

**CS/ECE/ME 532**  
**Unit 5 Practice Problems**

- 1. Support vector machines.** We are trying to predict whether a certain chemical reaction will take place as a function of our experimental conditions: temperature, pressure, concentration of catalyst, and several other factors. For each experiment  $i = 1, \dots, m$  we record the experimental conditions in the vector  $a_i \in \mathbb{R}^n$  and the outcome in the scalar  $b_i \in \{-1, 1\}$  (+1 if the reaction occurred and -1 if it did not). We will use an SVM to train our linear classifier. Namely, we solve:

$$\underset{x}{\text{minimize}} \quad \sum_{i=1}^m (1 - b_i a_i^\top x)_+ \quad \text{where } (u)_+ = \max(0, u) \text{ is the soft thresholding operator}$$

- a) Derive a gradient descent method for solving this problem. Explicitly give the computations required at each step. **Note:** you may ignore points where the function is non-differentiable.

**SOLUTION:** Using the definition of soft-threshold, we have:

$$(1 - b_i a_i^\top x)_+ = \begin{cases} 0 & \text{if } b_i a_i^\top x > 1 \\ 1 - b_i a_i^\top x & \text{if } b_i a_i^\top x < 1 \end{cases}$$

Therefore the gradient is given by:

$$\nabla_x (1 - b_i a_i^\top x)_+ = \begin{cases} 0 & \text{if } b_i a_i^\top x > 1 \\ -b_i a_i & \text{if } b_i a_i^\top x < 1 \end{cases}$$

We can write this compactly as  $\nabla_x (1 - b_i a_i^\top x)_+ = -\frac{1}{2} b_i (1 + \text{sign}(1 - b_i a_i^\top x)) a_i$ . A gradient descent algorithm involves the entire gradient and would look like:

1. initialize  $x_0$
2. compute  $x_{k+1} = x_k + \frac{\gamma}{2} \sum_{i=1}^m b_i (1 + \text{sign}(1 - b_i a_i^\top x_k)) a_i$  for  $k = 0, 1, \dots$

- b) Explain what happens to the algorithm if you land at an  $x_k$  that classifies all the points perfectly, and by a substantial margin.

**SOLUTION:** If classification is perfect, this means  $b_i a_i^\top x > 0$  for all  $i$ . If the margin is large enough so that  $b_i a_i^\top x > 1$  as well, then the gradient will be zero. So the gradient descent iterations stop.

## 2. Regularization

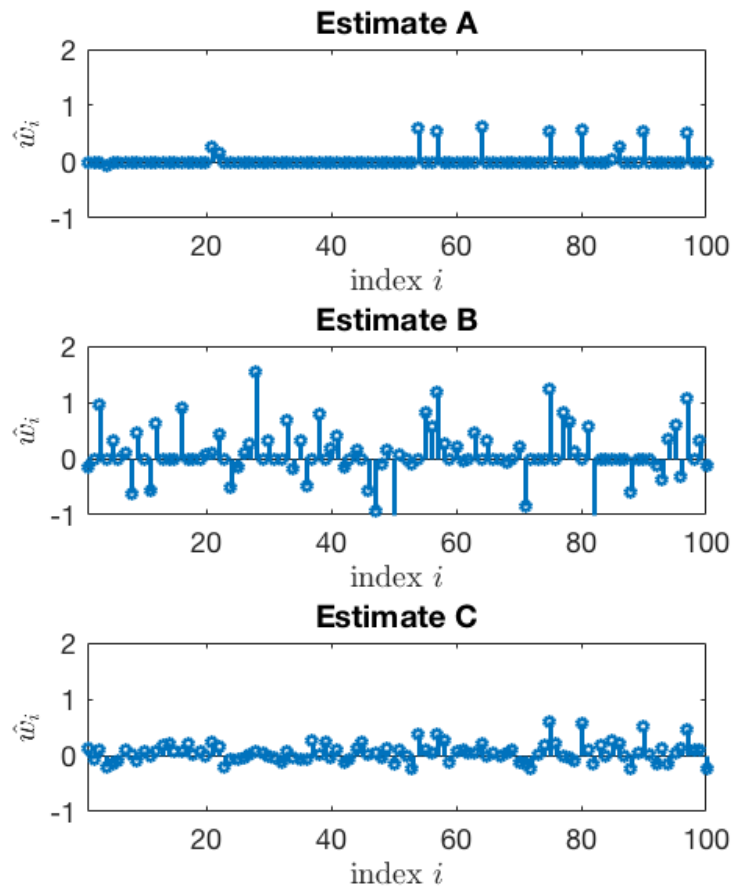
- a) We observe  $n = 60$  training samples of the form  $(\mathbf{x}_i, y_i) \in \mathbb{R}^p \times \mathbb{R}$  for  $i = 1, \dots, n$ , where  $p = 100$ . For these samples, we compute the least-squares estimator, the ridge regression estimator with squared error loss, and the LASSO estimator. Write expressions for each of the three estimators (e.g.,  $\hat{\mathbf{w}} = \arg \min \dots$ ). **SOLUTION:**

$$(\text{least squares}) \hat{\mathbf{w}} = \arg \min \|y - Xw\|_2^2$$

$$(\text{ridge}) \hat{\mathbf{w}} = \arg \min \|y - Xw\|_2^2 + \lambda \|w\|_2^2$$

$$(\text{lasso}) \hat{\mathbf{w}} = \arg \min \|y - Xw\|_2^2 + \lambda \|w\|_1$$

- b) The three estimates are in the plots below. Identify which estimator is in which plot and explain your reasoning.



**SOLUTION:** A is Lasso – sparsest

B is least squares because norm of  $w$  is clearly larger than in C. C is ridge.

3. You use gradient-descent based iterative algorithms for finding the 2-by-1 vector of weights  $\mathbf{w}$  that solves three different least-squares problems:

$$\text{A: } \min_{\mathbf{w}} \|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2$$

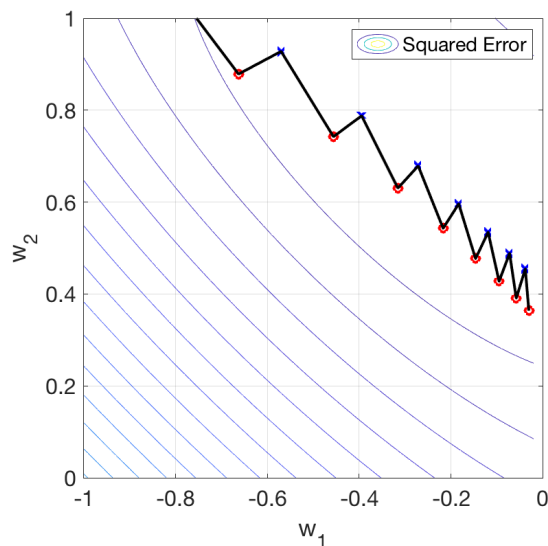
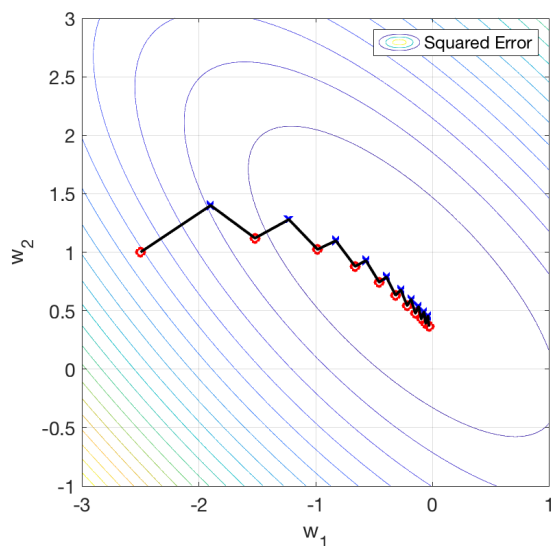
$$\text{B: } \min_{\mathbf{w}} \{\|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2 + \lambda\|\mathbf{w}\|_2^2\}$$

$$\text{C: } \min_{\mathbf{w}} \{\|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2 + \lambda\|\mathbf{w}\|_1\}$$

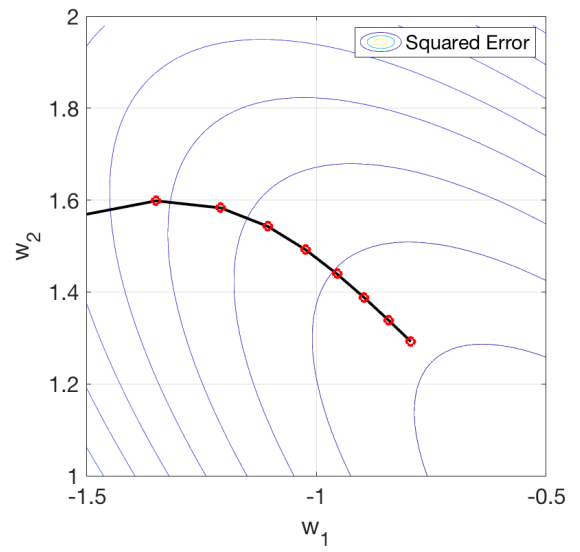
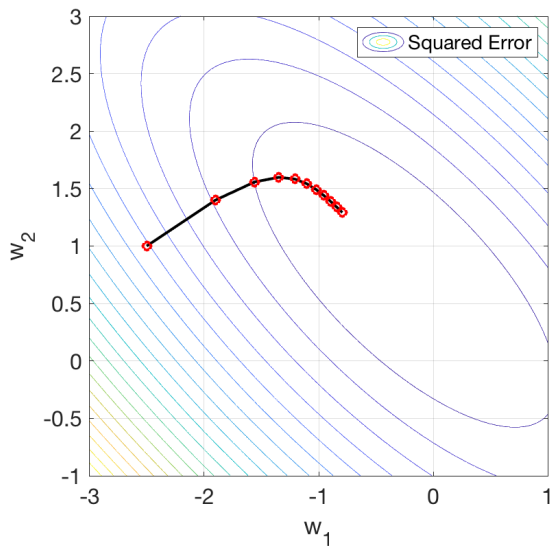
The graphs shown in each part below depict the trajectories of the weights for the first ten iterations. Identify which of these problems correspond to each of the trajectories. **Give a the reason for each of your answers.**

Note that  $\mathbf{X}$  and  $\mathbf{y}$  are the same in all cases. Successive iterations of the weights are denoted by the circles. The x symbol denotes the intermediate step within each iteration. The trajectory shown in the right panel is a closer view of a section of the trajectory shown in the left panel.

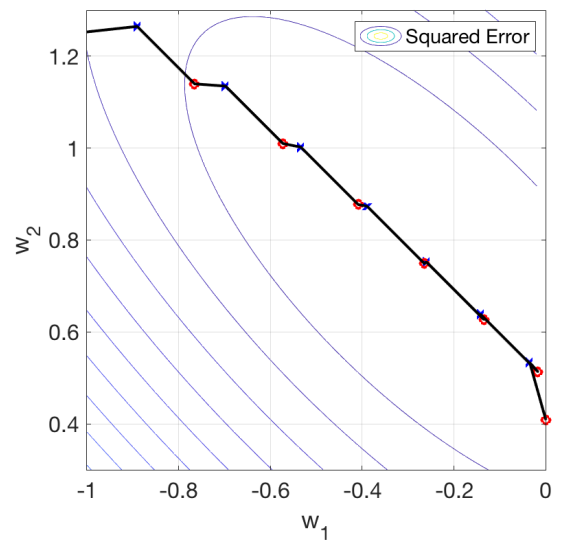
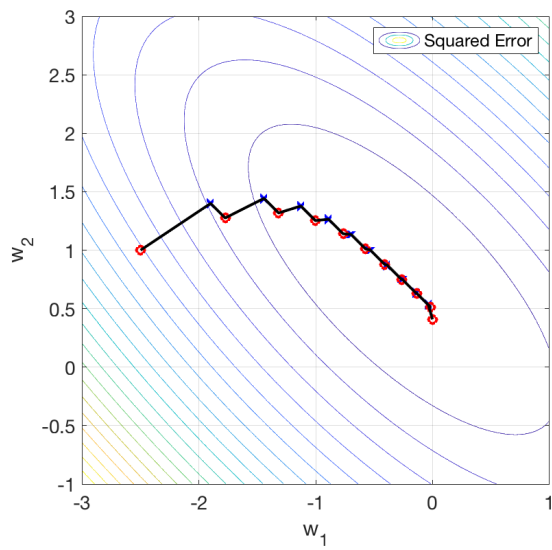
a) Answer: -----



b) Answer: -----



c) Answer: -----



**SOLUTION:**

a) B, Ridge Regression

b) A, Least Squares

c) C, LASSO