

## Assignment 3

1. (5) Consider the matrices:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}. \quad (1)$$

- Derive (on a piece of paper) orthogonal projectors on  $\text{range}(A)$  and  $\text{range}(B)$ .
  - Derive (on a piece of paper) QR decomposition of matrices  $A$  and  $B$ .
2. (5) Consider a particle of unit mass, which is prepared at  $t = 0$  at  $x = 0$  at rest  $v = 0$ . The particle is exposed to piece-wise constant external force  $f_i$  at  $i - 1 < t \leq i$ , with  $i = 1, 2, \dots, 10$ . Let  $a = (x(t = 10), v(t = 10))$  be a vector composed of coordinate and velocity of a particle at  $t = 10$ . Derive the matrix  $A$  such that  $a = Af$  (note that  $A$  is of a shape  $2 \times 10$ ). Using (a numerical) SVD decomposition, evaluate  $f$  of minimal Euclidean norm such that  $a = (1, 0)$ .
3. (10) Using SVD decomposition to perform the change of variables, solve the following linear systems  $Ax = b$  for  $x$  in the least squares sense:

$$A = \begin{bmatrix} 1/\sqrt{2} & -1/\sqrt{2} \\ 1/2 & 1/2 \\ -1/2 & -1/2 \end{bmatrix}, \quad b = (1, 0, 1)^T \quad (2)$$

$$A = \begin{bmatrix} 1/\sqrt{2} & 1/2 & -1/2 \\ -1/\sqrt{2} & 1/2 & -1/2 \end{bmatrix}, \quad b = (1, -1)^T. \quad (3)$$

4. (5) Consider the function  $f(x) = 10 \sin(x)$ . Generate a dataset  $D$  that will consist of  $n = 7$  points drawn as follows. For each point randomly draw  $x_i$  uniformly in  $[0, 6]$  and define  $y_i = f(x_i) + \epsilon_i$ , where  $\epsilon_i$  are iid standard gaussian random numbers. Plot  $D$  together with the true function  $f(x)$ . Fit a linear  $l(x) = w_0 + w_1x$  and a cubic  $c(x) = w_0 + w_1x + w_2x^2 + w_3x^3$  models to  $D$ . Plot those models together with the dataset  $D$ .
5. (10) In the file `image_data.hdf` you will find the image  $A$  and the filter  $C$ . The image, stored in the matrix  $A$  is obtained from certain original image  $A_0$  via convoluting it with the filter  $C$  and adding some noise. The filter  $C$  blurs an image, simultaneously increasing its size from  $16 \times 51$  to  $25 \times 60$ . The filter is defined as a matrix, acting on an image  $A$  flattened to a vector  $a$ :

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```
def mat2vec(A):
    A = np.flipud(A)
    a = np.reshape(A, np.prod(A.shape))
    return a
```

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with inverse transform, from vector  $a$  to matrix  $A$  given by

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```
def vec2mat(a, shape):
    A = np.reshape(a, shape)
    A = np.flipud(A)
    return A
```

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In terms of the associated vectors  $a$  and  $a_0$ , one may write

$$a_0 \rightarrow a = Ca_0 + \epsilon, \quad (4)$$

where  $\epsilon$  is a vector of iid Gaussian random numbers. Your task will be to recover an original image  $A_0$ , being supplied by the image  $A$  and the filter  $C$ .

- Plot the image  $A$ .
- Explore how the filter  $C$  acts on images.

- A naive way to recover  $A_0$  from  $A$  would be to solve  $a = Ca_0$  for  $a_0$ . Is this system under- or over-determined? Using SVD of the filter matrix  $C$ , evaluate  $a_0$  and plot the corresponding  $A_0$ .
- In order to improve the result, consider keeping certain fraction of singular values of  $C$ . Choose a value delivering the best empirical recovery quality.

6. (10) Consider the problem

$$\text{minimize } \|Ax - b\|_2 \quad \text{subject to } Cx = 0 \quad \text{with respect to } x, \quad (5)$$

where  $A$  and  $C$  are matrices and  $x$  and  $b$  are vectors. Using the method of Lagrange multipliers, and assuming both  $A^T A$  and  $C(A^T A)^{-1} C^T$  to be invertible, derive explicit expression for optimal  $x$ .

7. (20\*) Here we will consider the problem of localization of points in a 2D plane. Consider  $n$  points, for which we have the *approximate* locations  $r_i = (x_i, y_i)$ . We measure  $k$  angles between certain points:  $\theta_{ijk} = \angle(r_k - r_i, r_j - r_i)$ . Our goal is to use the results of the measurements to improve the estimation of the locations  $r_i$ .

To be specific, consider  $n = 3$  points, for which we have approximate locations  $r_1 = (-1, 0)$ ,  $r_2 = (0, 1)$ ,  $r_3 = (1, 0)$  and  $k = 1$  measurement  $\theta_{123} = 9\pi/40$ . Clearly, our estimates  $r_{1,2,3}$  are not consistent with the measured angle and we have to adjust the estimate:  $r_i \rightarrow \bar{r}_i = r_i + dr_i$  where  $dr_i$  should be found from the condition

$$\theta_{123} = \arccos \frac{(\bar{r}_3 - \bar{r}_1) \cdot (\bar{r}_2 - \bar{r}_1)}{|\bar{r}_3 - \bar{r}_1| |\bar{r}_2 - \bar{r}_1|}, \quad (6)$$

which can be linearized in  $dr_i$ , assuming this correction will end up small. In this approach, one constructs a single (in general,  $k$ ) equation for six (in general,  $2n$ ) variables, so the system will typically be underdetermined. We can consider this system in the least squares sense, which amounts to determining the smallest correction to all  $r_i$  which makes the updated locations consistent with observations. In the particular numerical example above, one may find  $dr_1 = (-h, 0)$ ,  $dr_2 = (h, -h)$ ,  $dr_3 = (0, h)$  where  $h = \pi/80 \approx 0.04$ .

Your task is to write the code, which will accept the current estimate of the positions  $r_i$  ( $n \times 2$ , float) and measurement results  $\theta_{ijk}$ , which are specified by i) indices of points ( $k \times 3$ , int) and ii) angles ( $k$ , float); and will output the derived correction to the point positions  $dr_i$  ( $n \times 2$ , float). You can use the numerical example in this exercise to test your code. This dataset is provided in `localization_data_1.hdf` (it also includes the correct answer to the problem instance,  $dr_i$  which you can compare your result to). You can find additional dataset with the same structure in `localization_data_2.hdf`.