Name : ABID ALI
Student_No : 2019380141

Assignment 12

18.1 Consider the problem faced by an infant learning to speak and understand a language. Explain how this process fits into the general learning model. Describe the percepts and actions of the infant, and the types of learning the infant must do. Describe the sub functions the infant is trying to learn in terms of inputs and outputs, and available example data.

Answer:

The aim here is to couch language learning in the framework of the chapter, not to solve the problem! This is a very interesting topic for class discussion, raising issues of nature vs. nurture, the indeterminacy of meaning and reference, and so on. Basic references include Chomsky (1957) and Quine (1960).
The first step is to appreciate the variety of knowledge that goes under the heading "language." The infant must learn to recognize and produce speech, learn vocabulary, learn grammar, learn the semantic and pragmatic interpretation of a speech act, and learn strategies for disambiguation, among other things. The performance elements for this (in humans) and their associated learning mechanisms are obviously very complex and as yet little is known about them.

A naive model of the learning environment considers just the exchange of speech sounds. In reality, the physical context of each utterance is crucial: a child must see the context in which "watermelon" is uttered in order to learn to associate "watermelon" with watermelons. Thus, the environment consists not just of other humans but also the physical objects and events about which discourse takes place. Auditory sensors detect speech sounds, while other senses (primarily visual) provide information on the physical context. The relevant effectors are the speech organs and the motor capacities that allow the infant to respond to speech or that elicit verbal feedback.

The performance standard could simply be the infant's general utility function, however that is realized, so that the infant performs reinforcement learning to perform and respond to speech acts so as to improve its well-being—for example, by obtaining food and attention. However, humans' built-in capacity for mimicry suggests that the production of sounds similar to those produced by other humans is a goal in itself. The child (once he or she learns to differentiate sounds and learn about pointing or other means of indicating salient objects) is also exposed to examples of supervised learning: an adult says "shoe" or "belly button" while indicating the appropriate object. So sentences produced by adults provide labeled positive examples, and the response of adults to the infant's speech acts provides further classification feedback. Mostly, it seems that adults do not correct the child's speech, so there are very few negative classifications of the child's attempted sentences. This is significant because early work on language learning (such as the work of Gold, 1967) concentrated just on identifying the set of strings that are grammatical, assuming a particular grammatical formalism. If there are only positive examples, then there is nothing to rule out the grammar $S \rightarrow Word*$ Some theorists (notably Chomsky and Fodor) used what they call the "poverty of the stimulus" argument to say that the basic universal grammar of languages must be innate, because otherwise (given the lack of negative examples) there would be no way that a child could learn a language (under the assumptions of language learning as learning a set of grammatical strings). Critics have called this the "poverty of the imagination" argument—I can't think of a learning mechanism that would work, so it must be innate. Indeed, if we go to probabilistic context free grammars, then it is possible to learn a language without negative examples.

18.2 Repeat Exercise 18.1 for the case of learning to play tennis (or some other sport with which you are familiar). Is this supervised learning or reinforcement learning?

Answer:

Learning tennis is much simpler than learning to speak. The requisite skills can be divided into movement, playing strokes, and strategy. The environment consists of the court, ball, opponent, and one's own body. The relevant sensors are the visual system and proprioception (the sense of forces on and position of one's own body parts). The effectors are the muscles involved in moving to the ball and hitting the stroke. The learning process involves both supervised learning and reinforcement learning. Supervised learning occurs in acquiring the predictive transition models, e.g., where the opponent will hit the ball, where the ball will land, and what trajectory the ball will have after one's own stroke (e.g., if I hit a half-volley *this* way, it goes into the net, but if I hit it *that* way, it clears the net). Reinforcement learning occurs when points are won and lost—this is particularly important for strategic aspects of play such as shot placement and positioning (e.g., in 60% of the points where I hit a lob in response to a cross-court shot, I end up losing the point). In the early stages, reinforcement also occurs when a shot succeeds in clearing the net and landing in the opponent's court. Achieving this small success is itself a sequential process involving many motor control commands, and there is no teacher available to tell the learner's motor cortex which motor control commands to issue.

18.6 Consider the following data set comprised of three binary input attributes (A_1, A_2, and A_3) and one binary output:

Example	A_1	A_2	A_3	Output y
$\mathbf{x}_1$	1	0	0	0
$\mathbf{x}_2$	1	0	1	0
$\mathbf{x}_3$	0	1	0	0
$\mathbf{x}_4$	1	1	1	1
$\mathbf{x}_5$	1	1	0	1

Use the algorithm in Figure 18.5 (page 702) to learn a decision tree for these data. Show the computations made to determine the attribute to split at each node.

Answer:

Note that to compute each split, we need to compute $Remainder(A_i)$ for each attribute A_i, and select the attribute the provides the minimal remaining information, since the existing information prior to the split is the same for all attributes we may choose to split on.

Computations for first split: remainders for $A1$, $A2$, and $A3$ are

$(4/5)(-2/4 \log(2/4) - 2/4 \log(2/4)) + (1/5)(-0 - 1/1 \log(1/1)) = 0.800$

$(3/5)(-2/3 \log(2/3) - 1/3 \log(1/3)) + (2/5)(-0 - 2/2 \log(2/2)) \approx 0.551$

$(2/5)(-1/2 \log(1/2) - 1/2 \log(1/2)) + (3/5)(-1/3 \log(1/3) - 2/3 \log(2/3)) \approx 0.951$

Choose A_2 for first split since it minimizes the remaining information needed to classify all examples.

Note that all examples with $A_2 = 0$, are correctly classified as $B = 0$. So we only need to consider the three remaining examples (x_3, x_4, x_5) for which $A_2 = 1$. After splitting on A_2, we compute the remaining information for the other two attributes on the three remaining examples (x_3, x_4, x_5) that have $A_2 = 1$.

The remainders for $A1$ and $A3$ are

$(2/3)(-2/2 \log(2/2) - 0) + (1/3)(-0 - 1/1 \log(1/1)) = 0$

$(1/3)(-1/1 \log(1/1) - 0) + (2/3)(-1/2 \log(1/2) - 1/2 \log(1/2)) \approx 0.667.$

So, we select attribute A1 to split on, which correctly classifies all remaining examples.

18.7 A decision *graph* is a generalization of a decision tree that allows nodes (i.e., attributes used for splits) to have multiple parents, rather than just a single parent. The resulting graph must still be acyclic. Now, consider the XOR function of *three* binary input attributes, which produces the value 1 if and only if an odd number of the three input attributes has value 1.

a. Draw a minimal-sized decision *tree* for the three-input XOR function.
b. Draw a minimal-sized decision *graph* for the three-input XOR function.
Answer:

See Figure S18.1, where nodes on successive rows measure attributes A_1, A_2, and A_3. (Any fixed ordering works.)

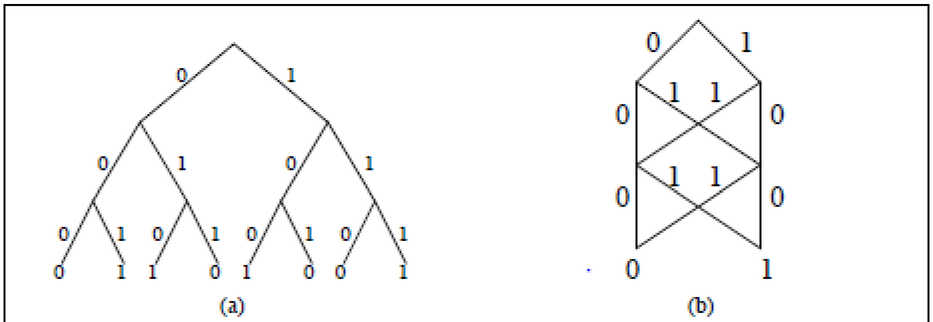

Figure S18.1 XOR function representations: (a) decision tree, and (b) decision graph.