

**University of Wisconsin-Madison**  
**Computer Sciences Department**

**CS 760 — Machine Learning**

*Fall 1997*

**Midterm Exam**

*(one page of notes allowed)*

*100 points, 90 minutes*

*December 3, 1997*

Write your answers on these pages and show your work. If you feel that a question is not fully specified, state any assumptions you need to make in order to solve the problem. You may use the backs of these sheets for scratch work. Notice that all questions do not have the same point-value. Divide your time appropriately.

Before starting, write your name on this and all other pages of this exam. Also, make sure your exam contains five (5) problems on ten (10) pages.

<b>Problem</b>	<b>Score</b>	<b>Max Score</b>
1	_____	25
2	_____	25
3	_____	25
4	_____	15
5	_____	10
Total	_____	100

### 1. Learning from Labelled Examples (25 pts)

Part A Assume you are given the following three features with the possible values shown. The first two are nominally valued, while the third is real-valued.

$$\begin{aligned} F1 &\in \{v1, v2\} \\ F2 &\in \{v3, v4, v5\} \\ F3 &\in [0, 9] \end{aligned}$$

Using *ID3* and its max-gain formula, produce a decision tree that accounts for the following training examples. **Show all your work.**

F1 = v1	F2 = v3	F3 = 7	+
F1 = v2	F2 = v4	F3 = 8	+
F1 = v1	F2 = v5	F3 = 9	-
F1 = v1	F2 = v3	F3 = 2	-

Part B Discuss how one could apply the *Naive Bayes* algorithm to the above training data. Explain how the resulting classifier would categorize the following testset example:

$$F1 = v1 \quad F2 = v4 \quad F3 = 3 \quad ?$$

Part C Explain how a *two-nearest neighbor* algorithm would categorize the test example of Part B, given the above training set.

Part D According to the *Bayesian interpretation of what a neural network should optimize* that was discussed in lecture, which error function is most appropriate for categorical problems like the above? For this case, what statistical interpretation should we give to the network's output?

How would your answers to the above questions change if the task was to learn a real-valued function?

**2. Reinforcement Learning and Neural Networks (25 pts)**

Part A     Imagine an environment like the Agent World, but where the learner can only move LEFT or RIGHT. The agent’s sensors report the distances to the left wall and right walls. The world is 3 meters wide, the agent’s step size is 1 meter, and the agent always starts 1 meter from the right wall. Finally, the agent gets a reward of +2 when moving left and of +1 when moving right, unless it tries to move into a wall, in which case its reward is -10. (Assume the agent is dimensionless - i.e., has zero width - and that the agent can abut the wall without penalty.)

Apply the one-step, Q-learning algorithm to this problem, using a *table* to represent your Q-function (all entries in the table should initially be zero); let  $\gamma = 0.9$ . In the space below, show the state of the Q-table after the first two (2) steps of the learner. For simplicity, always follow the current policy during learning (i.e., *no* exploration) and break ties by moving to the right. Briefly explain why the steps were chosen.

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initial state of the Q table:

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state of the Q table after the agent’s first step:

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state of the Q table after the agent’s second step:

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Part B     Instead of using a Q-table, imagine you used a *perceptron* to learn the Q function. Assume your perceptron has two inputs - the (unnormalized) distances to the left and right walls - and that all the free parameters in your perceptron are initialized to 1.

Under the assumptions of Part A, what would be the first training example given to this perceptron? Explain your answer. Finally, show the changes (if any) in the perceptron that result from this training example (using the delta rule with  $\eta = 0.1$ ).

Part C     Describe one (1) important strength and one (1) major weakness of using a compact representation like neural networks, rather than complete tables, to represent Q functions.

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strength:

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weakness:

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Part D In HW 4's Agent World simulator, agents get a reward (penalty) of -2 immediately upon pushing a mineral and a reward of +25 if this mineral later hits another player. Assume that a pushed mineral *always* hits one (and only one) other player after *exactly*  $N$  time steps. Using  $\gamma = 0.9$ , for what range of values for  $N$  would the optimal policy never involve pushing a mineral?

Obviously, in terms of the real (undiscounted) score of the game, under the above assumptions it would always be a good idea to push minerals. Why, then, do we use discounting in our Q function?

### 3. Experimental Methodology and Computational Learning Theory (25 pts)

Part A Assume that you have drawn (with replacement) 1000 examples from some fixed distribution for a two-category problem, and that after dealing with the overfitting problem, your learning algorithm categorizes 898 of these training examples correctly.

You next draw (again, with replacement) another 100 examples and measure the accuracy of your learned concept (without doing any further learning, i.e., without adjusting the concept learned from the first 1000 examples). Of this second set of examples, your algorithm categorizes 85 of them correctly.

Within what interval can you say, with 95% confidence, that the true accuracy of your learned concept lies?

State and briefly explain one (1) major assumption underlying the above calculation.

Part B Assume that it is known that the true concept for the above problem is in the following family of functions:

*circles of radius  $R$  centered at point  $X, Y$*

where  $R \in \{1, 2, 3, 4, 5\}$ ,  $X \in \{3, 4, 5, 6\}$ ,  $Y \in \{-1, 0, 1\}$

Provide an upper bound on the number of training examples needed so that, with probability 0.95, a concept that is consistent with the training examples has an error rate of no more than 15%.

Part C Briefly discuss what you believe to be the important difference between the analyses of expected future error rate in Parts A and B.

Part D Assume your preferred learning algorithm has one problem-specific parameter (with 7 possible values) to set. Imagine you are given a new dataset of 500 labelled examples. Briefly discuss:

(i) how you would go about choosing a good setting for this parameter

(ii) how you would estimate the future performance of the concept learned by your algorithm on the task represented by these 500 examples

(iii) the most important assumption about this dataset and its acquisition that you are making when you apply the experimental methodology you described

**4. Short Essays (15 pts)**

Briefly explain the importance in machine learning of the following:

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*VC Dimension*

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*ensembles*

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*building-block hypothesis*

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*decision-tree pruning*

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*policy iteration*

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**5. Longer Essays (10 pts)**

IF YOU WISH, YOU MAY RIP OFF THIS FINAL QUESTION, TAKE IT HOME WITH YOU, AND RETURN IT IN CLASS ON MONDAY. HOWEVER, DO NOT DISCUSS YOUR ANSWERS WITH ANYONE ELSE UNTIL AFTER MONDAY'S CLASS (this constraint holds even if you turn in your answer to this question today). You may type your answers on a separate sheet of paper, but do not use more than one side of a normal sheet of paper and use a reasonably large font.

Part A Describe what you believe to be the most important *idea* in machine learning (other than those topics listed in Question 4). Justify your answer.

Part B Describe what you believe to be the most important *open issue* in machine learning. Briefly sketch an approach for addressing it.