

## MATH 437 Homework 7 (20 points)

1. Consider the system

$$\begin{aligned}x_1^2 - x_2^2 &= 0, \\x_1^3 + x_2^3 - 16 &= 0.\end{aligned}$$

- (a) (2 points) Write down Newton's method for this system.
- (b) (2 points) Compute 7 iterations of Newton's method for this system, starting with the initial condition  $x_1 = x_2 = 1$ . Report the iterations in a table with columns  $n$ ,  $x_1^{(n)}$ ,  $x_2^{(n)}$ , where  $x_i^{(n)}$  is the value of  $x_i$  at the  $n$ th iteration and  $n = 0, \dots, 7$ .

- (a) *Hint.* Define a function  $F : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $F(x)$  is related to the given system. Then, compute the Jacobian matrix

$$\nabla F(x)_{i,j} := \partial_j F_i(x).$$

Newton's method is then

$$x^{(n+1)} = x^{(n)} - \nabla F(x^{(n)})^{-1} F(x^{(n)}).$$

Note: the original system in the homework posted by the professor cannot be solved with Newton's method, because the Jacobian of  $F$  becomes singular at the root for that system. Thus, I modified the problem to be solveable. □

- (b) *Hint.* See `problem_1b.py`. □

2. (4 points) Consider the minimization problem

$$\min_{x_1, x_2 \in \mathbb{R}} \{(x_1 + x_2 - 4)^2 + (x_1^2 + x_2^2 - 8)^2\}.$$

Write the gradient descent method for this problem and compute 2 iterations starting with initial guess  $x_1 = x_2 = 1$ .

*Hint.* Define a function  $g : \mathbb{R}^2 \rightarrow \mathbb{R}$  where  $g(x)$  is related to the minimization problem. Then, compute its gradient

$$\nabla g(x)_j := \partial_j g(x).$$

The gradient descent method involves computing an optimal step size  $0 < \alpha_n \leq 1$  such that

$$x^{(n+1)} := x^{(n)} - \alpha_n \frac{g(x^{(n)})}{\|g(x^{(n)})\|_{\ell^2}}$$

so that  $g(x^{(n+1)}) \leq g(x^{(n)})$ . Explain how to find  $\alpha_n$  by minimizing a related quadratic polynomial. For the implementation, see `problem_2.py`. □

3. (4 points) Find a singular-value decomposition  $A = U\Sigma V^T$  for the matrix

$$A := \begin{bmatrix} 2 & 1 \\ 1 & 0 \\ 0 & 2 \end{bmatrix}.$$

*Hint.* Recall that  $U$  is a  $m \times m$  orthogonal matrix,  $\Sigma$  is a  $m \times n$  matrix with the singular values on the main diagonal, and  $V$  is a  $n \times n$  orthogonal matrix. Find the singular values and the columns of  $V$  by first finding the eigenvalues and eigenvectors of  $A^T A$ . Use the columns of  $V$  to find the first  $n$  columns of  $U$ , and then extend to an orthonormal basis of  $\mathbb{R}^m$  to find the remaining columns of  $U$ .  $\square$

4. Let  $M \geq N$ . Given  $N$  vectors  $a_1, \dots, a_N \in \mathbb{R}^M$ , we form the  $M \times N$  matrix  $A := [a_1 \cdots a_N]$ . Let  $\sigma_1 \geq \cdots \geq \sigma_N \geq 0$  denote the singular values of  $A$ , and let  $u_1, \dots, u_N \in \mathbb{R}^M$  be the columns of  $U$  in a singular-value decomposition  $A = U\Sigma V^T$ , where  $u_j$  corresponds to  $\sigma_j$  and  $\sigma_j$  is the  $j$ th diagonal entry of  $\Sigma$ . It is known that  $u_1$  is a minimizer for

$$\min_{\substack{u \in \mathbb{R}^M \\ \|u\|_2=1}} \sum_{j=1}^N \|a_j - \langle a_j, u \rangle_2 u\|_2^2,$$

where

$$\langle v, w \rangle_2 := \sum_{i=1}^M v_i w_i$$

and

$$\|w\|_2^2 := \sum_{i=1}^M w_i^2.$$

We investigate this via a computational example.

- (a) (2 points) Let  $M = 80$  and  $N = 20$ . Construct a  $M \times N$  matrix  $A$  with random entries. Perform a singular-value decomposition of  $A$  to find the unit eigenvector  $u_1$  corresponding to the largest singular value.
- (b) (1 point) Compute the projection error

$$\text{Err} := \sum_{j=1}^N \|a_j - \langle a_j, u_1 \rangle_2 u_1\|_2^2$$

and the relative projection error

$$E := \frac{\text{Err}}{\sum_{j=1}^N \|a_j\|_2^2}.$$

- (c) (1 point) Construct a random unit vector  $u \in \mathbb{R}^M$  and compute the projection

$$\sum_{j=1}^N \|a_j - \langle a_j, u \rangle_2 u\|_2^2.$$

*Hint.* See `problem_4.py`.  $\square$

5. Given  $f, g : \mathbb{R}^2 \rightarrow \mathbb{R}$ , consider the system

$$\begin{aligned} x &= f(x, y), \\ y &= g(x, y), \end{aligned}$$

and the non-standard fixed-point iteration

$$\begin{aligned} x_{n+1} &= f(x_n, y_n), \\ y_{n+1} &= g(x_{n+1}, y_n). \end{aligned}$$

- (a) (2 points) Determine the convergence criteria for this method.

- (b) (2 points) Let  $f(x, y) = 2y$  and  $g(x, y) = (x - y)/2$ . Find the matrices  $T_1$  and  $T_2$  such that the non-standard fixed point iteration in matrix form is

$$\begin{bmatrix} x_{n+1} \\ y_{n+1} \end{bmatrix} = T_1 \begin{bmatrix} x_n \\ y_n \end{bmatrix},$$

and the standard fixed-point iteration in matrix form is

$$\begin{aligned} x_{n+1} &= f(x_n, y_n), \\ y_{n+1} &= g(x_n, y_n). \end{aligned} \implies \begin{bmatrix} x_{n+1} \\ y_{n+1} \end{bmatrix} = T_2 \begin{bmatrix} x_n \\ y_n \end{bmatrix}.$$

Find the spectral radius of the matrices  $T_1$  and  $T_2$ . Based on this, which method, if any, converges?

- (a) *Hint.* Let  $x_{n+1}, y_{n+1}$  be obtained from the method above, and let  $x, y$  be the solution to

$$\begin{aligned} x &= f(x, y), \\ y &= g(x, y). \end{aligned}$$

Assume that  $f$  and  $g$  are smooth functions. To determine a convergence criteria, we look at the error in each component

$$\begin{aligned} x_{n+1} - x &= f(x_n, y_n) - f(x, y), \\ y_{n+1} - y &= g(x_{n+1}, y_n) - g(x, y). \end{aligned}$$

By using Taylor's theorem on each equation, obtain an equation in matrix-vector form:

$$\begin{bmatrix} x_{n+1} - x \\ y_{n+1} - y \end{bmatrix} = T_1(\xi_n, \eta_n) \begin{bmatrix} x_n - x \\ y_n - y \end{bmatrix},$$

where  $T_1(\xi_n, \eta_n)$  is a  $2 \times 2$  matrix whose entries are composed of partial derivatives of  $f$  and  $g$  at some points  $\xi_n$  and  $\eta_n$  that come from Taylor's theorem. The method converges if and only if the spectral radius of this matrix is strictly less than 1.  $\square$

- (b) *Hint.* You already computed the matrix  $T_1$  in the previous step. Just substitute for  $f$  and  $g$  and find its largest eigenvalue in magnitude. The matrix  $T_2$  is just the Jacobian of the function  $F(x, y) = (f(x, y), g(x, y))$ . The class notes discuss this in more detail.  $\square$