



# CS 237B: Principles of Robot Autonomy II

## Problem Set 3: Human-Robot Interaction

Due March 8th, 2024 11:59PM

### Submission Instructions

You will submit your homework to Gradescope. Your submission will consist of:

1. a single pdf with your written answers for report questions (denoted by the  symbol). This must be typeset (e.g.,  $\text{\LaTeX}$  or Word).
2. a .zip folder containing your code for the programming questions (denoted by the  symbol). **Also include the `policies` folder in your submission.**

### Honor Code

- **Collaboration:** You may collaborate with other students on the homework. However, each student should independently write up their own solutions and **clearly list the names of their collaborators** in their write-up.
- **Committing code to GitHub:** Please do not push your homework code to public GitHub repositories (for example, a fork of our repository). If you wish to commit your solutions to GitHub, please create a **private repository** by making a new copy of our repository, rather than forking it.

### Introduction

For this homework, you will explore different elements of human-robot interaction. In particular you will investigate some basics of

1. Imitation learning,
2. Intent inference, and
3. Shared autonomy

Imitation learning will form the biggest chunk of the homework, and so it will require a good deal of programming and neural network training.

In terms of software development, you will use Tensorflow and the simplistic 2D driving simulator CARLO in this assignment. While CARLO is publicly available at <https://github.com/Stanford-ILIAD/CARLO>, we made some changes for this homework, and you will therefore use the version we provide.

The problems in this homework are dependent on each other, so you must solve them sequentially<sup>1</sup>.

Starter code for this problem set has been made available online through github; to get started download the code by running `git clone https://github.com/PrinciplesofRobotAutonomy/CS237B_HW3.git`.

## Install Additional Software Dependencies

Homework 3 continues to use the virtual environment from the previous homeworks with added dependencies. To maintain consistency within this class, we already listed all dependencies on `requirements.txt` in the git repository you cloned. Navigate to the repo and activate your virtual environment. For Anaconda:





```
$ conda activate cs237b
```

Once you're in the virtual environment, run:

```
$ pip install -r requirements.txt
```

Now we're ready to go!

## Problem 1: Getting Started

- (i)  Weight initialization is an important consideration in the design of a neural network model. Explain what problems or advantages may arise in a deep neural network if we initialize all weights and biases with 0.
- (ii)  The data you are going to use in this homework is complex and requires modeling nonlinearities. Often in such cases, it becomes very important how the weights are initialized for training time and finding better optima. Read about "Xavier initialization" (first proposed in [1]) and explain what it is trying to do and why it is helpful. In your codes for the subsequent problems, use Xavier initialization for the weights you are going to train<sup>2</sup>. You may manually implement it or you may use `tf.keras.initializers.GlorotUniform`.
- (iii)  In the starter code we provided for this homework, we incorporated a different optimizer called Adam [3]. Read about Adam optimizer, and explain how it might be helpful to accelerate learning or how it might bring other advantages. Also discuss the potential drawbacks you think Adam might have.
- (iv)  Let's say you are training a neural network using SGD in two different ways: (1) You train the network with some constant learning rate  $\alpha$  for 500 epochs<sup>3</sup>. For each epoch, you record the batches you used. (2) Using the same initialization and same batches for every epoch, you train the network with the same learning rate  $\alpha$  for 250 epochs, and then stop the execution. You then restart the optimization and train for another 250 epochs starting from the resultant network of the previous 250 epochs, again by following the batches of (1). So you exactly followed (1) in (2), but stopped and restarted the optimization once. Would you obtain the same network from (1) and (2)? What if you repeat the same experiment using Adam optimizer? Explain.

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<sup>1</sup>In particular, Problems 2-4 rely on Problem 1; Problems 3-4 rely on Problem 2.

<sup>2</sup>If you want to use Kaiming initialization [2], that should also work.

<sup>3</sup>An epoch consists of several optimization iterations where each data sample is seen by the network exactly once.

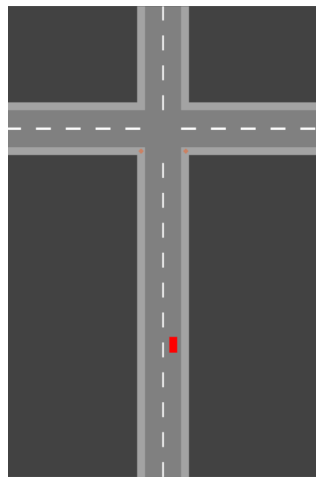
In this homework, you will work in the driving setting. Particularly, you are going to implement various imitation learning models, and then use them for intent inference and shared autonomy. Being interested in directly learning policies as opposed to learning reward functions first, we model the driving environment as a partially observable Markov decision process (POMDP):  $\langle \mathcal{S}, \mathcal{O}, \Omega, \mathcal{A}, f \rangle$ , where  $\mathcal{S}$  is the set of states,  $\mathcal{O}$  the set of observations,  $\Omega$  is a probability distribution over the set of observations given the state, i.e.  $\Omega(o | s)$  gives the probability of observing  $o \in \mathcal{O}$  while the system state is  $s \in \mathcal{S}$ . For example, in an environment with multiple vehicles,  $s \in \mathcal{S}$  will contain the states (positions, velocities, etc) of all the vehicles, whereas  $o \in \mathcal{O}$  might be missing the information about the vehicles that are occluded behind buildings. Or in a single-vehicle scenario,  $o \in \mathcal{O}$  might have only noisy measurements of the states.  $\mathcal{A}$  denotes the set of actions. For driving, we assume the actions are two-dimensional: steering angle and throttle. While braking could be encoded as a different action dimension, we assume negative throttle will correspond to braking. Finally,  $f$  gives the transition probabilities. That is,  $f(s' | s, a)$  is the probability of reaching state  $s' \in \mathcal{S}$  from state  $s \in \mathcal{S}$  by taking action  $a \in \mathcal{A}$ .

There are many open-source 3D driving simulators, such as CARLA [4], which are based on game engines to provide realistic dynamics and visuals. However, setting up CARLA and training driving policies on raw camera input (or Lidar data) require both a powerful computing infrastructure and a lot of effort. You will instead use CARLO (short for CARLA - Low Budget), which is a very simplistic 2D driving simulator [5] that uses the bicycle model to simulate vehicles [6].

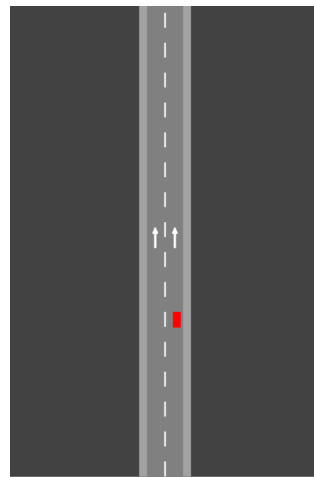
Feel free to interactively play with CARLO in some scenarios we provide by running

```
python play.py --scenario intersection
```

where you can replace scenario name as “intersection” or “lanechange”. These scenarios are also visualized in Fig. 1. In the code, you can see the use of `step` function, which transitions the environment from its current state to the next state given the action and returns the new observation. Mathematically, it first draws a sample from  $f(\cdot | s, a)$  where  $s \in \mathcal{S}$  is the current state, and then returns a sample from the observation distribution  $\Omega$  conditioned on the new state.



(a) Intersection Scenario



(b) Lanechange Scenario



Figure 1: Visualizations of the two CARLO scenarios you will use in this homework. In the intersection scenario, the goal is to stay on the right lane and turn left, go straight or turn right without having a collision with the pedestrians standing in the two corners of the intersection and without crashing into the buildings. Every time the scenario is initiated, the intersection is in a different location. The agent is allowed to observe: the car's position, speed, heading angle and the location of the intersection. In the lanechange scenario, the goal is to follow any lane without going off the road. The agent is allowed to observe: the car's position, speed and heading angle.

## Problem 2: Behavior Cloning

Behavior cloning is the simplest imitation learning method that dates back to 1989 when ALVINN was proposed as a method for autonomous driving [7]. To understand how behavior cloning works, let's first define an expert policy in the POMDP we defined in Problem 1: Let  $\pi^*$  denote an expert policy such that  $\pi^*(a | o, g)$  is the probability of taking action  $a \in \mathcal{A}$  when the agent observes  $o \in \mathcal{O}$  and the goal is  $g \in \mathcal{G}$ . In driving,  $\mathcal{G}$  may consist of possible destinations. For example in the intersection scenario (see Fig. 1a),  $\mathcal{G}$  might be {"left", "straight", "right"}, and in the lanechange scenario (see Fig. 1b) it might be {"left", "right"}, which represent the lane the expert wants to follow. Throughout the homework, we will assume  $\mathcal{G}$  is a discrete set.

Let's assume we have access to a data set for each  $g \in \mathcal{G}$ , that consists of  $(o, a)$  pairs, where each pair is obtained such that  $a$  is a sample drawn from  $\pi^*(\cdot | o, g)$ . Let's denote each such data set  $\mathcal{D}_g = \{(o^{(i)}, a^{(i)})\}_{i=1}^N$  where  $N$  is the number of data samples<sup>4</sup>. Our goal is then to recover  $\pi^*$  using these data sets.

For this homework, we collected hundreds of expert demonstrations in the two scenarios with all the different goals. These data sets are in the [data](#) folder<sup>5</sup>. Now, you are going to implement behavior cloning to learn a policy that imitates the expert policy.

- (i)  The most straightforward way to perform behavior cloning is to assume there exists an underlying *deterministic* policy, but the data set contains some noise in the actions. Then, you can simply try to learn a function  $h(o, g)$  that outputs the estimated expert action. Modeling this function as a neural network, let's write it as  $h_\theta(o, g)$  where  $\theta$  denotes the network parameters (weights and biases). Assuming a loss function  $L$  between two actions, write an optimization problem to learn the expert policy by optimizing  $\theta$ .
- (ii)  Fill in the missing parts of [train\\_il.py](#) to solve the optimization problem you defined in the previous question. You can use any loss function that you think is reasonable. You can also design your neural network structure however you wish. In our experience, small networks were able to efficiently recover the expert policy. Do not forget to use Xavier initialization for the neural network weights! Additionally, pay attention to what your neural network is / should be able to output.

After filling in the training code, run

```
python train_il.py --scenario intersection --goal left
--epochs <number_of_epochs> --lr <learning_rate>
```

to train a policy for the intersection scenario for the goal of turning left. You should set the number of epochs and the learning rate for the Adam optimizer. In our experience, the training should take around 5 minutes. Once the number of epochs is completed, the code is going to save the policy in the [policies](#) folder. If you want to continue to train from the latest saved policy, simply add `--restore` in the command above. After training, test your policy by running:


```
python test_il.py --scenario intersection --goal left --visualize
```

You should be able to see at least a few successful left-turns out of 10 episodes. If you are not satisfied with the result, you may want to play with the learning rate, number of epochs, and most importantly the loss function. For example: You may want to change how you weigh different terms of the actions in the loss function. If your trained policy is not able to achieve proper steering, for example, then perhaps you should penalize the differences in the steering dimension more heavily.

<sup>4</sup> $N$  might be different for each scenario and goal, but let's ignore this for notation simplicity.

<sup>5</sup>Each data set is given as a matrix. Each row is a time step in the POMDP. The last two columns are the actions that the expert took when the observation is the remaining columns.


Repeat what you did in this question for the “straight” and “right” goals by changing the `--goal` argument. Make sure to use the same neural network structure for all three goals and obtain reasonably well-performing policies<sup>6</sup>.

- (iii)  Describe the full training procedure you used for each goal (learning rate and the number of epochs; also elaborate if you retrained the network using `--restore` and/or if you used different loss functions for different goals).

- (iv)  Run


```
python test_il.py --scenario intersection --goal left
```

to test the policy without visualization and report the success rate you achieved (it will take a few seconds and be printed on the terminal). Repeat this for all three goals.


- (v)  What loss function did you use? Write it mathematically. If you perfectly overfit the data, what would be the minimum loss you see? Is it bounded below?

So far, you trained a neural network, for each goal, that outputs an action given an observation. It is a deterministic function, which means you will get the exact same action if you feed the same observation. While this is adequate in many situations, some applications require learning the distribution  $\pi^*(\cdot | o, g)$ . For example, imagine you want the robot to predict what the human might do and then you are going to optimize for the worst case. In such a setting, it is not enough to predict the expected human action, but the distribution should be learned. To be able to learn the distribution, we are going to use a simple version of Mixture Density Networks [8].

In this approach, the neural network outputs a distribution instead of an action sample. To be more precise, the network is going to output the parameters of a distribution. In this homework, you are going to use a Gaussian distribution, so the network should output two quantities: mean vector and covariance matrix.

- (vi)  You could further simplify the problem by assuming the action dimensions (steering and throttle) are conditionally independent from each other, given the observation. Then you would need to learn four scalars:  $\mu_{\text{steering}}, \mu_{\text{throttle}}, \sigma_{\text{steering}}^2, \sigma_{\text{throttle}}^2$ . The only constraint would be to make sure the last two quantities are non-negative. This could be achieved by simply using a ReLU only for those two nodes. However, this approach is too restrictive—we cannot just assume steering and throttle are independent!

You will instead learn the entries of the mean vector and the covariance matrix. However, the covariance matrix needs to be a positive semi-definite (PSD) matrix! How can you ensure this? **HINT:**  $AA^T$  is always PSD for any matrix  $A$ .

- (vii)  To train the network that outputs a single bivariate Gaussian distribution for a given observation, you are going to maximize the likelihood of the data set. Let’s denote the probability density of drawing  $\mathbf{x}$  from a bivariate Gaussian distribution with mean  $\boldsymbol{\mu}$  and covariance matrix  $\Sigma$  as  $\mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \Sigma)$ . Let’s also denote the mean vector and the covariance matrix produced by the neural network for observation  $o^{(i)}$  as  $\boldsymbol{\mu}^{(i)}$  and  $\Sigma^{(i)}$ , respectively, i.e.  $h_{\theta}(o^{(i)}) = (\boldsymbol{\mu}^{(i)}, \Sigma^{(i)})$ . Then, we can write the likelihood of an entire data set as


$$\text{Likelihood} = \prod_{i=1}^N \mathcal{N}(a^{(i)} | \boldsymbol{\mu}^{(i)}, \Sigma^{(i)})$$

<sup>6</sup>While you are allowed to change the loss function for different goals, this is not necessary in our experience.


As this might be too small and cause numerical issues, you are going to use mean log-likelihood instead:

$$\text{Mean Log-Likelihood} = \frac{1}{N} \sum_{i=1}^N \log \left( \mathcal{N} \left( a^{(i)} \mid \boldsymbol{\mu}^{(i)}, \Sigma^{(i)} \right) \right)$$

Since you will be maximizing this quantity, you can think of the negative mean log-likelihood as the loss function. Then, if you perfectly overfit the data, what would be the minimum loss you see? Is it bounded below?

- (viii)  Fill in the missing parts of `train_ildist.py` to solve the optimization problem described in the previous question. You can design your neural network structure however you wish<sup>7</sup>. Repeat everything you did in question (ii) of this problem for `train_ildist.py`. Training this neural network might be much harder than the previous ones because of instabilities. While it is possible to train each network in 15 minutes, hyperparameter tuning might make it take much longer. Consider adopting the following hints to minimize the time you spend for training:

- Use really small (narrow and shallow) networks.
- Start training with some learning rate for a relatively small number of epochs, and then retrain the network more by steadily decreasing the learning rate (and using `--restore`).
- If you don't see a monotonically decreasing loss in the very beginning, then terminate the execution and re-run, because initialization really matters. If you cannot avoid this situation, then decrease your learning rate further and try again.

- (ix)  Describe the full training procedure you used to train the mixture density network for each goal (learning rate and the number of epochs; also elaborate if you retrained the network using `--restore` and/or if you used different loss functions for different goals).


- (x)  Run

```
python test_ildist.py --scenario intersection --goal left
```

to test the policy without visualization and report the success rate you achieved (it will take a few seconds and be printed on the terminal). Repeat this for all three goals.

<sup>7</sup>Again, make sure to use the same neural network structure for different goals.

## Problem 3: Conditional Imitation Learning

- (i)  Using the same code you wrote in the previous question, run

```
python train_il.py --scenario intersection --goal all
    --epochs <number_of_epochs> --lr <learning_rate>
```

to train a policy for the intersection scenario collectively for all goals. And check the result by running


```
python test_il.py --scenario intersection --goal all --visualize
```

What are some problems associated with this policy? Do you have control over which direction the car is going?

Imagine you are in your autonomous vehicle. And every time it encounters an intersection, the car just takes the same direction. Obviously, this is not desirable. Of course, one way to solve this problem is to allow the user to select which goal to pursue and then use the corresponding policy trained with that specific goal.


However, data is a very expensive resource in many applications, so we don't want to waste it by using it only for one specific goal. Furthermore, training different neural networks for each goal might take too much time. Conditional Imitation Learning (CoIL) has been proposed as a solution to this problem [9]. Take a look at their Figure 3.

In their first approach (Fig. 3a of their paper), they feed the goal of the user (the high-level command) as an input to the neural network. The output is then the action for this specific goal. In the second approach (Fig. 3b), they use *branching*: The observations are fed into the first layers of the network. Depending on the user-specified goal, the outputs of these first layers are fed into different last layers. They showed the second approach works better. Therefore, you are going to implement the second approach.

- (ii)  Fill in the missing parts of [train\\_coil.py](#) to implement the second approach discussed above. Note that you want to learn a mapping between observations and actions, so the network will not output a distribution. You are again free to design your loss function, which may or may not be different from the previous one. For training, run

```
python train_coil.py --scenario intersection --epochs <number_of_epochs>
    --lr <learning_rate>
```

to train a CoIL policy for the intersection scenario. You can again use `--restore` if needed.


- (iii)  Test your trained CoIL policy for 10 episodes by running

```
python test_coil.py --scenario intersection --visualize
```

Don't forget to provide high-level commands using the arrow keys in your keyboard! After you are confident that the policy you trained achieves to reach the goals reasonably often (at least a few times), run

```
python test_coil.py --scenario intersection --goal left
```


and report the success rate. Repeat this last step for every goal.

- (iv)  Describe the full training procedure you used (learning rate and the number of epochs; also elaborate if you retrained the network using `--restore`).




## Problem 4: Intent Inference & Shared Autonomy

Referring back to Problem 2, it is often very useful to learn the expert’s policy as a distribution. One such case is when we want to perform intent inference. In this problem, we are interested in predicting what goal the user has based on their actions.


- (i)  In Problem 2 of this homework, you already implemented `train_ildist.py` which trains a neural network that you can use to compute  $P(a \mid o, g)$ . Now, we are interested in computing  $P(g \mid o, a)$ . Write this in terms of  $P(a \mid o, g)$  (and some other probability expressions).

Assuming a uniform prior over the goals (for  $P(g \mid o)$ ), how can you compute  $P(g \mid o, a)$ ?

- (ii)  Fill in the missing parts of `intent_inference.py`. And run

```
python intent_inference.py --scenario intersection
```

Drive the car using the arrow keys.


- (iii)  Running the above command, drive the car in each direction for 5 times. Out of the 15 episodes you drove, how many of them ended up predicting the correct intent? What might be some reasons why it fails? Discuss.

To give another example of when having a distribution over actions is useful, let’s consider a scenario when the robot knows the optimal actions given the user goal. We are going to consider a setting where the user is driving the car, but the robot also provides help. Mathematically, the user is going to take an action  $a_H \in \mathcal{A}$  based on the observation  $o \in \mathcal{O}$  and the goal  $g \in \mathcal{G}$  they have. The robot is also going to take a *simultaneous* action  $a_R \in \mathcal{A}$ , again based on the observation  $o \in \mathcal{O}$  and the predicted user goal  $\hat{g} \in \mathcal{G}$ . The action being simultaneous means the robot does not know  $a_H$  while taking  $a_R$ . However, it has access to the previous observations and human actions. The system is then going to evolve as

$$s' \sim f(\cdot \mid s, a_H + a_R)$$

where we implicitly assume an addition operation is defined over  $\mathcal{A}$ . This is an instance of shared autonomy where the human and the user shares the control of the system.

For this question, let’s say the actions can be linearly combined, i.e. when adding two actions, you can simply add the steering and throttle values.

- (iv)  We already know from the previous subproblems that we can use our trained neural networks to predict the user’s goal. For the subsequent parts, run

```
python train_ildist.py --scenario lanechange --goal left
  --epochs <number_of_epochs> --lr <learning_rate>
```

to train the mixed density network for the lanechange scenario. Again, you can use `--restore` argument if needed. Also, remember the training hints we provided to speed up the process. Similar to before, test the trained network by running

```
python test_ildist.py --scenario lanechange --goal left --visualize
```

Repeat the training and test for the “right” goal, too.


You are going to use these networks to predict the user goal. For each goal  $g \in \mathcal{G}$  and observation  $o \in \mathcal{O}$ , let  $m : \mathcal{G} \times \mathcal{O} \rightarrow \mathcal{A}$  be a function that gives the optimal action (with respect to the robot) to achieve the given goal under the given observation. Then, at time step  $t$ , the robot should take an action  $a_R$  to make sure

$$\begin{aligned} a_R + \mathbb{E}_g [a_H | g, o^t] &= \mathbb{E}_g [m(g, o^t) | o^t] \\ &= \sum_{g \in \mathcal{G}} P(g | o^{t-1}, \dots, o^0, a^{t-1}, \dots, a^0) m(g, o^t) \end{aligned}$$

You can use different various heuristics to compute the probability term inside the summation by using the probabilities  $P(g|o^{t-1}, a^{t-1}), \dots, P(g|o^0, a^0)$ . For example, you could take a moving average of these terms. Let's denote  $P(g | o^{t-1}, \dots, o^0, a^{t-1}, \dots, a^0)$  as  $P_g$  for simplicity. Then,

$$\begin{aligned} a_R &= \sum_{g \in \mathcal{G}} P_g m(g, o^t) - \mathbb{E}_g [a_H | o^t, g] \\ &= \sum_{g \in \mathcal{G}} P_g m(g, o^t) - \sum_{g \in \mathcal{G}} \sum_{a_H \in \mathcal{A}} P_g P(a_H | o^t, g) a_H \\ &= \sum_{g \in \mathcal{G}} P_g \left[ m(g, o^t) - \sum_{a_H \in \mathcal{A}} P(a_H | o^t, g) a_H \right] \end{aligned}$$


where you can also obtain  $P(a_H | o^t, g)$  using the same mixture density networks.

- (v)  We further want to enforce some constraints on  $a_R$ . Specifically, we don't want the steering and throttle provided by  $a_R$  to be too large. Hence, you will simply apply a threshold to the computed  $a_R$ . From a human-robot interaction perspective, what is the reason we are enforcing this constraint on  $a_R$ ?

- (vi)  Fill in the missing parts of [shared\\_autonomy.py](#) that implements what we discussed above. Then, run

```
python shared_autonomy.py --scenario lanechange
```

and control the vehicle's steering using the arrow keys in your keyboard. In this part, you are controlling only the steering, and the throttle is automatically determined.

- (vii)  When you control the vehicle with shared autonomy, do you feel the help by the robot? Is it really helpful or does it make things worse? Elaborate on how it is helpful or why it might be harming your performance. These are open-ended questions, and your responses will depend a lot on the performance of the trained mixed density networks.

## References

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