Final Exam
CSCI 1420 - Spring 2020

Instructions

Timeline: The final will be posted on the course homepage no later than noon Eastern U.S. time on Thursday, May 7. It must be submitted on Gradescope by 11:59 PM Eastern U.S. time on Friday, May 8. No late days may be used on the final. For every minute past the deadline it is late, one percentage point will be deducted from the grade.

Exam Format: There are eight problems, each worth 1/7 of the exam. You may choose one problem to count as extra credit, worth 1/2 of a regular problem. To indicate your choice, mark the blank line where indicated for that problem. If you do not make a choice, or your choice is otherwise unclear, the last problem will be treated as extra credit. We will not adjust a student’s selection to optimize their score.

Submission Format: You may submit a PDF using the provided Latex, or you may submit handwritten answers. You are encouraged to use Latex if possible, as any illegible parts of answers will be marked incorrect.

Academic Integrity: The course collaboration policy does not apply to this exam. Instead, you may not communicate with anyone other than course staff about the exam in any way. You may consult the course textbook, course notes, slides, homeworks, recorded lectures and discussion sessions, or existing messages on Piazza. You may not post anything new that is public to Piazza during the exam period. (See below.) Violating these instructions will be considered academic dishonesty.

Getting Help: If you have any questions about the content of the exam or technical difficulties, please first consult the “Official FAQ” that will be pinned on Piazza. If your question is not answered there, please email the HTA list: cs1420headtas@lists.brown.edu . We will respond as soon as possible, but please keep in mind that latency of up to 20 minutes is reasonable. In addition, the mailing list is only monitored from 9 AM to midnight Eastern U.S. time, so please plan accordingly.

If you have any other issues or concerns, such as challenging or unexpected circumstances, please contact Steve directly: stephen.bach@brown.edu.
Problem 1 (Representations)

Consider the following training data set with two classes in $\mathbb{R}^2$.

For each of the following hypothesis classes, state whether it can perfectly fit the above training data. Explain your answer.

a. Greedy split decision trees with up to 2 layers (i.e., a root node, up to two child internal nodes, and up to four leaves):

b. Greedy split decision trees with an arbitrary number of layers (so the same attribute can be split multiple times because they are continuous, but each split divides the attribute into two children or leaves):

c. Neural network with step activation functions, 2 layers, and an arbitrary number of hidden neurons:
Problem 2 (Loss Functions)

___ Mark here to count this problem as extra credit.

a. Suppose we learn a linear regression model using the squared loss. Let $d_1$ be the maximum distance between the learned hyperplane and any point $\mathbf{x}$ in the training data. In other words, $d_1$ is the distance between the hyperplane of best fit and the farthest outlier. Then suppose we learn another linear regression model on the same data using a hypothetical “quartic loss”:

$$
\ell_{\text{qu}}(h, (\mathbf{x}, y)) = (h(\mathbf{x}) - y)^4 .
$$

Let $d_2$ be defined an analogous way, the distance between the hyperplane of best fit using the quartic loss and the farthest outlier in the training data. How do you expect $d_1$ and $d_2$ to compare? Why?

b. What is an advantage of using the 0-1 loss for binary classification, versus the log loss? Vice versa, what is an advantage of using the log loss for binary classification, versus the 0-1 loss?
Problem 3 (Optimizers)

Consider the hypothesis class of one-dimensional segmentations into three sections, $H = \{ h_{a,b,s} : a \in \mathbb{R}, b \in \mathbb{R}, \text{ and } s \in \{-1, 1\}^3 \}$, where:

$$h_{a,b,s}(x) = \begin{cases} s_1 & \text{if } x \leq a \\ s_2 & \text{if } x > a \text{ and } x \leq b \\ s_3 & \text{otherwise} \end{cases}$$

and $\mathcal{X} = \mathbb{R}, \mathcal{Y} = \{-1, 1\}$, and $a < b$.

Describe an algorithm for computing the ERM for this class in the realizable case. (You can assume 0-1 loss, although the solution will be the same for any reasonable loss function.) State the computational complexity of the algorithm in the context of a training data set of size $m$. 
Problem 4 (Empirical and Expected Risk)

Mark here to count this problem as extra credit.

For this problem, we are looking for responses that both indicate your assessment as to a possible accuracy change and your understanding of the algorithm that led to this assessment. Answers should be one or two sentences long and focus on the relevant and important issue.

a. Suppose we train an AdaBoost ensemble of $K$ halfspaces and achieve a nonzero empirical risk. We then remove a member of the ensemble and keep all of the other parameters of the classifier the same. What will likely happen to the empirical risk of this new classifier, relative to the old one? Why?

b. Suppose we train a two-layer neural network to perform classification and achieve a non-zero empirical risk. We then add another fully connected hidden layer and retrain on the same data. What will likely happen to the empirical risk of this new classifier, relative to the old one? Why?

c. Suppose we sample a large amount of data set from an arbitrary (i.e., not necessarily Naive Bayes) generative model $P(x, y)$. We then train a logistic regression classifier on the data. We also copy the generative model, randomly re-initialize its parameters, and re-estimate them using maximum likelihood estimation on the same data. We then use the resulting posterior $P(y|x)$ as a second classifier. How will the expected risk of the two classifiers likely compare? Why?
Problem 5 (Model Selection)

Consider the following (partially labeled) model selection curves for two \( \ell_2 \)-regularized logistic regression classifiers:

The training of the two classifiers differed only in the input data. The first model ("Model 1") was trained by regularized risk minimization using the log loss. The second model ("Model 2") was trained in an identical fashion, but had some features removed from each example.

Describe the likely interpretation of the following parts of the above figure, based on the bias-complexity tradeoff. Include a specific statement of what that part of the figure represents, and provide a brief explanation justifying your interpretation.

The horizontal axis (with values \( 10^{-5} \) through \( 10^{-1} \)):

Curve A (solid line):

Curve B (dotted line):

Curve C (dashed line):

Curve D (dashed/dotted line):
Problem 6 (Generative Models)

Consider the following training data for binary classification of two-bit vectors, i.e., $\mathcal{X} = \{0,1\}^2$ and $\mathcal{Y} = \{0,1\}$:

<table>
<thead>
<tr>
<th>$x_1$</th>
<th>$x_2$</th>
<th>$y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
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Using a maximum likelihood Naive Bayes model with Laplace smoothing of 1 (both feature likelihoods and the class prior), what is the probability $P(y = 1|x_1 = 1, x_2 = 1)$, i.e., the probability that a test example $(1,1)$ has the label 1? Assume that the distributions $P(y)$ and all $P(x_i|y)$ are Bernoulli, i.e., binary. Show your work.
Problem 7 (Unsupervised Learning)

--- Mark here to count this problem as extra credit.

For this problem, we are looking for responses that both indicate your assessment as to a possible accuracy change and your understanding of the algorithm that led to this assessment. Answers should be two or three sentences long and focus on the relevant and important issue.

Suppose we applied principal component analysis (PCA) to a data set in $\mathbb{R}^5$ before learning a halfspace classifier on the reduced data set.

a. After decomposing the matrix $A$, we obtain the following eigenvalues: 5.5, 4, 0.1, and 0.01. Which value of $K$, the dimensionality of the linear subspace to which we will reduce the data, would you pick? Why?

b. Suppose you increased the value of $K$ beyond what you picked in part a. What would you expect to happen to the training error of the halfspace classifier? Why?

c. Suppose you decreased the value of $K$ beyond what you picked in part a. What would you expect to happen to the training error of the halfspace classifier? Why?

d. Suppose that one of the original five attributes is a legally protected attribute such as a person’s race or gender. Will training a halfspace classifier on the dimensionality-reduced data produced by PCA prevent the classifier from discriminating based on that attribute? Why? (For this question, discrimination is defined as an $\epsilon$ difference in the probability of outputing 1 conditioned on any two different values of the protected attribute $x$, i.e., $|p(y = 1|x = a) - p(y = 1|x = b)| > \epsilon$.)
Problem 8 (VC Dimension)

Consider (again, see problem 3) the hypothesis class of one-dimensional segmentations into three sections, $H = \{ h_{a,b,s} : a \in \mathbb{R}, b \in \mathbb{R}, \text{ and } s \in \{-1, 1\}^3 \}$, where:

$$ h_{a,b,s}(x) = \begin{cases} 
  s_1 & \text{if } x \leq a \\
  s_2 & \text{if } x > a \text{ and } x \leq b \\
  s_3 & \text{otherwise}
\end{cases} $$

and $X = \mathbb{R}$, $Y = \{-1, 1\}$, and $a < b$.

What is the VC dimension of this hypothesis class? Provide a complete proof.