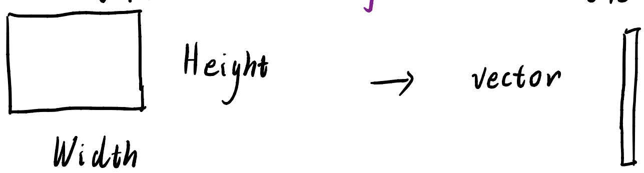
Note for Matrix (by Chen Yiyun)

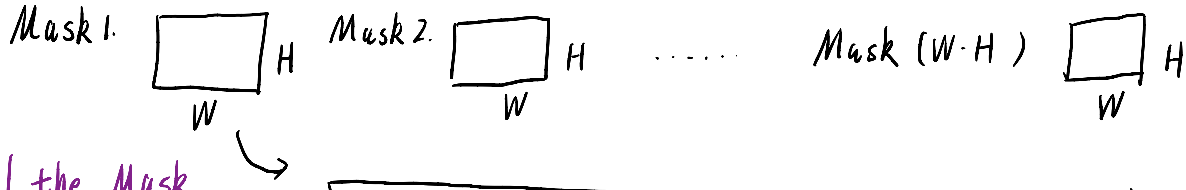
① Real Picture $\vec{i}$: input



one column

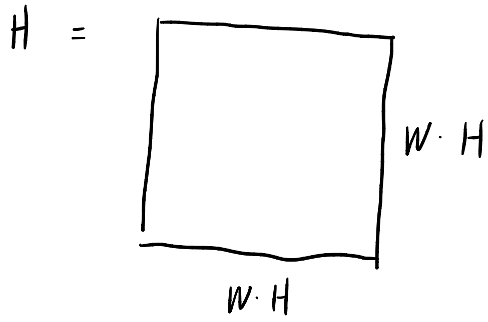
shape = (W · H , 1)

②



one row : shape (1, W·H)

the Mask Matrix.



During a single scan, we project one of these masks over our object.

③ Sensor result

$\vec{S} = H \cdot \vec{i}$ $\Rightarrow$ by $H^{-1} \cdot \vec{S} = \vec{i}$, we get $\vec{i}$ from the sensor result

Analysis of H

Part 1. Single Pixel → means sum of rows of H is 1.

① $H = I$ $\Rightarrow$ $\vec{S} = \vec{i}$

② H_alt = np.random.permutation (H) I

so masks are in random order, the result will be in random order

M = H_alt^{-1} = np.linalg.inv (H_alt)

Part 2 Multi - Pixels

① random H = generate Random Binary Mask (avg 1s Per Row = 300)

$\downarrow$

invertible, with approximately 300 pixels illuminated per scan.

☆ Eigenanalysis & the Robustness of Inverse - Based Reconstruction

$\vec{s} = H\vec{i} + \vec{w} + \vec{\sigma}$

$\vec{w}$: the random noise

$\vec{\sigma}$: a constant offset

$\downarrow$ $\vec{s} = H\vec{i} + \vec{w}$

$\vec{i}_{est} = H^{-1}\vec{s} = \vec{i} + H^{-1}\vec{w}$

$= \alpha_1 H^{-1}\vec{v}_1 + \cdots + \alpha_N H^{-1}\vec{v}_N$

$= \alpha_1 \frac{1}{\lambda_1}\vec{v}_1 + \cdots + \alpha_N \frac{1}{\lambda_N}\vec{v}_N$

Given H is diagonalizable

$\Rightarrow$ the $N \times N$ matrix H has precisely N linear - independent eigenvectors.

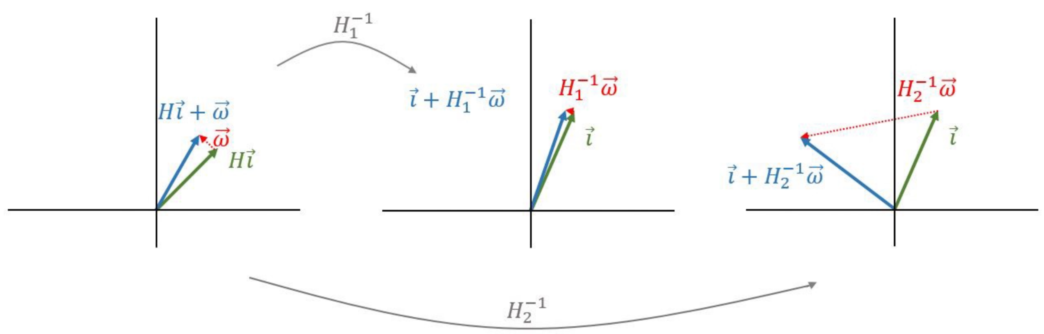
So $\vec{w}$ can be represented as

$\vec{w} = \alpha_1\vec{v}_1 + \cdots + \alpha_N \vec{v}_N$

Conculsion $\rightarrow$ regardless of the scaling constants α,

eigenvalue $\begin{cases} \text{large} \rightarrow \vec{w} \text{ attenuated} \\ \text{small} \rightarrow \vec{w} \text{ amplified} \end{cases}$

$\downarrow$ Graphical Interpretation



② the hadamard Matrix: https://mathworld.wolfram.com/HadamardMatrix.html