

# Homework 1

January 18, 2025

Please submit your HW on Canvas; include a PDF printout of any code and results, clearly labeled, e.g. from a Jupyter notebook. For coding problems, we recommend using Julia, but you can use other languages if you wish. It is due Friday January 24th by 11:59pm EST.

## Problem 1 (10 points)

Start reading the draft course notes (linked from <https://github.com/mitmath/matrixcalc/>). Find a place that you found confusing, and write a paragraph explaining the source of your confusion and (ideally) suggesting a possible improvement.

(Any other corrections/comments are welcome, too.)

## Problem 2 (10 points)

Later in the class we will look analytically at derivatives of eigenproblems. Here you will begin to look at them empirically, with numerical experiments, using finite differences  $\delta f = f(x + \delta x) - f(x) \approx f'(x)[\delta x]$ .

Let  $f(A) = \lambda$  be a function that maps a real-symmetric matrix  $A$  to one of its eigenvalues  $\lambda$  (e.g. the smallest one), satisfying  $Av = \lambda v$  for some eigenvector  $v$  normalized to  $\|v\| = 1$ , and suppose that the eigenvalue is *not* a multiple eigenvalue. Demonstrate through numerical evidence on random  $4 \times 4$  matrices that  $\nabla \lambda = vv^T$ .

(This result is known as the “Hellmann–Feynman theorem” in physics.)

## Problem 3 (4+4+4+4 points)

Find the derivatives  $f'$  of the following functions. If  $f$  maps column vectors or matrices to scalars, give  $\nabla f$  (so that  $f'(x)[dx] = \langle \nabla f, dx \rangle$  in the usual inner product). If  $f$  maps column vectors to column vectors, give the Jacobian matrix. Otherwise, simply write down  $f'$  as a linear operation.

1.  $f(x) = g.(x)$ , denoting (in Julia notation) element-wise application of some scalar function  $g$  (in terms of its scalar derivative  $g'$ ), for  $x \in \mathbb{R}^m$ .
2.  $f(A) = (A^T A)^{-1}$  where  $A$  is an  $m \times n$  matrix (with  $m \geq n$  so that  $A^T A$  is invertible for most  $A$ ).
3.  $f(x) = (I + xx^T)^{-1}x$  for  $x \in \mathbb{R}^n$ .
4.  $f(A) = \text{trace}(A^3)$  where  $A$  is an  $m \times m$  matrix.

## Problem 4 (5+5 points)

Use the “linear operator” definition of Kronecker products, where  $A \otimes B$  is interpreted as a linear operator on matrices given by  $(A \otimes B)[C] = BC A^T$ , to show

1. Associativity:

$$A \otimes (B \otimes C) = (A \otimes B) \otimes C.$$

2. Mixed Products:

$$(A \otimes B)(C \otimes D) = (AC \otimes BD).$$

### Problem 5 (4+4+4 points)

For this problem, recall that Newton's method finds a root  $f(x) = 0$  of a function  $f(x)$  by iteratively improving a guess  $x$  to  $x \rightarrow x - f'(x)^{-1}f(x)$ , assuming the derivative (or Jacobian)  $f'$  is square and invertible. It converges extremely rapidly if you start with a good enough initial guess.

If  $A$  is an  $n \times n$  matrix, an ordinary eigenvalue  $\lambda$  solves  $\det(A - \lambda I) = 0$ . More generally, you can find the roots  $\det M(\lambda) = 0$  where  $M(\lambda)$  is some arbitrary matrix-valued function of  $\lambda$ : this is called a *nonlinear eigenvalue problem* and arises in lots of applications. Newton's method (and variants thereof) can be a very good way to solve nonlinear eigenproblems!

1. If  $M$  maps scalars  $\lambda \in \mathbb{R}$  to  $n \times n$  matrices  $M(\lambda)$ , explain why  $M'(\lambda)$  (starting from the general definition of derivatives in class) is simply a matrix whose entries are the derivatives of each entry of  $M$  with respect to  $\lambda$ .
2. If  $f(\lambda) = \det M(\lambda)$ , find the Newton step  $f'(\lambda)^{-1}f(\lambda)$  in terms of  $M'(\lambda)$ . (Simplify your answer: one term cancels nicely.)
3. Implement Newton's method to solve  $\det M(\lambda) = 0$  for  $M(\lambda) = A - \lambda I + \alpha \lambda \sin(\lambda)B$  with example  $3 \times 3$  matrices  $A = \begin{bmatrix} -2 & -1 & -7 \\ -1 & 6 & 5 \\ -7 & 5 & 6 \end{bmatrix}$ ,  $B = \begin{bmatrix} 7 & -1 & 8 \\ -1 & 7 & -1 \\ 8 & -1 & 3 \end{bmatrix}$ , and  $\alpha = 0.01$ . As your starting guess, use the largest eigenvalue of  $A$  (i.e. a solution for  $\alpha = 0$ ), and find the resulting "nonlinear eigenvalue" of  $M(\lambda)$  to at least 6 significant digits. (It should require very few Newton steps!)

### Problem 6 (4+4+4+4 points)

Let  $f(A)$  be a function that maps  $m \times m$  matrices to  $m \times m$  matrices. Recall that its derivative  $f'(A)$  is a linear operator that maps any change  $\delta A$  in  $A$  to the corresponding change  $\delta f = f(A + \delta A) - f(A) \approx f'(A)[\delta A]$ , to first order in  $\delta A$ .

In this problem, you will study and prove a remarkable identity (Mathias, 1996): if  $f(A)$  is sufficiently smooth,<sup>1</sup> then for *any*  $\delta A$  (not necessarily small!) the following formula holds *exactly*:

$$f\left(\underbrace{\begin{bmatrix} A & \delta A \\ & A \end{bmatrix}}_M\right) = \begin{bmatrix} f(A) & f'(A)[\delta A] \\ & f(A) \end{bmatrix}.$$

That is, one applies  $f$  to a  $2m \times 2m$  "block upper-triangular" matrix  $M$  (blank lower-left = zeros), and the desired derivative is in the upper-right  $m \times m$  corner of the result  $f(M)$ . (Note: please do your *own* derivation here, don't just look it up.)

1. Check this identity numerically against a finite-difference approximation  $f(A + \delta A) - f(A)$ , which should match the exact  $f'(A)[\delta A]$  to a few digits, for  $f(A) = \exp(A)$  (the matrix exponential  $e^A$ , computed by `exp(A)` in Julia, or `expm` in Scipy or Matlab), for a random  $3 \times 3$  matrix  $A = \text{randn}(3,3)$  and a random small perturbation  $\delta A = \text{randn}(3,3) * 1\text{e-}8$ . Note that you can make the block matrix above in Julia by using `LinearAlgebra` followed by `M = [A δA; 0I A]`, and you can extract an upper-right corner by (e.g.) `M[1:3,4:6]`.

It is also worth verifying (by a finite-difference check) that the derivative of the matrix exponential is *not* simply multiplication by  $e^A$  (on either the left or right or both):  $(e^A)'[dA] \neq e^A dA$  or  $dA e^A$  or  $e^{A/2} dA e^{A/2}$ , unlike the scalar case.

2. Prove the identity by explicit computation for the cases:  $f(A) = I$ ,  $f(A) = A$ ,  $f(A) = A^2$ , and  $f(A) = A^3$ . (Two of these are trivial! This is "bargain-basement induction": do a few small examples and see the pattern.)
3. Prove the identity for  $f(A) = A^n$  for any  $n \geq 0$  by induction: assume it works for  $A^{n-1}$  and show using the product rule that it therefore must work for  $A^n$ . (You already proved the trivial  $n = 0$  base case in the previous part.)

*Remark:* Once it works for any  $A^n$ , it immediately follows that it works for any  $f(A)$  described by a Taylor series, such as  $\exp(A) = I + A + A^2/2 + A^3/6 + \dots + A^n/n! + \dots$ , since such a function is just a linear combination of  $A^n$  terms.

4. Prove the identity for  $f(A) = A^{-1}$ : since we know (from class) that  $f'(A)[\delta A] = -A^{-1} \delta A A^{-1}$ , plug this into the right-hand side of the formula above and show that it is the inverse of  $M$  (multiply by  $M$  and show you get  $I$ ).<sup>2</sup>

<sup>1</sup>The result is easiest to show when  $f(A)$  has a Taylor series (is "analytic"), and in fact you will do this below, but Higham (2008) shows that it remains true whenever  $f$  is  $2m - 1$  times differentiable, or even just differentiable if  $A$  is "normal" ( $AA^T = A^T A$ ).

<sup>2</sup>This is a special case of the famous "Schur complement" formula for the inverse of a  $2 \times 2$  block matrix.