dqn

December 7, 2023

1 Custom QDN implementation and evaluation

1.1 List of Contents

1.1.1 Provided classes

- default_params() this dictionary defines the default hyper-parameters
- TransitionBatch the basic class to summarize transitions and build an experience replay buffer.
- Runner interacts with one environment
- MultiRunner runs multiple `Runner` in parallel
- QController translates the model outputs into greedy actions
- EpsilonGreedyController performs epsilon-greedy exploration
- QLearner trains the model with Q-learning loss
- Experment encapsulates and executes a single experiment
- QLearningExperiment performs online Q-learning

1.1.2 Exercises

- A2.1a) Run online Q-learning
- A2.1b) Use a replay buffer in Q-learning
- A2.1c) Implement target networks wth hard updates
- A2.1d) Implement target networks with soft updates
- A2.1e) Implement Double Q-learning
- A2.1f) Run double Q-learning on MountainCar
- A2.1g) Run double Q-learning on LunarLander

[ ]:
```
# Pytorch and tools
import torch as th
from torch import Tensor, LongTensor
from torch.utils.data import DataLoader
import numpy as np
from copy import deepcopy
import numbers
from datetime import datetime

# Multi-threading
import threading
```

```python
# Plotting
from IPython import display
import matplotlib.pyplot as plt
import pylab as pl

# Reinforcement learning
import gymnasium as gym
import cv2
```

This dictionary defines the default hyper-paramerters that you will use in your experiments.

[ ]:
```python
def default_params():
    """These are the default parameters used int eh framework."""
    return {  # Debugging outputs and plotting during training
        "plot_frequency": 10,  # plots a debug message avery n steps
        "plot_train_samples": True,  # whether the x-axis is env.steps (True)␣
↪or episodes (False)
        "print_when_plot": False,  # prints debug message if True
        "print_dots": False,  # prints dots for every gradient update
        # Environment parameters
        "env": "CartPole-v1",  # the environment the agent is learning in
        "run_steps": 0,  # samples whole episodes if run_steps <= 0
        "max_episode_length": 200,  # maximum number of steps per episode
        # Runner parameters
        "max_episodes": int(1e6),  # experiment stops after this many episodes
        "max_steps": int(1e9),  # experiment stops after this many steps
        "multi_runner": False,  # uses multiple runners if True
        "parallel_environments": 4,  # number of parallel runners  (only if␣
↪multi_runner==True)
        # Exploration parameters
        "epsilon_anneal_time": int(
            5e3
        ),  # exploration anneals epsilon over these many steps
        "epsilon_finish": 0.1,  # annealing stops at (and keeps) this epsilon
        "epsilon_start": 1,  # annealing starts at this epsilon
        # Optimization parameters
        "lr": 5e-4,  # learning rate of optimizer
        "gamma": 0.99,  # discount factor gamma
        "batch_size": 2048,  # number of transitions in a mini-batch
        "grad_norm_clip": 1,  # gradent clipping if grad norm is larger than␣
↪this
        # DQN parameters
        "replay_buffer_size": int(
            1e5
        ),  # the number of transitions in the replay buffer
        "use_last_episode": True,  # whether the last episode is always sampled␣
↪from the buffer
```

```
        "target_model": True,  # whether a target model is used in DQN
        "target_update": "soft",  # 'soft' target update or hard update by␣
↪regular 'copy'
        "target_update_interval": 10,  # interval for the 'copy' target update
        "soft_target_update_param": 0.1,  # update parameter for the 'soft'␣
↪target update
        "double_q": True,  # whether DQN uses double Q-learning
        "grad_repeats": 1,  # how many gradient updates / runner call
        # Image input parameters
        "pixel_observations": False,  # use pixel observations (we will not use␣
↪this feature here)
        "pixel_resolution": (78, 78),  # scale image to this resoluton
        "pixel_grayscale": True,  # convert image into grayscale
        "pixel_add_last_obs": True,  # stacks 2 observations
        "pixel_last_obs_delay": 3,  # delay between the two stacked observations
    }
```

`TransitionBatches` are dictionaries of variables, e.g. states or actions, that are saved in contiguous Tensors.

[ ]:
```
class TransitionBatch:
    """Simple implementation of a batchof transitionsm (or another␣
↪dictionary-based tensor structure).
    Read and write operations are thread-safe, but the iterator is not (you␣
↪cannot interate
    over the same TransitionBatch in two threads at the same time)."""

    def __init__(self, max_size, transition_format, batch_size=32):
        self.lock = threading.Lock()
        self.indices = []
        self.size = 0
        self.first = 0
        self.max_size = max_size
        self.batch_size = batch_size
        self.dict = {}
        for key, spec in transition_format.items():
            self.dict[key] = th.zeros([max_size, *spec[0]], dtype=spec[1])

    def _clone_empty_batch(self, max_size=None, batch_size=None):
        """Clones this TransitionBatch without cloning the data."""
        max_size = self.max_size if max_size is None else max_size
        batch_size = self.batch_size if batch_size is None else batch_size
        return TransitionBatch(
            max_size=max_size, transition_format={}, batch_size=batch_size
        )

    def __getitem__(self, key):
```

```python
        """Access the TransitionBatch with the [] operator. Use as key either
        - the string name of a variable to get the full tensor of that variable,
        - a slice to get a time-slice over all variables in the batch,
        - a LongTensor that selects a subset of indices for all variables in the batch.
        """
        # Return the entry of the transition called "key"
        if isinstance(key, str):
            return self.dict[key]
        # Return a slice of the batch
        if isinstance(key, slice):
            key = slice(
                0 if key.start is None else key.start,
                self.size if key.stop is None else key.stop,
                1 if key.step is None else key.step,
            )
            self.lock.acquire()
            try:
                batch = self._clone_empty_batch()
                batch.size = (key.stop - key.start) // key.step
                for k, v in self.dict.items():
                    batch.dict[k] = v[key]
            finally:
                self.lock.release()
            return batch
        # Collect and return a set of transitions specified by the LongTensor "key"
        if isinstance(key, th.Tensor):
            self.lock.acquire()
            try:
                batch = self._clone_empty_batch(max_size=key.shape[0])
                batch.size = key.shape[0]
                for k, v in self.dict.items():
                    key = key.view(batch.size, *[1 for _ in range(len(v.shape[1:]))])
                    batch.dict[k] = v.gather(
                        dim=0, index=key.expand(batch.size, *v.shape[1:])
                    )
            finally:
                self.lock.release()
            return batch
        return None

    def get_first(self):
        """Returns a batch of the oldest entries of all variables."""
        batch = self._clone_empty_batch(max_size=1)
        self.lock.acquire()
```

```
        try:
            batch.size = 1
            for k, v in self.dict.items():
                batch.dict[k] = v[self.first].unsqueeze(dim=0)
        finally:
            self.lock.release()
        return batch

    def get_last(self):
        """Returns a batch of the newest entries of all variables."""
        batch = self._clone_empty_batch(max_size=1)
        self.lock.acquire()
        try:
            batch.size = 1
            for k, v in self.dict.items():
                batch.dict[k] = v[(self.first + self.size - 1) % self.size].
↪unsqueeze(
                    dim=0
                )
        finally:
            self.lock.release()
        return batch

    def add(self, trans: dict):
        """Adding transition dictionaries, which can contain Tensors of␣
↪arbitrary length."""
        if isinstance(trans, TransitionBatch):
            trans = trans.dict
        # Add all data in the dict
        self.lock.acquire()
        try:
            n = 0
            idx = None
            for k, v in trans.items():
                if idx is None:
                    n = v.shape[0]
                    idx = th.LongTensor(
                        [(self.first + self.size + i) % self.max_size for i in␣
↪range(n)]
                    )
                else:
                    assert (
                        n == v.shape[0]
                    ), "all tensors in a transition need to have the same␣
↪batch_size"
                idx = idx.view(idx.shape[0], *[1 for _ in range(len(v.shape) -␣
↪1)])
```

```
                self.dict[k].scatter_(dim=0, index=idx.expand_as(v), src=v)
            # Increase the size (and handle overflow)
            self.size += n
            if self.size > self.max_size:
                self.first = (self.first + n) % self.max_size
                self.size = self.max_size
        finally:
            self.lock.release()
        return self

    def trim(self):
        """Reduces the length of the max_size to its actual size (in-place).␣
↪Returns self."""
        self.lock.acquire()
        try:
            for k, v in self.dict.items():
                self.dict[k] = v[: self.size]
            self.max_size = self.size
        finally:
            self.lock.release()
        return self

    def replace(self, batch, index=0):
        """Replaces parts of this batch with another batch (which must be␣
↪smaller)."""
        self.lock.acquire()
        try:
            # assert batch.max_size <= self.max_size - index, "Replacement is␣
↪larger then target area in batch."
            assert (
                batch.size <= self.max_size - index
            ), "Replacement is larger then target area in batch."
            for k, v in batch.dict.items():
                if batch.size < batch.max_size:
                    v = v[: batch.size]
                self.dict[k][index : (index + batch.max_size)] = v
        finally:
            self.lock.release()

    def sample(self):
        """Samples a random mini-batch from the batch."""
        return self[th.randint(high=self.size, size=(self.batch_size, 1))]

    def __len__(self):
        """Returns the length of the batch."""
        return self.size
```

```python
    def __iter__(self):
        """Initializes an iterator over the batch."""
        self.indices = list(range(self.size))
        np.random.shuffle(self.indices)
        return self

    def __next__(self):
        """Iterates through batch, returns list of contiguous tensors."""
        if len(self.indices) == 0:
            raise StopIteration
        size = min(self.batch_size, len(self.indices))
        batch = self[th.LongTensor(self.indices[-size:])]
        self.indices = self.indices[:-size]
        return batch
```

Runner implements a simple runner class that uses a controller to interact with the environment by calling run() or run_episode().

[ ]:
```python
class Runner:
    """Implements a simple single-thread runner class."""

    def __init__(self, controller, params={}, exploration_step=1):
        self.env = gym.make(params.get("env", "CartPole-v0"))
        self.cont_actions = isinstance(self.env.action_space, gym.spaces.Box)
        self.controller = controller
        self.epi_len = params.get("max_episode_length", self.env.
 ↪_max_episode_steps)
        self.gamma = params.get("gamma", 0.99)
        self.use_pixels = params.get("pixel_observations", False)
        if self.use_pixels:
            self.grayscale = params.get("pixel_grayscale", True)
            self.add_last_obs = params.get("pixel_add_last_obs", False)
            self.last_obs_delay = params.get("pixel_last_obs_delay", 4)
            n_colors = 1 if self.grayscale else 3
            n_feats = n_colors * (2 if self.add_last_obs else 1)
            resolution = params.get("pixel_resolution", (25, 25))
            self.state_shape = (n_feats, *resolution)
            self.last_observations = TransitionBatch(
                max_size=self.last_obs_delay,
                transition_format={"img": ((n_colors, *resolution), th.
 ↪float32)},
            )
        else:
            self.state_shape = self.env.observation_space.shape
        # Set up current state and time step
        self.sum_rewards = 0
        self.state = None
```

```
        self.time = 0
        self._next_step()

    def close(self):
        """Closes the underlying environment. Should always when ending an␣
↪experiment."""
        self.env.close()

    def transition_format(self):
        """Returns the format of transtions: a dictionary of (shape, dtype)␣
↪entries for each key."""
        return {
            "actions": ((1,), th.long),
            "states": (self.state_shape, th.float32),
            "next_states": (self.state_shape, th.float32),
            "rewards": ((1,), th.float32),
            "dones": ((1,), th.bool),
            "returns": ((1,), th.float32),
        }

    def _wrap_transition(self, s, a, r, ns, d):
        """Takes a transition and returns a corresponding dictionary."""
        trans = {}
        form = self.transition_format()
        for key, val in [
            ("states", s),
            ("actions", a),
            ("rewards", r),
            ("next_states", ns),
            ("dones", d),
        ]:
            if not isinstance(val, th.Tensor):
                if isinstance(val, numbers.Number) or isinstance(val, bool):
                    val = [val]
                val = th.tensor(val, dtype=form[key][1])
            if len(val.shape) < len(form[key][0]) + 1:
                val = val.unsqueeze(dim=0)
            trans[key] = val
        return trans

    def _pixel_observation(self, reset=False):
        """Returns the pixel-observation fo the current state. Opens extra␣
↪window for rendering."""
        img = self.env.render(mode="rgb_array")
        img = cv2.resize(img, dsize=self.state_shape[1:], interpolation=cv2.
↪INTER_CUBIC)
        img = (
```

```python
            th.from_numpy(img.astype(np.float32) / 255)
            .transpose(dim0=0, dim1=2)
            .unsqueeze(dim=0)
        )
        if self.grayscale:
            img = img.mean(dim=1, keepdim=True)
        if self.add_last_obs:
            if reset:
                self.last_observations.size = 0
            if self.last_observations.size < self.last_observations.max_size:
                obs = img * 0
            else:
                obs = self.last_observations.get_first()["img"].clone()
            self.last_observations.add({"img": img})
            img = th.cat([obs, img], dim=1)
        return img

    def _run_step(self, a):
        """Make a step in the environment (and update internal bookeeping)"""
        ns, r, t, d, _ = self.env.step(a.item())
        self.sum_rewards += r
        if self.use_pixels:
            ns = self._pixel_observation()
        return r, ns, t, d or t  # reward, next state, terminal, done

    def _next_step(self, done=True, next_state=None):
        """Switch to the next time-step (and update internal bookeeping)"""
        self.time = 0 if done else self.time + 1
        if done:
            self.sum_rewards = 0
            self.state, _ = self.env.reset()
            if self.use_pixels:
                self.state = self._pixel_observation(reset=True)
        else:
            self.state = next_state

    def run(self, n_steps, transition_buffer=None, trim=True, return_dict=None):
        """Runs n_steps in the environment and stores them in the␣
↪trainsition_buffer (newly created if None).
        If n_steps <= 0, stops at the end of an episode and optionally trins␣
↪the transition_buffer.
        Returns a dictionary containing the transition_buffer and episode␣
↪statstics."""
        my_transition_buffer = TransitionBatch(
            n_steps if n_steps > 0 else self.epi_len, self.transition_format()
        )
        time, episode_start, episode_lengths, episode_rewards = 0, 0, [], []
```

```python
        max_steps = n_steps if n_steps > 0 else self.epi_len
        for t in range(max_steps):
            # One step in the envionment
            a = self.controller.choose(self.state)
            r, ns, terminal, done = self._run_step(a)
            my_transition_buffer.add(
                self._wrap_transition(self.state, a, r, ns, terminal)
            )
            if self.env._elapsed_steps == self.epi_len:
                done = True
            # Compute discounted returns if episode has ended or max_steps has␣
↪been reached
            if done or t == (max_steps - 1):
                my_transition_buffer["returns"][t] =␣
↪my_transition_buffer["rewards"][t]
                for i in range(t - 1, episode_start - 1, -1):
                    my_transition_buffer["returns"][i] = (
                        my_transition_buffer["rewards"][i]
                        + self.gamma * my_transition_buffer["returns"][i + 1]
                    )
                episode_start = t + 1
            # Remember statistics and advance (potentially initilaizing a new␣
↪episode)
            if done:
                episode_lengths.append(self.time + 1)
                episode_rewards.append(self.sum_rewards)
            self._next_step(done=done, next_state=ns)
            time += 1
            # If n_steps <= 0, we return after one episode (trimmed if␣
↪specified)
            if done and n_steps <= 0:
                my_transition_buffer.trim()
                break
        # Add the sampled transitions to the given transition buffer
        transition_buffer = (
            my_transition_buffer
            if transition_buffer is None
            else transition_buffer.add(my_transition_buffer)
        )
        if trim:
            transition_buffer.trim()
        # Return statistics (mean reward, mean length and environment steps)
        if return_dict is None:
            return_dict = {}
        return_dict.update(
            {
                "buffer": transition_buffer,
```

```
                "episode_reward": None
                if len(episode_rewards) == 0
                else np.mean(episode_rewards),
                "episode_length": None
                if len(episode_lengths) == 0
                else np.mean(episode_lengths),
                "env_steps": time,
            }
        )
        return return_dict

    def run_episode(self, transition_buffer=None, trim=True, return_dict=None):
        """Runs one episode in the environemnt.
        Returns a dictionary containing the transition_buffer and episode␣
↪statstics."""
        return self.run(0, transition_buffer, trim, return_dict)
```

MultiRunner runs a number of Runner instances in parallel.

```
[ ]: class MultiRunner:
    """Simple class that runs multiple Runner objects in parallel and merges␣
↪their outputs."""

    def __init__(self, controller, params={}):
        self.workers = []
        self.runners = []
        n = params.get("parallel_environments", 1)
        for _ in range(n):
            self.runners.append(Runner(controller=controller, params=params))

    def transition_format(self):
        """Same transition-format as underlying Runners."""
        return self.runners[0].transition_format()

    def close(self):
        """Closes the underlying environment. Should always when ending an␣
↪experiment."""
        # Join all workers
        for w in self.workers:
            w.join()
        # Exit all environments
        for r in self.runners:
            r.close()

    def fork(self, target, common_args=None, specific_args=None):
        """Executes the function "target" on all runners. "common_args" is a␣
↪dictionary of
```

```python
        arguments that are passed to all runners, "specific_args" is a list of
        dictionaries that contain individual parameters for each runner."""
        # Fork all runners
        self.workers = []
        for i, r in enumerate(self.runners):
            r_args = [] if specific_args is None else [arg[i] for arg in␣
↪specific_args]
            self.workers.append(
                threading.Thread(target=target, args=(r, *common_args, *r_args))
            )
            self.workers[-1].start()
        # Join all runners
        for w in self.workers:
            w.join()

    def run(self, n_steps, transition_buffer=None, trim=True):
        """Runs n_steps, split amongst runners, and stores them in the␣
↪trainsition_buffer (newly created if None).
        If n_steps <= 0, stops at the end of an episode and optionally trims␣
↪the transition_buffer.
        Returns a dictionary containing the transition_buffer and episode␣
↪statstics."""
        n_steps = n_steps // len(self.runners)
        if transition_buffer is None:
            buffer_len = len(self.runners) * (
                n_steps if n_steps > 0 else self.runners[0].epi_len
            )
            transition_buffer = TransitionBatch(
                buffer_len, self.runners[0].transition_format()
            )
        return_dicts = [{} for _ in self.runners]
        self.fork(
            target=Runner.run,
            common_args=(n_steps, transition_buffer, False),
            specific_args=(return_dicts,),
        )
        if trim:
            transition_buffer.trim()
        rewards = [
            d["episode_reward"] for d in return_dicts if d["episode_reward"] is␣
↪not None
        ]
        lengths = [
            d["episode_length"] for d in return_dicts if d["episode_reward"] is␣
↪not None
        ]
```

```
        return {
            "buffer": transition_buffer,
            "episode_reward": np.mean(rewards) if len(rewards) > 0 else None,
            "episode_length": np.mean(lengths) if len(lengths) > 0 else None,
            "env_steps": len(transition_buffer),
        }

    def run_episode(self, transition_buffer=None, trim=True):
        """Runs one episode in the environemnt.
        Returns a dictionary containing the transition_buffer and episode␣
↪statstics."""
        return self.run(0, transition_buffer, trim)
```

A `QController` translates model responses into actions. Call `choose()` to select actions or `probabilities()` to get the probabilities with which the controller would choose the actions.

```
[ ]: class QController:
    """Controller for Q-value functions, synchronizes the model calls."""

    def __init__(self, model, num_actions=None, params={}):
        self.lock = threading.Lock()
        self.num_actions = (
            model[-1].out_features if num_actions is None else num_actions
        )
        self.model = model

    def copy(self):
        """Shallow copy of this controller that does not copy the model."""
        return QController(model=self.model, num_actions=self.num_actions)

    def parameters(self):
        """Returns a generator of the underlying model parameters."""
        return self.model.parameters()

    def sanitize_inputs(self, observation, **kwargs):
        """Casts numpy arrays as Tensors."""
        if isinstance(observation, np.ndarray):
            observation = th.Tensor(observation).unsqueeze(dim=0)
        return observation

    def choose(self, observation, **kwargs):
        """Returns the greedy actions the agent would choose when facing an␣
↪"observation"."""
        self.lock.acquire()
        try:
            mx = self.model(self.sanitize_inputs(observation))
            if mx.shape[-1] > self.num_actions:
```

```
                mx = mx[:, : self.num_actions]
        finally:
            self.lock.release()
        return th.max(mx, dim=-1)[1]

    def probabilities(self, observation, **kwargs):
        """Returns the probabilities with which the agent would choose actions␣
↪(here one-hot because greedy)."""
        self.lock.acquire()
        try:
            mx = self.model(self.sanitize_inputs(observation))
            if mx.shape[-1] > self.num_actions:
                mx = mx[:, : self.num_actions]
        finally:
            self.lock.release()
        return th.zeros(*mx.shape).scatter_(
            dim=-1, index=th.max(mx, dim=-1)[1].unsqueeze(dim=-1), src=th.
↪ones(1, 1)
        )
```

An `EpsilonGreedyController` is a controller that autonomously anneals an expsilon greedy exploration strategy.

```
[ ]: class EpsilonGreedyController:
    """A wrapper that makes any controller into an epsilon-greedy controller.
    Keeps track of training-steps to decay exploration automatically."""

    def __init__(self, controller, params={}, exploration_step=1):
        self.controller = controller
        self.num_actions = controller.num_actions
        self.max_eps = params.get("epsilon_start", 1.0)
        self.min_eps = params.get("epsilon_finish", 0.05)
        self.anneal_time = int(
            params.get("epsilon_anneal_time", 10000) / exploration_step
        )
        self.num_decisions = 0

    def epsilon(self):
        """Returns current epsilon."""
        return (
            max(1 - self.num_decisions / (self.anneal_time - 1), 0)
            * (self.max_eps - self.min_eps)
            + self.min_eps
        )

    def choose(self, observation, increase_counter=True, **kwargs):
```

```
        """Returns the (possibly random) actions the agent takes when faced␣
↪with "observation".
        Decays epsilon only when increase_counter=True"."""
        eps = self.epsilon()
        if increase_counter:
            self.num_decisions += 1
        if np.random.rand() < eps:
            return th.randint(self.controller.num_actions, (1,), dtype=th.long)
        else:
            return self.controller.choose(observation, **kwargs)

    def probabilities(self, observation, **kwargs):
        """Returns the probabilities with which the agent would choose actions.
↪"""
        eps = self.epsilon()
        return eps * th.ones(1, 1) / self.num_actions + (
            1 - eps
        ) * self.controller.probabilities(observation, **kwargs)
```

A `QLearner` is a learner class that performs Q-learning. At the moment this does not include target models or double Q-learning, which you will add in later exercises.

```
[ ]: class QLearner:
        """A basic learner class that performs Q-learning train() steps."""

        def __init__(self, model, params={}):
            self.model = model
            self.all_parameters = list(model.parameters())
            self.gamma = params.get("gamma", 0.99)
            self.optimizer = th.optim.Adam(self.all_parameters, lr=params.get("lr",␣
↪5e-4))
            self.criterion = th.nn.MSELoss()
            self.grad_norm_clip = params.get("grad_norm_clip", 10)
            self.target_model = None  # Target models are not yet implemented!

        def target_model_update(self):
            """This function updates the target network. No target network is␣
↪implemented yet."""
            pass

        def q_values(self, states, target=False):
            """Reutrns the Q-values of the given "states".
            I supposed to use the target network if "target=True", but this is not␣
↪implemented here.
            """
            return self.model(states)
```

```
    def _current_values(self, batch):
        """Computes the Q-values of the 'states' and 'actions' of the given␣
↪"batch"."""
        qvalues = self.q_values(batch["states"])
        return qvalues.gather(dim=-1, index=batch["actions"])

    def _next_state_values(self, batch):
        """Computes the Q-values of the 'next_states' of the given "batch".
        Is greedy w.r.t. to current Q-network or target-network, depending on␣
↪parameters.
        """
        with th.no_grad():  # Next state values do not need gradients in DQN
            # Compute the next states values (with target or current network)
            qvalues = self.q_values(batch["next_states"], target=True)
            # Compute the maximum over Q-values
            return qvalues.max(dim=-1, keepdim=True)[0]

    def train(self, batch):
        """Performs one gradient decent step of DQN."""
        self.model.train(True)
        # Compute TD-loss
        targets = batch["rewards"] + self.gamma * (
            ~batch["dones"] * self._next_state_values(batch)
        )
        loss = self.criterion(self._current_values(batch), targets.detach())
        # Backpropagate loss
        self.optimizer.zero_grad()
        loss.backward()
        grad_norm = th.nn.utils.clip_grad_norm_(
            self.all_parameters, self.grad_norm_clip
        )
        self.optimizer.step()
        # Update target network (if specified) and return loss
        self.target_model_update()
        return loss.item()
```

An `Experiment` is an abstract class that starts and maintains a single learning experiment (i.e. random seed). The experiment is started using `run()` and can be interrupted at any time using `close()`. Afterwards the experiment can be restarted at any time calling `run()` again.

[ ]:
```
class Experiment:
    """Abstract class of an experiment. Contains logging and plotting␣
↪functionality."""

    def __init__(self, params, model, **kwargs):
        self.params = params
        self.plot_frequency = params.get("plot_frequency", 100)
```

```
        self.plot_train_samples = params.get("plot_train_samples", True)
        self.print_when_plot = params.get("print_when_plot", False)
        self.print_dots = params.get("print_dots", False)
        self.episode_returns = []
        self.episode_lengths = []
        self.episode_losses = []
        self.env_steps = []
        self.total_run_time = 0.0

    def plot_training(self, update=False):
        """Plots logged training results. Use "update=True" if the plot is continuously updated
        or use "update=False" if this is the final call (otherwise there will be double plotting).
        """
        # Smooth curves
        window = max(int(len(self.episode_returns) / 50), 10)
        if len(self.episode_losses) < window + 2:
            return
        returns = np.convolve(self.episode_returns, np.ones(window) / window, "valid")
        lengths = np.convolve(self.episode_lengths, np.ones(window) / window, "valid")
        losses = np.convolve(self.episode_losses, np.ones(window) / window, "valid")
        env_steps = np.convolve(self.env_steps, np.ones(window) / window, "valid")
        # Determine x-axis based on samples or episodes
        if self.plot_train_samples:
            x_returns = env_steps
            x_losses = env_steps[(len(env_steps) - len(losses)) :]
        else:
            x_returns = [i + window for i in range(len(returns))]
            x_losses = [
                i + len(returns) - len(losses) + window for i in range(len(losses))
            ]
        # Create plot
        colors = ["b", "g", "r"]
        fig = plt.gcf()
        fig.set_size_inches(16, 4)
        plt.clf()
        # Plot the losses in the left subplot
        pl.subplot(1, 3, 1)
        pl.plot(env_steps, returns, colors[0])
```

```
        pl.xlabel("environment steps" if self.plot_train_samples else␣
↪"episodes")
        pl.ylabel("episode return")
        # Plot the episode lengths in the middle subplot
        ax = pl.subplot(1, 3, 2)
        ax.plot(env_steps, lengths, colors[0])
        ax.set_xlabel("environment steps" if self.plot_train_samples else␣
↪"episodes")
        ax.set_ylabel("episode length")
        # Plot the losses in the right subplot
        ax = pl.subplot(1, 3, 3)
        ax.plot(x_losses, losses, colors[0])
        ax.set_xlabel("environment steps" if self.plot_train_samples else␣
↪"episodes")
        ax.set_ylabel("loss")
        # dynamic plot update
        display.clear_output(wait=True)
        if update:
            display.display(pl.gcf())

    def close(self):
        """Frees all allocated runtime ressources, but allows to continue the␣
↪experiment later.
        Calling the run() method after close must be able to pick up the␣
↪experiment where it was.
        """
        pass

    def run(self):
        """Starts (or continues) the experiment."""
        assert (
            False
        ), "You need to extend the Expeirment class and override the method␣
↪run(). "
```

QLearningExperiment performs online Q-learning using QLearner. One can specify another learner, which you will do in later exercises.

```
[ ]: class QLearningExperiment(Experiment):
         """Experiment that perfoms DQN. You can provide your own learner."""

         def __init__(self, params, model, learner=None, **kwargs):
             super().__init__(params, model, **kwargs)
             self.max_episodes = params.get("max_episodes", int(1e6))
             self.max_steps = params.get("max_steps", int(1e9))
             self.run_steps = params.get("run_steps", 0)
             self.grad_repeats = params.get("grad_repeats", 1)
```

```python
        self.controller = QController(
            model, num_actions=gym.make(params["env"]).action_space.n,␣
↪params=params
        )
        self.controller = EpsilonGreedyController(
            controller=self.controller, params=params
        )
        self.runner = (
            MultiRunner(self.controller, params=params)
            if params.get("multi_runner", True)
            else Runner(self.controller, params=params)
        )
        self.learner = QLearner(model, params=params) if learner is None else␣
↪learner

    def close(self):
        """Overrides Experiment.close()."""
        self.runner.close()

    def _learn_from_episode(self, episode):
        """This function uses the episode to train.
        Although not implemented, one could also add the episode to a replay␣
↪buffer here.
        Returns the training loss for logging or None if train() was not called.
↪"""
        # Call train (params['grad_repeats']) times
        total_loss = 0
        for i in range(self.grad_repeats):
            total_loss += self.learner.train(episode["buffer"])
        return total_loss / self.grad_repeats

    def run(self):
        """Starts (or continues) the experiment."""
        # Plot previous results if they exist
        if self.plot_frequency is not None and len(self.episode_losses) > 2:
            self.plot_training(update=True)
        # Start (or continue experiment)
        env_steps = 0 if len(self.env_steps) == 0 else self.env_steps[-1]
        for e in range(self.max_episodes):
            begin_time = datetime.now()
            # Run an episode (or parts of it)
            if self.run_steps > 0:
                episode = self.runner.run(n_steps=self.run_steps, trim=False)
            else:
                episode = self.runner.run_episode()
            # Log the results
            env_steps += episode["env_steps"]
```

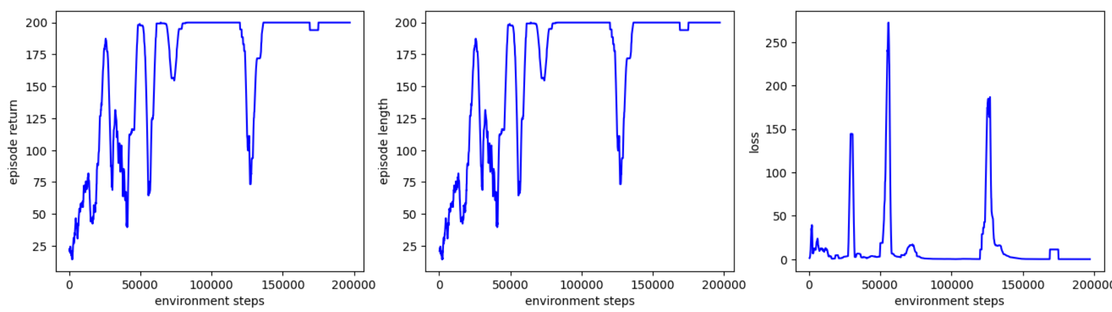
```
            if episode["episode_length"] is not None:
                self.episode_lengths.append(episode["episode_length"])
                self.episode_returns.append(episode["episode_reward"])
                self.env_steps.append(env_steps)
            # Make one (or more) learning steps with the episode
            loss = self._learn_from_episode(episode)
            if loss is not None:
                self.episode_losses.append(loss)
            self.total_run_time += (datetime.now() - begin_time).total_seconds()
            # Quit if maximal number of environment steps is reached
            if env_steps >= self.max_steps:
                break
            # Show intermediate results
            if self.print_dots:
                print(".", end="")
            if (
                self.plot_frequency is not None
                and (e + 1) % self.plot_frequency == 0
                and len(self.episode_losses) > 2
            ):
                self.plot_training(update=True)
                if self.print_when_plot:
                    print(
                        "Update %u, 100-epi-return %.4g +- %.3g, length %u,␣
↪loss %g, run-time %g sec."
                        % (
                            len(self.episode_returns),
                            np.mean(self.episode_returns[-100:]),
                            np.std(self.episode_returns[-100:]),
                            np.mean(self.episode_lengths[-100:]),
                            np.mean(self.episode_losses[-100:]),
                            self.total_run_time,
                        )
                    )
```

1.2 A2.1a) Run the given online Q-learning algorithm

Go through the implementation in the given Jupyter Notebook. Run online Q-learning, that is, use the `QLearningExperiment` with the `QLearner` class on the `CartPole-v1` environment for $200k$ steps in the environment.

[ ]:
```
# A2.1a) Run the given Online Q-learning algorithm without target networks or␣
↪experience replay

# Executing this code-block defines a new experiment
params = default_params()
params["max_steps"] = int(2e5)
```

```python
env = gym.make(params["env"])
n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
model = th.nn.Sequential(
    th.nn.Linear(state_dim, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, 512),
    th.nn.ReLU(),
    th.nn.Linear(512, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, n_actions),
)
experiment = QLearningExperiment(params, model, learner=QLearner(model, params=params))

# Re-executing this code-block picks up the experiment where you left off
try:
    experiment.run()
except KeyboardInterrupt:
    experiment.close()
experiment.plot_training()
```



1.3 A2.1b) Use a replay buffer in Q-learning

Implement online Q-learning with an experience replay buffer by extending the given skeleton of the `DQNExperiment` class. Train your implementation again in the `CartPole-v1` environment for 200k steps.

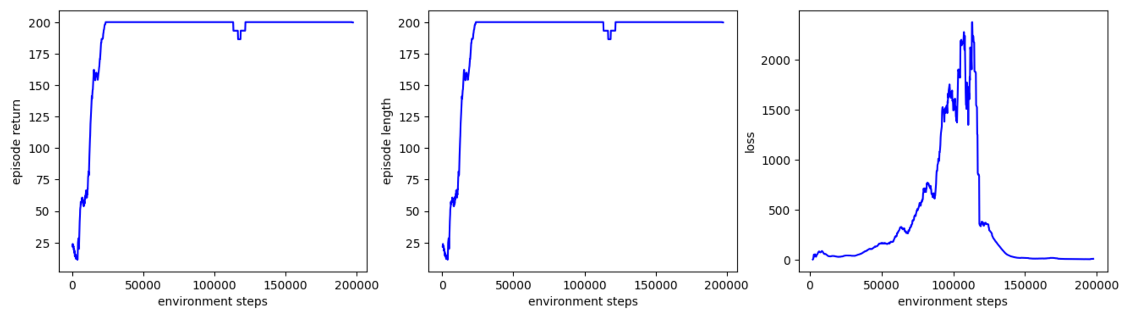
[ ]:

```python
# A2.1b) Extend the QLearningExperiment class to use a replay buffer during training.
#        If the replay buffer does not contain enough transitions for a mini-batch, training should be omitted.
#        Bonus: make sure the last episode is always used for optimization (params['use_last_episode']=True)
class DQNExperiment(QLearningExperiment):
    """Experiment that perfoms DQN. You can provide your own learner."""
```

```python
    def __init__(self, params, model, learner=None, **kwargs):
        super().__init__(params, model, learner=learner, **kwargs)
        self.use_last_episode = params.get("use_last_episode", True)
        self.replay_buffer = TransitionBatch(
            params.get("replay_buffer_size", int(1e5)),
            self.runner.transition_format(),
            batch_size=params.get("batch_size", 1024),
        )

    # YOUR CODE HERE!!!
    # def _learn_from_episode(self, episode):
    #     return super()._learn_from_episode(episode)

    def _learn_from_episode(self, episode):
        """This function uses the episode to train.
        Although not implemented, one could also add the episode to a replay␣
↪buffer here.
        Returns the training loss for logging or None if train() was not called.
↪"""
        # Call train (params['grad_repeats']) times
        total_loss = 0
        self.replay_buffer.add(episode["buffer"])
        # print(len(self.replay_buffer))
        if len(self.replay_buffer) < self.replay_buffer.batch_size:
            return None
        sample = self.replay_buffer.sample()
        # print(type(sample))
        for i in range(self.grad_repeats):
            total_loss += self.learner.train(sample)
        return total_loss / self.grad_repeats
```

[ ]:
```python
# Executing this code-block defines a new experiment
params = default_params()
params["max_steps"] = int(2e5)
params["use_last_episode"] = True
env = gym.make(params["env"])
n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
model = th.nn.Sequential(
    th.nn.Linear(state_dim, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, 512),
    th.nn.ReLU(),
    th.nn.Linear(512, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, n_actions),
)
```

```python
experiment = DQNExperiment(params, model)

# Re-executing this code-block picks up the experiment where you left off
try:
    experiment.run()
except KeyboardInterrupt:
    experiment.close()
experiment.plot_training()
```



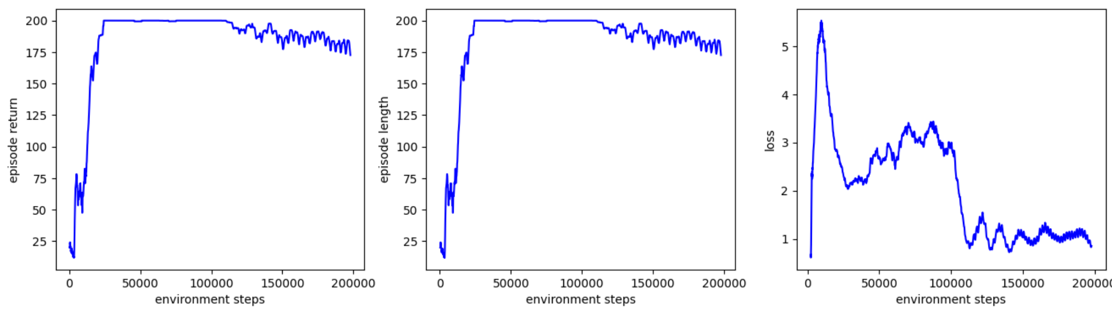
1.4 A2.1c) Implement target networks with hard updates

Extend the `QLearning` class with target-networks that use a hard update rule. Train your implementation again in the `CartPole-v1` environment for $200k$ steps.

[ ]:
```python
# A2.1c) Implement a target network with hard target updates (params['target_update'] = 'copy')
#        every (params['target_update_interval'] = 10) gradient update steps.
#        Make sure (params['target_model'] = False) maintains the old functionality.
#        Hint: use (self.target_model.load_state_dict(self.model.state_dict())) to copy the model
class QLearnerHardTarget(QLearner):
    def __init__(self, model, params={}):
        super().__init__(model, params)
        self.target_update = params.get("target_update", "hard")
        self.target_update_interval = params.get("target_update_interval", 200)
        self.target_update_calls = 0
        if params.get("target_model", True):
            self.target_model = deepcopy(model)
            for p in self.target_model.parameters():
                p.requires_grad = False
        assert (
            self.target_model is None
            or self.target_update == "soft"
            or self.target_update == "copy"
```

```python
        ), 'If a target model is specified, it needs to be updated using the␣
↪"soft" or "copy" options.'

    # YOUR CODE HERE!!!
    def q_values(self, states, target=False):
        if target == True and self.target_model is not None:
            return self.target_model(states)
        else:
            return self.model(states)
        # return super().q_values(states, target)

    def target_model_update(self):
        if self.target_model is None:
            pass
        self.target_update_calls += 1
        if self.target_update_calls % self.target_update_interval == 0:
            self.target_model.load_state_dict(self.model.state_dict())
```

[ ]:
```python
# Executing this code-block defines a new experiment
params = default_params()
params["max_steps"] = int(2e5)
params["target_model"] = True
params["target_update"] = "copy"
params["target_update_interval"] = 10
env = gym.make(params["env"])
n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
model = th.nn.Sequential(
    th.nn.Linear(state_dim, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, 512),
    th.nn.ReLU(),
    th.nn.Linear(512, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, n_actions),
)
experiment = DQNExperiment(params, model, learner=QLearnerHardTarget(model,␣
↪params))

# Re-executing this code-block picks up the experiment where you left off
try:
    experiment.run()
except KeyboardInterrupt:
    experiment.close()
experiment.plot_training()
```



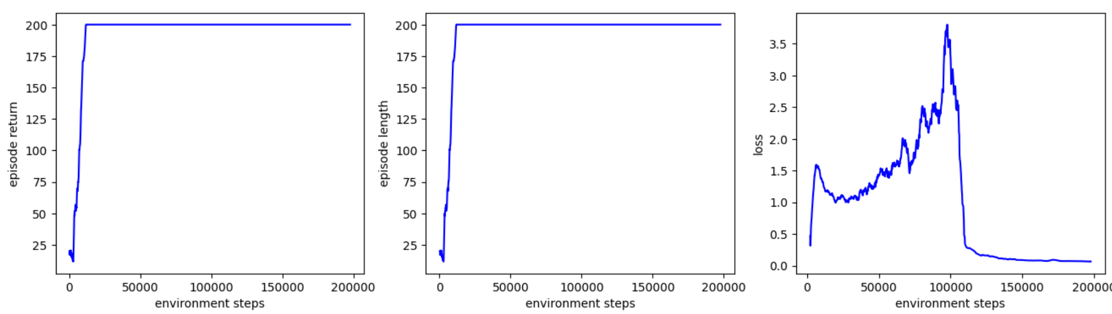
1.5 A2.1d) Implement target networks with soft updates

Extend your implementation with a soft-update rule for the target network and test it in the environment `CartPole-v1` for 200k steps.

[ ]:
```python
# A2.1d) Implement a target network with soft target updates (params['target_update'] = 'soft').
#        The decay parameter is given by params['soft_target_update_param').
#        Make sure all other parameters maintain the old functionality.
#        Hint: you can iterate through model.parameters()
class QLearnerSoftTarget(QLearnerHardTarget):
    def __init__(self, model, params={}):
        super().__init__(model, params)
        self.target_update = params.get("target_update", "soft")
        self.soft_target_update_param = params.get("soft_target_update_param", 0.1)

    # YOUR CODE HERE!!!

    def target_model_update(self):
        if self.target_model is None:
            pass
        self.target_update_calls += 1
        for t_param, param in zip(
            self.target_model.parameters(), self.model.parameters()
        ):
            t_param.data.copy_(
                (1.0 - self.soft_target_update_param) * t_param.data
                + self.soft_target_update_param * param.data
            )
```

[ ]:
```python
# Executing this code-block defines a new experiment
params = default_params()
params["max_steps"] = int(2e5)
params["target_model"] = True
```

```python
params["target_update"] = "soft"
params["soft_target_update_param"] = 0.1
env = gym.make(params["env"])
n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
model = th.nn.Sequential(
    th.nn.Linear(state_dim, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, 512),
    th.nn.ReLU(),
    th.nn.Linear(512, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, n_actions),
)
experiment = DQNExperiment(params, model, learner=QLearnerSoftTarget(model, params))

# Re-executing this code-block picks up the experiment where you left off
try:
    experiment.run()
except KeyboardInterrupt:
    experiment.close()
experiment.plot_training()
```



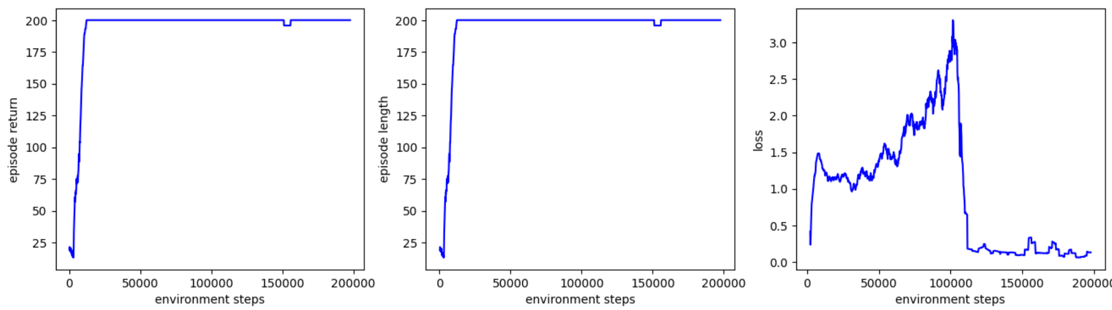
1.6 A2.1e) Implement double Q-learning

Extend your implementation with double-Q-learning and test it in the `CartPole-v1` environment for 200k steps.

[ ]:
```python
# A2.1e) Implement double Q-leanring when (params['double_q'] = True)
class DoubleQLearner(QLearnerSoftTarget):
    def __init__(self, model, params={}):
        super().__init__(model, params)
        self.double_q = params.get("double_q", True)

    # YOUR CODE HERE!!!
```

```
    def _next_state_values(self, batch):
        with th.no_grad():
            qvalues = self.q_values(batch["next_states"], target=False)
            _, actions = qvalues.max(dim=-1, keepdim=True)
            eval_qvalues = self.q_values(batch["next_states"], target=True)

            return eval_qvalues.gather(dim=-1, index=actions)
```

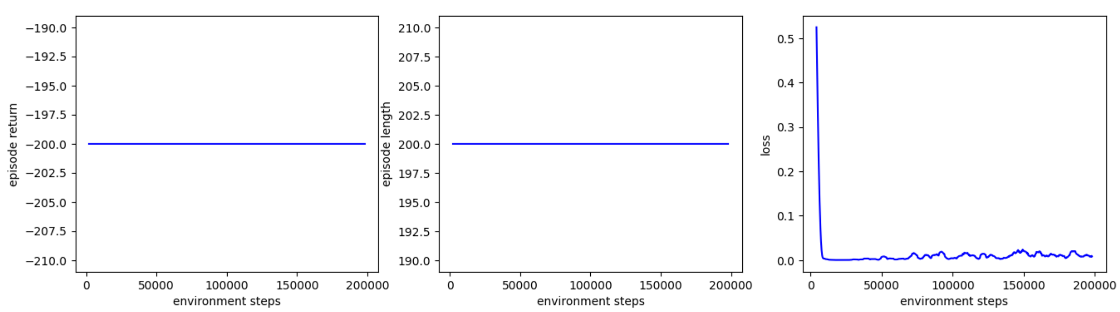
[ ]:
```
# Executing this code-block defines a new experiment
params = default_params()
params["max_steps"] = int(2e5)
params["double_q"] = True
env = gym.make(params["env"])
n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
model = th.nn.Sequential(
    th.nn.Linear(state_dim, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, 512),
    th.nn.ReLU(),
    th.nn.Linear(512, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, n_actions),
)
experiment = DQNExperiment(params, model, learner=DoubleQLearner(model, params))

# Re-executing this code-block picks up the experiment where you left off
try:
    experiment.run()
except KeyboardInterrupt:
    experiment.close()
experiment.plot_training()
```



1.7 A2.1f) Run double Q-learning on MountainCar

Run your implementation of `DoubleQLearner` on the `MountainCar-v0` environment for $200k$ steps. In all likelihood, your agent will not be able to solve the task (reach the goal), and learning should not pick up at all. Explain why that is.

```
[ ]: # A2.1f) Run your implementation of DoubleQLearner on the MountainCar-v0␣
     ↪environment.
     #        Why does the agent not learn to solve the task?

     # Executing this code-block defines a new experiment
     params = default_params()
     params["env"] = "MountainCar-v0"
     params["max_steps"] = int(2e5)
     params["epsilon_anneal_time"] = int(1e5)  # exploration is probably important
     env = gym.make(params["env"])
     n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
     model = th.nn.Sequential(
         th.nn.Linear(state_dim, 128),
         th.nn.ReLU(),
         th.nn.Linear(128, 512),
         th.nn.ReLU(),
         th.nn.Linear(512, 128),
         th.nn.ReLU(),
         th.nn.Linear(128, n_actions),
     )
     experiment = DQNExperiment(params, model, learner=DoubleQLearner(model, params))

     # Re-executing this code-block picks up the experiment where you left off
     try:
         experiment.run()
     except KeyboardInterrupt:
         experiment.close()
     experiment.plot_training()
```

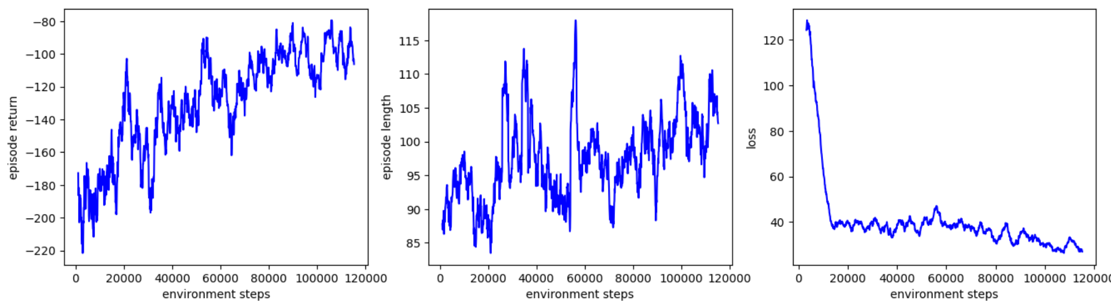


The only positive reward in MountainClimber comes from reaching the right top of the hill, which requires a coordinated movement. The chances of a random agent reaching it are very low, so there is no prior experience the model could learn from. A possible solution would be to increase the initial exploration phase, i.e. increase the lower size limit of the replay buffer.

1.8 A2.1g) Run double Q-learning on LunarLander

Run your implementation on the `LunarLander-v2` environment for at least 5 million environment steps (more is better). This can take a while, expect 1-3 hours of computation time. Do you get similar results as shown in the lecture?

[ ]:
```
# A2.1g) Run your implementation of DoubleQLearner on the LunarLander-v2␣
↪environment for 2M time steps.
#        Do you get similar curves for "episode return", "epsode length" and␣
↪"loss" as in the lecture?

# Executing this code-block defines a new experiment
params = default_params()
params["env"] = "LunarLander-v2"
params["max_steps"] = int(1e7)
params["max_episode_length"] = 350
params["replay_buffer_size"] = int(
    1e6
)  # This should probably be a bit larger than usual
params["epsilon_anneal_time"] = int(
    5e5
)  # You can play around with this parameter as well
env = gym.make(params["env"])
n_actions, state_dim = env.action_space.n, env.observation_space.shape[0]
model = th.nn.Sequential(
    th.nn.Linear(state_dim, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, 512),
    th.nn.ReLU(),
    th.nn.Linear(512, 128),
    th.nn.ReLU(),
    th.nn.Linear(128, n_actions),
)
experiment = DQNExperiment(params, model, learner=DoubleQLearner(model, params))

# Re-executing this code-block picks up the experiment where you left off
try:
    experiment.run()
except KeyboardInterrupt:
    experiment.close()
experiment.plot_training()
```




```
The Kernel crashed while executing code in the the current cell or a previous␣
↪cell. Please review the code in the cell(s) to identify a possible cause of␣
↪the failure. Click <a href='https://aka.ms/vscodeJupyterKernelCrash'>here</a>␣
↪for more info. View Jupyter <a href='command:jupyter.viewOutput'>log</a> for␣
↪further details.
```