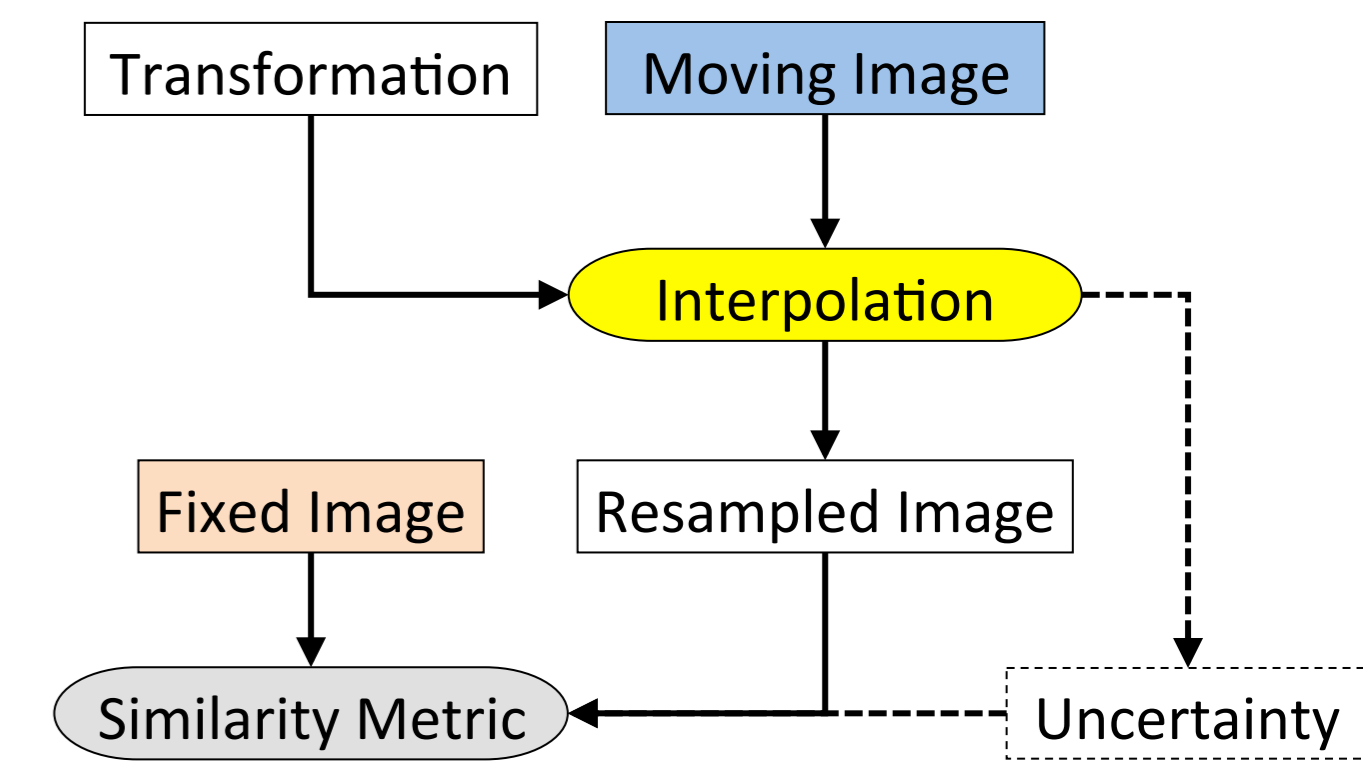
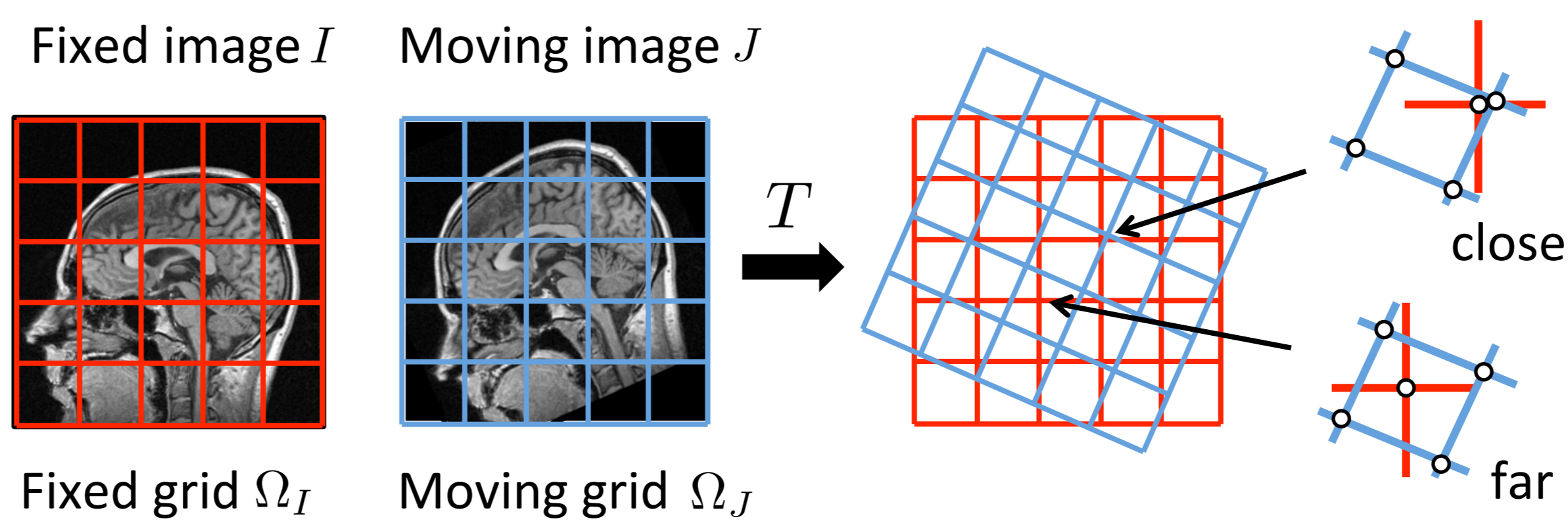


Introduction

- Intensity-based registration requires interpolation for computing the similarity of images
- Uncertainty of interpolation varies across the image
- Problem:** All locations have same influence on similarity
- Goal:** Estimate interpolation uncertainty and propagate uncertainty to similarity measure



Estimate Interpolation Uncertainty with Gaussian Processes

Image resampling as Bayesian prediction

- Gaussian process over images $J \sim \mathcal{GP}(\mathbf{0}, k)$
- Predict resampled image

$$p(J^* | J; X^*, X) = \mathcal{N}(\mu_J, \Sigma_J)$$

$$\mu_J = k(X^*, X) \cdot [k(X, X) + \sigma_J^2 \mathbf{I}]^{-1} \cdot J$$

$$\Sigma_J = k(X^*, X^*) - k(X^*, X) \cdot [k(X, X) + \sigma_J^2 \mathbf{I}]^{-1} \cdot k(X, X^*)$$

Model details

- Observations on transformed grid

$$X = T(\Omega_J)$$

- Prediction on fixed grid

$$X^* = \Omega_I$$

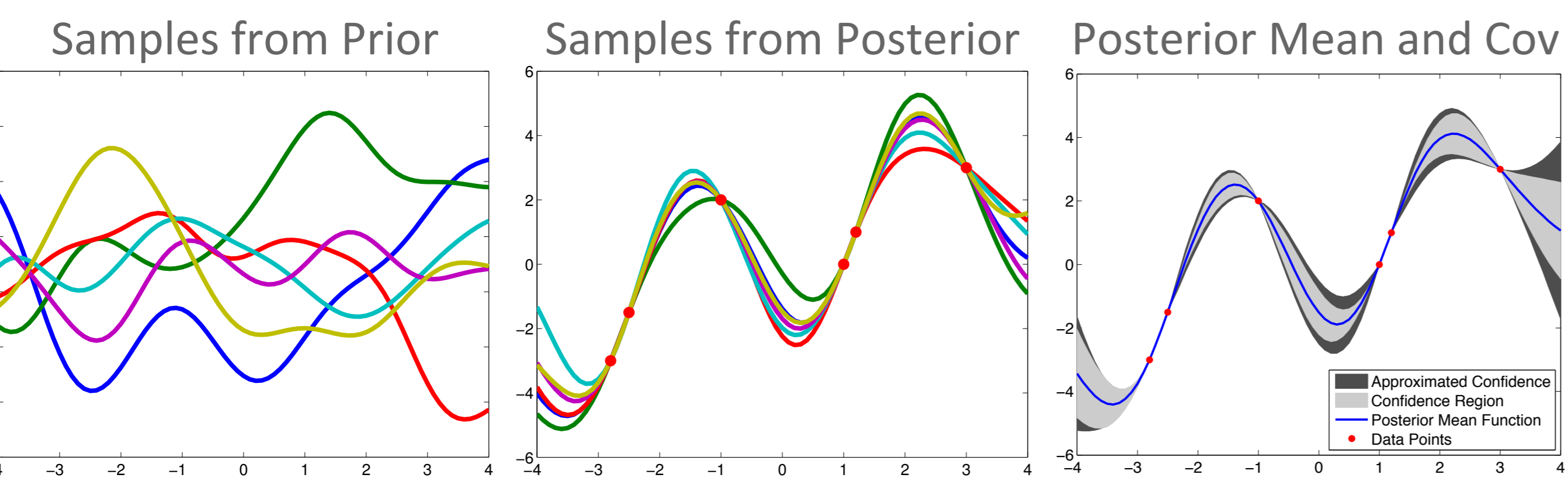
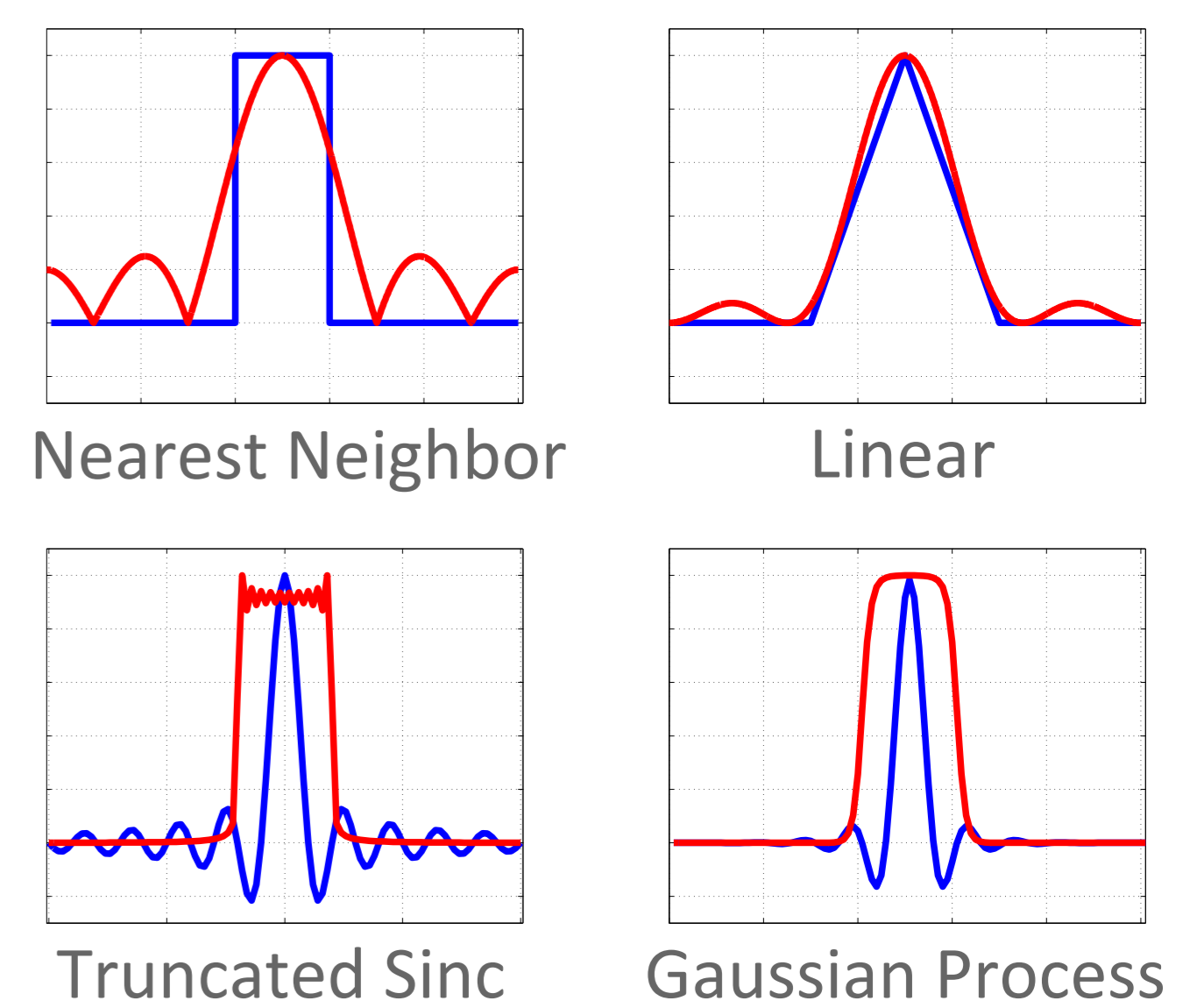
- Squared exponential kernel

$$k(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2 \cdot l^2}\right)$$

- Gaussian image noise

$$\varepsilon \sim \mathcal{N}(0, \sigma_J)$$

Comparison of interpolation functions in **spatial** and **frequency** domain

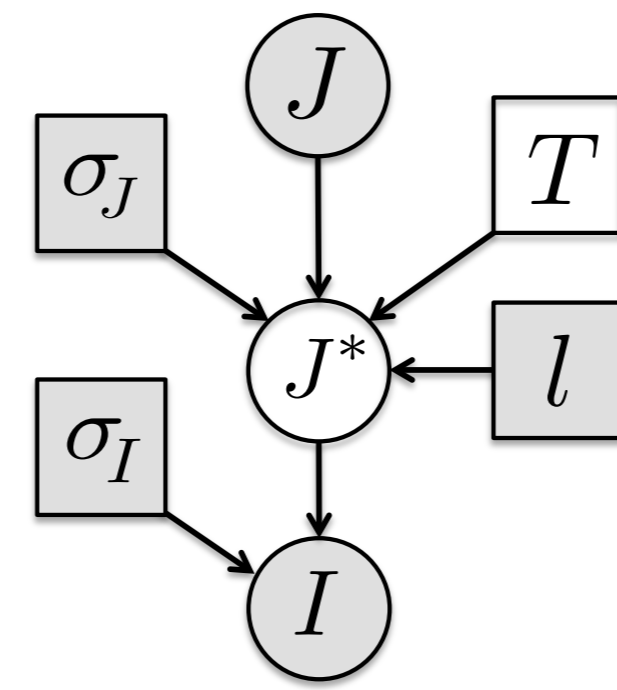


Registration with Interpolation Uncertainty Estimation

Integrate uncertainty into similarity measure

- Graphical model factorizes as

$$p(I, J, J^*; T, \sigma_J, \sigma_I, l) = p(J^* | J; T, \sigma_J, l) \cdot p(I | J^*; \sigma_I) \\ = \mathcal{N}(\mu_J, \Sigma_J) \cdot \mathcal{N}(J^*, \sigma_I^2 \mathbf{I})$$



- Marginalize over latent random variable

$$p(I, J; T, \sigma_I, \sigma_J, l) = \int p(I, J, J^*; T, \sigma_I, \sigma_J, l) dJ^* \\ = \int \mathcal{N}(J^*; \mu_J, \Sigma_J) \cdot \mathcal{N}(I; J^*, \sigma_I^2 \mathbf{I}) dJ^* \\ = \mathcal{N}(\mu_J, \Sigma_J + \sigma_I^2 \mathbf{I})$$

- Log-likelihood function as similarity metric

$$\log p(I, J; T, \sigma_I, \sigma_J, l) = \log[(2\pi)^{-\frac{k}{2}} |\Sigma|^{-\frac{1}{2}}] - \frac{1}{2} (I - \mu_J)^\top \Sigma^{-1} (I - \mu_J) \\ \Sigma = \Sigma_J + \sigma_I^2 \mathbf{I}$$

- Maximum likelihood estimation to retrieve transformation

$$\hat{T} = \arg \max_T \log p(I, J; T, \sigma_J, \sigma_I, l)$$

Parameters

- Length scale l in kernel determines smoothness of image, e.g., scale-space creation

$$\varepsilon_I \sim \mathcal{N}(0, \sigma_I^2)$$

- Gaussian noise in both images

$$\varepsilon_J \sim \mathcal{N}(0, \sigma_J^2)$$

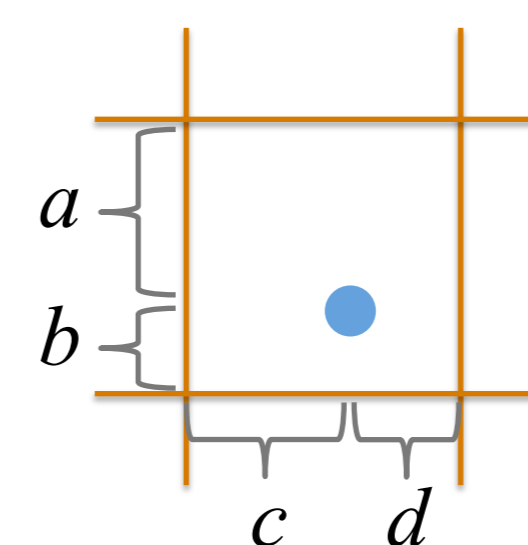
Practical considerations

- Block-wise estimation for 3D images due to large kernel size
- Approximation of the similarity measure by variances on the diagonal (closely related to sum of squared differences)

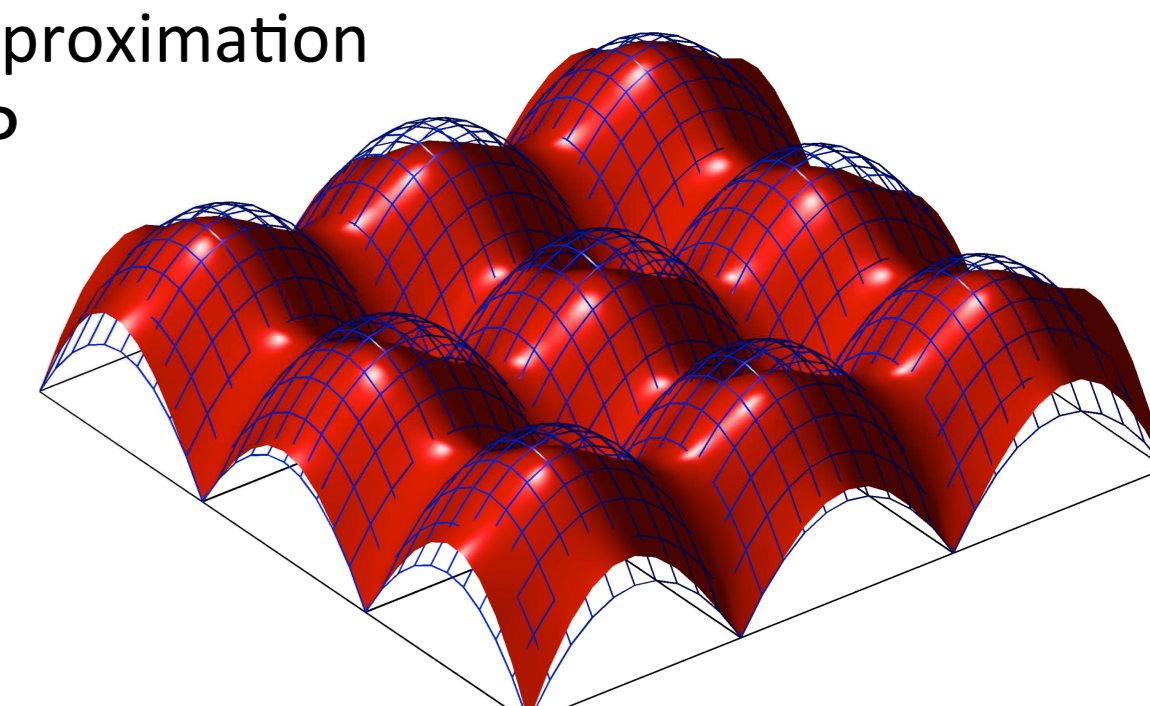
$$\log p(I, J; T, \sigma_I, \sigma_J, l) \approx - \sum_{x \in \Omega_I} \frac{(I(x) - \mu_J(x))^2}{2 \cdot \Sigma_{xx}}$$

- Approximation of variance by weights from linear interpolation

$$V = ab + cd$$



Blue: Approximation
Red: GP

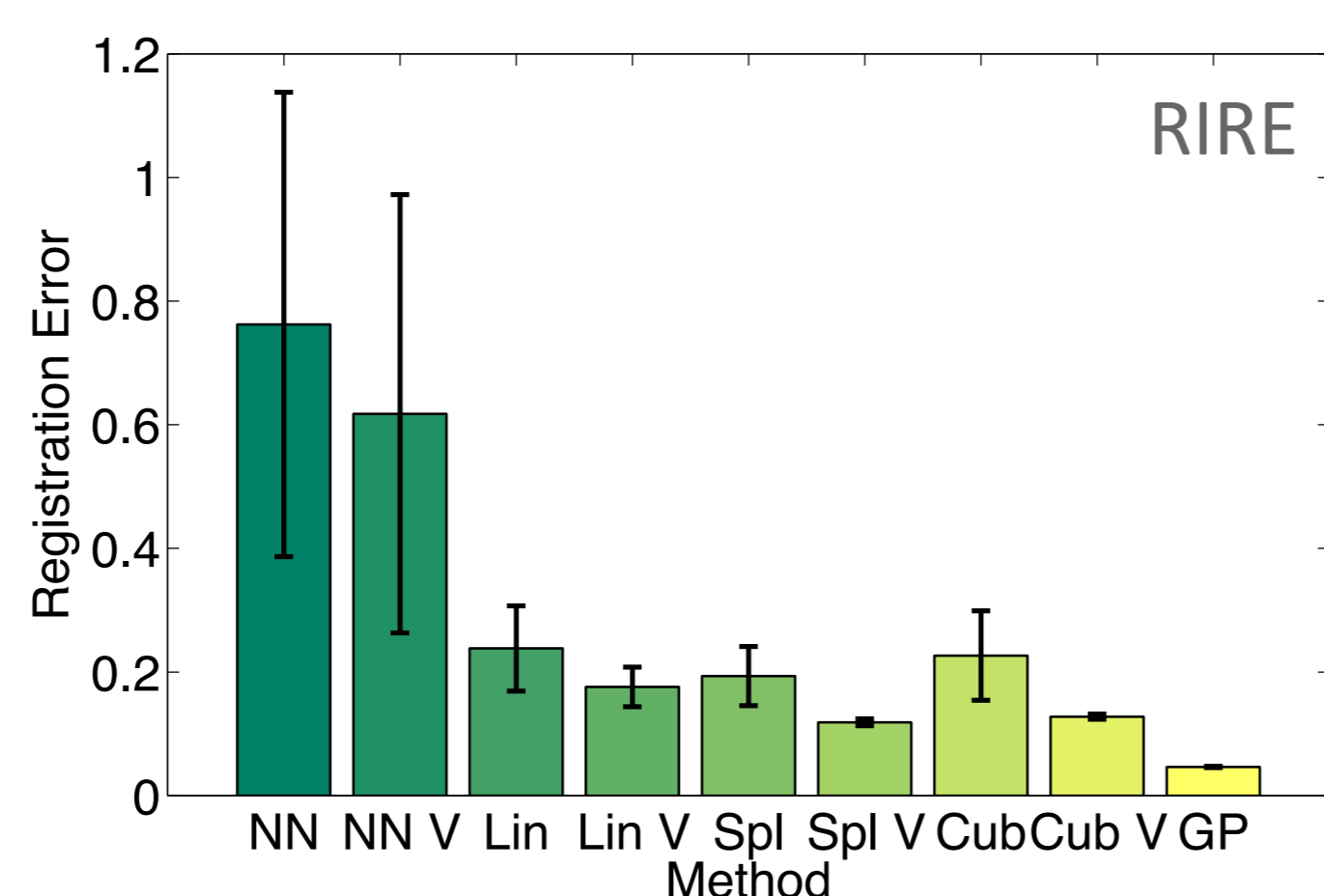
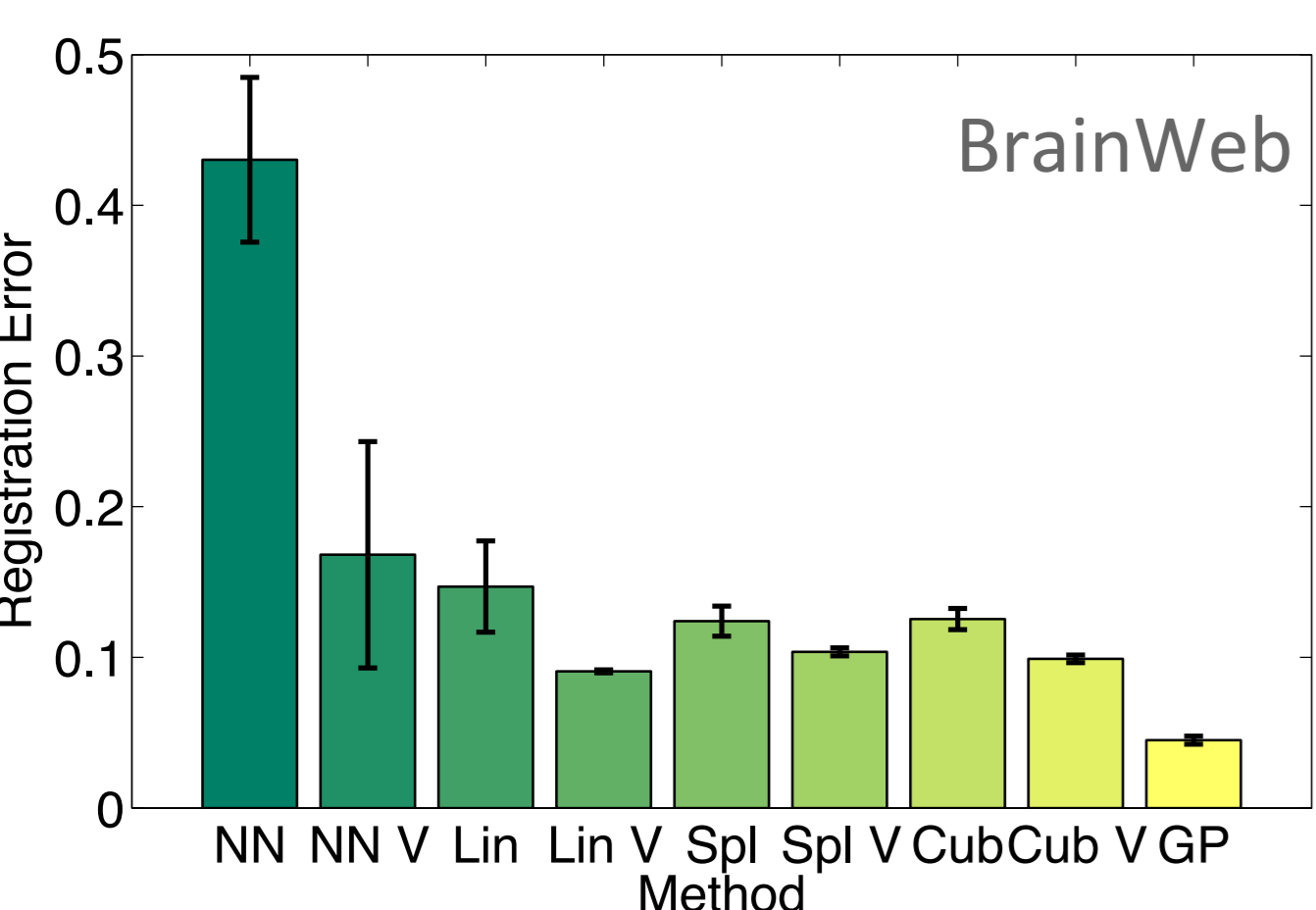


Registration Experiments:

- Three MR datasets: (i) BrainWeb, (ii) RIRE, (iii) Head
- Comparison of registration errors for different interpolation schemes: nearest neighbor, linear, spline, cubic, GP ($\sigma_I^2 = \sigma_J^2 = 0.1$)
- Variance approximation indicated with 'V'
- Statistics over 50 runs from random initial transformations

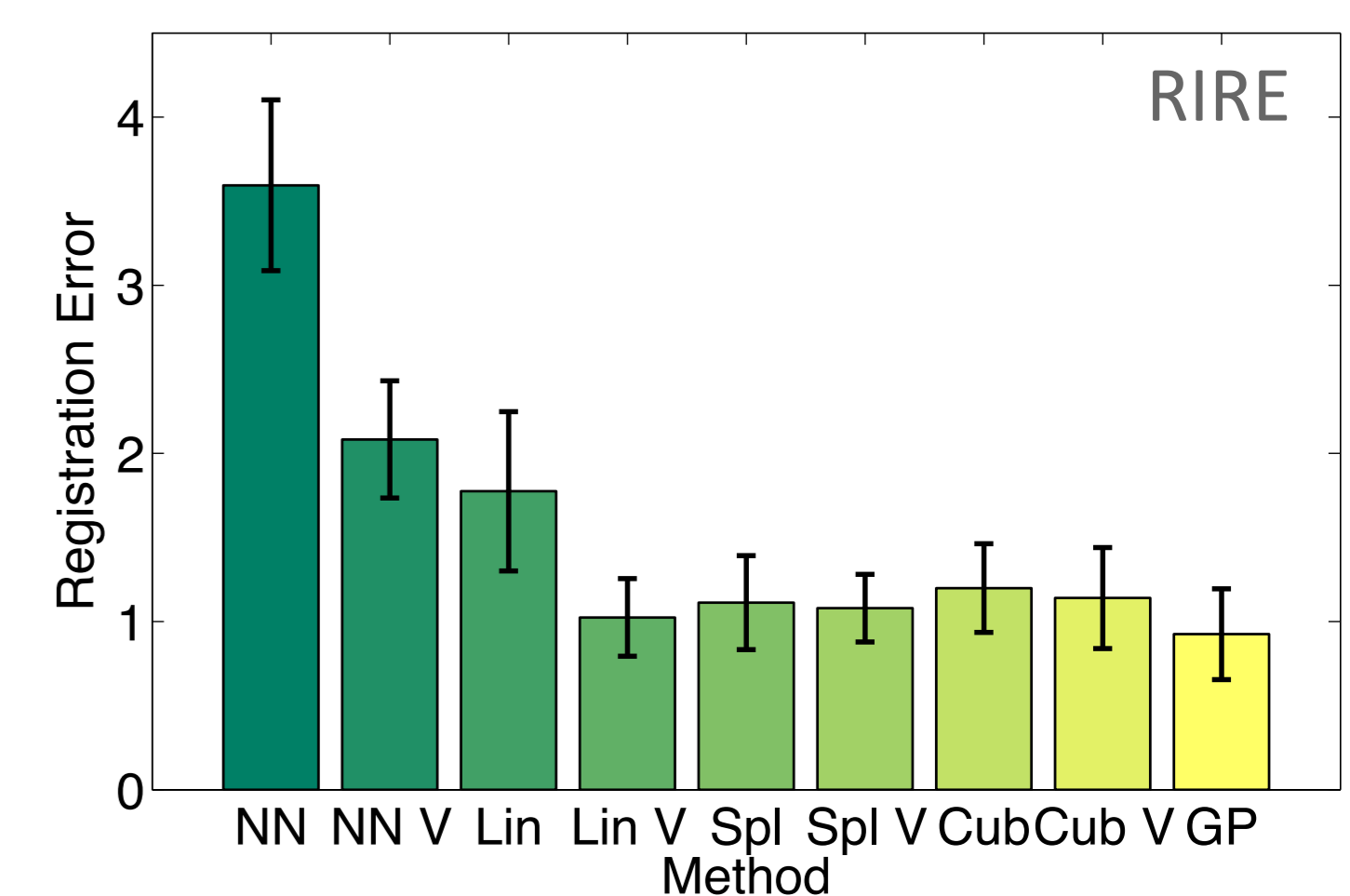
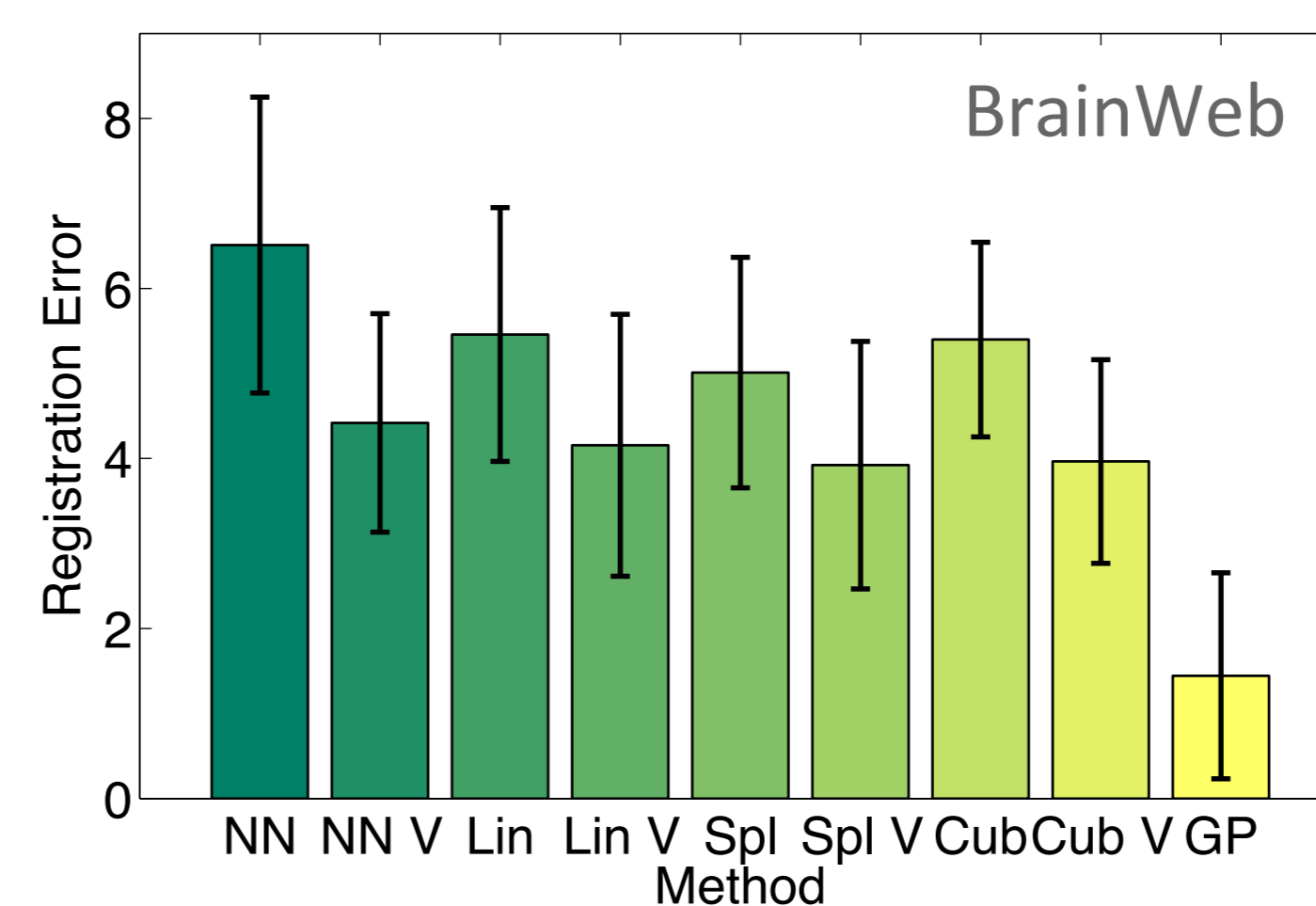
2D registration results

- Full covariance matrix
- Length scale: $l=2.5$



3D registration results

- Diagonal entries of covariance matrix
- Partitioning the image in $8 \times 8 \times 8$ cubes, length scale $l=2.5$



Head results

- Diagonal entries of covariance matrix
- Partitioning the image in $8 \times 8 \times 8$ cubes
- Length scale $l=2.5$
- MR acquisitions on two different grids

