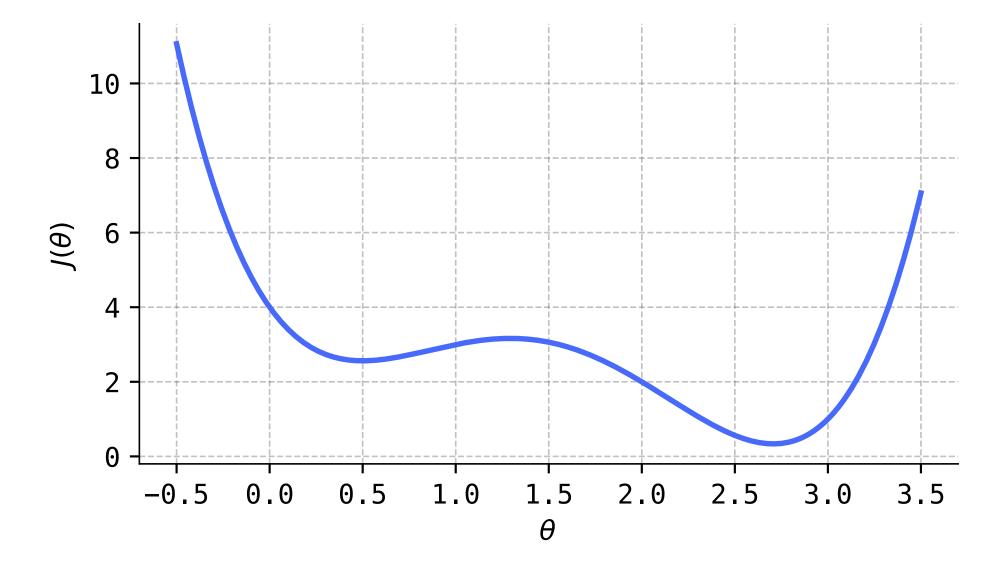
11. Optimization



Definition 11.1

Let $J:\mathbb{R}^n o\mathbb{R}$ be a function. A vector $m{ heta}^\star$ is a *local minimizer* of $J(m{ heta})$ provided that

$$J({m{ heta}}^\star) \leq J({m{ heta}})$$

for all θ in a neighborhood of θ^* ; if this inequality holds for all θ , then θ^* is called a global minimizer of $J(\theta)$. If we flip the inequality the other direction, then we obtain the definitions of local and global maximizers. Collectively, local and global minimizers and maximizers of $J(m{ heta})$ are called *extremizers*, and the values $J(m{ heta}^{\star})$ of the function where $m{ heta}^{\star}$ is an extremizer are called extrema or extreme values.

Algorithm 11.1 (Single-variable gradient descent)

Input: A differentiable objective function $J:\mathbb{R} o \mathbb{R}$, an initial guess $heta_0 \in \mathbb{R}$ for a local minimizer $heta^\star$, a learning rate lpha>0, and the number N of gradient steps.

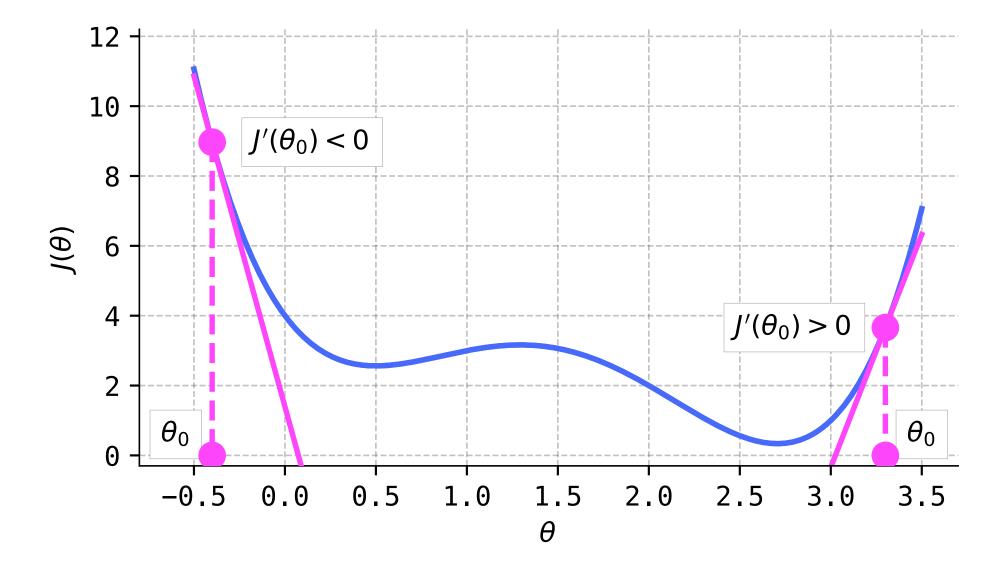
Output: An approximation to a local minimizer θ^* .

$$\theta := \theta_0$$

For t from 0 to N-1, do:

$$\theta := \theta - \alpha J'(\theta)$$

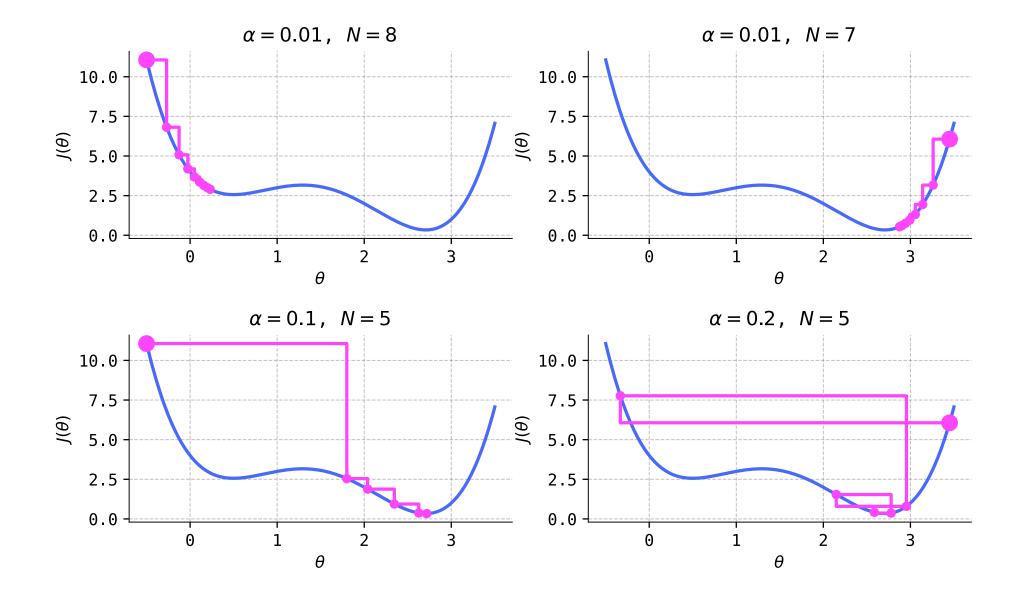
Return θ





Observation 11.1

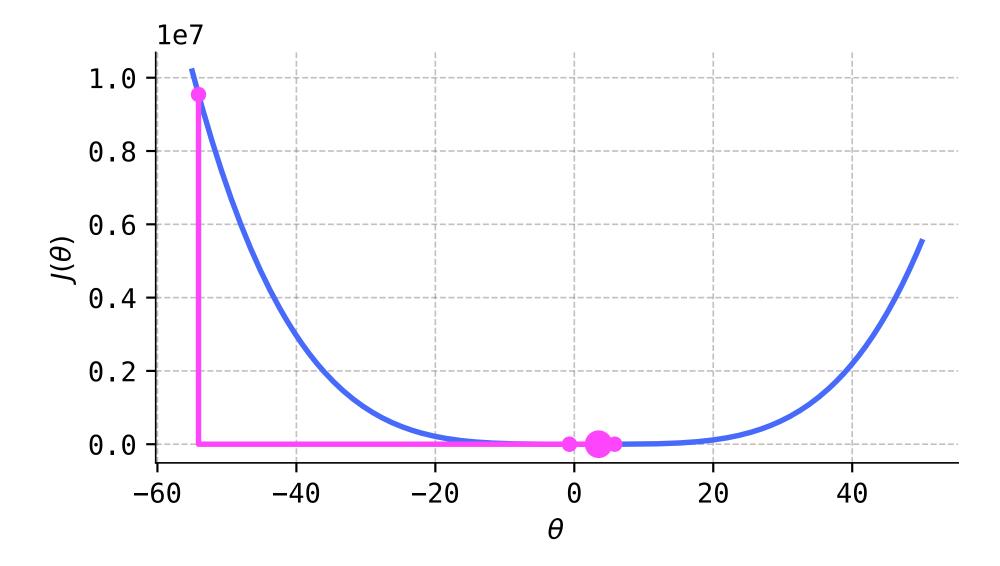
- ullet The negative derivative -J'(heta) always "points downhill."
- When the gradient descent algorithm works, it locates a minimizer by following the negative derivative "downhill."





Problem Prompt

Do problem 1 on the worksheet.





Problem Prompt

Do problems 2 and 3 on the worksheet.

Algorithm 11.2 (Single-variable gradient descent with learning rate decay)

Input: A differentiable objective function $J:\mathbb{R} o \mathbb{R}$, an initial guess $heta_0 \in \mathbb{R}$ for a local minimizer $heta^\star$, a learning rate lpha>0, a decay rate $eta\in[0,1)$, and the number N of gradient steps.

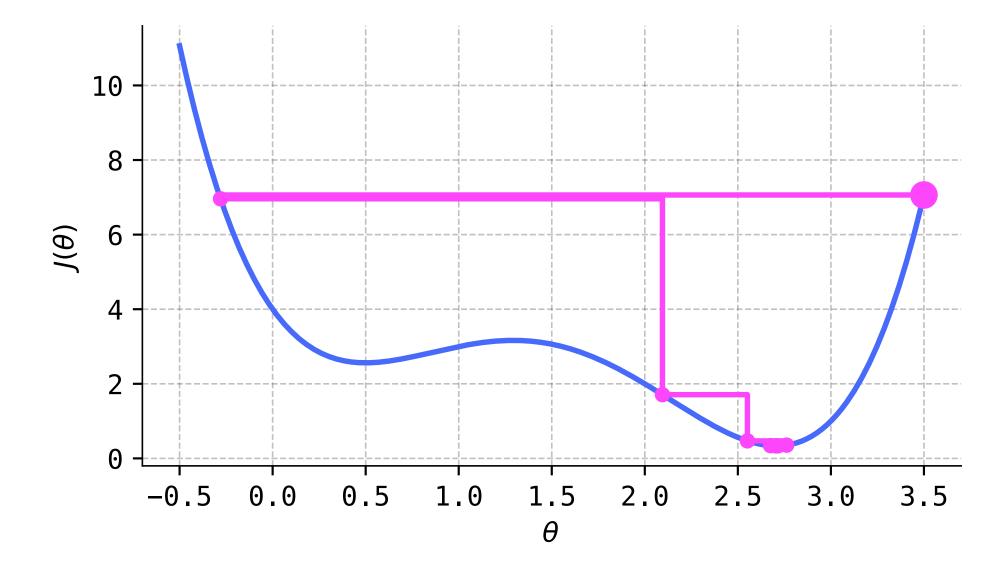
Output: An approximation to a local minimizer θ^* .

$$\theta := \theta_0$$

For t from 0 to N-1, do:

$$heta:= heta-lpha(1-eta)^{t+1}J'(heta)$$

Return θ





Problem Prompt

Do problem 4 on the worksheet.

