

## CS 5691: Pattern Recognition and Machine Learning

### Worksheet 3

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1. Consider the following 2-dimensional binary classification dataset with 8 points given by

$$X^T = \begin{bmatrix} -2 & -2 & -1 & -1 & 1 & 1 & 2 & 3 \\ -1 & 2 & 1 & 2 & 1 & 3 & 3 & 2 \end{bmatrix}$$
$$\mathbf{y}^T = [+1, +1, +1, -1, -1, +1, -1, -1]$$

Run one iteration of gradient descent with the logistic regression objective by hand. No bias required, only the 2-dimensional weight vector is to be optimised. Choose the step size  $\eta = 1$ . Initialise at  $\mathbf{w} = [0, 0]^T$ .

2. Consider a regression problem with training data  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)\}$  with  $\mathbf{x}_i \in \mathbb{R}^d$  and  $y_i \in \mathbb{R}$ . The Support Vector Regression algorithm, essentially solves the below problem:

$$\begin{aligned} \min_{\mathbf{w}, b} \quad & \frac{1}{2} \|\mathbf{w}\|^2 \\ \text{s.t.} \quad & \mathbf{w}^T \mathbf{x}_i + b \leq y_i + \epsilon \\ & \mathbf{w}^T \mathbf{x}_i + b \geq y_i - \epsilon \end{aligned}$$

for some fixed  $\epsilon > 0$ . Derive the Lagrangian dual optimisation problem to the above problem.

3. Consider the following 2-dimensional binary classification dataset with 8 points given by

$$X^T = \begin{bmatrix} 1 & 1 & 2 & 4 & 5 \\ 1 & 0 & 5 & 4 & 2 \end{bmatrix}$$
$$\mathbf{y}^T = [+1, +1, -1, -1, -1]$$

Consider the hard margin SVM problem with linear kernel  $k(\mathbf{u}, \mathbf{v}) = \mathbf{u}^T \mathbf{v}$ .

- Give the support vectors just by looking at the data. Give reasons.
  - Give the dual solution  $\boldsymbol{\alpha}^*$  using the answer to the above part.
  - Check if the entire solution got above is the right answer using KKT conditions. (Thus also checking the first part guessed by “eyeballing”.)
  - Derive the primal solution  $\mathbf{w}^*, b^*$  from the dual solution  $\boldsymbol{\alpha}^*$  and draw a figure illustrating the final solution.
4. Let  $\mathbf{u} \in \mathbb{R}^d$  be a point. Let  $\mathbf{w} \in \mathbb{R}^d, b \in \mathbb{R}$  and the hyperplane given by  $\mathbf{w}, b$  is  $\{\mathbf{x} \in \mathbb{R}^d : \mathbf{w}^T \mathbf{x} + b = 0\}$ . Consider the following problem of projection of the point  $\mathbf{u}$  on to a (hyper)plane given by  $\mathbf{w}, b$ .

$$\begin{aligned} \min_{\mathbf{v} \in \mathbb{R}^d} \quad & \frac{1}{2} \|\mathbf{v} - \mathbf{u}\|^2 \\ \text{s.t.} \quad & \mathbf{w}^T \mathbf{v} + b = 0 \end{aligned}$$

Derive the solution to the above problem via solving the Lagrangian dual (which is an unconstrained quadratic problem, and hence can be easily solved). Show that distance of the point  $\mathbf{u}$  to the hyperplane given by  $\mathbf{w}, b$  is  $\frac{|\mathbf{w}^T \mathbf{u} + b|}{\|\mathbf{w}\|}$ .

5. Let  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)\}$  be a binary classification dataset. Let  $\mathbf{w}^*, b^*$  be any solution to the problem below:

$$\begin{aligned} \max_{\mathbf{w} \in \mathbb{R}^d, b \in \mathbb{R}} \quad & \frac{1}{\|\mathbf{w}\|} \\ \text{s.t.} \quad & y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 \end{aligned}$$

Show that  $\min_{i \in [n]} y_i(\mathbf{w}^T \mathbf{x}_i + b) = 1$ .

6. Consider the following 2-dimensional binary classification dataset with 8 points given by

$$X^T = \begin{bmatrix} 1 & 1 & 2 & 2 & 4 & 4 & 5 & 5 \\ 0 & 1 & 0 & 1 & 3 & 4 & 3 & 4 \end{bmatrix}$$

$$\mathbf{y}^T = [-1, -1, -1, -1, +1, +1, +1, +1]$$

Consider the hard-margin linear SVM problem. Evaluate the following  $\mathbf{w}, b$ . By evaluate, check if it satisfies feasibility, and give the objective value.

- |   |   |
|---|---|
| (a) $\mathbf{w} = [\frac{1}{2}, 0], b = \frac{-3}{2}$ | (f) $\mathbf{w} = [\frac{1}{4}, \frac{1}{4}], b = \frac{-5}{4}$ |
| (b) $\mathbf{w} = [1, 0], b = -3$                     | (g) $\mathbf{w} = [\frac{1}{2}, \frac{1}{2}], b = \frac{-5}{2}$ |
| (c) $\mathbf{w} = [2, 0], b = -6$                     | (h) $\mathbf{w} = [1, 1], b = -5$                               |
| (d) $\mathbf{w} = [1, 0], b = -4$                     | (i) $\mathbf{w} = [1, 1], b = -6$                               |
| (e) $\mathbf{w} = [1, 0], b = -5$                     | (j) $\mathbf{w} = [1, 1], b = -7$                               |

7. Consider the following 2-dimensional binary classification dataset with 12 points given by

$$X^T = \begin{bmatrix} 1 & 1 & 1 & 2 & 2 & 2 & 4 & 4 & 5 & 5 & 6 & 6 \\ -1 & 0 & 1 & -1 & 0 & 1 & 3 & 4 & 3 & 4 & 3 & 4 \end{bmatrix}$$

$$\mathbf{y}^T = [-1, -1, -1, -1, +1, -1, +1, -1, +1, +1, +1, +1]$$

Consider the soft-margin linear SVM problem with  $C = 0.1, 1, 10, 100$ . For each  $C$  evaluate the following  $\mathbf{w}, b$ . By evaluate, I mean you should give a the slack variables  $\xi$  that make the  $\mathbf{w}, b, \xi$  feasible, and also give the value of the objective.

- |   |   |
|---|---|
| (a) $\mathbf{w} = [\frac{1}{2}, 0], b = \frac{-3}{2}$ | (f) $\mathbf{w} = [\frac{1}{4}, \frac{1}{4}], b = \frac{-5}{4}$ |
| (b) $\mathbf{w} = [1, 0], b = -3$                     | (g) $\mathbf{w} = [\frac{1}{2}, \frac{1}{2}], b = \frac{-5}{2}$ |
| (c) $\mathbf{w} = [2, 0], b = -6$                     | (h) $\mathbf{w} = [1, 1], b = -5$                               |
| (d) $\mathbf{w} = [1, 0], b = -4$                     | (i) $\mathbf{w} = [1, 1], b = -6$                               |
| (e) $\mathbf{w} = [1, 0], b = -5$                     | (j) $\mathbf{w} = [1, 1], b = -7$                               |

8. Consider the following 2-dimensional binary classification dataset with 10 points given by

$$X^T = \begin{bmatrix} 1 & 1 & 2 & 2 & 4 & 4 & 5 & 5 & 2.9 & 3.1 \\ 0 & 1 & 0 & 1 & 3 & 4 & 3 & 4 & 6 & 6 \end{bmatrix}$$

$$\mathbf{y}^T = [-1, -1, -1, -1, +1, +1, +1, +1, -1, +1]$$

Consider the soft-margin linear SVM problem with  $C = 0.1, 1, 10, 100$ . For each  $C$  evaluate the following  $\mathbf{w}, b$ . By evaluate, I mean you should give a the slack variables  $\xi$  that make the  $\mathbf{w}, b, \xi$  feasible, and also give the value of the objective.

- |   |   |
|---|---|
| (a) $\mathbf{w} = [\frac{1}{2}, 0], b = \frac{-3}{2}$ | (f) $\mathbf{w} = [\frac{1}{4}, \frac{1}{4}], b = \frac{-5}{4}$ |
| (b) $\mathbf{w} = [1, 0], b = -3$                     | (g) $\mathbf{w} = [\frac{1}{2}, \frac{1}{2}], b = \frac{-5}{2}$ |
| (c) $\mathbf{w} = [4, 0], b = -12$                    | (h) $\mathbf{w} = [1, 1], b = -5$                               |
| (d) $\mathbf{w} = [16, 0], b = -48$                   | (i) $\mathbf{w} = [2, 2], b = -10$                              |
| (e) $\mathbf{w} = [64, 0], b = -192$                  | (j) $\mathbf{w} = [4, 4], b = -20$                              |

9. Consider the following 2-dimensional binary classification dataset with 10 points given by

$$X^T = \begin{bmatrix} 1 & 1 & 2 & 2 & 4 & 4 & 5 & 5 & 2.9 & 3.1 \\ 0 & 1 & 0 & 1 & 3 & 4 & 3 & 4 & 6 & 6 \end{bmatrix}$$

$$\mathbf{y}^T = [-1, -1, -1, -1, +1, +1, +1, +1, -1, +1]$$

Consider the hard-margin linear SVM problem. Guess the support vectors, and use it to solve the dual SVM problem to get  $\alpha^*$ . Verify your guess by checking if the  $\alpha^*$  satisfies the KKT conditions of the dual. Use  $\alpha^*$  to get the primal optimal solutions  $\mathbf{w}^*, b^*$ .

10. Consider the following 2-dimensional binary classification dataset with 12 points given by

$$X^\top = \begin{bmatrix} 1 & 1 & 1 & 2 & 2 & 2 & 4 & 4 & 5 & 5 & 6 & 6 \\ -1 & 0 & 1 & -1 & 0 & 1 & 3 & 4 & 3 & 4 & 3 & 4 \end{bmatrix}$$

$$\mathbf{y}^\top = [-1, -1, -1, -1, +1, -1, +1, -1, +1, +1, +1, +1]$$

Consider the soft-margin linear SVM problem with  $C = 0.1, 1, 10, 100$ . Use software to just get the points  $i$ , where  $\alpha_i^* = 0$  or  $\alpha_i^* = C$  for the above problem (for each value of  $C$ ). And use just that to derive the dual optimal solution  $\alpha^*$  and the primal optimal solution  $\mathbf{w}^*, b^*$ . (In a test you can reasonably expect that the support vectors will be given to you, and you can just do the rest.)

11. Consider the following 2-dimensional binary classification dataset with 10 points given by

$$X^\top = \begin{bmatrix} 1 & 1 & 2 & 2 & 4 & 4 & 5 & 5 & 2.9 & 3.1 \\ 0 & 1 & 0 & 1 & 3 & 4 & 3 & 4 & 6 & 6 \end{bmatrix}$$

$$\mathbf{y}^\top = [-1, -1, -1, -1, +1, +1, +1, +1, -1, +1]$$

Consider the soft-margin linear SVM problem with  $C = 0.01, 0.1, 1, 10, 100$ . Use software to just get the points  $i$ , where  $\alpha_i^* = 0$  or  $\alpha_i^* = C$  for the above problem (for each value of  $C$ ). And use just that to derive the dual optimal solution  $\alpha^*$  and the primal optimal solution  $\mathbf{w}^*, b^*$ . Try and explain why the optimal  $\mathbf{w}^*, b^*$  changes with  $C$  as above.

12. Consider the following 1-dimensional binary classification dataset with 8 points given by

$$X^\top = [1, 2, 4, 5, 6, 7, 9, 10]$$

$$\mathbf{y}^\top = [+1, +1, -1, -1, -1, -1, +1, +1]$$

Solve the Kernel hard margin SVM problem with the kernel  $k(u, v) = \exp(-\gamma(u - v)^2)$ . Try  $\gamma = 0.1$  and  $\gamma = 10$ . For each  $\gamma$ , use software to just get the support vectors for the above problem. And use just that to derive the dual optimal solution  $\alpha^*$ . Give the primal solution corresponding to  $b^*$ . (The solution part corresponding to  $\mathbf{w}^*$  is infinite dimensional). Draw a plot of the decision function given by

$$\hat{y}(x) = \phi(x)^\top \mathbf{w}^* + b^* = \sum_{i=1}^8 \alpha_i^* k(x, x_i) + b^*$$

13. Consider the following 2-dimensional binary classification dataset with 9 points given by

$$X^\top = \begin{bmatrix} 0 & 0 & 1 & 1 & 3 & 2 & 3 & 4 & 5 \\ 0 & 1 & 0 & 1 & 3 & 5 & 4 & 3 & 2 \end{bmatrix}$$

$$\mathbf{y}^\top = [+1, +1, +1, +1, -1, -1, -1, -1, -1]$$

Consider the hard margin linear SVM problem. Argue what would the support vectors be. Use this to derive the dual optimal  $\alpha^*$ , and hence the primal optimal  $\mathbf{w}^*, b^*$ .

Repeat the above if the point  $\mathbf{x}_5 = [3, 3]$  is removed.

*Hint : The dual optimal  $\alpha^*$  need not be unique, even if the primal optimal  $\mathbf{w}^*, b^*$  are. Bonus points for arguing why this can be so for the Hard-margin SVM solution.*

14. Consider a soft margin SVM problem with  $C$  set to some constant. Let  $\alpha^*$  be the dual solution, and let  $\mathbf{w}^*, b^*$  be the dual solution. Let the dataset be  $(\mathbf{x}_i, y_i)$  with  $i$  ranging from 1 to  $n$ .

- If  $\alpha_i^* = 0$  what are the possible range of values of  $(\mathbf{w}^*)^\top \mathbf{x}_i + b^*$ ?
- If  $0 < \alpha_i^* < C$  what are the possible range of values of  $(\mathbf{w}^*)^\top \mathbf{x}_i + b^*$ ?
- If  $\alpha_i^* = C$  what are the possible range of values of  $(\mathbf{w}^*)^\top \mathbf{x}_i + b^*$ ?