

CE 191: Civil and Environmental Engineering Systems Analysis

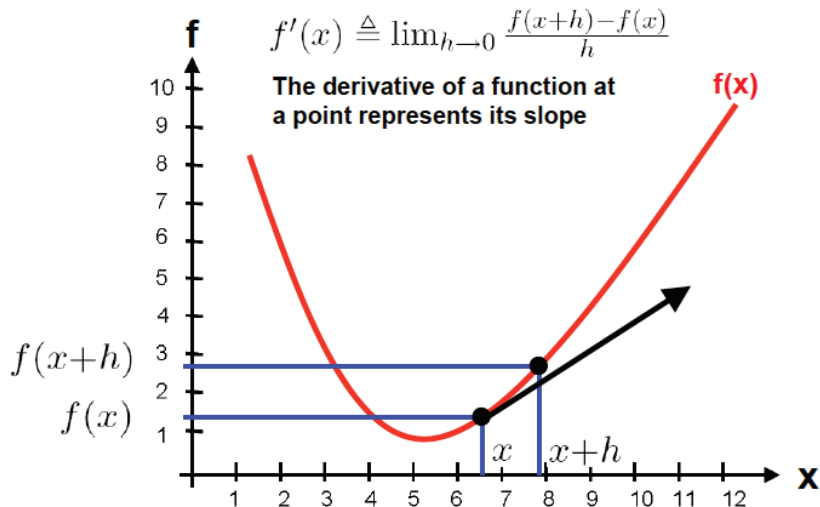
LEC 11 : Gradient Descent

Professor Scott Moura
Civil & Environmental Engineering
University of California, Berkeley

Fall 2014



Recall Definition of Derivative



Gradient Descent

Goal: Find the minimum of a differentiable function, starting from an initial guess, which cannot be easily visualized.

Exs:

$$f(x) = \exp(\sin x^2) + \sqrt{x^4 + 3} \sin \left[\exp \left(\frac{-1}{1 + \epsilon|x|} \right) \right]$$

$$g(x, y, z) = \sin \left(\frac{1}{2}x^2 - \frac{1}{4}y^2 + \frac{1}{8}z^2 \right) \cos(2x + 1 - e^y)$$

Main idea:

- 1 Make an initial guess
- 2 Compute the derivative at this point (i.e. slope)
- 3 Follow the direction of the slope (i.e. descend)
- 4 Stop when the slope becomes zero

Recall Definition of Derivative

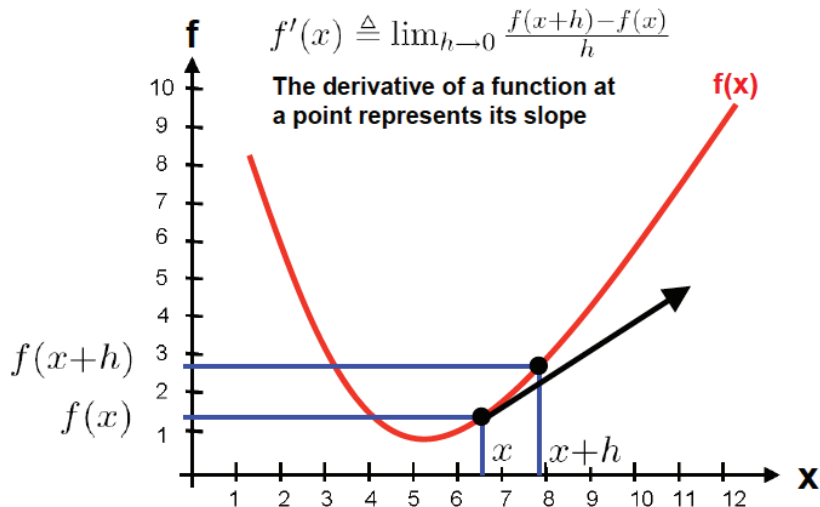


Illustration of Gradient Descent

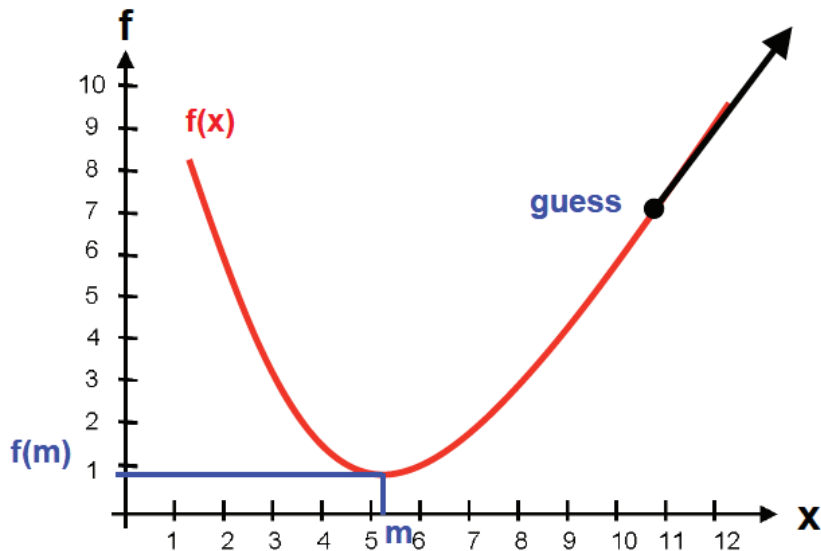


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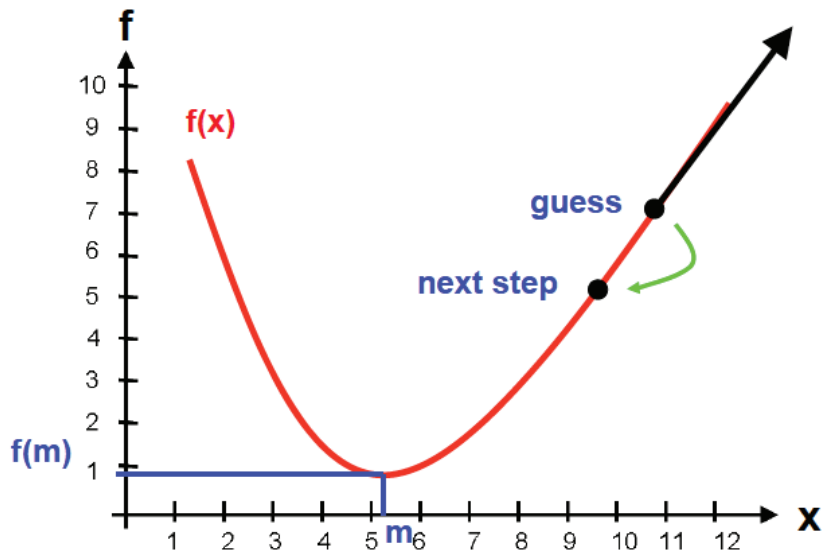


Illustration of Gradient Descent

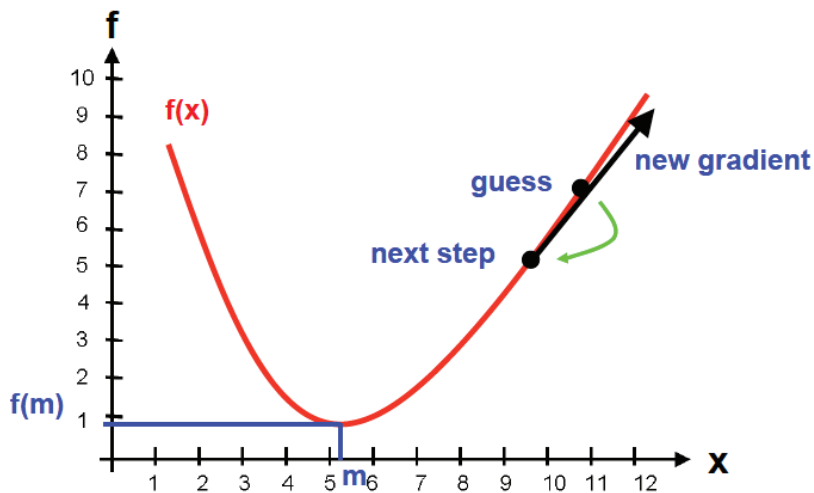


Illustration of Gradient Descent

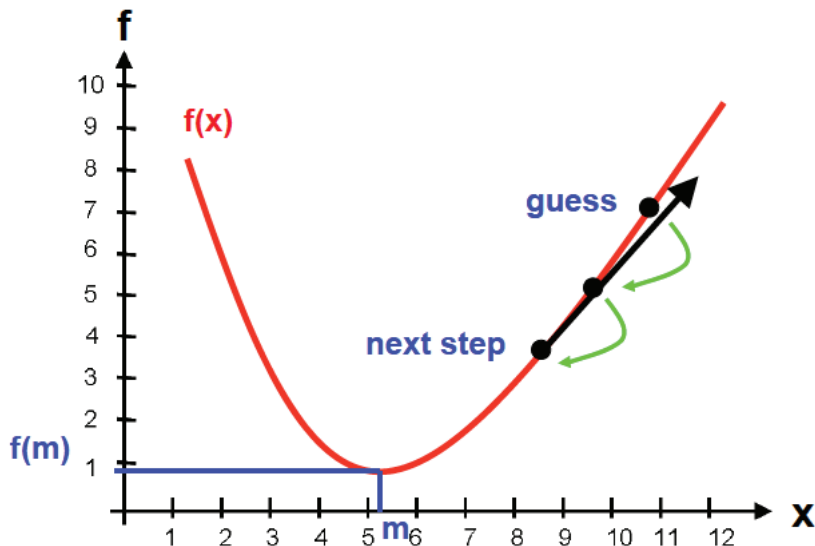
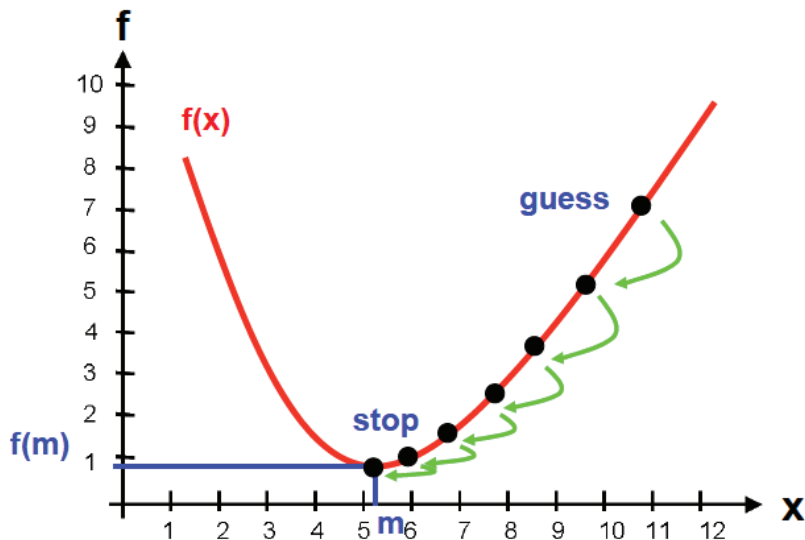
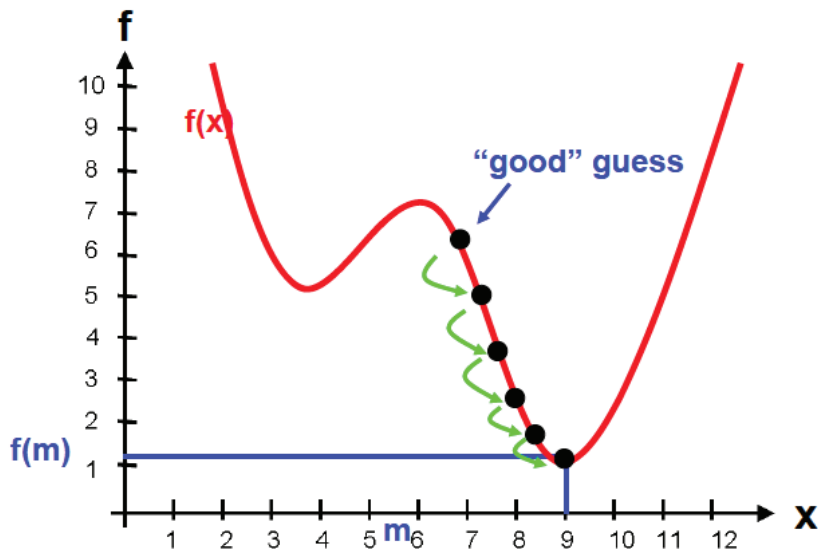


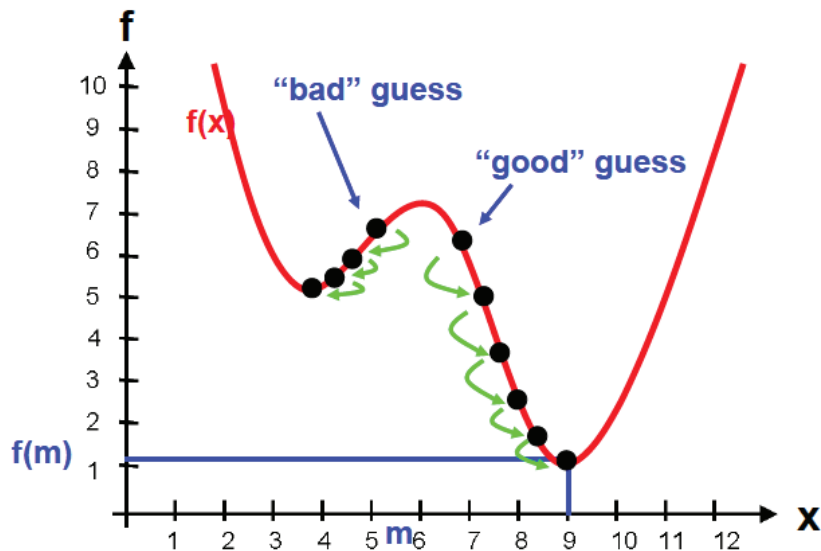
Illustration of Gradient Descent



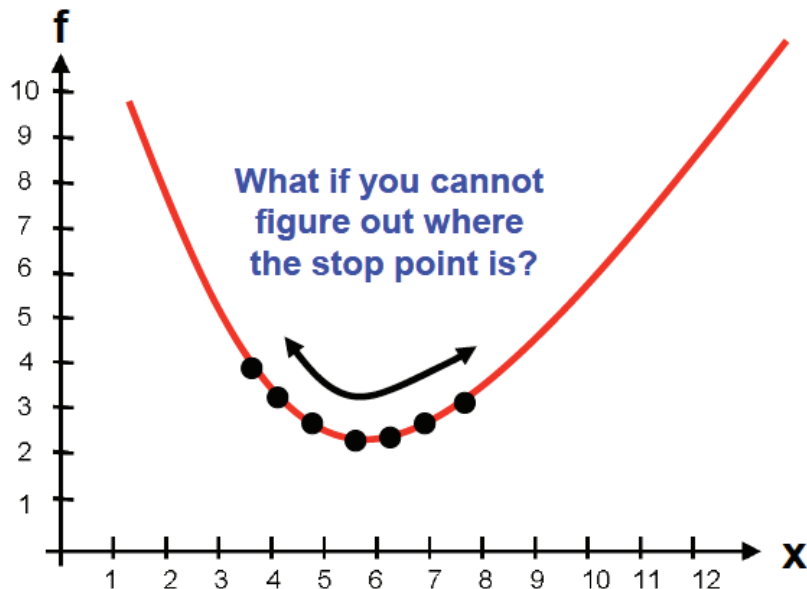
Problem 1: Non-convex function



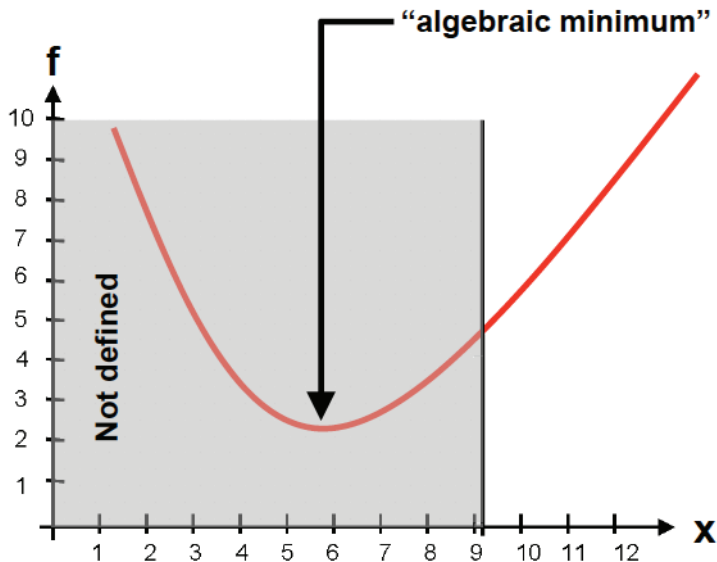
Problem 1: Non-convex function



Problem 2: How to stop?



Problem 3: How to hit a wall?



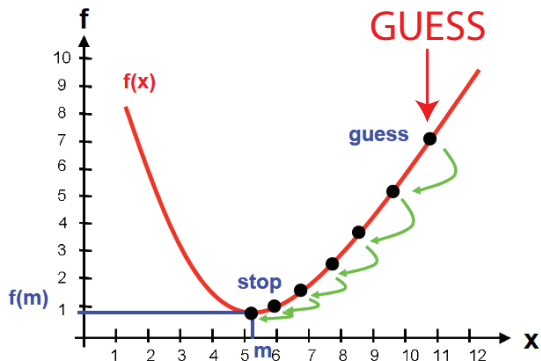
Gradient Descent Algorithm

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- Update

Until stopping criterion is satisfied



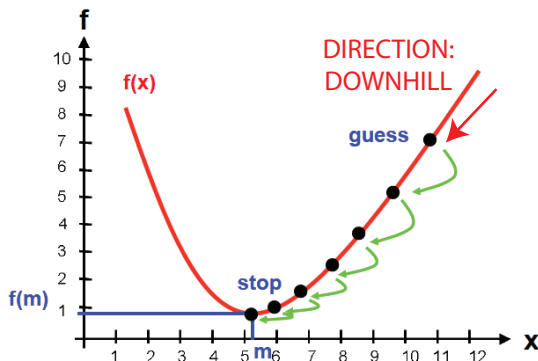
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Gradient Descent Algorithm

Start with an initial guess

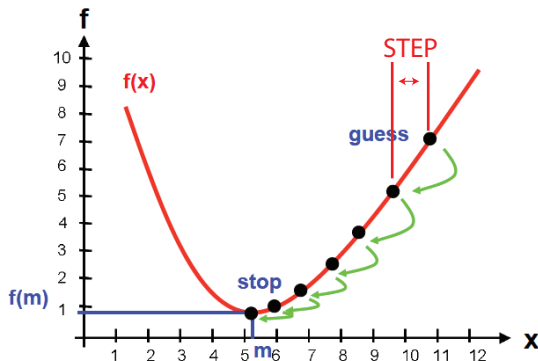
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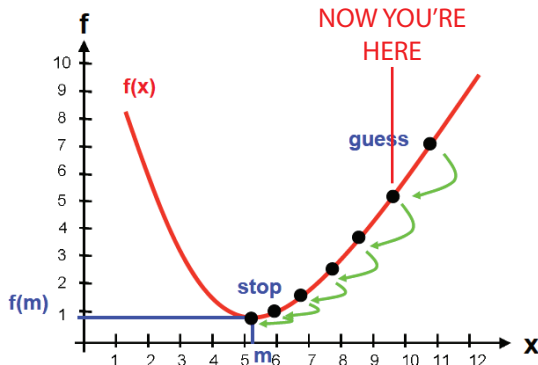
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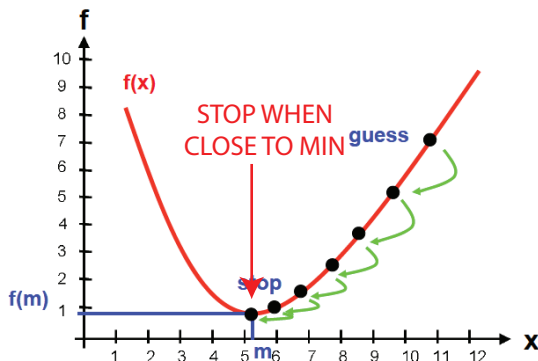
Gradient Descent Algorithm

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Gradient Descent Algorithm

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- Update

Until stopping criterion is satisfied

Pseudo-code:

guess x_0

direction = $-f'(x)$

step = $h > 0$

$x_{k+1} = x_k - h \cdot f'(x_k)$

stop when $f'(x_k) \approx 0$

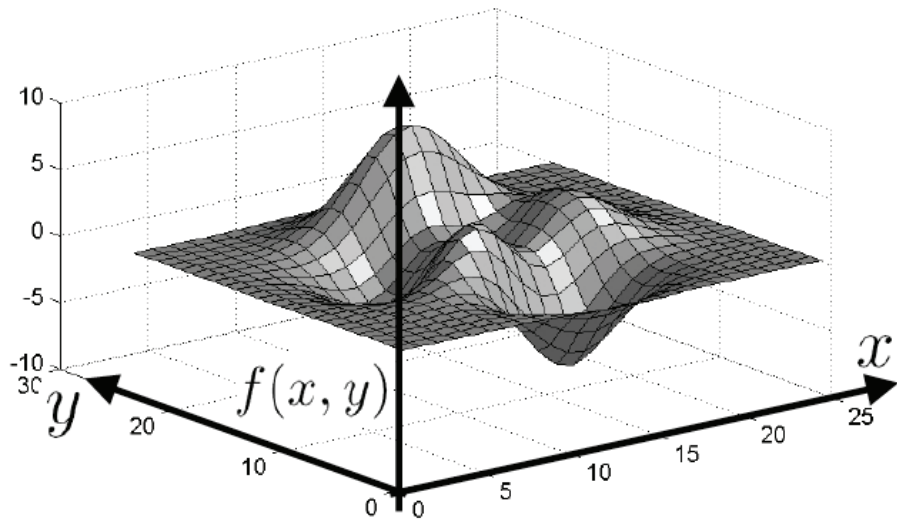
Gradient in 2D

Definition of gradient in 2D

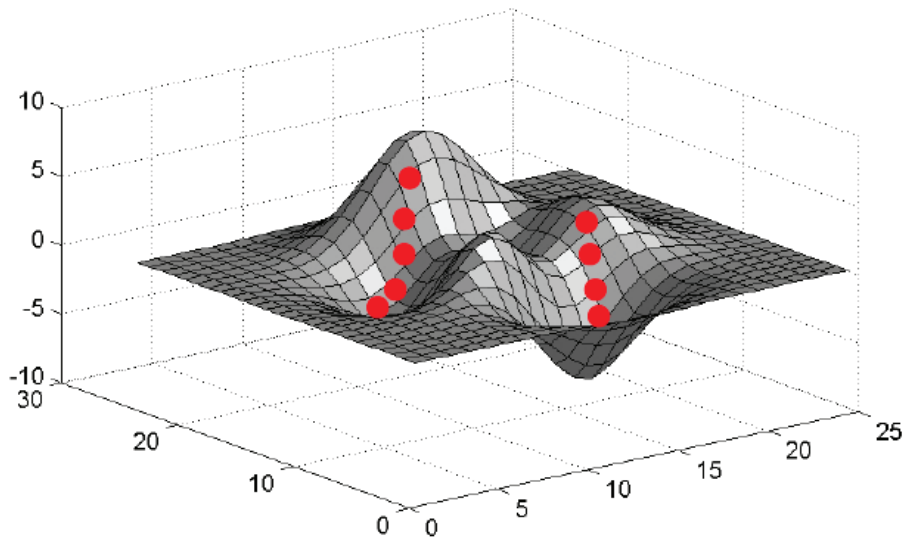
$$\nabla f(x, y) = \begin{bmatrix} \frac{\partial f}{\partial x}(x, y) \\ \frac{\partial f}{\partial y}(x, y) \end{bmatrix}$$

Generalization of derivative in two dimensions

Gradient Descent in 2D



Gradient Descent in 2D



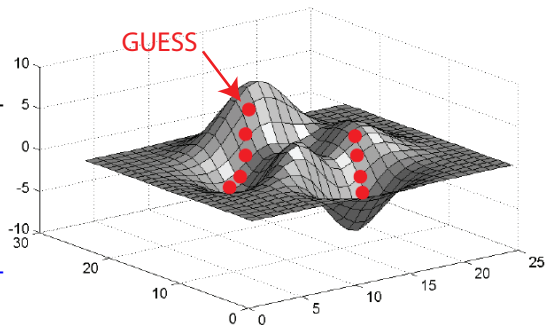
Gradient Descent Algorithm in 2D

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- Update

Until stopping criterion is satisfied



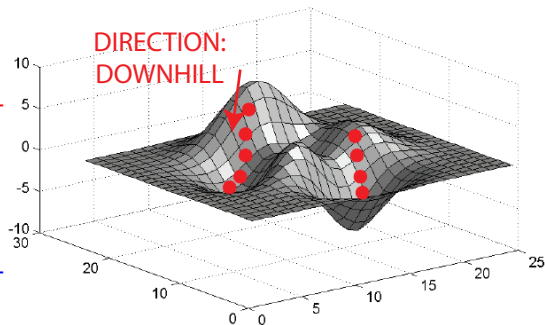
Gradient Descent Algorithm in 2D

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- Update

Until stopping criterion is satisfied



Gradient Descent Algorithm in 2D

Start with an initial guess

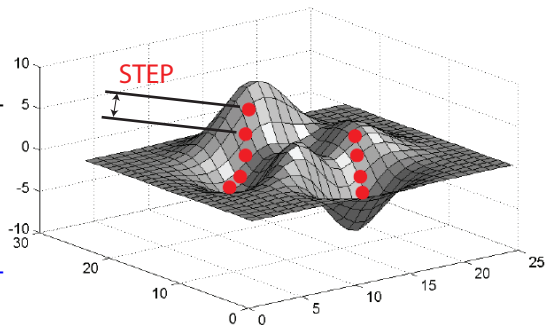
Repeat

- Determine a descent direction

- Choose a step size

- Update

Until stopping criterion is satisfied



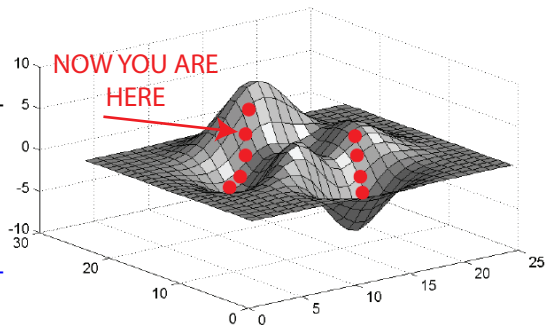
Gradient Descent Algorithm in 2D

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- **Update**

Until stopping criterion is satisfied



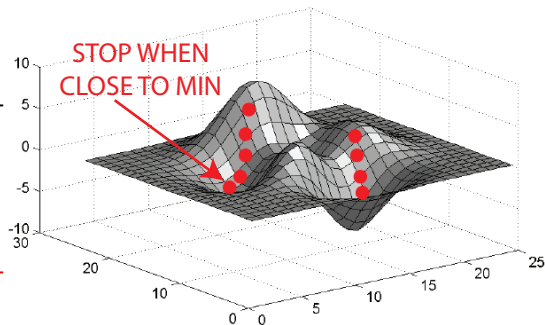
Gradient Descent Algorithm in 2D

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- Update

Until stopping criterion is satisfied



Gradient Descent Algorithm in 2D

Start with an initial guess

Repeat

- Determine a descent direction
- Choose a step size
- Update

Until stopping criterion is satisfied

Pseudo-code:

guess x_0

direction = $-\nabla f(x)$

step = $h > 0$

$x_{k+1} = x_k - h \cdot \nabla f(x_k)$

stop when $\nabla f(x_k) \approx 0$

Gradient in Multiple Dimensions

Can be generalized to multiple dimensions

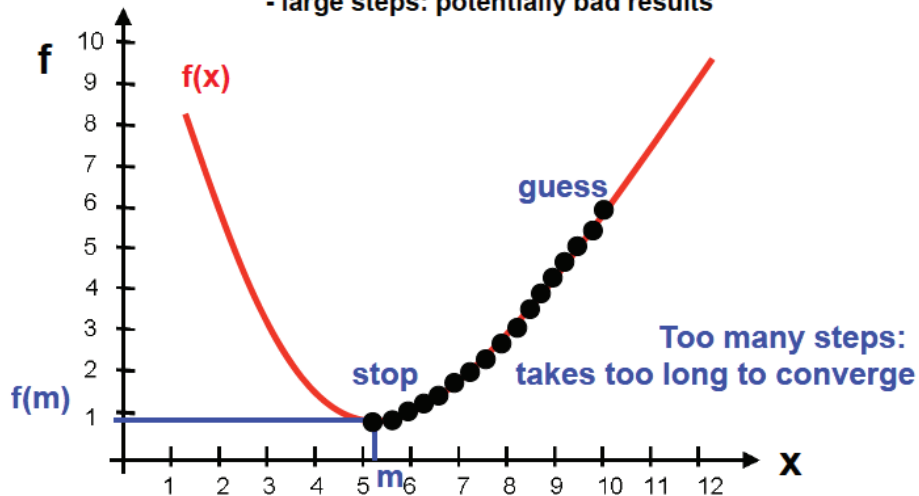
$$\nabla f(x_1, x_2, \dots, x_N) = \left[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_N} \right]$$

Generalization of derivative in two dimensions

Problem 1: Choice of Step

When updating the current computation:

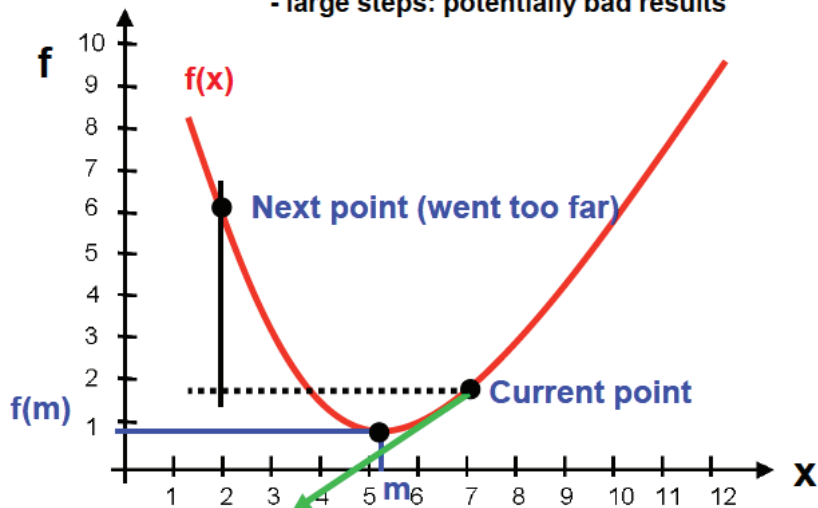
- small steps: inefficient
- large steps: potentially bad results



Problem 1: Choice of Step

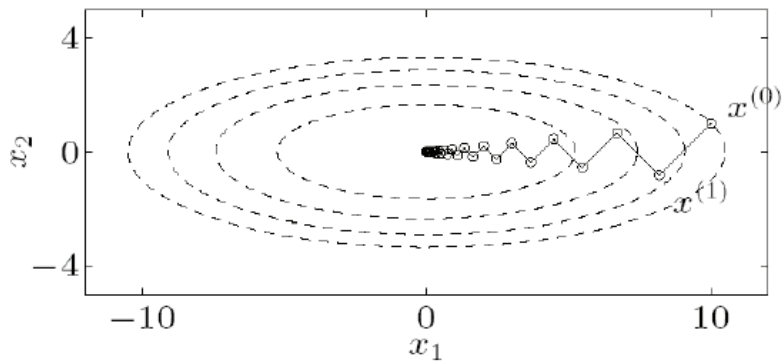
When updating the current computation:

- small steps: inefficient
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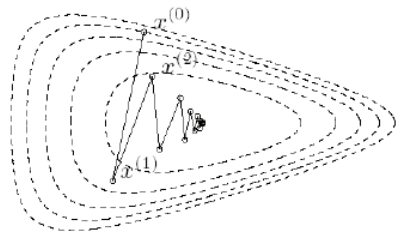
Problem 2: Ping pong effect

$$f(x_1, x_2) = \frac{1}{2} (x_1^2 + \gamma x_2^2), \quad \gamma > 0$$

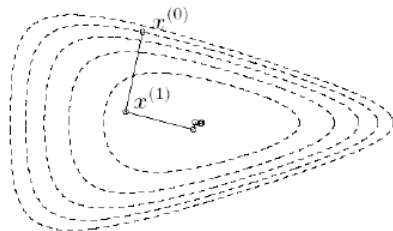


Problem 2: Ping pong effect

$$f(x_1, x_2) = e^{x_1+3x_2-0.1} + e^{x_1-3x_2-0.1} + e^{-x_2-0.1}$$



backtracking line search



exact line search

More info: Section 9.2 of Boyd's CVX Textbook

Problem 3: Stopping Criterion

One intuitive criterion

$$|f'(x_k)| \leq \epsilon, \quad \text{for some small } \epsilon > 0$$

Or in multiple (e.g. N) dimensions

$$\|\nabla f(x_k)\|_2 \leq \epsilon, \quad \text{for some small } \epsilon > 0$$

where the 2-norm, expanded, is

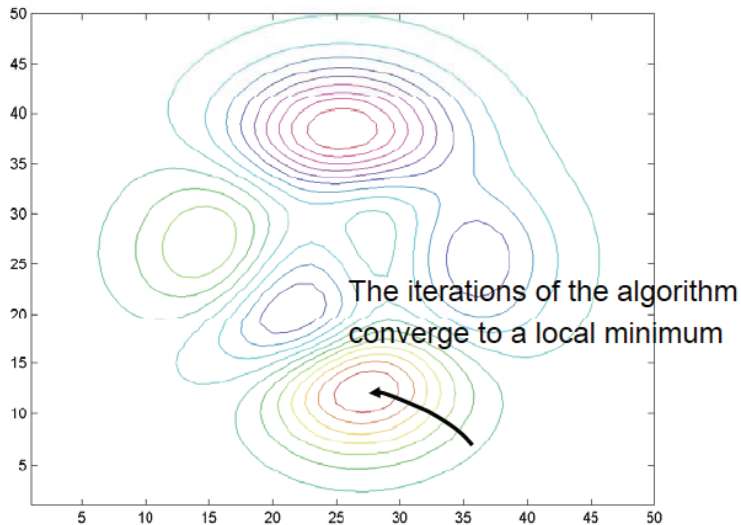
$$\|\nabla f(x_k)\|_2 = \sqrt{\sum_{i=1}^N \left[\frac{\partial f}{\partial x_i}(x_k) \right]^2} = \sqrt{\left[\frac{\partial f}{\partial x_1}(x_k) \right]^2 + \left[\frac{\partial f}{\partial x_2}(x_k) \right]^2 \cdots \left[\frac{\partial f}{\partial x_N}(x_k) \right]^2} \leq \epsilon$$

Several methods exist to alleviate these three problems

- Linear search methods (e.g. backtracking or exact line search)
- Normalized Steepest Descent
- Newton steps

Fundamental Problem: Local Minima

Example of Local Minima



Additional Reading

Boyd & Vandenberghe, Chapter 9

Papalambros & Wilde, Section 4.5, 4.6

EE 227 - Convex Optimization with Prof. El Gaothi