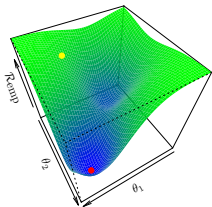


# Introduction to Machine Learning

## ML-Basics

## Optimization

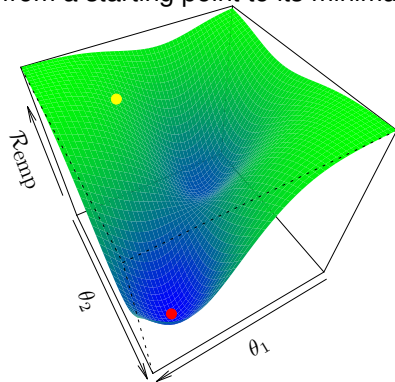


### Learning goals

- Understand how the risk function is optimized to learn the optimal parameters of a model
- Understand the idea of gradient descent as a basic risk optimizer

# LEARNING AS PARAMETER OPTIMIZATION

- We have seen, we can operationalize the search for a model  $f$  that matches training data best, by looking for its parametrization  $\theta \in \Theta$  with lowest empirical risk  $\mathcal{R}_{\text{emp}}(\theta)$ .
- Therefore, we usually traverse the error surface downwards; often by local search from a starting point to its minimum.



# LEARNING AS PARAMETER OPTIMIZATION

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.

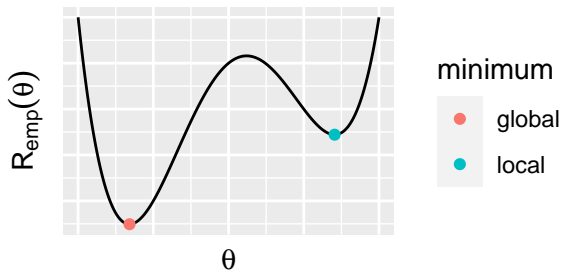


# LOCAL MINIMA

If  $\mathcal{R}_{\text{emp}}$  is continuous in  $\theta$  we can define a **local minimum**  $\hat{\theta}$ :

$$\exists \epsilon > 0 \forall \theta \text{ with } \|\hat{\theta} - \theta\| < \epsilon : \mathcal{R}_{\text{emp}}(\hat{\theta}) \leq \mathcal{R}_{\text{emp}}(\theta).$$

Clearly every global minimum is also a local minimum. Finding a local minimum is easier than finding a global minimum.

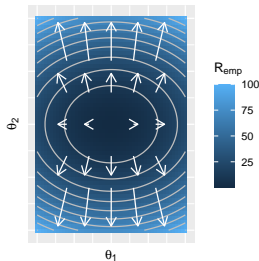


# LOCAL MINIMA AND STATIONARY POINTS

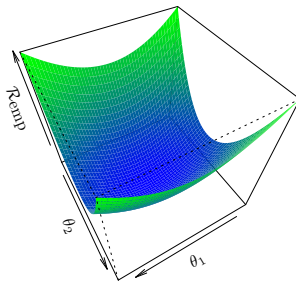
If  $\mathcal{R}_{\text{emp}}$  is continuously differentiable in  $\theta$  then a **sufficient condition** for a local minimum is that  $\hat{\theta}$  is **stationary** with 0 gradient, so no local improvement is possible:

$$\frac{\partial}{\partial \theta} \mathcal{R}_{\text{emp}}(\hat{\theta}) = 0$$

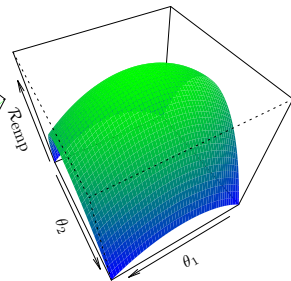
and the Hessian  $\frac{\partial^2}{\partial \theta^2} \mathcal{R}_{\text{emp}}(\hat{\theta})$  is positive definite. While the neg. gradient points into the direction of fastest local decrease, the Hessian measures local curvature of  $\mathcal{R}_{\text{emp}}$ .



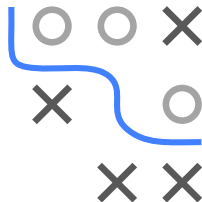
$$\frac{\partial}{\partial \theta} \mathcal{R}_{\text{emp}}(\theta)$$



const. pos. def. Hessian



const. neg. def. Hessian



# LEAST SQUARES ESTIMATOR

Now, for given features  $\mathbf{X} \in \mathbb{R}^{n \times p}$  and target  $\mathbf{y} \in \mathbb{R}^n$ , we want to find the best linear model regarding the squared error loss, i.e.,

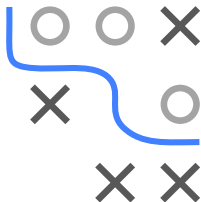
$$\mathcal{R}_{\text{emp}}(\boldsymbol{\theta}) = \|\mathbf{X}\boldsymbol{\theta} - \mathbf{y}\|_2^2 = \sum_{i=1}^n (\boldsymbol{\theta}^\top \mathbf{x}^{(i)} - y^{(i)})^2.$$

With the sufficient condition for continuously differentiable functions it can be shown that the **least squares estimator**

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

is a local minimum of  $\mathcal{R}_{\text{emp}}$ . If  $\mathbf{X}$  is full-rank,  $\mathcal{R}_{\text{emp}}$  is strictly convex and there is only one local minimum - which is also global.

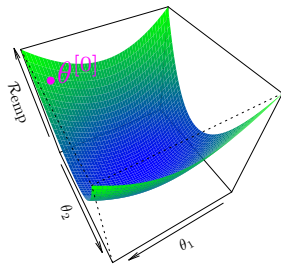
**Note:** Often such analytical solutions in ML are not possible, and we rather have to use iterative numerical optimization.



# GRADIENT DESCENT

The simple idea of GD is to iteratively go from the current candidate  $\theta^{[t]}$  in the direction of the negative gradient, i.e., the direction of the steepest descent, with learning rate  $\alpha$  to the next  $\theta^{[t+1]}$ :

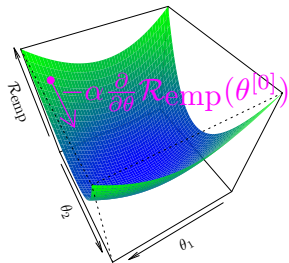
$$\theta^{[t+1]} = \theta^{[t]} - \alpha \frac{\partial}{\partial \theta} \mathcal{R}_{\text{emp}}(\theta^{[t]}).$$



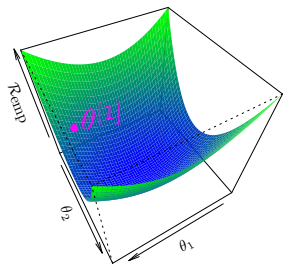
We choose a random start  $\theta^{[0]}$  with risk  $\mathcal{R}_{\text{emp}}(\theta^{[0]}) = 76.25$ .



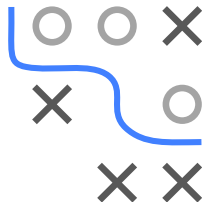
# GRADIENT DESCENT - EXAMPLE



Now we follow in the direction of the negative gradient at  $\theta^{[0]}$ .

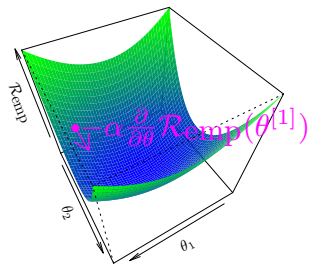


We arrive at  $\theta^{[1]}$  with risk  $\mathcal{R}_{\text{emp}}(\theta^{[1]}) \approx 42.73$ .  
We improved:  
 $\mathcal{R}_{\text{emp}}(\theta^{[1]}) < \mathcal{R}_{\text{emp}}(\theta^{[0]})$ .

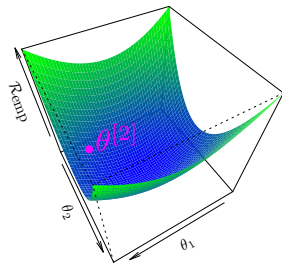




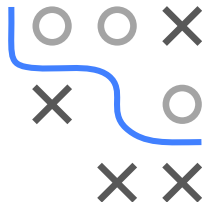
# GRADIENT DESCENT - EXAMPLE



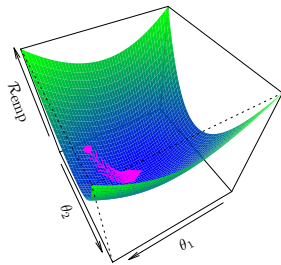
Again we follow in the direction of the negative gradient, but now at  $\theta^{[1]}$ .



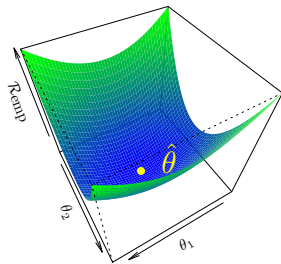
Now  $\theta^{[2]}$  has risk  $\mathcal{R}_{\text{emp}}(\theta^{[2]}) \approx 25.08$ .



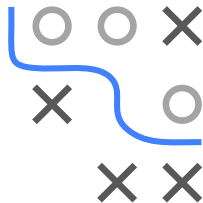
# GRADIENT DESCENT - EXAMPLE



We iterate this until some form of convergence or termination.



We arrive close to a stationary  $\hat{\theta}$  which is hopefully at least a local minimum.





## FURTHER TOPICS

- GD is a so-called first-order method. Second-order methods use the Hessian to refine the search direction for faster convergence.
- There exist many improvements of GD, e.g., to smartly control the learn rate, to escape saddle points, to mimic second order behavior without computing the expensive Hessian.
- If the gradient of GD is not derived from the empirical risk of the whole data set, but instead from a randomly selected subset, we call this **stochastic gradient descent** (SGD). For large-scale problems this can lead to higher computational efficiency.

