

## Worksheet 5 (March 31st, 2021)

### 1 Pseudo-inverse for ill-conditioned systems

We will revisit here square linear systems  $\mathbf{Ax} = \mathbf{b}$ . A classic example of a very ill-conditioned  $n \times n$  matrix  $\mathbf{A}$  is the Hilbert matrix, defined by

$$a_{ij} = \frac{1}{i + j - 1}.$$

Note: *This problem is **not** about the Hilbert matrix per se, but about ill-conditioned matrices in general, so do not focus on this specific matrix (one reason we are using it is that we will encounter it again in a later homework on polynomial approximation). We will later talk about the Vandermonde matrix (related to polynomial interpolation) which is another example of an ill-conditioned matrix that you could use equally well.*

#### 1.1 Conditioning numbers

Form the Hilbert matrix in MATLAB and compute the conditioning number  $\kappa_2(\mathbf{A}) = \|\mathbf{A}\|_2 \|\mathbf{A}^{-1}\|_2$  for increasing size of the matrix  $n = 10, 12, 14, 15, 16$  using MATLAB's `cond` function (which by default uses the  $L_2$  norm), and compare to the built-in function `rcond`, which estimates the *inverse* of the conditioning number in the  $L_1$  norm in a rapid but approximate way. For what  $n$  does the Hilbert matrix become too ill-conditioned for double precision floating-point arithmetic?

From now on set  $n = 15$ .

#### 1.2 Solving ill-conditioned systems

Compute a right-hand side (rhs) vector  $\mathbf{b} = \mathbf{Ax}$  so that the exact solution is  $\mathbf{x} = [1, 1, \dots, 1]$  (all unit entries). Solve the linear system using MATLAB's built-in solver and report the error  $\delta x$  in the approximate solution  $\hat{\mathbf{x}}$  (for example, in the Euclidian norm,  $\delta x = \|\mathbf{x} - \hat{\mathbf{x}}\|_2$ ). How many digits of accuracy do you get in the solution  $\mathbf{x}$ ? Do your results conform to the theoretical expectation discussed in class?

Also compute and report the relative norm of the residual  $\|\mathbf{Ax} - \mathbf{b}\| / \|\mathbf{b}\|$  and comment on your observations.

Note: A method is called *backward stable* if it computes the *exact* solution to a nearby problem, i.e., if the residual is small.

## 1.3 Solving systems using the SVD

For this section start by using the built-in function `pinv` if you cannot quickly write your own version, and then come back at the end to writing your own pseudo inverse function (validate it against the built-in function). However, it will be crucial to read the documentation `pinv` to set properly the “tolerance” parameter (see below)!

Compute the SVD decomposition of  $\mathbf{A}$ . Look at the singular values of  $\mathbf{A}$  and compute the conditioning number of  $\mathbf{A}$  based on this [Hint: The MATLAB function `diag` can be used to extract the diagonal of a matrix or to construct a diagonal matrix].

Construct the matrix pseudo-inverse  $\mathbf{A}^\dagger$  from the SVD or using `pinv`. Use the pseudo-inverse to compute the solution  $\hat{\mathbf{x}} = \mathbf{A}^\dagger \mathbf{b}$ , and see if this is any more accurate than the previous direct solution.

### 1.3.1 Regularized Pseudo-Inverse

For a given relative tolerance  $\varepsilon \ll 1$ , a modified or regularized pseudo-inverse  $\hat{\mathbf{A}}^\dagger$  is obtained by first setting to zero all singular values that are smaller than  $\varepsilon \sigma_1$ , where  $\sigma_1$  is the largest singular value. This can be obtained in MATLAB using the built-in function `pinv` as  $\hat{\mathbf{A}}^\dagger = \text{pinv}(A, \varepsilon \sigma_1)$ .

For several logarithmically-spaced tolerances (for example,  $\varepsilon = 10^{-i}$  for  $i = 1, 2, \dots, 16$ ), compute the modified pseudo-inverse and then a solution  $\hat{\mathbf{x}} = \hat{\mathbf{A}}^\dagger \mathbf{b}$ . Plot the relative error in the modified solution versus the tolerance on a log-log scale. You should see a clear minimum error for some  $\varepsilon = \tilde{\varepsilon}$ . Report this optimal  $\tilde{\varepsilon}$  and the smallest error that you can get.