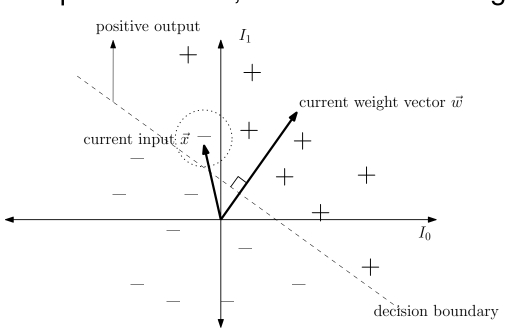
Machine Learning Midterm Exam Practice #2 : Lastname : ______________, First name: ______________

If I cheat, I will accept an automatic 'F' in this course. **Signature:** ________________ **Date:** _________

Problem 1 (10 points) Consider sample complexity. Haussler's theorem states that the sample complexity m is related to the error tolerance ϵ, size of the hypothesis space $|H|$ and the failure probability δ as follows: $m \geq \frac{1}{\epsilon}(\ln|H| + \ln(1/\delta))$. However, this is useless in case the hypothesis space is infinite in size, since we will need infinitely many inputs. Explain how a finite sample complexity can be still be derived despite this kind of difficulty with infinite hypothesis spaces. Hint: you will need a finite quantity that characterizes H despite $|H| = \infty$.

Problem 2 (10 points) Consider the estimation of mistake bounds. The Halving algorithm starts with a version space $VS(H,D)$ and takes a majority vote among the hypotheses in $VS(H,D)$ to make a decision on newly shown inputs from the true distribution $\mathcal{D}$. If the majority vote is incorrect (mistake is made), the incorrect hypotheses in the version space are discarded, and the process is repeated. Let N be the initial size of $VS(H,D)$. (1) In the worst case, how many mistakes are made (write a mathematical formula involving N), and (2) state whether this becomes the lower bound or upper bound for the optimal mistake bound?

Problem 3 (10 points) Consider the single layer perceptron. In the plot below, with the current weight vector $\vec{w}$ (and its associated decision boundary) and the current input $\vec{x}$ with a target value of -1, (1) illustrate what $\vec{w}$ would be (draw the exact vector based on $\vec{w}$ and $\vec{x}$) and (2) illustrate what the decision boundary will be like. Assume the learning rate $\eta = 1/4 = 0.25$. Hint: Think what the shown perceptron's output is for this input $\vec{x}$, and from that compute the error, to see how $\vec{w}$ changes.



Problem 4 (10 points) Consider gradient descent-based learning. The hidden to output weight is updated based on $\frac{\partial E}{\partial w_i} = -\sum_{d \in D}(t_d - o_d)o_d(1 - o_d)x_{i,d}$ when the output neuron has a sigmoid activation function ($o_d = \sigma(net_d)$). How will the equation above for $\frac{\partial E}{\partial w_i}$ change if the output neuron uses a linear activation function ($o_d = net_d$)? Write the formula. Hint: consider what $\frac{\partial o_d}{\partial net_d}$ is for the two different activation functions.

Problem 5 (10 points) Explain how recurrent neural networks can be trained using the backpropagation algorithm which only works for networks with acyclic topology.

Problem 6 (10 points) The original definition of the Q-function is shown below, but the three functions marked below are unknown to the agent. How does the final Q-learning algorithm overcome this kind of lack of knowledge? Show the new learning equation and which parts in the new equation correspond to (1), (2), and (3).

$$Q(s,a) \equiv \underbrace{r(s,a)}_{(1)} + \gamma \overbrace{V^*(\underbrace{\delta(s,a)}_{(2)})}^{(3)}$$

corresponding terms (1) __________

(2) __________

(3) __________

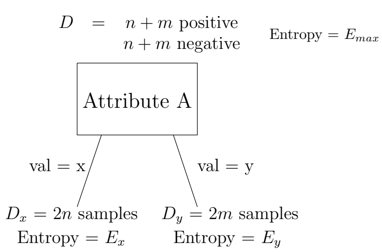
Problem 7 (10 points) Consider the following domain, with actions $up, down, left, right$ and deterministic action outcomes. Reward is nonzero only for moves into the goal G. The learning algorithm is SARSA(λ) that uses the eligibility trace. If the state transition was $s7 \rightarrow s8 \rightarrow s5 \rightarrow s2 \rightarrow s3 \rightarrow s6 \rightarrow G$, 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.

s1	s2	s3
s4	s5	s6
s7	s8	G

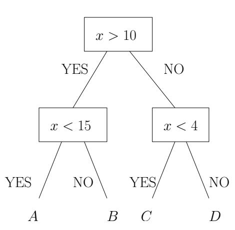
Q(s,a)	up	down	left	right
s1				
s2				
s3				
s4				
s5				
s6				
s7				
s8				

Hint: you have to mark 6 cells in the Q table.

Problem 8 (10 points) Consider decision tree learning. In the plot below, a data set D containing $n+m$ positive and $n+m$ negative samples (hence $|D| = 2(n+m)$) is tested with an attribute A which has two possible values x and y. The resulting split gives data sets D_x and D_y, with $|D_x| = 2n$ and $|D_y| = 2m$, and entropy of E_x and E_y, respectively. Show that $Gain(D, A) \geq 0$ using the mathematical definition of $Gain(D, A)$ and the above conditions. Hint 1: $E_x \leq E_{max}$ and $E_y \leq E_{max}$. Hint 2: Try multiplying both sides of Hint 1 with -1.



Problem 9 (10 points) Consider the regression tree below. If the data set was as given below, what would be the value of the leaf node B?



x	f(x)
2	1.5
3	2.5
5	9
7	11
11	3
13	7
17	13
19	15

Problem 10 (10 points) Consider the problem of neural code. Explain how the internal state invariance criterion can be used to understand the meaning of encoded internal brain state s, without direct access to the stimulus information I. Explain in terms of the encoded stimulus property and the property of the action.