50.039 Theory and Practice of Deep Learning

W11-S3bonus More on Deep Q-learning Reinforcement Learning

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For those of you looking for something a bit more advanced!

Definitely out-of-scope, but interesting nonetheless!

A representation problem

- **Problem:** in many RL problems, the states and/or actions sets are not necessarily finite.
- In that case, it is impossible to represent the Q and V functions as tables.
- **And, even worse, for these problems, coming up with a closed form expression of the V and Q functions might prove challenging.**

Initialized

Q-Table		Actions			
		South (0)	North (1)	East (2)	West (3)
States	0	0	0	0	0
	⋮	⋮	⋮	⋮	⋮
	327	0	0	0	0
	⋮	⋮	⋮	⋮	⋮
	499	0	0	0	0

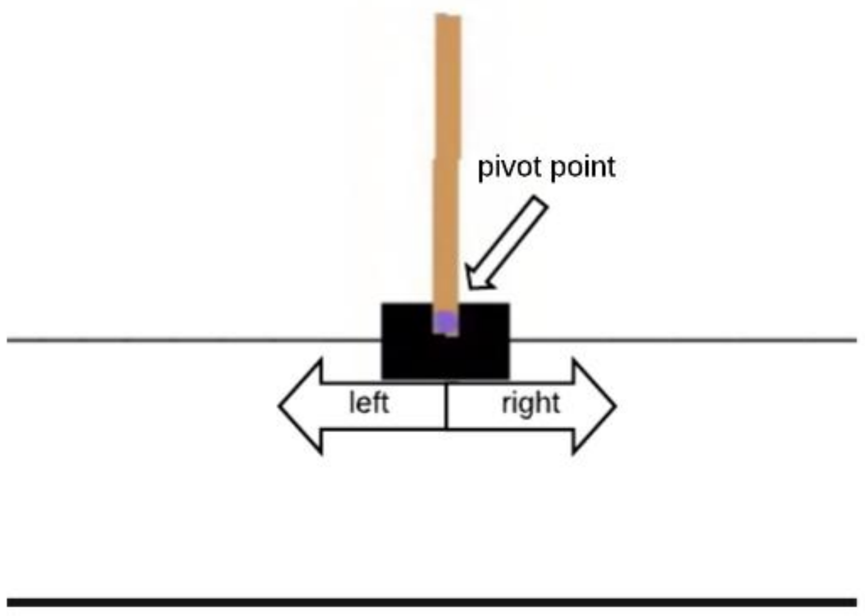
Training

Q-Table		Actions			
		South (0)	North (1)	East (2)	West (3)
States	0	0	0	0	0
	⋮	⋮	⋮	⋮	⋮
	328	-2.30108105	-1.97092096	-2.30357004	-2.20591839
	⋮	⋮	⋮	⋮	⋮
	499	9.96984239	4.02706992	12.96022777	29

Toy example #3 (shown, but implementation out of the scope of this class)

Example: the cart-pole problem.

- **State:** our current visualization of the cart (i.e. an image).
- **Actions:** 2 of them, go left or go right at a fixed speed.
- **Reward:** +1 for each unit of time where the cart does not leave the screen and the pole does not fall below a certain angle.
- **Next state generation:** cart and pole both follow simple programmed rules of physics.



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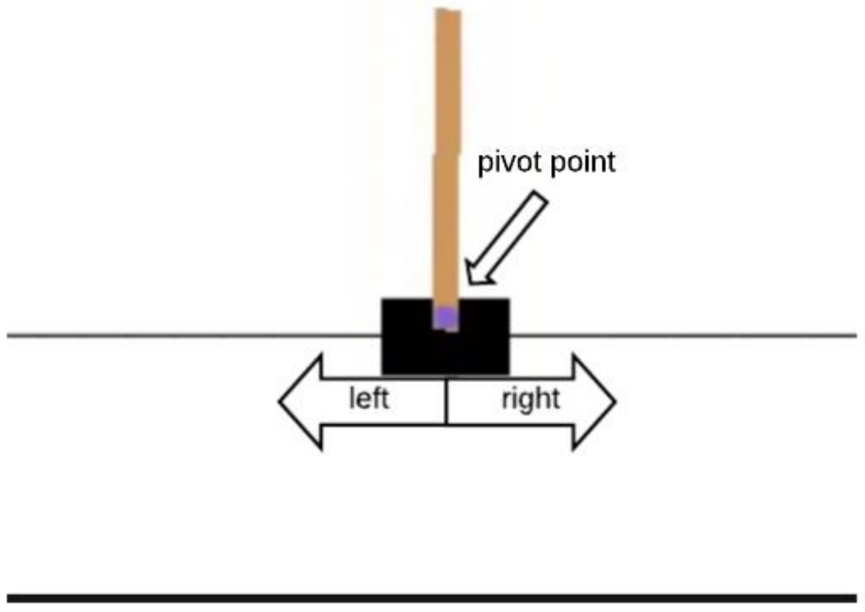

- **How do we address this issue?**
- **Give it to an AI! (as usual)**

Toy example #3 (shown, but implementation out of the scope of this class)

- **Solution:** replace the Q-table with a Deep Neural Network, whose job is to estimate the value of each action (left/right) in the current state.
- The objective is then to train, just like before with our Q-table.
- **However, we are no longer changing the table values but the Neural Net parameters!**

```python
class DQN(nn.Module):

    def __init__(self, h, w, outputs):
        super(DQN, self).__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=5, stride=2)
        self.bn1 = nn.BatchNorm2d(16)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=5, stride=2)
        self.bn2 = nn.BatchNorm2d(32)
        self.conv3 = nn.Conv2d(32, 32, kernel_size=5, stride=2)
        self.bn3 = nn.BatchNorm2d(32)

        # Number of Linear input connections depends on output of conv2d layers
        # and therefore the input image size, so compute it.
        def conv2d_size_out(size, kernel_size = 5, stride = 2):
            return (size - (kernel_size - 1) - 1) // stride  + 1
        convw = conv2d_size_out(conv2d_size_out(conv2d_size_out(w)))
        convh = conv2d_size_out(conv2d_size_out(conv2d_size_out(h)))
        linear_input_size = convw * convh * 32
        self.head = nn.Linear(linear_input_size, outputs)

    # Called with either one element to determine next action, or a batch
    # during optimization. Returns tensor([[left0exp,right0exp]...]).
    def forward(self, x):
        x = F.relu(self.bn1(self.conv1(x)))
        x = F.relu(self.bn2(self.conv2(x)))
        x = F.relu(self.bn3(self.conv3(x)))
        return self.head(x.view(x.size(0), -1))
```

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- On each round of the game, use the Q network to compute the Q-value of both actions (left/right) in the current state.
- Use the one with the maximal value (**exploitation**) or a randomly chosen action (**exploration**).
- Use ***ϵ*-greedy policy** to decide how to explore/exploit.

```
def select_action(state):
    global steps_done
    sample = random.random()
    eps_threshold = EPS_END + (EPS_START - EPS_END) * \
        math.exp(-1. * steps_done / EPS_DECAY)
    steps_done += 1
    if sample > eps_threshold:
        with torch.no_grad():
            # Here, t.max(1) will return largest column value of each row.
            # Second column on max result is index of where max element was
            # found, so we pick action with the larger expected reward.
            return policy_net(state).max(1)[1].view(1, 1)
    else:
        return torch.tensor([[random.randrange(n_actions)]], device=device, dtype=torch.long)
```

Toy example #3

To train this DNN, we need a dataset of some sort.

- Do so by playing the game multiple times and keeping a history of the (state, action, rewards, next_state, done) tuples.
- Here, done indicates that the game has ended (out of screen or low angle on pole).
- Structure is roughly similar to our dataloaders?

```python
# Define namedtuples for transitions and history
Transition = namedtuple('Transition', ('state', 'action', 'next_state', 'reward'))
```

```python
class ReplayMemory(object):

    def __init__(self, capacity):
        self.capacity = capacity
        self.memory = []
        self.position = 0

    def push(self, *args):
        """
        Saves a transition to memory.
        """
        if len(self.memory) < self.capacity:
            self.memory.append(None)
        self.memory[self.position] = Transition(*args)
        self.position = (self.position + 1) % self.capacity

    def sample(self, batch_size):
        """
        Get sample from history.
        """
        return random.sample(self.memory, batch_size)

    def __len__(self):
        """
        Get length of history (number of samples).
        """
        return len(self.memory)
```

Toy example #3 (shown, but implementation out of the scope of this class)

- **Core idea for memory replay:** we are trying to approximate a complex, nonlinear function Q, with a Neural Network.
- To do this, we must calculate targets using the **Bellman equation** and then consider that we have a **supervised learning** problem at hand.
- **Important:** However, one of the fundamental requirements for SGD optimization is that the training data is independent and identically distributed and when the Agent interacts with the game, the sequence of experience tuples can be highly correlated.
- The naive Q-learning algorithm that learns from each of these experiences tuples in sequential order runs the risk of getting swayed by the effects of this correlation.

Toy example #3 (shown, but implementation out of the scope of this class)

Definition (experience buffer in RL):

- We can prevent action values from oscillating or diverging catastrophically using a large buffer of our past experience and sample training data from it, instead of using our latest experience.
- This is called an **experience buffer**.
- The experience buffer contains a collection of experience tuples (state, action, rewards, next_state).
- The tuples are gradually added to the buffer as the agents keep on interacting with the game.

Toy example #3 (shown, but implementation out of the scope of this class)

Definition (experience replay):

- The simplest implementation is a buffer of fixed size, with new data added to the end of the experience buffer, so that it pushes the oldest experience out of it.
- The act of sampling a small batch of tuples from the experience buffer in order to learn is known as **experience replay**.
- In addition to breaking harmful correlations, experience replay allows us to learn more from individual tuples multiple times, recall rare occurrences, and in general make better use of our experience.

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To train this DNN, we need a loss function and weight update procedure of some sort, as well.

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- **Problem:** update $Q(s_t, a)$ via $Q(s_{t+1}, a)$. However, both states have only one step between them. This makes them very similar, and it is very hard for a Neural Network to distinguish between them.

Toy example #3 (shown, but implementation out of the scope of this class)

Solution: use **two Neural Networks**, one for **training** $Q(s_t, a)$ and one for producing **targets** $Q(s_{t+1}, a)$, or **evaluating** the other.

- That is, the predicted Q values of this second Q-network called the target network, are used to backpropagate through and train the main Q-network.
- **Note:** the target network's parameters are <u>not trained</u>, but they are periodically synchronized with the parameters of the main Q-network.
- The idea is that using the target network's Q values to train the main Q-network will improve the stability of the training.

```python
def optimize_model():
    if len(memory) < BATCH_SIZE:
        return
    transitions = memory.sample(BATCH_SIZE)
    # Transpose the batch (see https://stackoverflow.com/a/19343/3343043 for
    # detailed explanation). This converts batch-array of Transitions
    # to Transition of batch-arrays.
    batch = Transition(*zip(*transitions))

    # Compute a mask of non-final states and concatenate the batch elements
    # (a final state would've been the one after which simulation ended)
    non_final_mask = torch.tensor(tuple(map(lambda s: s is not None,
                                          batch.next_state)), device=device, dtype=torch.bool)
    non_final_next_states = torch.cat([s for s in batch.next_state
                                                if s is not None])
    state_batch = torch.cat(batch.state)
    action_batch = torch.cat(batch.action)
    reward_batch = torch.cat(batch.reward)

    # Compute Q(s_t, a) - the model computes Q(s_t), then we select the
    # columns of actions taken. These are the actions which would've been taken
    # for each batch state according to policy_net
    state_action_values = policy_net(state_batch).gather(1, action_batch)

    # Compute V(s_{t+1}) for all next states.
    # Expected values of actions for non_final_next_states are computed based
    # on the "older" target_net; selecting their best reward with max(1)[0].
    # This is merged based on the mask, such that we'll have either the expected
    # state value or 0 in case the state was final.
    next_state_values = torch.zeros(BATCH_SIZE, device=device)
    next_state_values[non_final_mask] = target_net(non_final_next_states).max(1)[0].detach()
    # Compute the expected Q values
    expected_state_action_values = (next_state_values * GAMMA) + reward_batch

    # Compute Huber loss
    loss = F.smooth_l1_loss(state_action_values, expected_state_action_values.unsqueeze(1))

    # Optimize the model
    optimizer.zero_grad()
    loss.backward()
    for param in policy_net.parameters():
        param.grad.data.clamp_(-1, 1)
    optimizer.step()
```

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To train this DNN, we need a loss function and weight update procedure of some sort.

To create a loss function, let us first recall that

$$Q_t^{\pi}(s_t, a_t) = R_t(s_t, a_t) + \gamma Q_{t+1}^{\pi}(s_{t+1}, \pi(s_{t+1}))$$

Let us denote the error δ as

$$\delta = Q_t^{\pi}(s_t, a_t) - \left(R_t(s_t, a_t) + \gamma \max_a Q_{t+1}^{\pi}(s_{t+1}, a) \right)$$

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To train this DNN, we need a loss function and weight update procedure of some sort.

To train our DNN, we want to minimize this error δ.

We will use the L1 norm on delta to do so.

$$L(\delta) = |\delta|$$

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We will use the L1 norm on delta to do so.

Note: we can also use a slightly different loss function known as the **Huber loss**, which is slightly more robust to outliers.

$$L_d(\delta) = \begin{cases} \frac{1}{2}\delta^2 & if\ |\delta| \leq d \\ d\left(|\delta| - \frac{1}{2}d\right) & else \end{cases}$$

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    # Optimize the model
    optimizer.zero_grad()
    loss.backward()
    for param in policy_net.parameters():
        param.grad.data.clamp_(-1, 1)
    optimizer.step()
```

Trainer function

- Our trainer function will play the game 500 times.
- Keep track of different histories over the 500 games.
- Sample from history to train our main Q-Network.
- Backpropagate with mixed main and target Q-networks values.
- Occasionally update the target network.

```python
"""
Full trainer on 500 iteration (for meaningful improvements)
"""
num_episodes = 500
for i_episode in range(num_episodes):
    print("Episode:", i_episode)
    # Initialize the environment and state
    env.reset()
    last_screen = get_screen()
    current_screen = get_screen()
    state = current_screen - last_screen
    for t in count():
        # Select and perform an action
        action = select_action(state)
        _, reward, done, _ = env.step(action.item())
        reward = torch.tensor([reward], device=device)

        # Observe new state
        last_screen = current_screen
        current_screen = get_screen()
        if not done:
            next_state = current_screen - last_screen
        else:
            next_state = None

        # Store the transition in memory
        memory.push(state, action, next_state, reward)

        # Move to the next state
        state = next_state

        # Perform one step of the optimization (on the policy network)
        optimize_model()
        if done:
            episode_durations.append(t + 1)
            plot_durations()
            break
    # Update the target network, copying all weights and biases in DQN
    if i_episode % TARGET_UPDATE == 0:
        target_net.load_state_dict(policy_net.state_dict())
```

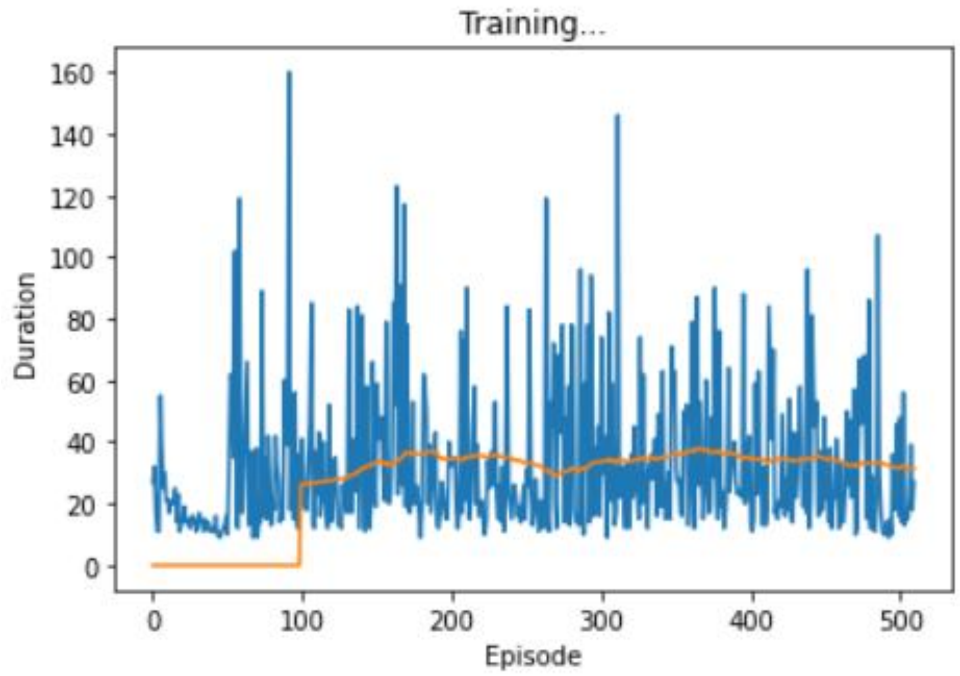
Training results

- Our RL agent will learn to balance the pole on the cart, by playing the game.
- Can display the length of each game/episode to see the progression!

- This RL approach of training some DNNs to replace the Q functions is commonly referred to as **Deep Q-learning**.

```python
def plot_durations():
    """
    Show episode durations for each episode.
    """
    plt.figure(2)
    plt.clf()
    durations_t = torch.tensor(episode_durations, dtype=torch.float)
    plt.title('Training...')
    plt.xlabel('Episode')
    plt.ylabel('Duration')
    plt.plot(durations_t.numpy())
    # Take 100 episode averages and plot them too
    if len(durations_t) >= 100:
        means = durations_t.unfold(0, 100, 1).mean(1).view(-1)
        means = torch.cat((torch.zeros(99), means))
        plt.plot(means.numpy())

```



Following this cart-pole balance idea…

- Train an AI to keep a robot on its feet, despite some *"minor environment perturbations"* *(a polite way of saying you kick the hell out of the robot for fun).*
- Video: https://www.youtube.com/watch?v=NR32ULxbjYc
- **BostonDynamics** blog: https://blog.bostondynamics.com/

Following this idea of using computer vision to identify state and act...

- Train an AI to play video games with Deep Reinforcement Learning (Mnih, 2013)!
- Paper: https://www.cs.toronto.edu/~vmnih/docs/dqn.pdf
- Video: https://www.youtube.com/watch?v=TmPfTpjtdgg