

Problem Set 4

Deadline: 12:00pm EDT, 26 September 2019

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CS 8803 - Interactive Robot Learning

September 26, 2019

Instructions: Write your name in the top, left-hand corner. **You may work with others (collaborate) to complete this assignment.** Here, “collaborate” means that you talk about the assignment, teach/learn from each other, and even compare answers. However, you *must* write your own code, but you *may* help debug each other’s code. The execution of the coding must be done on your own. Finally, you must list the names of the people with whom you collaborated. Sign here acknowledging adherence to completing this assignment according to these instructions:

Signature: _____

Collaborators: _____

Problem 1. Using MATLAB’s built-in Baum-Welch solver for HMMs, a similar package in Python, etc., synthesize an HMM model for the Keyser Söze example from Lecture 6 using the same initial conditions as in Slide 41. Assume $\pi = [1, 0]$. Report the resulting transition and observation matrices below.

$$T = \begin{bmatrix} 0.7284, & 0.2716 \\ 0.0945, & 0.9055 \end{bmatrix}$$
$$M = \begin{bmatrix} 0.5801, & 0.0000, & 0.4199 \\ 0.0000, & 0.7631, & 0.2369 \end{bmatrix}$$

Problem 2. What is an ANOVA? Don't just give a definition, but also state its purpose/function.

Analysis of variance (ANOVA) are collection of statistical models and their associated estimation procedures to analyze the differences between groups in sample. ANOVA can test whether three or more population means are equal, while t-test can only show the significant difference between the means of two groups.

Problem 3. Can you perform pairwise tests without performing an ANOVA first (and find statistical significance doing so)?

If we do not perform an ANOVA to find out if there are significant differences between the groups (reject or cannot reject the null hypothesis), the pairwise tests are likely to be invalid, then we can use Bonferroni correction to account for the chance that we get lucky through pairwise comparisons.

Problem 4. What is a Likert item vs. a Likert scale?

A likert item is an ordinal scale to solicit an experimental participants level of agreement with a statement regarding an experimental condition they experience. A likert scale is a summation across a set of Likert items.

Problem 5. Provide a good reason and a bad reason to throw out an outlier.

Good reason: The outliers may be in fact erroneous due to some factors such as the equipment issues.

Bad reason: The outliers may be not bad data and due to random variation, and can indicate something to help improve the model.

Problem 6. Does an ANOVA assume the data are normally distributed? If not, what is supposed to be normally distributed?.

The data do not have to be normally distributed in an ANOVA. The parametric ANOVA (one-way or two-way ANOVA) relies on an assumption of normality.

Problem 7. In PSet 3, you generated a dataset of 10,000 episodes for a Q-learning algorithm. For this problem, we will explore how active learning could come into play here. You may choose to complete one of the following two parts for Problem 7.

1. For the final 1,000 episodes, generate a data set of each state-action pair taken by the Q-learning algorithm (i.e., $D = \{\langle s_{e,t}, a_{e,t} \rangle\}$).

Train a neural network classifier using Python or MATLAB that takes in the $4 \times 4 \times 8$ matrix describing s_t as a vector and outputs the probability of taking each of the five actions in that state. Use a binary cross entropy loss for training the algorithm to correctly predict the probability of taking $a_{e,t}$ in $s_{e,t}$ is 1.

Using entropy as a measure, find the state in your data set, $s \in D$, that maximizes the entropy over actions. Report a bar plot where the vertical axis is the probability assigned to each action, the horizontal axis has each of the five actions.

2. For the final 1,000 episodes, generate a data set of each state paired with the q-values of each action for that state taken by the Q-learning algorithm (i.e., $D = \{\langle s_{e,t}, Q(s_{e,t}, a_1), Q(s_{e,t}, a_2), \dots, Q(s_{e,t}, a_5) \rangle\}$).

Train a bag of 5 a neural network regression models using Python or MATLAB that takes in the $4 \times 4 \times 8$ matrix describing s_t as a vector and outputs a 1×5 vector of the corresponding q-values. Use least squares regression. Each neural network should be trained with 80% of the data sampled randomly with replacement.

Using variance as a measure, find the state in your data set, $s \in D$, that maximizes the variance between what the model's predict is the max Q-value for that state. Report a bar plot where the vertical axis is the max q-value for that state and the horizontal axis has each of the five neural network models.

Does this state have action labels that are in conflict? In other words, does the dataset have the agent being in this state multiple times but choosing different actions?

For either approach, does the state you choose have action labels that are in conflict? In other words, does the dataset have the agent being in this state multiple times but choosing different actions?

I choose to complete the first one. The results are different among different implementations, whereas the results show something in common and interesting. In most cases, the chosen state only shows up in the dataset for once or twice. Sometimes, the chosen state can be visited by the agent for multiple times but the agent was very likely to choose different actions (which means the action labels are in conflict). In many times, the chosen state have the agent in (3,2), so I choose these states to present the results in the following part. The tuple of binary values represents: (agent, stench, wumpus, visited).

- The chosen state shows up in the dataset for once:
The state is: $\{(1,1): (0,0,0,1); (1,2): (0,1,0,1); (1,3): (0,0,0,0); (1,4): (0,0,0,0); (2,1): (0,0,0,1); (2,2): (0,0,0,1); (2,3): (0,0,0,0); (2,4): (0,0,0,0); (3,1): (0,0,0,0); (3,2): (1,0,0,1); (3,3): (0,0,0,0); (3,4): (0,0,0,0); (4,1): (0,0,0,0); (4,2): (0,0,0,0); (4,3): (0,0,0,0); (4,4): (0,0,0,0)\}$

The bar graph is depicted as Figure 1.

The corresponding action in the dataset is: left.

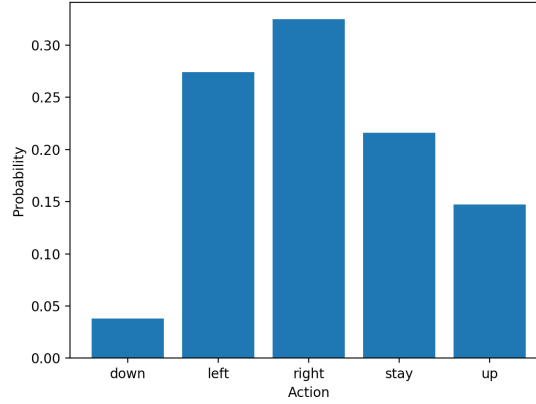


Figure 1: Case 1

- The chosen state shows up in the dataset for twice:

The state is: $\{(1,1): (0,0,0,1); (1,2): (0,0,0,0); (1,3): (0,0,0,0); (1,4): (0,0,0,0); (2,1): (0,0,0,1); (2,2): (0,1,0,1); (2,3): (0,0,0,0); (2,4): (0,0,0,0); (3,1): (0,0,0,0); (3,2): (1,0,0,1); (3,3): (0,0,0,0); (3,4): (0,0,0,0); (4,1): (0,0,0,0); (4,2): (0,0,0,1); (4,3): (0,0,0,0); (4,4): (0,0,0,0)\}$

The bar graph is depicted as Figure 2.

The corresponding actions in the dataset are: stay, right.

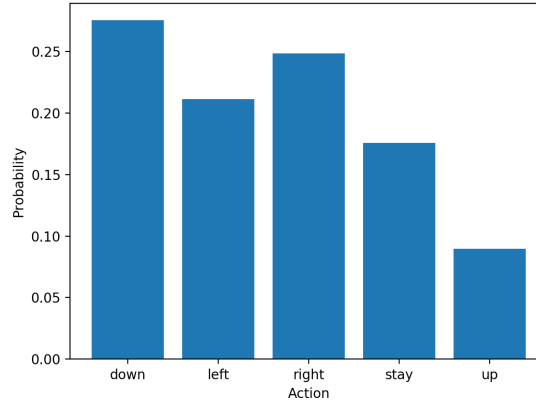


Figure 2: Case 2

- The chosen state shows up in the dataset for multiple times:

The state is: $\{(1,1): (0,0,0,1); (1,2): (0,1,0,1); (1,3): (0,0,0,0); (1,4): (0,0,0,0); (2,1): (0,0,0,0); (2,2): (0,1,0,1); (2,3): (0,0,0,0); (2,4): (0,0,0,0); (3,1): (0,0,0,0); (3,2):$

(1,1,0,1); (3,3): (0,0,0,0); (3,4): (0,0,0,0); (4,1): (0,0,0,0); (4,2): (0,0,0,0); (4,3): (0,0,0,0); (4,4): (0,0,0,0)}

The bar graph is depicted as Figure 3.

The corresponding actions in the dataset are: stay, down, left, left.

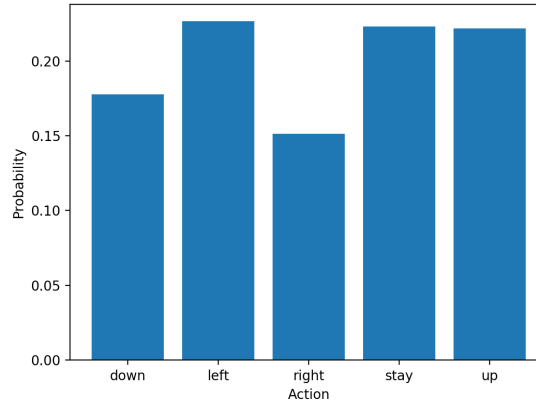


Figure 3: Case 3

- The chosen state shows up in the dataset for multiple times (another case):
 The state is: $\{(1,1): (0,0,0,1); (1,2): (0,1,0,1); (1,3): (0,0,0,0); (1,4): (0,0,0,0); (2,1): (0,0,0,0); (2,2): (0,1,0,1); (2,3): (0,0,0,0); (2,4): (0,0,0,0); (3,1): (0,0,0,0); (3,2): (1,0,0,1); (3,3): (0,0,0,0); (3,4): (0,0,0,0); (4,1): (0,0,0,0); (4,2): (0,0,0,0); (4,3): (0,0,0,0); (4,4): (0,0,0,0)\}$

The bar graph is depicted as Figure 4.

The corresponding actions in the dataset are: stay, left, left, up, left, right, down.

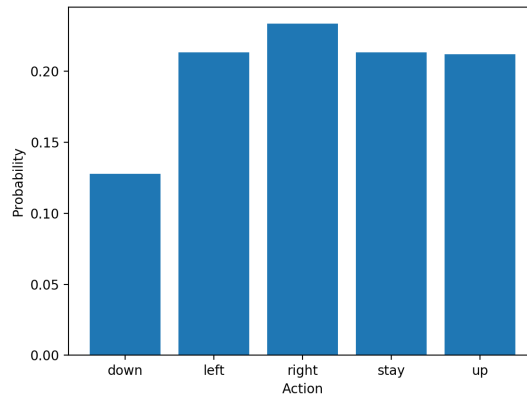


Figure 4: Case 4