

## Problem 1

### Solution

- (a) Let  $t = \sqrt{1+x}$ . Since  $x \geq 0$ , we have  $t \geq 1$ . Let  $h(t) = 2\log(t) - t$ , then we have to prove that  $h(t) \leq 0$  holds for all  $t \geq 1$ . Since  $h'(t) = \frac{2}{t} - 1$ , we have  $h(t) \leq h(2) < 0$ .
- (b) Let  $h(m) = \frac{\log(m)}{m}$ ,  $m \geq 1$ . We have  $h'(m) = \frac{1-\log(m)}{m^2}$ . Thus,  $h(m)$  is decreasing when  $m \geq e$ . If  $n = 1$ , then  $m < \log(m) \implies m < 0$ . (Actually, the inequality on left hand is not possible for all  $m$ , and thus it can imply any statement.) Similarly, it is trivial if  $m = 1$ . For the cases where  $n \geq 2$  and  $m \geq 2$ , we proceed by contradiction. Suppose that  $m \geq 2n \log(n) > e$ . Since  $\frac{m}{\log(m)}$  is increasing when  $m \geq e$  and  $n \geq 2 \log(n)$  (conclusion of (a)), we have  $\frac{m}{\log(m)} \geq \frac{2n \log(n)}{\log(2n \log(n))} \geq \frac{2n \log(n)}{\log(n^2)} = n$ . Thus  $m < n \log(m) \implies m < 2n \log(n)$ .

## Problem 2

### Solution

The Lagrangian of this problem is

$$L(w, b, \xi, \mu, \lambda) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i + \sum_{i=1}^n \mu_i (1 - \xi_i - y_i(w^\top x_i + b)) - \sum_{i=1}^n \lambda_i \xi_i, \quad \mu_i \geq 0 \text{ and } \lambda_i \geq 0.$$

Let the gradient of  $L$  w.r.t  $w$ ,  $b$  and  $\xi$  be 0. We have

$$\nabla_w L = w - \sum_{i=1}^n \mu_i y_i x_i = 0,$$

$$\nabla_b L = \sum_{i=1}^n \mu_i y_i = 0,$$

$$\nabla_{\xi_i} L = C - \lambda_i - \mu_i = 0, \quad \forall i.$$

Since  $C = \lambda_i - \mu_i = 0$ ,  $\forall i$  and  $\lambda_i \geq 0$ , we have  $\mu_i \leq C$ . By substituting  $w = \sum_{i=1}^n \mu_i y_i x_i$ , we have  $D(\mu, \lambda) = \sum_{i=1}^n \mu_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \mu_i \mu_j y_i y_j (x_i^\top x_j)$ . Thus the dual problem is of the same form as the soft-margin version with additional constraints that  $\mu_i \leq C$ ,  $\forall i$ .

## Problem 3

### Solution

Let  $L_t(\alpha) = \sum_{i=1}^n \exp\left(-\sum_{s=1}^{t-1} \alpha_s y_i h_s(x_i) - \alpha y_i h_t(x_i)\right)$ . Then,  $\alpha_t = \arg \min L_t(\alpha)$ . Suppose that  $h_{t+1} = h_t$ . Then,  $L_{t+1}(\alpha) = L_t(\alpha + \alpha_t)$ . Thus,  $\alpha_{t+1} = 0 = \arg \min L_{t+1}(\alpha)$ . However, since  $\epsilon_t < \frac{1}{2}$ ,  $\alpha_{t+1} = \frac{1}{2} \ln \frac{1-\epsilon_{t+1}}{\epsilon_{t+1}} > 0$ . Thus, by contradiction,  $h_{t+1} \neq h_t$ .

## Problem 4

### Solution

- (a) 91%.
- (b) As shown in Fig. 1, test accuracy improves as number of learners increases.

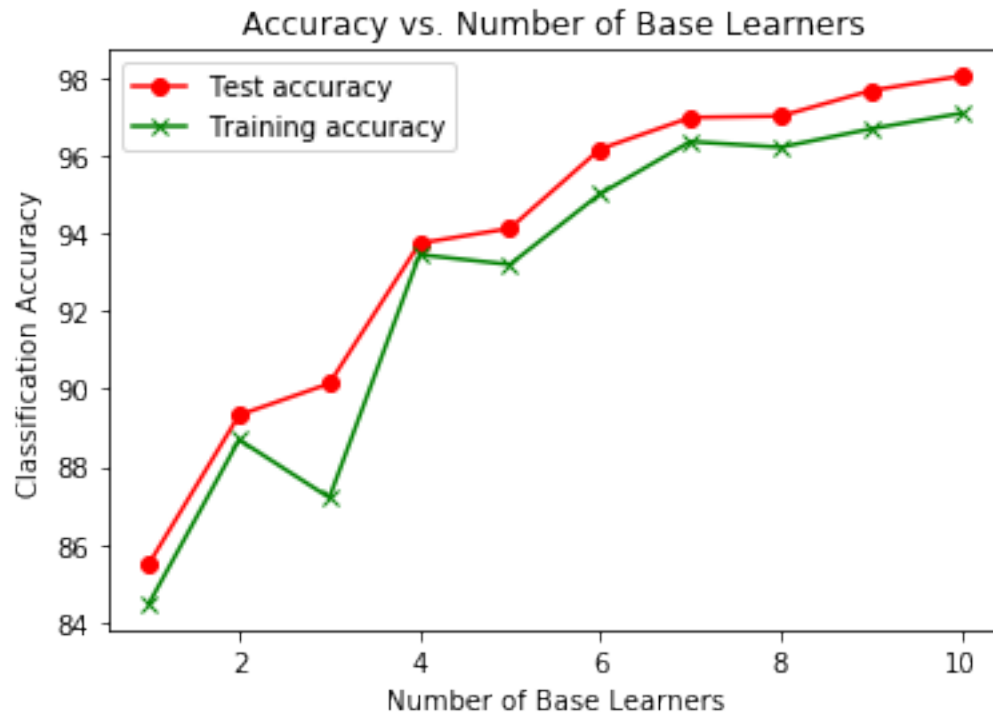


Figure 1: Results of AdaBoost.

## Problem 4

### Solution

- (a) Accuracies are 50%, 50%, 52%, 69%, 97%, 98% respectively.
- (b) Linear kernel: 98%. Poly kernel: 99%. RBF kernel: 100%. Sigmoid kernel: 81%.