LEARNING AS PARAMETER OPTIMIZATION / 2

The ERM optimization problem is:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \mathcal{R}_{\text{emp}}(\theta).$$

For a **(global) minimum** $\hat{\theta}$ it obviously holds that

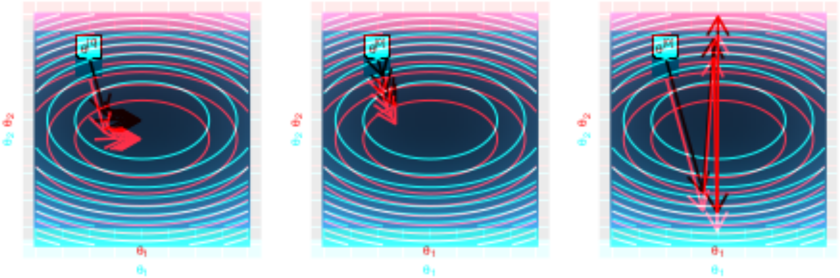
$$\forall \theta \in \Theta : \quad \mathcal{R}_{\text{emp}}(\hat{\theta}) \leq \mathcal{R}_{\text{emp}}(\theta).$$

This does not imply that $\hat{\theta}$ is unique.

Which kind of numerical technique is reasonable for this problem strongly depends on model and parameter structure (continuous params? uni-modal $\mathcal{R}_{\text{emp}}(\theta)$?). Here, we will only discuss very simple scenarios.

GRADIENT DESCENT - LEARNING RATE

- The negative gradient is a direction that looks locally promising to reduce $\mathcal{R}_{\text{emp}}$.
- Hence it weights components higher in which $\mathcal{R}_{\text{emp}}$ decreases more.
- However, the length of $-\frac{\partial}{\partial\theta}\mathcal{R}_{\text{emp}}$ measures only the local decrease rate, i.e., there are no guarantees that we will not go "too far".
- We use a learning rate α to scale the step length in each iteration. Too much can lead to overstepping and no converge, too low leads to slow convergence.
- Usually, a simple constant rate or rate-decrease mechanisms to enforce local convergence are used



good convergence for α_1 | poor convergence for $\alpha_2 (< \alpha_1)$ | no convergence for $\alpha_3 (> \alpha_1)$