

MOR – 2023 – MS²SC

Practical work of model reduction and data compression

Session 1 : data compression (a-posteriori)



600

 $\underline{\underline{M}}$ (gray level matrix)

POD by Singular Values Decomposition (SVD)

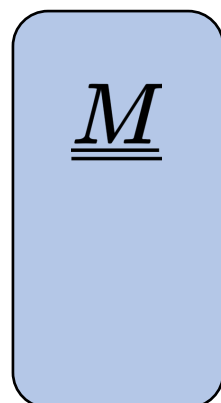
600

$$\underline{\underline{M}} = \underline{\underline{U}} \underline{\underline{S}} \underline{\underline{V}}^T$$

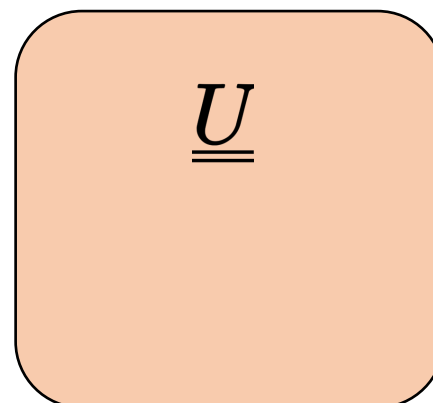
left eigenvectors

right eigenvectors

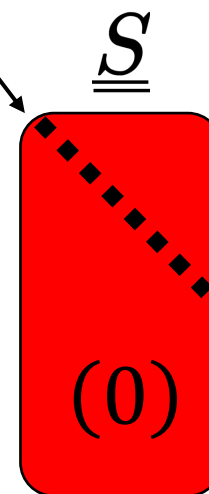
Singulars values

 $m \times n$

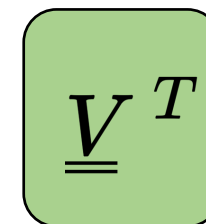
=

 $m \times m$

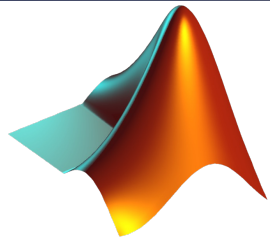
X

 $m \times n$

X

 $n \times n$

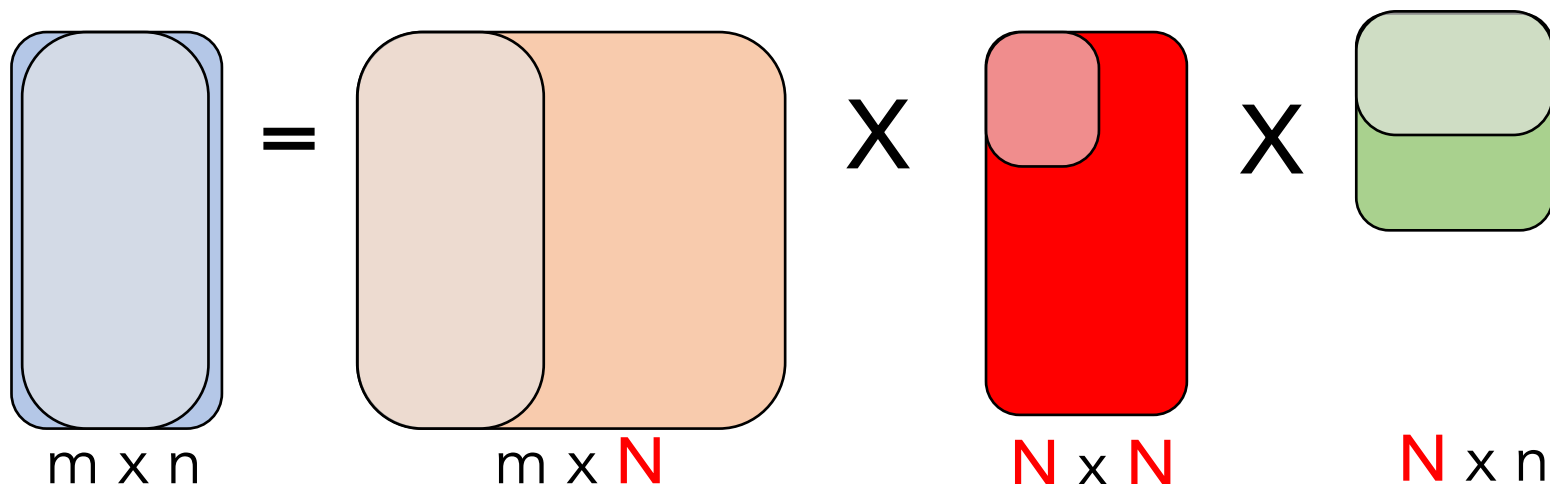
On Matlab :




$$[U, S, V] = \text{svd}(M);$$

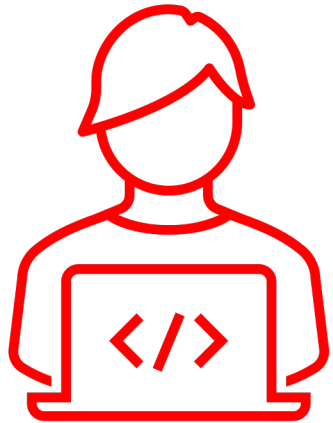
Choose a number of modes : N

With a few modes we can reconstruct the original image : $\underline{\underline{M}}_{\text{POD}} = \sum_{i=1}^N S_i \underline{U}_i \underline{V}_i^{\top}$



1. Calculate for a number **N** of POD modes the storage gain achieved by this approach.

$$\frac{\|\underline{\underline{M}}^{\text{POD}} - \underline{\underline{M}}\|}{\|\underline{\underline{M}}\|}$$




2. Plot the evolution of the relative reconstruction error as a function of the number of modes.
3. Deduce an appropriate number of modes and the effective gain achieved with the previous question.

$$U : \mathcal{W} \times \mathcal{I} \longrightarrow \mathbb{R}$$

$$(x, t) \longmapsto U(x, t)$$

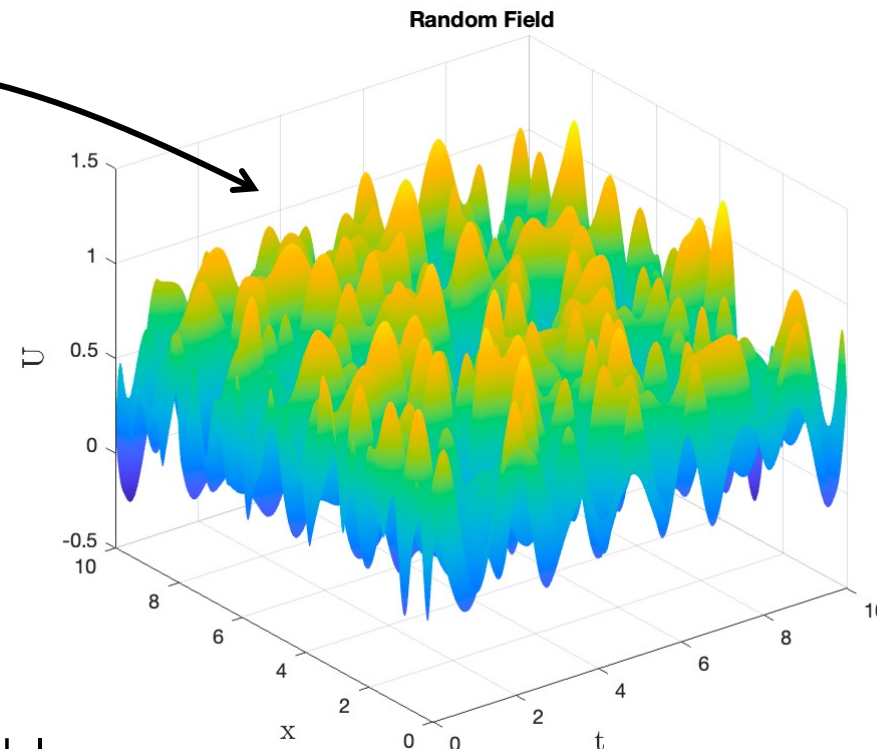
Matrix $N_x \times N_t$

number of modes \xrightarrow{m}

$$\underline{\underline{U}}(x, t) \approx \underline{\underline{U}}^m(x, t) = \sum_{i=1}^m \underline{\underline{\Lambda}}_i(x) \underline{\underline{\Gamma}}_i^\top(t)$$

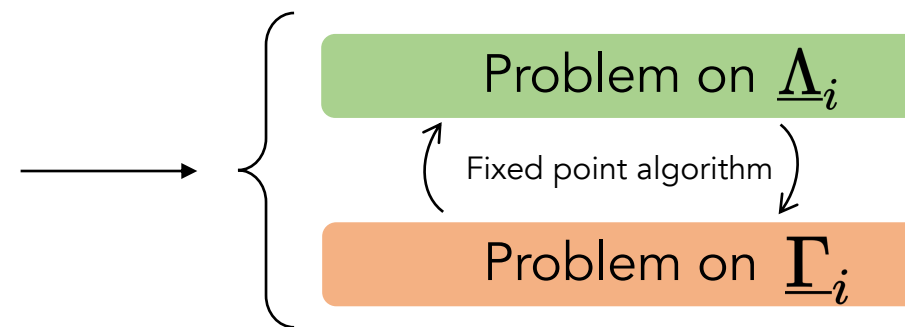
vector $N_x \times 1$

vector $1 \times N_t$



We are looking for the solution of the following minimization problem:

$$\left\{ \begin{array}{l} \underline{\underline{\Gamma}}_i, \underline{\underline{\Lambda}}_i = \arg \min_{\mathcal{I} \times \mathcal{W}} \left(\left\| \underline{\underline{U}} - \underline{\underline{U}}_{\text{PGD}}^{i-1} - \underline{\underline{\Lambda}}_i \underline{\underline{\Gamma}}_i^\top \right\|^2 \right) \\ \underline{\underline{U}}_{\text{PGD}}^{i-1} = \sum_{k=1}^{i-1} \underline{\underline{\Lambda}}_k(x) \underline{\underline{\Gamma}}_k^\top(t) \end{array} \right.$$



cf. your lesson !

How to compute

$$\int_0^L a(x) \cdot b(x) dx \quad ?$$

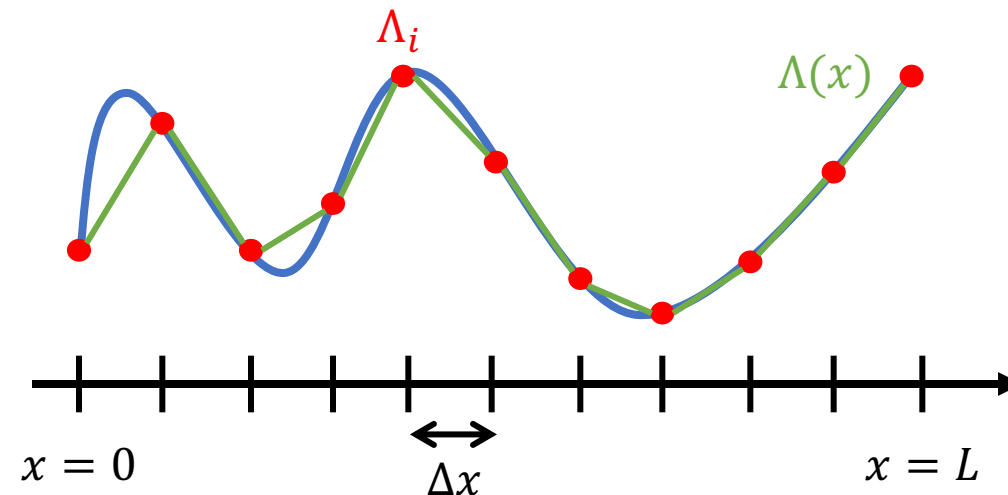
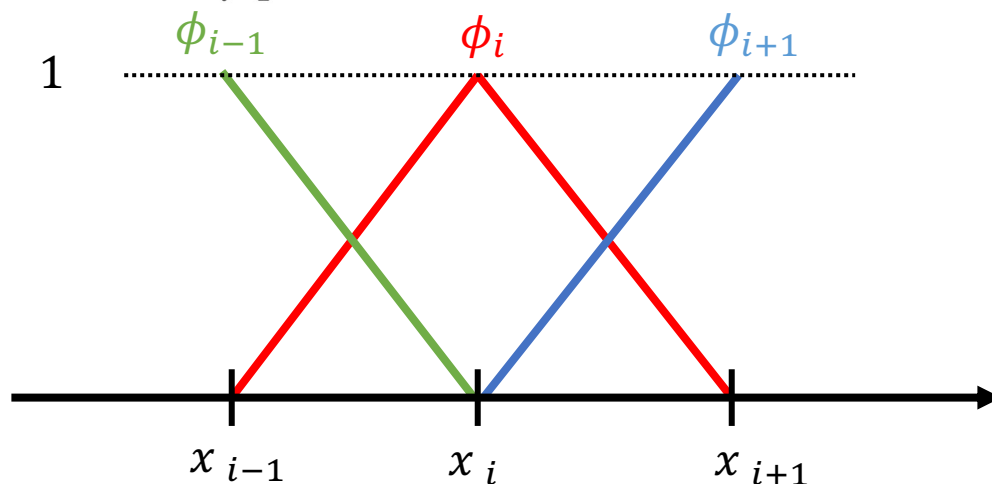
(We apply the same approach for the temporal integrals.)

The $\underline{\Lambda}$ and $\underline{\Gamma}$ are discrete fields defined at points.

To compute the integrals we will interpolate these discrete fields using **shape functions** (in the same way as for the finite element method). For this tutorial we will use the simplest shape functions : **piecewise linear**.

In this way, we have :

$$\underline{\Lambda}(x) = \sum_{i=1}^{N_x} \phi_i(x) \times \Lambda_i \text{ with } \begin{cases} \Lambda_i = \Lambda(x_i) \\ x_i = i \times \Delta x \end{cases}$$



In our case the shape functions are written as :

$$\begin{cases} \phi_i(x_i) = 1 \\ \phi_i(x) = \frac{x - x_{i-1}}{\Delta x} \text{ if } x \in [x_{i-1}; x_i] \\ \phi_i(x) = \frac{x_{i+1} - x}{\Delta x} \text{ if } x \in [x_i; x_{i+1}] \\ 0 \text{ otherwise} \end{cases}$$

Thus, with the use of these shape functions, the integral of a product of functions is written as :

$$\int_0^L a(x) \cdot b(x)dx = \sum_{i=0}^{N_x-1} \int_{x_i}^{x_{i+1}} a(x) \cdot b(x)dx$$

With :

$$a(x) = \sum_{j=1}^{N_x} \phi_j(x)a_j$$

$$b(x) = \sum_{j=1}^{N_x} \phi_j(x)b_j$$

Taking advantage of the fact that only functions of form ϕ_i and ϕ_{i+1} are nonzero on the interval $[x_i; x_{i+1}]$ (they are identically zero everywhere outside) the previously defined integral becomes :

$$\sum_{i=0}^{N_x-1} \int_{x_i}^{x_{i+1}} (a_i\phi_i + a_{i+1}\phi_{i+1}) \times (b_i\phi_i + b_{i+1}\phi_{i+1}) dx$$

in algebraic form :

$$\begin{pmatrix} a_i \\ a_{i+1} \end{pmatrix}^T \cdot \begin{pmatrix} \phi_i^2 & \phi_i\phi_{i+1} \\ \phi_i\phi_{i+1} & \phi_{i+1}^2 \end{pmatrix} \cdot \begin{pmatrix} b_i \\ b_{i+1} \end{pmatrix}$$

$$\int_{x_i}^{x_{i+1}} \text{constant} dx = \begin{pmatrix} a_i \\ a_{i+1} \end{pmatrix}^T \cdot \underbrace{\begin{pmatrix} \int_{x_i}^{x_{i+1}} \phi_i^2 dx & \int_{x_i}^{x_{i+1}} \phi_i \phi_{i+1} dx \\ \int_{x_i}^{x_{i+1}} \phi_i \phi_{i+1} dx & \int_{x_i}^{x_{i+1}} \phi_{i+1}^2 dx \end{pmatrix}}_{\underline{\underline{m}}} \cdot \begin{pmatrix} b_i \\ b_{i+1} \end{pmatrix}$$

(mass) elementary matrix

Let us note :

$$\int_{x_i}^{x_{i+1}} \phi_i^2 dx = \int_{x_i}^{x_{i+1}} \phi_{i+1}^2 dx$$

Show that :



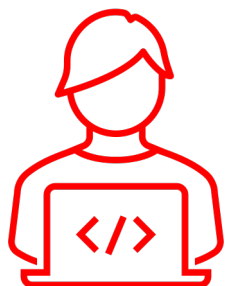
$$\underline{\underline{m}} = \Delta x \cdot \begin{pmatrix} 1/3 & 1/6 \\ 1/6 & 1/3 \end{pmatrix}$$

(Here, we have
 $N_x + 1$ nodes and
 N_x elements...)

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_{N_x-1} \\ a_{N_x} \end{bmatrix}^T \begin{bmatrix} \text{red box} \\ \text{blue box} \\ \text{green box} \\ \vdots \\ \text{yellow box} \\ \text{purple box} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ \vdots \\ b_{N_x-1} \\ b_{N_x} \end{bmatrix}$$

where $\begin{bmatrix} \text{red box} \\ \text{blue box} \\ \vdots \\ \text{yellow box} \\ \text{purple box} \end{bmatrix} = \frac{\Delta x}{6} \begin{pmatrix} 2 & 1 \\ 1 & 2 \\ & & 2 & 1 \\ & & 1 & 2 \end{pmatrix}$

$$\int_0^L a(x) \cdot b(x) dx = \underline{a}^T \underline{\underline{I}}_x \underline{b}$$

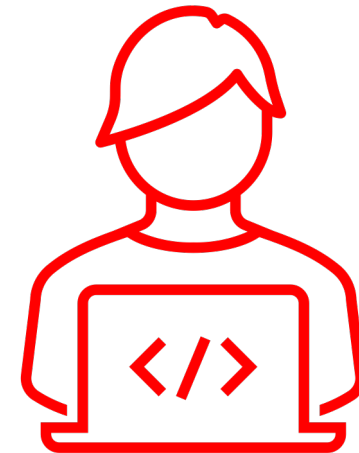


In this case we have two strategies:

- either we assemble the elementary matrices (cf. FEM)
- or we build directly the operator in one shot (faster and easier by taking advantage of the matlab functions : *diag* & *ones*)

PSEUDO ALGORITHM FOR PGD APPROXIMATION (FIXED POINT) :

1. we compute : $\underline{u}^* \leftarrow \underline{u}_f - \underline{u}_{PGD}^{i-1}$ ← field to approximate
 2. we initialize : $\underline{\Gamma}_i^{\text{new}} \leftarrow \text{linspace}(0, T, N_T)^T$ ← *It's a choice !*
 3. we compute : $\underline{\Lambda}_i^{\text{new}} \leftarrow \frac{\int_I \underline{u}^*(x, t) \underline{\Gamma}_i^{\text{new}} dt}{\int_I (\underline{\Gamma}_i^{\text{new}})^2 dt}$ ← N_x integrations on time
 4. we normalize (for uniqueness) : $\underline{\Lambda}_i^{\text{new}} \leftarrow \frac{\underline{\Lambda}_i^{\text{new}}}{\sqrt{\int_{\mathcal{W}} (\underline{\Lambda}_i^{\text{new}})^2 dx}}$ ← space interval
 5. $\underline{\Gamma}_i^{\text{old}} \leftarrow \underline{\Gamma}_i^{\text{new}}$
 6. we compute : $\underline{\Gamma}_i^{\text{new}} \leftarrow \frac{\int_{\mathcal{W}} \underline{u}^*(x, t) \underline{\Lambda}_i^{\text{new}} dx}{\int_{\mathcal{W}} (\underline{\Lambda}_i^{\text{new}})^2 dx}$ ← N_t integrations on space
 7. calculation of the stagnation criterion : $s = \frac{\int_I (\underline{\Gamma}_i^{\text{new}} - \underline{\Gamma}_i^{\text{old}})^2 dt}{\int_I (\underline{\Gamma}_i^{\text{old}})^2 dt}$ ← time interval
 8. If $s < \text{threshold}$:
 - We save the modes : $\underline{\Lambda}_i \leftarrow \underline{\Lambda}_i^{\text{new}}$ et $\underline{\Gamma}_i \leftarrow \underline{\Gamma}_i^{\text{new}}$
 - $\underline{U}_{PGD} = \underline{U}_{PGD} + \underline{\Gamma}_i \times \underline{\Lambda}_i^T$
 - we update the field to approximate : $\underline{u}^* \leftarrow \underline{u}^* - \underline{\Gamma}_i \times \underline{\Lambda}_i^T$
 - we are looking for the next mode ($i + 1$)
- If NOT
- we return to step 3 until convergence of the fixed point !
- It's a choice, begin with : 10^{-3}*



Fixed point

$$\text{Error} = \frac{\|\underline{\underline{U}}^{\text{ref}} - \underline{\underline{U}}^{\text{PGD}}\|_{\mathcal{U}}}{\|\underline{\underline{U}}^{\text{ref}}\|_{\mathcal{U}}}$$

As a reminder : $\mathcal{U} = \mathcal{W} \times \mathcal{I}$.

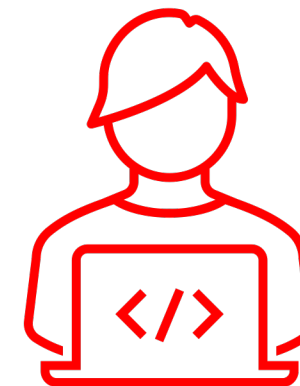
We also define :

$$\|\bullet\|_{\mathcal{U}} = \left(\int_{\mathcal{W} \times \mathcal{I}} \bullet^2 \, d\Omega \, dt \right)^{1/2}$$

So :



$$\text{Error} = \frac{\int_{\mathcal{W}} \int_{\mathcal{I}} \left(\underline{\underline{U}}^{\text{ref}} - \underline{\underline{U}}^{\text{PGD}} \right)^2 \, dt \, d\Omega}{\int_{\mathcal{W}} \int_{\mathcal{I}} \left(\underline{\underline{U}}^{\text{ref}} \right)^2 \, dt \, d\Omega}$$



HOW TO CALCULATE THIS ERROR NUMERICALLY?

1. First we integrate on \mathcal{I} , we obtain a vector of size N_x
2. Then we integrate on \mathcal{W} , we get a **scalar**.

Plot the evolution of the relative reconstruction error as a function of the number of modes.

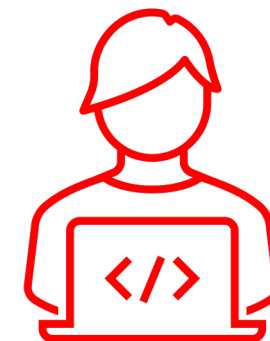
Scalar product
based on space
operator here

WHY ORTHOGONALIZE THE MODES?

- to avoid redundancy of information between modes
- this will be useful for TP 2 for the "update phase"

HOW TO ORTHOGONALIZE THE MODES?

- Gram-Schmidt algorithm



We want : $(\underline{\Lambda}_i, \underline{\Lambda}_j) = \delta_{ij}$.

So, for : $\underline{\Lambda}_{m+1}^{\text{new}}$, we write :

$$\underline{\Lambda}_{m+1} = \underline{\Lambda}_{m+1}^{\text{new}} - \sum_{i=1}^m \underbrace{(\underline{\Lambda}_{m+1}^{\text{new}}, \underline{\Lambda}_i)}_{=\sqrt{\int_{\mathcal{W}} \dots dx}} \cdot \underline{\Lambda}_i$$

This step consists in removing from $\underline{\Lambda}_{m+1}^{\text{new}}$ its different projections on the $\Lambda_i, \forall i \in [1, m]$.

In this way, we obtain : $(\underline{\Lambda}_{m+1}, \underline{\Lambda}_i) = 0, \forall i \in [1, m]$.

However, as we "remove" information at the level of $\underline{\Lambda}_{m+1}$, we have to "add" it in the Γ . It then comes :

$$\underline{\Gamma}_i \leftarrow \underline{\Gamma}_i + \underline{\Gamma}_{m+1} \cdot (\underline{\Lambda}_{m+1}^{new}, \underline{\Lambda}_i), \forall i \in [1, m]$$

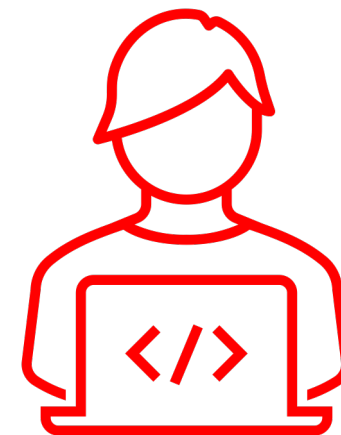
We must finally normalize :



$$\underline{\Lambda}_i^{\text{new}} \leftarrow \frac{\underline{\Lambda}_{m+1}^{\text{new}}}{\sqrt{\int_{\mathcal{W}} (\underline{\Lambda}_{m+1})^2 dx}}$$

$$\underline{\Gamma}_i^{\text{new}} \leftarrow \underline{\Gamma}_{m+1}^{\text{new}} \times \sqrt{\int_{\mathcal{W}} (\underline{\Lambda}_{m+1})^2 dx}$$

Implement the PGD algorithm for the approximation of the Maria Callas image.



To go further: apply these different methods to color images of your choice