

UNIVERSITY OF PENNSYLVANIA
ESE 650: LEARNING IN ROBOTICS
HOMEWORK 1

Changelog:

Read the following instructions carefully before beginning to work on the homework.

- You will submit neatly written solutions via Gradescope. You can use L^AT_EX (encouraged) but you can also write by hand. You can use hw_template.tex on Canvas in the “hw” folder to do so. If your handwriting is *unambiguously legible*, you can submit PDF scans/tablet-created PDFs.
- Please start a new problem on a fresh page and mark all the pages corresponding to each problem. Failure to do so may result in your work not graded completely.
- Clearly indicate the name and Penn email ID on your submitted solutions.
- For each problem in the homework, you should mention the total amount of time you spent on it.
- You can be informal while typesetting the solutions, e.g., if you want to draw a picture feel free to draw it on paper clearly, click a picture and include it in your solution. Do not spend undue time on typesetting solutions.
- You will see an entry of the form “HW 0 PDF” where you will upload the PDF of your solutions. You will also see entries like “HW 0 Problem 1 Code” where you will upload your solution for the respective problems. **For each programming problem, you should create a fresh Python file.** This file should contain all the code to reproduce the results of the problem and you will upload the .py file to Gradescope. If we have installed Autograder for a particular problem, you will use the Autograder. Name your file to be “pennkey_hw0_problem1.py”, e.g., I will name my code for Problem 1 as “pratikac_hw0_problem1.py”.
- **You should include all the relevant plots in the PDF, without doing so you will not get full credit.** You can, for instance, export your Jupyter notebook as a PDF (you can also use text cells to write your solutions) and export the same notebook as a Python file to upload your code.
- **Your PDF solutions should be completely self-contained. If the question requires you to produce a plot, you must have it in the PDF to get credit. We will run the Python file to check if your solution reproduces the results in the PDF.**

Credit. The points for the problems add up to 115. You only need to solve for 100 points to get full credit, i.e., your final score will be $\min(\text{your total points}, 100)$.

1 **Problem 1 (50 points, Bayes filter).** In this problem, we are given a robot operating in a 2D
2 grid world. Every cell in the grid world is characterized by a color (0 or 1). The robot is
3 equipped with a noisy odometer and a noisy color sensor. Given a stream of actions and
4 corresponding observations, implement a Bayes filter to keep track of the robot's current
5 position. The sensor reads the color of the cell of the grid world correctly with probability
6 0.9 and incorrectly with probability 0.1. At each step, the robot can take an action to move in
7 4 directions (north, east, south, west). Execution of these actions is noisy, so after the robot
8 performs this action, it actually makes the move with probability 0.9 and stays at the same
9 spot without moving with probability 0.1.

10 When the robot is at the edge of the grid world and is tasked with executing an action that
11 would take it outside the boundaries of the grid world, the robot remains in the same state
12 with probability 1. Start with a uniform prior on all states. For example if you have a world
13 with 4 states (x_1, x_2, x_3, x_4) then $P(X_0 = x_1) = P(X_0 = x_2) = P(X_0 = x_3) = P(X_0 =$
14 $x_4) = 0.25$.

15 You are given a zip file with some starter code for this problem: this consists of the Python
16 scripts `example_test.py` and `histogram_filter.py` (Bayes filter is also called the Histogram
17 filter) and a starter file containing some data: `starter.npz`. The `starter.npz` file contains a binary
18 color-map (the grid), a sequence of actions, a sequence of observations, and a sequence
19 of the correct belief states. This is provided for you to debug your code. We have already
20 implemented code in `example_test.py` for you to test your implementation of the histogram
21 filter which you will code up in the `histogram_filter.py`.

22 The action tuples for `histogram_filter.py` correspond to:

$$(1, 0) = \text{Right}, (-1, 0) = \text{Left}, (0, -1) = \text{Down}, (0, 1) = \text{Up}$$

23 However, the given `starter.npz` data uses a different action coordinate which is:

$$(1, 0) = \text{Down}, (-1, 0) = \text{Up}, (0, 1) = \text{Right}, (0, -1) = \text{Left}$$

24 Therefore, we rotate the belief states using `np.rot90()` to make the coordinates consistent
25 with the provided data as can be seen in `example_test.py`

26 Be careful not to change the function signature, or your code will not pass the tests on
27 the autograder. You will turn in your assignment using Gradescope. Note that there may be
28 slight differences in the output of your implemented Bayes filter and the outputs given in the
29 given data even when your code is correct.

30 **Problem 2 (35 points, Learning HMMs).** In this problem, we are going to implement
31 what is called the Baum-Welch algorithm for HMMs. Recall that an HMM with observation
32 matrix M has an underlying Markov chain with an initial distribution π and state-transition
33 matrix T . Let us denote our HMM by

$$\lambda = (\pi, T, M).$$

- 1 Say someone had given us an HMM λ which gave us a sequence of observations Y_1, \dots, Y_t .
- 2 Since these observations happened, they tell us something more about our given state-
- 3 transition and observation matrices, for example, given these observations, we can go back
- 4 and modify T, M to be such that the observation sequence is more likely, i.e., it improves

$$P(Y_1, \dots, Y_t | \lambda).$$

- 5 (a) **(15 points)** Assume that we are tracking a criminal who shuttles merchandise between
- 6 Los Angeles (x_1) and New York (x_2). The state transition matrix between these states is

$$T = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix};$$

- 7 e.g., given the person is in LA, he is likely to stay in LA or go to NY with equal probability.
- 8 We can make observations about this person, we either observe him to be in LA (y_1), NY
- 9 (y_2), or do not observe anything at all (null, y_3).

$$M = \begin{bmatrix} 0.4 & 0.1 & 0.5 \\ 0.1 & 0.5 & 0.4 \end{bmatrix}.$$

- 10 Say that we are tracking the person and we observed an observation sequence of 20 periods
(null, LA, LA, null, NY, null, NY, NY, NY, null, NY, NY, NY, NY, NY, null, null, LA, LA, NY).
- 11 Assume that we do not know where the criminal is at the first time-step, so the initial
- 12 distribution π is uniform.
- 13 We first compute the probability of each state given all the observations, i.e.,

$$\gamma_k(x) = P(X_k = x | Y_1, \dots, Y_t, \lambda) = \frac{\alpha_k(x) \beta_k(x)}{\sum_x \alpha_t(x)}.$$

- 14 which is simply our smoothing probability computed using the HMM λ computed using the
- 15 forward and backward variables α_k, β_k . You should check that $\gamma_k(x)$ should be a legitimate
- 16 probability distribution, i.e., $\sum_x \gamma_k(x) = 1$.

- 17 Compute the smoothing probabilities $\gamma_k(x)$ for all 20 time-steps and both states and show
- 18 it in a table like we had in the lecture notes. You should also show the corresponding tables
- 19 for the forward and backward probabilities α_k s and β_k s.

- 20 You should get the point-wise most likely sequence of states after doing so to be
(LA, LA, LA, LA, NY, LA, NY, NY, NY, LA, NY, NY, NY, NY, NY, LA, LA, LA, LA, NY).
- 21 Notice how smoothing fills in the missing observations above.

- 22 (b) **(5 points)** We now discuss how to update the model λ given our observations. First
- 23 observe that

$$E[\text{number of times the Markov chain was in state } x] = \sum_{k=1}^{t-1} \gamma_k(x).$$

1 Let us define a new quantity

$$\xi_k(x, x') = P(X_k = x, X_{k+1} = x' | Y_1, \dots, Y_t, \lambda)$$

- 2 to be the probability of being at a state x at time k and then moving to state x' at time $k + 1$,
3 conditional upon all the observations we have received from our HMM. Show that

$$\xi_k(x, x') = \eta \alpha_k(x) T_{x,x'} M_{x',y_{k+1}} \beta_{k+1}(x')$$

- 4 where η is a normalizing constant that makes $\sum_{x,x'} \xi_k(x, x') = 1$.

5 (c) (5 points) We can now use our estimate from the previous part to get

$$E[\text{number of transitions from } x \text{ to } x'] = \sum_{k=1}^{t-1} \xi_k(x, x').$$

- 6 We now construct an updated model for our HMM as follows. The initial distribution of the
7 states, instead of being π , is our smoothing probability

$$\pi' = \gamma_1(x).$$

- 8 Entries of the new transition matrix can be computed by

$$T'_{x,x'} = \frac{E[\text{number of transitions from } x \text{ to } x']}{E[\text{number of times the Markov chain was in state } x]} = \frac{\sum_{k=1}^{t-1} \xi_k(x, x')}{\sum_{k=1}^{t-1} \gamma_k(x)}.$$

- 9 Entries of the new observation matrix can be computed by

$$M'_{x,y} = \frac{E[\text{number of times in state } x, \text{ when observation was } y]}{E[\text{number of times the Markov chain was in state } x]} = \frac{\sum_{k=1}^t \gamma_k(x) \mathbf{1}_{\{y_k=y\}}}{\sum_{k=1}^t \gamma_k(x)}.$$

- 10 where $\mathbf{1}_{\{y_k=y\}}$ denotes that the observation at the k^{th} timestep was y . Let the new HMM
11 model be

$$\lambda' = (\pi', T', M')$$

- 12 Write down the new HMM model λ' and see if any entries have changed as compared to λ .

- 13 (d) (5 points) Compare the two HMMs λ and λ' . Compute the two probabilities and show
14 that

$$P(Y_1, \dots, Y_t | \lambda) < P(Y_1, \dots, Y_t | \lambda').$$

- 15 This is exactly what Baum et al. proved in the paper Baum, Leonard E., et al. "A
16 maximization technique occurring in the statistical analysis of probabilistic functions of
17 Markov chains." The annals of mathematical statistics 41.1 (1970): 164-171. You can see
18 that the Baum-Welch algorithm is quite powerful to learn real-world Markov chains, e.g., the
19 running gait of your dog (what is the state here?) given observations of its limb positions.
20 Given some elementary model of the dynamics T and an observation model M , you can
21 sequentially update both of them to guess a better model of the dynamics.

- 22 **Problem 3 (20 points, Forward-Backward algorithm).** Answer the following questions.

1 (a) **(15 points)** Using our forward and backward variables

$$\alpha_k(x) = P(Y_1, \dots, Y_k, X_k = x)$$

$$\beta_k(x) = P(Y_{k+1}, \dots, Y_t | X_k = x).$$

2 for a sequence of observations Y_1, \dots, Y_t of length $t > 1$, the state transition matrix

3 $T_{ij} = P(X_{k+1} = x_j | X_k = x_i)$ and the observation matrix $M_{ij} = P(Y_k = y_j | X_k = x_i)$,

4 write down how you will compute the following probabilities

5 (1) $P(X_{k+1} = x_j | X_k = x_i, Y_1, \dots, Y_t)$,

6 (2) $P(X_k = x_i | X_{k+1} = x_j, Y_1, \dots, Y_t)$,

7 (3) $P(X_{k-1} = x_i, X_k = x_j, X_{k+1} = x_l | Y_1, \dots, Y_t)$.

8 You do not need to consider the boundary cases like $k \in \{1, t\}$.

9 (b) **(5 points)** Viterbi's algorithm finds the most likely state trajectory of the HMM's

10 associated Markov chain given a sequence of observations Y_1, \dots, Y_t . Explain why, in
11 general, the solution of the decoding problem, i.e.,

$$(x_1^*, \dots, x_t^*) = \underset{(x_1, \dots, x_t)}{\operatorname{argmax}} P(X_1 = x_1, \dots, X_t = x_t | Y_1, \dots, Y_t).$$

12 is not the same as the sequence obtained by the most likely state at each time computed by

13 the smoothing, i.e.,

$$(\hat{x}_1, \dots, \hat{x}_t) \text{ where } \hat{x}_k = \underset{x}{\operatorname{argmax}} P(X_k = x | Y_1, \dots, Y_t).$$

14 Give an example where the two *are the same*.

15 **Problem 4 (15 points, Optimal estimation).** We will study the simplest case of a filtering
16 problem, namely estimation of a static, scalar variable $X \in \mathbb{R}$. We take two noisy
17 measurements of the scalar X of the form

$$Y_i = h_i X + \epsilon_i; \quad i = 1, 2$$

18 where $h_1 = 1$ and $h_2 = 2$. The noise in our measurements $\epsilon_i \in \mathbb{R}$ are distributed as

$$E[\epsilon_i] = 0, \text{ and } E[\epsilon_i^2] = \sigma_i^2.$$

19 The two noise terms are uncorrelated with each other. Assume that our signal X is not
20 correlated with noise $E[X\epsilon_i] = 0$ for both $i = 1, 2$.

21 (a) **(10 points)** Assume that the optimal estimate of the variable is of the form

$$\hat{X} = a_1 Y_1 + a_2 Y_2$$

22 where constants a_1 and a_2 are independent of X . Compute the values of a_1, a_2 that

23 (i) make sure that the estimate \hat{X} is unbiased, and

24 (ii) minimize the mean-square estimation error $E[(X - \hat{X})^2]$.

1 Use these values of a_1, a_2 to compute the minimum value of the mean-square
2 estimation error. You should solve this problem from first principles, without using
3 any expressions for the Kalman filter that we may derive in the class.

4 (b) **(5 points)** Discuss how the optimal estimator uses the two measurements for the
5 following cases

6 (i) $\sigma_2 \gg \sigma_1$

7 (ii) $\sigma_2 = \sigma_1$

8 (iii) $\sigma_2 \ll \sigma_1$.

9 Do your answers agree with your intuition? Explain.