1 Introduction

1.1 Relevant Books:

Amazingly, there are none. As a result, you all are guinea pigs.

1.2 Classical Control and Learning versus Active Learning

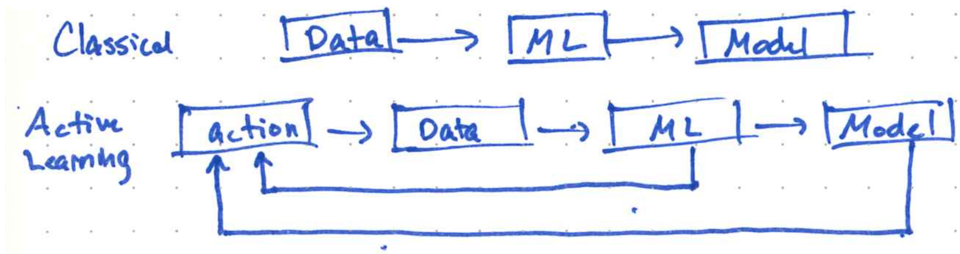

Figure 1: Classical passive learning and control versus active learning and control

In the classical, passive view of machine learning (or estimation/filtering or system identification), data is acquired and then passed through an algorithm (e.g., some machine learning algorithm) to arrive at a *model*. In the setting of *active sensing* the data is connected to actions taken (e.g., by a robot moving in space), and those actions are determined by a combination of the model and the learning process itself.

1.3 Motivating Examples

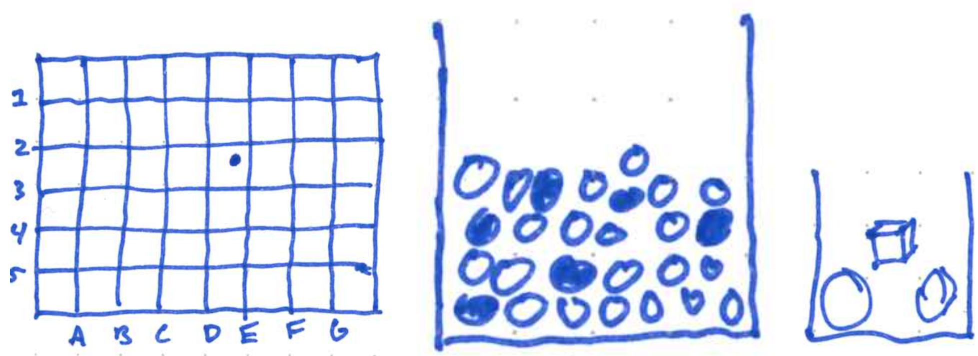

Figure 2: Active sensing scenarios. From left to right: a) what should your strategy be to get from somewhere in the environment to the dot? b) How should you determine the number of dark marbles in a bag from only drawing one marble at a time? c) How should you discriminate between objects in a bag?

Imagine that you need to use *beams* labeled 1-5 and A-G to get from the pictured initial condition to the final position shown in the figure. What is the right strategy. Without taking into consideration the sensor, you could just design a trajectory that is simply a line from the initial condition to the final location. But if there is uncertainty in the evolution, the beams (that give you labels 1-5 and A-G any time you cross them) provide extra information. Even more so, finding an intersection of two beams tells you *exactly* where you are, so finding the intersection of beam

2 and beam E would be particularly advantageous. From that location, the impact of uncertainty will be at its minimum because the target location is so close to the intersection location.

1.4 A simple example

Suppose you have a very simple system, like that seen in Fig 3. You can move in $\mathbb{R}^2$—up and down, right and left—and can take binary measurements. These observations $o(t)$ are either "0" when the region is light or "1" when the region is dark. Can you make it to the goal state, noted by the $*$ in the figure? Here we have a state x governed by the differential equation $\dot{x} = u$ and a measurement model that looks like $\Upsilon = \begin{cases} 1 \text{ if } x \in dark \\ 0 \text{ if } x \in light \end{cases}$ Probably one should expect that this model is slightly uncertain, so adding noise to the model could make sense.

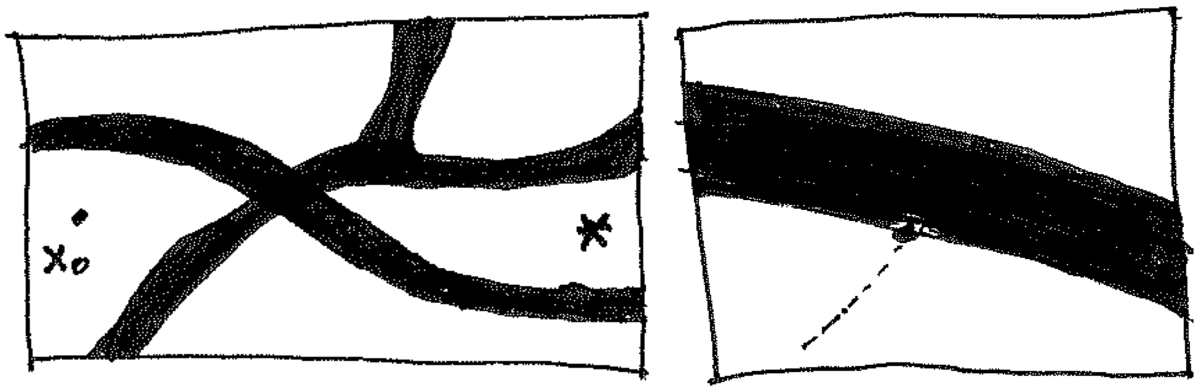

Figure 3: Imagine traversing a map with a binary sensor that can only read "0" in light areas and "2" in dark areas. This is likely the most simple sensor imagineable. How would you use it to get to the target $*$?

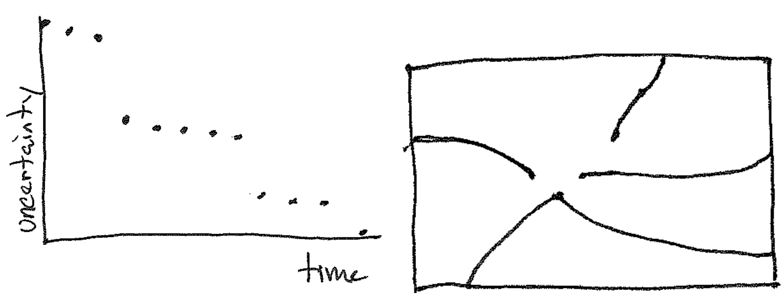

Figure 4: Imagine traversing a map with a binary sensor that can only read "0" in light areas and "1" in dark areas. This is likely the most simple sensor imagineable. How would you use it to get to the target $*$? When the robot is moving—for instance, moving up—it will eventually hit a dark region of the map. When it does so, its probabilities change dramatically, because now its belief gets updated to something like the probability on the left.

How will the uncertainty evolve as a function of movement? Consider Fig. 3(b), where the robot starts in a light region and takes several steps "up". As it does so, it receives "0" after "0", confirming it was not in the region just below a shaded in region. Then, eventually, it hits a dark region and suddenly it knows that it is along one of the bottom contours. These precipitous jumps in uncertainty, seen in Fig. **??** are great for the robot. They potentially mean that the robot can ignore incremental probablity updates in favor of looking for these large jumps in information.

1.5 Components of Active Sensing and Active Learning

1. States x that can be impacted by decisions u; these are functions of time.
2. Uncertain parameters θ that can be estimated through sensory observations o (also functions of time).
3. Sensors:
   (a) range sensors
   (b) cameras
   (c) touch sensors (binary contact sensor, pressure, temperature, shear force, texture)
   (d) exotic nonlinear sensors, like electrosense.
4. Dynamic models describing how the sensor can move.

$$\dot{x} = f(x, u) \quad x(0) = x_0$$

   where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, and $f(\cdot, \cdot)$ is a vector field. This motion model typically comes from either a principle (e.g., Newton's laws $\sum F = ma$ or Kirchhoff's laws or some such principle) or from data.
5. Measurement model $\Upsilon(x)$ describing sensor physics and sensor noise. This sensor model can come from physical modeling or from data.
6. Uncertainty models. Where does the uncertainty come from?
   (a) Is it from noise (e.g., stochastic forcing, like Brownian motion)?
   (b) Is it from spatial uncertainty (e.g., occlusions).
   (c) Is there uncertainty in what you are trying to find (e.g., distractors that look like what you are looking for)?
   (d) Is there uncertainty about structure of the world (e.g., how many predators are trying to eat you)?
7. Filters. These update *beliefs* about the world, typically represented as parameters.
8. Transition models of the world. This is a way of modeling how the world might behave. For example, you might be tracking something, and your model of how it behaves will not be anywhere near as good
9. Information measures. These will be the measures used to drive decisions.
   (a) How would you measure the value of visiting a region to improve your own state?
   (b) How would you measure the value of visiting a region to improve your understanding of someone else's state?

These will form the outline of the class, as we cover control, estimation, information theory, and techniques in active learning.