

1 Introduction (10 points)

In a typical board game, the target function to learn can be either

$$\text{Choose Move} \quad M : \text{Board} \rightarrow \text{Move}$$

or

$$\text{Evaluate Board} \quad V : \text{Board} \rightarrow \text{Value}.$$

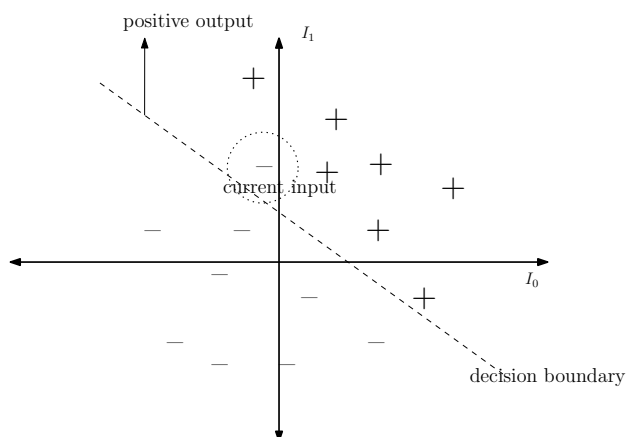
Explain which one is better when you are trying to learn the target function using supervised learning. Hint: discuss which estimated target, $\hat{M}(b)$ or $\hat{V}(b)$, can be defined recursively more easily.

2 Supervised learning (20 points)

Why do you need a training set D of fewer samples to ϵ -exhaust a version space $VS_{H,D}$ when ϵ is large? Explain in terms of tolerable level of error ϵ .

3 Neural networks (20 points)

Given a single perceptron unit (dashed decision boundary) and the inputs as shown below, when the current input was the input marked with the dotted circle, which way will the decision boundary tilt (clockwise or counterclockwise)? (Hint: Illustrate the weight vector [direction has to be correct but the length you can choose] in relation to the decision boundary and the current input vector, and show how the weight vector changes in relation to the previous weight vector and the current input vector. Consider the perceptron learning rule with $\eta = 1.0$.)



4 Reinforcement learning (20 points)

Consider the following domain, with usual actions *up*, *down*, *left*, *right* and deterministic action outcomes. Reward is nonzero only for moves into the goal *G*. The learning algorithm is SARSA(λ) that uses the eligibility trace.

If the trajectory was $s1 \rightarrow s4 \rightarrow s7 \rightarrow s8 \rightarrow s5 \rightarrow s6 \rightarrow G$, after the last move ($s6 \rightarrow G$), which of the Q table entries below will be updated? Mark them, and rank the cells that you marked with 1, 2, 3, ..., where 1 corresponds to the highest amount of increase in Q , and 2 the second highest, etc. (Hint: you have to mark 6 cells in the Q table.)

s1	s2	s3
s4	s5	s6
s7	s8	G

Q(s,a)	up	down	left	right
s1				
s2				
s3				
s4				
s5				
s6				
s7				
s8				

5 Decision tree learning (20 points)

Why does maximizing information gain lead to short decision trees? Do not write down the formula for information gain. This is a conceptual question. Explain in terms of the decision outcomes based on the selected attribute.

6 Genetic algorithms (10 points)

Schema theorem states that

$$E[m(s, t+1)] \geq \underbrace{\frac{\hat{u}(s, t)}{\bar{f}(t)}}_{[1]} \underbrace{m(s, t) \left(1 - p_c \frac{d(s)}{l-1}\right)}_{[2]} \underbrace{(1 - p_m)^{o(s)}}_{[3]},$$

where $m(s, t)$ = instances of schema s in population at time t , $\bar{f}(t)$ = average fitness of population at time t , $\hat{u}(s, t)$ = ave. fitness of instances of s at time t , p_c = probability of single point crossover operator, p_m = probability of mutation operator, l = length of single bit strings, $o(s)$ number of defined (non “*”) bits in s , and $d(s)$ = distance between leftmost and rightmost defined bits in s .

Which of the above terms [1], [2], [3] is affected by the evolutionary selection process? Explain in terms of role the played by the quantities involved in determining schema survival, e.g., “higher X leads to lower/higher chance of Y”.