Breakout_dueling_dqn

December 10, 2019

[1]:
```
import math, random

import gym
import numpy as np

import torch
import torch.nn as nn
import torch.optim as optim
import torch.autograd as autograd
import torch.nn.functional as F

import copy
import os
import ipywidgets as widgets
import tqdm
# import pandas as pd
```

[2]:
```
from IPython.display import clear_output
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
plt.rcParams['figure.figsize'] = [12, 4]
```

Use Cuda

[3]:
```
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

[4]:
```
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)
```

Smoothing

[5]:
```
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]
```

Cart Pole Environment

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

Epsilon greedy exploration

[7]:
```
# epsilon_start = 1.0
# epsilon_final = 0.01
# epsilon_decay = 50000

# epsilon_by_frame = lambda frame_idx: epsilon_final + (epsilon_start -␣
 ↪epsilon_final) * math.exp(-1. * frame_idx / epsilon_decay)
```

[8]:
```
# plt.plot([epsilon_by_frame(i) for i in range(1_000_00)])
```

[9]:
```
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
```

```python
# test code, do not edit

def _test_schedule(schedule, step, value, ndigits=5):
    """Tests that the schedule returns the correct value."""
    v = schedule.value(step)
    if not round(v, ndigits) == round(value, ndigits):
        raise Exception(
            f'For step {step}, the scheduler returned {v} instead of {value}'
        )


_schedule = ExponentialSchedule(0.1, 0.2, 3)
_test_schedule(_schedule, -1, 0.1)
_test_schedule(_schedule, 0, 0.1)
_test_schedule(_schedule, 1, 0.141421356237309515)
_test_schedule(_schedule, 2, 0.2)
_test_schedule(_schedule, 3, 0.2)
del _schedule

_schedule = ExponentialSchedule(0.5, 0.1, 5)
_test_schedule(_schedule, -1, 0.5)
_test_schedule(_schedule, 0, 0.5)
_test_schedule(_schedule, 1, 0.33437015248821106)
_test_schedule(_schedule, 2, 0.22360679774997905)
_test_schedule(_schedule, 3, 0.14953487812212207)
_test_schedule(_schedule, 4, 0.1)
_test_schedule(_schedule, 5, 0.1)
del _schedule
```

Dueling Deep Q Network

[10]:
```python
class DuelingDQN(nn.Module):
    def __init__(self, num_inputs, num_outputs):
        super(DuelingDQN, self).__init__()



        self.feature = nn.Sequential(
            nn.Linear(num_inputs, 128),
            nn.ReLU()
        )

        self.advantage = nn.Sequential(
            nn.Linear(128, 128),
            nn.ReLU(),
            nn.Linear(128, num_outputs)
        )

        self.value = nn.Sequential(
```

```
            nn.Linear(128, 128),
            nn.ReLU(),
            nn.Linear(128, 1)
        )

    def forward(self, x):
        x = self.feature(x)
        advantage = self.advantage(x)
        value     = self.value(x)
        return value + advantage  - advantage.mean()

    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
```

[11]:
```
current_model = DuelingDQN(env.observation_space.shape[0], env.action_space.n)
target_model  = DuelingDQN(env.observation_space.shape[0], env.action_space.n)

if USE_CUDA:
    current_model = current_model.cuda()
    target_model  = target_model.cuda()

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

replay_buffer = ReplayBuffer(10_000)
```

Synchronize current policy net and target net

[12]:
```
def update_target(current_model, target_model):
    target_model.load_state_dict(current_model.state_dict())
```

[13]:
```
update_target(current_model, target_model)
```

Computing Temporal Difference Loss

[14]:
```
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)))
    action     = Variable(torch.LongTensor(action))
```

```
    reward     = Variable(torch.FloatTensor(reward))
    done       = Variable(torch.FloatTensor(done))

    q_values      = current_model(state)
    next_q_values = target_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 - expected_q_value.detach()).pow(2).mean()

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

#     return loss
    return loss
```

[15]:
```
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))
```

```python
    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()
```

Training

[16]:
```python
# num_frames = 10000
num_frames = 1_00_00
batch_size = 128
gamma      = 0.99

losses = []
returns = []
lengths = []
episode_reward = []
t_episode = 0
i_episode = 0
exploration = ExponentialSchedule(1.0, 0.05, 30_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 = current_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()
```

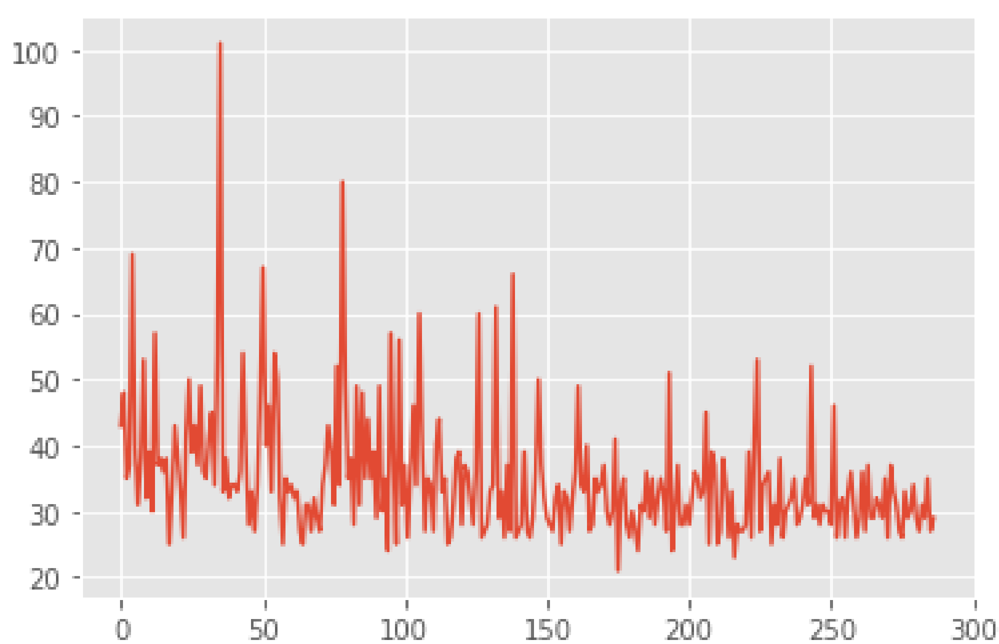
```
        G = 0
        for i in reversed(episode_reward):
            G = i + G * gamma
        returns.append(G)
        episode_reward = []
        pbar.set_description(
                f'Episode: {i_episode} | Steps: {t_episode + 1} | Return: {G:5.
↪2f} | Epsilon: {epsilon:4.2f}'
            )
        lengths.append(t_episode+1)
        t_episode = 0
        i_episode += 1
    else:
        t_episode += 1

    if len(replay_buffer) > 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, lengths, losses)

    if frame_idx % 1000 == 0:
        update_target(current_model, target_model)
```

```
HBox(children=(IntProgress(value=0, layout=Layout(flex='2'), max=10000), HTML(value='')), layout
```

[17]:
```
plot(frame_idx, returns, lengths, losses)
```

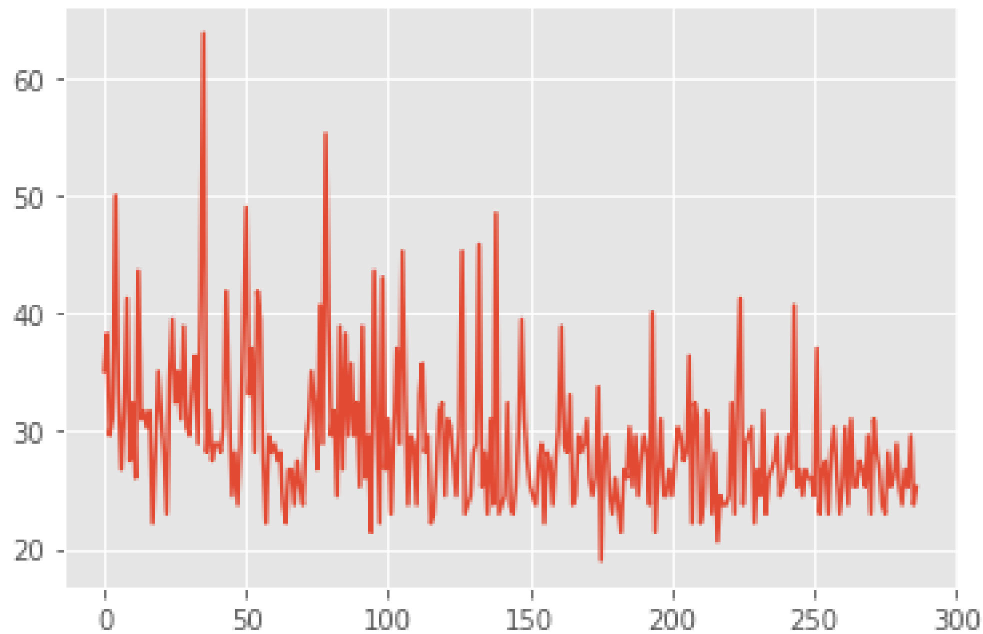
[18]: `plt.plot(lengths)`

[18]: `[<matplotlib.lines.Line2D at 0x7fbfd1015048>]`



[19]:
```
plt.plot(returns)
```

[19]: [<matplotlib.lines.Line2D at 0x7fbfd10b5358>]



Atari Environment

[20]:
```
from wrappers import make_atari, wrap_deepmind, wrap_pytorch
```

[21]:
```
env_id = "BreakoutNoFrameskip-v4"
#env_id = "PongNoFrameskip-v4"
env    = make_atari(env_id)
env    = wrap_deepmind(env)
env    = wrap_pytorch(env)
```

[22]:
```
class DuelingCnnDQN(nn.Module):
    def __init__(self, input_shape, num_outputs):
        super(DuelingCnnDQN, self).__init__()


        self.input_shape = input_shape
        self.num_actions = num_outputs

        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.advantage = nn.Sequential(
            nn.Linear(self.feature_size(), 512),
            nn.ReLU(),
            nn.Linear(512, num_outputs)
        )

        self.value = nn.Sequential(
            nn.Linear(self.feature_size(), 512),
            nn.ReLU(),
            nn.Linear(512, 1)
        )

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        advantage = self.advantage(x)
        value     = self.value(x)
        return value + advantage  - advantage.mean()

    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
```

[23]:
```
current_model = DuelingCnnDQN(env.observation_space.shape, env.action_space.n)
target_model  = DuelingCnnDQN(env.observation_space.shape, env.action_space.n)

if USE_CUDA:
    current_model = current_model.cuda()
    target_model  = target_model.cuda()
```

```python
optimizer = optim.Adam(current_model.parameters(), lr=0.0001)

replay_initial = 10_000
replay_buffer = ReplayBuffer(100_000)
# replay_initial = 50
# replay_buffer = ReplayBuffer(100)

update_target(current_model, target_model)
```

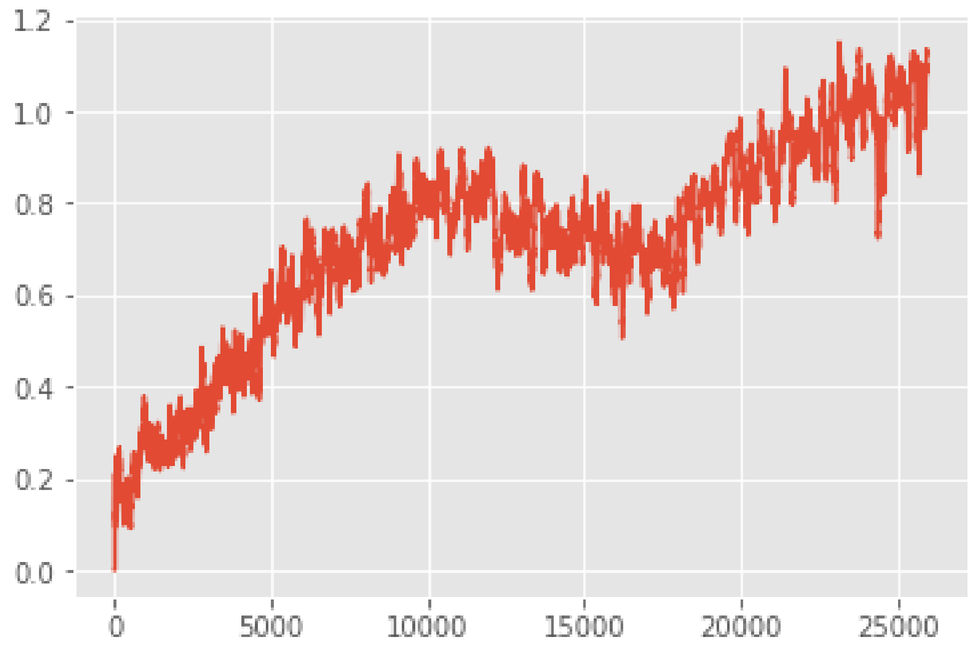
[24]:
```python
num_frames = 2_000_000
# num_frames = 1000
batch_size = 32
gamma      = 0.99

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 = current_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:
        loss = compute_td_loss(batch_size)
        losses.append(loss.item())

#     if frame_idx % 10000 == 0:
#         plot(frame_idx, all_rewards, losses)

    if frame_idx % 1000 == 0:
        update_target(current_model, target_model)
```

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

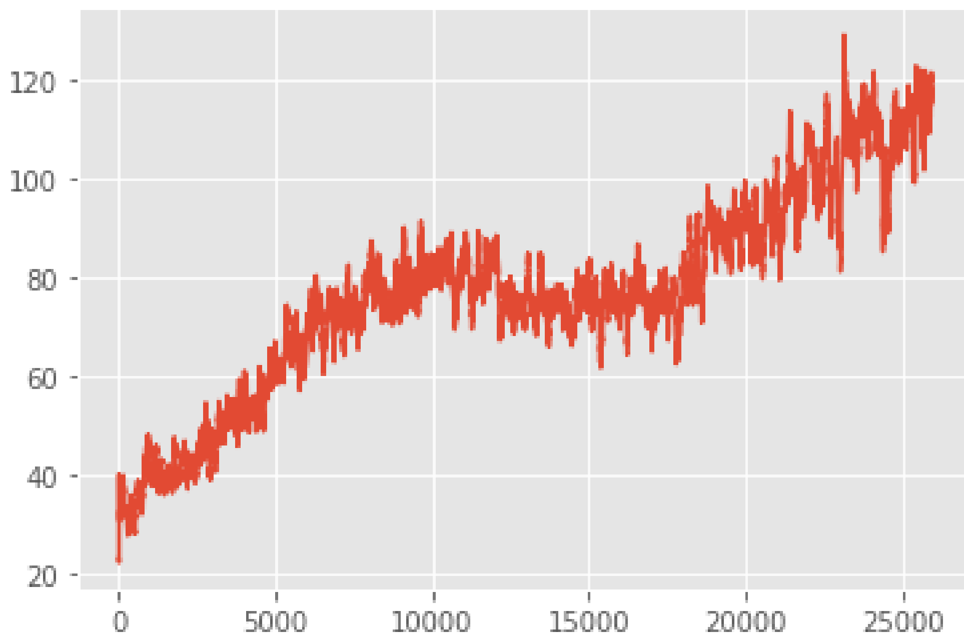
[25]:
```
plt.plot(rolling_average(returns, window_size = 100))
```

[25]:
```
[<matplotlib.lines.Line2D at 0x7fbf767b2b38>]
```



[26]:
```
plt.plot(rolling_average(lengths, window_size = 100))
```

[26]:
```
[<matplotlib.lines.Line2D at 0x7fbf76707e10>]
```



[27]:
```
import pandas as pd

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

df = pd.DataFrame({"lengths" : a1, "returns" : b1})
df.to_csv("breakout_eps1_dueling_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)
```

[ ]:
```

```