

# RL study with Mujoco-Humanoid

251210 Term-Proj

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# 1. Operate Env.

- 운영체제 : Ubuntu 24.04.3 LTS
- GPU : RTX-4090
- Python -version : 3.11.14
- Requirements.txt 에 라이브러리 기재
- GitHub 리포에 프로젝트 업로드

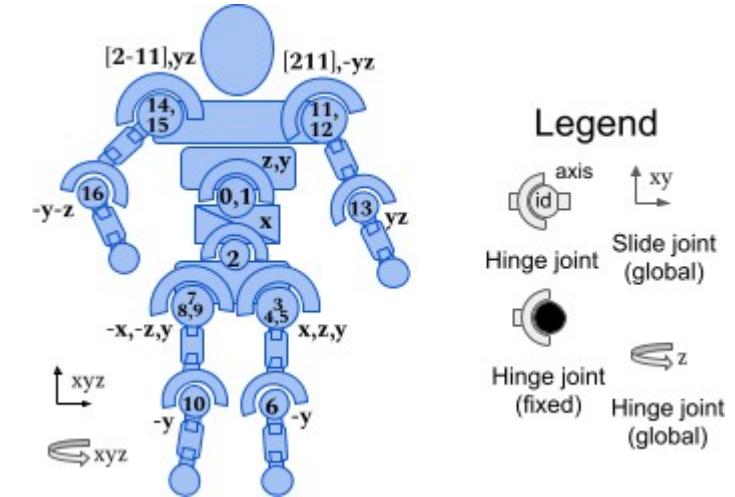
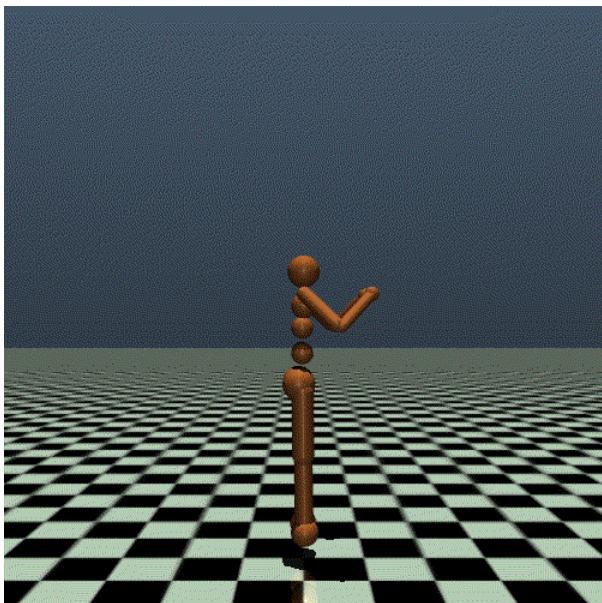
```
kimm-linux@kimm-linux-System-Product-Name:~$ lsb_release -a
No LSB modules are available.
Distributor ID: Ubuntu
Description:    Ubuntu 24.04.3 LTS
Release:        24.04
Codename:       noble

kimm-linux@kimm-linux-System-Product-Name:~$ nvidia-smi
Tue Dec  9 15:29:40 2025
+-----+
| NVIDIA-SMI 580.95.05      Driver Version: 580.95.05     CUDA Version: 13.0 |
+-----+
| GPU  Name           Persistence-M | Bus-Id     Disp.A | Volatile Uncorr. ECC | | |
| Fan  Temp     Perf            Pwr:Usage/Cap | Memory-Usage | GPU-Util  Compute M. |
|          |                               |             |              |                  MIG M. |
+-----+
| 0  NVIDIA GeForce RTX 4090     Off  | 00000000:41:00.0 On   |          Off | | |
| 0%   57C    P2            86W / 480W | 1334MiB / 24564MiB | 4%     Default |
|          |                               |             |              |                  N/A |
+-----+
+-----+
| Processes:
| GPU  GI  CI          PID  Type  Process name          GPU Memory |
| ID   ID          ID          ID  name                Usage  |
+-----+
| 0    N/A N/A  372276    G  /usr/lib/xorg/Xorg          296MiB |
| 0    N/A N/A  373858    G  /usr/bin/gnome-shell        34MiB  |
| 0    N/A N/A  374641    G  /usr/share/code/code        68MiB  |
| 0    N/A N/A  377821    G  ...rack-uuid=3190708988185955192 88MiB  |
| 0    N/A N/A  508339    C  ...edRL/termPro/.venv/bin/python 792MiB |
+-----+
```



## 2. Mujoco-Humanoid

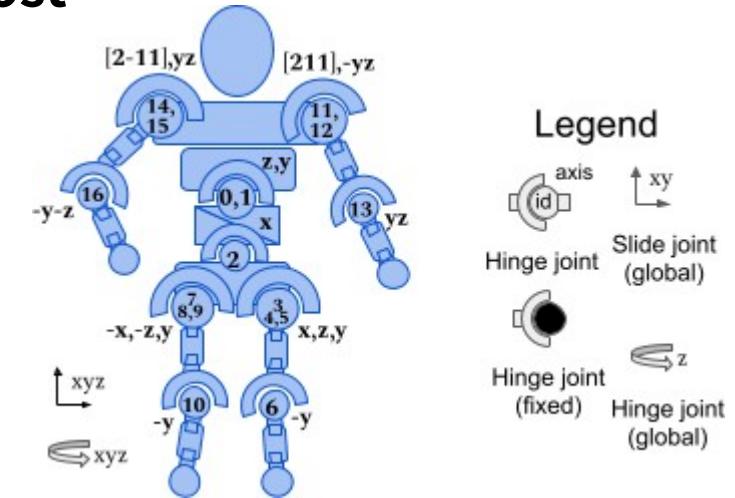
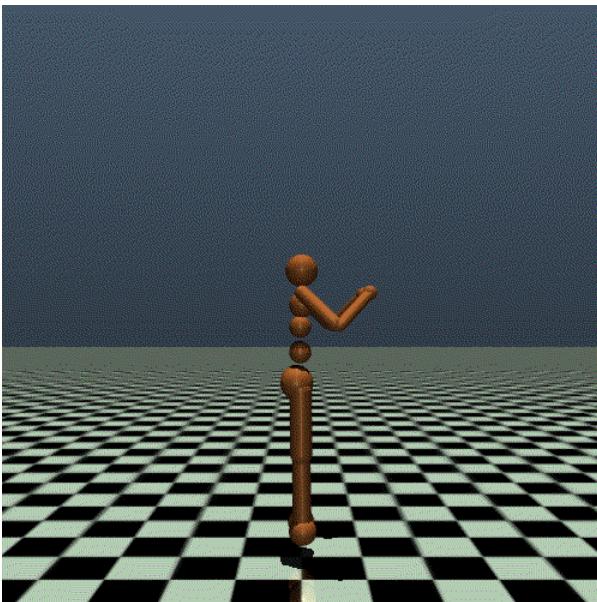
- Action Space : 제어출력 . 17 개의 조인트의 토크값
- Observation Space: 13 개의 파츠에 대한 속성값 (348)  
( 위치 , 각도 , 속도 , 각속도 )



Action Space	Box(-.4 .4 (17,), float32)
Observation Space	Box(-inf, inf, (348,), )
Reward	Healthy + forward – ctrl - contact

# 2. Mujoco-Humanoid

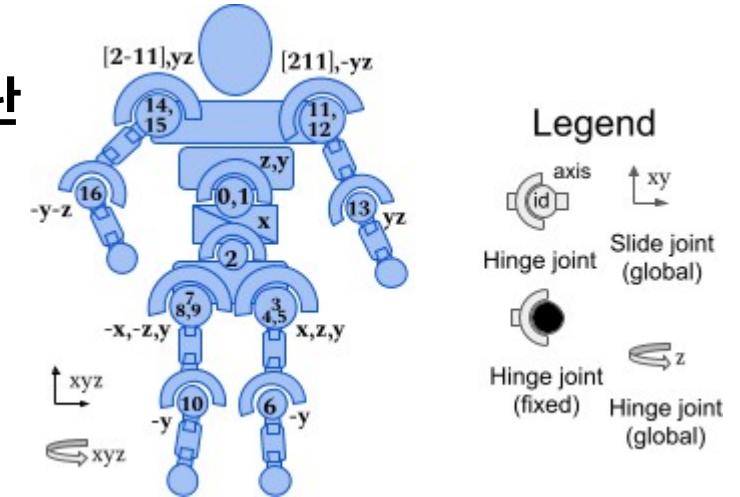
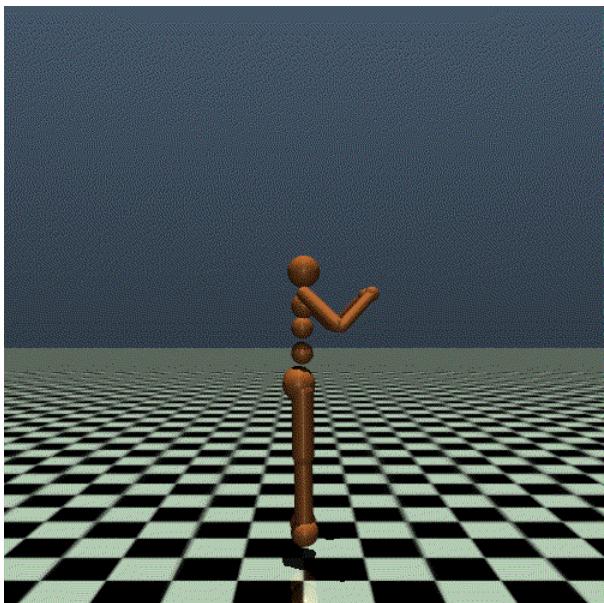
- Reward: `healthy_r` + `forward_r` - `ctrl_cost` - `contact_cost`
    - `healthy_reward`: 매 스텝 서있으면 받는 보상
    - `forward_reward`: 앞으로 나아가면 받는 보상
    - `ctrl_cost`: 제어출력이 너무 강하면 받는 비용
    - `contact_cost`: 지면에 부드럽게 발을 딩도록 하는 비용



Action Space	<code>Box(-.4 .4 (17,), float32)</code>
Observation Space	<code>Box(-inf, inf, (348,), )</code>
Reward	<code>Healthy + forward – ctrl - contact</code>

## 2. Mujoco-Humanoid

- Episode End
  - Termination : 휴머노이드가 쓰러지면 중단
  - Truncation : 휴머노이드가 1000 timestep 을 버티면 중단

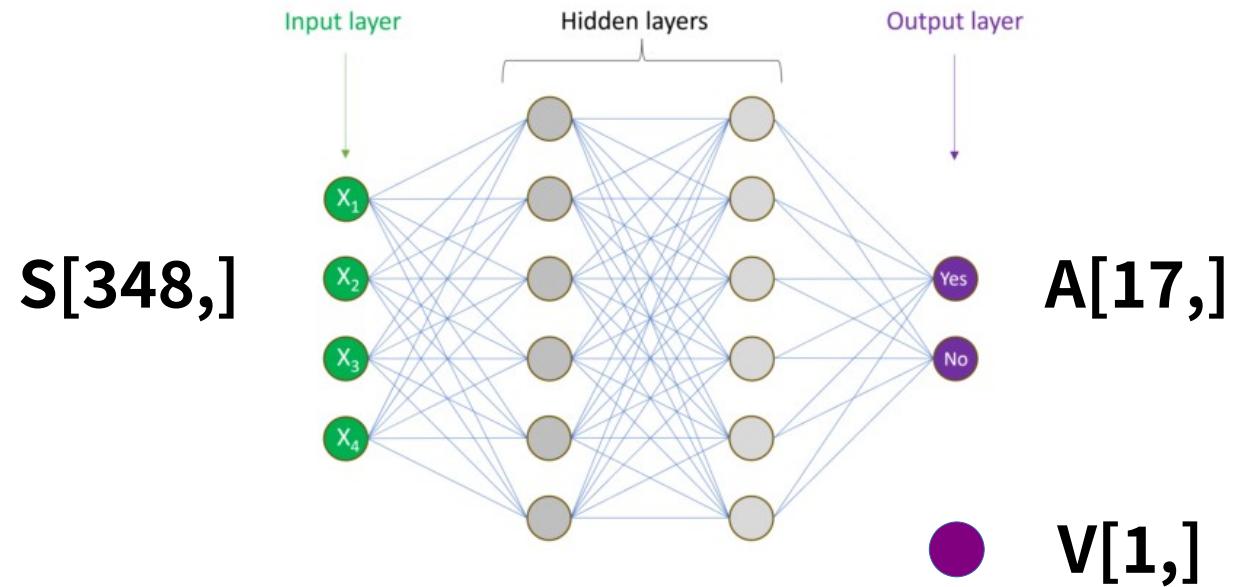
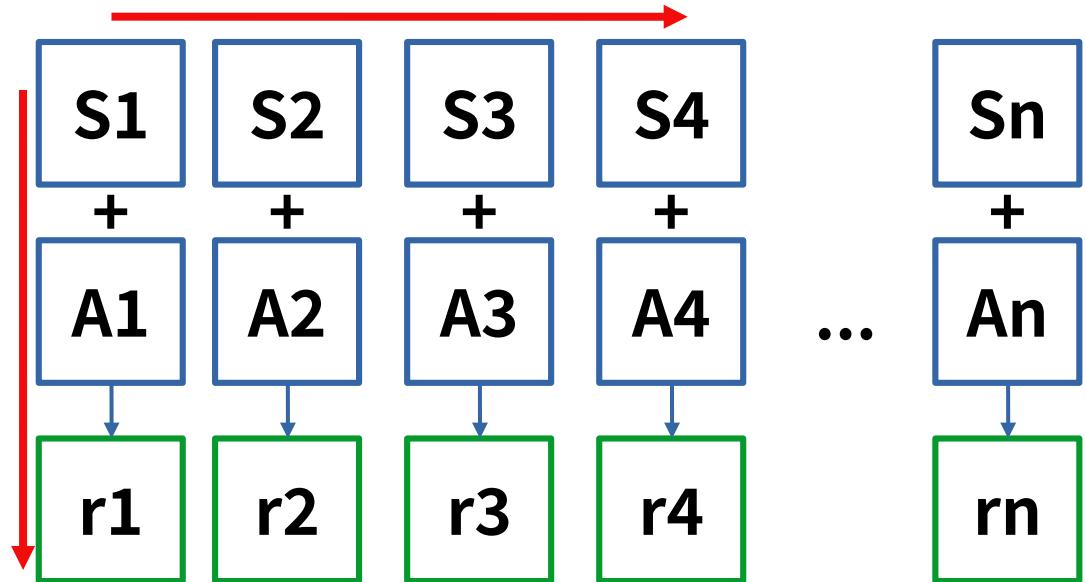


Action Space	Box(-.4 .4 (17,), float32)
Observation Space	Box(-inf, inf, (348,), )
Reward	Healthy + forward – ctrl - contact

### 3. PPO Algorithm

- 입력을 상태값 , 출력을  $A[17,]$ ,  $V[1,]$  으로 하는 네트워크
- SB3.PPO 라이브러리는  $[, 64, 64,]$  default
- $V[1,]$  Critic 이 예측한 기대 보상

Action Space	Box(-.4 .4 (17,), float32)
Observation Space	Box(-inf, inf, (348,), )
Reward	Healthy + forward – ctrl - contact



### 3. PPO Algorithm

- PPO 에서는 환경이 준 보상 (reward)로 return 을 만들고 , 그 return 으로 Advantage 를 계산해서 학습
- 순간적인 보상 (reward) 를 모아 에피소드 전체 간에 누적 보상인 return 을 활용해 학습
- Advantage : Act 가 기댓값보다 얼마나 잘했는지 / 못했는지

$$A_t = R_t - V_\phi(s_t)$$



$$R_t = r_t + \gamma R_{t+1}$$

States	s1, s2, s3, s4, ..., sn
Actions	a1, a2, a3, a4, ..., an
Rewards	r1, r2, r3, r4, ..., rn
Discounted Rewards	R1, R2, R3, R4, ..., Rn
Values	V(s1), V(s2), V(s3), ..., V(sn)
Advantage	A1, A2, A3, A4, ..., An

# 4. Train

- 파라미터가 DL 과 상이하게 사용됨에 유의
  - n\_envs : 병렬 환경 개수
  - n\_steps : rollout 길이 ( 얼마나 모으고 학습시작할지 )
  - n\_epochs : rollout 데이터를 가지고 몇 번 SGD 반복할지
  - batch\_size : 1 iter(rollout) 데이터의 양
    - 이 데이터를 가지고 (n\_epochs) 번 학습
  - total\_timesteps : 이를 5M step 반복
  - net\_arch : 은닉층의 노드 갯수
- 10M step 학습해도 잘 서있지 못함

```
n_envs = 32
n_steps = 1024
n_epochs = 10
batch_size = n_envs * n_steps
total_timesteps = 5_000_000
net_arch=[256, 256]
```

hyper\_param



10Mstep\_



5Mstep\_

# 4. Train

- 목표 : ep\_len\_mean=1000 이상 서있기
- 학습 파라미터 수정
  - 1) Gamma= 0.9 → 0.9999 로 수정 ( 미래보상에 집중 )
  - 2) 네트워크 크기 [64,64] → [256, 256] ( 정보 손실 방지 )
  - 3) log\_std\_init = -2.0 → -1.0 ( 탐색을 늘림 )
  - 4) 보상함수의 healthy\_reward 올림 ( 서있는것에 보상 )

```
n_envs = 32
n_steps = 2048
n_epochs = 10
batch_size = n_envs * n_steps
total_timesteps = 5_000_000
net_arch=[256, 256]

log_std_init=-0.5
gamma=0.9999
target_kl=0.01
LR = 5e-4
learning_rate=cosine_schedule(LR)
healthy_reward=5.0
```

hyper\_param

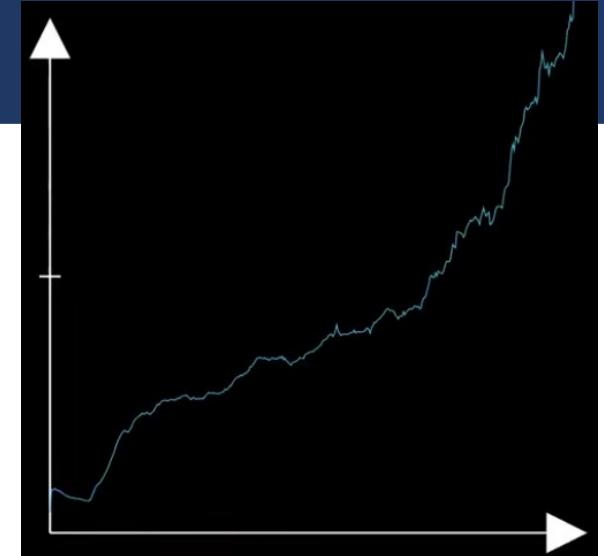
Timesteps: 3648000   Best ep_len_mean: 85.48   Current ep_len_mean: 82.20	
-----	
rollout/	
ep_len_mean	82
ep_rew_mean	420
time/	
fps	2214
iterations	95
time_elapsed	1405
total_timesteps	3112960
train/	
approx_kl	0.039049152
clip_fraction	0.226
clip_range	0.2
entropy_loss	-24.8
explained_variance	0.912
learning_rate	0.001
loss	4.56
n_updates	2470
policy_gradient_loss	-0.0232
std	0.134
value_loss	10.1

logs

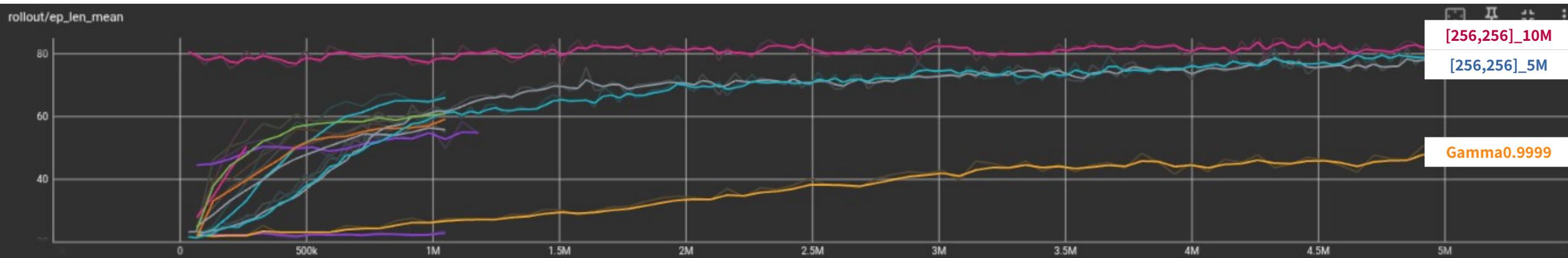


# 4. Train

- 학습결과 : 모두 얼마 지나지 않아 넘어짐
- 두 가지 가정을 하게됨
  - 하이퍼파라미터 설정이 잘못됨
  - 학습과정세팅 자체가 잘못됨



Desired (2Mstep)

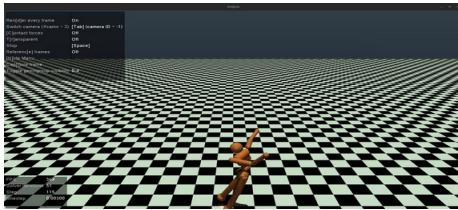


My experiment

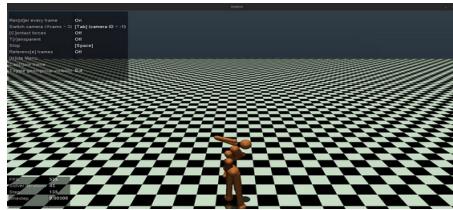


# 5. inference

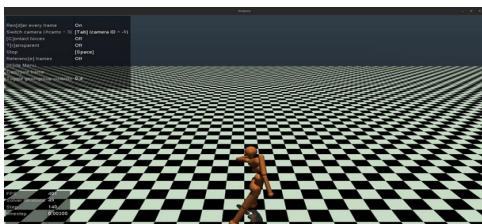
- 계속 시도중이나 가만히 서있질 못함 ...



[256,256]\_cossche\_0.0005LR\_  
0.9999gamma\_5Mstep



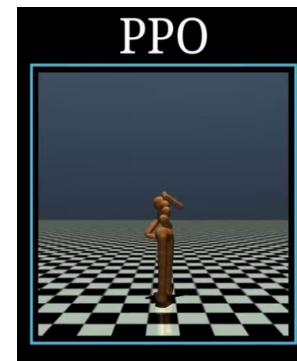
ep\_len focused model



[256,256]\_5Mstep



[256,256]\_5Mstep + -3.0exp\_1M



Desired

## 6. Ref

- 교수님 Base code (pendulum\_ppo.py)
- Reinforcement Learning behind Humanoid Robot Explained  
(<https://www.youtube.com/watch?v=QwJcF08hfs8&t=29s>)
- Gym docu - Humanoid  
(<https://gymnasium.farama.org/v0.27.0/environments/mujoco/humanoid/>)

