problem_attempt

November 16, 2022

0.0.1 TDT17 - Implement the actor-critic architecture

The problem description is given in the provided pdf. This notebook will give you the tools necessary to solve the problem of implementing the actor-critic architecture and apply it so solve a simple problem of getting a decent score in the towers of hanoi game. You only need to add code in the places marked with `TODO`. If done correctly according to the provided pseudocode, you should be able to run the notebook, and find a solution to the towers of hanoi problem where the number of moves are between 15-20 regurarly. 15 is the optimal number of moves.

You only need to change the code in the main `while` loop in the last cell. I have done the initial setup for you.

COPILOT NOT ALLOWED **GOOD LUCK!**

Parameters

[31]:
```
class Parameters():

    def __init__(self):
        # World parameters
        self.world_type = "hanoi_towers"

        # Episodes and steps
        self.num_episodes = 200
        self.episode_length = 300

        # Critic parameters
        self.critic_type = "table"
        self.input_dims = {"hanoi_towers": self.
↪get_tower_params()["peg_amount"]}
        self.critic_neural_dimentions = (self.input_dims[self.world_type], 20,␣
↪30, 5, 1)
        self.critic_learning_rate = 0.00065
        self.critic_eligibility_decay = 0.99
        self.critic_discount = 0.99

        # Actor parameters
        self.actor_learning_rate = 0.8
        self.actor_eligibility_decay = 0.7
        self.actor_discount = 0.98
```

```python
        self.epsilon = 0.9
        self.epsilon_decay = 0.98

        # Visualization
        self.visualize = True


    def get_tower_params(self):
        return {
                "peg_amount": 3,  # [3, 5]
                "disc_amount": 4, # [2, 6]
                "episode_length": self.episode_length,
                "win_reward": 5 if self.critic_type == "neural" else 100
            }

    def get_problem_parameters(self):
        if self.world_type == "hanoi_towers":
            return self.get_tower_params()
```

World representation (Environment)

[32]:
```python
from functools import reduce

class HanoiTowersWorld():

    def __init__(self, parameters):
        self.params = parameters
        self.peg_amount = self.params["peg_amount"]
        self.disc_amount = self.params["disc_amount"]
        self.peg_states = self.generate_peg_states()
        self.reset()

    def reset(self):
        """
            Resets the world state and variables.

            num_moves is used for checking if we have lost (timeout basically)
            first_peg will contain all the discs. For a 4 disc problem, this␣
↪will look like [1, 2, 3, 4]
            rest_of_pegs are the rest of the pegs, and they are all empty as␣
↪all the discs are on the first peg
            The initial state will be these two lists added together
        """
        self.num_moves = 1
        first_peg = [[i + 1 for i in range(self.disc_amount)][::-1]]
        rest_of_pegs = [[] for _ in range(self.peg_amount - 1)]
        self.world_state = first_peg + rest_of_pegs
```

```python
    def generate_peg_states(self):
        """
            This method will number the possible states in the problem so that we can look at a peg and say:
                "Yep. Thats peg state 2"
            This makes it easier to make connections between state and action for the neural network (if we use that approach)
            The list for a  4 disc problem will look like this:
            [[], [4], [3], [4, 3], [2], [4, 2], [3, 2], [4, 3, 2], [1], [4, 1], [3, 1], [4, 3, 1], [2, 1], [4, 2, 1], [3, 2, 1], [4, 3, 2, 1]]
        """
        def powerset(lst):
            return reduce(lambda result, x: result + [subset + [x] for subset in result],lst, [[]])
        return powerset([i for i in range(self.disc_amount, 0, -1)])

    def calculate_world_state(self):
        """
            Will return a list of peg states representing the current state.
            The length of the list depends on the amount of pegs in the problem
        """
        state = []
        for peg in self.world_state:
            state.append(self.peg_states.index(peg)) # Indexes the powerset calculated in generate_peg_states to get the number
        return state

    def get_current_state(self):
        """
            As the state has to be hashable, we convert the state representation to a tuple of integers
        """
        return tuple(self.calculate_world_state())

    def get_possible_actions(self):
        """
            This method will return a list of possible actions to perform.
            It will loop through the pegs and check if a disc is eligable to move from one to another.
            If it is, then it will be added to the list in this representation (example):
                -- [(2, 0, 1), (1, 2, 0), (1, 2, 1)] --
                This means that:
                   disc 2 can move from peg 0 to peg 1
                   disc 1 can move from peg 2 to peg 0
```

```
                    disc 1 can move from peg 2 to peg 1

            So it returns a list of tuples with (disc, peg_from, peg_to)
        """
        possible_moves = []
        for i, peg1 in enumerate(self.world_state):
            if len(peg1) == 0:
                continue
            for j, peg2 in enumerate(self.world_state):
                if len(peg2) == 0: # If the peg is empty, we can move the disc␣
↪there
                    possible_moves.append((peg1[-1], i, j))
                else:
                    if peg1[-1] < peg2[-1]: # The disc has to be smaller than␣
↪the one it lands on
                        possible_moves.append((peg1[-1], i, j))
        return possible_moves

    def perform_action(self, action):
        """
            This method performs the action selected by the actor. It will␣
↪select one of the elements in the list returned from get_possible_actions
            and will decode the message in the same way as the comment above.
              -- (2, 1, 0) --
              Will move disc 2 from peg 1 to peg 0
        """
        self.num_moves = self.num_moves + 1
        peg_from = action[1]
        peg_to = action[2]
        disc = self.world_state[peg_from][-1] # The disc on top of the peg we␣
↪are moving it from
        self.world_state[peg_from] = self.world_state[peg_from][:-1] # Removes␣
↪the last element (removes the disc)
        self.world_state[peg_to] = self.world_state[peg_to] + [disc] # Adds␣
↪element (places disc)

    def get_visualization(self):
        """
            The visual representation for this problem is a bit weird. It will␣
↪seperate each peg with a "|" and each disc with ","
            This is because the actual state representation of the pegs is␣
↪encoded into the integers explaned earlier.
            The string returned from this method is decoded in the visualizer␣
↪as follows:
            -- Initial position for 3 pegs and 4 discs --
                4,3,2,1||
```

```
                (1) Splits on "|" giving: ["4,3,2,1", "", ""]
                (2) Split each peg on "," giving: [["4", "3", "2", "1"], [], []]

                Now we can use the list to represent the pegs and discs
        """
        string = ""
        for disk in self.world_state:
            string += ",".join([str(x) for x in disk])
            string += "|"
        return string[:-1]

    def winning_state(self):
        """
            The state is winning if the last peg contains all the discs
        """
        return len(self.world_state[-1]) == self.disc_amount

    def losing_state(self):
        """
            The state is losing (timed out) if the AI has tried for too many␣
↪moves
        """
        return self.num_moves == self.params["episode_length"]

    def is_end_state(self):
        """
            Returns true if the world is in an end state (either winning or␣
↪losing)
        """
        return self.winning_state() or self.losing_state()

    def get_reward(self):
        """
            We will give a negative reward trying to tell the AI to find the␣
↪solution with the "least worse" total reward (the smallest negative number)
            If we hit the winning state, we give the AI an additional reward␣
↪spesified in parameters.py. These are different for the table and neural␣
↪network critics.
        """
        if self.winning_state():
            return self.params["win_reward"]
        return -1
```

Actor and Critic Both the actor and the critic uses table-based representation for the policy and value function respectively. These representations can also be implemented as neural networks, as discussed in the provided video.

[33]:
```python
import random

class Actor():

    def __init__(self, learning_rate, eligibility_decay, discount, epsilon, epsilon_decay):
        """
            Constructor initializing values for the Actor class.
            Everything except the "policy" and "eligibility" is provided by the caller.
        """
        self.learning_rate = learning_rate
        self.eligibility_decay = eligibility_decay
        self.discount = discount
        self.epsilon = epsilon
        self.epsilon_decay = epsilon_decay
        self.policy = {}
        self.eligibility = {}
        self.SAPs = []

    def add_to_sap(self, sap):
        """
            Will add the state and action to the history of the given episode
        """
        self.SAPs.append(sap)

    def add_to_policy(self, sap):
        """
            If the state-action pair is not in the policy, we add it with a reward of 0.
        """
        if sap not in self.policy:
            # This works as an initialization for unseen states.
            self.policy[sap] = 0

    def add_to_eligibility(self, sap):
        """
            If the state-action pair is not in the eligibility, we add it with a reward of 1.
        """
        if sap not in self.eligibility:
            # This works as an initialization for unseen states.
            # Same asline 3 in the algorithm under section 3.1 in actor-critic.pdf
            self.eligibility[sap] = 1

    def reset(self):
```

```
        """
            Resets eligibility to empty dictionary
        """
        # Updates epsilon for each episode
        self.epsilon = self.epsilon * self.epsilon_decay
        self.eligibility = {}
        self.SAPs = []

    def select_action(self, state, possible_actions):
        """
            Decides which action the actor should do. If the random value is␣
↪larger than the epsilon it
            loops through the possible actions given from the world, and␣
↪calculates the best action by choosing the one with the best reward.
            If the random value is smaller than epsilon, a random action is␣
↪chosen.
            This works as line 2 in the algorithm under section 3.1 in␣
↪actor-critic.pdf.
        """
        best_action = random.choice(possible_actions)
        random_value = random.random()
        if random_value > self.epsilon:
            highest_reward = float("-inf")
            for move in possible_actions:
                sap = (state, move)
                self.add_to_policy(sap)
                reward = self.policy[sap]
                if reward > highest_reward:
                    best_action = move
                    highest_reward = reward
        return best_action

    def learn(self, error):
        """
            Updates the "policy" and "eligibility" with the given error and␣
↪actor properties.
        """
        for sap in self.SAPs:
            self.add_to_policy(sap)
            self.add_to_eligibility(sap)
            # Works as line 6c in the already referenced algorithm
            self.policy[sap] = self.policy[sap] + self.learning_rate * error *␣
↪self.eligibility[sap]
            # Works as line 6d in the already referenced algorithm
            self.eligibility[sap] = self.discount * self.eligibility_decay *␣
↪self.eligibility[sap]
```

```python
class Critic():

    def __init__(self, learning_rate, eligibility_decay, discount):
        """
            Constructor initializing values for the TableCritic class.
            Everything except the "rewards", "eligibility" and "error" is␣
↪provided by the caller.
        """
        self.learning_rate = learning_rate
        self.eligibility_decay = eligibility_decay
        self.discount = discount
        self.rewards = {}
        self.eligibility = {}
        self.error = 0
        self.SRPs = []

    def add_to_srp(self, srp):
        """
            Will add the state and reward to the history of the given episode
        """
        self.SRPs.append(srp)

    def reset(self):
        """
            Resets eligibility to empty dictionary
        """
        self.eligibility = {}
        self.SRPs = []

    def learn(self):
        """
            Updates the "rewards" and "eligibility" with the given error and␣
↪actor properties.
        """
        if len(self.SRPs) == 2:
            self.eligibility[self.SRPs[0][0]] = self.discount * self.
↪eligibility_decay
        self.eligibility[self.SRPs[-1][0]] = 1
        for SRP in self.SRPs:
            # Works as line 6a in the algorithm in section 3.1 in actor-critic.
↪pdf
            self.rewards[SRP[0]] = self.rewards[SRP[0]] + self.learning_rate *␣
↪self.error * self.eligibility[SRP[0]]
            # Works as line 6b in the same algorithm
            self.eligibility[SRP[0]] = self.discount * self.eligibility_decay *␣
↪self.eligibility[SRP[0]]
```

```
    def calculate_error(self, prev, new, reward):
        """
            The parameter "states" is a tuple containing the old and new state.
            The method will update the td_error for the critic based on the␣
↪actual reward and the two states.
        """
        if new not in self.rewards:
                self.rewards[new] = random.random() / 10
        if prev not in self.rewards:
                self.rewards[prev] = random.random() / 10
        # Works as line 4 in the algorithm in section 3.1 in actor-critic.pdf
        self.error = reward + (self.discount * self.rewards[new]) - self.
↪rewards[prev]
        return self.error
```

Visualizer

[34]:
```
import matplotlib.pyplot as plt
import numpy as np

class Visualiser():
    """
        Generalized visualizer using the correct subclass depending on the␣
↪world_type
    """

    def __init__(self, data, params):
        self.worker = HanoiTowersVisualizer(data, params)

    def show(self):
        """
            Every subclass has this method, and creates the visualization needed
        """
        return self.worker.show()

class HanoiTowersVisualizer():
    """
        Used for the Towers of Hanoi visualization
    """

    def __init__(self, data, params):
        self.episodes = data[0]
        self.episode = data[1]
        self.params = params

    def show(self):
        spes = self.params.get_problem_parameters()
```

```
        disc_amount = spes["disc_amount"]

        length = len(self.episode)
        print("Final episode ran for", length - 1, "moves" )
        print("The run was a " + ("SUCCESS" if len(self.episode[-1].
↪split("|")[-1].split(",")) == disc_amount else "FAILURE"))
        self.make_graph()


    def make_graph(self):
        plt.figure()
        plt.title('Results for the Towers of Hanoi')
        # Axis variables
        episode_lengths = [len(e) - 1 for e in self.episodes] # - 1 as we want␣
↪the amount of moves, and not states (16 states means 15 moves)
        plt.plot(np.arange(len(self.episodes)), episode_lengths)
        plt.xlabel("Episode number")
        plt.ylabel("Move count")

        plt.show()
```

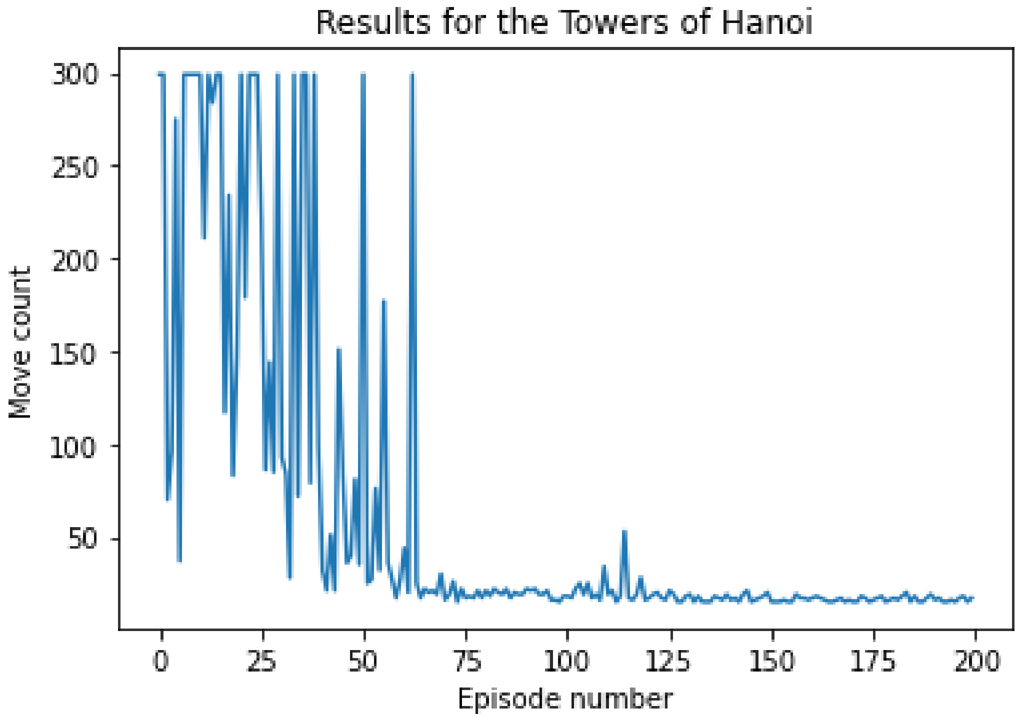
Main loop and run function

[35]:
```
PARAMS = Parameters()

def run_episode(actor, critic, world):
    # Resetting things before each episode
    world.reset()
    actor.reset()
    critic.reset()

    # Initializing state-action list and state-reward list
    state, reward = world.get_current_state(), world.get_reward()
    # Agent chooses first action
    action = actor.select_action(state, world.get_possible_actions())
    # Adding the state-action and state-reward pairs to the episode history in␣
↪actor and critic
    actor.add_to_sap((state, action))
    critic.add_to_srp((state, reward))

    # Storing episode states for visualization
    episode_visualization = [world.get_visualization()]

    # ================================= CODE BETWEEN HERE␣
↪=================================

    # Run episode steps
```

```
    while True:

        # DONE: Fetch world state and the next action chosen
        state = world.get_current_state()
        action = actor.select_action(state, world.get_possible_actions())

        # DONE: Add the state-action pair as a tuple to the actor's SAPs␣
↪(State-Action Pairs)
        actor.add_to_sap((state, action))

        # DONE: Perform the action in the world
        world.perform_action(action)

        # DONE: Fetch the new world state and the reward
        new_state = world.get_current_state()
        reward = world.get_reward()

        # DONE: Add the state-reward pair as a tuple to the critic's SRPs␣
↪(State-Reward pairs)
        critic.add_to_srp((state, reward))

        # DONE: Use the critic to calculate the error based on the previous␣
↪state, the new state and the reward
        error = critic.calculate_error(state, new_state, reward)

        # DONE: Use the error to learn the actor, and call the critics learn␣
↪method
        actor.learn(error)
        critic.learn()

        # Storing data used for visualization
        episode_visualization.append(world.get_visualization())

        # Checking if we are done, and updating neural network if we're using it
        if world.is_end_state():
            break

    # ================================= END OF CODE CHANGES␣
↪=================================

    # Returns the data needed for visualization. It is only used when the␣
↪parameter is set, but will always be returned
    return episode_visualization

def visualize(actor, critic, world):
    if PARAMS.visualize:
```

```
        # Setting epsilon to 0 so that the greedy-strategy is on display
        actor.epsilon = 0

        # Asking actor what to do for every state (1-99) for plotting
        if PARAMS.world_type == "the_gambler":
            data = []
            for i in range(1, 100):
                bet = actor.select_action(i, [j for j in range(1, min(i + 1,␣
↪100 - i + 1))])
                data.append(bet)
            data = [0] + data + [0] # This is to secure shapes (0 and 100 are␣
↪end states, but should be on the graph)
        else:
            # Running an episode
            episode = run_episode(actor, critic, world)
            data = (episodes, episode)

        # Visualizing results
        visualiser = Visualiser(data, PARAMS)
        visualiser.show()


if __name__ == "__main__":
    # Initializing actor, critic and world
    critic = Critic(PARAMS.critic_learning_rate, PARAMS.
↪critic_eligibility_decay, PARAMS.critic_discount)
    actor = Actor(PARAMS.actor_learning_rate, PARAMS.actor_eligibility_decay,␣
↪PARAMS.actor_discount, PARAMS.epsilon, PARAMS.epsilon_decay)
    world = HanoiTowersWorld(PARAMS.get_problem_parameters())

    # Used for visualization in both pole balancing and towers of hanoi
    episodes = []

    # Running episodes
    for episode_nr in range(PARAMS.num_episodes):
        episodes.append(run_episode(actor, critic, world))

    print(f"---- Ran {episode_nr + 1} episodes ----")

    visualize(actor, critic, world)
```

```
---- Ran 200 episodes ----
Final episode ran for 16 moves
The run was a SUCCESS
```


Results for the Towers of Hanoi
Move count
300
250
200
150
100
50
0
25
50
75
100
125
150
175
200
Episode number