Breakout-dqn

December 10, 2019

[1]:
```
%%javascript
IPython.OutputArea.prototype._should_scroll = function(lines) {
    return false;
}
```

```
<IPython.core.display.Javascript object>
```

[2]:
```
import math, random
# import pandas as pd
import gym
import numpy as np
import tqdm
import torch
import torch.nn as nn
import torch.optim as optim
import torch.autograd as autograd
import torch.nn.functional as F
```

[3]:
```
from IPython.display import clear_output
import matplotlib.pyplot as plt
%matplotlib inline
```

Use Cuda

[4]:
```
USE_CUDA = torch.cuda.is_available()
Variable = lambda *args, **kwargs: autograd.Variable(*args, **kwargs).cuda() if␣
↪USE_CUDA else autograd.Variable(*args, **kwargs)
```

Replay Buffer

[5]:
```
from collections import deque

class ReplayBuffer(object):
    def __init__(self, capacity):
        self.buffer = deque(maxlen=capacity)

    def push(self, state, action, reward, next_state, done):
        state      = np.expand_dims(state, 0)
        next_state = np.expand_dims(next_state, 0)
```

```
        self.buffer.append((state, action, reward, next_state, done))

    def sample(self, batch_size):
        state, action, reward, next_state, done = zip(*random.sample(self.buffer, batch_size))
        return np.concatenate(state), action, reward, np.concatenate(next_state), done

    def __len__(self):
        return len(self.buffer)
```

Cart Pole Environment

[6]:
```
env_id = "CartPole-v1"
env = gym.make(env_id)
```

Epsilon greedy exploration

[7]:
```
class ExponentialSchedule:
    def __init__(self, value_from, value_to, num_steps):
        """Exponential schedule from `value_from` to `value_to` in `num_steps` steps.

        $value(t) = a \exp (b t)$

        :param value_from: initial value
        :param value_to: final value
        :param num_steps: number of steps for the exponential schedule
        """
        self.value_from = value_from
        self.value_to = value_to
        self.num_steps = num_steps

        # YOUR CODE HERE:  determine the `a` and `b` parameters such that the schedule is correct
        self.a = self.value_from
        self.b = np.log(self.a/self.value_to)/ (self.num_steps-1)

    def value(self, step) -> float:
        """Return exponentially interpolated value between `value_from` and `value_to`interpolated value between.

        returns {
            `value_from`, if step == 0 or less
            `value_to`, if step == num_steps - 1 or more
            the exponential interpolation between `value_from` and `value_to`, if 0 <= steps < num_steps
        }
```

```
        :param step:  The step at which to compute the interpolation.
        :rtype: float.  The interpolated value.
        """

        # YOUR CODE HERE:  implement the schedule rule as described in the␣
↪docstring,
        # using attributes `self.a` and `self.b`.
        #value = ...

        if step <= 0:
            value = self.value_from
            return value

        if step >= self.num_steps - 1:
            value = self.value_to
            return value

        value = self.a/np.exp(self.b*step)
        return value
```

Deep Q Network

[8]:
```
class DQN(nn.Module):
    def __init__(self, num_inputs, num_actions):
        super(DQN, self).__init__()

        self.layers = nn.Sequential(
            nn.Linear(env.observation_space.shape[0], 128),
            nn.ReLU(),
            nn.Linear(128, 128),
            nn.ReLU(),
            nn.Linear(128, env.action_space.n)
        )

    def forward(self, x):
        return self.layers(x)

    def act(self, state, epsilon):
        if random.random() > epsilon:
            #state   = Variable(torch.FloatTensor(state).unsqueeze(0),␣
↪volatile=True)
            with torch.no_grad():
                state = Variable(torch.FloatTensor(state).unsqueeze(0))
            q_value = self.forward(state)
#             action  = q_value.max(1)[1].data[0]
            action = q_value.max(1)[1].item()
        else:
```

```
            action = random.randrange(env.action_space.n)
        return action
```

[9]:
```
model = DQN(env.observation_space.shape[0], env.action_space.n)

if USE_CUDA:
    model = model.cuda()

optimizer = optim.Adam(model.parameters(),lr=5e-3)

replay_buffer = ReplayBuffer(5000)
```

Computing Temporal Difference Loss

[10]:
```
def compute_td_loss(batch_size):
    state, action, reward, next_state, done = replay_buffer.sample(batch_size)

    state      = Variable(torch.FloatTensor(np.float32(state)))
    #next_state = Variable(torch.FloatTensor(np.float32(next_state)),␣
↪volatile=True)
    with torch.no_grad():
        next_state = Variable(torch.FloatTensor(np.float32(next_state)))
    action     = Variable(torch.LongTensor(action))
    reward     = Variable(torch.FloatTensor(reward))
    done       = Variable(torch.FloatTensor(done))

    q_values      = model(state)
    next_q_values = model(next_state)

    q_value          = q_values.gather(1, action.unsqueeze(1)).squeeze(1)
    next_q_value     = next_q_values.max(1)[0]
    expected_q_value = reward + gamma * next_q_value * (1 - done)

    loss = (q_value - Variable(expected_q_value.data)).pow(2).mean()

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    return loss
```

[11]:
```
def plot(frame_idx, rewards, losses):
    clear_output(True)
    plt.figure(figsize=(20,5))
    plt.subplot(131)
    plt.title('frame %s. reward: %s' % (frame_idx, np.mean(rewards[-10:])))
    plt.plot(rewards)
    plt.subplot(132)
    plt.title('loss')
```

```
    plt.plot(losses)
    plt.show()
```

Training

[12]:

```
num_frames = 100_000
batch_size = 128
gamma      = 0.99

losses = []
all_rewards = []
t_episode = 0
i_episode = 0
episode_reward = []
lengths = []
exploration = ExponentialSchedule(1.0, 0.05, 30_000)

pbar = tqdm.tnrange(num_frames, ncols='100%')
state = env.reset()
for frame_idx in pbar:
    epsilon = exploration.value(frame_idx)
    action = model.act(state, epsilon)

    next_state, reward, done, _ = env.step(action)
    episode_reward.append(reward)

    replay_buffer.push(state, action, reward, next_state, done)

    state = next_state
    t_episode += 1
    if done:
        lengths.append(t_episode)
        state = env.reset()
        G = 0
        for i in reversed(episode_reward):
            G = i + G*gamma
        all_rewards.append(G)
        episode_reward = []
        i_episode += 1
        pbar.set_description(
                f'Episode: {i_episode} | Steps: {t_episode + 1} | Return: {G:5.
 ↪2f} | Epsilon: {epsilon:4.2f}'
            )
        t_episode = 0

    if len(replay_buffer) > batch_size:
        loss = compute_td_loss(batch_size)
#          losses.append(loss.data[0])
```

```
        losses.append(loss.item())

    #if frame_idx % 200 == 0:
    #    plot(frame_idx, all_rewards, losses)
```

```
HBox(children=(IntProgress(value=0, layout=Layout(flex='2'), max=100000), HTML(value='')), layou
```

Atari Environment

[13]:
```
from wrappers import make_atari, wrap_deepmind, wrap_pytorch
```

[14]:
```
env_id = "BreakoutNoFrameskip-v4"
env    = make_atari(env_id)
env    = wrap_deepmind(env)
env    = wrap_pytorch(env)
```

[15]:
```
class CnnDQN(nn.Module):
    def __init__(self, input_shape, num_actions):
        super(CnnDQN, self).__init__()

        self.input_shape = input_shape
        self.num_actions = num_actions

        self.features = nn.Sequential(
            nn.Conv2d(input_shape[0], 32, kernel_size=8, stride=4),
            nn.ReLU(),
            nn.Conv2d(32, 64, kernel_size=4, stride=2),
            nn.ReLU(),
            nn.Conv2d(64, 64, kernel_size=3, stride=1),
            nn.ReLU()
        )

        self.fc = nn.Sequential(
            nn.Linear(self.feature_size(), 512),
            nn.ReLU(),
            nn.Linear(512, self.num_actions)
        )

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.fc(x)
        return x

    def feature_size(self):
        return self.features(autograd.Variable(torch.zeros(1, *self.
↪input_shape))).view(1, -1).size(1)
```

```
    def act(self, state, epsilon):
        if random.random() > epsilon:
            #state   = Variable(torch.FloatTensor(np.float32(state)).
↪unsqueeze(0), volatile=True)
            with torch.no_grad():
                state = Variable(torch.FloatTensor(np.float32(state)).
↪unsqueeze(0))
            q_value = self.forward(state)
            action  = q_value.max(1)[1].data[0]
        else:
            action = random.randrange(env.action_space.n)
        return action
```

[16]:
```
model = CnnDQN(env.observation_space.shape, env.action_space.n)

if USE_CUDA:
    model = model.cuda()

optimizer = optim.Adam(model.parameters(), lr=0.0001)

replay_initial = 10_000
replay_buffer = ReplayBuffer(100_000)
```

[17]:
```
num_frames = 2_000_000
batch_size = 32
gamma      = 0.99
losses = []
returns = []
lengths = []
episode_reward = []
t_episode = 0
i_episode = 0
exploration = ExponentialSchedule(1.0, 0.05, 1_000_000)
state = env.reset()
pbar = tqdm.tnrange(num_frames, ncols='100%')
# for frame_idx in range(1, num_frames + 1):
for frame_idx in pbar:
#     epsilon = epsilon_by_frame(frame_idx)
    epsilon = exploration.value(frame_idx)
    action = model.act(state, epsilon)
    next_state, reward, done, _ = env.step(action)
    replay_buffer.push(state, action, reward, next_state, done)
    state = next_state
    episode_reward.append(reward)
    if done:
        state = env.reset()
        G = 0
```

```
        for i in reversed(episode_reward):
            G = i + G * gamma
        returns.append(G)
        episode_reward = []
        pbar.set_description(
                f'Episode: {i_episode} | Steps: {t_episode + 1} | Return: {G:5.
→2f} | Epsilon: {epsilon:4.2f}'
            )
        lengths.append(t_episode+1)
        t_episode = 0
        i_episode += 1
    else:
        t_episode += 1
    if len(replay_buffer) > replay_initial:0
        loss = compute_td_loss(batch_size)
        losses.append(loss.item())
#      if frame_idx % 10000 == 0:
#          plot(frame_idx, all_rewards, losses)
```

```
HBox(children=(IntProgress(value=0, layout=Layout(flex='2'), max=2000000), HTML(value='')), layo
```

[18]:
```
def plot(frame_idx, returns, lengths, losses):
    clear_output(True)
    # YOUR PLOTS HERE
    epochs = np.arange(len(returns))
    # smooth data
    smoothed_returns = rolling_average(returns, window_size = 100)
    smoothed_lengths = rolling_average(lengths, window_size = 100)
    smoothed_losses = rolling_average(losses, window_size = 100)
    # plot the returns
    fig = plt.figure(figsize=(14, 10))
    ax1 = fig.add_subplot(311)
    line_1, = ax1.plot(epochs, returns, 'salmon', linewidth=2.0)
    line_2, = ax1.plot(epochs, smoothed_returns, 'r', linewidth=2.0)
    plt.xlabel('Number of episodes')
    plt.ylabel('Averaged returns')
    plt.title('Returns')
    plt.legend((line_1, line_2), ('raw', 'smoothed'))
    ax2 = fig.add_subplot(312)
    line_1, = ax2.plot(epochs, lengths, 'lightblue', linewidth=2.0)
    line_2, = ax2.plot(epochs, smoothed_lengths, 'b', linewidth=2.0)
    plt.xlabel('Number of episodes')
    plt.ylabel('Averaged lengths')
    plt.title('Lengths')
```

```
    plt.legend((line_1, line_2), ('raw', 'smoothed'))
    ax3 = fig.add_subplot(313)
    epochs = np.arange(len(losses))
    line_1, = ax3.plot(epochs, losses, 'lightgreen', linewidth=2.0)
    line_2, = ax3.plot(epochs, smoothed_losses, 'g', linewidth=2.0)
    plt.xlabel('Number of time step')
    plt.ylabel('Loss')
    plt.title('Loss')
    plt.legend((line_1, line_2), ('raw', 'smoothed'))
    plt.show()
#     plt.figure(figsize=(100,25))
#     plt.subplot(131)
#     plt.title('frame %s. reward: %s' % (frame_idx, np.mean(rewards[-10:])))
#     plt.plot(returns)
#     plt.subplot(132)
#     plt.title('loss')
#     plt.plot(losses)
#     plt.show()
```

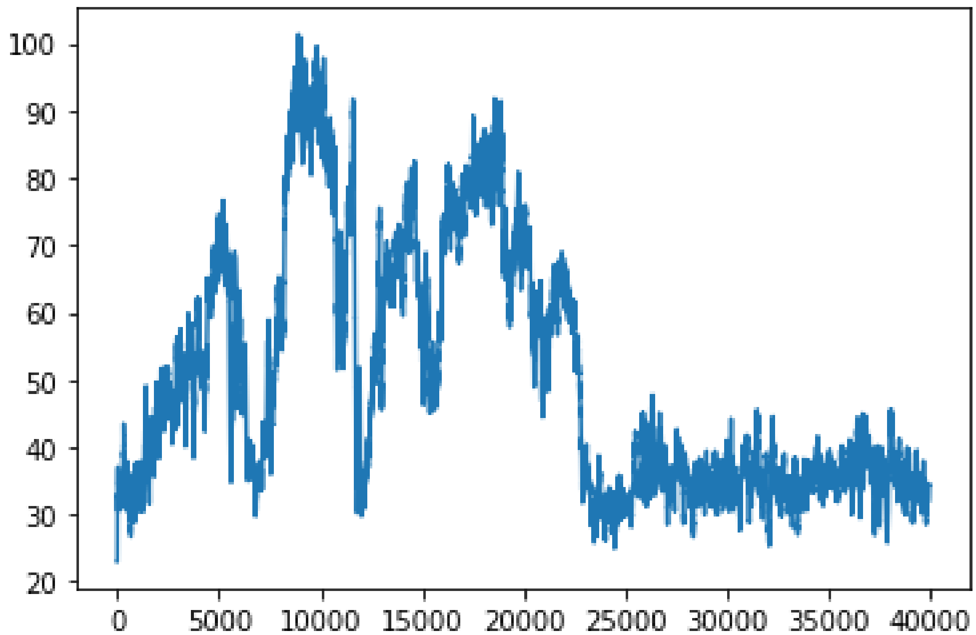
[19]:
```
def rolling_average(data, *, window_size):
    """Smoothen the 1-d data array using a rollin average.

    Args:
        data: 1-d numpy.array
        window_size: size of the smoothing window

    Returns:
        smooth_data: a 1-d numpy.array with the same size as data
    """
#     assert data.ndim == 1
    kernel = np.ones(window_size)
    smooth_data = np.convolve(data, kernel) / np.convolve(
        np.ones_like(data), kernel
    )
    return smooth_data[: -window_size + 1]
```

[20]:
```
plt.plot(rolling_average(lengths, window_size = 100))
```

[20]:
```
[<matplotlib.lines.Line2D at 0x7f7685d03470>]
```



[ ]:

```

```

[21]:

```
import pandas as pd

a1 = np.array(lengths)
b1 = np.array(returns)

df = pd.DataFrame({"lengths" : a1, "returns" : b1})
df.to_csv("breakout_eps_dqn.csv", index=False)
```

```
/usr/local/lib/python3.6/site-packages/pandas/compat/__init__.py:85:
UserWarning: Could not import the lzma module. Your installed Python is
incomplete. Attempting to use lzma compression will result in a RuntimeError.
  warnings.warn(msg)
```

[ ]:

```

```