Minimizing Functions of Multiple Variables

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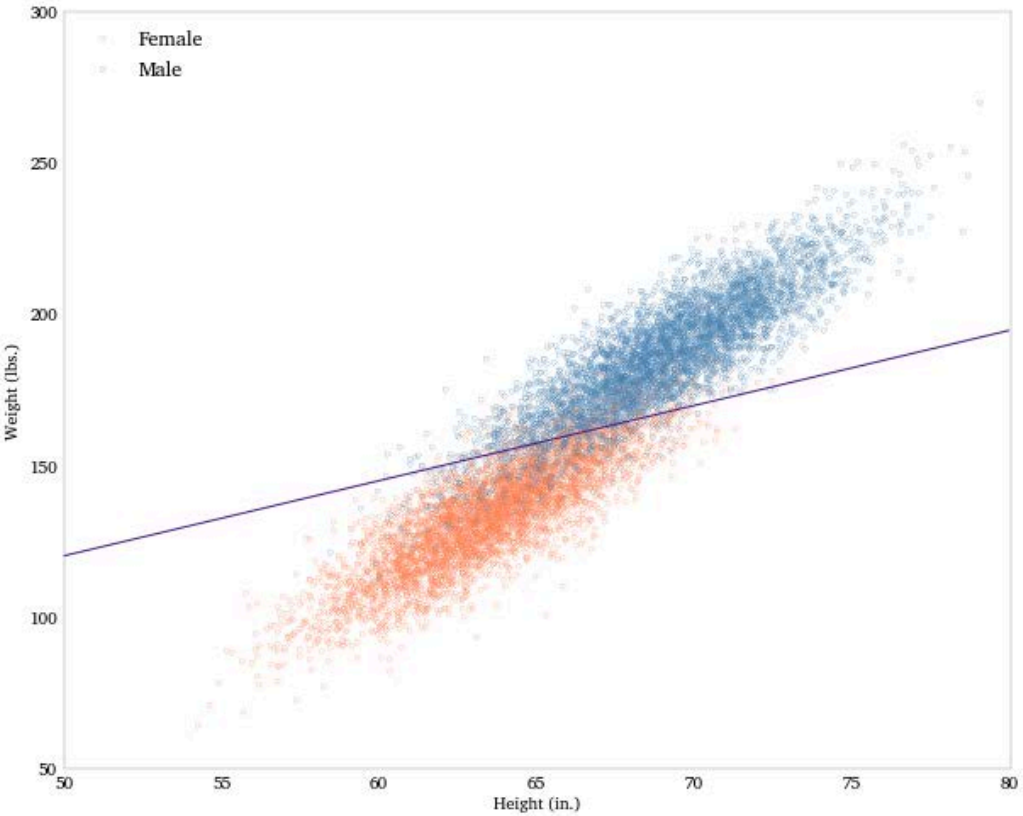
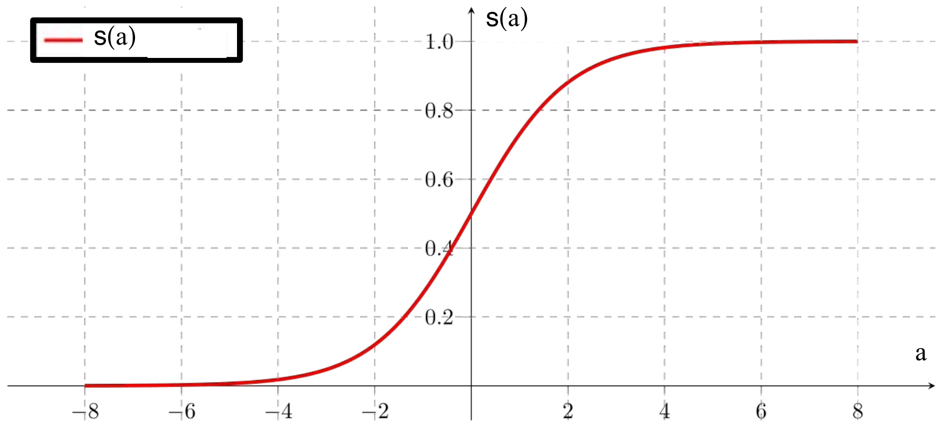
IC-CVLab

Reminder: Logistic Regression



$$y(\mathbf{x}; \tilde{\mathbf{w}}) = \sigma(\tilde{\mathbf{w}} \cdot \tilde{\mathbf{x}})$$

$$= \frac{1}{1 + \exp(-\tilde{\mathbf{w}} \cdot \tilde{\mathbf{x}})}$$



Given a **training** set $\{(\mathbf{x}_n, t_n)_{1 \le n \le N}\}$ minimize

$$E(\tilde{\mathbf{w}}) = -\sum_n \left(t_n \ln y(\mathbf{x}_n) + (1 - t_n)\ln(1 - y(\mathbf{x}_n))\right)$$

with respect to $\tilde{\mathbf{w}}$.

—> Convex optimization problem.

Reminder: Maximizing the Margin

$$\mathbf{w}^* = argmin_{(\mathbf{w},\{\xi_\mathbf{n}\})} \frac{1}{2} ||\mathbf{w}||^2 + C \sum_{n=1}^{N} \xi_n,$$

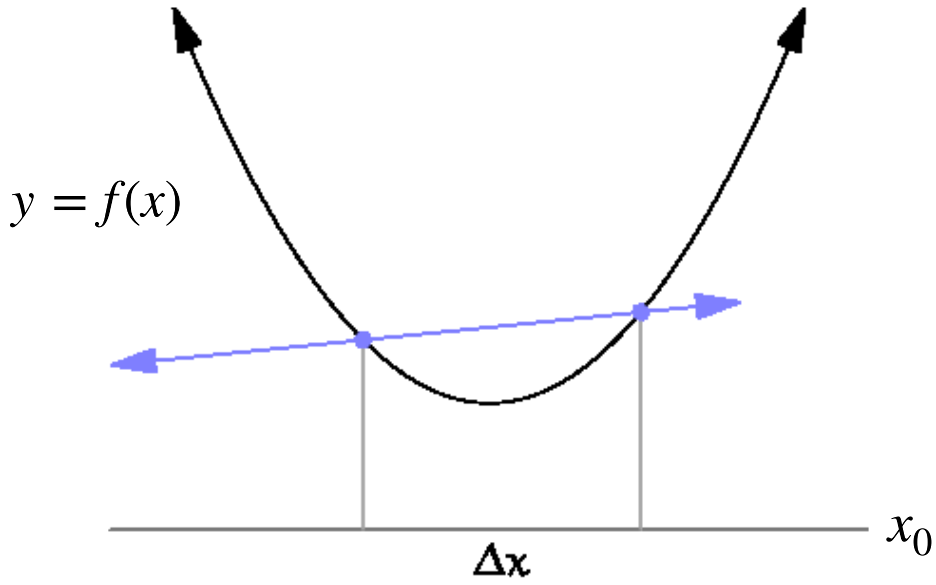
$$\text{subject to } \forall n, \quad t_n \cdot (\tilde{\mathbf{w}} \cdot \mathbf{x}_n) \geq 1 - \xi_n \text{ and } \xi_n \geq 0.$$

- C is constant that controls how costly constraint violations are.
- The problem is still convex.

- How do you minimize a function of several variables?
- Why do we prefer convex problems?
- How do you impose constraints?

—> Let’s talk about that today.

Derivative of a 1-Variable Function

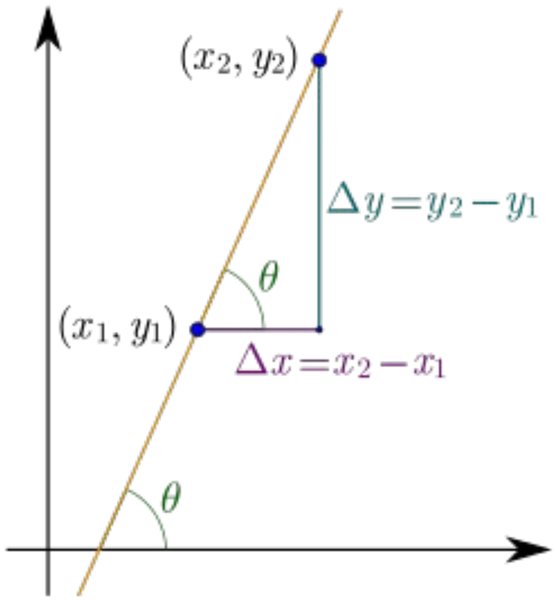


- The derivative of a function $y = f(x)$ of a single variable x is the rate at which y changes as x changes.
- It is measured for an infinitesimal change in x, starting from a point x_0, and written as

$$f'(x_0) = \frac{dy}{dx} = \lim_{\Delta x \to 0} \frac{f(x_0 + \Delta x) - f(x_0)}{\Delta x}$$

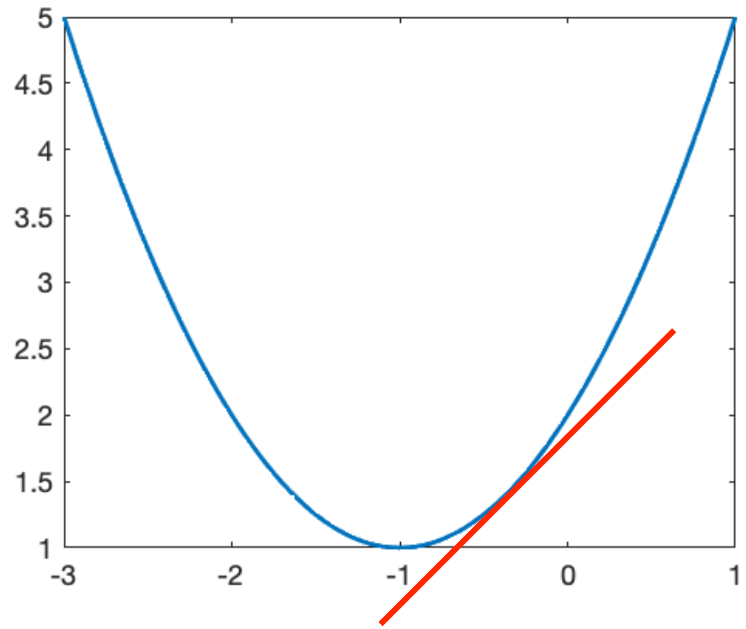
—> The derivative is the slope of the tangent at x_0.

Derivative of a Linear Function



- The tangent to the function is the function itself: The slope is constant.
- For example, $y = 2x - 1$ and $\dfrac{dy}{dx} = 2$.

Derivative of a Non-Linear Function



- The tangent to the function varies with x and so does the slope.
- For example, $y = x^2 + 2x + 2$ and $\dfrac{dy}{dx} = 2x + 2$.

Evolution of the Tangent

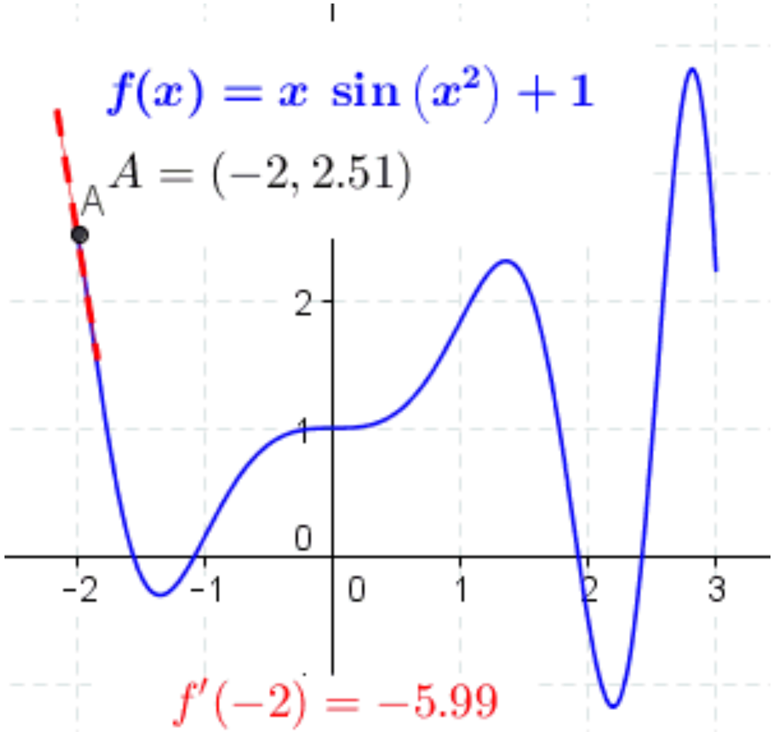
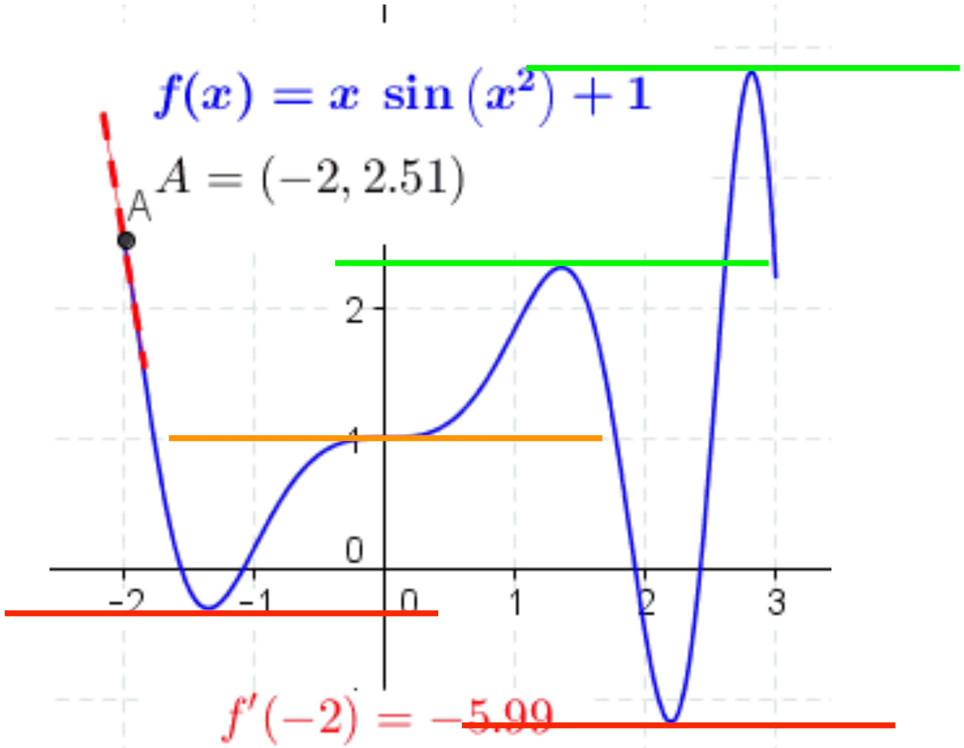


Figure from Wikipedia

$$y = x\sin(x^2) + 1$$

$$\frac{dy}{dx} = \sin(x^2) + 2x^2\cos(x^2)$$

First and Second Derivatives



$$y = x\sin(x^2) + 1$$

$$\frac{dy}{dx} = \sin(x^2) + 2x^2\cos(x^2)$$

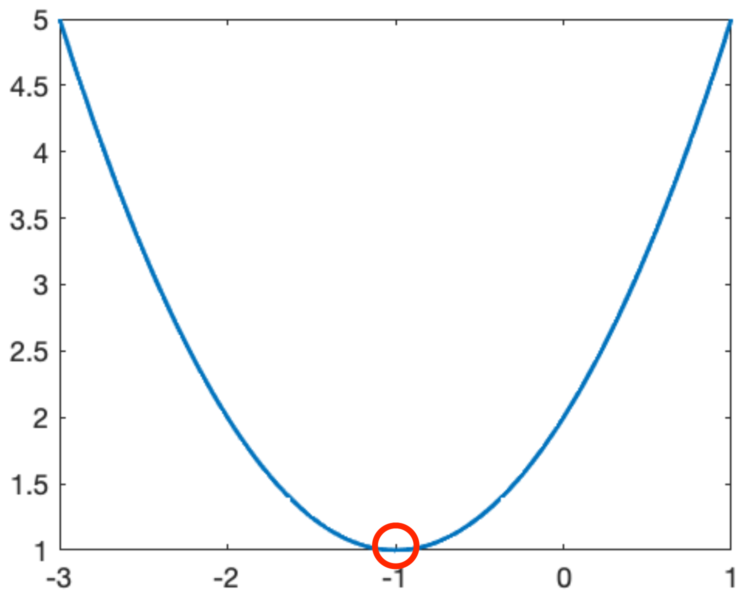
$$\frac{d^2y}{dx^2} = 6x\cos(x^2) - 4x^3\sin(x^2)$$

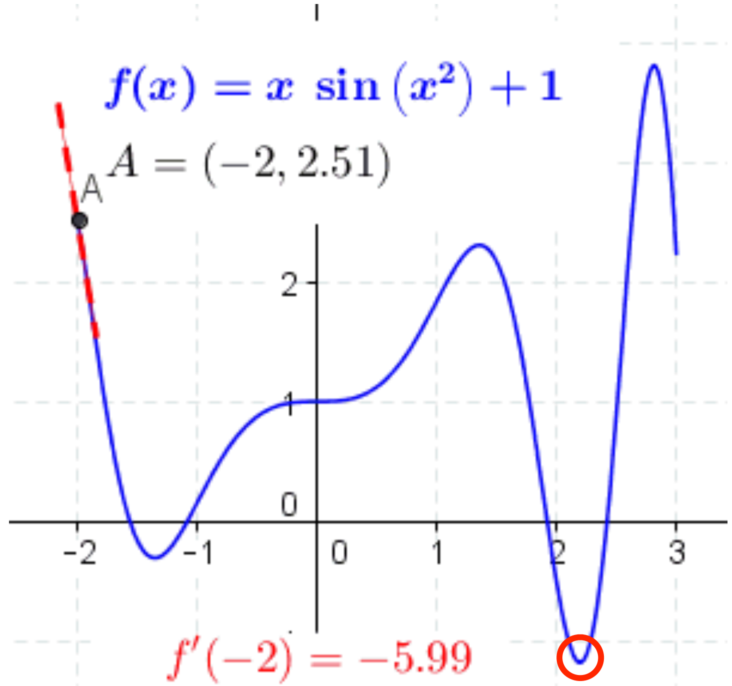
$$\frac{dy}{dx} = 0 \text{ and } \frac{d^2y}{dx^2} > 0 : \text{Minimum}$$

$$\frac{dy}{dx} = 0 \text{ and } \frac{d^2y}{dx^2} < 0 : \text{Maximum}$$

$$\frac{dy}{dx} = 0 \text{ and } \frac{d^2y}{dx^2} = 0 : \text{Saddle}$$

Convex vs Non-Convex



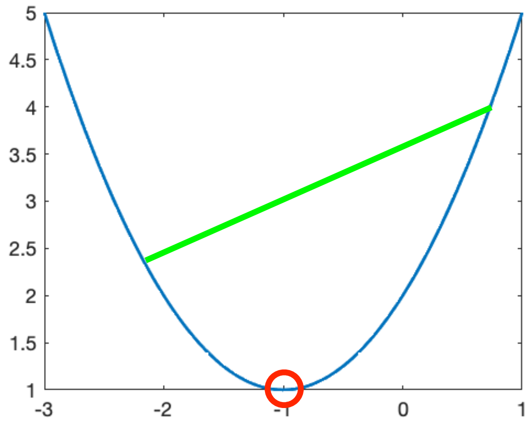


- There is only one minimum.
- The second derivative is >= 0.

- There are several **local** minima.
- There is one global minimum.

—> Non-convex functions are much more difficult to minimize than convex ones.

Minimizing a Convex Function



The line segment between any two points on the curve lies above the curve.

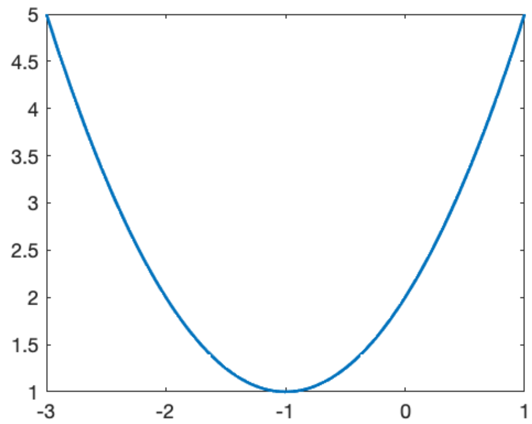
$$\frac{df(x^*)}{dx} = 0$$

For some simple functions this can be done in closed form, that is, by solving an equation.

Minimizing a Simple Convex Function

$$f(x) = x^2 + 2x + 2$$

$$\frac{df(x)}{dx} = 2x + 2$$



$$\frac{df(x^*)}{dx} = 0 \Leftrightarrow 2x^* + 2 = 0$$

$$\Leftrightarrow 2x^* = -2$$

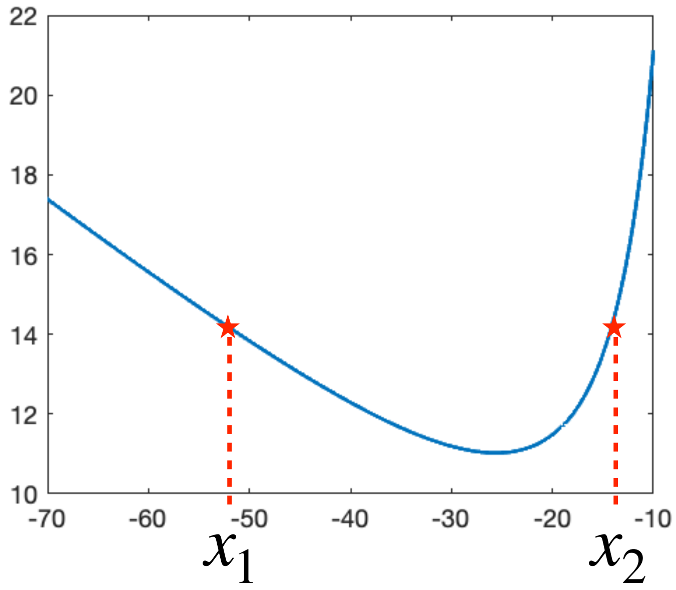
$$\Leftrightarrow x^* = -1$$

EPFL

Minimizing a Generic Convex Function

When the minimum cannot be found in closed-form, we use the derivative:

At x_1, the slope is negative. Hence, one should move in the positive direction ($\Delta x > 0$) to go towards the minimum



At x_2, the slope is positive. Hence, one should move in the negative direction ($\Delta x < 0$) to go towards the minimum

—> One should move in the direction opposite to the derivative for minimization

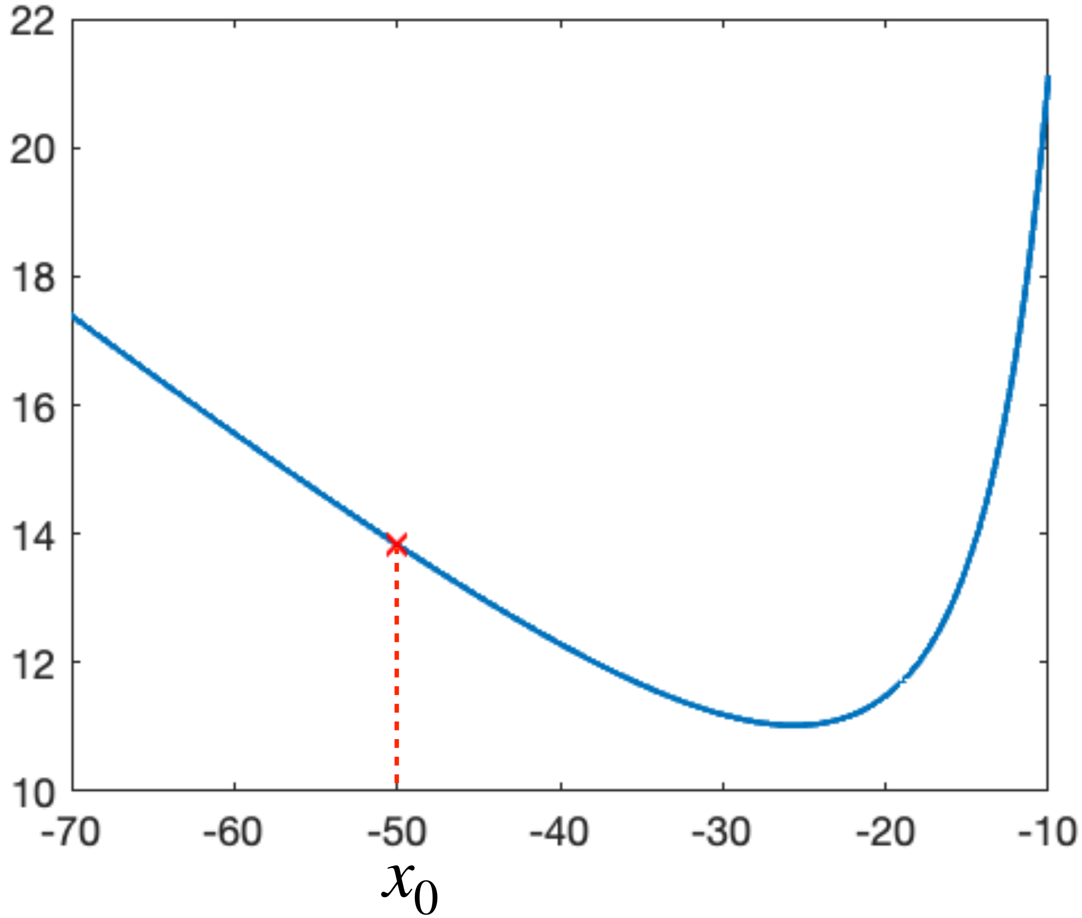
Minimizing a Convex Function

Simplest algorithm:

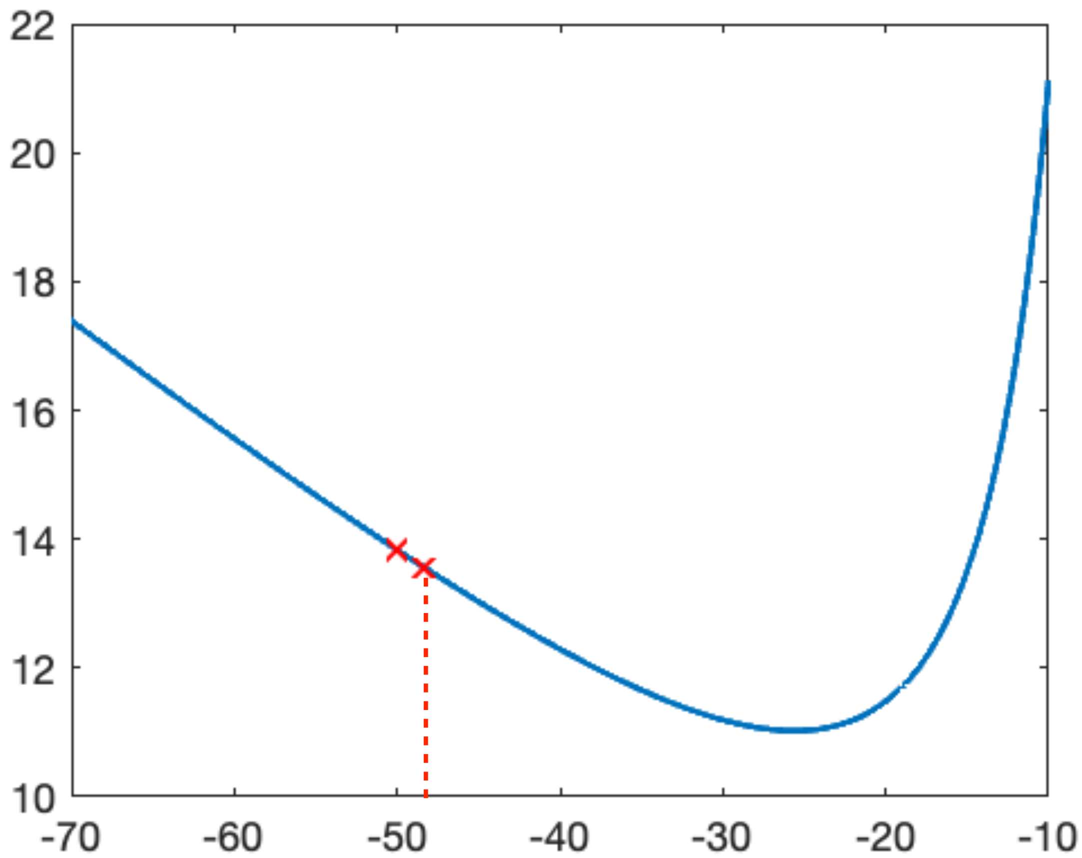
1. Initialize x_0 (e.g., randomly)
2. While not converged
   2.1. Update $x_k \leftarrow x_{k-1} - \eta \frac{df(x_{k-1})}{dx}$

- η defines the step size of each iteration.
- In ML, it is often referred to as the *learning rate*.

Minimizing a Convex Function



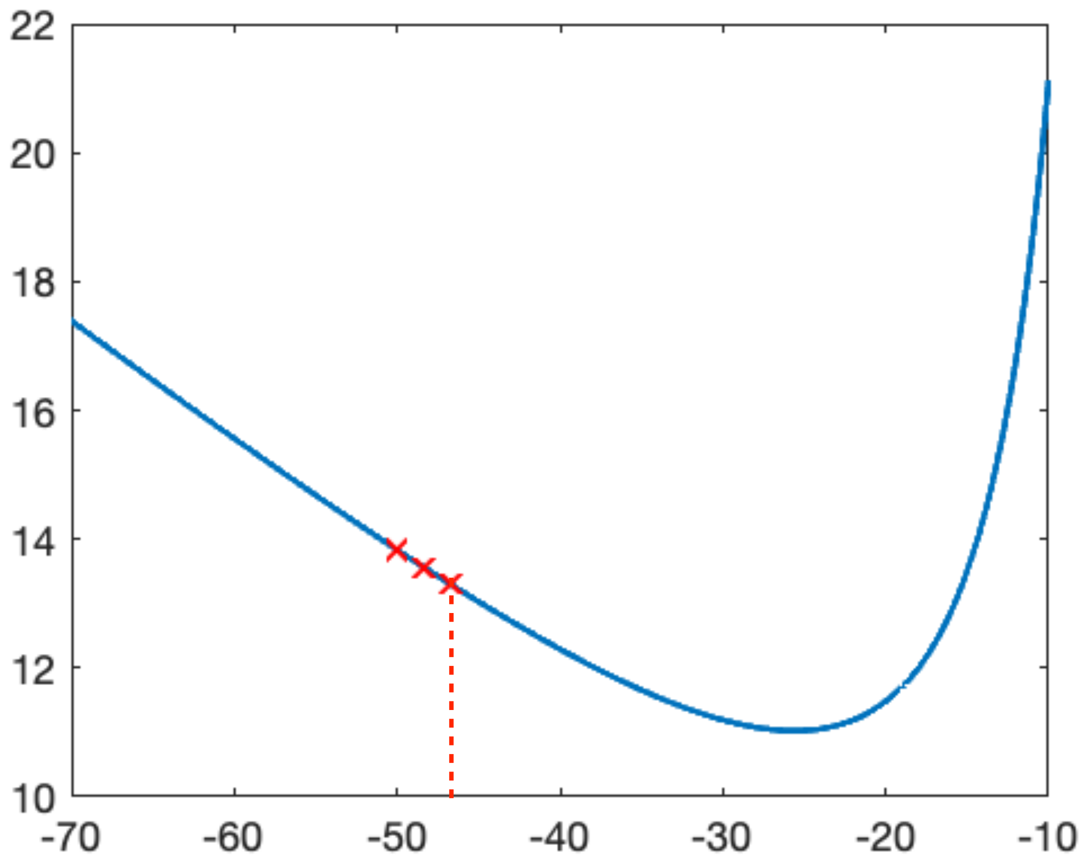
Minimizing a Convex Function



x_1

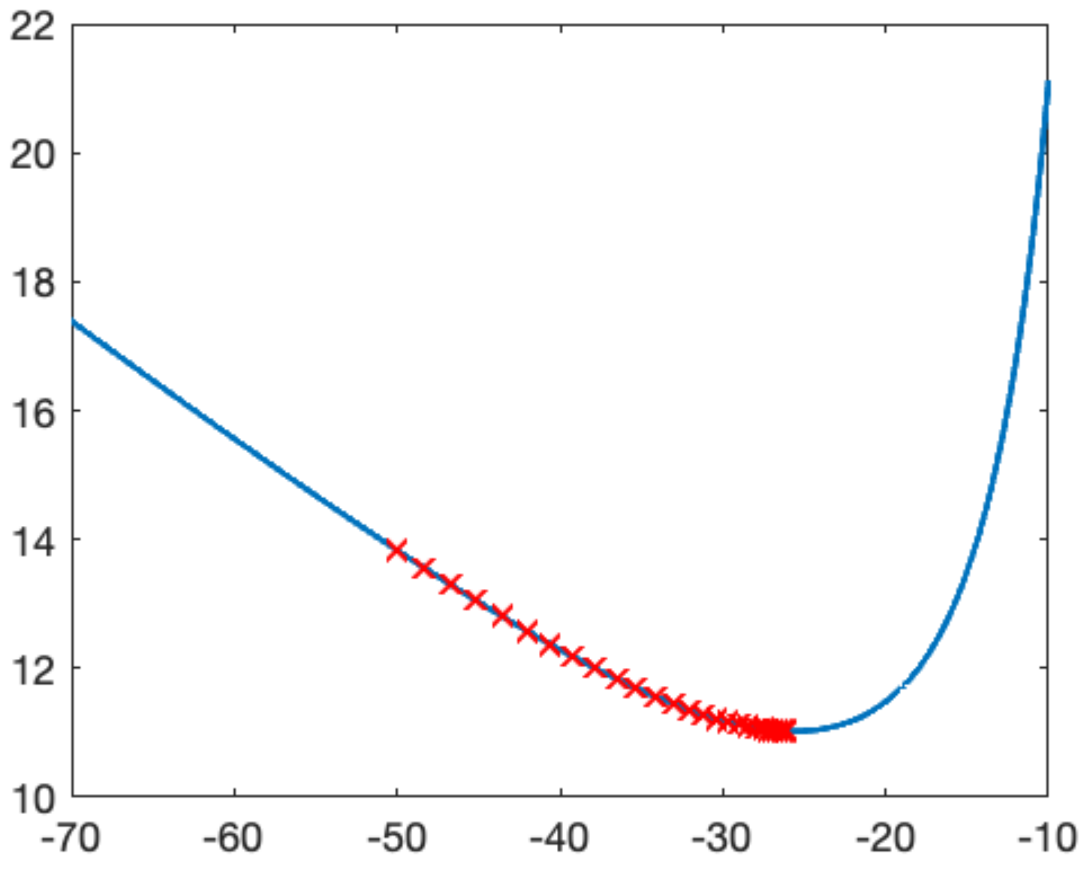
$$x_0 - \eta \frac{df(x_0)}{dx}$$

Minimizing a Convex Function



$$x_2 \leftarrow x_1 - \eta \frac{df(x_1)}{dx}$$

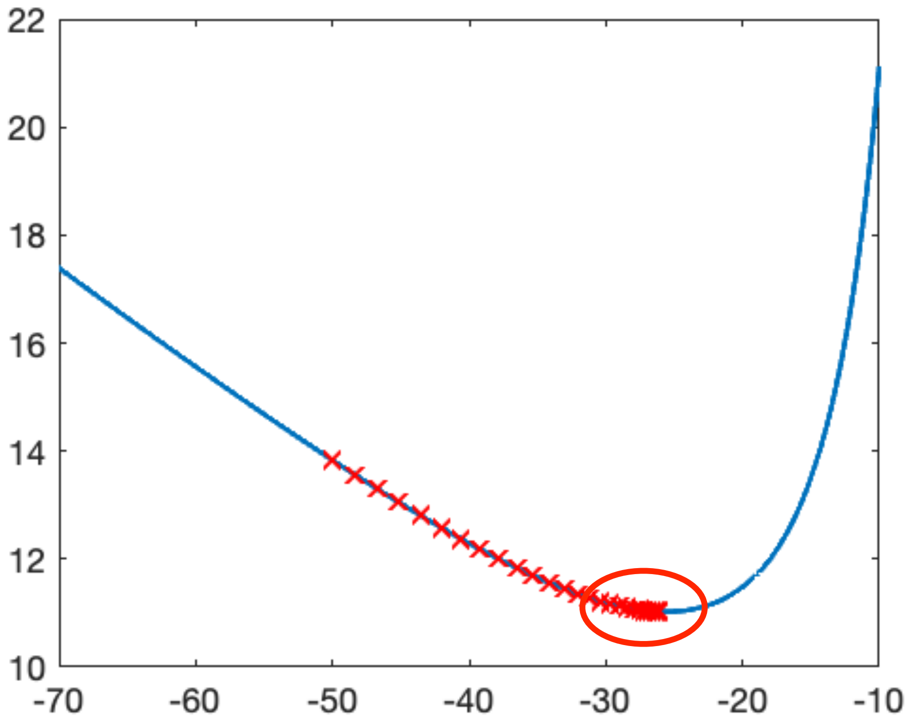
Minimizing a Convex Function



Minimizing a Convex Function

Potential stopping Criteria:

- Change in function value less than threshold: $|f(x_{i-1}) - f(x_i)| < \delta$.
- Change in parameter value less than threshold: $|x_{i-1} - x_i| < \delta$.
- Maximum number of iterations reached without a guarantee to have reached the minimum.



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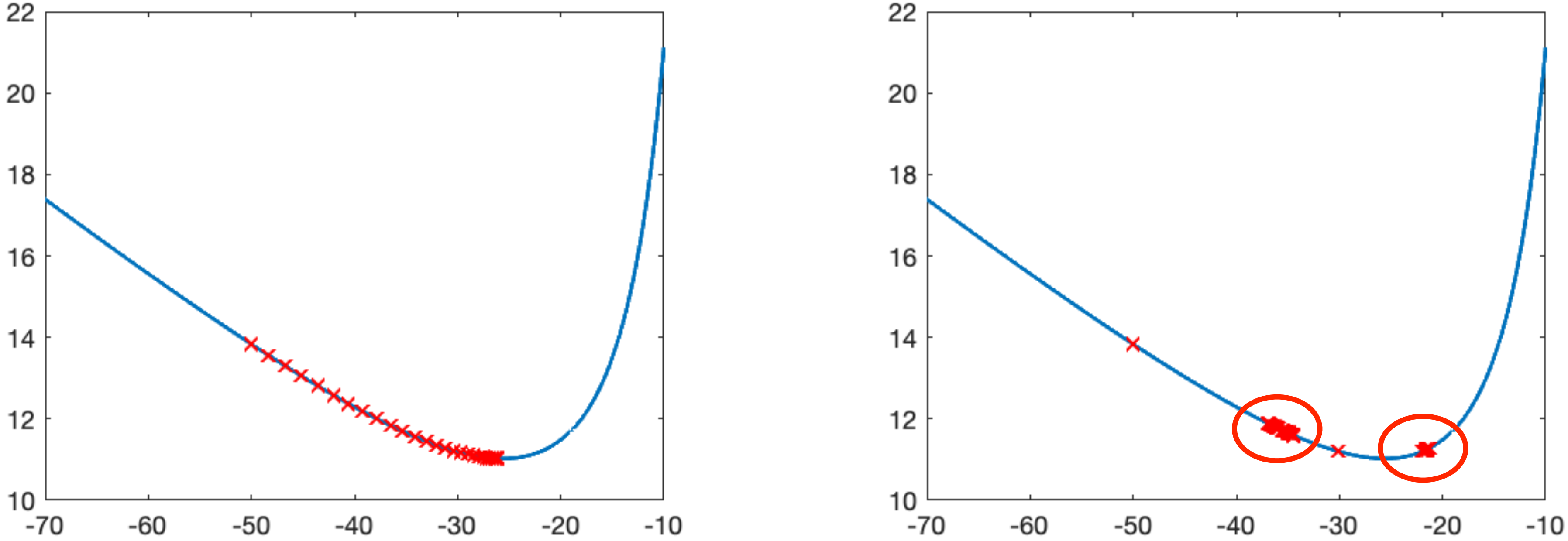
Influence of the Step Size

$\eta = 10$

$\eta = 120$

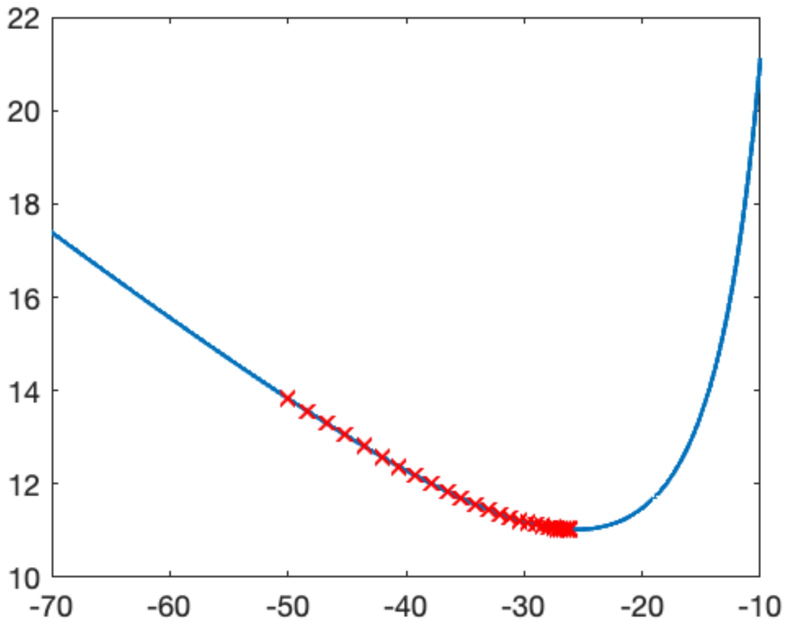


The steps are of the appropriate size for convergence.

The steps are too large and the algorithm starts jumping between these two points.

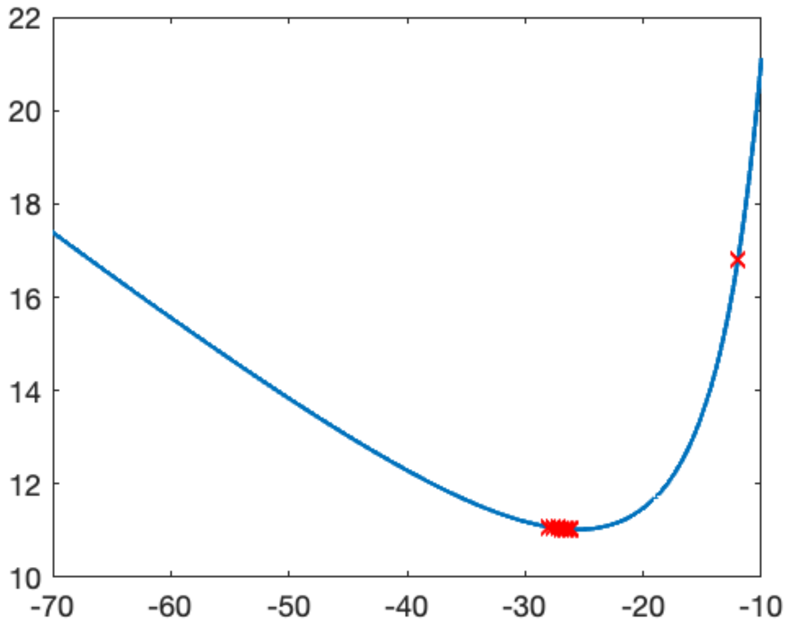
Influence of the Starting Point

$x_0 = -50$



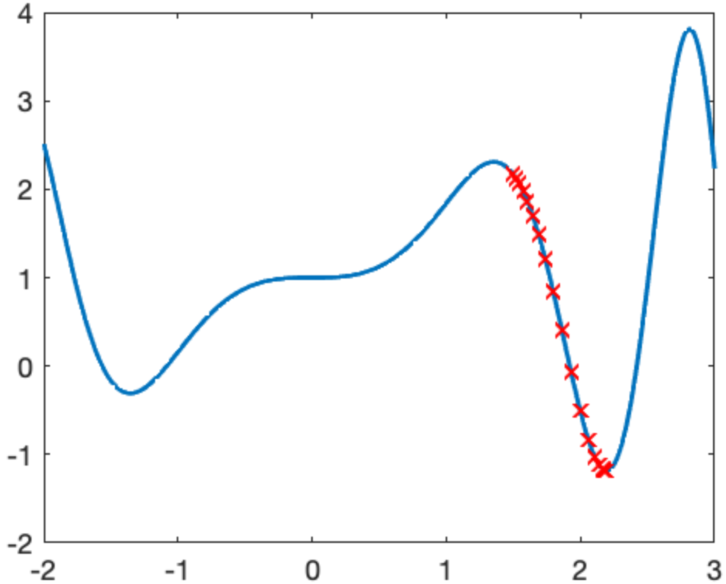
Converges.

$x_0 = -12$

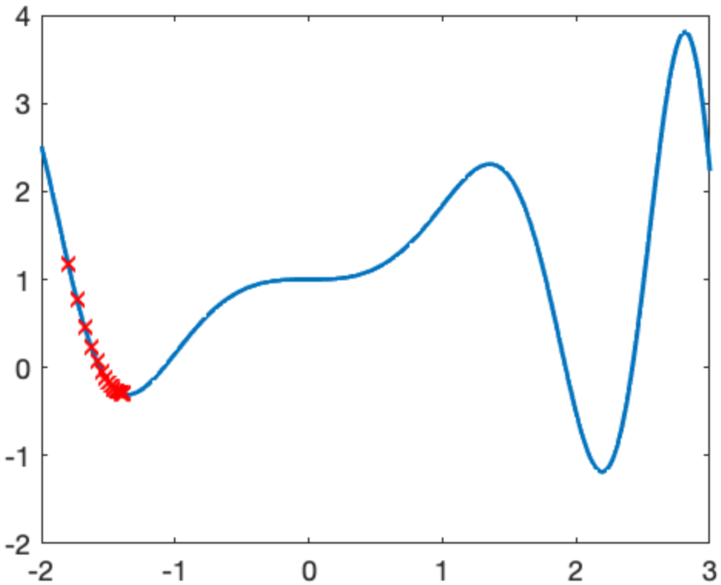


Converges to the same place, but faster.

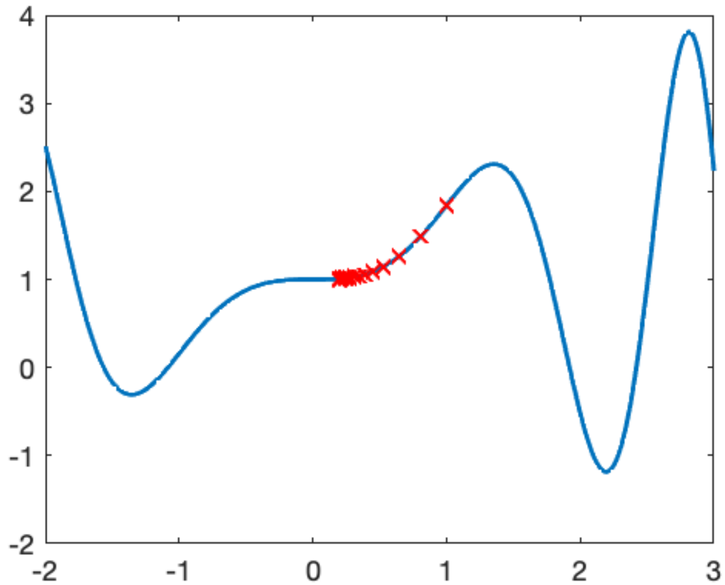
Minimizing a Non-Convex Function



$x_0 = 1.5$
Global minimum



$x_0 = -1.8$
Local minimum

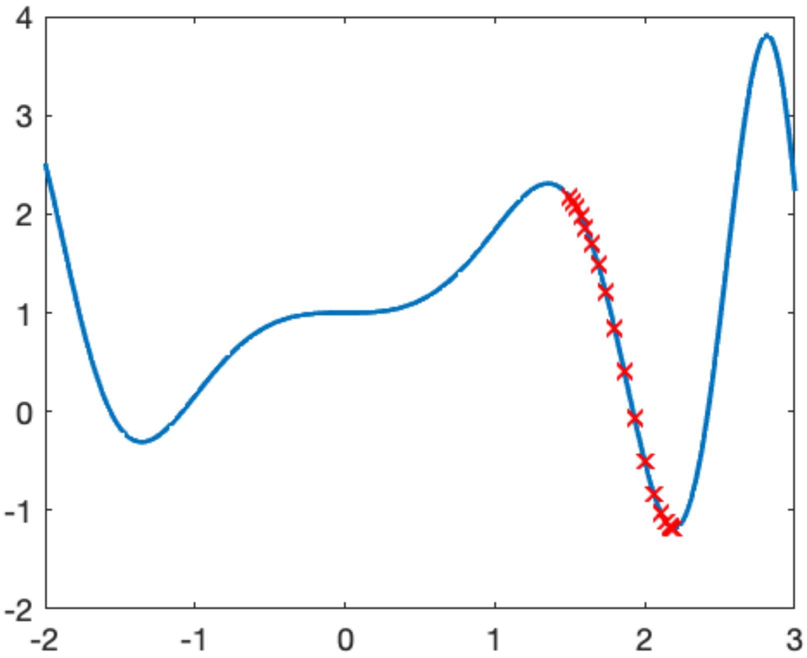


$x_0 = 1$
Saddle point

Minimizing a Non-Convex Function

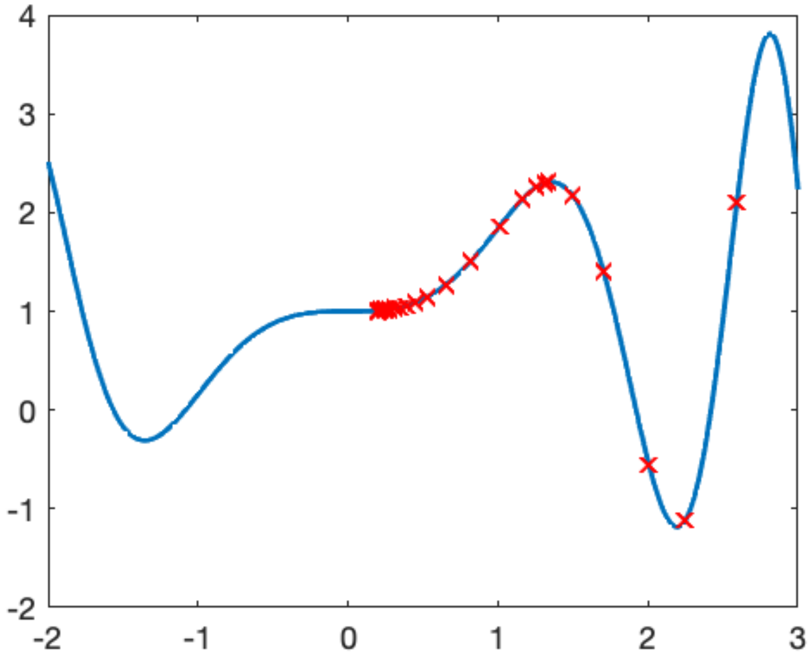
$\eta = 0.01, \;\; x_0 = 1.5$

Global minimum



$\eta = 0.1, \;\; x_0 = 1.5$

Saddle point



- No guarantees when the function is not convex!
- Choosing η is not always easy. We'll get back to that.

Functions of Multiple Variables

Multivariate function:

$$f : R^D \rightarrow R$$

$$y = f(\mathbf{x}) = f(x_1, \ldots, x_D)$$

Partial derivative:

$$\frac{\delta y}{\delta x_d} = \lim_{\Delta x \rightarrow 0} \frac{f(\ldots, x_d + \Delta x, \ldots) - f(\ldots, x_d, \ldots)}{\Delta x}$$

Gradient vector:

$$\nabla f = [\frac{\delta f}{\delta x_1}, \ldots, \frac{\delta f}{\delta x_D}]$$

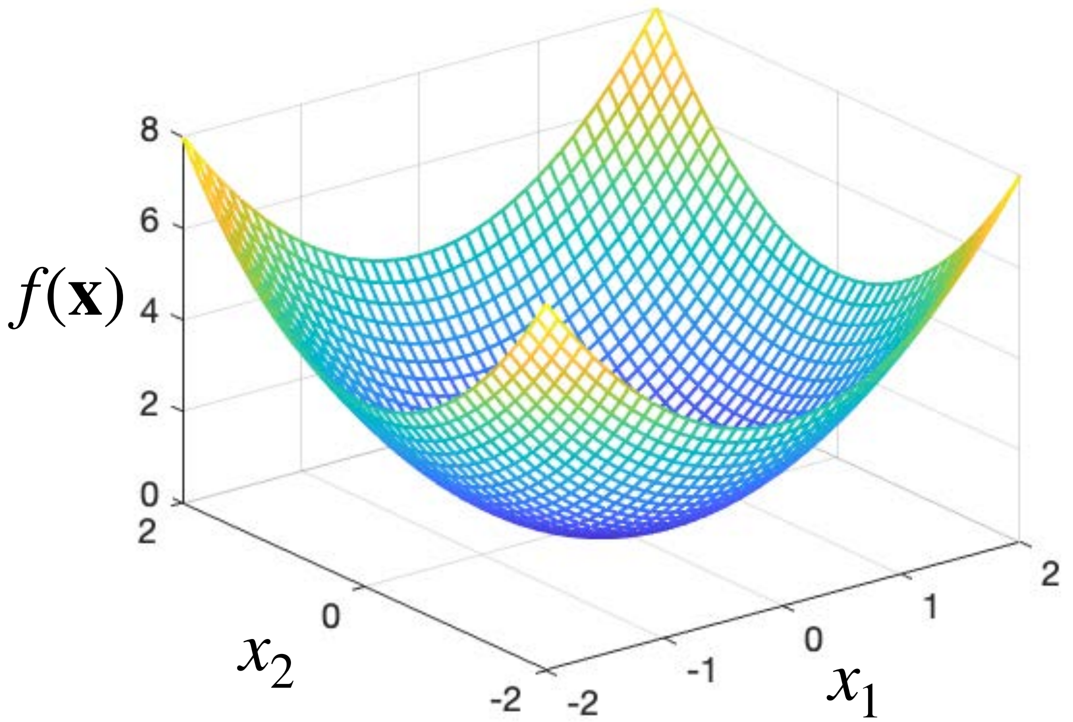
Quadratic Function

$$f(\mathbf{x}) = x_1^2 + x_2^2$$

$$\frac{\partial f}{\partial x_1} = 2x_1$$

$$\frac{\partial f}{\partial x_2} = 2x_2$$

$$\nabla f(\mathbf{x}) = \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix} \in \mathbb{R}^2$$



The color also represents the value of $f(\mathbf{x})$

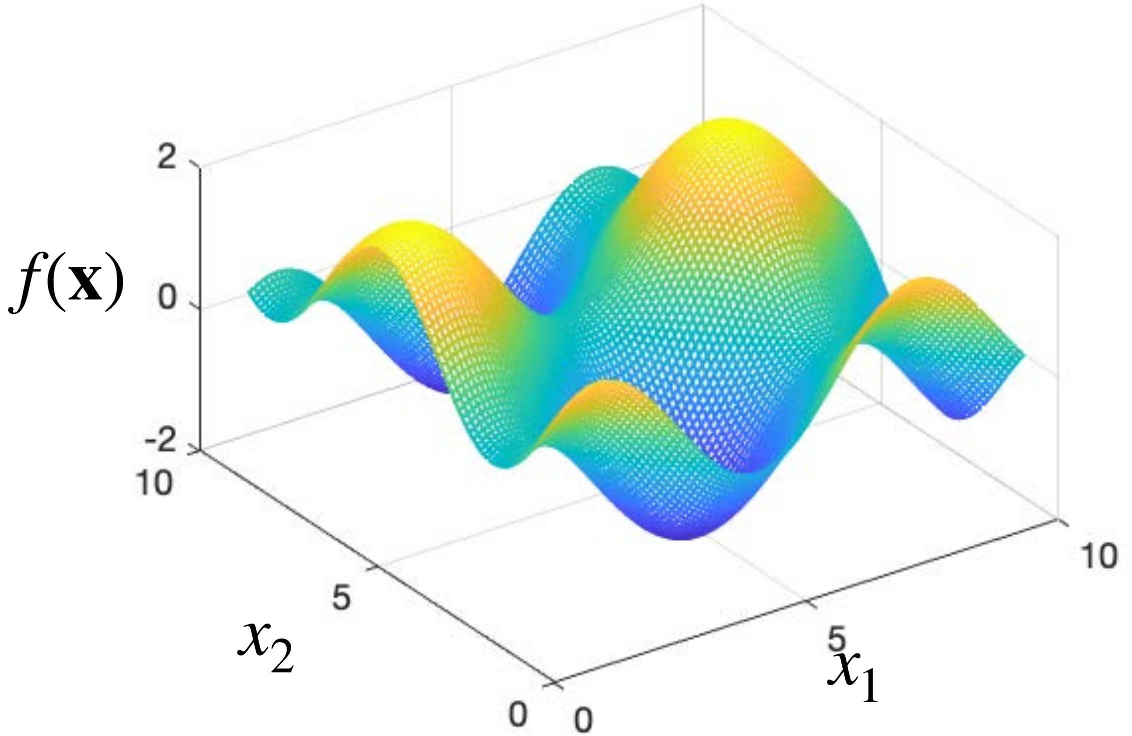
Sinusoidal Function

$$f(\mathbf{x}) = \sin x_1 + \cos x_2$$

$$\frac{\partial f}{\partial x_1} = \cos(x_1)$$

$$\frac{\partial f}{\partial x_2} = -\sin(x_2)$$

$$\nabla f(\mathbf{x}) = \begin{bmatrix} \cos(x_1) \\ -\sin(x_2) \end{bmatrix} \in \mathbb{R}^2$$



The color also represents the value of $f(\mathbf{x})$

Gradient in 4 Dimensions

$$f(\mathbf{x}) = x_1^2 x_2^2 + x_1 x_2 x_3 + x_3 x_4 + 2x_4 + 1$$

$$\frac{\partial f}{\partial x_1} = 2x_1 x_2^2 + x_2 x_3$$

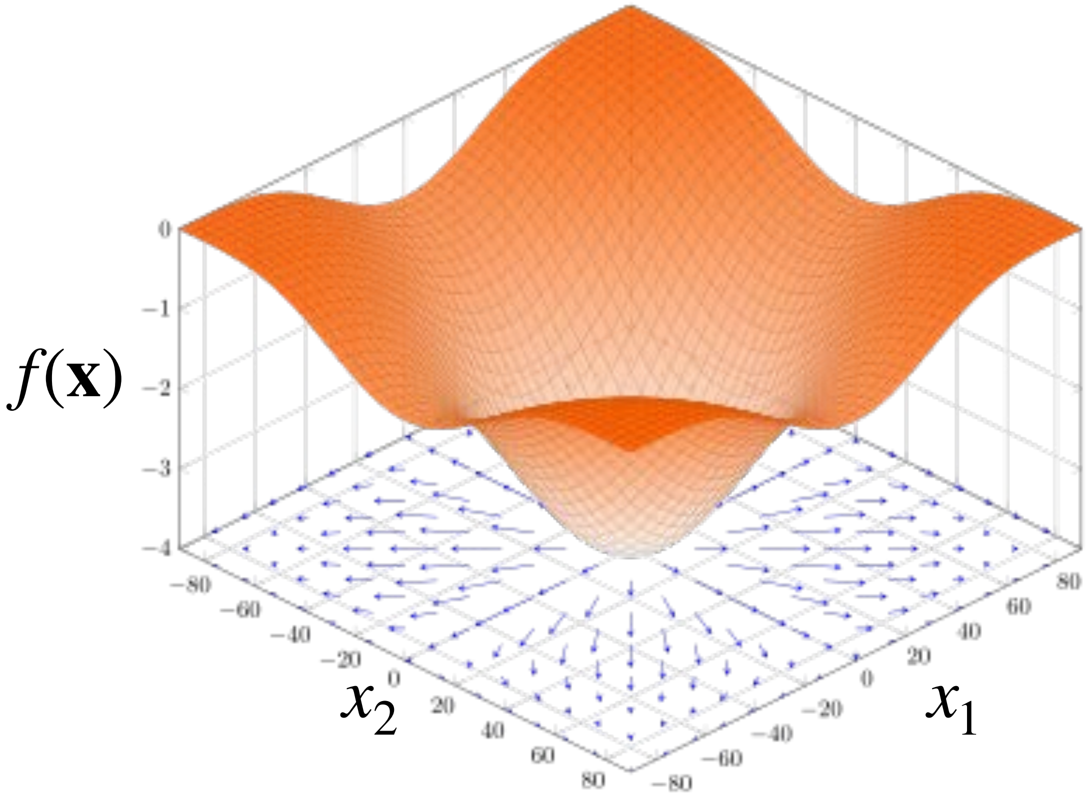
$$\frac{\partial f}{\partial x_2} = 2x_2 x_1^2 + x_1 x_3$$

$$\frac{\partial f}{\partial x_3} = x_1 x_2 + x_4$$

$$\frac{\partial f}{\partial x_4} = x_3 + 2$$

$$\nabla f(\mathbf{x}) = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \frac{\partial f}{\partial x_3} \\ \frac{\partial f}{\partial x_4} \end{bmatrix} \in \mathbb{R}^4$$

Gradient Properties

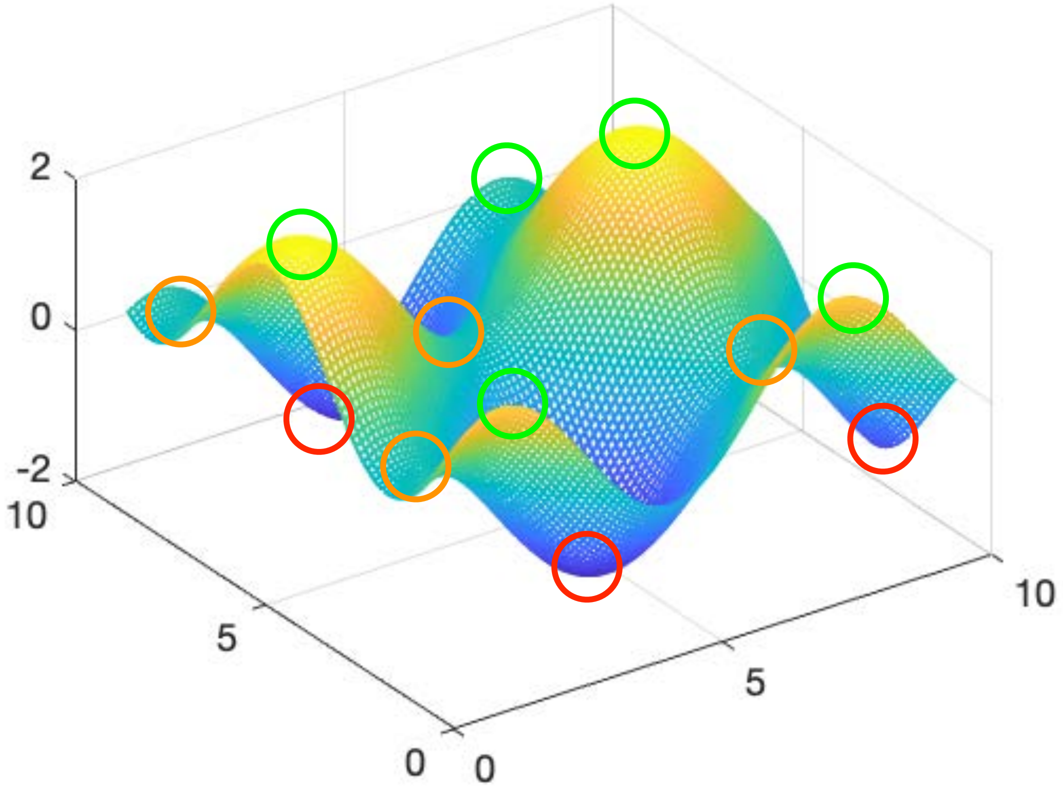


- The gradient at a point $\mathbf{x}$ indicates the direction of greatest increase of the function at $\mathbf{x}$.
- Its magnitude is the rate of increase in that direction.

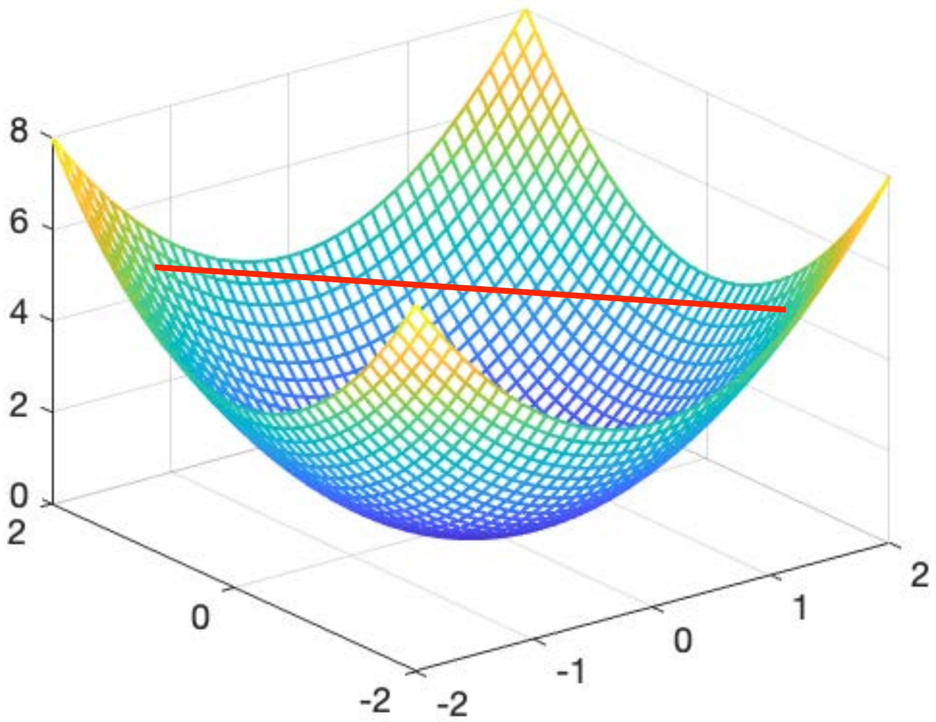
Gradient Properties

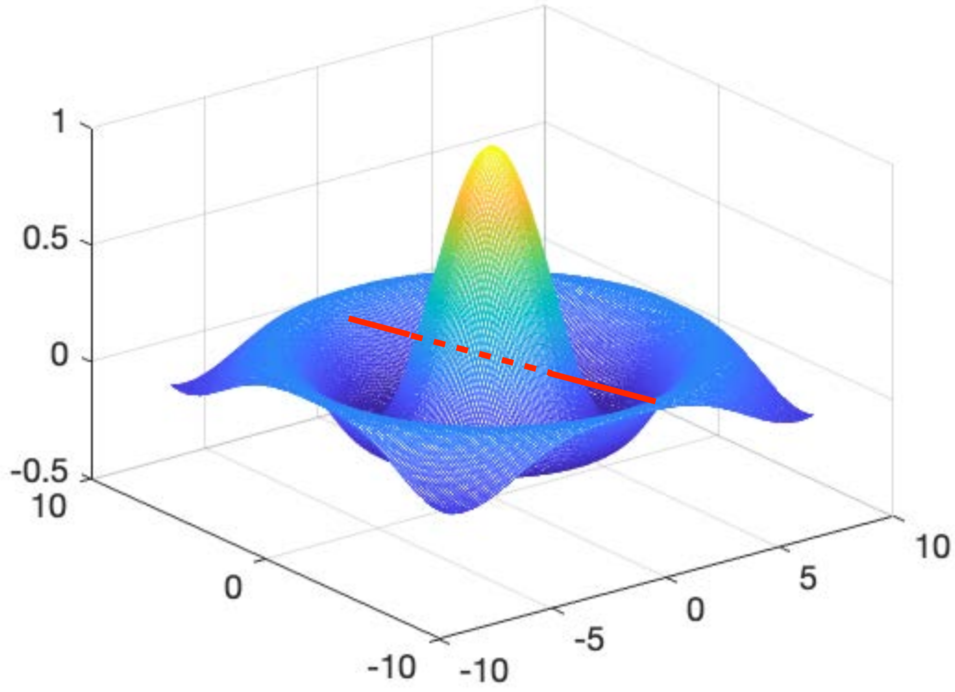
The gradient vanishes (becomes a zero vector) at the stationary points of the function:

- Minima,
- Maxima,
- Saddle points.



Convex vs Non-Convex

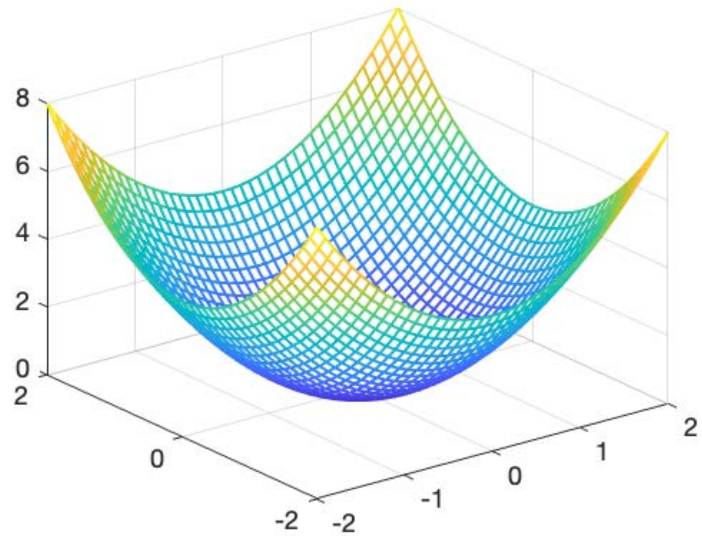




Convex: The line segment between any two points on the function lies above the function

Non-convex: At least one line segment between two points lies in part below the function.

Minimizing a Convex Function



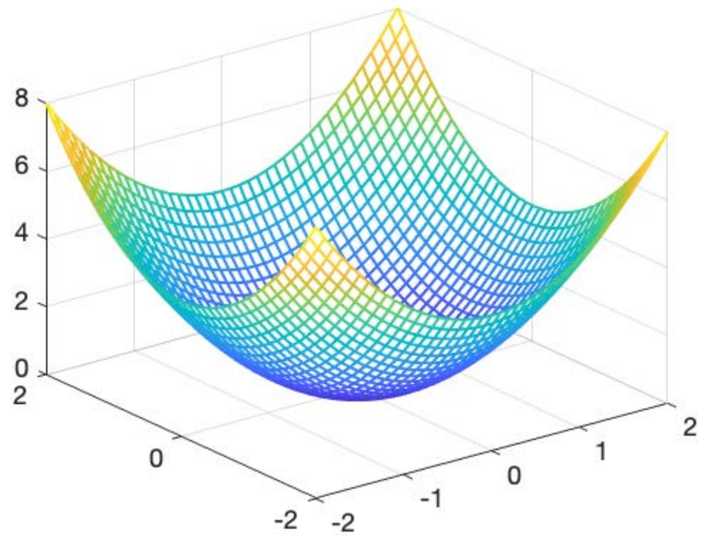
$$\nabla f(\mathbf{x}^*) = \mathbf{0}$$

- Because the gradient is a vector, this yields a system of equations.
- It can still be solved in closed form for some functions.

Minimizing a Simple Convex Function

$$f(\mathbf{x}) = x_1^2 + x_2^2$$

$$\frac{\partial f}{\partial x_1} = 2x_1 \qquad \frac{\partial f}{\partial x_2} = 2x_2$$

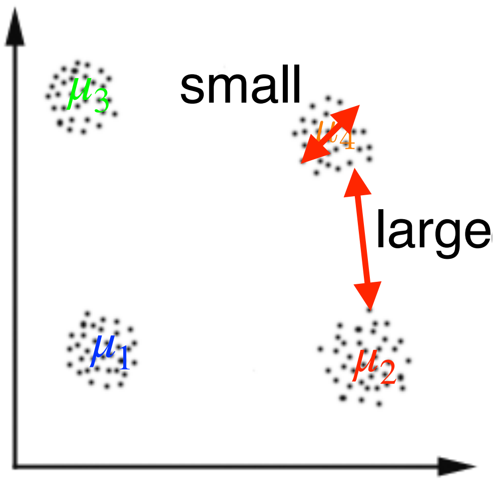


$$\nabla f(\mathbf{x}) = 0 \Leftrightarrow \begin{cases} 2x_1 = 0 \\ 2x_2 = 0 \end{cases}$$

$$\Leftrightarrow x_1 = x_2 = 0$$

EPFL

Revisiting K means



- Cluster k is formed by the points $\{\mathbf{x}_{i_1^k}, \ldots, \mathbf{x}_{i_{n^k}^k}\}$.
- μ_k is the **center of gravity** of cluster k.

- The distances between the points within a cluster should be small.
- The distances across clusters should be large.
- This can be encoded via the distance to cluster centers $\{\mu_1, \ldots, \mu_K\}$:

$$\longrightarrow \text{Minimize } \sum_{k=1}^{K} \sum_{j=1}^{n_k} (\mathbf{x}_{i_j^k} - \mu_k)^2$$

where $\{\mathbf{x}_{i_1^k}, \ldots, \mathbf{x}_{i_{n^k}^k}\}$ are the n^k samples that belong to cluster k.

Revisiting K means

The minimization problem can be reformulated as:

$$\min_{\{\mu_k\},\{r_i^k\}} R(\{\mu_k\},\{r_i^k\}) \text{ with } R = \sum_{i=1}^{N}\sum_{k=1}^{K} r_i^k \|\mathbf{x}_i - \mu_k\|^2$$

$$\text{such that } r_i^k \in \{0,1\}, \ \ \forall i, k$$

$$\text{and } \sum_{k=1}^{K} r_i^k = 1, \ \ \forall i$$

—> We find the solution by alternating between the two types of variables.

Revisiting K means

$$\min_{\{r_i^k\}} \sum_{i=1}^{N} \sum_{k=1}^{K} r_i^k \|\mathbf{x}_i - \mu_k\|^2$$

such that $\quad r_i^k \in \{0,1\}, \;\; \forall i, k$

$$\sum_{k=1}^{K} r_i^k = 1, \;\; \forall i$$

- Because of the constraints, for each sample, only one r_i^k can be 1.
- We take it to be the one corresponding to the nearest center:

$$r_i^k = \begin{cases} 1, \;\; \text{if } k = \underset{j}{\operatorname{argmin}} \|\mathbf{x}_i - \mu_j\|^2 \\ 0, \;\; \text{otherwise} \end{cases}$$

EPFL

Revisiting K means

$$\min_{\{\mu_k\}} \sum_{i=1}^{N} \sum_{k=1}^{K} r_i^k \|\mathbf{x}_i - \mu_k\|^2$$

- This can be done by zeroing out the partial derivative for each center:

$$\frac{\partial R}{\partial \mu_k} = 2 \sum_{i=1}^{N} r_i^k (\mathbf{x}_i - \mu_k) = 0$$

- This yields:

$$\mu_k = \frac{\sum_{i=1}^{N} r_i^k \mathbf{x}_i}{\sum_{i=1}^{N} r_i^k}$$

- This corresponds to the mean of the samples assigned to cluster k.

Back to Logistic Regression

- Replace the step function by a smooth function σ.
- The prediction becomes $y(\mathbf{x}; \tilde{\mathbf{w}}) = \sigma(\tilde{\mathbf{w}} \cdot \tilde{\mathbf{x}})$.
- Given the training set $\{(\mathbf{x}_n, t_n)_{1 \leq n \leq N}\}$ where $t_n \in \{0, 1\}$, minimize the cross-entropy

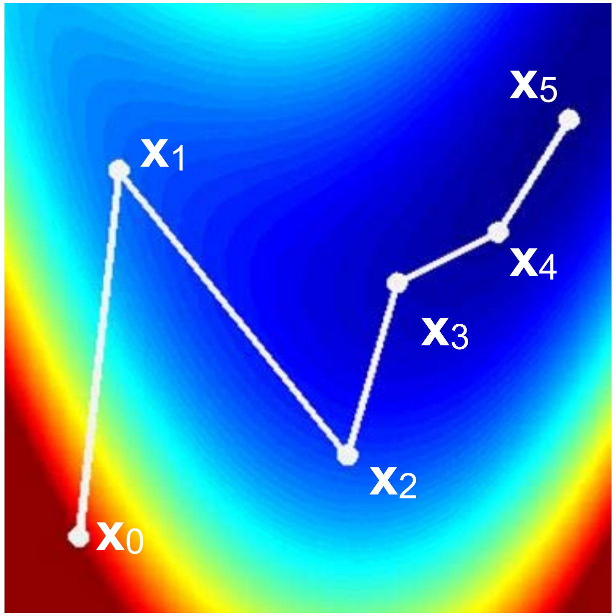
$$E(\tilde{\mathbf{w}}) = -\sum_n \{t_n \ln y_n + (1 - t_n) \ln(1 - y_n)\}$$

$$y_n = y(\mathbf{x}_n; \tilde{\mathbf{w}})$$

with respect to $\tilde{\mathbf{w}}$.

E is convex but cannot be minimized in closed form!

Gradient Descent



The gradient replaces the derivative.

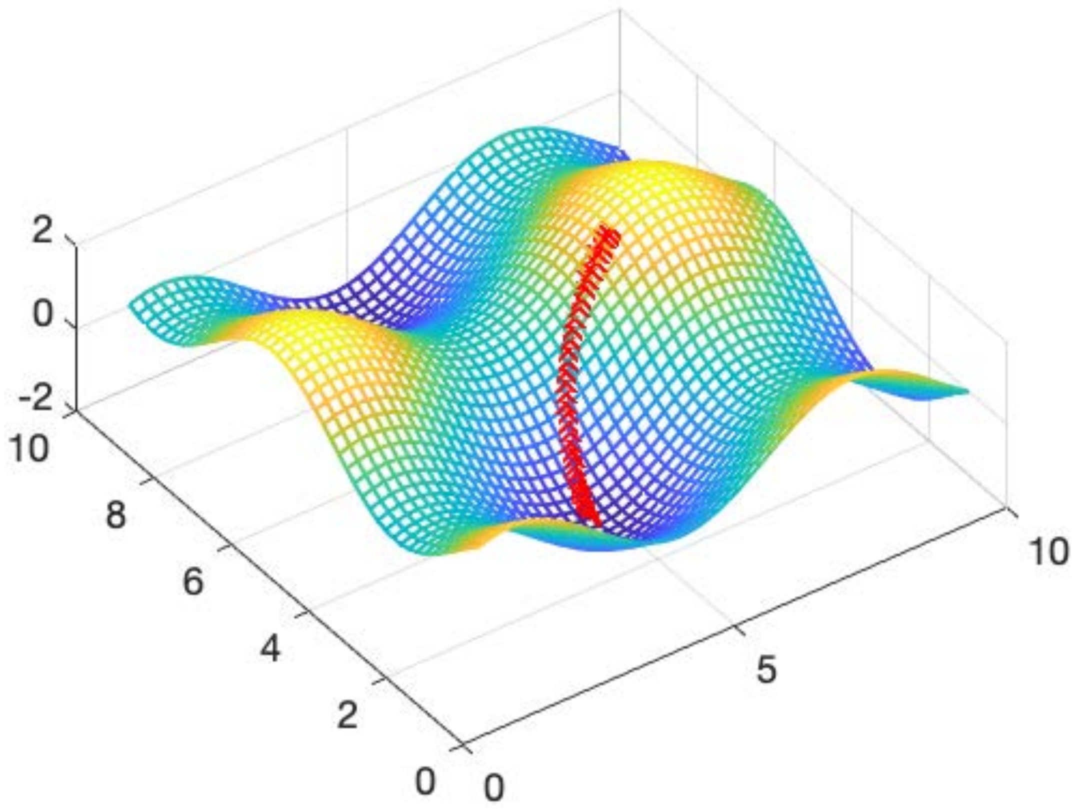
Simplest algorithm:

1. Initialize $\mathbf{x}_0$ (e.g., randomly)
2. While not converged
   2.1. Update $\mathbf{x}_k \leftarrow \mathbf{x}_{k-1} - \eta \nabla f$

- η defines the step size of each iteration.
- In ML, it is often referred to as the *learning rate.*

EPFL

Minimizing a Non-convex Function



$$f(\mathbf{x}) = \sin x_1 + \cos x_2$$

$$\nabla f(\mathbf{x}) = \begin{bmatrix} \cos(x_1) \\ -\sin(x_2) \end{bmatrix} \in \mathbb{R}^2$$

Stopping criteria:

- Thresholding the change in function value.
- Thresholding the change in parameters, i.e. $\|\mathbf{x}_{k-1} - \mathbf{x}_k\| < \delta$.

Theoretical Justification

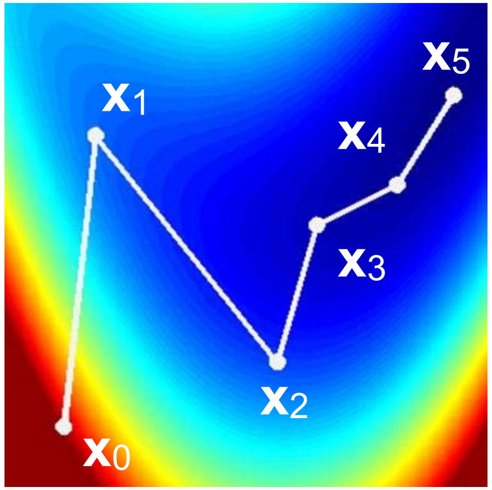
Steepest gradient descent:

$$\mathbf{x}_k \leftarrow \mathbf{x}_{k-1} - \eta \nabla f$$

First order Taylor expansion:

$$f(\mathbf{x} + \mathbf{dx}) \approx f(\mathbf{x}) + \nabla f(\mathbf{x})^T \mathbf{dx}$$

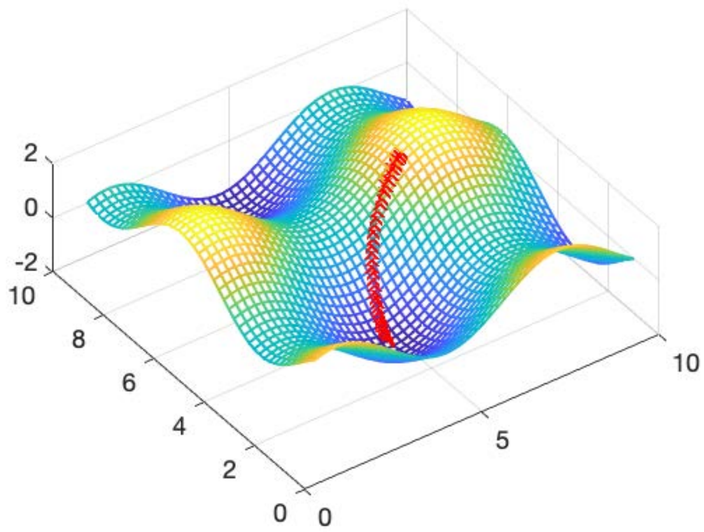
$$f(\mathbf{x} - \eta \nabla f(\mathbf{x})) \approx f(\mathbf{x}) - \eta \|\nabla f(\mathbf{x})\|^2 < f(\mathbf{x})$$



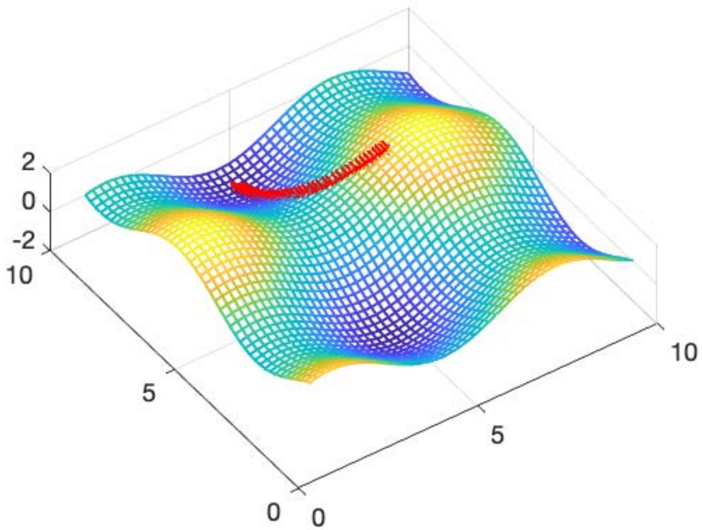
Issues:

- Justification but no guarantee
- How do we choose η?
- Many iterations in long and narrow valleys.

Potential Trouble Spots

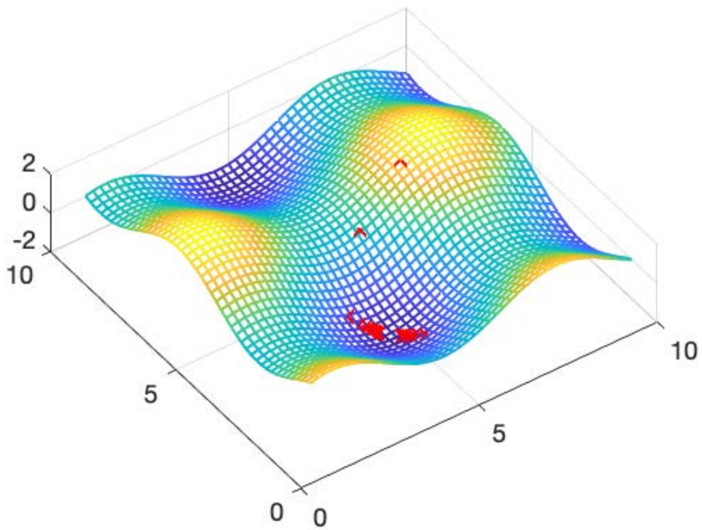


$\mathbf{x}_0 = [7.0, 6.0]^T$
$\eta = 0.1$



$\mathbf{x}_0 = [7.0, 6.5]^T$
$\eta = 0.1$

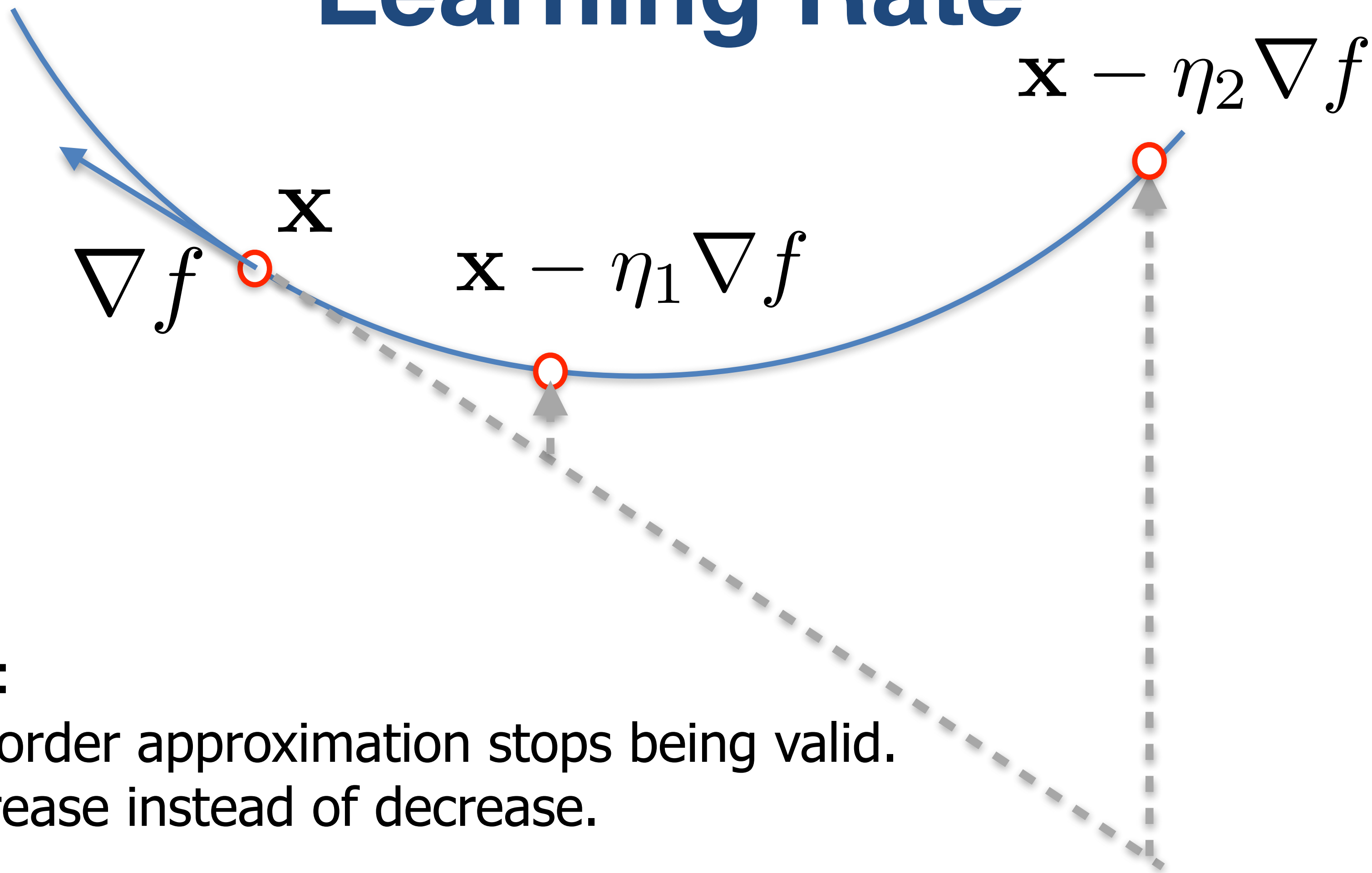
Sensitive to initialization



$\mathbf{x}_0 = [7.0, 6.0]^T$
$\eta = 2.0$

Large η causes oscillations

Learning Rate



η too large:

- The first order approximation stops being valid.
- f can increase instead of decrease.

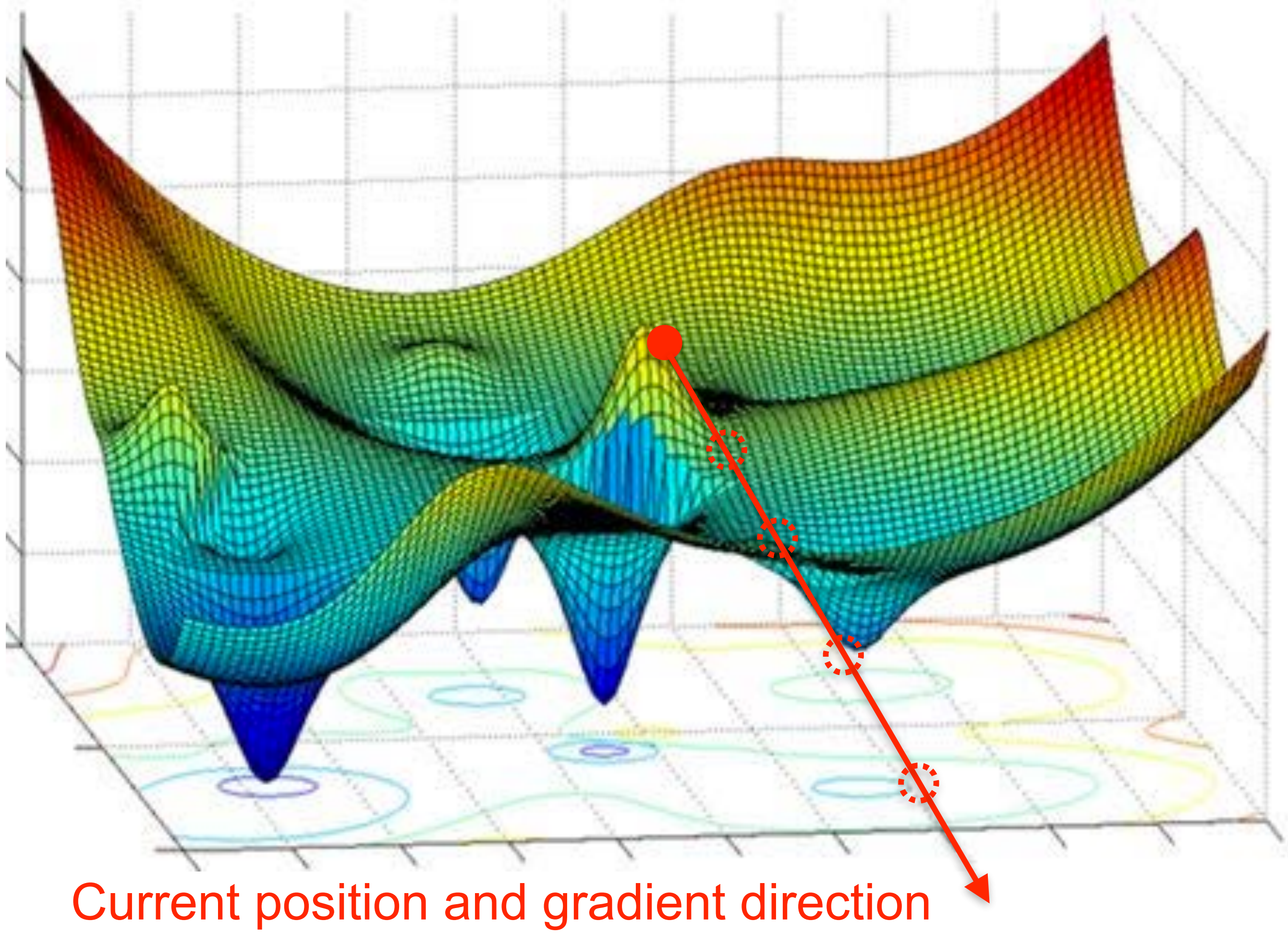
η too small:

- Convergence rate will be very slow.

Partial solution:

- Instead of using a fixed learning rate perform a line search in the direction of the gradient.

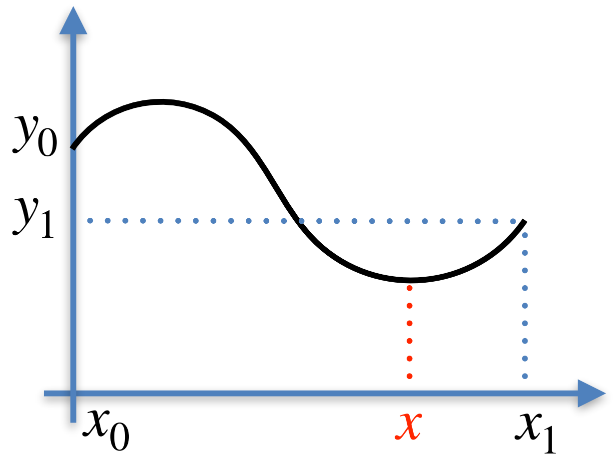
Line Search



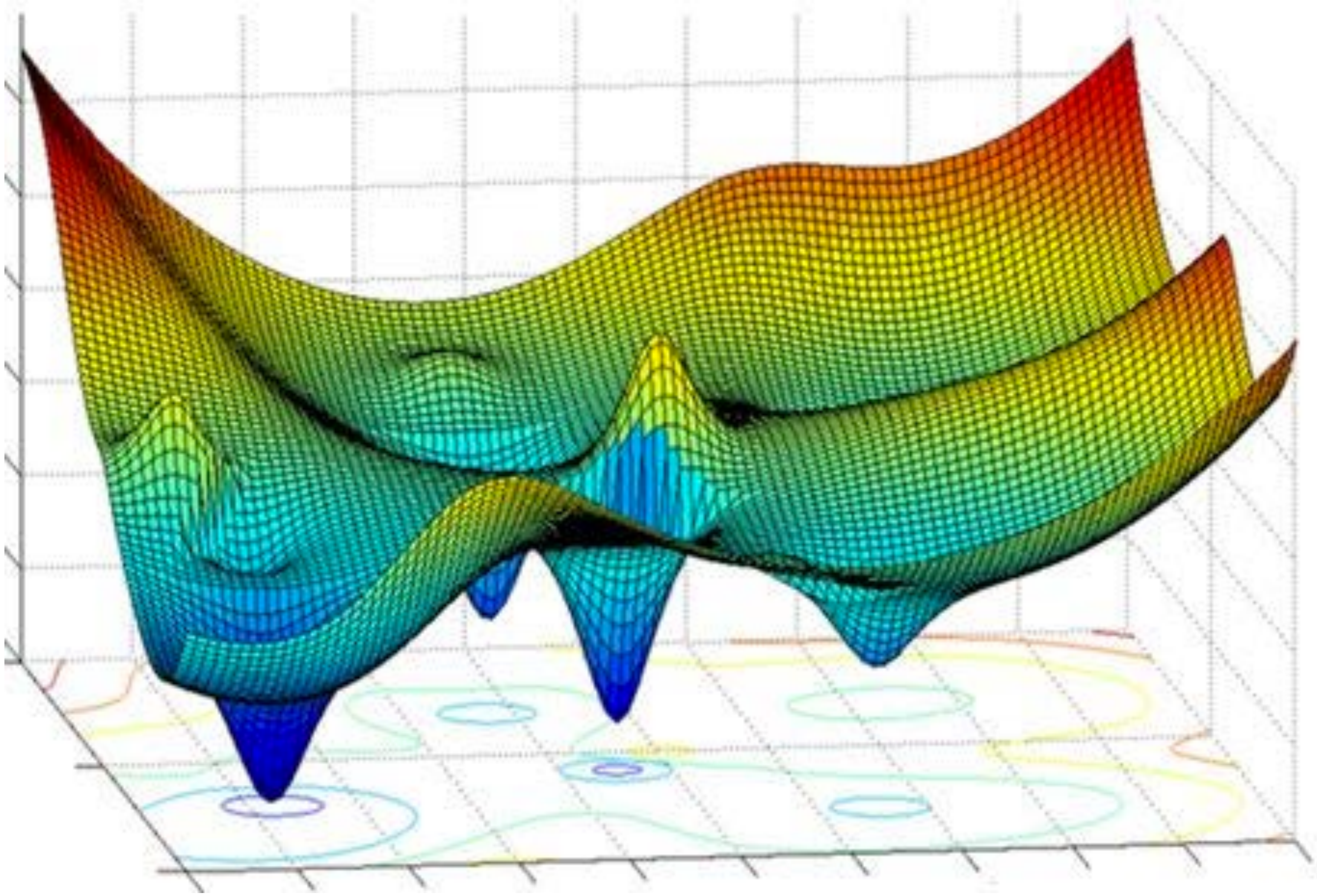
- Search along the gradient direction for a minimum.
- This is a 1D search and therefore doable.

Python Implementation

```
def steepestGrad(objF,x0,nIt=100,eps=1e-6,step=1.0):

    for i in range(nIt):

        y0,g0=objF(x0)                              # Compute the value of objF and its gradient.
        x1=x0-step*g0                               # Take a step in the direction of the gradient.
        y1,_=objF(x1)                               # Compute the new value of objF.
        while(y1>y0):                               # Check that the function value has decreased.
            if(np.allclose(x0,x1,eps)):             # Stopping condition.
                return x0
            step=step/2.0                           # Reduce the step size.
            x1   =x0-step*g0                        # Try again.
            y1,_=objF(x1)

        x0,y0=dichoSearch(objF,x0,y0,x1,y1,params) # We have y1 < y0. Perform dichotomy search.

    return x0

def dichoSearch(objF,x0,y0,x2,y2,minD=1e-5):

    if(np.allclose(x0,x2,minD)):
        return x0,y0
    # Find interval mid point
    x1=(x0+x2)/2
    y1=objF(x1)
    # Pick left or right interval
     if(y0<y2):
        return(dichoSearch(objF,x0,y0,x1,y1,minD))
    else:
        return(dichoSearch(objF,x1,y2,x2,y2,minD))
```

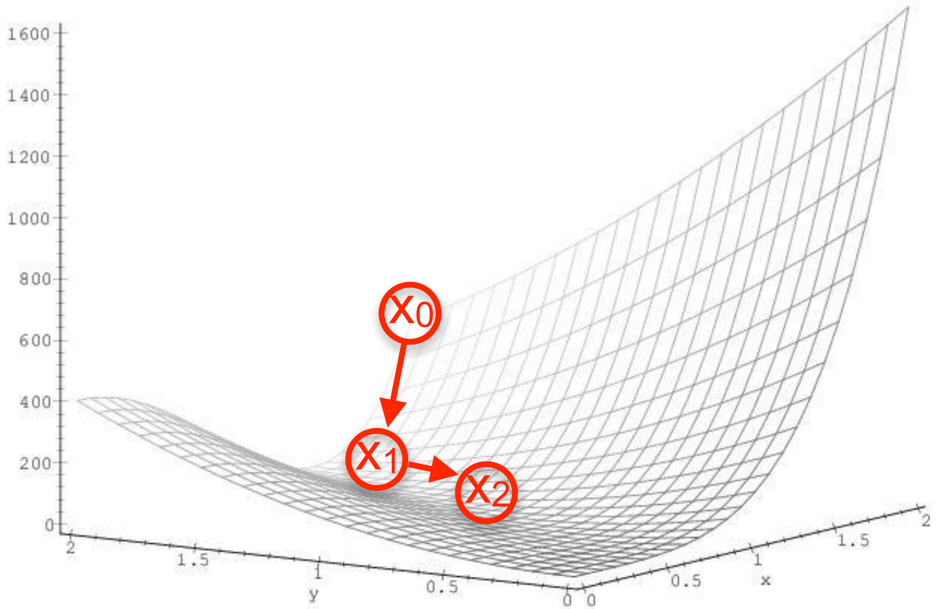


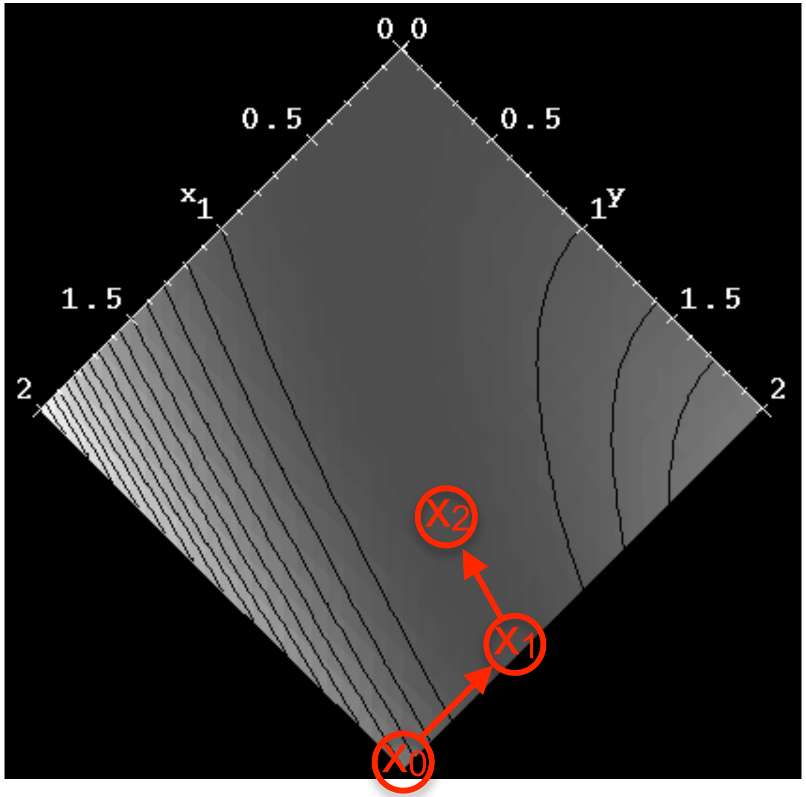
Local Minima



The result depends critically on the starting point and is very likely to be closest local minimum, which is not usually the global one.

Zig-Zagging towards the Solution





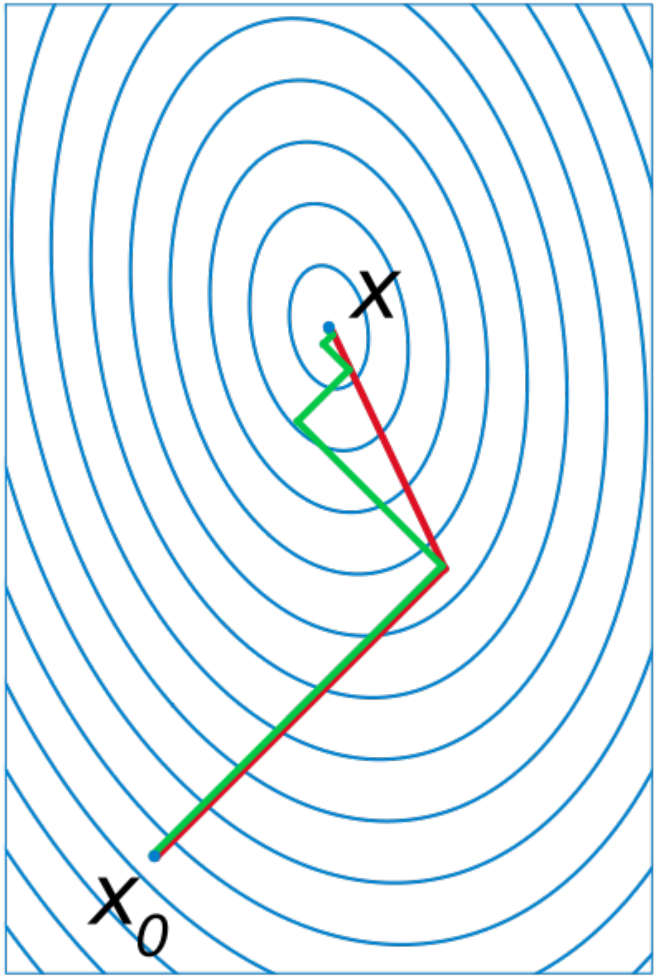
- Successive line searches tend to be perpendicular to each other.
- They would be if we found a true local minimum each time.

EPFL

Conjugate Gradient

Take the search direction to be a weighted average of the gradient vector and the previous search directions:

1. Start at $\mathbf{x}_0$.
2. $\mathbf{g}_0 = \nabla F(\mathbf{x}_0)$.
3. For k from 0 to $n-1$:
   (a) Find α_k that minimizes $f(\mathbf{x}_k + \alpha_k \mathbf{g}_k)$.
   (b) $\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{g}_k$.
   (c) $\beta_k = \frac{\|\nabla f(\mathbf{x}_{k+1})\|^2}{\|\nabla f(\mathbf{x}_k)\|^2}$.
   (d) $\mathbf{g}_{k+1} = -\nabla f(\mathbf{x}_{k+1}) + \beta_k \mathbf{g}_k$.
4. $\mathbf{x}_0 = \mathbf{x}_n$ and go to step 2 until convergence.



—> Faster convergence.

Optional: Python Implementation

```
def conjugateGrad(objF,x0,nIt=100,eps=1e-10,step=1.0):

    y0,g0=objF(x0)
    h0=-g0                                  # g: Function gradient.
    g0 =h0                                  # h: Conjugate direction.

    for i in range(1,nIt):
        l0=np.linalg.norm(h0)
        if(l0<eps):
            print('Gradient has vanished.')
            break
        x1   =x0+(step/l0)*h0
        y1,_=objF(x1)
        while(y1>y0):                       # Check that the function value has decreased.
            if(np.allclose(x0,x1,eps)):     # Stopping condition.
                return x0
            step=step/2.0
            x1   =x0+(step/np.linalg.norm(h0))*h0
            y1,_=objF(x1,False)

        x1,y1=lineSearch(objF,x0,y0,x1,y1)
        y1,g1=objF(x1)                      # Recompute value and gradient.
        g1=-g1
        h1=g1

        if((i%n)>0):                        # Compute conjugate direction but reset every n iterations.
            gamma=np.dot((g1-g0),g1)/np.dot(g0,g0) # Modified Polak Ribiere, i.e. only if gamma > 0.
            if(gamma>0):
                h1=g1+gamma*h0

        # Switch variables
        g0=g1
        h0=h1
        x0=x1
        y0=y1
```

EPFL

Optional: In Real Life (1)

```
import scipy

def f(x):
    ……   # return the value of the function.
def g(x):
    ……. # return the gradient of the function.

x0= …. # starting point.
x1= scipy.optimize.fmin_cg(f,x0,fprime=g,epsilon=eps,maxiter=nIt)
```

Optional: In Real Life (2)

conjugate gradient python

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scipy.sparse.linalg.cg — SciPy v1.2.1 Reference Guide - SciPy.org
https://docs.scipy.org/doc/scipy/reference/generated/scipy.sparse.linalg.cg.html
scipy.sparse.linalg. cg (A, b, x0=None, tol=1e-05, maxiter=None, M=None, callback=None, atol=None)¶. Use **Conjugate Gradient** iteration to solve Ax = b .

scipy.optimize.fmin_cg — SciPy v0.14.0 Reference Guide
https://docs.scipy.org/doc/scipy-0.14.0/reference/.../scipy.optimize.fmin_cg.html
Minimize a function using a nonlinear **conjugate gradient** algorithm. ... Defaults to None, in which case the gradient is approximated numerically (see epsilon, ...

conjugate gradient method implemented with python · GitHub
https://gist.github.com/sfujiwara/b135e0981d703986b6c2
from scipy.sparse.linalg import cg. ... Solve a linear equation Ax = b with **conjugate gradient** method. ... A: 2d **numpy**.array of positive semi-definite (symmetric) matrix.

The Concept of Conjugate Gradient Descent in Python - Ilya Kuzovkin
ikuz.eu/2015/04/15/the-concept-of-conjugate-gradient-descent-in-python/
Apr 15, 2015 - While reading "An Introduction to the **Conjugate Gradient** Method Without the Agonizing Pain" I decided to boost understand by repeating the ...

Optional: In Real Life (3)

Playground

Load a preset...

Assume that f is a function and g its gradient written in python, use conjugate gradient to minmize them.

```
#import necessary packages
import numpy as np
from scipy.optimize import minimize

#define the function and gradient
def f(x):
   return np.sum(x**2)

def g(x):
   return 2*x

#set the initial guess
x0 = np.array([1,2,3])

#minimize using conjugate gradient
res = minimize(f, x0, method='CG', jac=g)

#print out the result
print(res.x)
```

Optional: Second Order Methods

Second order Taylor expansion:

$$f(\mathbf{x}+\mathbf{dx}) \approx f(\mathbf{x}) + \nabla f(\mathbf{x})^T \mathbf{dx} + \frac{1}{2}\mathbf{dx}^T H(\mathbf{x})\mathbf{dx}$$

$$\nabla f(\mathbf{x}+\mathbf{dx}) \approx \nabla f(\mathbf{x}) + H(\mathbf{x})\mathbf{dx}$$

Newton method:

$$\text{Solve } H(\mathbf{x})\mathbf{dx} = -\nabla f(\mathbf{x})$$

$$\Rightarrow \mathbf{dx} = -H(\mathbf{x})^{-1}\nabla f(\mathbf{x})$$

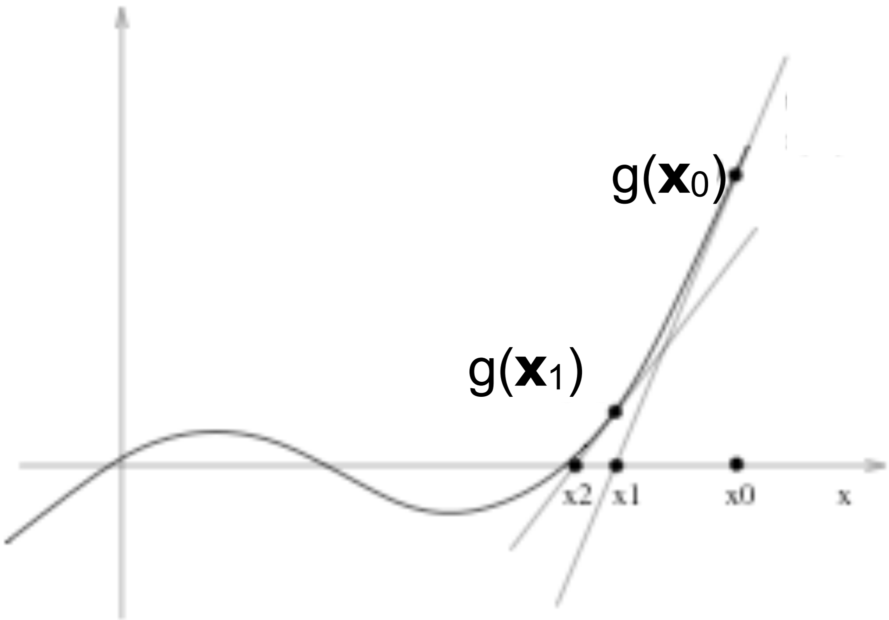
$$\nabla f(\mathbf{x}+\mathbf{dx}) \approx 0$$

$$\begin{aligned} f(\mathbf{x}+\mathbf{dx})) &\approx f(\mathbf{x}) - \nabla f(\mathbf{x})^T H(\mathbf{x})^{-1}\nabla f(\mathbf{x}) \\ &+ \frac{1}{2}\nabla f(\mathbf{x})^T H(\mathbf{x})^{-1} \cancel{H(\mathbf{x}) H(\mathbf{x})^{-1}} \nabla f(\mathbf{x}) \\ &\approx f(\mathbf{x}) - \frac{1}{2}\nabla f(\mathbf{x})^T H(\mathbf{x})^{-1}\nabla f(\mathbf{x}) \end{aligned}$$

Optional: Newton in 1D

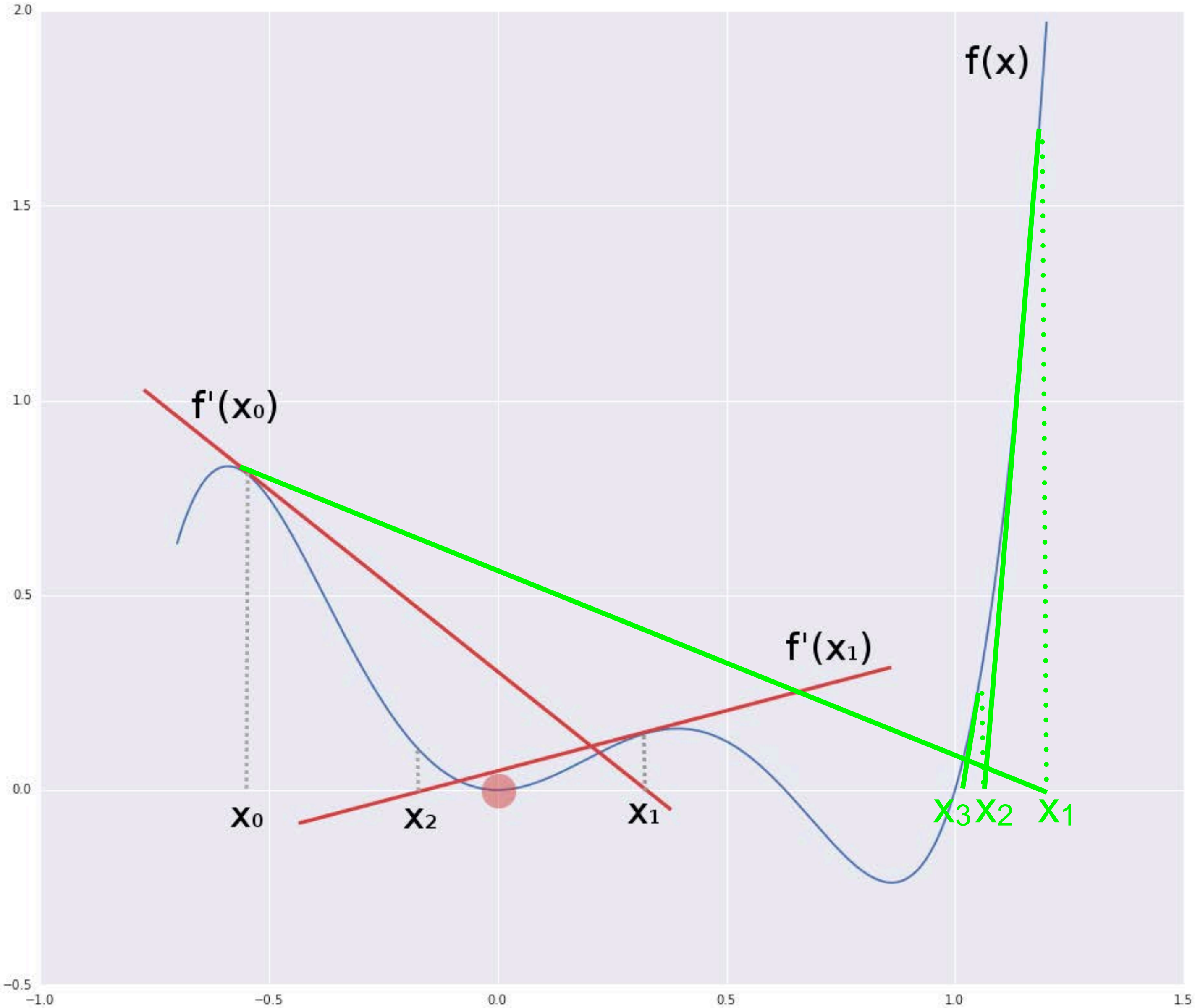
$$0 = g(x + dx) = g(x) + g'(x)dx$$

$$\Rightarrow dx = -\frac{g(x)}{g'(x)}$$



$$x \leftarrow x - \frac{g(x)}{g'(x)}$$

Optional: Finding Polynomial Roots

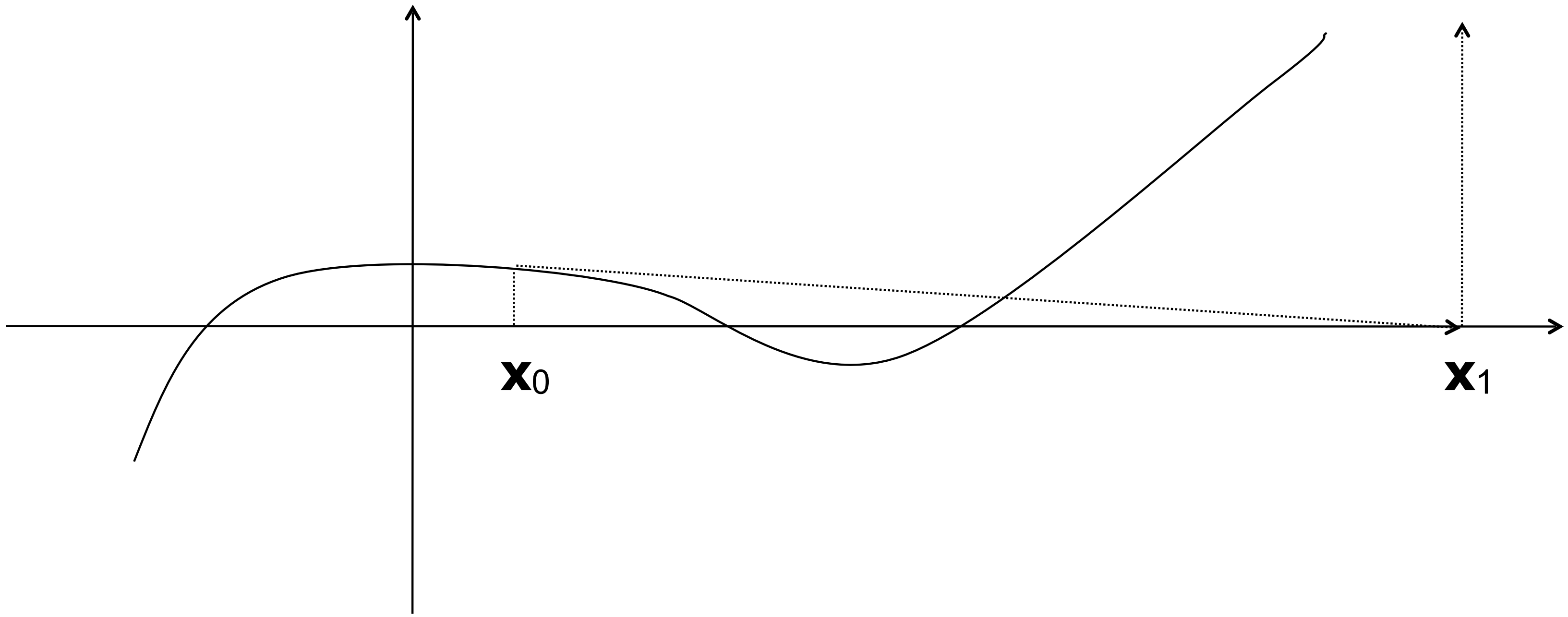


$$f(x) = 6x^5 - 5x^4 - 4x^3 + 3x^2$$

- There is more than one root.
- The one you find depends on the starting point.

EPFL

Optional: Potential Instability



- Individual steps can be very large, leading to instability.

Optional: Damped Newton

Second order Taylor expansion:

$$f(\mathbf{x}+\mathbf{dx}) \approx f(\mathbf{x}) + \nabla f(\mathbf{x})^T \mathbf{dx} + \frac{1}{2}\mathbf{dx}^T H(\mathbf{x})\mathbf{dx}$$

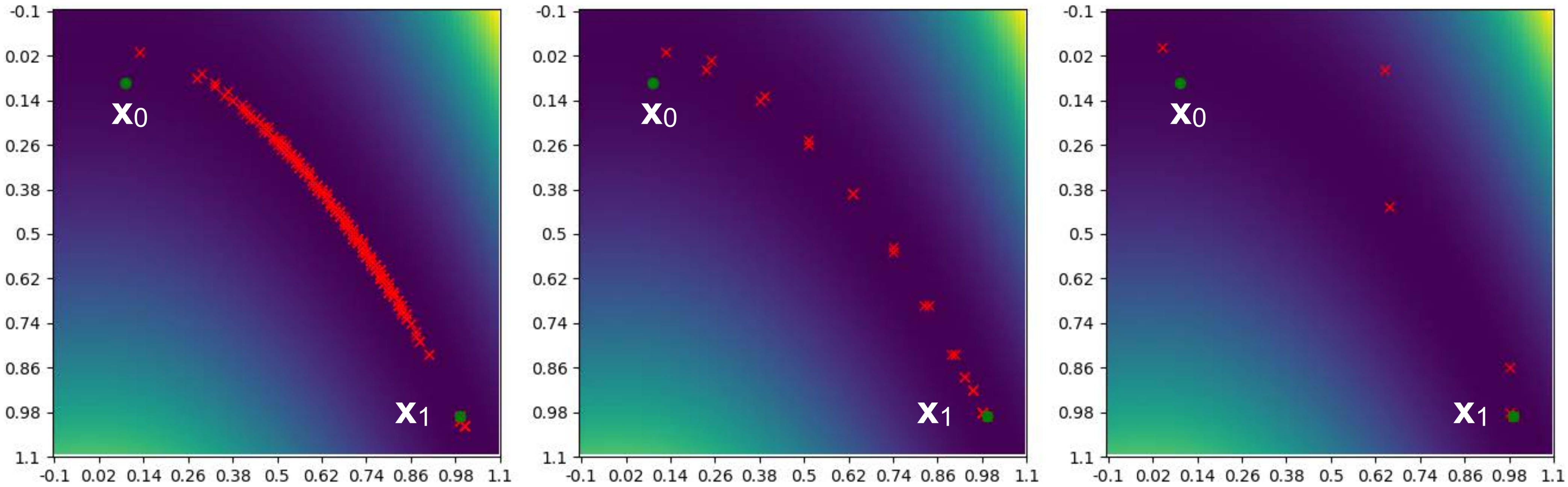
$$\nabla f(\mathbf{x}+\mathbf{dx}) \approx \nabla f(\mathbf{x}) + H(\mathbf{x})\mathbf{dx}$$

Introduce a damping term:

$$\mathbf{x} \leftarrow \mathbf{x} + \mathbf{dx} \text{ with } \begin{cases} \text{Regular Newton Method: } H(\mathbf{x})\mathbf{dx} = -\nabla f(\mathbf{x}) \\ \text{Damped Newton: } (H(\mathbf{x}) + \lambda \mathbf{I})\mathbf{dx} = -\nabla f(\mathbf{x}) \end{cases}$$

- $\lambda = 0$: Regular Newton
- $\lambda >> 0$: Gradient descent

Optional: Qualitative Comparison



Steepest gradient　　Conjugate gradient　　Damped Newton

Damped Newton converges much faster!

Optional: Python Implementation

```
def dampedNewton(objF,x,nIt=10,lbda=None):

    for i in range(nIt):
        f,g,H=objF(x)                    # Evaluate f, its gradient, and its Hessian.
        x -= linSolve(H,g,lbda=lbda)     # Solve (H + λ I) x = g
    return x



def linSolve(A,b,lbda=None):

    if(lbda is not None):
        A=A+lbda*np.eye(A.shape[0])  # A <— A + λ I
    x=np.linalg.solve(A,b)           # Solve A x = b
    return(x)
```

Back to Maximizing the Margin

$$\mathbf{w}^* = argmin_{(\mathbf{w},\{\xi_\mathbf{n}\})}\frac{1}{2}||\mathbf{w}||^2 + C\sum_{n=1}^{N}\xi_n,$$

$$\text{subject to } \forall n, \quad t_n \cdot (\tilde{\mathbf{w}} \cdot \mathbf{x}_n) \geq 1 - \xi_n \text{ and } \xi_n \geq 0.$$

- C is constant that controls how costly constraint violations are.
- The problem is still convex.

——-> Minimization under constraints.

Adding Constraints

- In general, a constrained optimization problem can then be written as:

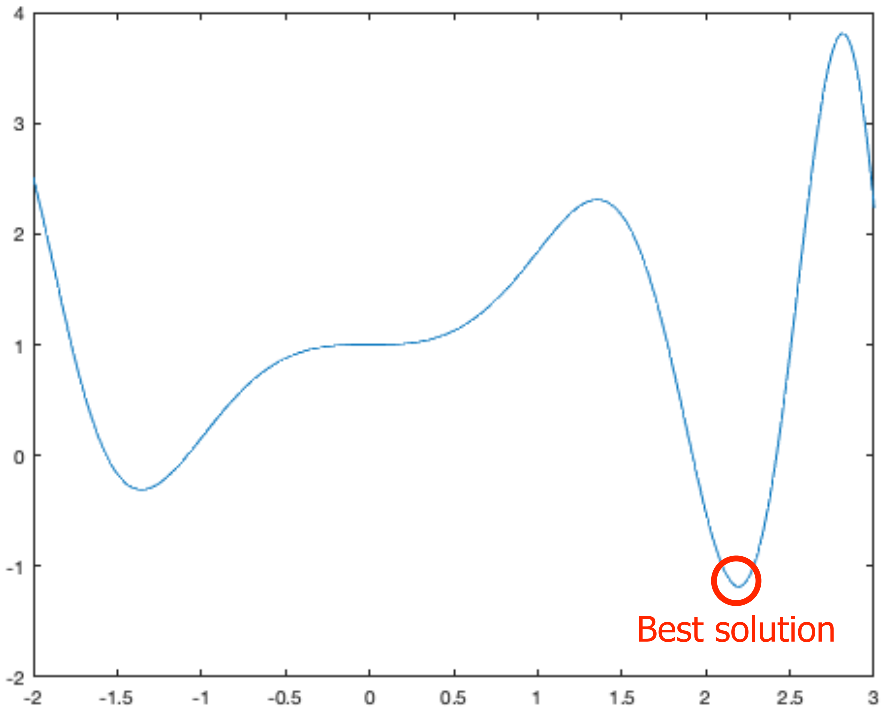
$$
\begin{aligned}
&\min_{\mathbf{x}} \; f(\mathbf{x}) \\
&\text{subject to} \quad f_i(\mathbf{x}) \leq 0, \quad i = 1,\ldots,M \qquad (M \text{ inequality constraints}) \\
&\qquad\qquad\quad\;\; h_i(\mathbf{x}) = 0, \quad i = 1,\ldots,P \qquad (P \text{ equality constraints})
\end{aligned}
$$

- Note that the constrained problem will typically not have the same solution as the unconstrained one.

Adding Constraints: Example

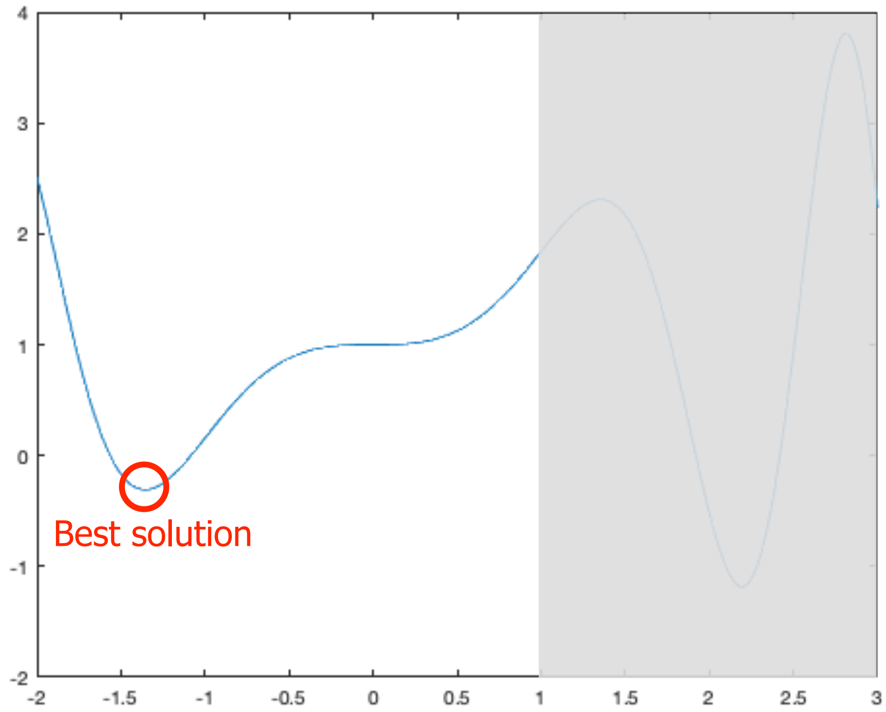
$$f(x) = x\sin(x^2) + 1$$

Unconstrained



Constrained

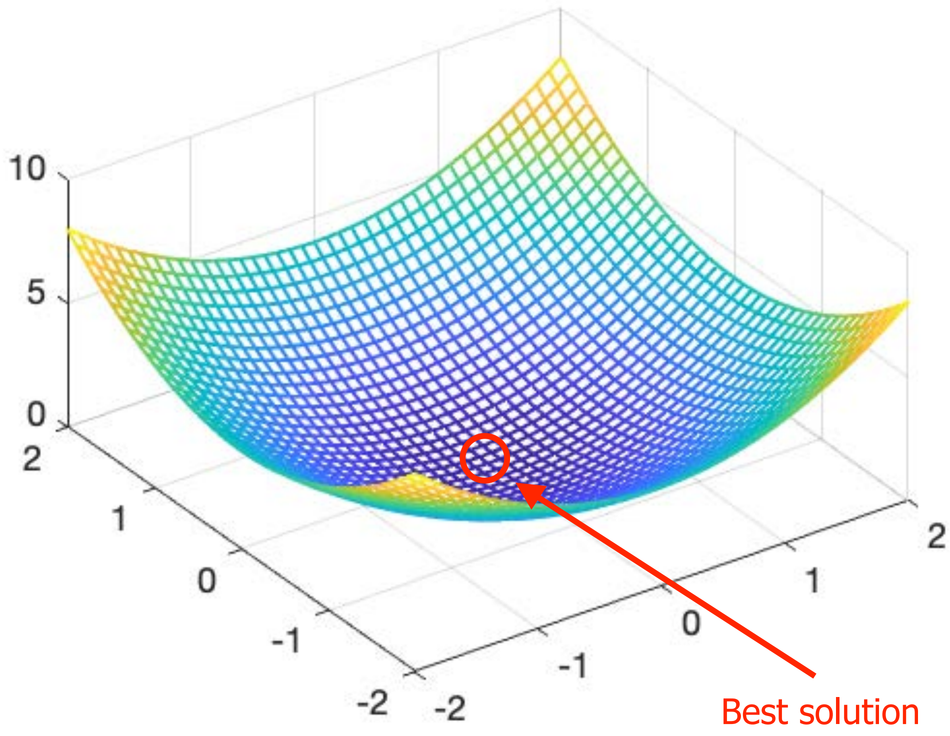
$f_1(x) = x - 1 \leq 0$



Adding Constraints: Example

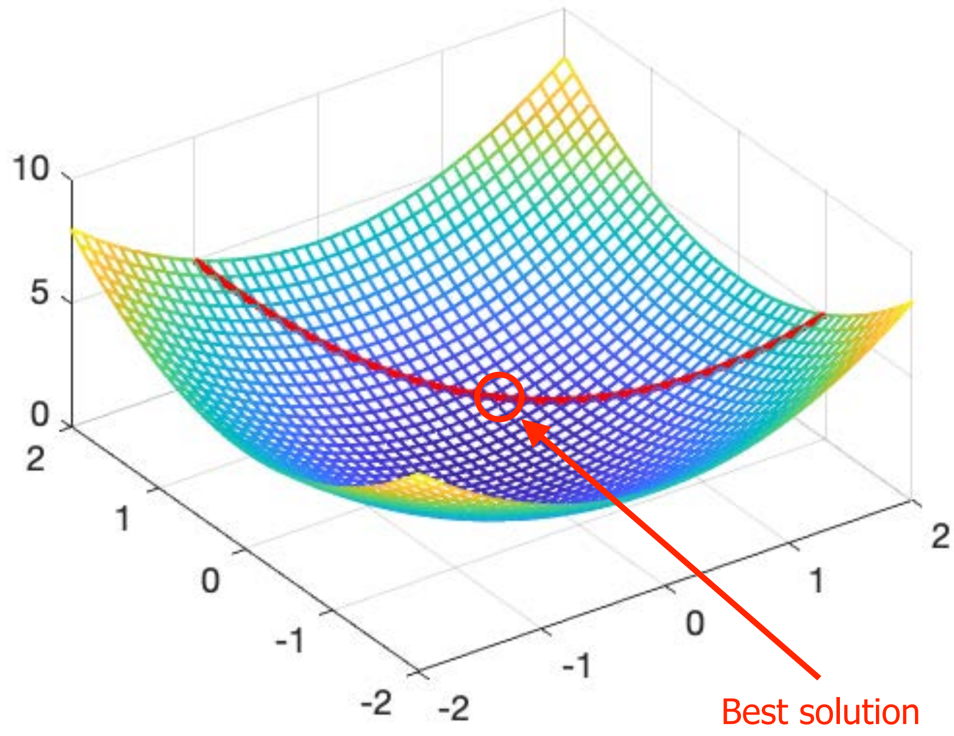
$$f(\mathbf{x}) = x_1^2 + x_2^2$$

Unconstrained

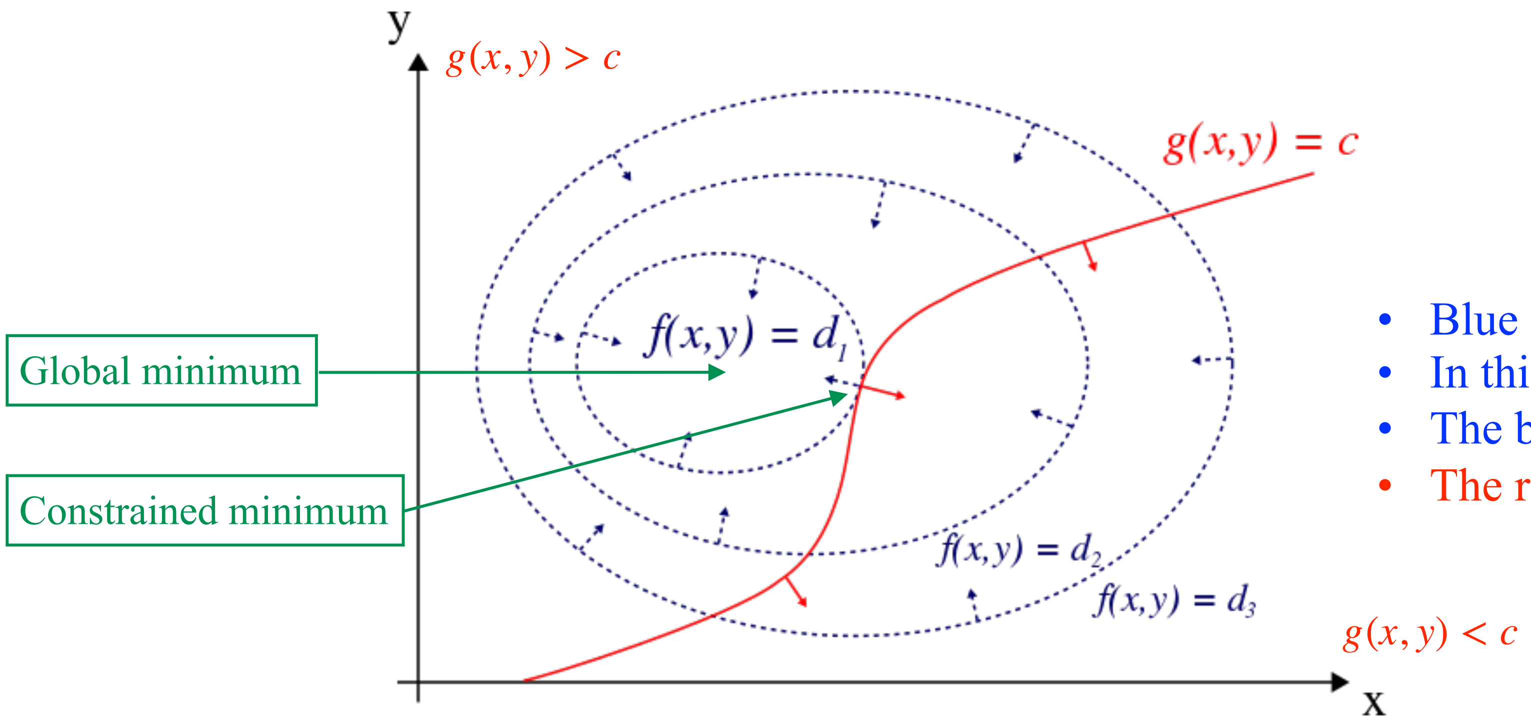


Constrained

$h_1(x) = x_1 + x_2 - 1 = 0$



Implicit Function Theorem



- Blue dotted lines are "level" lines.
- In this example, $d_1 < d_2 < d_3$.
- The blue arrows represent ∇f.
- The red arrows represent ∇g.

- Minimize $f(x, y)$ subject to $g(x, y) \leq c$.
- At the constrained minimum

$$\exists \lambda \in R, \nabla f = \lambda \nabla g$$

- λ is known as a Lagrange multiplier.

Lagrangian

$$\min_{\mathbf{x}} \; f(\mathbf{x})$$

$$\text{subject to} \quad f_i(\mathbf{x}) \le 0, \quad i = 1, \ldots, M$$
$$h_i(\mathbf{x}) = 0, \quad i = 1, \ldots, P$$

The Lagrangian is taken to be:

$$L(\mathbf{x}, \lambda, \nu) = f(\mathbf{x}) + \sum_{i=1}^{M} \lambda_i f_i(\mathbf{x}) + \sum_{i=1}^{P} \nu_i h_i(\mathbf{x})$$

- λ_i is the Lagrange multiplier associated with $f_i(\mathbf{x}) \le 0$
- ν_i is the Lagrange multiplier associated with $h_i(\mathbf{x}) = 0$

Lagrangian

$$\min_{\mathbf{x}} \; f(\mathbf{x})$$

$$\text{subject to} \quad f_i(\mathbf{x}) \leq 0, \quad i = 1, \ldots, M$$
$$h_i(\mathbf{x}) = 0, \quad i = 1, \ldots, P$$

$$L(\mathbf{x}, \lambda, \nu) = f(\mathbf{x}) + \sum_{i=1}^{M} \lambda_i f_i(\mathbf{x}) + \sum_{i=1}^{P} \nu_i h_i(\mathbf{x})$$

A solution of the constrained minimization problem must be such that L is minimized with respect to the components of vector $\mathbf{w}$ and maximized with respect to the Lagrange multipliers, which must remain greater or equal to zero.

KKT Conditions

$$\min_{\mathbf{x}} \; f(\mathbf{x})$$

$$\text{subject to} \quad f_i(\mathbf{x}) \leq 0, \quad i = 1, \ldots, M$$
$$h_i(\mathbf{x}) = 0, \quad i = 1, \ldots, P$$

$$L(\mathbf{x}, \lambda, \nu) = f(\mathbf{x}) + \sum_{i=1}^{M} \lambda_i f_i(\mathbf{x}) + \sum_{i=1}^{P} \nu_i h_i(\mathbf{x})$$

At the minimum

$$\nabla_{\mathbf{x}} L = 0$$

$$\nabla_{\lambda} L = 0$$

System of equations that can be solved.

$$\nabla_{\nu} L = 0$$

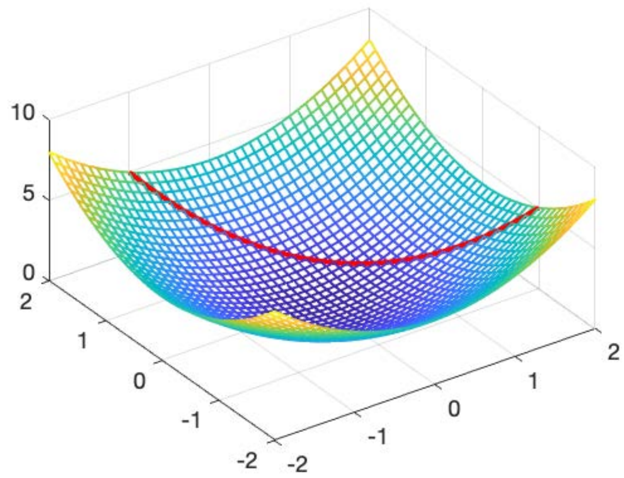
$$\lambda_i f(\mathbf{x}_i) = 0 \quad i = 1, \ldots, M$$

Bishop, Chapter 7.1

Example 1

$$\min_{\mathbf{x}} x_1^2 + x_2^2$$

subject to $x_1 + x_2 - 1 = 0$



$$L(\mathbf{x}, \nu_1) = x_1^2 + x_2^2 + \nu_1 \left(x_1 + x_2 - 1\right)$$

At the minimum:

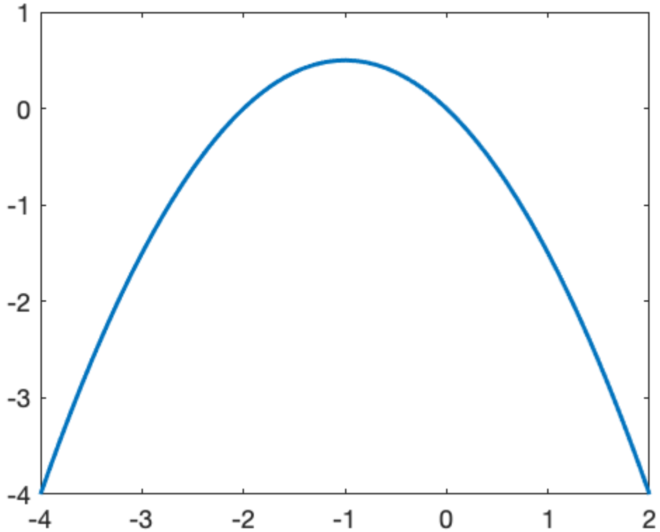
$$\nabla_{\mathbf{x}} L(\mathbf{x}, \nu_1) = \begin{bmatrix} 2x_1 + \nu_1 \\ 2x_2 + \nu_1 \end{bmatrix} = \mathbf{0} \Leftrightarrow \mathbf{x}^* = \begin{bmatrix} -\nu_1/2 \\ -\nu_1/2 \end{bmatrix}$$

Example 1

$$g(\nu_1) = L\left(\begin{bmatrix} -\nu_1/2 \\ -\nu_1/2 \end{bmatrix}, \nu_1\right) = \frac{1}{4}\nu_1^2 + \frac{1}{4}\nu_1^2 + \nu_1\left(-\frac{1}{2}\nu_1 - \frac{1}{2}\nu_1 - 1\right)$$

$$= -\frac{1}{2}\nu_1^2 - \nu_1$$

$g(\nu_1)$

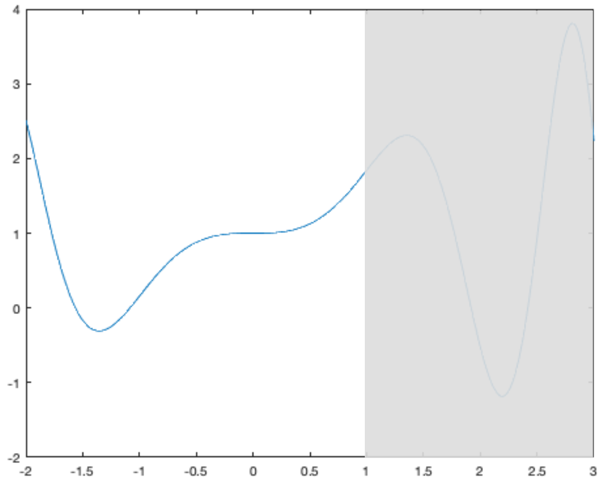


ν_1

- We can ν_1 find that maximizes g: $\nu_1 = -1.0$.
- In turn this gives us $\mathbf{x}^* = \begin{bmatrix} -\nu_1/2 \\ -\nu_1/2 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$.

Example 2

$$\min_x \; x \sin(x^2) + 1$$
$$\text{subject to} \;\; x - 1 \leq 0$$



$$L(x, \lambda_1) = x \sin(x^2) + 1 + \lambda_1 \, (x - 1)$$

There is no closed form solution to the minimization of L w.r.t. x.

- We write $$g(\lambda_1) = \min_x \; L(x, \lambda_1)$$ $$= \min_x \; x \sin(x^2) + 1 + \lambda_1 \, (x - 1)$$
- We maximize w.r.t. λ_1

Lagrange Dual Function

$$g(\lambda, \nu) = \inf_{\mathbf{x}} \; L(\mathbf{x}, \lambda, \nu)$$
$$= \inf_{\mathbf{x}} \left(f(\mathbf{x}) + \sum_{i=1}^{M} \lambda_i f_i(\mathbf{x}) + \sum_{i=1}^{P} \nu_i h_i(\mathbf{x}) \right)$$

- $g(\lambda, \nu)$ is a concave function, i.e. opposite of convex, single maximum also.
- We can find λ and ν by maximizing g:

$$\lambda^*, \nu^* = argmax_{\lambda,\nu} \; g(\lambda, \nu)$$
$$x^* = argmin_{\mathbf{x}} \; L(\mathbf{x}, \lambda^*, \nu^*)$$

—> We have turned our constrained optimization problem into an unconstrained one.

Optimization in Short

- Convex functions have a global minimum.
- It can be found using either 1st or 2nd order methods. The latter is usually faster but requires computing second derivatives.
- Non-convex functions can be optimized in a similar manner but this will usually yield a local minimum.
- Constraints can be imposed using the Lagrangian formalism.