

Test 3

▼ 1

Find the best approximate solution of $Ax = b$ using Cholesky

$$A = \begin{bmatrix} 2 & 1 \\ -3 & -1 \\ 1 & -4 \end{bmatrix}, b = \begin{bmatrix} 3 \\ -3 \\ -3 \end{bmatrix}$$

~~1. Compute $S = A^T A$~~

$$S = \begin{bmatrix} 14 & 1 \\ 1 & 18 \end{bmatrix}$$

~~2. Cholesky Decomposition~~

$$L = \begin{bmatrix} 3.742 & 0 \\ 0.267 & 4.234 \end{bmatrix}$$

3. Cholesky-based formula for the best approximate solution

$$\begin{bmatrix} 3.742 & 0 \\ 0.267 & 4.234 \end{bmatrix} \cdot y = \begin{bmatrix} 12 \\ 18 \end{bmatrix}$$

$$\begin{bmatrix} 3.742 & 0.267 \\ 0 & 4.234 \end{bmatrix} \cdot x = y$$

4. Best approximate solution

$$x = \begin{bmatrix} 0.789 \\ 0.956 \end{bmatrix}$$

~~5. Error~~

$$e = \begin{bmatrix} -0.466 \\ -0.323 \\ -0.036 \end{bmatrix}$$

$$\|e\| = 0.568$$

▼ 2

Find the best approximate solution of $Ax = b$ using QR

$$A = \begin{bmatrix} 2 & 1 \\ -3 & -1 \\ 1 & -4 \end{bmatrix}, b = \begin{bmatrix} 3 \\ -3 \\ -3 \end{bmatrix}$$

~~1. QR Decomposition~~

$$Q = \begin{bmatrix} \del{0.535} & \del{0.202} \\ \del{-0.802} & \del{-0.186} \\ \del{0.267} & \del{-0.962} \end{bmatrix}, R = \begin{bmatrix} \del{3.742} & \del{0.267} \\ \del{0.000} & \del{4.234} \end{bmatrix}$$

2. QR-based formula for the best approximate solution

$$\begin{bmatrix} 3.742 & 0.267 \\ 0.000 & 4.234 \end{bmatrix} x = \begin{bmatrix} 3.207 \\ 4.049 \end{bmatrix}$$

3. Best approximate solution

$$x = \begin{bmatrix} 0.789 \\ 0.956 \end{bmatrix}$$

~~4. Error~~

$$e = \begin{bmatrix} \del{-0.466} \\ \del{-0.323} \\ \del{-0.036} \end{bmatrix}$$

~~$\|e\| = 0.568$~~

▼ 3

Find the best approximate solution of $Ax = b$ using SVD

$$A = \begin{bmatrix} 2 & 1 \\ -3 & -1 \\ 1 & -4 \end{bmatrix}, b = \begin{bmatrix} 3 \\ -3 \\ -3 \end{bmatrix}$$

~~1. SVD of A~~

$$U = \begin{bmatrix} \del{0.336} & \del{0.463} \\ \del{-0.389} & \del{-0.725} \\ \del{-0.858} & \del{0.510} \end{bmatrix}, \Sigma = \begin{bmatrix} \del{4.270} & \del{0.000} \\ \del{0.000} & \del{3.710} \end{bmatrix}, V = \begin{bmatrix} \del{0.230} & \del{0.973} \\ \del{0.973} & \del{-0.230} \end{bmatrix}$$

2. SVD-based formula for the best approximate solution

$$x = V \Sigma^{-1} U^t b$$

3. Best approximate solution

$$x = \begin{bmatrix} 0.789 \\ 0.956 \end{bmatrix}$$

4. Error

$$e = \begin{bmatrix} -0.466 \\ -0.323 \\ -0.036 \end{bmatrix}$$

$\|e\| = 0.568$

▼ 4

Find the smallest solution of $Ax = b$

$$A = \begin{bmatrix} 2 & -3 & 1 \\ 1 & -1 & -4 \end{bmatrix}, b = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

1. SVD of A^t

$$U = \begin{bmatrix} 0.336 & 0.463 \\ -0.389 & 0.725 \\ -0.858 & 0.510 \end{bmatrix}, \Sigma = \begin{bmatrix} 4.270 & 0.000 \\ 0.000 & 3.710 \end{bmatrix}, V = \begin{bmatrix} 0.230 & 0.973 \\ 0.973 & -0.230 \end{bmatrix}$$

2. SVD-based formula for the smallest solution

$$x = U \Sigma^{-1} V^t b$$

3. Smallest solution

$$x = \begin{bmatrix} 0.235 \\ -0.299 \\ -0.367 \end{bmatrix}$$

▼ 5

Compress/Decompress the image A using SVD

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$

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1. SVD of A

$$U = \begin{bmatrix} -0.405 & -0.915 \\ -0.915 & 0.405 \end{bmatrix}, \Sigma = \begin{bmatrix} 5.465 & 0.000 \\ 0.000 & 0.366 \end{bmatrix}, V = \begin{bmatrix} -0.576 & 0.817 \\ -0.817 & -0.576 \end{bmatrix}$$

2. Using 1 singular values.

Compressing

$$U_c = \begin{bmatrix} -0.405 \\ -0.915 \end{bmatrix}, \Sigma_c = [5.465], V_c = \begin{bmatrix} -0.576 \\ -0.817 \end{bmatrix}$$

Decompressing

$$A_c = \begin{bmatrix} 1.274 & 1.807 \\ 2.879 & 4.085 \end{bmatrix}$$

□ |

~~3. Using 2 singular values.~~

~~Compressing~~

$$\cancel{U_c} = \begin{bmatrix} \cancel{-0.405} & \cancel{0.915} \\ \cancel{-0.915} & \cancel{0.405} \end{bmatrix}, \cancel{\Sigma_c} = \begin{bmatrix} \cancel{5.465} & \cancel{0.000} \\ \cancel{0.000} & \cancel{0.366} \end{bmatrix}, \cancel{V_c} = \begin{bmatrix} \cancel{-0.576} & \cancel{0.817} \\ \cancel{-0.817} & \cancel{-0.576} \end{bmatrix}$$

~~Decompressing~~

$$\cancel{A_c} = \begin{bmatrix} \cancel{1.000} & \cancel{2.000} \\ \cancel{3.000} & \cancel{4.000} \end{bmatrix}$$

□ |

▼ 6

Images: original A and watermark W

$$A = \begin{bmatrix} 1.000 & 2.000 \\ 3.000 & 4.000 \end{bmatrix}$$

$$W = \begin{bmatrix} 0.000 & 0.000 \\ 0.000 & 1.000 \end{bmatrix}$$

□ |

1. Embed the watermark

~~a. SVD of A~~

$$\cancel{U} = \begin{bmatrix} \cancel{-0.405} & \cancel{0.915} \\ \cancel{-0.915} & \cancel{0.405} \end{bmatrix}$$

$$\cancel{\Sigma} = \begin{bmatrix} \cancel{5.465} & \cancel{0.000} \\ \cancel{0.000} & \cancel{0.366} \end{bmatrix}$$

$$\cancel{V} = \begin{bmatrix} \cancel{-0.576} & \cancel{0.817} \\ \cancel{-0.817} & \cancel{-0.576} \end{bmatrix}$$

- b. Embed the watermark into the singular value matrix
 $k=0.100$

$$\Sigma_w = \begin{bmatrix} 5.465 & 0.000 \\ 0.000 & 0.466 \end{bmatrix}$$

- c. Construct the watermarked image

$$A_w = \begin{bmatrix} 0.925 & 2.053 \\ 3.033 & 3.977 \end{bmatrix}$$

□ |

2. Bad person distorts the watermarked image

- a. Filter

$$filter = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 100 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

- b. Convolution

$$A_{wd} = \begin{bmatrix} 0.936 & 2.042 \\ 3.042 & 3.967 \end{bmatrix}$$

□ |

3. Detect the watermark

- a. Recover the watermarked singular values

$$\Sigma_{wd} = \begin{bmatrix} 5.462 & -0.018 \\ -0.002 & 0.457 \end{bmatrix}$$

- b. Recover the watermark

$$W_d = \begin{bmatrix} -0.032 & -0.182 \\ -0.016 & 0.910 \end{bmatrix}$$

□ |

7. We need to solve

$$A^tAx = A^tb$$

Let

$$A^tA = LL^t$$

Then

$$LL^tx = A^tb$$

Hence we can solve the followings instead

$$Ly = A^tb$$

$$L^tx = y$$

8. We need to solve

$$A^tAx = A^tb$$

Let

$$A = QR$$

Then

$$(QR)^tQRx = (QR)^tb$$

$$R^tQ^tQRx = R^tQ^tb$$

$$R^tRx = R^tQ^tb$$

$$Rx = Q^tb$$

9. We need to solve

$$A^tAx = A^tb$$

Let

$$A = U\Sigma V^t$$

Then

$$(U\Sigma V^t)^tU\Sigma V^tx = (U\Sigma V^t)^tb$$

$$V\Sigma^tU^tU\Sigma V^tx = V\Sigma^tU^tb$$

$$V\Sigma^t\Sigma V^tx = V\Sigma^tU^tb$$

$$\Sigma V^tx = U^tb$$

$$V^tx = \Sigma^{-1}U^tb$$

$$x = (V^t)^{-1}\Sigma^{-1}U^tb$$

$$x = V\Sigma^{-1}U^tb$$

10. We need to compute

$$x = A^t(AA^t)^{-1}b$$

Let

$$A^t = U\Sigma V^t$$

Then

$$\begin{aligned}x &= A^t(AA^t)^{-1}b \\&= U\Sigma V^t((U\Sigma V^t)^t U\Sigma V^t)^{-1}b \\&= U\Sigma V^t(V\Sigma^t U^t U\Sigma V^t)^{-1}b \\&= U\Sigma V^t(V\Sigma^2 V^t)^{-1}b \\&= U\Sigma V^t V^{t-1} \Sigma^{-2} V^{-1}b \\&= U\Sigma^{-1} V^t b\end{aligned}$$