

1. Consider the email spam classification problem of Murphy Problem 8.1. Suppose you intend to use a linear perceptron classifier on that data (not logistic regression as directed in Problem 8.1). In the parts below, unless stated otherwise, assume the dataset of $N = 4601$ samples is split into $N_{Tr} = 3000$ for training and $N_{Test} = 1601$ for testing. Also, for the tolerance δ in the VC generalization bound, use 0.1 (for a certainty of 0.9). The parts below have short answers.

Hint: You may use the relation that if \mathcal{H} is a linear perceptron classifier in D dimensions (D features), $d_{VC}(\mathcal{H}) = D + 1$. (This will be proved in Problem 2.)

- a) What is the VC dimension of the hypothesis set?
- b) Expressing the upper bound on the out-of-sample error as $E_{out}(h_g) \leq E_{in}(h_g) + \epsilon_{vc}$
For $E_{in}(h_g)$ measured on the training data, use d_{vc} from part (a) to get a value for ϵ_{vc} .
- c) To get a lower ϵ_{vc} , suppose you reduce the number of features to $D = 10$, and also increase the training set size to 10,000. Now what is ϵ_{vc} ?
- d) Suppose that you had control over the number of training samples N_{Tr} (by collecting more email data). How many training samples would ensure a generalization error of $\epsilon_{vc} = 0.1$ again with probability 0.9 (the same tolerance $\delta = 0.1$), and using the reduced feature set (10 features)?
- e) Instead suppose you use the test set to measure $E_{in}(h_g)$, so let's call it $E_{test}(h_g)$. What is the hypothesis set now? What is its cardinality?
- f) Continuing from part (e), use the bound:
$$E_{out}(h_g) \leq E_{test}(h_g) + \epsilon$$
Use the original feature set and the original test set, so that $N_{Test} = 1601$. Give an appropriate expression for ϵ and calculate it numerically.

2. **AML Exercise 2.4** (page 52). In addition to the hints given in the book, you can solve the problem by following the steps outlined below.

For part (a):

- i. Write a point \underline{x}_i as a $d+1$ dimensional vector;
- ii. Construct the $(d+1) \times (d+1)$ matrix suggested by the book;
- iii. Write $\underline{h}(\underline{X})$, the output of the perceptron, as function of \underline{X} and the weights \underline{w} (note that $\underline{h}(\underline{X})$ is a $d+1$ dimensional vector with elements $+1$ and -1);
- iv. Using the nonsingularity of \underline{X} , justify how any $\underline{h}(\underline{X})$ can be obtained.

For part (b):

- i. Write a point \underline{x}_k as a linear combination of the other $d+1$ points;
- ii. Write $h(\underline{x}_k)$ (output for the chosen point) and substitute the value of \underline{x}_k by the expression just found on the previous item (**Hint:** use the $\text{sgn}\{\cdot\}$ function);
- iii. What part of your expression in (ii) determines the class assignment of each point \underline{x}_i , for $i \neq k$?
- iv. You have just proven (part (a)) that $\underline{h}(\underline{X})$ with $\underline{X}_{(d+1) \times (d+1)}$ can be shattered.

When we add a $(d+2)^{\text{th}}$ line to \underline{X} can it still be shattered? In other words, can you choose the value of $h(\underline{x}_k)$? Justify your answer. **Hint:** you can choose the class label of the other $(d+1)$ points.

3. AML **Problem 2.24** (page 75), except

>> Replace part (a) with:

(a.1) For a single given dataset, give an expression for $g^{(D)}(x)$. (AML notation)

(a.2) Find $\bar{g}(x)$ analytically; express your answer in simplest form.

>> For parts (b) and (c), obtain $E_D\{E_{out}\}$ by direct numerical computation, not by adding bias and var.

>> For part (d), obtain $\text{bias}(x)$, $\text{var}(x)$, bias , var , and $E_D\{E_{out}\}$, all by analytical (pencil and paper) techniques.

4. AML **Problem 2.13 (a), (b).**

5. AML **Problem 4.4 (a)-(c)**, plus additional parts (i)-(iii) below.

>> For part (c), assume both $g_{10}(x)$ and $f(x)$ are given as functions of x , and you can express your answer in terms of them; and define

$$E_{out}(g_{10}) = E_{x,y} \left\{ [g_{10}(x) - y(x)]^2 \right\}.$$

- (i) In Fig. 4.3(a), set $\sigma^2 = 0.5$, and traverse the horizontal line from $N \approx 60$ to $N \approx 130$. Explain why \mathcal{H}_{10} transitions from overfit to good fit (relative to \mathcal{H}_2).
- (ii) Also in Fig. 4.3(a), set $N = 100$, and traverse the vertical line from $\sigma^2 = 0$ to $\sigma^2 = 2$. Explain why \mathcal{H}_{10} transitions from good fit to overfit (relative to \mathcal{H}_2).
- (iii) In Fig. 4.3(b), set $N \approx 75$, and traverse the vertical line from $Q_f = 0$ to $Q_f = 100$. Explain the behavior.