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4. Tabular Q-learning for Home World game

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Project due May 10, 2023 08:59 -03 Completed

In this section you will evaluate the tabular Q-learning algorithms for the *Home world* game. The state observable to the player is described in text. Therefore we have to choose a mechanism to map textual descriptions into vector representations.

In this section you will consider a simple approach that assigns a unique index for each description. In particular, we will build two dictionaries:

- `dict_room_desc` that takes the room description text as the key and returns a unique index
- `dict_quest_desc` that takes the quest description text as the key and returns a unique index

For instance, consider an observable state $\mathbf{s} = (\mathbf{s}_r, \mathbf{s}_q)$, where \mathbf{s}_r and \mathbf{s}_q are the text descriptions of the current room and the current request, respectively. Then $i_r = \text{dict_room_desc}[\mathbf{s}_r]$ gives the scalar index for \mathbf{s}_r and $i_q = \text{dict_quest_desc}[\mathbf{s}_q]$ gives the scalar index for \mathbf{s}_q . That is, the textual state \mathbf{s} is mapped to a tuple $\mathbf{I} = (i_r, i_q)$.

Normally, we would build these dictionaries as we train our agent, collecting descriptions from the list of known descriptions. For the purpose of this project, these dictionaries will be pre-built.

Evaluating Tabular Q-learning on Home World

1.0/1 point (graded)

The following python files are provided:

- `framework.py` contains various functions for the text-based game environment that are implemented for you. Some functions that you can call to train and testing your reinforcement learning algorithms:
 - `newGame()`
 - Args: None
 - Return: A tuple where the first element is a description of the initial room, the second element is a description of the quest for this new game episode, and the last element is a boolean value *False* implying that the game is not over.
 - `step_game()`
 - Args:
 - `current_room_desc` : An description of the current room
 - `current_quest_desc` : A description of the current quest state

In this section, you will evaluate your learning algorithm for the Home world game. The measure an agent's performance is the cumulative discounted reward obtained per episode over many episodes.

The evaluation procedure is as follows. Each experiment (or run) consists of multiple epochs. Each epoch consists of `NUM_EPOCHS` epochs. In each epoch:

1. You first train the agent on `NUM_EPIS_TRAIN` episodes, following an `epsilon`-greedy policy with `TRAINING_EP` and updating the `Q` values.
2. Then, you have a testing phase of running `NUM_EPIS_TEST` episodes of the game with the `epsilon`-greedy policy with `TESTING_EP`, which makes the agent choose the best action based on the current `Q`-values of the time. At the testing phase of each epoch, you will compute the cumulative discounted reward for each episode and then obtain the average reward over the testing episodes.

Finally, at the end of the experiment, you will get a sequence of data (of size `NUM_EPOCHS`) representing the testing performance at each epoch.

Note that there is randomness in both the training and testing phase. You will run the experiment multiple times and then compute the averaged reward performance over `NUM_RUNS` experiments.

Most of these operations are handled by the boilerplate code provided in the `agent_training.py` functions `run`, `run_epoch` and `main`, but you will need to complete the `run_episode` function.

Write a `run_episode` function that takes a boolean argument (whether the episode is for training or testing) and runs one episode.

Reminder: You should implement this function locally first. Make sure you can achieve a high score on the Home World game before submitting your code.

Available Functions: You have access to the NumPy python library as `np`, framework functions `framework.newGame()` and `framework.step_game()`, constants `TRAINING_EP` and `TESTING_EP`, dictionaries `dict_room_desc` and `dict_quest_desc` and previously implemented functions `epsilon_greedy` and `tabular_q_learning`.

```
1 def run_episode(for_training):
2     """ Runs one episode
3     If for training, update Q function
4     If for testing, computes and return cumulative discounted reward
5
6     Args:
7         for_training (bool): True if for training
8
9     Returns:
10        None
11    """
12    epsilon = TRAINING_EP if for_training else TESTING_EP
13    gamma_step = 1
```

Report performance

2/2 points (graded)

In your Q-learning algorithm, initialize `Q` at zero. Set `NUM_RUNS`, `NUM_EPIS_TRAIN`, `NUM_EPIS_TEST`, `TRAINING_EP`, `TESTING_EP` and the learning rate.

Please enter the number of epochs when the learning algorithm converges. That is, the average episodic rewards become stable.



Please enter the *average episodic rewards* of your Q-learning algorithm when it converges.

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