

SC301 - Numerical Linear Algebra (3-0-0-3)

Aditya Tatu



Lecture 1

Why $Ax = b$?

- Bar code scanner:



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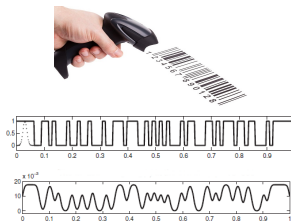


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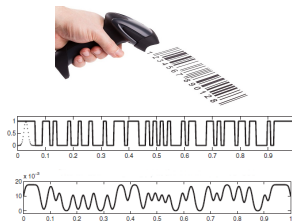


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- Assuming Gaussian smoothing, the input-output relation is

$$0 \leq s \leq 1, \quad g(s) = \int_0^1 \exp\left(-\frac{(s-t)^2}{\sigma^2}\right) f(t) dt.$$

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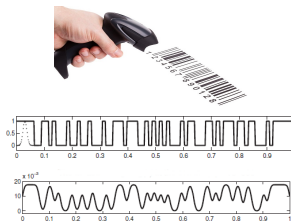


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- Sampling gives $Ax = b$.

● X-ray tomography:

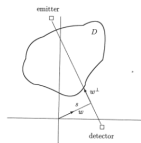


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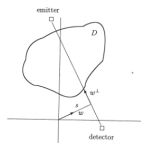


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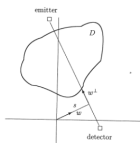


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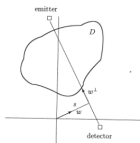


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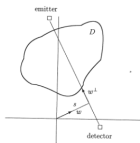


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- **Image deblurring:**
- Image blurred by camera being out of focus, object motion.

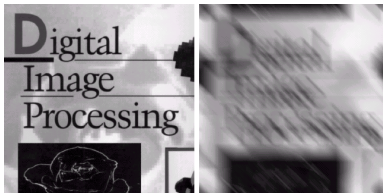


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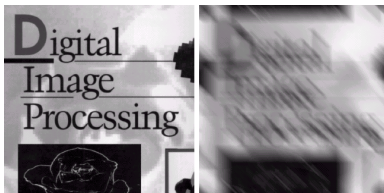


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- Blur is assumed to be linear position invariant, modeled by a point spread function h ; relation between original and blurred image is

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$$\forall (i, j) \in [1, N_x] \times [1, N_y], g(x_i, y_j) \\ = \frac{f(x_i + h, y_j) + f(x_i, y_j + h) + f(x_i - h, y_j) + f(x_i, y_j - h) - 4f(x_i, y_j)}{h^2}.$$

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● Compute f such that $Lf = g$.

Eigenvalues and Eigenvectors

● Principal Component Analysis:

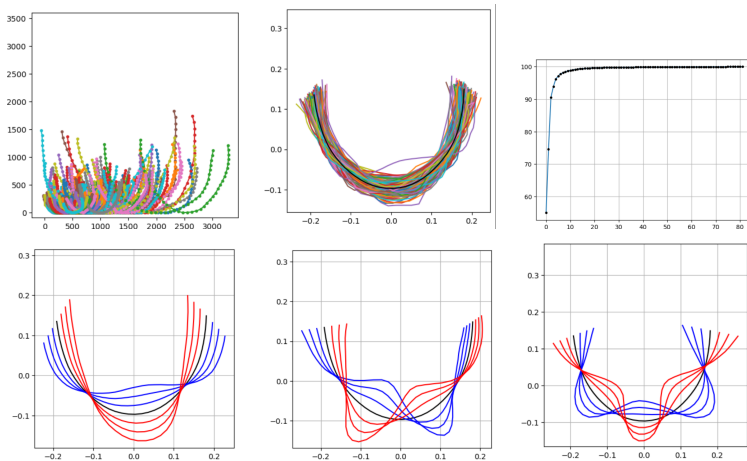


Figure: PCA of jawlines of 300 faces

- **Nonlinear dimensionality reduction: ISOMAP**

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- Compute the inter-point distance matrix D .

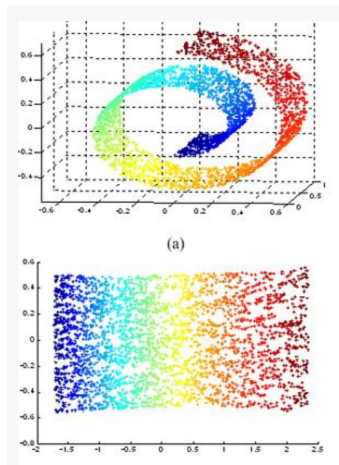


Figure: The swissroll and its embedding using two largest eigenvectors of D .

● Fourier Analysis on meshes:

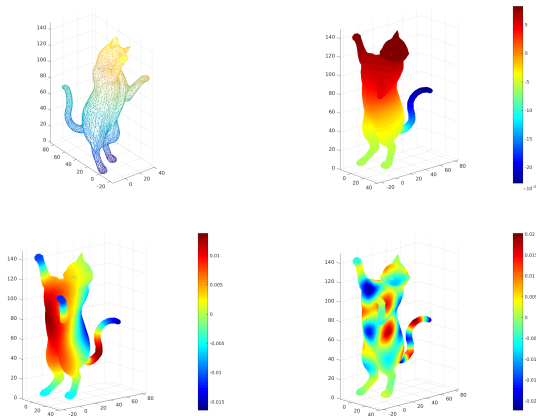


Figure: (top-left) Cat mesh, (top-right) Fundamental harmonic, (bottom-left) 10th harmonic, (bottom-right) 50th harmonic.

Singular Value Decomposition: $A = U\Sigma V^T$

- **Least Squares:**

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- **Image compression:**

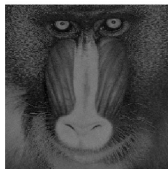
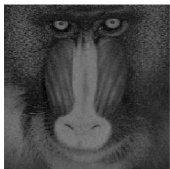
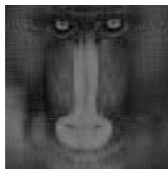


Figure: (top-left) Original image, (top-right) Rank-10 approx.
(bottom-left) Rank-50 approx., (bottom-right) Rank-100 approx.

- **Review: LA and Number representation:** Vector spaces $\mathbb{R}^n, \mathbb{C}^n$, Subspaces, Linear dependence/independence, Rank, Eigenvalues & Eigenvectors, Inner products and Norms, Orthogonality. Floating point representation, errors.

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- **SVD:** Applications and algorithms. Ill-posed Inverse problems.

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- Evaluation:
 - ▶ In Sem-1 and 2: 25% each.
 - ▶ End Sem: 35%
 - ▶ Quiz: 15%.

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- ▶ How about $A \in \mathbb{R}^{n \times n}$, $n \sim 10000$?