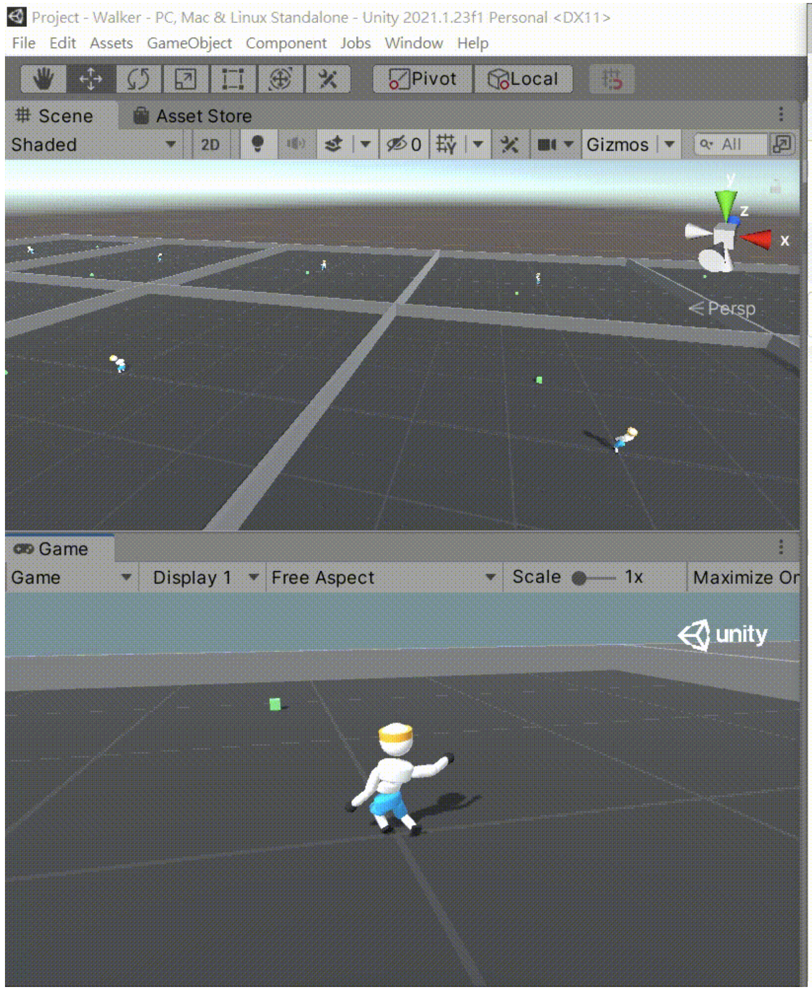
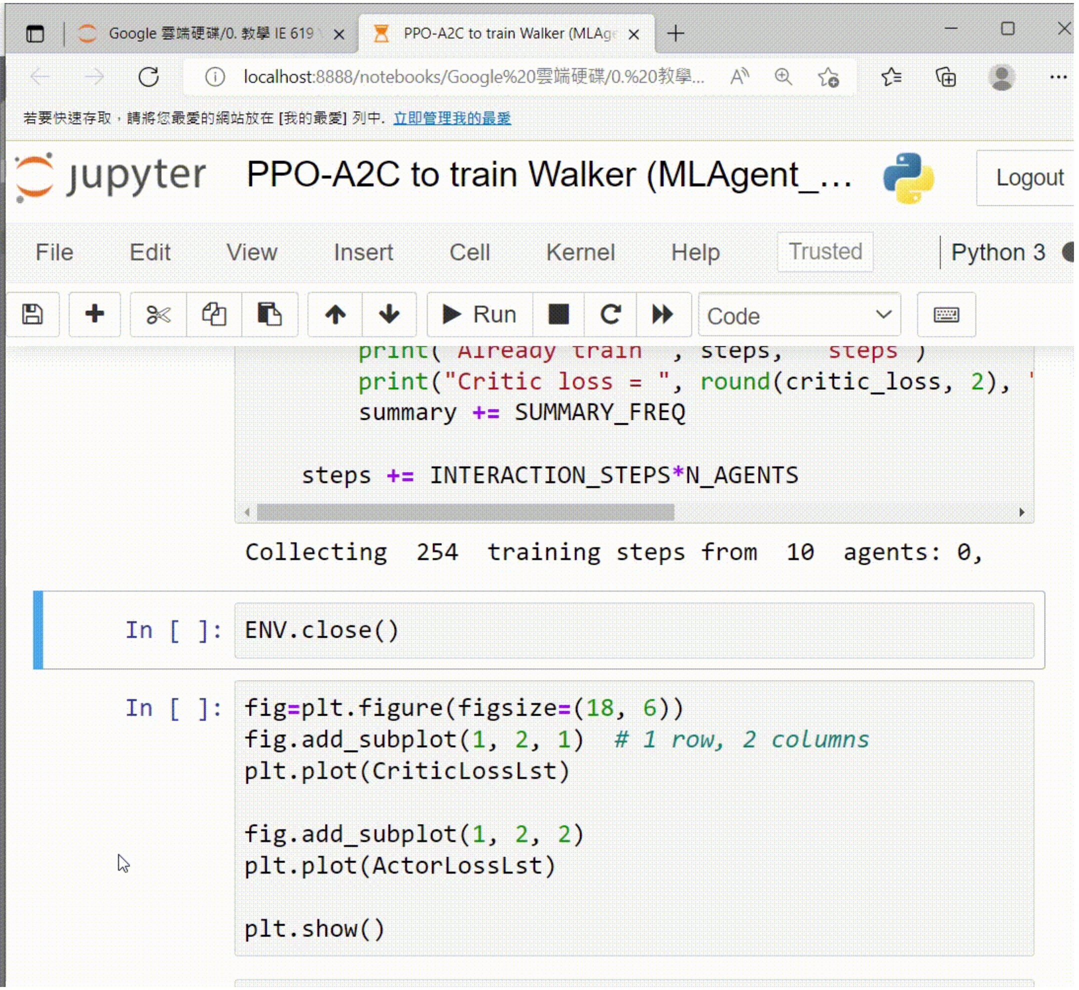
Ipython notebook version

Walker in ML agent 19 project

PPO-A2C to train Walker (MLAgent_19).ipynb

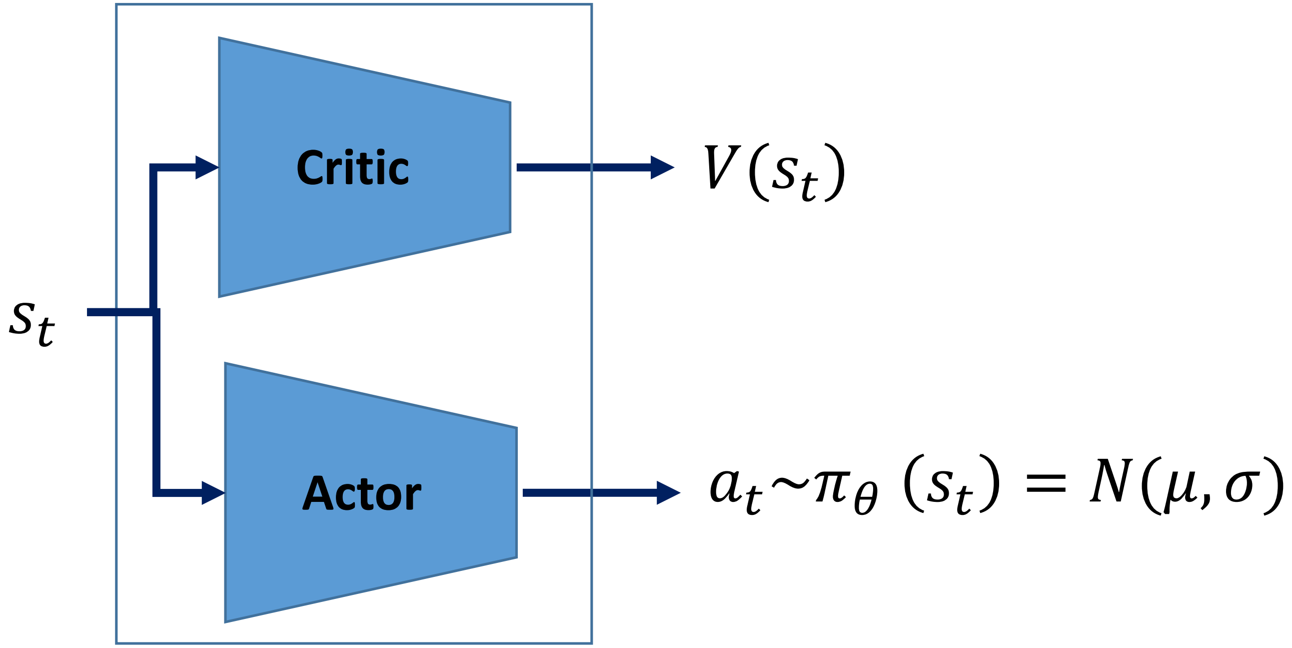




Actor and critic NN

```
self.critic = nn.Sequential(
    nn.Linear(N_STATES, HIDDEN_UNITS),
    nn.LayerNorm(HIDDEN_UNITS),
    nn.Linear(HIDDEN_UNITS, HIDDEN_UNITS),
    nn.LayerNorm(HIDDEN_UNITS),
    nn.Linear(HIDDEN_UNITS, 1)
)
```

```
self.actor = nn.Sequential(
    nn.Linear(N_STATES, HIDDEN_UNITS),
    nn.LayerNorm(HIDDEN_UNITS),
    nn.Linear(HIDDEN_UNITS, HIDDEN_UNITS),
    nn.LayerNorm(HIDDEN_UNITS),
    nn.Linear(HIDDEN_UNITS, N_ACTIONS)
)
```




```
def forward(self, x):
    value = self.critic(x)
    mu    = self.actor(x)
    std   = self.log_std.exp().expand_as(mu)
    dist  = Normal(mu, std)
    return dist, value
```

Advantage actor-critic

$$\max J(\pi) = E_{\tau\sim\pi}\left(R(\tau)\right)$$

$$\theta_{k+1} = \theta_k + \alpha\nabla_\theta J(\pi_\theta)$$

REINFORCE (Monte Carlo PG)

$$\nabla_\theta J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T}\nabla_\theta log\pi_\theta(a_t|s_t)\Phi_t\right] \qquad \Phi_t = \sum_{t'=t}^{T}\gamma^{t'-t}r_{t'}$$

Advantage Actor-Critic

$$\nabla_\theta J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T}\nabla_\theta log\pi_\theta(a_t|s_t)\big(Q^\pi(s_t,a_t) - V^\pi(s_t)\big)\right]$$

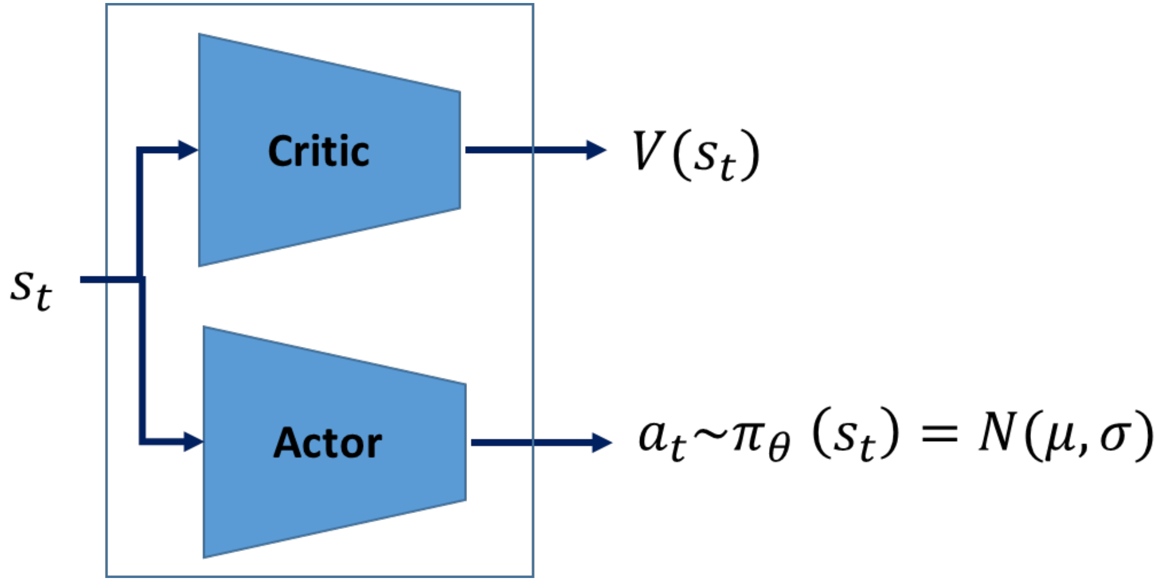
$$= E_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T}\nabla_\theta log\pi_\theta(a_t|s_t)(r(s_t,a_t) + \gamma V^\pi(s_{t+1}) - V^\pi(s_t))\right]$$

Pass state to Actor and Critics NN

[13]:
```
s = torch.FloatTensor(s)
dist, value = NET(s.to(device))
print(dist, "\n", value)
```

Pass s to Actor and Critic NN to get $\pi_\theta(s_t) = N(\mu,\sigma)$ and $V(s_t)$

```
Normal(loc: torch.Size([10, 39]), scale: torch.Size([10, 39]))
 tensor([[1.7525],
        [1.3020],
        [1.8764],
        [1.7034],
        [1.7539],
        [1.6710],
        [2.0807],
        [1.8870],
        [2.0875],
```



Sampling action values

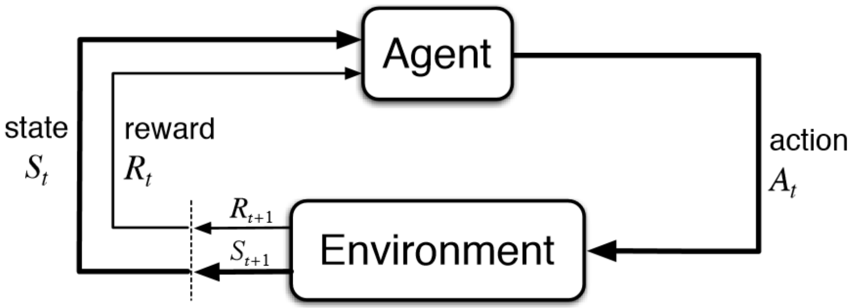
```
In [14]: a = dist.sample()
         log_prob = dist.log_prob(a)
         print(a, "\n", log_prob)
```

$a_t \sim \pi_\theta\ (s_t) = N(\mu, \sigma)$

$log\pi_\theta(a_t|s_t)$

```
                      2.1507, -1.0720,  1.5543, -2.0371, -3.5
5,
                     -2.0914,  3.4678, -1.9880, -2.7836,  2.7
2,
                      2.1310,  2.9008, -3.7953,  0.6812, -1.0
0,
                      2.7232,  1.2273, -0.9963, -3.4695,  2.5
                    [ 2.7992, -2.0890, -2.9866,  3.2485, -1.9
8,
                      3.3492,  3.6204, -0.6714,  0.3952, -0.7
7,
                     -3.0459, -2.8508,  1.2497, -0.8889,  2.1
```

One interaction step between Unity and PyTorch




```
def Interact_with_Unity_one_step (DecisionSteps):
    # ENV and NET are global variables
    s = DecisionSteps.obs[0]
    s = torch.FloatTensor(s)
    dist, value = NET(s.to(device))
    a = dist.sample()
    log_prob = dist.log_prob(a)

    a = a.cpu().detach().numpy()
    a = ActionTuple(np.array(a, dtype=np.float32))
    ENV.set_actions(BEHAVIOR_NAME, a)
    ENV.step()
    a = a._continuous #convert from ActionTuple to np
    a = torch.FloatTensor(a) # convert from np.array
    return s, value, a, log_prob
```

Collect training trajectories

```
def collect_training_data (print_message):
    while step < INTERACTION_STEPS
        If we have no decision agents → continue next loop without increase step
        else
            Interacts with Unity one step
            If this or next decision step misses some agents → Continue next loop without
                                                                increase step and do not collect data
            else this and next decision steps includes all agents
            (This ensures that we can collect s and s_next from all agents, otherwise program
             will have error!)
                Collect (s, V, a, r, s_next) from all agents
                Collect reward and mask from next terminal steps
                Collect reward and mask from next decision steps
                step = step +1
```

Collect training trajectories

$$\nabla_\theta J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=1}^{T} \nabla_\theta log\pi_\theta(a_t|s_t)\big(Q^\pi(s_t,a_t) - V^\pi(s_t)\big)\right]$$
$$= E_{\tau\sim\pi_\theta}\left[\sum_{t=1}^{T} \nabla_\theta log\pi_\theta(a_t|s_t)(r(s_t,a_t) + \gamma V^\pi(s_{t+1}) - V^\pi(s_t)\,)\right]$$

T = INTERACTION_STEPS

Agent 1: $\tau = \big(s_1, V_1, a_1, \log p(a_1|s_1), r_1, mask_1 \ldots, s_T, V_T, a_{1,T}, \log p(a_T|s_T), r_T, mask_T\big)$
Agent 2: τ

…

Agent 10: τ

Store training trajectory data

```
def collect_training_data (print_message):
```

```
AgentID = DecisionSteps.agent_id[idx]
STATES[step][AgentID]=s[idx]
VALUES[step][AgentID]=value[idx]
ACTIONS[step][AgentID]=a[idx]
LOG_PROBS[step][AgentID]=log_prob[idx]
```

```
def Collect REWARDS and MASKS
```

```
AgentID = AgentSteps.agent_id[idx]
REWARDS[step][AgentID]=r[idx]
MASKS[step][AgentID]= flag
NEXT_STATES[step][AgentID]=s[idx]
```

Step *i*

$$\begin{bmatrix} s_{step_1,agent_1} \\ s_{step_1,agent_2} \\ \cdots \\ s_{step_1,agent_{10}} \end{bmatrix} \begin{bmatrix} V_{step_1,agent_1} \\ V_{step_1,agent_2} \\ \cdots \\ V_{step_1,agent_{10}} \end{bmatrix} \begin{bmatrix} a_{step_1,agent_1} \\ a_{step_1,agent_2} \\ \cdots \\ a_{step_1,agent_{10}} \end{bmatrix}$$

$$\begin{bmatrix} \log p(a_{step_1,agent_1} | s_{step_1,agent_1}) \\ \log p(a_{step_1,agent_2} | s_{step_1,agent_2}) \\ \cdots \\ \log p(a_{step_1,agent_{10}} | s_{step_1,agent_{10}}) \end{bmatrix}$$

$$\begin{bmatrix} r_{step_1,agent_1} \\ r_{step_1,agent_2} \\ \cdots \\ r_{step_1,agent_{10}} \end{bmatrix} \begin{bmatrix} mask_{step_1,agent_1} \\ mask_{step_1,agent_2} \\ \cdots \\ maks_{step_1,agent_{10}} \end{bmatrix}$$

$$\begin{bmatrix} s\_next_{step_1,agent_1} \\ s\_next_{step_1,agent_2} \\ \cdots \\ s\_next_{step_1,agent_{10}} \end{bmatrix}$$

Store training trajectory data

```
[25]: print(len(LOG_PROBS), LOG_PROBS[0].shape)
      print(len(VALUES), VALUES[0].shape)
      print(len(REWARDS), REWARDS[0].shape)
      print(len(MASKS), MASKS[0].shape)
      print(len(STATES), STATES[0].shape)
      print(len(ACTIONS), ACTIONS[0].shape)
      print(len(NEXT_STATES), NEXT_STATES[0].shape)
```

```
254 torch.Size([10, 39])
254 torch.Size([10, 1])
254 torch.Size([10, 1])
254 torch.Size([10, 1])
254 torch.Size([10, 243])
254 torch.Size([10, 39])
254 torch.Size([10, 243])
```

Training trajectory data from 10 agents each conducting 254 steps

Calculate Advantage from training trajectories

$$\nabla_\theta J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=1}^{T} \nabla_\theta log\pi_\theta(a_t|s_t)\left(Q^\pi(s_t,a_t) - V^\pi(s_t)\right)\right]$$
$$= E_{\tau\sim\pi_\theta}\left[\sum_{t=1}^{T} \nabla_\theta log\pi_\theta(a_t|s_t)(r(s_t,a_t) + \gamma V^\pi(s_{t+1}) - V^\pi(s_t))\right]$$

```
def compute_gae(next_value):

    return returns
```

```
[28]: RETURNS = compute_gae(
```

```
254 torch.Size([10, 39])
254 torch.Size([10, 1])
254 torch.Size([10, 1])
254 torch.Size([10, 1])
254 torch.Size([10, 243])
254 torch.Size([10, 39])
254 torch.Size([10, 243])
```

$$\Delta_{20} = r_{20} + (\gamma * v_{21} * mask_{20} - v_{20})$$
$$gae_{20} = \Delta_{20} + \gamma * \lambda * mask_{20} * gae_{initial}$$
$$return_{20} = gae_{20} + v_{20}$$

$$\Delta_{19} = r_{19} + (\gamma * v_{20} * mask_{19} - v_{19})$$
$$gae_{19\sim20} = \Delta_{19} + \gamma * \tau * mask_{19} * gae_{20}$$
$$return_{19} = gae_{19\sim20} + v_{19}$$

...

$$\Delta_{1} = r_{1} + (\gamma * v_{2} * mask_{1} - v_{1})$$
$$gae_{1\sim20} = \Delta_{1} + \gamma * \tau * mask_{1} * gae_{2\sim20}$$
$$return_{1} = gae_{1\sim20} + v_{1}$$

Merge training trajectory data from multiple agents

[29]:
```
MERGED_RETURNS    = torch.cat(RETURNS).detach()
MERGED_LOG_PROBS = torch.cat(LOG_PROBS).detach()
MERGED_VALUES     = torch.cat(VALUES).detach()
MERGED_STATES     = torch.cat(STATES)
MERGED_NEXT_STATES    = torch.cat(NEXT_STATES)
MERGED_ACTIONS    = torch.cat(ACTIONS)
MERGED_ADVANTAGES = MERGED_RETURNS - MERGED_VALUES
```

[30]:
```
print(len(MERGED_RETURNS), MERGED_RETURNS[0].shape)
print(len(MERGED_LOG_PROBS), MERGED_LOG_PROBS[0].shape)
print(len(MERGED_VALUES), MERGED_VALUES[0].shape)
print(len(MERGED_STATES), MERGED_STATES[0].shape)
print(len(MERGED_NEXT_STATES), MERGED_NEXT_STATES[0].shape)
print(len(MERGED_ACTIONS), MERGED_ACTIONS[0].shape)
print(len(MERGED_ADVANTAGES), MERGED_ADVANTAGES[0].shape)
```

```
2540 torch.Size([1])
2540 torch.Size([39])
2540 torch.Size([1])
2540 torch.Size([243])
2540 torch.Size([243])
2540 torch.Size([39])
2540 torch.Size([1])
```

2540 = 10 agents each conducting 254 steps

$$\begin{bmatrix} s_{step_1,agent_1} \\ \vdots \\ s_{step_1,agent_{10}} \\ s_{step_2,agent_1} \\ \vdots \\ s_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \begin{bmatrix} V_{step_1,agent_1} \\ \vdots \\ V_{step_1,agent_{10}} \\ V_{step_2,agent_1} \\ \vdots \\ V_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \begin{bmatrix} a_{step_1,agent_1} \\ \vdots \\ a_{step_1,agent_{10}} \\ a_{step_2,agent_1} \\ \vdots \\ a_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \begin{bmatrix} \log p(a_{step_1,agent_1} | s_{step_1,agent_1}) \\ \vdots \\ \log p(a_{step_1,agent_{10}} | s_{step_1,agent_{10}}) \\ \log p(a_{step_2,agent_1} | s_{step_{12},agent_1}) \\ \vdots \\ \log p(a_{step_2,agent_{10}} | s_{step_2,agent_{10}}) \\ \vdots \end{bmatrix} \begin{bmatrix} Return_{step_1,agent_1} \\ \vdots \\ Return_{step_1,agent_{10}} \\ Return_{step_2,agent_1} \\ \vdots \\ Return_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \cdots$$

Sampling a batch of training data from buffer

```python
def ppo_iter():
    buffer_size = MERGED_STATES.size(0)
    for _ in range(buffer_size// BATCH_SIZE ):
        rand_ids = np.random.randint(0, buffer_size, BATCH_SIZE )
        yield MERGED_STATES[rand_ids, :], MERGED_ACTIONS[rand_ids,
              MERGED_LOG_PROBS[rand_ids, :], MERGED_RETURNS[rand_i
```

$$\begin{bmatrix} s_{step_1,agent_1} \\ \vdots \\ \\ s_{step_1,agent_{10}} \\ s_{step_2,agent_1} \\ \vdots \\ s_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \begin{bmatrix} V_{step_1,agent_1} \\ \vdots \\ \\ V_{step_1,agent_{10}} \\ V_{step_2,agent_1} \\ \vdots \\ V_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \begin{bmatrix} a_{step_1,agent_1} \\ \vdots \\ \\ a_{step_1,agent_{10}} \\ a_{step_2,agent_1} \\ \vdots \\ a_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \begin{bmatrix} \log p(a_{step_1,agent_1} | s_{step_1,agent_1}) \\ \vdots \\ \log p(a_{step_1,agent_{10}} | s_{step_1,agent_{10}}) \\ \log p(a_{step_2,agent_1} | s_{step_{12},agent_1}) \\ \vdots \\ \log p(a_{step_2,agent_{10}} | s_{step_2,agent_{10}}) \\ \vdots \end{bmatrix} \begin{bmatrix} Return_{step_1,agent_1} \\ \vdots \\ \\ Return_{step_1,agent_{10}} \\ Return_{step_2,agent_1} \\ \vdots \\ Return_{step_2,agent_{10}} \\ \vdots \end{bmatrix} \cdots$$

Loss function for critic NN

```
def ppo_update():
```

```
for b_s, b_a, b_s_, b_old_LOG_PROBS, b_return, b_advantage in ppo_iter():
```

```
dist, value = NET(b_s.to(device))
critic_loss = (b_return.to(device) - value).pow(2).mean()
```

BS = batch size

$$Loss_V = \frac{1}{BS}\sum_{i=1}^{BS}\left(Return_i - V^{\pi_\theta}(s_i)\right)^2$$

PPO update

```
def ppo_update():
    for b_s, b_a, b_s_, b_old_LOG_PROBS, b_return, b_advantage in ppo_iter():
        entropy = dist.entropy().mean()
        b_a_new = dist.sample()
        b_new_LOG_PROBS = dist.log_prob(b_a_new)
        ratio = (b_new_LOG_PROBS - b_old_LOG_PROBS.to(device)).exp()
        surr1 = ratio * b_advantage.to(device)
        surr2 = torch.clamp(ratio, 1.0-EPSILON, 1.0+EPSILON) * b_advantage.to(device)
        actor_loss  = - torch.min(surr1, surr2).mean()
```

$$Loss_\pi = \sum_{(s_t,a_t)} min\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}A^{\theta'}(s_t,a_t), clip\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right)A^{\theta'}(s_t,a_t)\right)$$

Entropy regularization

```
def ppo_update():
    for b_s, b_a, b_s_, b_old_LOG_PROBS, b_return, b_advantage in ppo_iter():
            loss = 0.5 * critic_loss + actor_loss - 0.001 * entropy
            OPTIMIZER.zero_grad()
            loss.backward()
            OPTIMIZER.step()
```

$$L = 0.5 \cdot Loss_V + Loss_\pi - 0.01 \cdot entropy$$

py version

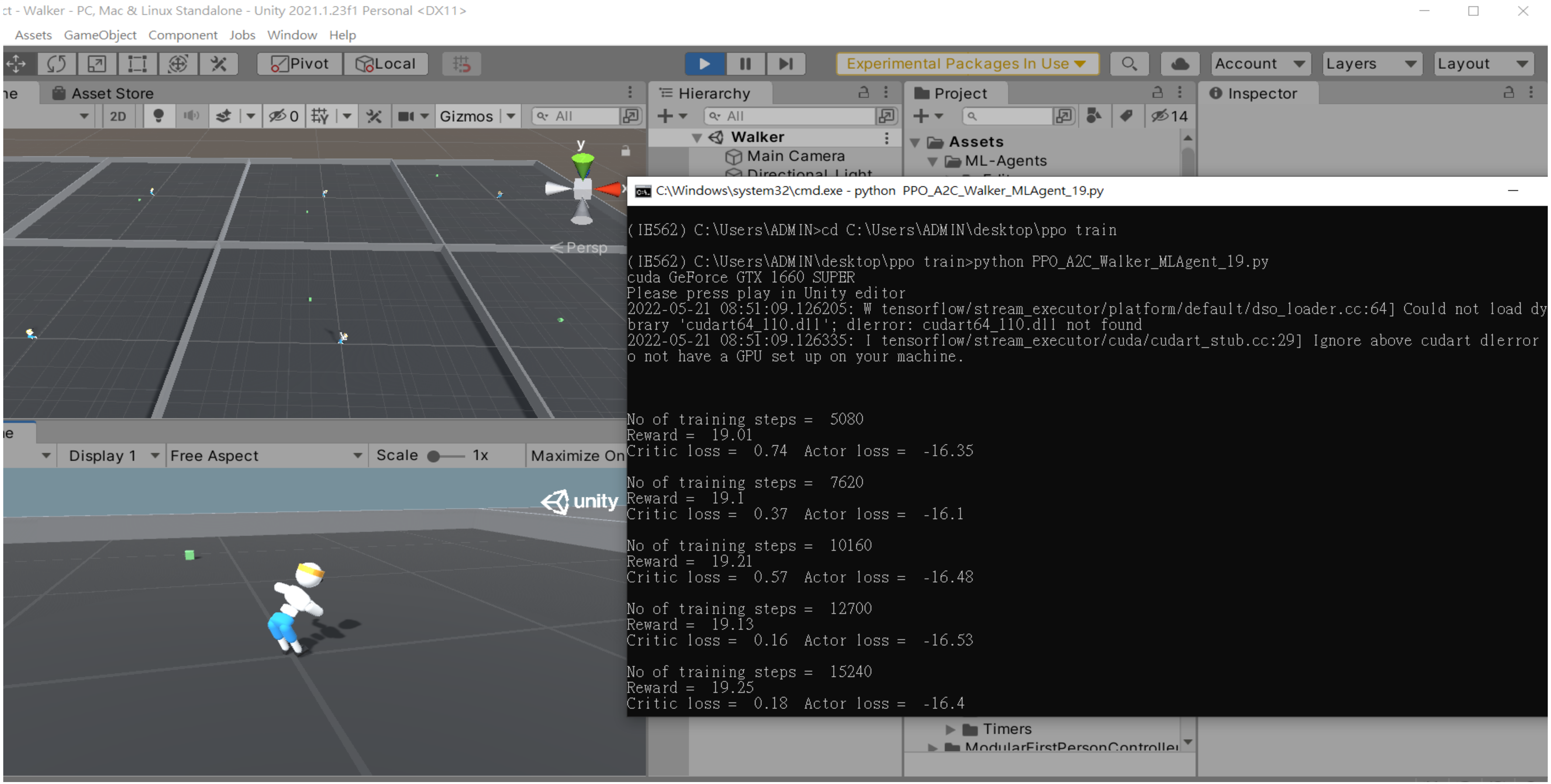
1. Open terminal window from Anaconda
2. cd to the directory where the file "PPO_A2C_Walker_MLAgent_19.py" is located
3. >> python PPO_A2C_Walker_MLAgent_19.py
4. Press Play in Unity to start training

C:\Windows\system32\cmd.exe

```
(IE562) C:\Users\ADMIN>cd C:\Users\ADMIN\desktop\ppo train

(IE562) C:\Users\ADMIN\desktop\ppo train>python PPO_A2C_Walker_MLAgent_19.py
cuda GeForce GTX 1660 SUPER
Please press play in Unity editor
2022-05-21 08:51:09.126205: W tensorflow/stream_executor/platform/default/dso_lo
brary 'cudart64_110.dll'; dlerror: cudart64_110.dll not found
2022-05-21 08:51:09.126335: I tensorflow/stream_executor/cuda/cudart_stub.cc:29]
o not have a GPU set up on your machine.
```

py version


ct - Walker - PC, Mac & Linux Standalone - Unity 2021.1.23f1 Personal <DX11>
Assets GameObject Component Jobs Window Help
Pivot
Local
Experimental Packages In Use
Account
Layers
Layout
Asset Store
Hierarchy
Project
Inspector
Gizmos
Walker
Main Camera
Assets
ML-Agents
Persp
Display 1
Free Aspect
Scale
1x
Maximize On
unity
Timers
C:\Windows\system32\cmd.exe - python PPO_A2C_Walker_MLAgent_19.py
(IE562) C:\Users\ADMIN>cd C:\Users\ADMIN\desktop\ppo train
(IE562) C:\Users\ADMIN\desktop\ppo train>python PPO_A2C_Walker_MLAgent_19.py
cuda GeForce GTX 1660 SUPER
Please press play in Unity editor
2022-05-21 08:51:09.126205: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dy
brary 'cudart64_110.dll'; dlerror: cudart64_110.dll not found
2022-05-21 08:51:09.126335: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror
o not have a GPU set up on your machine.
No of training steps = 5080
Reward = 19.01
Critic loss = 0.74 Actor loss = -16.35
No of training steps = 7620
Reward = 19.1
Critic loss = 0.37 Actor loss = -16.1
No of training steps = 10160
Reward = 19.21
Critic loss = 0.57 Actor loss = -16.48
No of training steps = 12700
Reward = 19.13
Critic loss = 0.16 Actor loss = -16.53
No of training steps = 15240
Reward = 19.25
Critic loss = 0.18 Actor loss = -16.4

Calculate reward

```
if(steps > summary):
    print("No of training steps = ", steps)
    mean_reward = float(torch.mean(MERGED_RETURNS))
    print("Reward = ", round(mean_reward, 2))
    print("Critic loss = ", round(critic_loss, 2), " Actor loss = ", round(actor_loss, 2))

    writer.add_scalar("Loss/Actor loss", actor_loss, steps)
    writer.add_scalar("Loss/Critic loss", critic_loss, steps)
    writer.add_scalar("Reward", actor_loss, steps)

    fname = "NN_" + str(steps) + ".pth"
    torch.save(NET.state_dict(), fname)
    summary += SUMMARY_FREQ
```

Write reward and loss to tensorboard

```
from torch.utils.tensorboard import SummaryWriter

writer = SummaryWriter()

writer.add_scalar("Loss/Actor loss", actor_loss, steps)
writer.add_scalar("Loss/Critic loss", critic_loss, steps)
writer.add_scalar("Reward", actor_loss, steps)
```

Write reward and loss to tensorboard

- runs
- NN_5080.pth
- NN_7620.pth
- NN_10160.pth
- NN_12700.pth
- NN_15240.pth
- NN_20320.pth
- NN_22860.pth
- NN_25400.pth
- NN_27940.pth
- PPO_A2C_Walker_MLAgent_19.py

\DMIN › desktop › ppo train › runs

名稱

May21_09-24-25_DESKTOP-AQI6BIB

› ppo train › runs › May21_09-24-25_DESKTOP-AQI6BIB

名稱	修改日期
events.out.tfevents.1653096267.DESKT...	2022/5/21 上午 09:28

Visualize training performance using tensor board

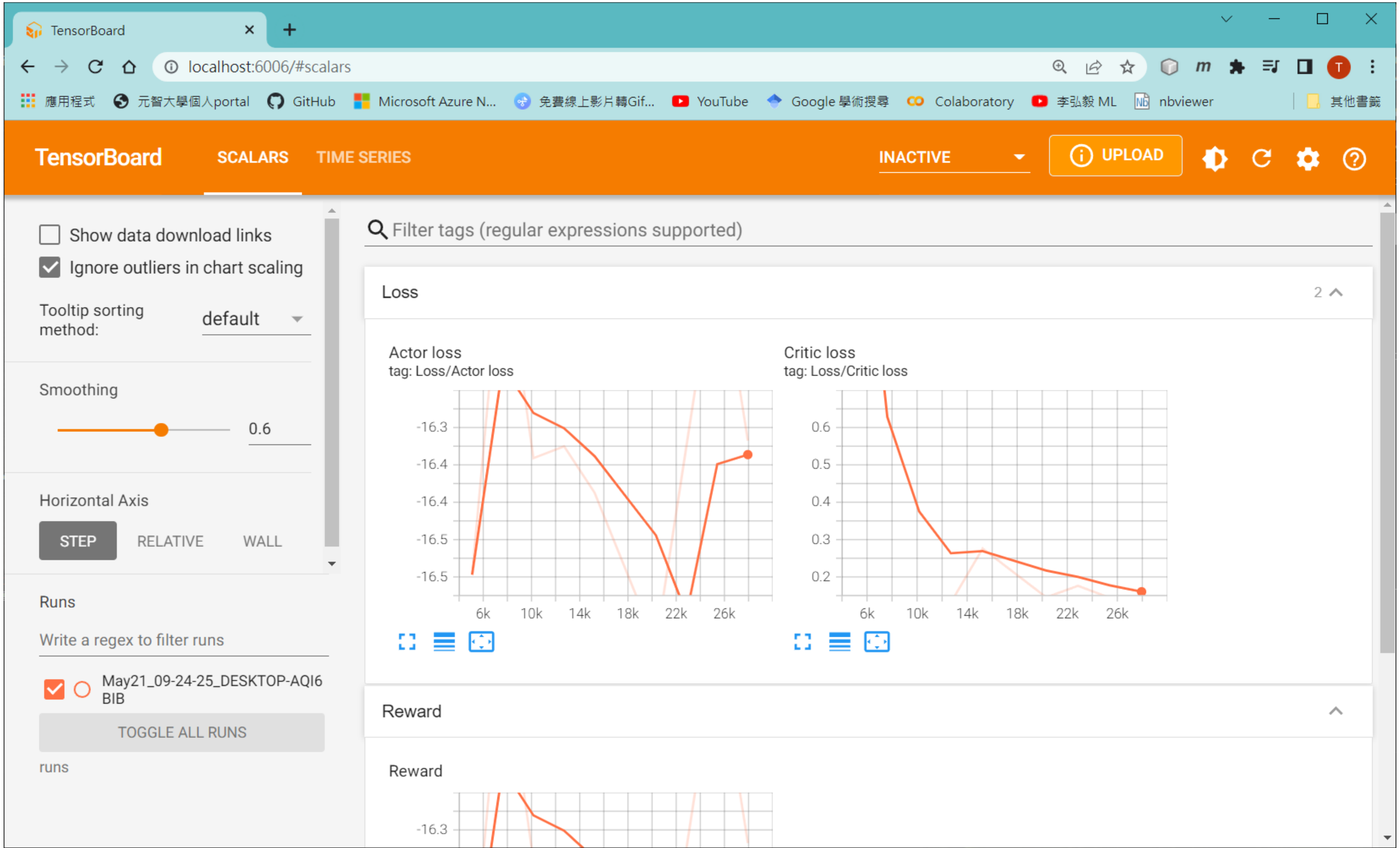
1. Open terminal window from Anaconda
2. cd to the directory where the file "PPO_A2C_Walker_MLAgent_19.py" is located
3. >> tensorboard --logdir=runs
4. Open web browser: localhost:6006

```
(IE562) C:\Users\ADMIN>cd C:\Users\ADMIN\desktop\ppo train

(IE562) C:\Users\ADMIN\desktop\ppo train>tensorboard --logdir=runs
2022-05-21 09:05:45.345759: W tensorflow/stream_executor/platform/de
ry 'cudart64_110.dll'; dlerror: cudart64_110.dll not found
```

```
lease make sure the missing libraries mentioned above are installed properly if you would li
ide at https://www.tensorflow.org/install/gpu for how to download and setup the required lib
Skipping registering GPU devices...
Serving TensorBoard on localhost; to expose to the network, use a proxy or pass --bind_all
TensorBoard 2.6.0 at http://localhost:6006/ (Press CTRL+C to quit)
```

Visualize training performance using tensor board



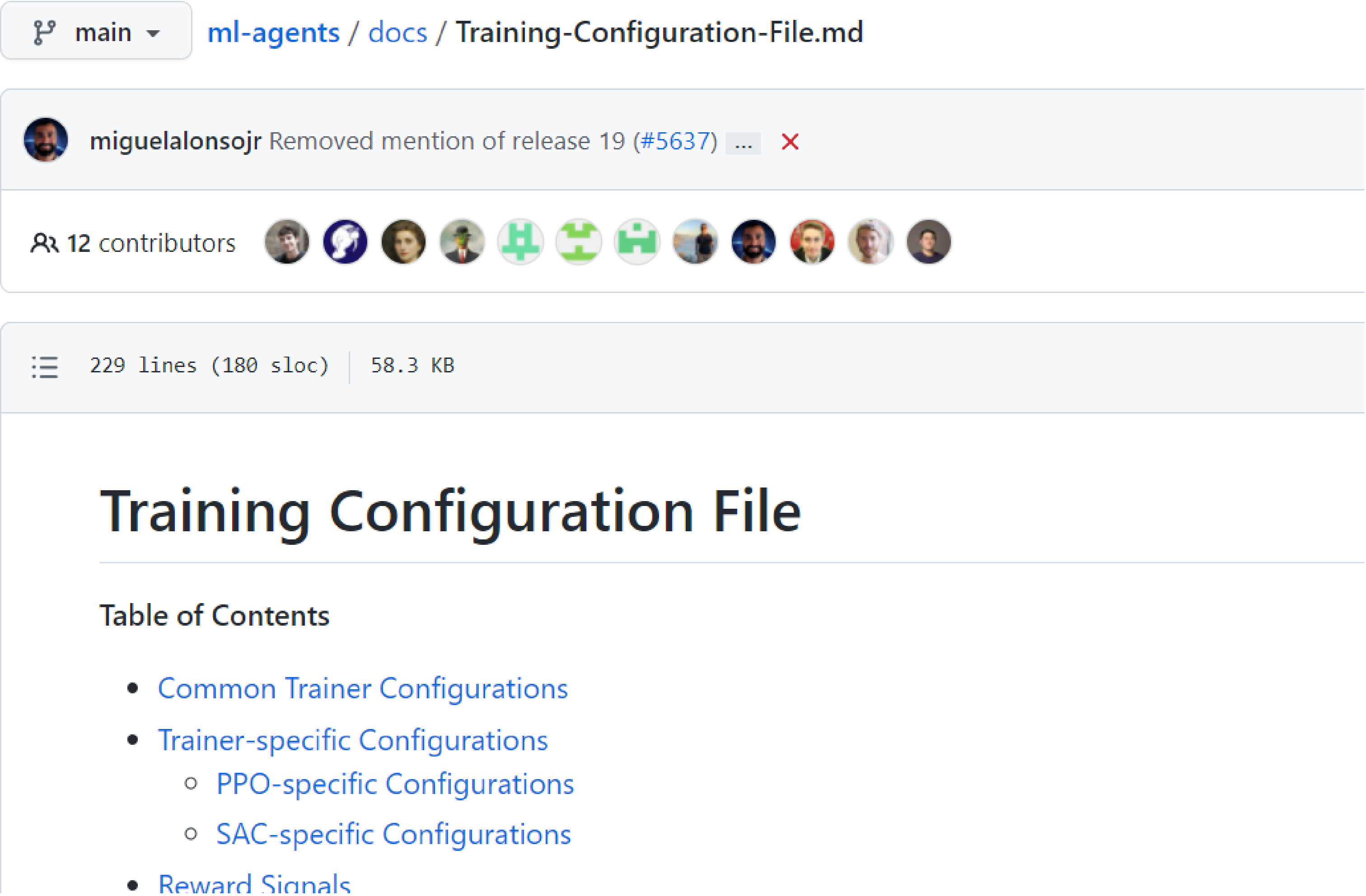
Save NN

```
fname = "NN_" + str(steps) + ".pth"
torch.save(NET.state_dict(), fname)
```

runs
NN_5080.pth
NN_7620.pth
NN_10160.pth
NN_12700.pth
NN_15240.pth
NN_20320.pth
NN_22860.pth
NN_25400.pth
NN_27940.pth
PPO_A2C_Walker_MLAgent_19.py

Training parameter setting

- Unity ML Agent Github → docs → Training configuration file



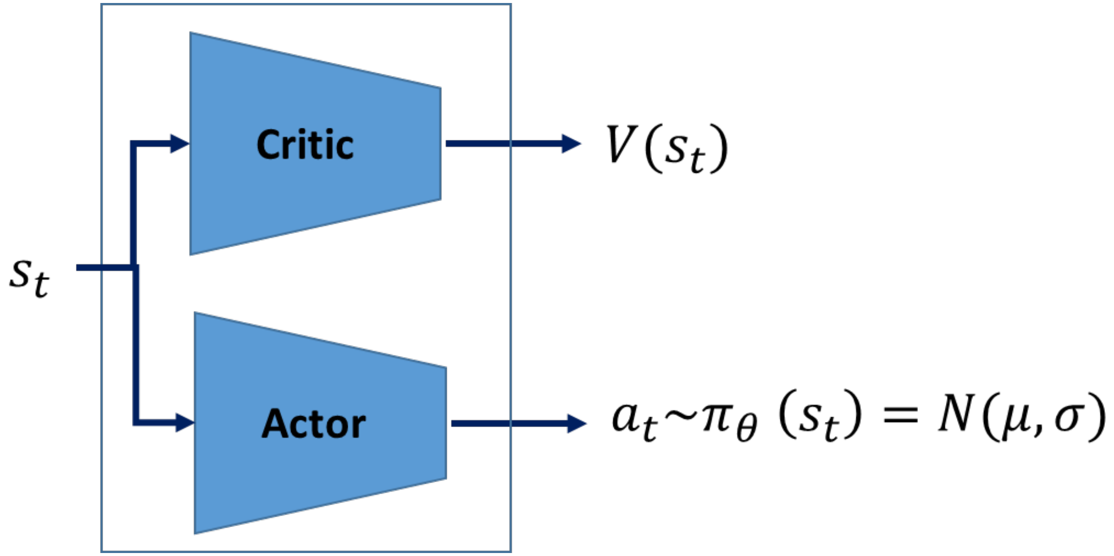
Class practice – NN structure

Unity ML Agent implementation

```
network_settings:
  normalize: true
  hidden_units: 512
  num_layers: 3
  vis_encode_type: simple
```

My py implementation

```
N_STATES   = 243
N_ACTIONS  = 39
HIDDEN_UNITS = 512
```



NN structure

`network_settings -> hidden_units`	(default = `128`) Number of units in the hidden layers of the neural network. Correspond to how many units are in each fully connected layer of the neural network. For simple problems where the correct action is a straightforward combination of the observation inputs, this should be small. For problems where the action is a very complex interaction between the observation variables, this should be larger. Typical range: `32` - `512`
`network_settings -> num_layers`	(default = `2`) The number of hidden layers in the neural network. Corresponds to how many hidden layers are present after the observation input, or after the CNN encoding of the visual observation. For simple problems, fewer layers are likely to train faster and more efficiently. More layers may be necessary for more complex control problems. Typical range: `1` - `3`
`network_settings -> normalize`	(default = `false`) Whether normalization is applied to the vector observation inputs. This normalization is based on the running average and variance of the vector observation. Normalization can be helpful in cases with complex continuous control problems, but may be harmful with simpler discrete control problems.

Class practice – Number of training steps and summarize frequency

Unity ML Agent implementation

```
keep_checkpoints: 5
max_steps: 30000000
time_horizon: 1000
summary_freq: 30000
```

My py implementation

```
MAX_STEPS = 30000
SUMMARY_FREQ = 3000
TIME_HORIZON = 1000
```

Class practice – Buffer size and batch size

Unity ML Agent implementation

```
batch_size: 2048
buffer_size: 20480
learning_rate: 0.0003
```

My py implementation

```
INTERACTION_STEPS = 254
BATCH_SIZE = 254

LEARNING_RATE = 0.0003
N_AGENTS = 10  #The num
```

```
def collect_training_data (print_message):
```

Buffer size = No_Agents * Interaction_Steps

Buffer size and batch size

`hyperparameters -> batch_size`	Number of experiences in each iteration of gradient descent. **This should always be multiple times smaller than `buffer_size`**. If you are using continuous actions, this value should be large (on the order of 1000s). If you are using only discrete actions, this value should be smaller (on the order of 10s). Typical range: (Continuous - PPO): `512` - `5120`; (Continuous - SAC): `128` - `1024`; (Discrete, PPO & SAC): `32` - `512`.
`hyperparameters -> buffer_size`	(default = `10240` for PPO and `50000` for SAC) **PPO:** Number of experiences to collect before updating the policy model. Corresponds to how many experiences should be collected before we do any learning or updating of the model. **This should be multiple times larger than `batch_size`**. Typically a larger `buffer_size` corresponds to more stable training updates. **SAC:** The max size of the experience buffer - on the order of thousands of times longer than your episodes, so that SAC can learn from old as well as new experiences. Typical range: PPO: `2048` - `409600`; SAC: `50000` - `1000000`

Class practice – Training epochs

Unity ML Agent implementation

lambd: 0.95
num_epoch: 3
learning_rate_schedule

My py implementation

```
GAMMA = 0.995
LAMBD = 0.95
BETA = 0.005
EPSILON = 0.2
N_EPOCH = 3
```

```
def ppo_update():
    for epoch in range(N_EPOCH):
        for b_s, b_a, b_s_, b_old_LOG_PROBS, b_
            dist, value = NET(b_s.to(device))
            critic_loss = (b_return.to(device)
            entropy = dist.entropy().mean()
```

$$Loss_{\pi} = \sum_{(s_t,a_t)} min\left(\frac{p_{\theta}(a_t|s_t)}{p_{\theta'}(a_t|s_t)} A^{\theta'}(s_t,a_t), clip\left(\frac{p_{\theta}(a_t|s_t)}{p_{\theta'}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right) A^{\theta'}(s_t,a_t)\right)$$

Training epochs

`hyperparameters -> num_epoch`	(default = `3`) Number of passes to make through the experience buffer when performing gradient descent optimization.The larger the batch_size, the larger it is acceptable to make this. Decreasing this will ensure more stable updates, at the cost of slower learning. Typical range: `3` - `10`

Class practice – Reward signals

- Test with ML agent and my py

Unity ML Agent implementation

```
reward_signals:
  extrinsic:
    gamma: 0.995
    strength: 1.0
```

My py implementation

```
GAMMA = 0.995
LAMBD = 0.95
BETA = 0.005
EPSILON = 0.2
N_EPOCH = 3
```

$$\Delta_{19} = r_{19} + (\gamma * v_{20} * mask_{19} - v_{19})$$
$$gae_{19\sim 20} = \Delta_{19} + \gamma * \tau * mask_{19} * gae_{20}$$
$$return_{19} = gae_{19\sim 20} + v_{19}$$

Reward signals

Setting	Description
`extrinsic -> strength`	(default = `1.0`) Factor by which to multiply the reward given by the environment. Typical ranges will vary depending on the reward signal. Typical range: `1.00`
`extrinsic -> gamma`	(default = `0.99`) Discount factor for future rewards coming from the environment. This can be thought of as how far into the future the agent should care about possible rewards. In situations when the agent should be acting in the present in order to prepare for rewards in the distant future, this value should be large. In cases when rewards are more immediate, it can be smaller. Must be strictly smaller than 1. Typical range: `0.8` - `0.995`

Class practice – Accumulated rewards

Unity ML Agent implementation

```
hyperparameters:
  batch_size: 2048
  buffer_size: 20480
  learning_rate: 0.0003
  beta: 0.005
  epsilon: 0.2
  lambd: 0.95
  num_epoch: 3
  learning_rate_schedule: linear
```

My py implementation

```
GAMMA = 0.995
LAMBD = 0.95
BETA = 0.005
EPSILON = 0.2
N_EPOCH = 3
```

$$\Delta_{19} = r_{19} + (\gamma * v_{20} * mask_{19} - v_{19})$$
$$gae_{19\sim20} = \Delta_{19} + \gamma * \tau * mask_{19} * gae_{20}$$
$$return_{19} = gae_{19\sim20} + v_{19}$$

$$\nabla_\theta J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=1}^{T} \nabla_\theta log\pi_\theta(a_t|s_t)(r(s_t,a_t) + \gamma V^\pi(s_{t+1}) - V^\pi(s_t))\right]$$

Accumulated rewards

`hyperparameters -> lambd`	(default = `0.95`) Regularization parameter (lambda) used when calculating the Generalized Advantage Estimate (GAE). This can be thought of as how much the agent relies on its current value estimate when calculating an updated value estimate. Low values correspond to relying more on the current value estimate (which can be high bias), and high values correspond to relying more on the actual rewards received in the environment (which can be high variance). The parameter provides a trade-off between the two, and the right value can lead to a more stable training process. Typical range: `0.9` - `0.95`

Class practice – Entropy regularization

Unity ML Agent implementation

learning_rate: 0.
beta: 0.005
epsilon: 0.2
lambd: 0.95

My py implementation

```
GAMMA = 0.995
LAMBD = 0.95
BETA = 0.005
EPSILON = 0.2
N_EPOCH = 3
```

$$L = 0.5 \cdot Loss_V + Loss_\pi - 0.005 \cdot entropy$$

Entropy regularization

`hyperparameters -> beta`	(default = `5.0e-3`) Strength of the entropy regularization, which makes the policy "more random." This ensures that agents properly explore the action space during training. Increasing this will ensure more random actions are taken. This should be adjusted such that the entropy (measurable from TensorBoard) slowly decreases alongside increases in reward. If entropy drops too quickly, increase beta. If entropy drops too slowly, decrease `beta`. Typical range: `1e-4` - `1e-2`

HW4 – PPO-A2C training

- Group of max. 3
- Select a rewarding scheme you like the most from HW3
- Try different PPO-AC training parameters (smaller NN, larger buffer size and epochs, larger entropy) and train with both ML agent implementation and my py implementation
- Use tensorboard visualization (reward and loss plots) to compare and discuss
- Due: Next class meeting
- Upload ppt to Teams

HW4 – PPO-A2C training

- Experiment 1: Smaller NN (243-512-512-512-39 → 243-N-N-N-39) (try N=254 or 128)
- Experiment 2: Larger buffer and batch size (20480, 2048) → … (expect more stable training)
- Experiment 3: Larger training epochs (3 → 10) (expect more unstable training)
- Experiment 4: Larger entropy regularization (0.005 → 0.05) (expect more unstable training but more interesting behaviors)

Reference – OpenAI version

Documentation: PyTorch Version

spinup.ppo_pytorch(*env_fn, actor_critic=<MagicMock spec='str' id='140554322637768'>, ac_kwargs={}, seed=0, steps_per_epoch=4000, epochs=50, gamma=0.99, clip_ratio=0.2, pi_lr=0.0003, vf_lr=0.001, train_pi_iters=80, train_v_iters=80, lam=0.97, max_ep_len=1000, target_kl=0.01, logger_kwargs={}, save_freq=10*)

Proximal Policy Optimization (by clipping),

with early stopping based on approximate KL