

## Homework 2: Linear Regression

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**DO NOT POLLUTE!** AVOID PRINTING, OR PRINT 2-SIDED MULTIPAGE.**Problem 2.1**

To minimize the MSE of  $\theta$ , we compute our estimator  $\hat{\theta}$ :

$$\hat{\theta} = \arg \min_{\theta} \|y - \mathbf{X}\theta\|_2^2$$

Expanding that out, we find:

$$\begin{aligned}\|y - \mathbf{X}\theta\|_2^2 &= (y - \mathbf{X}\theta)^\top (y - \mathbf{X}\theta) \\ &= y^\top y - y^\top \mathbf{X}\theta - \theta^\top \mathbf{X}^\top y + \theta^\top \mathbf{X}^\top \mathbf{X}\theta \\ &= y^\top y - 2\theta^\top \mathbf{X}^\top y + \theta^\top \mathbf{X}^\top \mathbf{X}\theta\end{aligned}$$

From there, we take the derivative w.r.t.  $\theta$ :

$$\frac{d}{d\theta} = 2\mathbf{X}^\top \mathbf{X}\theta - 2\mathbf{X}^\top y$$

After setting this derivative to zero and solving for  $\theta$ , we find that our solution is:

$$\hat{\theta} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top y$$

**Problem 2.2**

Since know that  $\epsilon$  is distributed normally, we can use the normal distribution formula to derive our expression for the MLE of  $\theta^*$ :

$$\mathbb{P}(y, \mathbf{X} | \theta, \Sigma^*) = \frac{1}{\sqrt{2\pi\Sigma^*}} e^{-\frac{1}{2\Sigma^*} (y - \theta\mathbf{X})^\top (y - \theta\mathbf{X})}$$

Maximizing for  $\theta$ , we find that the MLE is notably the same as the minimizer of the MSE from Problem 2.1 above.

$$\begin{aligned}\hat{\theta} &= \arg \min_{\theta} \|y - \mathbf{X}\theta\|_2^2 \\ \hat{\theta} &= (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top y\end{aligned}$$

**Problem 2.3**

**Problem 2.4**

**Problem 2.5**

**Problem 2.6**

**Problem 2.7**

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