

PROBLEMS

Due Friday Feb. 10, 2023 @ 4pm

1. Consider the cost function

$$J(\beta) = \|\mathbf{y} - \mathbf{X}\beta\|^2 + \beta^\top \mathbf{R}\beta$$

for a fixed matrix \mathbf{R} for which $\mathbf{R} + \mathbf{R}^\top$ is positive definite. Show $\beta_{\text{opt}} = \arg \min_{\beta} J(\beta)$ equals

$$\beta_{\text{opt}} = (\mathbf{X}^\top \mathbf{X} + \tfrac{1}{2}\mathbf{R} + \tfrac{1}{2}\mathbf{R}^\top)^{-1} \mathbf{X}^\top \mathbf{y}.$$

Hint: Use the gradient-zeroing technique that was used to derive β_{ls} in the lecture.

2. Suppose that we have a model

$$y = \hat{f}(x; \theta) + \epsilon$$

with zero-mean σ^2 -variance Gaussian noise ϵ and

$$\hat{f}(x; \theta) = e^\theta x$$

with unknown $\theta \in \mathbb{R}$. We would like to fit θ to a dataset $\{(x_i, y_i)\}_{i=1}^n$ of independent draws from this model.

- (a) Derive an expression for the negative log likelihood function. Simplify as much as possible
 - (b) Find the maximum-likelihood estimate of θ . *Hint:* Set the gradient of the negative loglikelihood to zero.
3. Say that $\mathbf{y} = [y_1, \dots, y_n]^\top$ are independent samples of a Gaussian random variable Y with mean 1 and unknown variance σ^2 . That is, the pdf of Y equals

$$p_Y(y | \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(y-1)^2\right).$$

- (a) Derive an expression for the maximum-likelihood estimate of the standard deviation σ from \mathbf{y} , i.e., $\hat{\sigma} = \arg \max_{\sigma} p(\mathbf{y} | \sigma^2)$.
- (b) Derive an expression for the maximum-likelihood estimate of the variance σ^2 from \mathbf{y} , i.e., $\hat{\sigma}^2 = \arg \max_{\sigma^2} p(\mathbf{y} | \sigma^2)$. Does it agree with your answer to part (a)?

In your derivations, be very careful to distinguish scalar quantities like y from vector quantities like \mathbf{y} . (When writing by hand, it's typical to underline vector quantities.)