

MFDNN HW1

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Problem 1 : *Least-squares derivatives.*

(a)

$$\begin{aligned}\frac{\partial}{\partial \theta_j} l_i(\theta) &= \frac{\partial}{\partial \theta_j} \left[\frac{1}{2} (X_{i1}\theta_1 + X_{i2}\theta_2 + \cdots + X_{ip}\theta_p - Y_i)^2 \right] = (X_i^\top \theta - Y_i) X_{ij} \\ \Rightarrow \nabla_\theta l_i(\theta) &= \begin{bmatrix} \frac{\partial}{\partial \theta_1} l_i(\theta) \\ \vdots \\ \frac{\partial}{\partial \theta_p} l_i(\theta) \end{bmatrix} = \begin{bmatrix} (X_i^\top \theta - Y_i) X_{i1} \\ \vdots \\ (X_i^\top \theta - Y_i) X_{ip} \end{bmatrix} = (X_i^\top \theta - Y_i) \cdot X_i\end{aligned}$$

(b)

$$\mathcal{L}(\theta) = \frac{1}{2} \sum_{i=1}^N (X_i^\top \theta - Y_i)^2 = \sum_{i=1}^N l_i(\theta)$$

$$\begin{aligned}\nabla_\theta \mathcal{L}(\theta) &= \begin{bmatrix} \frac{\partial}{\partial \theta_1} \mathcal{L}(\theta) \\ \vdots \\ \frac{\partial}{\partial \theta_p} \mathcal{L}(\theta) \end{bmatrix} = \sum_{i=1}^N \begin{bmatrix} \frac{\partial}{\partial \theta_1} l_i(\theta) \\ \vdots \\ \frac{\partial}{\partial \theta_p} l_i(\theta) \end{bmatrix} = \sum_{i=1}^N \nabla_\theta l_i(\theta) = \sum_{i=1}^N X_i (X_i^\top \theta - Y_i) \\ &= X^\top (X\theta - Y) \quad (\text{by the given fact, } M \cdot v = \sum_{i=1}^N M_{:,i} \cdot v_i)\end{aligned}$$

Problem 2 : *Diverging univariate GD*

$$\begin{aligned}f(\theta) &= \frac{\theta^2}{2}, f'(\theta) = \theta \\ \Rightarrow \theta^{k+1} &= \theta^k - \alpha \theta^k = (1 - \alpha) \theta^k \\ \Rightarrow \theta^n &= (1 - \alpha)^n \theta^0 \rightarrow \text{diverge as } n \rightarrow \infty \\ &(\text{since } |1 - \alpha| > 1)\end{aligned}$$

Problem 3 : *Diverging multivariate GD.*

For optimal θ^* , $\nabla f'(\theta^*) = 0$

$$\Leftrightarrow X^\top(X\theta^* - Y) = 0$$

$$\Leftrightarrow X^\top X\theta^* = X^\top Y$$

$$\Leftrightarrow \theta^* = (X^\top X)^{-1}X^\top Y$$

$$\begin{aligned}\theta^{k+1} - \theta^* &= \theta^k - \alpha X^\top(X\theta^k - Y) - \theta^* \\ &= \theta^k - \alpha X^\top X\theta^k + \alpha X^\top Y - \theta^* \\ &= \theta^k - \alpha X^\top X\theta^k + \alpha X^\top X\theta^* - \theta^* \\ &= (I - \alpha X^\top X)(\theta^k - \theta^*)\end{aligned}$$

Since $X^\top X$ is symmetric and invertible, there exists p orthonormal eigenvectors with corresponding positive eigenvalues. ($\exists(v_i, \lambda_i)_{i=1, \dots, p}$) Moreover, for each pair (v_i, λ_i) ,

$$\begin{aligned}(I - \alpha X^\top X)v_i &= v_i - \alpha X^\top Xv_i \\ &= v_i - \alpha \lambda_i v_i \\ &= (1 - \alpha \lambda_i)v_i\end{aligned}$$

that is, $(v_i, 1 - \alpha \lambda_i)_{i=1, \dots, p}$ are eigenpair of $I - \alpha X^\top X$. WLOG, assume that the indices of pair are arranged in diagonal component order.

Note that there exists nonempty subset of indices J_α such that $1 - \alpha \lambda_i < -1$, for $i \in J_\alpha$ since

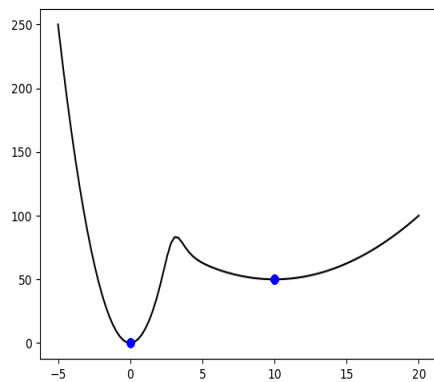
$$\alpha \rho(X^\top X) > 2$$

$$\rightarrow \exists J_\alpha \neq \emptyset \text{ s.t. } \alpha \lambda_i > 2 \quad i \in J_\alpha$$

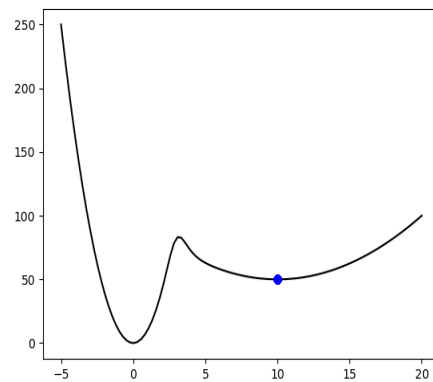
Thus, for $\theta^0 \in \mathbb{R}^p$ except $a_i = 0 \quad \forall i \in J_\alpha$, with $\theta^0 - \theta^* = a_1 v_1 + \dots + a_p v_p$, $\theta^n - \theta^* = (I - \alpha X^\top X)^n(\theta^0 - \theta^*)$ diverges since

$$\begin{aligned}&(I - \alpha X^\top X)^n(a_1 v_1 + \dots + a_p v_p) \\ &= a_1(1 - \alpha \lambda_1)^n v_1 + \dots + a_p(1 - \alpha \lambda_p)^n v_p \rightarrow \infty \text{ as } n \rightarrow \infty.\end{aligned}$$

Problem 4 : *GD converging to wide local minima.*



(a) $\alpha = 0.01$



(b) $\alpha = 0.3$

Figure 1: 100 samples with 10000 steps

```
[3951506666864.5513, -1142421625081.9802, -545796775867.0929, 2404255799815.7935, 4392988097827.8774, 4094255043826.4023, 21
```

Figure 2: 6+ samples with only 10 steps, $\alpha = 4$

Problem 5 : *Implementing GD with duck typing.*

```
C:\Users\ao105\anaconda3\python.exe "C:\Users\ao105\iCloudDrive\2024-Spring\Mathematical Foundations of Deep Neural Networks\HW1\conv10.py"
9.036073614024657

Process finished with exit code 0
```

Figure 3: Result