Machine Learning Laboratory

(410302)

BE Sem I Honors in AI/ML

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Mini Project

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Problem Statement

Introduction

Reinforcement learning is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward.

Cartpole problem

Cartpole - known also as an Inverted Pendulum is a pendulum with a center of gravity above its pivot point. It’s unstable, but can be controlled by moving the pivot point under the center of mass. The goal is to keep the cartpole balanced by applying appropriate forces to a pivot point.

In this Mini project, we will implement a deep reinforcement learning algorithms for solving the cartpole problem and analyze the performance of the model.

Problem Statement:Evaluating the performance of Deep Reinforcement Learning for solving the Cartpole Problem

Algorithm Employed: Rainbow

A selection of the below six extensions that each have addressed a limitation and improved overall performance were integrated into a single integrated agent, Rainbow for improved performance on RL tasks [8]:

1. Double Q-learning
2. Prioritized replay
3. Dueling networks
4. Multi-step learning
5. Distributional RL
6. Noisy Nets

1. V. Mnih et al., "Human-level control through deep reinforcement learning." Nature, 518 (7540):529–533, 2015.
2. van Hasselt et al., "Deep Reinforcement Learning with Double Q-learning." arXiv preprint arXiv:1509.06461, 2015.
3. T. Schaul et al., "Prioritized Experience Replay." arXiv preprint arXiv:1511.05952, 2015.
4. Z. Wang et al., "Dueling Network Architectures for Deep Reinforcement Learning." arXiv preprint arXiv:1511.06581, 2015.
5. M. Fortunato et al., "Noisy Networks for Exploration." arXiv preprint arXiv:1706.10295, 2017.
6. M. G. Bellemare et al., "A Distributional Perspective on Reinforcement Learning." arXiv preprint arXiv:1707.06887, 2017.
7. R. S. Sutton, "Learning to predict by the methods of temporal differences." Machine learning, 3(1):9–44, 1988.
8. M. Hessel et al., "Rainbow: Combining Improvements in Deep Reinforcement Learning." arXiv preprint arXiv:1710.02298, 2017.

Configurations for Colab

```
import sys
IN_COLAB = "google.colab" in sys.modules

if IN_COLAB:
    !apt install python-opengl
    !apt install ffmpeg
    !apt install xvfb
    !pip install pyvirtualdisplay
    !pip install gym
    from pyvirtualdisplay import Display

    # Start virtual display
    dis = Display(visible=0, size=(400, 400))
    dis.start()
```

```
Reading package lists... Done
Building dependency tree
Reading state information... Done
python-opengl is already the newest version (3.1.0+dfsg-1).
The following package was automatically installed and is no longer required:
```

```
  libnvidia-common-460
Use 'apt autoremove' to remove it.
0 upgraded, 0 newly installed, 0 to remove and 37 not upgraded.
Reading package lists... Done
Building dependency tree
Reading state information... Done
ffmpeg is already the newest version (7:3.4.8-0ubuntu0.2).
The following package was automatically installed and is no longer required:
  libnvidia-common-460
Use 'apt autoremove' to remove it.
0 upgraded, 0 newly installed, 0 to remove and 37 not upgraded.
Reading package lists... Done
Building dependency tree
Reading state information... Done
xvfb is already the newest version (2:1.19.6-1ubuntu4.9).
The following package was automatically installed and is no longer required:
  libnvidia-common-460
Use 'apt autoremove' to remove it.
0 upgraded, 0 newly installed, 0 to remove and 37 not upgraded.
Requirement already satisfied: pyvirtualdisplay in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: EasyProcess in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: gym in /usr/local/lib/python3.7/dist-packages (0.17.3)
Requirement already satisfied: cloudpickle<1.7.0,>=1.2.0 in /usr/local/lib/python3.7/
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: pyglet<=1.5.0,>=1.4.0 in /usr/local/lib/python3.7/dist
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packages (from
```

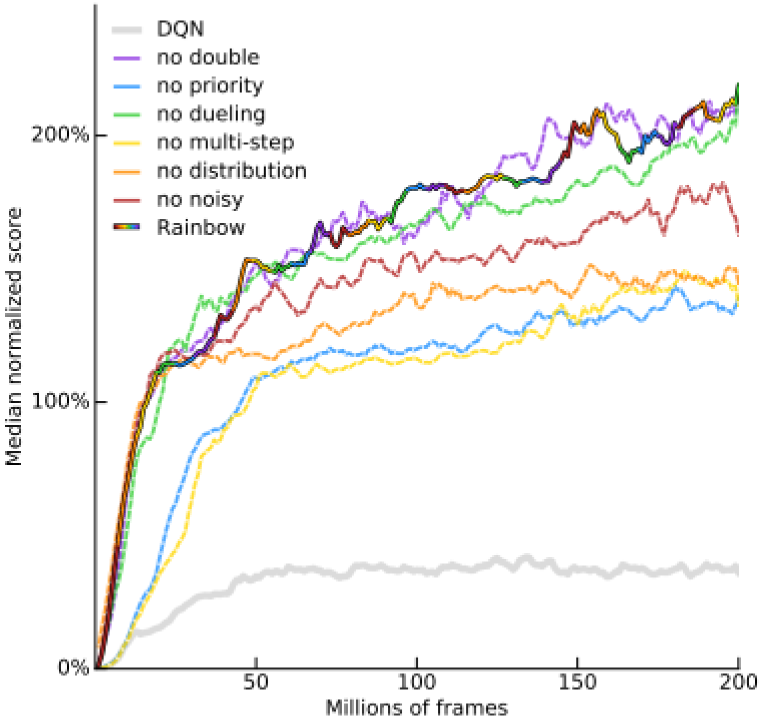
08. Rainbow

[M. Hessel et al., "Rainbow: Combining Improvements in Deep Reinforcement Learning." arXiv preprint arXiv:1710.02298, 2017.]

We will integrate all the following seven components into a single integrated agent, which is called Rainbow!

1. DQN
2. Double DQN
3. Prioritized Experience Replay
4. Dueling Network
5. Noisy Network
6. Categorical DQN
7. N-step Learning

This method shows an impressive performance on the Atari 2600 benchmark, both in terms of data efficiency and final performance.



However, the integration is not so simple because some of components are not independent each other, so we will look into a number of points that people especailly feel confused.

1. Noisy Network <-> Dueling Network
2. Dueling Network <-> Categorical DQN
3. Categorical DQN <-> Double DQN

```
import math
import os
import random
from collections import deque
from typing import Deque, Dict, List, Tuple

import gym
import matplotlib.pyplot as plt
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from IPython.display import clear_output
from torch.nn.utils import clip_grad_norm_

# download segment tree module
if IN_COLAB:
    !wget https://raw.githubusercontent.com/curt-park/rainbow-is-all-you-need/master/segme

from segment_tree import MinSegmentTree, SumSegmentTree
```

```
--2021-10-30 07:44:42--  https://raw.githubusercontent.com/curt-park/rainbow-is-all-y
```

```
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.111.133, 1
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.111.133|
HTTP request sent, awaiting response... 200 OK
Length: 4283 (4.2K) [text/plain]
Saving to: ‘segment_tree.py.1’

segment_tree.py.1   100%[===================>]   4.18K  --.-KB/s    in 0s

2021-10-30 07:44:42 (46.4 MB/s) - ‘segment_tree.py.1’ saved [4283/4283]
```

Replay buffer

Same as the basic N-step buffer.

(Please see *01.dqn.ipynb*, *07.n_step_learning.ipynb* for detailed description about the basic (n-step) replay buffer.)

```
class ReplayBuffer:
    """A simple numpy replay buffer."""

    def __init__(
        self,
        obs_dim: int,
        size: int,
        batch_size: int = 32,
        n_step: int = 1,
        gamma: float = 0.99
    ):
        self.obs_buf = np.zeros([size, obs_dim], dtype=np.float32)
        self.next_obs_buf = np.zeros([size, obs_dim], dtype=np.float32)
        self.acts_buf = np.zeros([size], dtype=np.float32)
        self.rews_buf = np.zeros([size], dtype=np.float32)
        self.done_buf = np.zeros(size, dtype=np.float32)
        self.max_size, self.batch_size = size, batch_size
        self.ptr, self.size, = 0, 0

        # for N-step Learning
        self.n_step_buffer = deque(maxlen=n_step)
        self.n_step = n_step
        self.gamma = gamma

    def store(
        self,
        obs: np.ndarray,
        act: np.ndarray,
        rew: float,
        next_obs: np.ndarray,
        done: bool,
    ) -> Tuple[np.ndarray, np.ndarray, float, np.ndarray, bool]:
        transition = (obs, act, rew, next_obs, done)
        self.n_step_buffer.append(transition)
```

```
        # single step transition is not ready
        if len(self.n_step_buffer) < self.n_step:
            return ()

        # make a n-step transition
        rew, next_obs, done = self._get_n_step_info(
            self.n_step_buffer, self.gamma
        )
        obs, act = self.n_step_buffer[0][:2]

        self.obs_buf[self.ptr] = obs
        self.next_obs_buf[self.ptr] = next_obs
        self.acts_buf[self.ptr] = act
        self.rews_buf[self.ptr] = rew
        self.done_buf[self.ptr] = done
        self.ptr = (self.ptr + 1) % self.max_size
        self.size = min(self.size + 1, self.max_size)

        return self.n_step_buffer[0]

    def sample_batch(self) -> Dict[str, np.ndarray]:
        idxs = np.random.choice(self.size, size=self.batch_size, replace=False)

        return dict(
            obs=self.obs_buf[idxs],
            next_obs=self.next_obs_buf[idxs],
            acts=self.acts_buf[idxs],
            rews=self.rews_buf[idxs],
            done=self.done_buf[idxs],
            # for N-step Learning
            indices=idxs,
        )

    def sample_batch_from_idxs(
        self, idxs: np.ndarray
    ) -> Dict[str, np.ndarray]:
        # for N-step Learning
        return dict(
            obs=self.obs_buf[idxs],
            next_obs=self.next_obs_buf[idxs],
            acts=self.acts_buf[idxs],
            rews=self.rews_buf[idxs],
            done=self.done_buf[idxs],
        )

    def _get_n_step_info(
        self, n_step_buffer: Deque, gamma: float
    ) -> Tuple[np.int64, np.ndarray, bool]:
        """Return n step rew, next_obs, and done."""
        # info of the last transition
        rew, next_obs, done = n_step_buffer[-1][-3:]

        for transition in reversed(list(n_step_buffer)[:-1]):
            r, n_o, d = transition[-3:]
```

```
            rew = r + gamma * rew * (1 - d)
            next_obs, done = (n_o, d) if d else (next_obs, done)

        return rew, next_obs, done

    def __len__(self) -> int:
        return self.size
```

Prioritized replay Buffer

`store` method returns boolean in order to inform if a N-step transition has been generated.

(Please see *02.per.ipynb* for detailed description about PER.)

```
class PrioritizedReplayBuffer(ReplayBuffer):
    """Prioritized Replay buffer.

    Attributes:
        max_priority (float): max priority
        tree_ptr (int): next index of tree
        alpha (float): alpha parameter for prioritized replay buffer
        sum_tree (SumSegmentTree): sum tree for prior
        min_tree (MinSegmentTree): min tree for min prior to get max weight

    """

    def __init__(
        self,
        obs_dim: int,
        size: int,
        batch_size: int = 32,
        alpha: float = 0.6,
        n_step: int = 1,
        gamma: float = 0.99,
    ):
        """Initialization."""
        assert alpha >= 0

        super(PrioritizedReplayBuffer, self).__init__(
            obs_dim, size, batch_size, n_step, gamma
        )
        self.max_priority, self.tree_ptr = 1.0, 0
        self.alpha = alpha

        # capacity must be positive and a power of 2.
        tree_capacity = 1
        while tree_capacity < self.max_size:
            tree_capacity *= 2

        self.sum_tree = SumSegmentTree(tree_capacity)
        self.min_tree = MinSegmentTree(tree_capacity)
```

```
    def store(
        self,
        obs: np.ndarray,
        act: int,
        rew: float,
        next_obs: np.ndarray,
        done: bool,
    ) -> Tuple[np.ndarray, np.ndarray, float, np.ndarray, bool]:
        """Store experience and priority."""
        transition = super().store(obs, act, rew, next_obs, done)

        if transition:
            self.sum_tree[self.tree_ptr] = self.max_priority ** self.alpha
            self.min_tree[self.tree_ptr] = self.max_priority ** self.alpha
            self.tree_ptr = (self.tree_ptr + 1) % self.max_size

        return transition

    def sample_batch(self, beta: float = 0.4) -> Dict[str, np.ndarray]:
        """Sample a batch of experiences."""
        assert len(self) >= self.batch_size
        assert beta > 0

        indices = self._sample_proportional()

        obs = self.obs_buf[indices]
        next_obs = self.next_obs_buf[indices]
        acts = self.acts_buf[indices]
        rews = self.rews_buf[indices]
        done = self.done_buf[indices]
        weights = np.array([self._calculate_weight(i, beta) for i in indices])

        return dict(
            obs=obs,
            next_obs=next_obs,
            acts=acts,
            rews=rews,
            done=done,
            weights=weights,
            indices=indices,
        )

    def update_priorities(self, indices: List[int], priorities: np.ndarray):
        """Update priorities of sampled transitions."""
        assert len(indices) == len(priorities)

        for idx, priority in zip(indices, priorities):
            assert priority > 0
            assert 0 <= idx < len(self)

            self.sum_tree[idx] = priority ** self.alpha
            self.min_tree[idx] = priority ** self.alpha

            self.max_priority = max(self.max_priority, priority)
```

```
    def _sample_proportional(self) -> List[int]:
        """Sample indices based on proportions."""
        indices = []
        p_total = self.sum_tree.sum(0, len(self) - 1)
        segment = p_total / self.batch_size

        for i in range(self.batch_size):
            a = segment * i
            b = segment * (i + 1)
            upperbound = random.uniform(a, b)
            idx = self.sum_tree.retrieve(upperbound)
            indices.append(idx)

        return indices

    def _calculate_weight(self, idx: int, beta: float):
        """Calculate the weight of the experience at idx."""
        # get max weight
        p_min = self.min_tree.min() / self.sum_tree.sum()
        max_weight = (p_min * len(self)) ** (-beta)

        # calculate weights
        p_sample = self.sum_tree[idx] / self.sum_tree.sum()
        weight = (p_sample * len(self)) ** (-beta)
        weight = weight / max_weight

        return weight
```

Noisy Layer

Please see *05.noisy_net.ipynb* for detailed description.

References:

- https://github.com/higgsfield/RL-Adventure/blob/master/5.noisy%20dqn.ipynb
- https://github.com/Kaixhin/Rainbow/blob/master/model.py

```
class NoisyLinear(nn.Module):
    """Noisy linear module for NoisyNet.



    Attributes:
        in_features (int): input size of linear module
        out_features (int): output size of linear module
        std_init (float): initial std value
        weight_mu (nn.Parameter): mean value weight parameter
        weight_sigma (nn.Parameter): std value weight parameter
        bias_mu (nn.Parameter): mean value bias parameter
        bias_sigma (nn.Parameter): std value bias parameter

    """
```

```
    def __init__(
        self,
        in_features: int,
        out_features: int,
        std_init: float = 0.5,
    ):
        """Initialization."""
        super(NoisyLinear, self).__init__()

        self.in_features = in_features
        self.out_features = out_features
        self.std_init = std_init

        self.weight_mu = nn.Parameter(torch.Tensor(out_features, in_features))
        self.weight_sigma = nn.Parameter(
            torch.Tensor(out_features, in_features)
        )
        self.register_buffer(
            "weight_epsilon", torch.Tensor(out_features, in_features)
        )

        self.bias_mu = nn.Parameter(torch.Tensor(out_features))
        self.bias_sigma = nn.Parameter(torch.Tensor(out_features))
        self.register_buffer("bias_epsilon", torch.Tensor(out_features))

        self.reset_parameters()
        self.reset_noise()

    def reset_parameters(self):
        """Reset trainable network parameters (factorized gaussian noise)."""
        mu_range = 1 / math.sqrt(self.in_features)
        self.weight_mu.data.uniform_(-mu_range, mu_range)
        self.weight_sigma.data.fill_(
            self.std_init / math.sqrt(self.in_features)
        )
        self.bias_mu.data.uniform_(-mu_range, mu_range)
        self.bias_sigma.data.fill_(
            self.std_init / math.sqrt(self.out_features)
        )

    def reset_noise(self):
        """Make new noise."""
        epsilon_in = self.scale_noise(self.in_features)
        epsilon_out = self.scale_noise(self.out_features)

        # outer product
        self.weight_epsilon.copy_(epsilon_out.ger(epsilon_in))
        self.bias_epsilon.copy_(epsilon_out)

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        """Forward method implementation.

        We don't use separate statements on train / eval mode.
        It doesn't show remarkable difference of performance.
        """
```

```
        return F.linear(
            x,
            self.weight_mu + self.weight_sigma * self.weight_epsilon,
            self.bias_mu + self.bias_sigma * self.bias_epsilon,
        )

    @staticmethod
    def scale_noise(size: int) -> torch.Tensor:
        """Set scale to make noise (factorized gaussian noise)."""
        x = torch.randn(size)

        return x.sign().mul(x.abs().sqrt())
```

NoisyNet + DuelingNet + Categorical DQN

NoisyNet + DuelingNet

NoisyLinear is employed for the last two layers of advantage and value layers. The noise should be reset at evey update step.

DuelingNet + Categorical DQN

The dueling network architecture is adapted for use with return distributions. The network has a shared representation, which is then fed into a value stream with atom_size outputs, and into an advantage stream with atom_size × out_dim outputs. For each atom, the value and advantage streams are aggregated, as in dueling DQN, and then passed through a softmax layer to obtain the normalized parametric distributions used to estimate the returns' distributions.

```
advantage = self.advantage_layer(adv_hid).view(-1, self.out_dim, self.atom_size)
value = self.value_layer(val_hid).view(-1, 1, self.atom_size)
q_atoms = value + advantage - advantage.mean(dim=1, keepdim=True)

dist = F.softmax(q_atoms, dim=-1)
```

(Please see *04.dueling.ipynb*, *05.noisy_net.ipynb*, *06.categorical_dqn.ipynb* for detailed description of each component's network architecture.)

```
class Network(nn.Module):
    def __init__(
        self,
        in_dim: int,
        out_dim: int,
        atom_size: int,
        support: torch.Tensor
    ):
        """Initialization."""
        super(Network, self).__init__()

        self.support = support
```

```
        self.out_dim = out_dim
        self.atom_size = atom_size

        # set common feature layer
        self.feature_layer = nn.Sequential(
            nn.Linear(in_dim, 128),
            nn.ReLU(),
        )

        # set advantage layer
        self.advantage_hidden_layer = NoisyLinear(128, 128)
        self.advantage_layer = NoisyLinear(128, out_dim * atom_size)

        # set value layer
        self.value_hidden_layer = NoisyLinear(128, 128)
        self.value_layer = NoisyLinear(128, atom_size)

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        """Forward method implementation."""
        dist = self.dist(x)
        q = torch.sum(dist * self.support, dim=2)

        return q

    def dist(self, x: torch.Tensor) -> torch.Tensor:
        """Get distribution for atoms."""
        feature = self.feature_layer(x)
        adv_hid = F.relu(self.advantage_hidden_layer(feature))
        val_hid = F.relu(self.value_hidden_layer(feature))

        advantage = self.advantage_layer(adv_hid).view(
            -1, self.out_dim, self.atom_size
        )
        value = self.value_layer(val_hid).view(-1, 1, self.atom_size)
        q_atoms = value + advantage - advantage.mean(dim=1, keepdim=True)

        dist = F.softmax(q_atoms, dim=-1)
        dist = dist.clamp(min=1e-3)  # for avoiding nans

        return dist

    def reset_noise(self):
        """Reset all noisy layers."""
        self.advantage_hidden_layer.reset_noise()
        self.advantage_layer.reset_noise()
        self.value_hidden_layer.reset_noise()
        self.value_layer.reset_noise()
```

Rainbow Agent

Here is a summary of DQNAgent class.

Method	Note
select_action	select an action from the input state.

Method	Note
step	take an action and return the response of the env.
compute_dqn_loss	return dqn loss.
update_model	update the model by gradient descent.
target_hard_update	hard update from the local model to the target model.
train	train the agent during num_frames.
test	test the agent (1 episode).
plot	plot the training progresses.

Categorical DQN + Double DQN

The idea of Double Q-learning is to reduce overestimations by decomposing the max operation in the target into action selection and action evaluation. Here, we use `self.dqn` instead of `self.dqn_target` to obtain the target actions.

```
# Categorical DQN + Double DQN
# target_dqn is used when we don't employ double DQN
next_action = self.dqn(next_state).argmax(1)
next_dist = self.dqn_target.dist(next_state)
next_dist = next_dist[range(self.batch_size), next_action]
```

```
class DQNAgent:
    """DQN Agent interacting with environment.

    Attribute:
        env (gym.Env): openAI Gym environment
        memory (PrioritizedReplayBuffer): replay memory to store transitions
        batch_size (int): batch size for sampling
        target_update (int): period for target model's hard update
        gamma (float): discount factor
        dqn (Network): model to train and select actions
        dqn_target (Network): target model to update
        optimizer (torch.optim): optimizer for training dqn
        transition (list): transition information including
                           state, action, reward, next_state, done
        v_min (float): min value of support
        v_max (float): max value of support
        atom_size (int): the unit number of support
        support (torch.Tensor): support for categorical dqn
        use_n_step (bool): whether to use n_step memory
        n_step (int): step number to calculate n-step td error
        memory_n (ReplayBuffer): n-step replay buffer
    """

    def __init__(
        self,
        env: gym.Env,
        memory_size: int,
```

```
        batch_size: int,
        target_update: int,
        gamma: float = 0.99,
        # PER parameters
        alpha: float = 0.2,
        beta: float = 0.6,
        prior_eps: float = 1e-6,
        # Categorical DQN parameters
        v_min: float = 0.0,
        v_max: float = 200.0,
        atom_size: int = 51,
        # N-step Learning
        n_step: int = 3,
    ):
        """Initialization.

        Args:
            env (gym.Env): openAI Gym environment
            memory_size (int): length of memory
            batch_size (int): batch size for sampling
            target_update (int): period for target model's hard update
            lr (float): learning rate
            gamma (float): discount factor
            alpha (float): determines how much prioritization is used
            beta (float): determines how much importance sampling is used
            prior_eps (float): guarantees every transition can be sampled
            v_min (float): min value of support
            v_max (float): max value of support
            atom_size (int): the unit number of support
            n_step (int): step number to calculate n-step td error
        """
        obs_dim = env.observation_space.shape[0]
        action_dim = env.action_space.n

        self.env = env
        self.batch_size = batch_size
        self.target_update = target_update
        self.gamma = gamma
        # NoisyNet: All attributes related to epsilon are removed

        # device: cpu / gpu
        self.device = torch.device(
            "cuda" if torch.cuda.is_available() else "cpu"
        )
        print(self.device)

        # PER
        # memory for 1-step Learning
        self.beta = beta
        self.prior_eps = prior_eps
        self.memory = PrioritizedReplayBuffer(
            obs_dim, memory_size, batch_size, alpha=alpha
        )

        # memory for N-step Learning
```

```
        self.use_n_step = True if n_step > 1 else False
        if self.use_n_step:
            self.n_step = n_step
            self.memory_n = ReplayBuffer(
                obs_dim, memory_size, batch_size, n_step=n_step, gamma=gamma
            )

        # Categorical DQN parameters
        self.v_min = v_min
        self.v_max = v_max
        self.atom_size = atom_size
        self.support = torch.linspace(
            self.v_min, self.v_max, self.atom_size
        ).to(self.device)

        # networks: dqn, dqn_target
        self.dqn = Network(
            obs_dim, action_dim, self.atom_size, self.support
        ).to(self.device)
        self.dqn_target = Network(
            obs_dim, action_dim, self.atom_size, self.support
        ).to(self.device)
        self.dqn_target.load_state_dict(self.dqn.state_dict())
        self.dqn_target.eval()

        # optimizer
        self.optimizer = optim.Adam(self.dqn.parameters())

        # transition to store in memory
        self.transition = list()

        # mode: train / test
        self.is_test = False

    def select_action(self, state: np.ndarray) -> np.ndarray:
        """Select an action from the input state."""
        # NoisyNet: no epsilon greedy action selection
        selected_action = self.dqn(
            torch.FloatTensor(state).to(self.device)
        ).argmax()
        selected_action = selected_action.detach().cpu().numpy()

        if not self.is_test:
            self.transition = [state, selected_action]

        return selected_action

    def step(self, action: np.ndarray) -> Tuple[np.ndarray, np.float64, bool]:
        """Take an action and return the response of the env."""
        next_state, reward, done, _ = self.env.step(action)

        if not self.is_test:
            self.transition += [reward, next_state, done]

            # N-step transition
```

```
            if self.use_n_step:
                one_step_transition = self.memory_n.store(*self.transition)
            # 1-step transition
            else:
                one_step_transition = self.transition

            # add a single step transition
            if one_step_transition:
                self.memory.store(*one_step_transition)

        return next_state, reward, done

    def update_model(self) -> torch.Tensor:
        """Update the model by gradient descent."""
        # PER needs beta to calculate weights
        samples = self.memory.sample_batch(self.beta)
        weights = torch.FloatTensor(
            samples["weights"].reshape(-1, 1)
        ).to(self.device)
        indices = samples["indices"]

        # 1-step Learning loss
        elementwise_loss = self._compute_dqn_loss(samples, self.gamma)

        # PER: importance sampling before average
        loss = torch.mean(elementwise_loss * weights)

        # N-step Learning loss
        # we are gonna combine 1-step loss and n-step loss so as to
        # prevent high-variance. The original rainbow employs n-step loss only.
        if self.use_n_step:
            gamma = self.gamma ** self.n_step
            samples = self.memory_n.sample_batch_from_idxs(indices)
            elementwise_loss_n_loss = self._compute_dqn_loss(samples, gamma)
            elementwise_loss += elementwise_loss_n_loss

            # PER: importance sampling before average
            loss = torch.mean(elementwise_loss * weights)

        self.optimizer.zero_grad()
        loss.backward()
        clip_grad_norm_(self.dqn.parameters(), 10.0)
        self.optimizer.step()

        # PER: update priorities
        loss_for_prior = elementwise_loss.detach().cpu().numpy()
        new_priorities = loss_for_prior + self.prior_eps
        self.memory.update_priorities(indices, new_priorities)

        # NoisyNet: reset noise
        self.dqn.reset_noise()
        self.dqn_target.reset_noise()

        return loss.item()
```

```
    def train(self, num_frames: int, plotting_interval: int = 200):
        """Train the agent."""
        self.is_test = False

        state = self.env.reset()
        update_cnt = 0
        losses = []
        scores = []
        score = 0

        for frame_idx in range(1, num_frames + 1):
            action = self.select_action(state)
            next_state, reward, done = self.step(action)

            state = next_state
            score += reward

            # NoisyNet: removed decrease of epsilon

            # PER: increase beta
            fraction = min(frame_idx / num_frames, 1.0)
            self.beta = self.beta + fraction * (1.0 - self.beta)

            # if episode ends
            if done:
                state = self.env.reset()
                scores.append(score)
                score = 0

            # if training is ready
            if len(self.memory) >= self.batch_size:
                loss = self.update_model()
                losses.append(loss)
                update_cnt += 1

                # if hard update is needed
                if update_cnt % self.target_update == 0:
                    self._target_hard_update()

            # plotting
            if frame_idx % plotting_interval == 0:
                self._plot(frame_idx, scores, losses)

        self.env.close()

    def test(self) -> List[np.ndarray]:
        """Test the agent."""
        self.is_test = True

        state = self.env.reset()
        done = False
        score = 0

        frames = []
        while not done:
```

```
            frames.append(self.env.render(mode="rgb_array"))
            action = self.select_action(state)
            next_state, reward, done = self.step(action)

            state = next_state
            score += reward

        print("score: ", score)
        self.env.close()

        return frames

    def _compute_dqn_loss(self, samples: Dict[str, np.ndarray], gamma: float) -> torch.Ten
        """Return categorical dqn loss."""
        device = self.device  # for shortening the following lines
        state = torch.FloatTensor(samples["obs"]).to(device)
        next_state = torch.FloatTensor(samples["next_obs"]).to(device)
        action = torch.LongTensor(samples["acts"]).to(device)
        reward = torch.FloatTensor(samples["rews"].reshape(-1, 1)).to(device)
        done = torch.FloatTensor(samples["done"].reshape(-1, 1)).to(device)

        # Categorical DQN algorithm
        delta_z = float(self.v_max - self.v_min) / (self.atom_size - 1)

        with torch.no_grad():
            # Double DQN
            next_action = self.dqn(next_state).argmax(1)
            next_dist = self.dqn_target.dist(next_state)
            next_dist = next_dist[range(self.batch_size), next_action]

            t_z = reward + (1 - done) * gamma * self.support
            t_z = t_z.clamp(min=self.v_min, max=self.v_max)
            b = (t_z - self.v_min) / delta_z
            l = b.floor().long()
            u = b.ceil().long()

            offset = (
                torch.linspace(
                    0, (self.batch_size - 1) * self.atom_size, self.batch_size
                ).long()
                .unsqueeze(1)
                .expand(self.batch_size, self.atom_size)
                .to(self.device)
            )

            proj_dist = torch.zeros(next_dist.size(), device=self.device)
            proj_dist.view(-1).index_add_(
                0, (l + offset).view(-1), (next_dist * (u.float() - b)).view(-1)
            )
            proj_dist.view(-1).index_add_(
                0, (u + offset).view(-1), (next_dist * (b - l.float())).view(-1)
            )

        dist = self.dqn.dist(state)
        log_p = torch.log(dist[range(self.batch_size), action])
```

```
        elementwise_loss = -(proj_dist * log_p).sum(1)

        return elementwise_loss

    def _target_hard_update(self):
        """Hard update: target <- local."""
        self.dqn_target.load_state_dict(self.dqn.state_dict())

    def _plot(
        self,
        frame_idx: int,
        scores: List[float],
        losses: List[float],
    ):
        """Plot the training progresses."""
        clear_output(True)
        plt.figure(figsize=(20, 5))
        plt.subplot(131)
        plt.title('frame %s. score: %s' % (frame_idx, np.mean(scores[-10:])))
        plt.plot(scores)
        plt.subplot(132)
        plt.title('loss')
        plt.plot(losses)
        plt.show()
```

Environment

You can see the code and configurations of CartPole-v0 from OpenAI's repository.

```
# environment
env_id = "CartPole-v0"
env = gym.make(env_id)
if IN_COLAB:
    env = gym.wrappers.Monitor(env, "videos", force=True)
```

Set random seed

```
seed = 777

def seed_torch(seed):
    torch.manual_seed(seed)
    if torch.backends.cudnn.enabled:
        torch.backends.cudnn.benchmark = False
        torch.backends.cudnn.deterministic = True

np.random.seed(seed)
random.seed(seed)
seed_torch(seed)
env.seed(seed)
```

```
[777]
```

Initialize

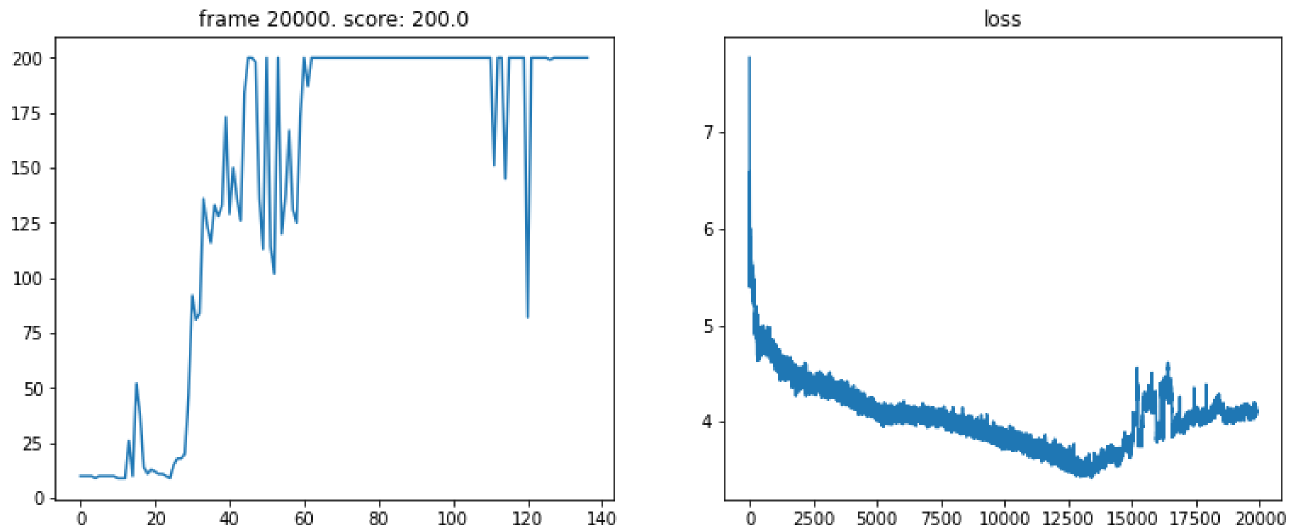
```
# parameters
num_frames = 20000
memory_size = 10000
batch_size = 128
target_update = 100

# train
agent = DQNAgent(env, memory_size, batch_size, target_update)
```

```
cpu
```

Train

```
agent.train(num_frames)
```



Test

Run the trained agent (1 episode).

```
frames = agent.test()
```

```
score:  200.0
```

Render

```
if IN_COLAB:  # for colab
    import base64
    import glob
    import io
    import os

    from IPython.display import HTML, display


    def ipython_show_video(path: str) -> None:
        """Show a video at `path` within IPython Notebook."""
        if not os.path.isfile(path):
            raise NameError("Cannot access: {}".format(path))

        video = io.open(path, "r+b").read()
        encoded = base64.b64encode(video)

        display(HTML(
            data="""
            <video alt="test" controls>
            <source src="data:video/mp4;base64,{0}" type="video/mp4" />
            </video>
            """.format(encoded.decode("ascii"))
        ))

    list_of_files = glob.glob("videos/*.mp4")
    latest_file = max(list_of_files, key=os.path.getctime)
    print(latest_file)
    ipython_show_video(latest_file)

else:  # for jupyter
    from matplotlib import animation
    from JSAnimation.IPython_display import display_animation
    from IPython.display import display


    def display_frames_as_gif(frames):
        """Displays a list of frames as a gif, with controls."""
        patch = plt.imshow(frames[0])
        plt.axis('off')

        def animate(i):
            patch.set_data(frames[i])

        anim = animation.FuncAnimation(
            plt.gcf(), animate, frames = len(frames), interval=50
        )
        display(display_animation(anim, default_mode='loop'))


    # display
    display_frames_as_gif(frames)
```

videos/openaigym.video.0.886.video000125.mp4

0:00 / 0:04

Conclusion

Thus in this Mini Project, we have observed the superior performance of Rainbow technique while solving the Cartpole problem and observed the performance of the model by rendering it on screen. It is interesting to observe the training curves and watching the model improve over time and plateau, with increase in training time. The end model is able to maintain the Cartpole balance as seen in the video above and we have learnt many interesting concepts about Reinforcement Learning in the process.

0s completed at 1:22 PM