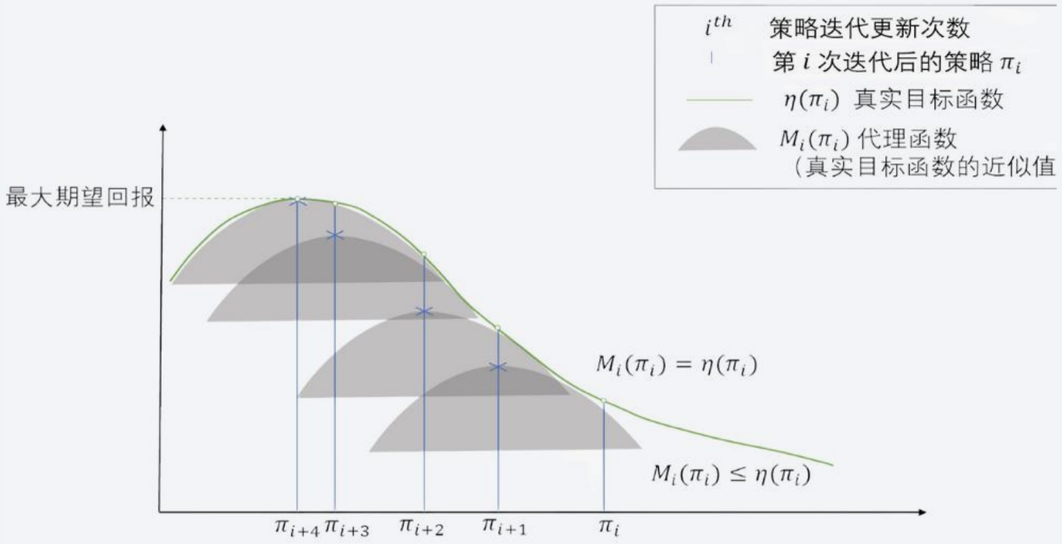
Loss: $\frac{\pi_\theta(a|s)}{\pi_{\theta_k}(a|s)} \hat{A}_{\theta_k}$



只有 IS 项的分子回传梯度，IS 项的分母和优势函数都不参与 BP

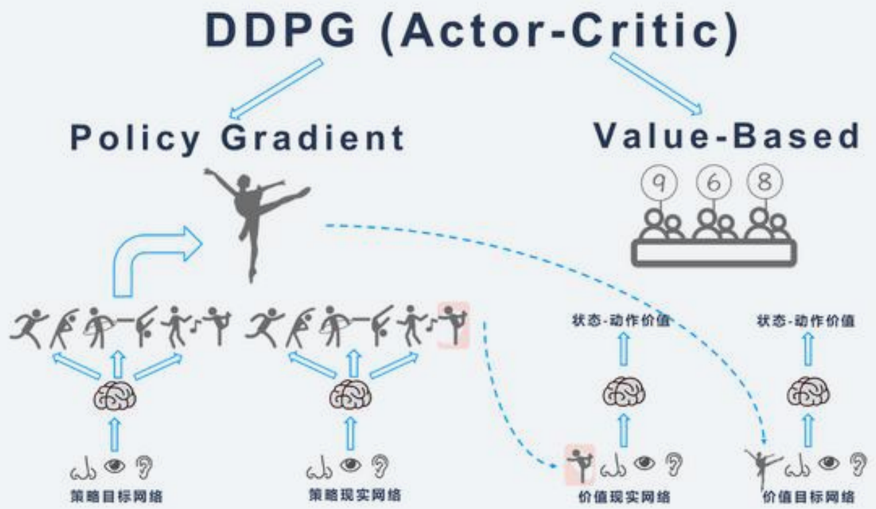
理论：PPO+连续动作 设计理念

PPO



PPO 围绕策略提升定理展开，而其价值函数主要起辅助评价作用

DDPG



DDPG 围绕优化动作价值函数展开，策略函数由对价值函数求极值的方式引导生成

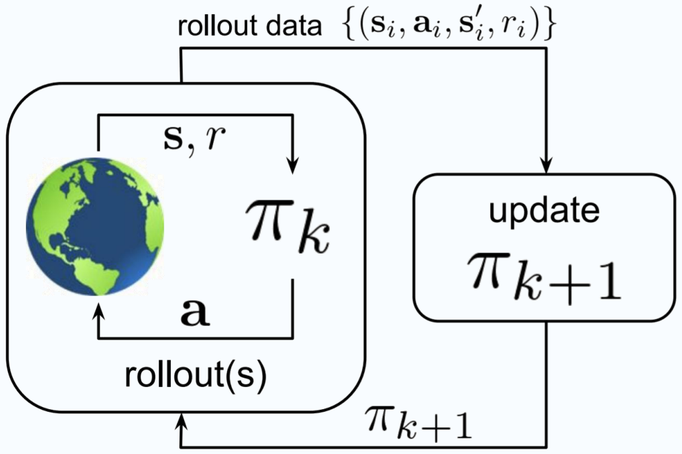
DDPG: https://arxiv.org/pdf/1509.02971.pdf

理论：PPO+连续动作 数据属性

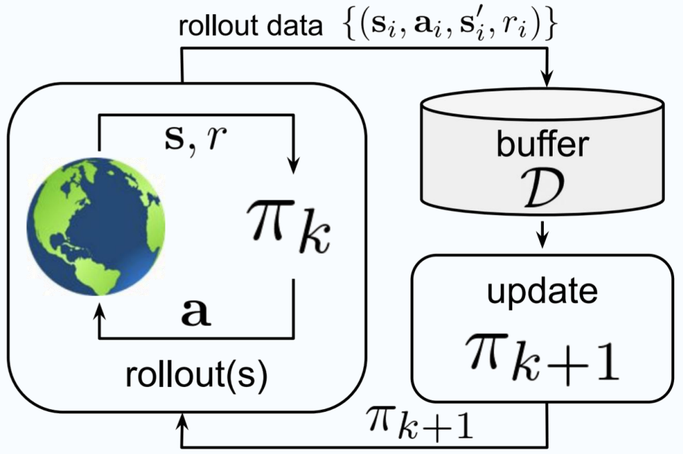
PPO

DDPG

(a) online reinforcement learning



(b) off-policy reinforcement learning



- PPO 为使其策略提升稳定有效，需要保持两个策略之间足够接近
- DDPG 取决于动作值函数的建模质量，更需要提高数据多样性

Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems: https://arxiv.org/pdf/2005.01643.pdf
关于 IS 的对比分析：https://github.com/opendilab/PPOxFamily/blob/main/chapter2_action/chapter2_supp_ppovsddpg.pdf

代码：PPO如何实现连续动作

PyTorch demo of PPO algorithm in continuous action space.

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View code on GitHub

Overview

The definition of continuous action policy network used in PPO, which is mainly composed of three parts: encoder, mu and log_sigma.

```python
from typing import Dict
import torch
import torch.nn as nn
from torch.distributions import Normal, Independent


class ContinuousPolicyNetwork(nn.Module):
    def __init__(self, obs_shape: int, action_shape: int) -> None:
```

PyTorch necessary requirements for extending `nn.Module` .

```python
        super(ContinuousPolicyNetwork, self).__init__()
```

Define encoder module, which maps raw state into embedding vector.
It could be different for various state, such as Convolution Neural Network for image state.
Here we use two-layer MLP for vector state.

```python
        self.encoder = nn.Sequential(
            nn.Linear(obs_shape, 16),
            nn.ReLU(),
            nn.Linear(16, 32),
            nn.ReLU(),
        )
```

Define mu module, which is a FC and outputs the argument mu for gaussian distribution.

```python
        self.mu = nn.Linear(32, action_shape)
```

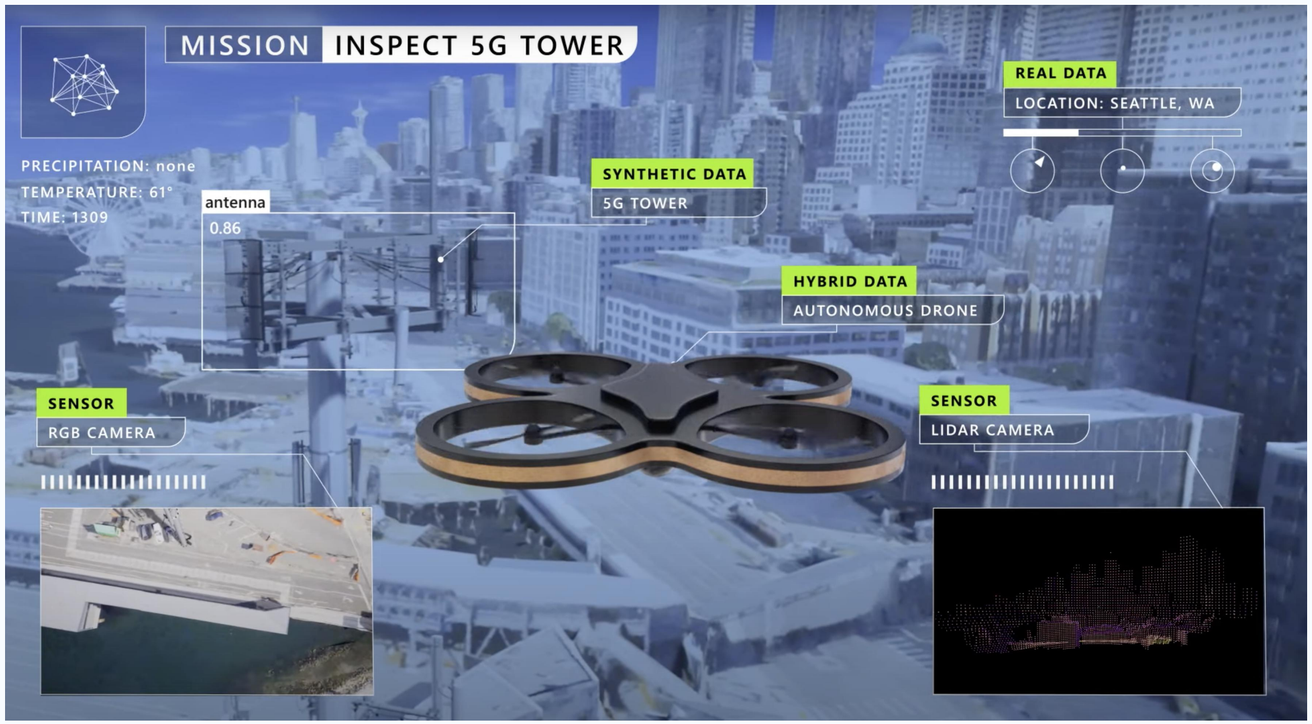
Define log_sigma module, which is a learnable parameter but independent to state.

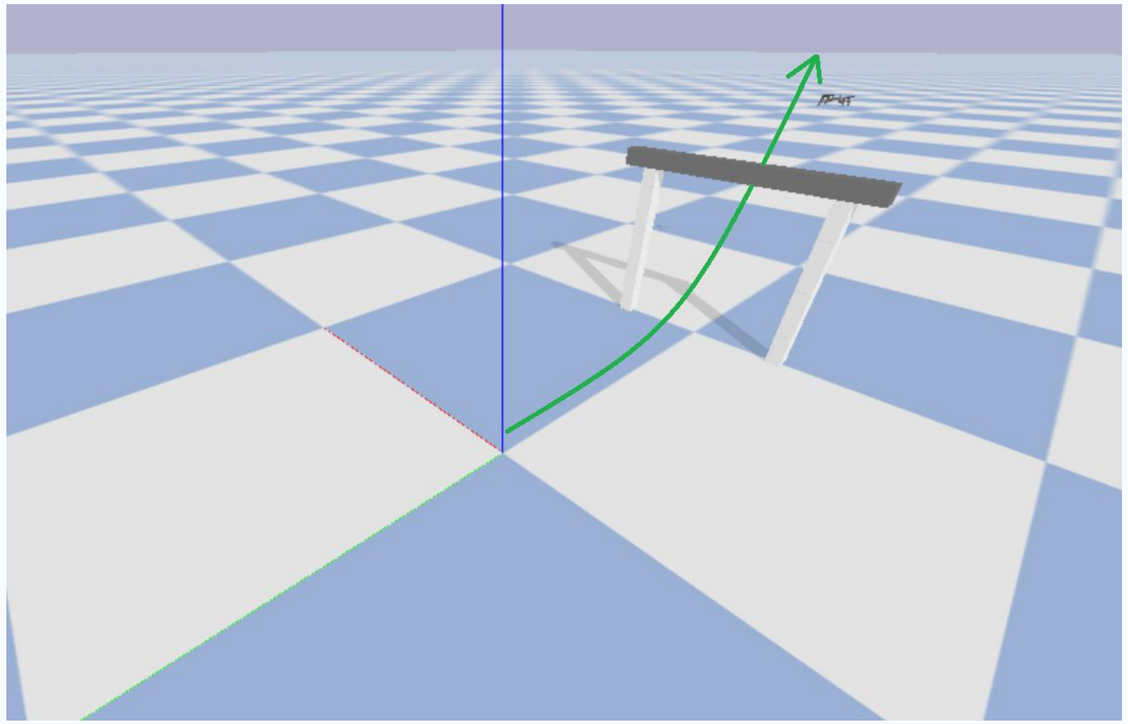
```python
        self.log_sigma = nn.Parameter(torch.zeros(1, action_shape))

```

完整示例：https://opendilab.github.io/PPOxFamily/

实践：PPO+无人机姿态控制

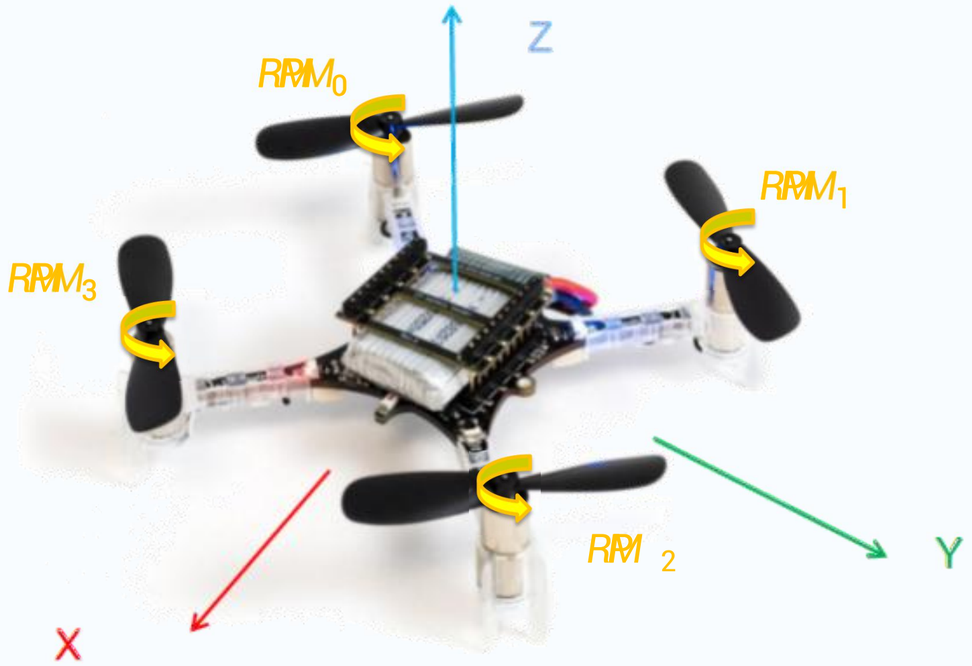




任务：四旋翼无人机从原点起飞，并持续飞行成功穿过一座门框

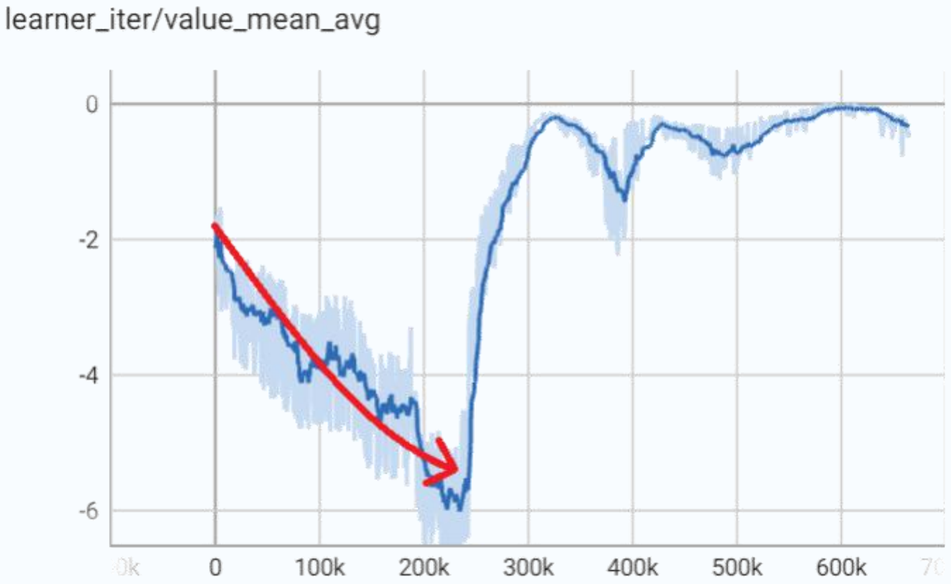
AirSim: https://www.youtube.com/watch?v=mhEw-fecjQY
gym-bullet-drones: https://github.com/utiasDSL/gym-pybullet-drones

实践：PPO+无人机姿态控制

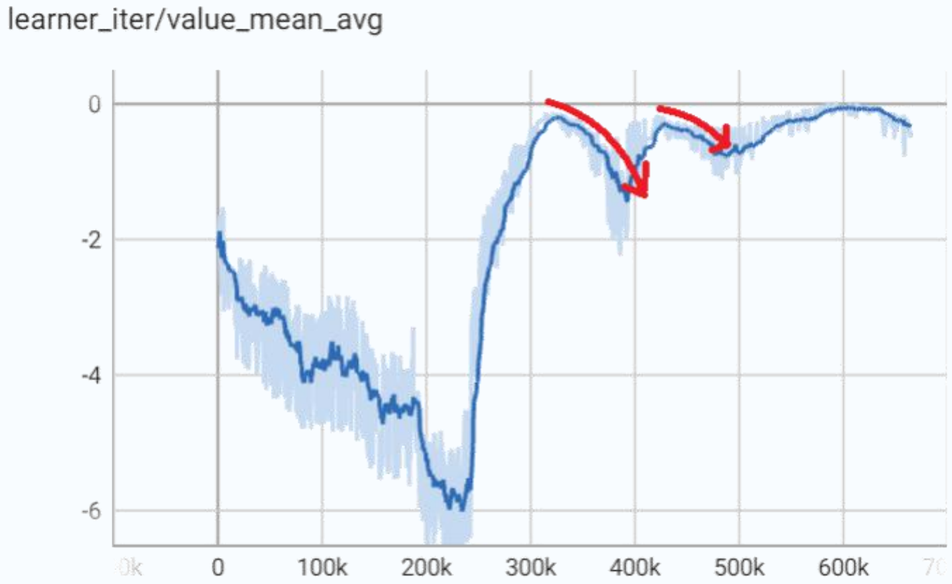


- **原始动作空间：** 4维连续动作，直接控制四个旋翼的转速
- **PID 辅助模式动作空间：** 3维连续动作，期望运动位置坐标
- **奖励空间：** 与期望轨迹点之间的距离

实践：PPO+无人机姿态控制



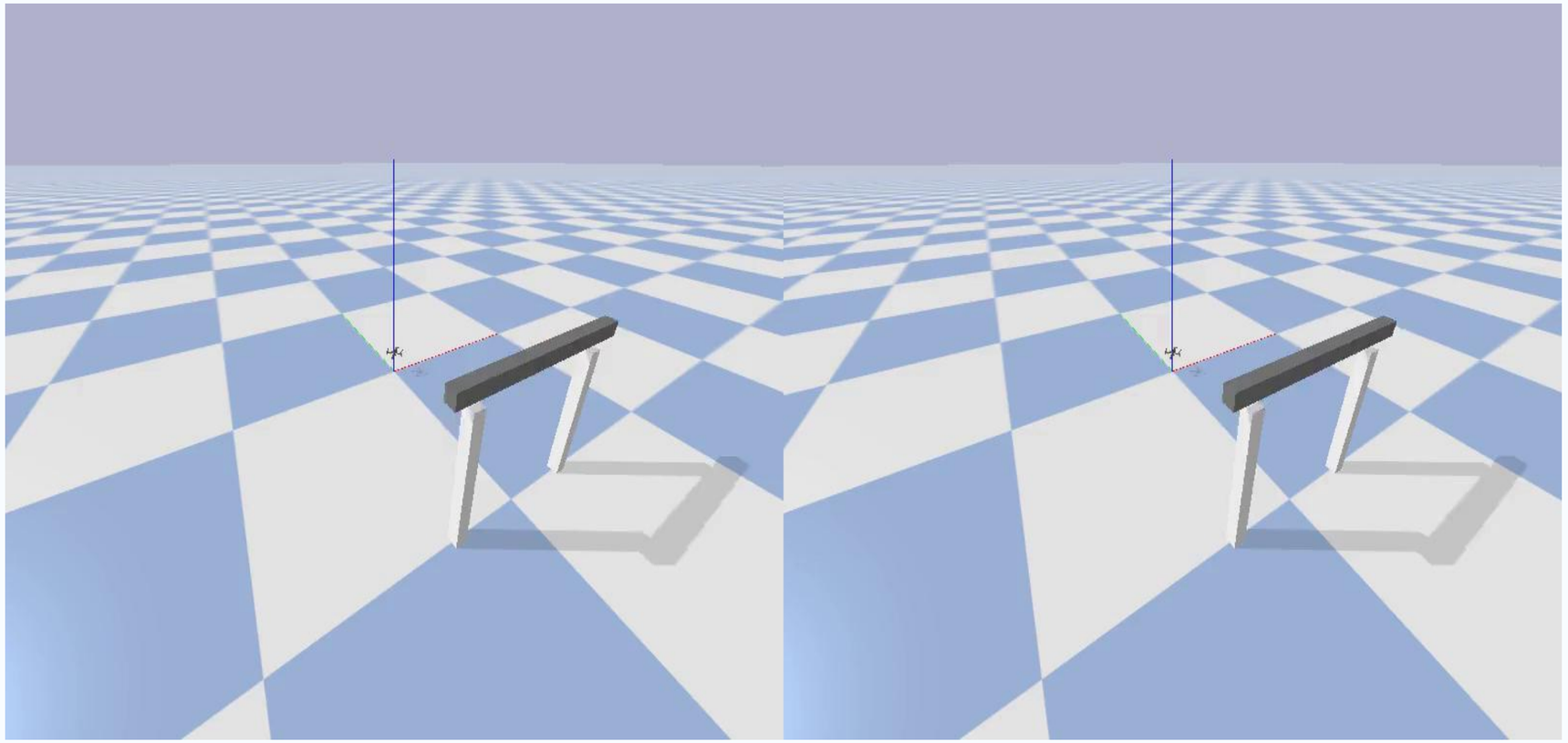
价值函数拟合阶段



策略提升阶段

实验细节：https://github.com/opendilab/PPOxFamily/issues/4

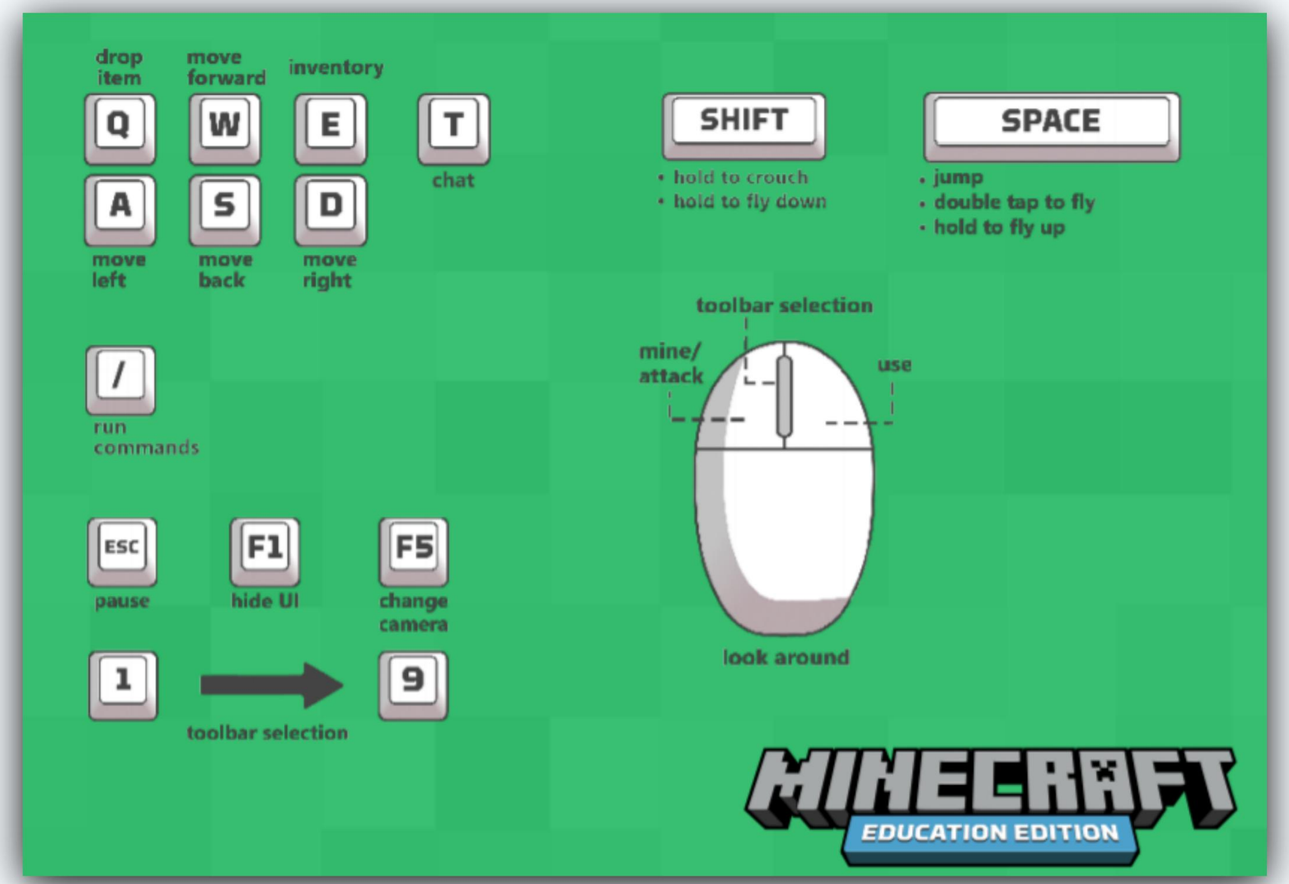
实践：PPO+无人机姿态控制



视频样例：https://github.com/opendilab/PPOxFamily/issues/4

Multi-Discrete

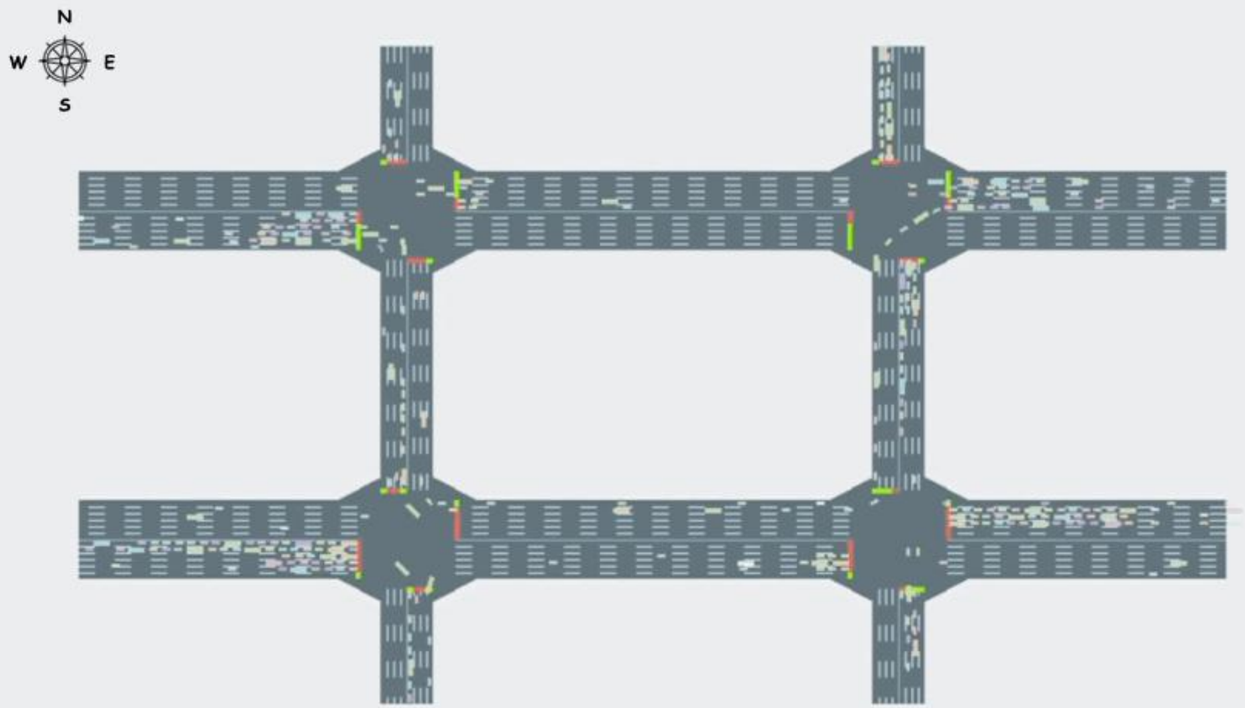
多维离散动作空间



https://learn71.ca/minecraft-challenge-accessibility/

Multi-Discrete

理论：PPO+多维离散定义

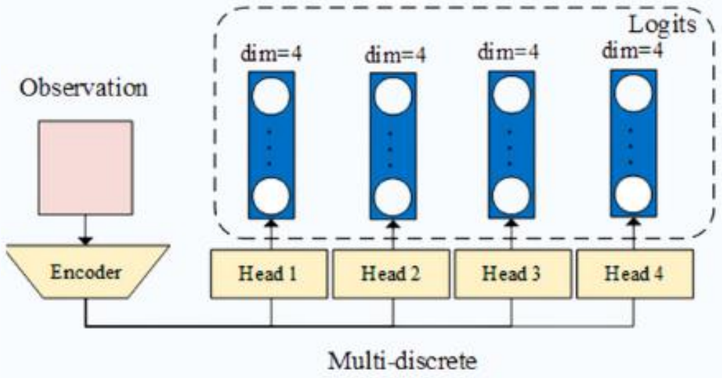


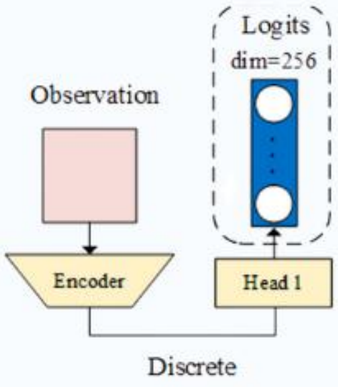
特点：

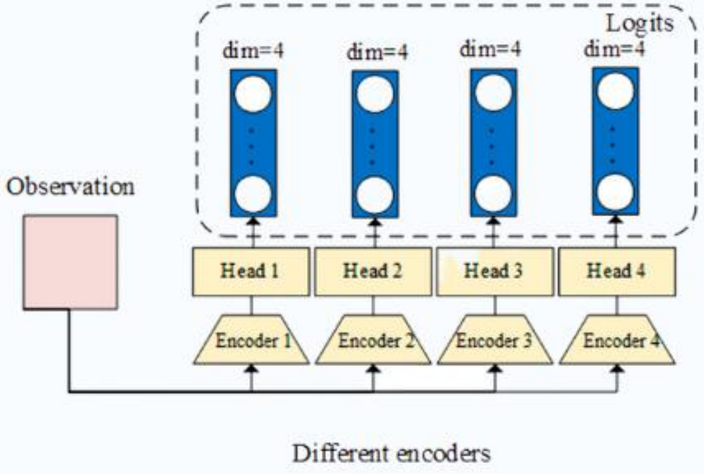
- 多个不同离散空间的组合（比如键盘，多路口信控）
- 离散动作的个数可能非常大
- 各个离散动作之间存在比较弱的联系

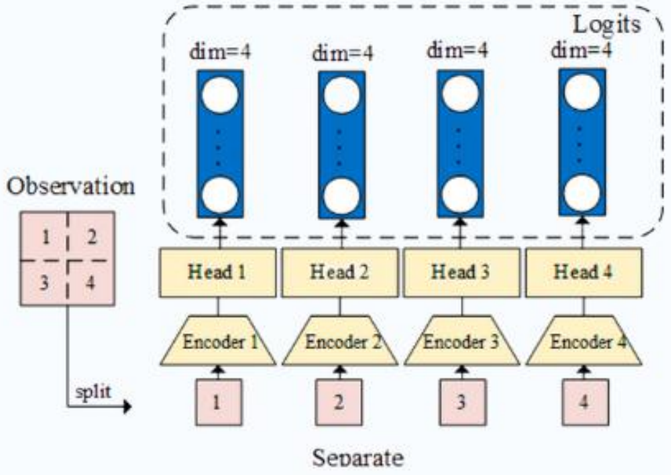
CityFlow: https://github.com/cityflow-project/CityFlow

理论：PPO+多维离散架构







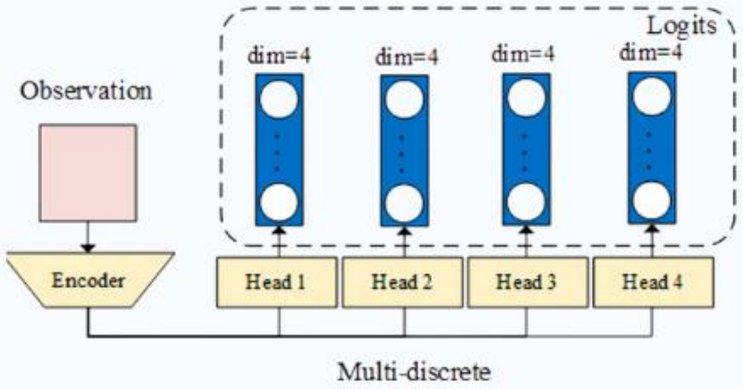


四种建模方法：

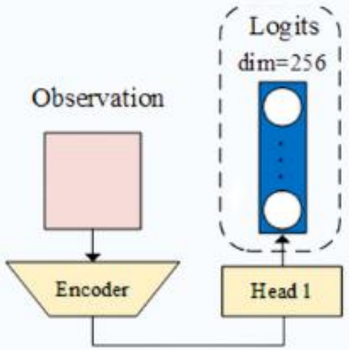
- Multi-Discrete
- Discrete
- Different encoders
- Separate

多个head的PPO优化目标各自计算，加起来一起BP

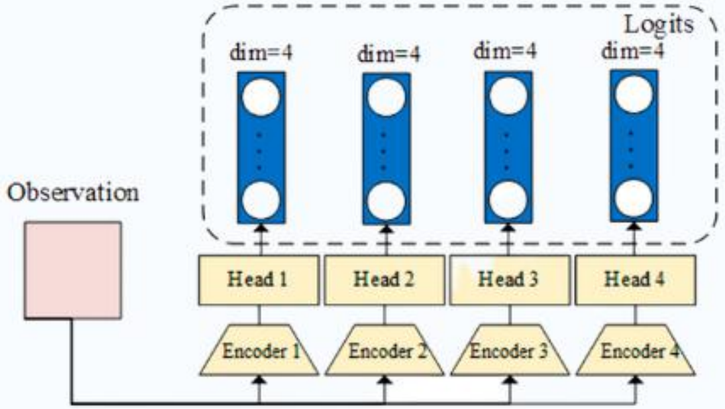
理论：PPO+多维离散架构



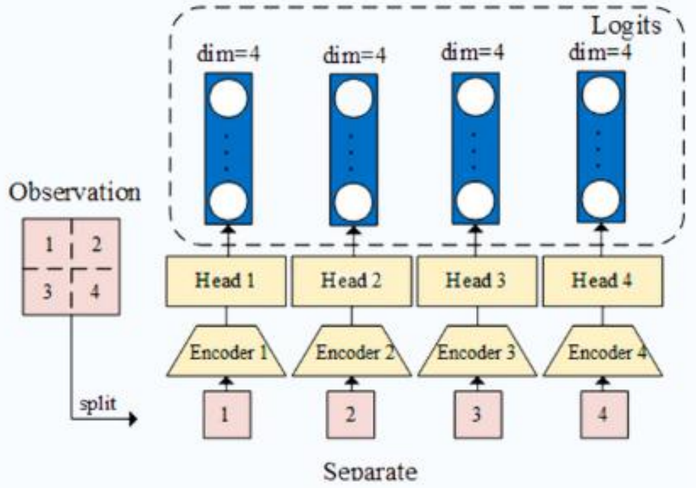
Multi-discrete



Discrete



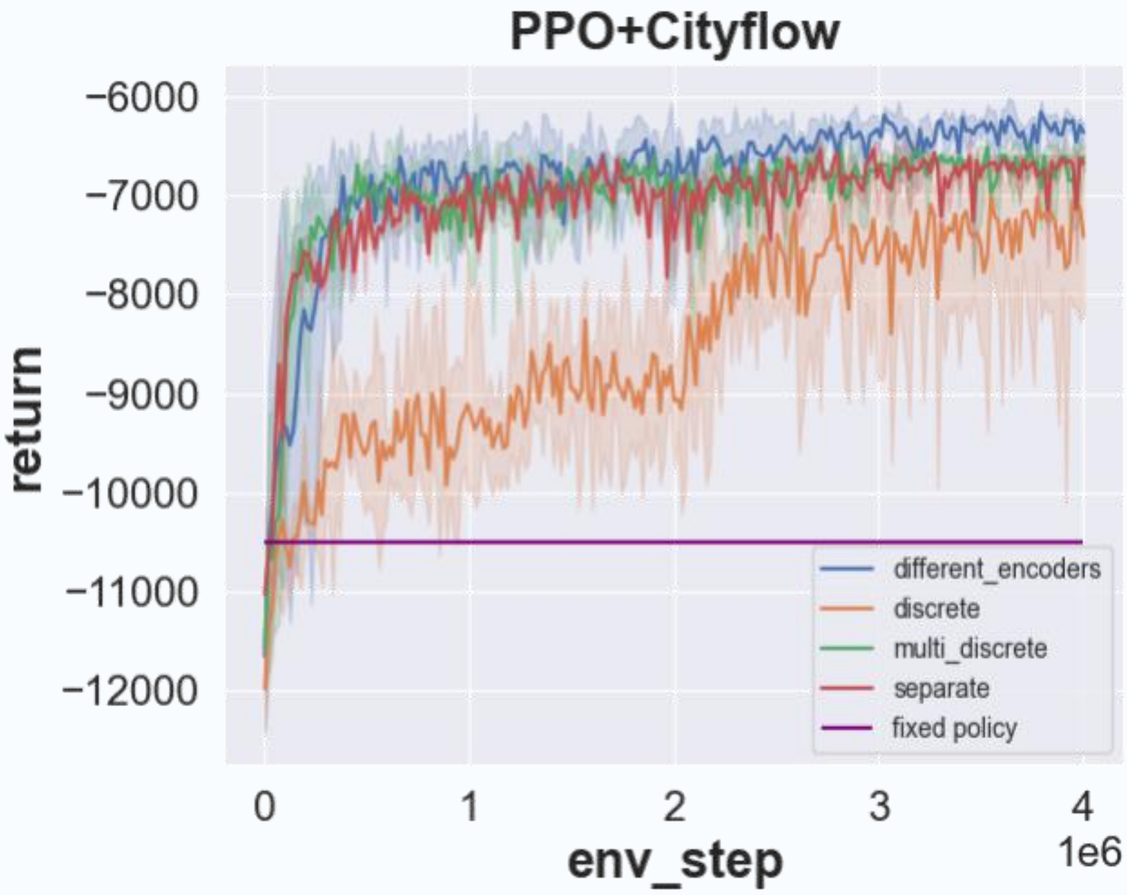
Different encoders

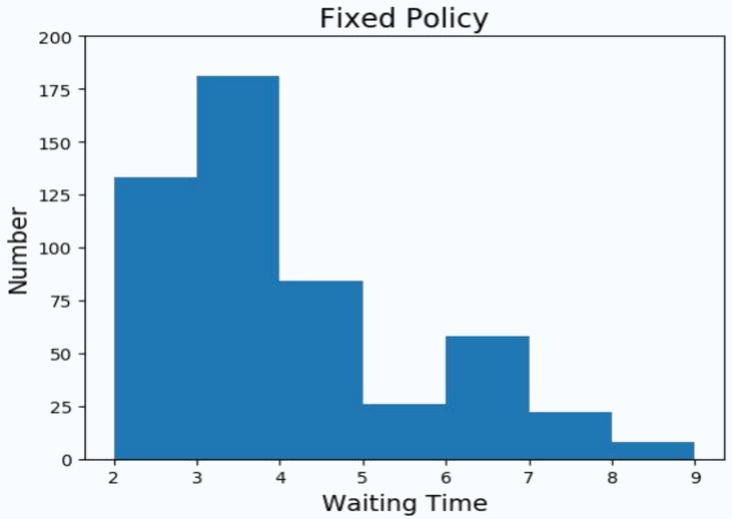


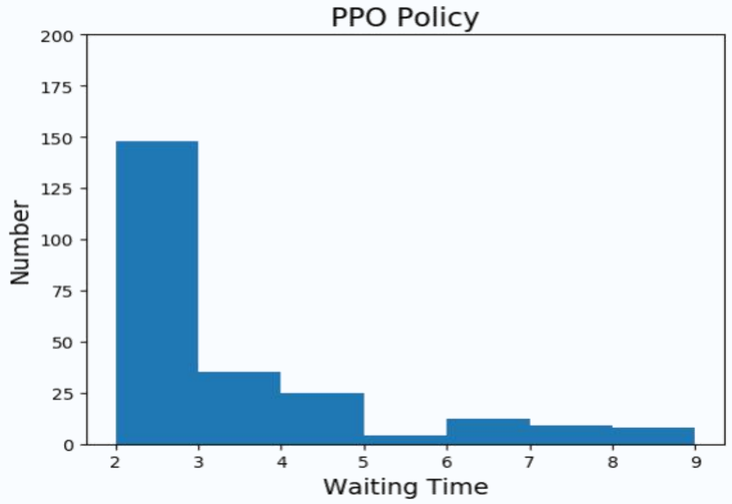
Separate

实验名	encoder 输入维度	head 输出维度	encoder 数量	head 数量
Multi-discrete	174	4	1	4
Discrete	174	256	1	1
Different encoders	174	4	4	4
Separate	44	4	4	4

实践：PPO+交通信号控制

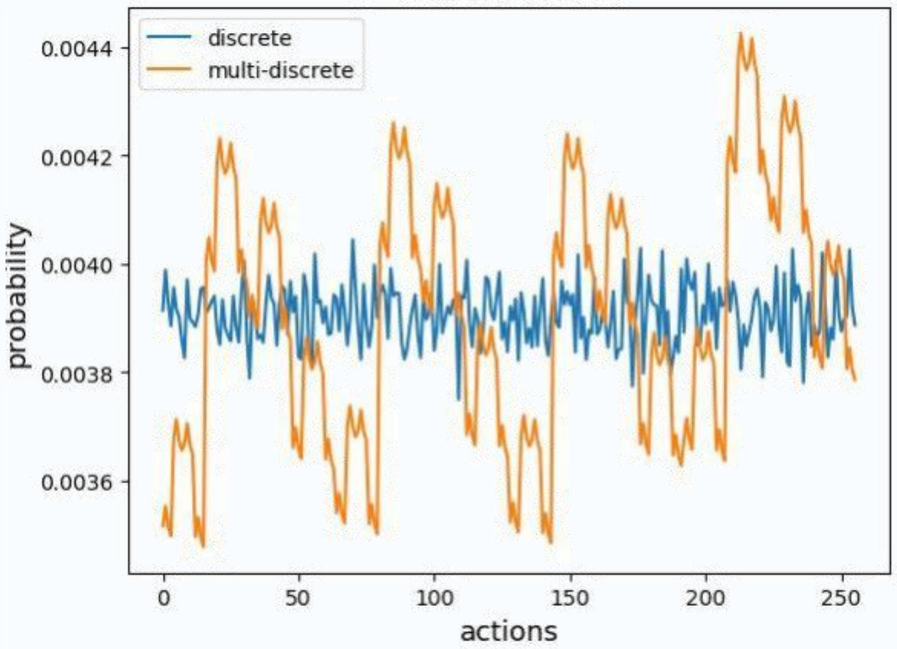


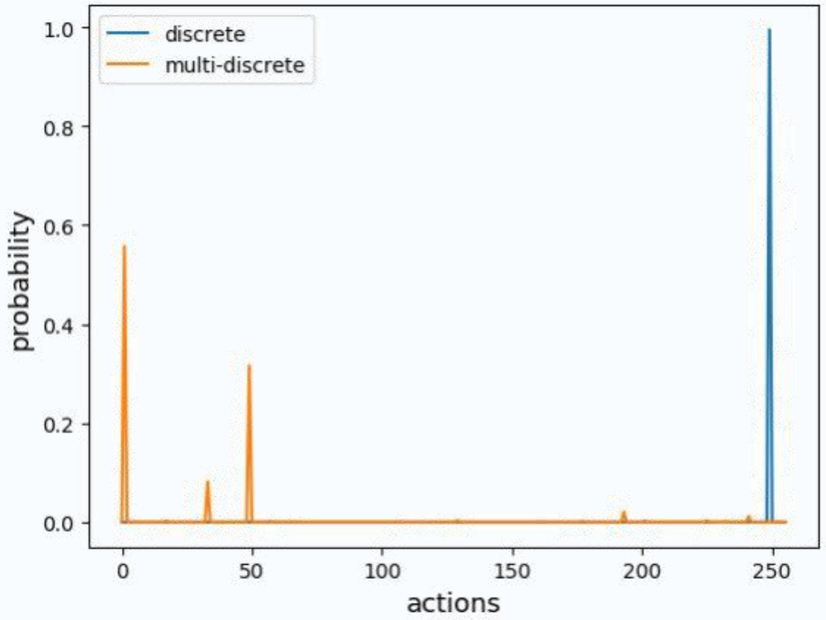




实践：PPO+交通信号控制

为什么 multi-discrete 在这个场景里优于 discrete（探索角度）





不同训练迭代下，策略选择各个动作的概率（左1k，右1w）

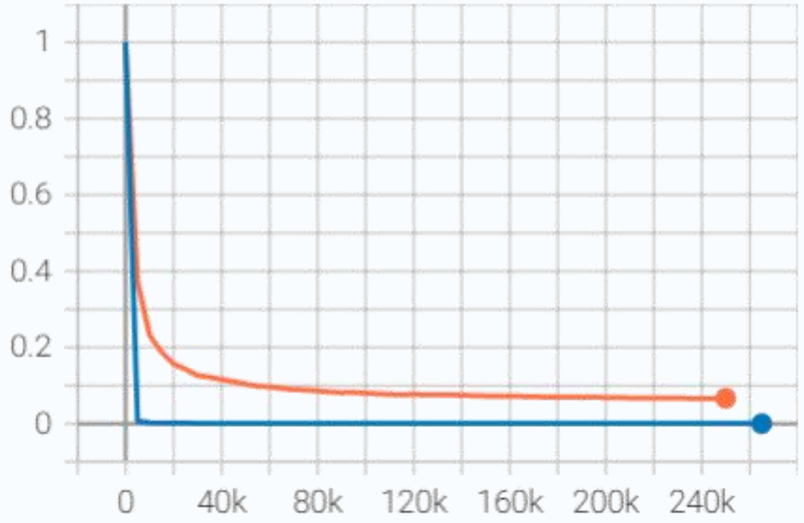
实验细节：https://github.com/opendilab/PPOxFamily/issues/4

实践：PPO+交通信号控制

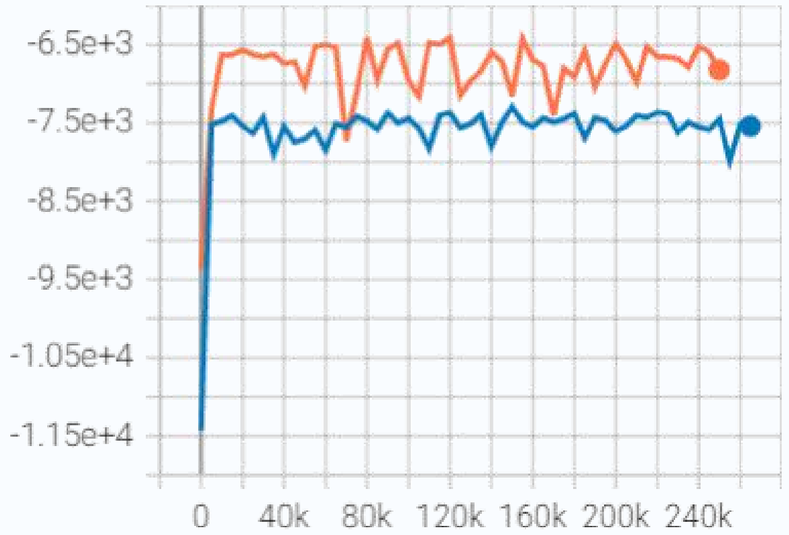
为什么 multi-discrete 在这个场景里优于 discrete（利用角度）

——专家数据集上的 Behavior Cloning 实验

Training Loss



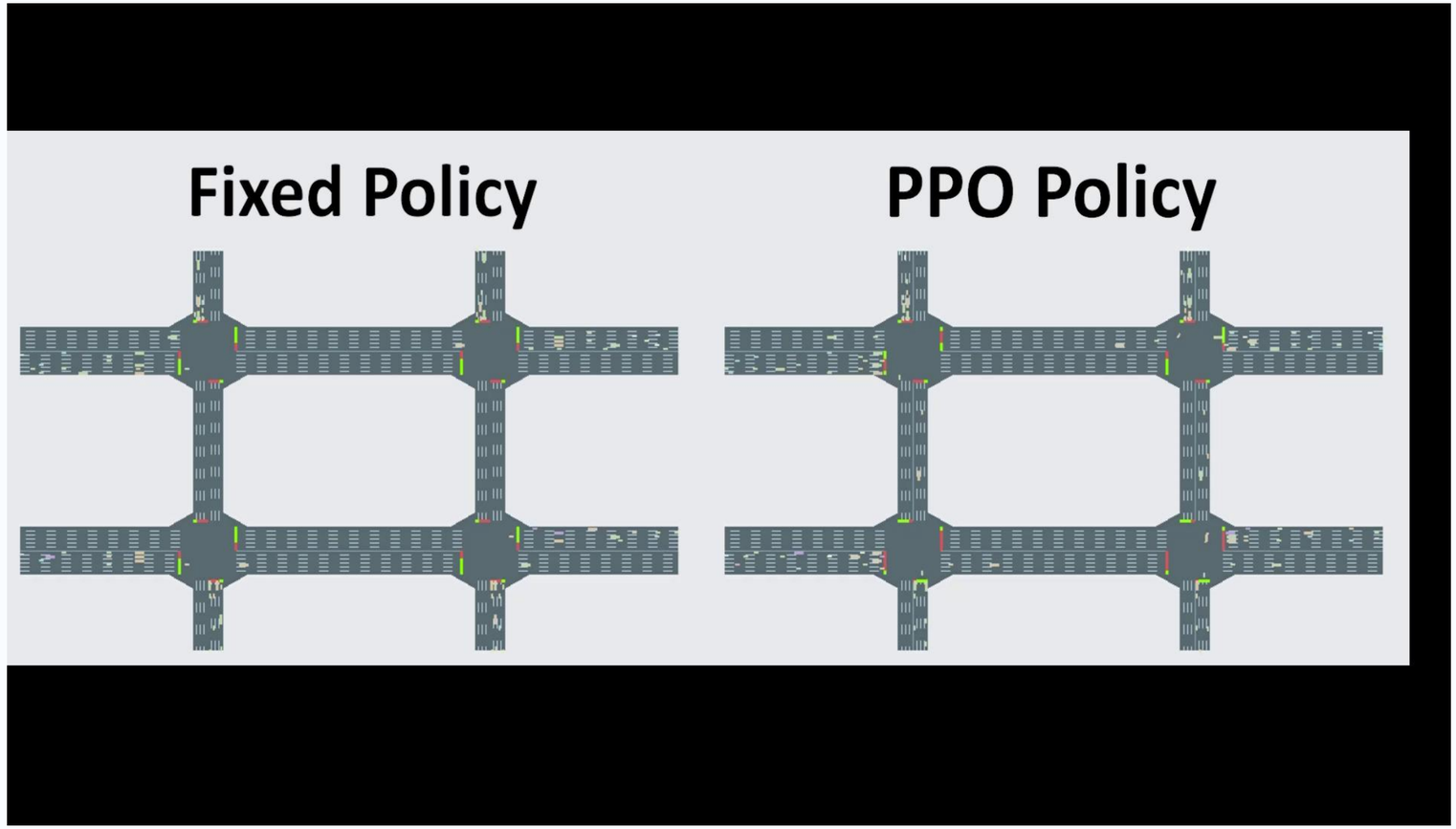
Evaluation Episode Return



蓝线是 discrete，橙线是 multi-discrete，横轴是训练迭代数

实验细节：https://github.com/opendilab/PPOxFamily/issues/4

实践：PPO+交通信号控制



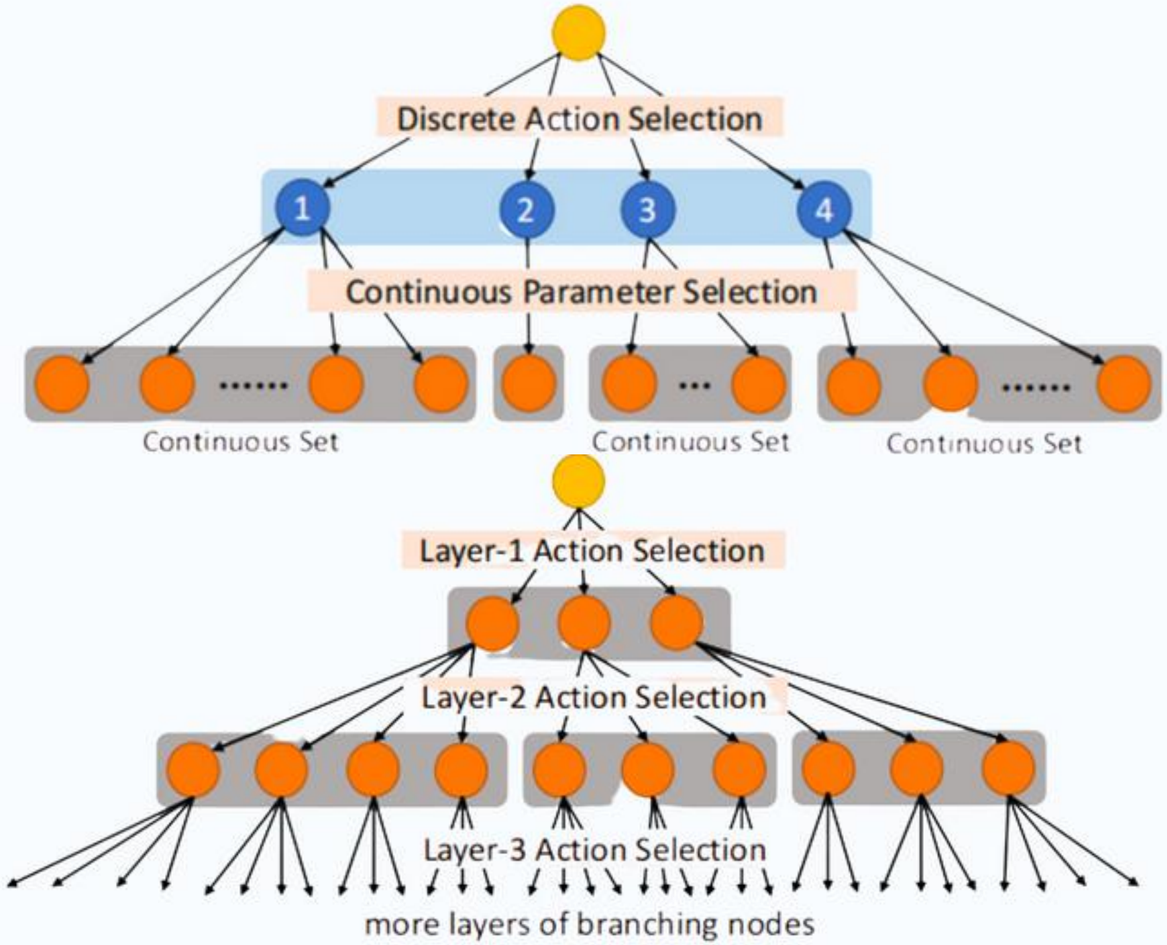
视频样例：https://github.com/opendilab/PPOxFamily/issues/4

Hybrid

混合动作空间

AlphaStar: https://www.deepmind.com/blog/alphastar-grandmaster-level-in-starcraft-ii-using-multi-agent-reinforcement-learning

理论：PPO+混合动作 定义



参数化动作空间：

- 离散动作类型和连续动作参数
- 动作类型和参数之间有强依赖关系
- 不同动作类型对应不同参数

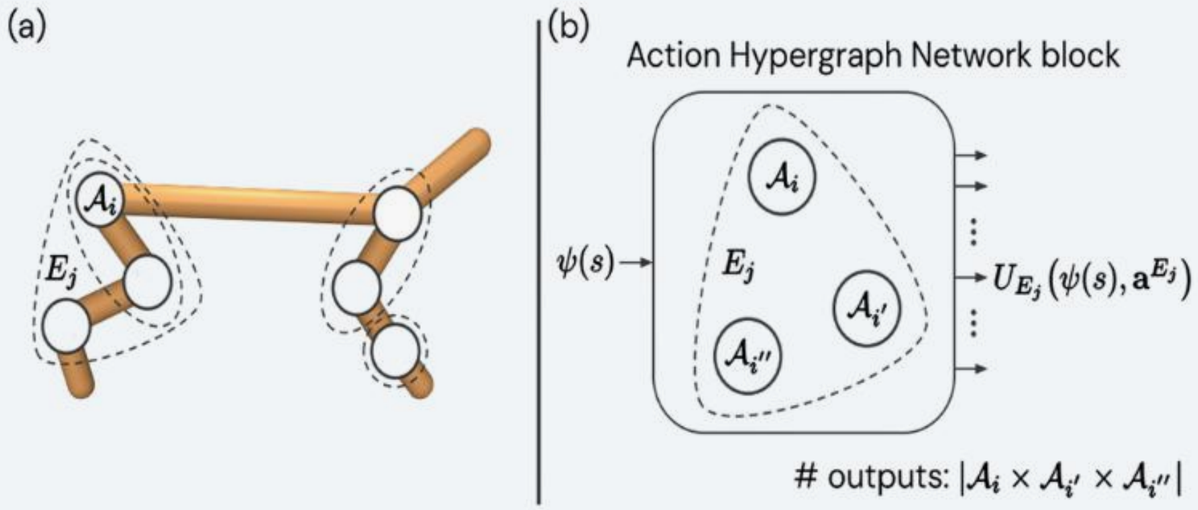
层次结构化动作空间：

- 树形结构、中间节点是离散动作，叶节点是离散或连续参数
- 各个子树之间的动作性质相差很大

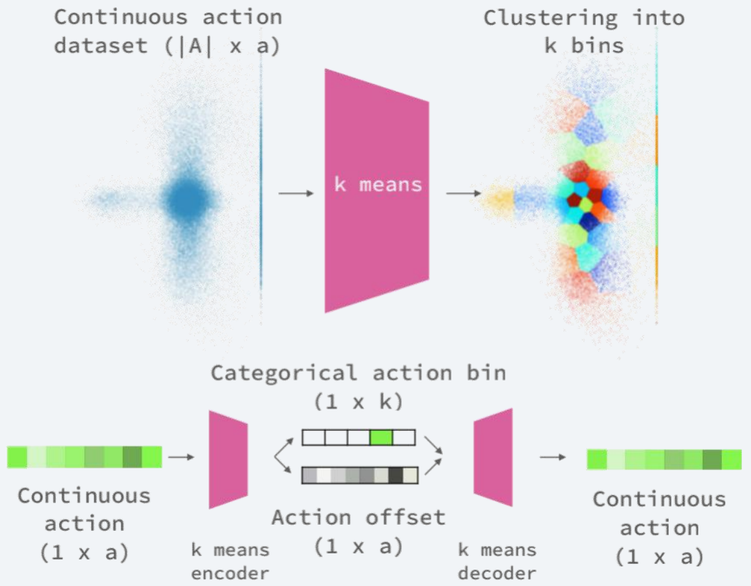
H-PPO: https://arxiv.org/pdf/1903.01344.pdf

理论：PPO+混合动作 离散化

根据动作空间的先验知识离散化

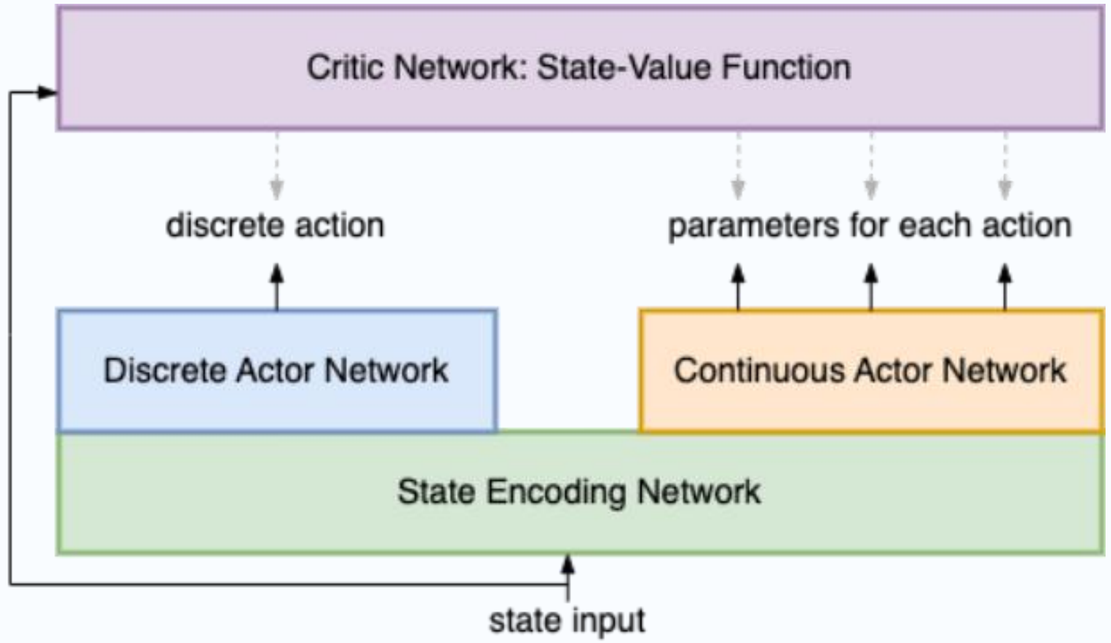


根据数据特性自动挖掘离散化



HGQN: https://openreview.net/pdf?id=Xv_s64FiXTv
Behavior Transformers: https://arxiv.org/pdf/2206.11251.pdf

理论：PPO+混合动作 HPPO



核心思路

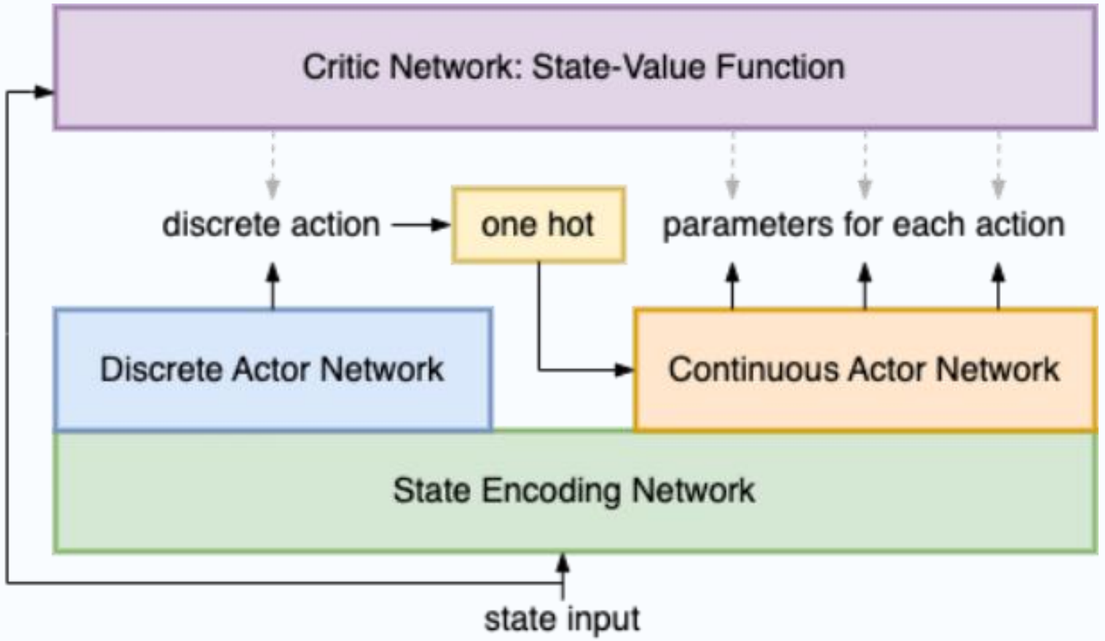
- 离散和连续部分各自使用相应的 PPO，但是共享特征编码部分
- 整体共用一个 Value 指导优化

优势： 实现简洁，可扩展性高

劣势： 并没有显式去建模动作间的依赖

H-PPO: https://arxiv.org/pdf/1903.01344.pdf

理论：HPPO优化方案 自回归

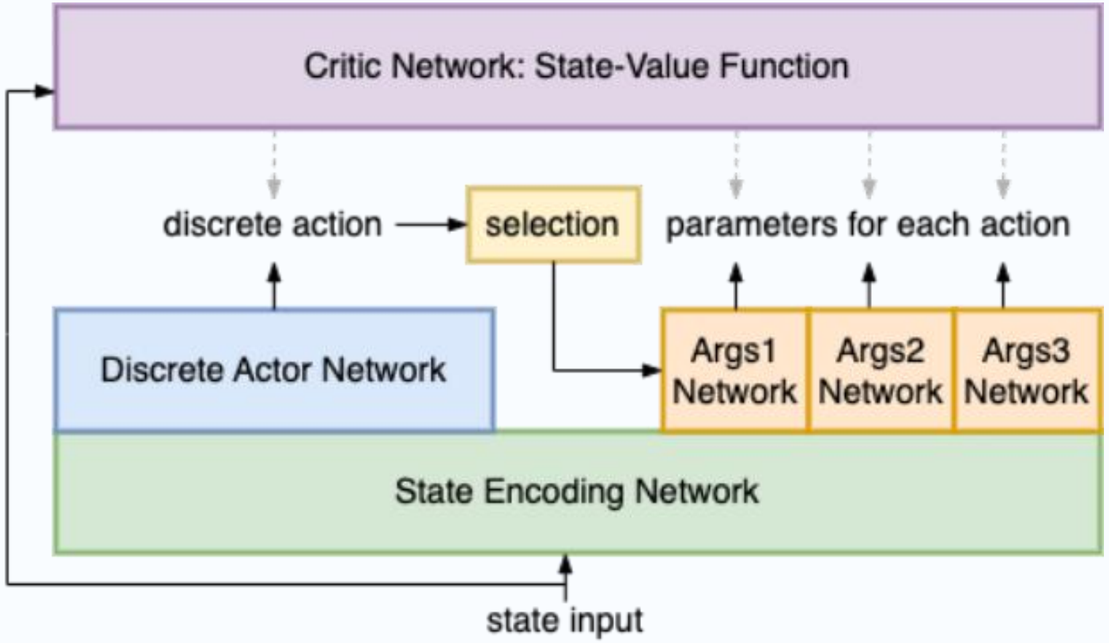


核心思路：

- 对于动作之间的强依赖关系，可以采用自回归（autogressive）的方式建模依赖关系

例如：离散的动作类型决定相应的连续参数（转向和转向角），可以将选出的离散动作进行one-hot编码，再和提取到的状态特征拼到一起，去预测连续参数

理论：HPPO优化方案 分离head



核心思路：

- 对于动作之间的强依赖关系，可以采用分离head的方式建模依赖关系

具体来说，对于每个离散动作的连续参数，单独设置一个连续策略网络，根据选出的离散动作，选择其中对应的一个连续网络输出（仅限于离散动作数量较少，否则开销过大）

更多混合动作空间的解决思路（动作空间表征学习）：https://github.com/opendilab/PPOxFamily/blob/main/chapter2_action/chapter2_supp_hyar.pdf

代码：使用mask和TreeTensor

PyTorch demo of PPO algorithm in hybrid action space.

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View code on GitHub

Overview

The definition of hybrid action policy network used in PPO, which is mainly composed of three parts: encoder, action_type head (discrete) and action_args head (continuous).

```python
from typing import Dict
import torch
import torch.nn as nn
from torch.distributions import Normal, Independent


class HybridPolicyNetwork(nn.Module):
    def __init__(self, obs_shape: int, action_shape: int) -> None:
```

PyTorch necessary requirements for extending `nn.Module`.

```python
        super(HybridPolicyNetwork, self).__init__()
```

Define encoder module, which maps raw state into embedding vector.
It could be different for various state, such as Convolution Neural Network for image state.
Here we use two-layer MLP for vector state.

```python
        self.encoder = nn.Sequential(
            nn.Linear(obs_shape, 16),
            nn.ReLU(),
            nn.Linear(16, 32),
            nn.ReLU(),
        )
```

Define action_type head module, which outputs discrete logit.

```python
        self.action_type_shape = action_shape['action_type_shape']
        self.action_type_head = nn.Linear(32, self.action_type_shape)
```

Define action_args head module, which outputs corresponding continuous action arguments.

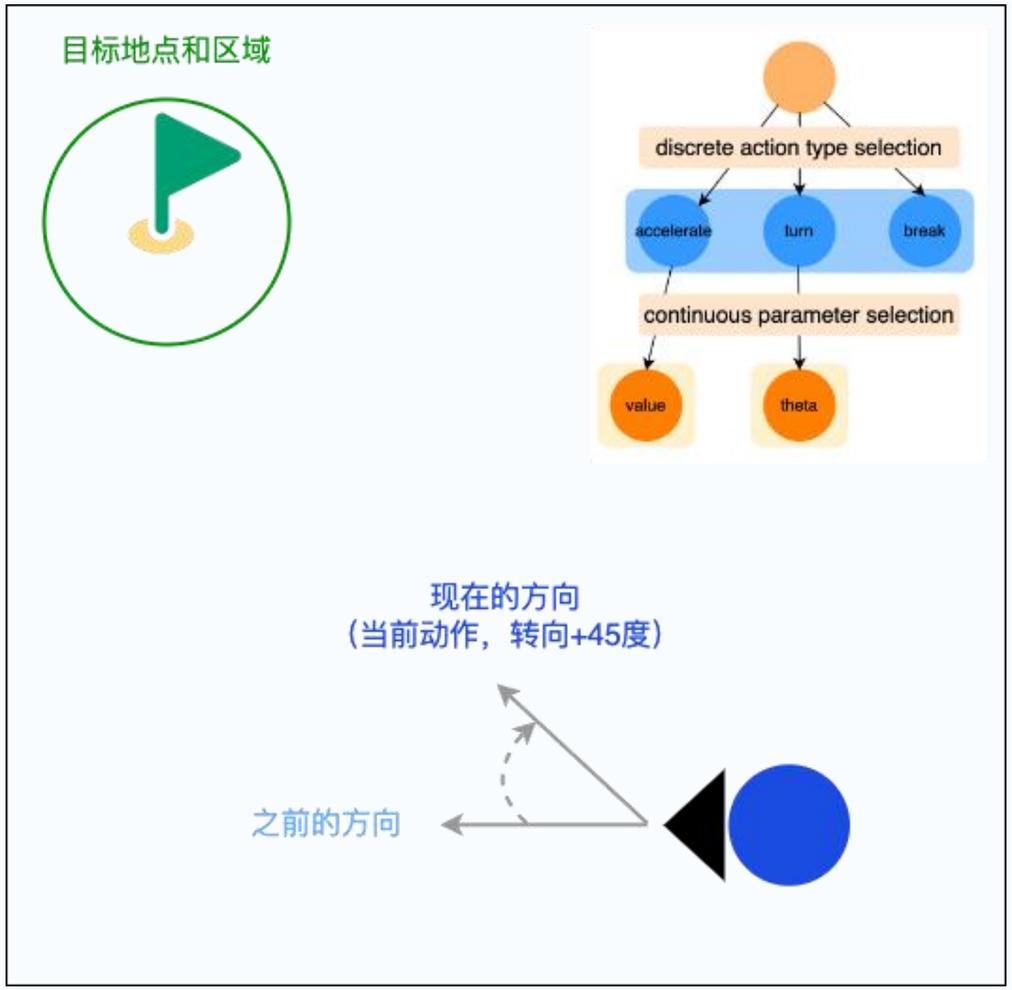
```python
        self.action_args_shape = action_shape['action_args_shape']
        self.action_args_mu = nn.Linear(32, self.action_args_shape)
        self.action_args_sigma = nn.Parameter(torch.zeros(1, self.action_args_shape))

```

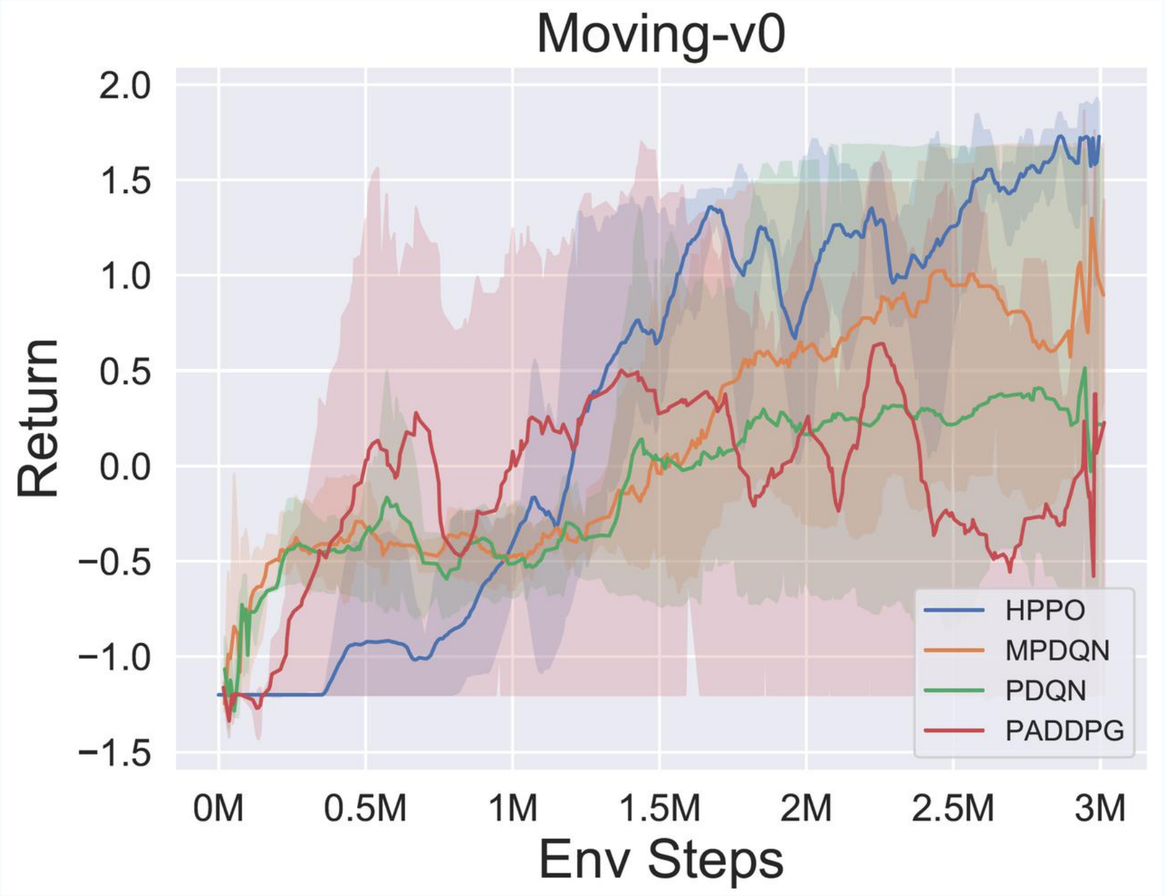
TensorTree on Nested Data

```python
import tensortree.torch as torch

# create a nested data tensor
t = torch.randn({
    'a': (6, 2, 3),
    'b': {'x': (6, 3), 'y': (6, 1, 4)},
})

# structural operations
print(torch.stack([t, t]))
print(torch.split(t, (1, 2, 3)))
# math calculations
print(t ** 2)
print(torch.sin(t).cos())
# access like attribute
print(t.b.y)
```

完整代码示例：https://opendilab.github.io/PPOxFamily/
TreeTensor：https://github.com/opendilab/DI-treetensor

实践：PPO+导航控制





环境文档：https://di-engine-docs.readthedocs.io/zh_CN/latest/13_envs/gym_hybrid_zh.html
相关对比算法参考博客：https://zhuanlan.zhihu.com/p/478728586

实践：PPO+导航控制

Random Agent

Trained Agent

实验环境：https://github.com/opendilab/DI-engine/tree/main/dizoo/gym_hybrid/envs
视频样例：https://github.com/opendilab/PPOxFamily/issues/4

下节预告

（三）降维之术：表征多模态观察空间

- 向量观察空间的千层套路
- 图片观察空间的最佳实践
- 结构化观察空间的奇技淫巧