

Assignment 3

Darwin Ding

September 22, 2016

Exercise 1.13

- (a) h will fail to approximate y if $h(x) = f(x) \neq y$ or $h(x) \neq f(x) = y$. For the first case, $P[h(x) = f(x)] = 1 - \mu$ and $P[f(x) \neq y] = 1 - \lambda$, so $P[h(x) = f(x) \neq y] = (1 - \mu)(1 - \lambda)$.

For the second case, $P[h(x) \neq f(x)] = \mu$ and $P[f(x) = y] = \lambda$, so $P[h(x) \neq f(x) = y] = \mu\lambda$.

Therefore, $P[\text{error}] = (1 - \mu)(1 - \lambda) + \mu\lambda$.

- (b) When $\lambda = 0.5$, the $P[\text{error}]$ from the previous part $= (1 - \mu)(1 - 0.5) + 0.5\mu = 0.5(1 - \mu + \mu) = 0.5$. At this probability, μ is not even present in the formula for the error in approximation, and since $P[\text{error}] = 0.5$, the noisy target is completely random.

Problem 1.11

Assume for an input data set size of N :

$a = \langle \text{number of input data points where } h(x) = 1 \text{ and } f(x) = 1 \rangle$

$b = \langle \text{number of points where } h(x) = 1 \text{ and } f(x) = -1 \rangle$

$c = \langle \text{number of points where } h(x) = -1 \text{ and } f(x) = 1 \rangle$

$d = \langle \text{number of points where } h(x) = -1 \text{ and } f(x) = -1 \rangle$

By definition, $N = a + b + c + d$.

We want to create an E_{in} function where all the above categories are weighted properly according to the matrices given in the chapter. This E_{in}

function should also vary from 0 to 1.

The resultant $E_{in} = (a*w_a + b*w_b + c*w_c + d*w_d)/(N*max(w_a, w_b, w_c, w_d))$ should do all of the above. w_a, w_b, w_c, w_d are all the weights given in the matrix in the chapter.

For the supermarket, $E_{in} = (b + 10c)/(10N)$

For the CIA, $E_{in} = (1000b + c)/(1000N)$

Problem 1.12

(a)

$$\begin{aligned} E_{in}(h) &= \sum_{n=1}^N (h - y_n)^2 \\ &= \sum_{n=1}^N h^2 - 2hy_n + y_n^2 \\ &= Nh^2 + \sum_{n=1}^N (-2hy_n + y_n^2) \end{aligned}$$

Since we're trying to find the minimum of such E_{in} , we can take the derivative with respect to h and set that derivative to 0 to find which

h gives the smallest E_{in} .

$$\begin{aligned}
\frac{dE_{in}(h)}{dh} &= 2Nh + \sum_{n=1}^N (-2y_n) \\
&= 2Nh + N - 2 \sum_{n=1}^N y_n \\
\frac{dE_{in}(h)}{dh} &= 0 = 2Nh - 2 \sum_{n=1}^N y_n \\
-2Nh &= -2 \sum_{n=1}^N y_n \\
h &= \frac{1}{N} \sum_{n=1}^N y_n
\end{aligned}$$

(b)

$$\begin{aligned}
E_{in}(h) &= \sum_{n=1}^N |h - y_n| \\
&= |h - y_1| + |h - y_2| + \dots + |h - y_N|
\end{aligned}$$

Again, we find the minimum by taking a derivative with respect to h.

$$\frac{dE_{in}(h)}{dh} = \frac{d|h - y_1|}{dh} + \frac{d|h - y_2|}{dh} + \dots + \frac{d|h - y_N|}{dh}$$

$d|x|/dx = |x|/x$ and $d(x - y_n)/dx = 1$ for all n, so we can use the chain rule to derive the individual derivatives of the absolute values in the summation above.

$$\frac{dE_{in}(h)}{dh} = \frac{|h - y_1|}{h - y_1} + \frac{|h - y_2|}{h - y_2} + \frac{|h - y_3|}{h - y_3} + \dots + \frac{|h - y_N|}{h - y_N}$$

Each of the fractions above has value either +1 (if $x - y_n > 0$) or -1 (if $x - y_n < 0$). In order to get to zero, half of the values have to be above h and half the values need to be below h.

- (c) As y_N approaches positive infinity, h_{mean} grows more and more as its sum increases, despite y_N being an outlier. However, h_{median} is not affected much at all due to the nature of medians naturally ignoring outliers. h_{median} may change, however, just due to the fact that if y_N used to be below the median and then became positive infinity, the median may increase by a point.

Exercise 2.1

- (a) Positive rays get broken really early on. At $N = 0$, you can put the ray anywhere and it'll make sense. At $N = 1$, putting the ray is still trivial. If the one point is $+1$, start the ray to the point's left. Otherwise, start it at its right.

However, at $N = 2$ things get a little trickier. No matter where you put the two points on the number line, if the one on the left is $+1$ and the one on the right is -1 , there is no possible way to positive ray the line. However, it is pretty trivial to ray the other 3 dichotomies. Since $3 < 4 = 2^2$, **$N = 2$ is a break point for the positive rays.**

This coincides with the growth function derived in the question, as $m_H(N) = N + 1 < 2^N$ for $N \geq 2$.

- (b) Positive intervals also get broken pretty quickly. $N = 0$ is again trivial. $N = 1$ is also pretty trivial, you simply surround the point if it is $+1$, or avoid it if it is -1 . For $N = 2$, it is still pretty easy to interval the points. For two -1 s, simply avoid both points. For one $+1$ and one -1 , you just interval tightly around the $+1$. For two $+1$ s, the interval just needs to hold both points.

However, at $N = 3$, you can no longer interval the points consistently. You can interval all of the dichotomies pretty easily until you run into $[+1, -1, +1]$. Unfortunately, any interval that contains all the $+1$ s here will by definition contain the -1 in the middle, which breaks the rule. Therefore **$N = 3$ is a break point for positive intervals.**

This is in accordance with the growth function derived, as $m_H(2) =$

$$\binom{2+1}{2} + 1 = 3 + 1 = 2^2, \text{ but } m_H(3) = \binom{3+1}{2} + 1 = 7 < 8 = 2^3.$$

- (c) Convex sets are, as the growth formula implies, impossible to break. If you adhere to the strong strategy of placing all of the points equidistant around a circle, no two lines connecting any of those points can ever leave the set. Because this axiom about points on a circle never really ends, **there is no break point for convex sets.**

This doesn't really need to be verified because $2^N = 2^N$ for all N .

Exercise 2.2

- (a) (a) Positive rays broke at $k = 2$, so we can plug this into the bound and compare to the calculated growth function:

$$m_H(N) = N + 1 \leq \binom{N}{0} + \binom{N}{1} = 1 + N$$

Clearly, this holds.

- (b) Positive intervals broke at $k = 3$, so plugging that into the bound and comparing to the growth function given:

$$\begin{aligned} m_H(N) &= .5N^2 + .5N + 1 \leq \binom{N}{0} + \binom{N}{1} + \binom{N}{2} \\ &= 1 + N + N(N-1)/2 \\ &= 1 + N + .5N^2 - N/2 \\ &= 1 + .5N + .5N^2 \end{aligned}$$

Clearly, this also holds.

- (c) We cannot apply this bound here, because $m_H(N) = 2^N$ for all N . Convex sets did not break.

Exercise 2.3

Since the VC dimension is pretty much defined as the break point $k - 1$:

- (a) Positive rays broke at $k = 2$, so the VC dimension is **1**

- (b) Positive intervals broke at $k = 3$, so the VC dimension is **2**
- (c) Convex sets did not break, so the VC dimension is ∞

Exercise 2.6

- (a) Our error bar function is $E_{out}(g) \leq E_{in}(g) + \sqrt{\frac{1}{2N} \log \frac{2|H|}{\delta}}$. With the same size hypothesis set ($H = 1000$ for both), and δ being the same for both (0.05), the lower N for E_{test} means that it has a lower error bar. However, the lower N also means that E_{test} might be more wild.
- (b) By having a larger test set, you will have less examples used for your actual training set. As a result, $E_{test} \approx E_{out}$ but E_{test} has no guarantees of lowness.