

# MAT 423: Homework 8 (11/07)

In the three exercises, we consider the following function to minimize:

$$\phi(x, y) = \frac{x^4}{4} - \frac{5x^3}{3} + 3x^2 + y^2.$$

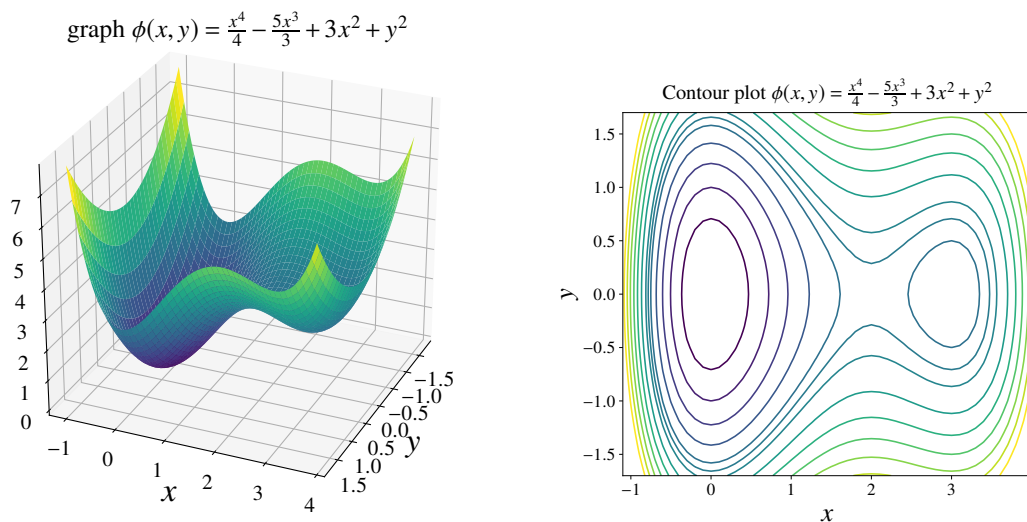


Figure 1: Surface plot of the function  $\phi(x, y)$  (left) and contour plot (right), i.e. curves where  $\phi(x, y) = \text{Constant}$ .

## Ex 1. [Warm up]

a) Show that  $\phi$  is *coercive*<sup>1</sup>, i.e.:

$$\phi(x, y) \xrightarrow{\|(x,y)\| \rightarrow +\infty} +\infty.$$

Deduce that there exists an infimum of  $\phi$  on  $\mathbb{R}^2$ :

$$\inf_{(x,y) \in \mathbb{R}^2} \phi(x, y) = \min_{(x,y) \in \mathbb{R}^2} \phi(x, y).$$

b) Find and study the critical points of  $\phi$ .  
Deduce the global minimum of  $\phi$  on  $\mathbb{R}^2$ .

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<sup>1</sup>In other words,  $\phi$  goes to infinity at infinity.

**Ex 2. [Newton vs BFGS]**

We would like to compare the Newton's method and the quasi-Newton BFGS to find critical points of  $\phi$  (i.e. solving  $\nabla\phi = \mathbf{0}$ ).

- a) Starting from  $\mathbf{x}^{(0)} = (\frac{1}{2}, 1)$ , compute explicitly the first iteration of the Newton's method:

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} - [D^2\phi(\mathbf{x}^{(0)})]^{-1}\nabla\phi(\mathbf{x}^{(0)}).$$

- b) Implement the BFGS method (see next page).  
Compare the evolution of  $\phi(\mathbf{x}^{(k)})$  with  $\mathbf{x}^{(k)}$  computed using **i)** the Newton's method and **ii)** the quasi-Newton method BFGS (plot in logarithm scale).
- c) Find another initial condition  $\mathbf{x}^{(0)}$  such that both methods do **not** converge to the global minimum.

**Ex 3. [Gradient descent]**

- a) Implement the gradient descent algorithm:

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \lambda\nabla\phi(\mathbf{x}^{(k)}), \tag{1}$$

where  $\lambda > 0$  is a fixed parameter (the "learning rate").

- b) Starting from  $\mathbf{x}^{(0)} = (\frac{1}{2}, 1)$ , study the convergence of the algorithm for different learning rates, i.e. taking  $\lambda = 0.05, 0.1, 0.2, 0.5$ .

*Extra)* One can *adapt* the learning rate  $\lambda$  while performing the gradient descent. The idea is to reduce  $\lambda$  when the updated value  $\phi(\mathbf{x}^{(k+1)})$  does not decay. The algorithm is as followed:

- 1) Starting from  $\mathbf{x}^{(k)}$  and  $\lambda$ , compute:

$$\tilde{\mathbf{x}} = \mathbf{x}^{(k)} - \lambda\nabla\phi(\mathbf{x}^{(k)}).$$

- 2) If  $\phi(\tilde{\mathbf{x}}) < \phi(\mathbf{x}^{(k)})$  then:

$$\text{let } \mathbf{x}^{(k+1)} = \tilde{\mathbf{x}}, \text{ keep } \lambda$$

else:

$$\text{let } \mathbf{x}^{(k+1)} = \mathbf{x}^{(k)}, \lambda = \frac{\lambda}{2}.$$

Go back to 1)

Apply the algorithm starting with  $\mathbf{x}^{(0)} = (\frac{1}{2}, 1)$  and  $\lambda = 0.5$ .

## Broyden–Fletcher–Goldfarb–Shanno (BFGS) method

- a) Initialization:  $\mathbf{x}^{(0)}, \mathbf{x}^{(1)}, A^{(0)}$
- Pick  $\mathbf{x}^{(0)}$  and define  $A^{(0)} = D^2\phi(\mathbf{x}^{(0)})$ .
  - Define the first iteration:  $\mathbf{x}^{(1)} = \mathbf{x}^{(0)} - [D^2\phi(\mathbf{x}^{(0)})]^{-1}\nabla\phi(\mathbf{x}^{(0)})$ .
- b) “ $n \rightsquigarrow n + 1$ ”. Denote  $\Delta\mathbf{x} = \mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}$  and  $\Delta\mathbf{y} = \nabla\phi(\mathbf{x}^{(k)}) - \nabla\phi(\mathbf{x}^{(k-1)})$ .
- Update  $A^{(k)}$  (to satisfy the secant formula):

$$A^{(k)} = A^{(k-1)} + \frac{\Delta\mathbf{y} \otimes \Delta\mathbf{y}}{\langle \Delta\mathbf{y}, \Delta\mathbf{x} \rangle} - \frac{A^{(k-1)}\Delta\mathbf{y} \otimes \Delta\mathbf{y}A^{(k-1)}}{\langle A^{(k-1)}\Delta\mathbf{x}, \Delta\mathbf{x} \rangle}$$

- Update  $\mathbf{x}^{(k+1)}$

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - [A^{(k)}]^{-1}\nabla\phi(\mathbf{x}^{(k)}).$$

The inverse of  $A^{(k)}$  should be computed using the formula:

$$[A^{(k)}]^{-1} = [A^{(k-1)}]^{-1} + \alpha\Delta\mathbf{x} \otimes \Delta\mathbf{x} + \beta(\Delta\mathbf{x} \otimes \mathbf{v} + \mathbf{v} \otimes \Delta\mathbf{x})$$

with :

$$\mathbf{v} = [A^{(k-1)}]^{-1}\Delta\mathbf{y} \quad , \quad \alpha = \frac{\langle \Delta\mathbf{x}, \Delta\mathbf{y} \rangle + \langle \mathbf{v}, \Delta\mathbf{y} \rangle}{\langle \Delta\mathbf{x}, \Delta\mathbf{y} \rangle^2} \quad , \quad \beta = -\frac{1}{\langle \Delta\mathbf{x}, \Delta\mathbf{y} \rangle}.$$

This formula is obtained using the Woodbury matrix identity (after some computations...).