Gradient Descent for Linear Regression

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 $\begin{tabular}{ll} Mathematical Foundations of Deep Learning \\ RWTH Aachen \end{tabular}$

Gradient Descent for Linear Regression

Linear Regression Problem

Let $\Phi: \mathbb{X} \to \mathbb{R}^d$ be a given feature mapping. We aim to solve

$$\min_{\theta \in \mathbb{R}^d} \frac{1}{2n} \sum_{j=1}^n (\theta^\top \Phi(x_j) - y_j)^2.$$

Assuming realizability: $y_j = \Phi^\top(x_j)\theta^*$ for some $\theta^* \in B_2(0, \alpha)$.

Algorithm 1: Projected Gradient Descent

1:
$$\theta(0) = 0$$

Initialization

2: for
$$t = 0, 1, ..., T - 1$$
 do

3:
$$ilde{ heta}(t+1) = heta(t) - \eta \cdot rac{1}{n} \sum_{j=1}^n \left(heta^ op(t) \Phi(x_j) - y_j
ight) \cdot \Phi(x_j)$$

4:
$$\theta(t+1) = \Pi_{B_2(0,\rho)} \{ \tilde{\theta}(t+1) \}$$

5: end for

Convergence Analysis

Lyapunov function $\mathcal{L}(\theta) = \|\theta - \theta^*\|_2^2$. Then, we have:

$$\begin{split} \mathcal{L}(\theta(t+1)) &= \|\Pi_{B_2(0,\rho)} \tilde{\theta}(t+1) - \Pi_{B_2(0,\rho)} \theta^{\star}\|_2^2 \leq \|\tilde{\theta}(t+1) - \theta^{\star}\|_2^2, \\ &= \|\theta(t) - \theta^{\star}\|_2^2 - 2\eta \nabla_{\theta} g(\theta(t)) \Big(\theta(t) - \theta^{\star}\Big) + \eta^2 \|\nabla_{\theta} g(\theta(t))\|_2^2. \end{split}$$

Thus, the Lyapunov drift becomes:

$$\mathcal{L}(\theta(t+1)) - \mathcal{L}(\theta(t)) \leq -2\eta \nabla_{\theta} g(\theta(t)) \Big(\theta(t) - \theta^{\star}\Big) + \eta^{2} \|\nabla_{\theta} g(\theta(t))\|_{2}^{2}.$$

Convexity: $-2\eta\nabla_{\theta}g(\theta(t))\Big(\theta(t)-\theta^{\star}\Big)\leq -2\cdot\eta\cdot g(\theta(t)).$ Lipschitz continuity:

$$\|\nabla g(\theta(t))\|_2 \leq \frac{1}{n} \Big(\|\theta(t)\|_2 \|\Phi(x_j)\|_2 + \alpha \|\Phi(x_j)\|_2 \Big) \|\Phi(x_j)\|_2 \leq (\alpha + \rho).$$

Convergence Analysis

Then,

$$\mathcal{L}(\theta(t+1)) - \mathcal{L}(\theta(t)) \leq -2\eta g(\theta(t)) + \eta^2(\alpha+\rho)^2.$$

By telescoping sum over t = 0, 1, ..., T - 1:

$$\mathcal{L}(\theta(T)) - \mathcal{L}(\theta(0)) \le -2\eta \sum_{t < T} g(\theta(t)) + \eta^2 T(\alpha + \rho)^2.$$

Rearranging terms:

$$\min_{0 \le t < T} g(\theta(t)) \le \frac{1}{T} \sum_{t < T} g(\theta(t)) \le \frac{\mathcal{L}(\theta(0))}{2\eta T} + \frac{\eta(\alpha + \rho)^2}{2}.$$

$$\mathcal{L}(\theta(0)) = \|\theta(0) - \theta^\star\|_2^2 \leq \alpha^2. \text{ Then, choosing } \eta = 1/\sqrt{\mathcal{T}}\text{,}$$

$$\min_{0 \le t < T} g(\theta(t)) \le \frac{\alpha^2 + (\alpha + \rho)^2}{2\sqrt{T}}.$$