Machine Learning, 2024 Spring Assignment 6

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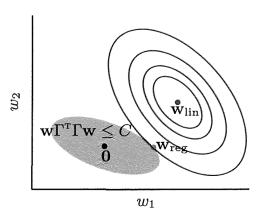
Notice

Plagiarizer will get 0 points. LaTeXis highly recommended. Otherwise you should write as legibly as possible.

Problem 1 In this problem, you will investigate the relationship between the soft order constraint and the augmented error. The regularized weight $\mathbf{w}_{\text{reg}}\,$ is a solution to

$$\min E_{\text{in}}\left(\mathbf{w}\right)$$
 subject to $\mathbf{w}^{\text{T}}\Gamma^{\text{T}}\Gamma\mathbf{w} \leq C$

- (a) If $\mathbf{w}_{\text{lin}}^{\text{T}} \Gamma^{\text{T}} \Gamma \mathbf{w}_{\text{lin}} \leq C$, then what is \mathbf{w}_{reg} ? (b) If $\mathbf{w}_{\text{lin}}^{\tau} \Gamma^{\top} \Gamma \mathbf{w}_{\text{lin}} > C$, the situation is illustrated below,



The constraint is satisfied in the shaded region and the contours of constant $E_{\rm in}$ are the ellipsoids (why ellipsoids?). What is $\mathbf{w}_{\rm reg}^{\rm T} \Gamma^{\rm T} \Gamma \mathbf{w}_{\rm reg}$?

(c) Show that with

$$\lambda_C = -\frac{1}{2C} \mathbf{w}_{\text{reg}}^{\text{T}} \, \nabla E_{\text{in}} \, \left(\mathbf{w}_{\text{reg}} \, \right)$$

 \mathbf{w}_{reg} minimizes $E_{\text{in}}(\mathbf{w}) + \lambda_C \mathbf{w}^{\text{T}} \Gamma^{\text{T}} \Gamma \mathbf{w}$. [Hint: use the previous part to solve for \mathbf{w}_{reg} as an equality constrained optimization problem using the method of Lagrange multipliers.]

- (d) Show that the following hold for λ_C :

- (i) If $\mathbf{w}_{\mathrm{lin}}^{\mathrm{T}} \Gamma^{\mathrm{T}} \Gamma \mathbf{w}_{\mathrm{lin}} \leq C$ then $\lambda_C = 0$ ($\mathbf{w}_{\mathrm{lin}}$ itself satisfies the constraint). (ii) If $\mathbf{w}_{\mathrm{lin}}^{\mathrm{T}} \Gamma^{\mathrm{T}} \Gamma \mathbf{w}_{\mathrm{lin}} > C$, then $\lambda_C > 0$ (the penalty term is positive). (iii) If $\mathbf{w}_{\mathrm{lin}}^{\mathrm{T}} \Gamma^{\mathrm{T}} \Gamma \mathbf{w}_{\mathrm{lin}} > C$, then λ_C is a strictly decreasing function of C. [Hint: show that $\frac{d\lambda_C}{dC} < 0$] for $C \in [0, \mathbf{w}_{\text{lin}}^T \Gamma^T \Gamma \mathbf{w}_{\text{lin}}]$.

Solution

Problem 2 [The Lasso algorithm] Rather than a soft order constraint on the squares of the weights, one could use the absolute values of the weights:

$$\min E_{\text{in}}\left(\mathbf{w}\right)$$
 subject to
$$\sum_{i=0}^{d}\left|w_{i}\right|\leq C$$

The model is called the lasso algorithm.

- (a) Formulate and implement this as a quadratic program.
- (b) What is the augmented error and discuss the algorithm for solving it. You can solve this problem using iterative soft-thresholding algorithm or a gradient projection method and present your pseudocode.

Solution

Problem 3 Similar to problem 3 in assignment 3 and assignment 4, you need to use the SUV dataset to implement (using Python or MATLAB) the L_1/L_2 regularization (penalty/augmented).

- Present your code.
- Present the path plots of L_1 and L_2 regularization. (Notice: you need to mark the selected value of the regular parameter)
- Analyze the weight difference between L_1 and L_2 regularization. (Notice: you need to describe the similarities and differences between the solutions of path plots)
- If you only want to build a model that contains 2 variables, which two features would you choose?

Solution