

# Sorbonne Université

Numerical Algorithms

**Practical 2** 

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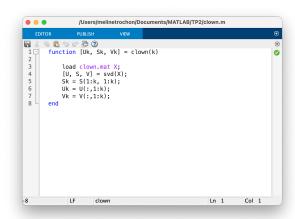
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## 1 Exercise 6

1.



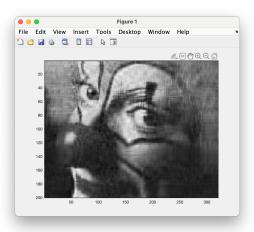


FIGURE 1 - The algorithm to compute the compression of the image the clown and the algorithm for k=20

2. A good candidate to be a measure of the quality of the compression would be  $\frac{\sigma_k}{\sigma_1}$ . Indeed, we want to trunks all the singular values that are to small in comparison to the bigger ones.

### 2 Exercise 7

1. We want to solve  $\min_f \|g-Kf\|_2^2$  (1). We can use the SVD-decomposition which gives  $\|g-Kf\|_2^2 = \|g-U\Sigma V^t f\|_2^2$ 

We complete U such that [U  $\tilde{U}$ ] is square orthogonal. then,

$$\|g - U\Sigma V^t f\|_2^2 = \|\begin{pmatrix} U^t \\ \tilde{U}^t \end{pmatrix} (g - U\Sigma V^t f)\|_2^2$$

(the norm doesn't change)

$$= \| \begin{pmatrix} U^t g - \Sigma V^t f \\ \tilde{U}^t g \end{pmatrix} \|_2^2$$

$$= \|\hat{U}^t g - \Sigma V^t f\|_2^2 + \|\tilde{U}^t g\|_2^2$$

The second term does not depend of f, so, we just have to solve the first one. That is to say that we are searching the solution of  $U^tg - \Sigma V^tf = 0$  Which means :  $f^* = \Sigma^{-1}VU^tg$ .

 $\Sigma^{-1}$  is a diagonal matrix with  $\sigma_i$ , i=1,...,n as values. We can show by identification that  $\Sigma^{-1}VU^tg=\sum_{i=1}^p\frac{u_i^t}{\sigma_j}v_i$  2.

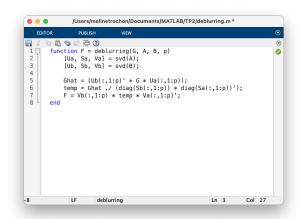




Figure 2 – The deblurring algorithm then the best image we found with p=52

## 3 Exercise 8

1.  $A^t$  is a stochastic Matrix if and only if

$$\sum_{i=0}^{n} A_{i,j}^{t} = 1, i = 1, ..., n$$
 (1)

If  $c_j=0,$   $A_{i,j}^t=1/n$  and (1) is verified. Let consider  $c_j\neq 0$ , we have

$$\sum_{i=0}^{n} \frac{pg_{i,j}}{c_j} + \delta$$

$$= \frac{p}{c_j} \sum_{j=0}^{n} g_{i,j} + \frac{n(1-p)}{n}$$

$$= \frac{pc_{i,j}}{c_{i,j}} + \frac{n(1-p)}{n} = 1$$

Therefore, A is a stochastic matrix.

In addition, if we consider the vector  $v \in (R)^n$  which is composed of 1, we can remark that, thanks to the properties of a stochastic matrix, we have  $Av = 1^*v$ . So 1 is an eigenvalue of A.

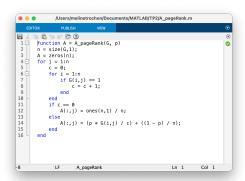
Then, we can prove that all the eigenvalues of A are less than 1. Indeed, we know by the Gershgorin circle theorem that :

$$\lambda_k \in \bigcup_{j=1,..,n} D(A_{j,j},r_j), k=1,..,n$$

where  $r_j = \sum_{i \neq j} A_{i,j}$  and we know as showed above that (1), and  $A_{i,j} \geq 0, i,j = 1,...,n$  So, we can conclude that  $\lambda_k \in [0,1], k = 1,...,n$ 

2. A is non negative, so, by the Perron-Frobenius theorem we have the result that the spectral radius  $\rho(A)$  is a unique eigenvalue of A. Then, because  $\rho(A)=1$  (showed previously) there exists an eigenvector associated to the eigenvalue 1 (non negative, by the theorem) . If we take  $\mathbf{x}=(\frac{1}{n},..,\frac{1}{n})^t$  this verifies the equality  $\sum_{i=1}^n x_i=1$ 

3.



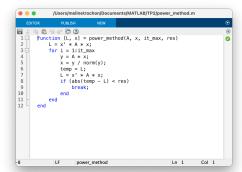


Figure 3 – Algorithms to create the matrix A and compute  $\Lambda$  and x

And we can provide a ranking according to their page\_rank by sorting the vector x.