Statistical Learning Methods for Neuroimaging Data Analysis
NESS 2022 Symposium Lecture 2
Image Analysis Methods

Hongtu Zhu, Ph.D and Professor
Departments of Biostatistics, Statistics, Genetics, and Computer Science,
Biomedical Research Imaging Center,
University of North Carolina at Chapel Hill
# Reading Materials

Part 1. Overview: Image Analysis
Individual Image Analysis

Reconstruction

Segmentation

Multimode analysis
DTI
FLAIR

Registration
Marc
Medical Image Analysis

Image Analysis

Biomarker segmentation & visualization

Detection

Diagnosis

Surgery Planning

Prognosis

Data Knowledge

sMRI

fMRI

DTI

Tumor image

The UNIVERSITY of NORTH CAROLINA at CHAPEL HILL
Image Processing

Raw Images

- Image Reconstruction
- Image Segmentation
- Image Registration
- Image Smoothing

Multiple Comparisons

Statistical Modelling
Image Processing

\[ f \]

\[ \hat{F} = T[f] \]
ill-posed inverse problems

\[ \hat{F} = T[f] \]

\[ d(F, \hat{F}) \to 0? \]
Population Image Analysis

Group Analysis

Image Genetics

Prediction

High risk

Low risk
Population Image Analysis

- Causal and mediation inference
- Experiment design
- Data integration
- Dimensional reduction methods
- Imaging genetics
- Imputation methods
- Knowledge-based system
- Object oriented data analysis
- Predictive models
- Statistical parametric mapping
Ecological Layout

Large-scale Database

Integration

Prediction

Deconvolution

Learning

The UNIVERSITY of NORTH CAROLINA at CHAPEL HILL
Part 2. Individual Image Analysis
DICOM is a standard for handling, storing, printing, and transmitting information in medical imaging.

- It includes a file format definition and a network communications protocol.
- The communication protocol is an application protocol that uses TCP/IP (Transmission Control Protocol/Internet Protocol) to communicate between systems.
- DICOM files can be exchanged between two entities that are capable of receiving image and patient data in DICOM format.
- DICOM enables the integration of scanners, servers, workstations, printers, and network hardware from multiple manufacturers into a picture archiving and communication system (PACS).
- The different devices come with DICOM conformance statements which clearly state the DICOM classes they support.
Analyze 7.5 is a 3-D biomedical image visualization and analysis product developed by the Biomedical Imaging Resource of the Mayo Clinic.

- An Analyze 7.5 data set is made of two files, a header file and an image file.
- The files have the same name with different file extensions.
- The header file has the file extension .hdr and the image file has the file extension .img.

```matlab
info = analyze75info(filename,'ByteOrder', endian)
```

reads the Analyze 7.5 header file using the byte ordering specified by endian, where `endian` can have either of the following values:

- 'ieee-le' Byte ordering is Little Endian;
- 'ieee-be' Byte ordering is Big Endian.

- Read image data from image file of Analyze 7.5 data set
  
  ```matlab
  X = analyze75read(filename)
  X = analyze75read(info)
  ```
NIfTI-1 is adapted from the widely used ANALYZE™ 7.5 file format. NIfTI-1 uses the "empty space" in the ANALYZE 7.5 header to add several new features.

These new features include:
- Affine coordinate definitions relating voxel index \((i,j,k)\) to spatial location \((x,y,z)\);
- Codes to indicate spatio-temporal slice ordering for FMRI;
- "Complete" set of 8-128 bit data types;
- Standardized way to store vector-valued datasets over 1-4 dimensional domains;
- Codes to indicate data "meaning";
- A standardized way to add "extension" data to the header;
- Dual file (.hdr & .img) or single file (.nii) storage.
RAS versus LAS

The default ANALYZE orientation is LAS (radiological orientation)
+X is Left
+Y is Anterior
+Z is Superior

for LAS (radiological convention) image, right cerebral hemisphere is at LEFT and left cerebral hemisphere is at RIGHT

The neurological convention is RAS (only the direction of X is swapped)
+X is Right
+Y is Anterior
+Z is Superior

for RAS (neurological convention) image, left cerebral hemisphere is at LEFT and right cerebral hemisphere is at RIGHT;

UseANALYZE.pdf

Input File Format ANALYZE

Output File Format NifTI
Image Inpainting

is an artistic synonym for **image interpolation**. Given some values at some points, determine continuous range of values.

**From Discrete Images to Continuous Images**

- **Uses:**
  - Synthesis
    - Morph between two images
    - Interpolate a curve between points
  - Continuous range of values between vertices.
  - Blowing up an image.
Image Interpolation

The objective is to find a function

\[ \mathcal{I}(x) = \text{inter}(T, \quad , xc) \]

\( T(\ ) = T(\ ) \) is the interpolation model

\[ \Omega = [\omega^1, \omega^2] \times \cdots \times [\omega^{2d-1}, \omega^{2d}] \]

\( xc = [x_j = (x_j^1, \cdots, x_j^d)]_{j=1}^{n} \) is a collection of \( n \) points.

\[ \mathcal{I}(x_j) = \text{DataT}(x_j) \quad \text{for} \quad j = 1, \cdots, n \]

\[ = [1, 2] \times [3, 4] \]

\( x_j = (x_j^1, x_j^2) \) cell-centered grids

The UNIVERSITY of NORTH CAROLINA at CHAPEL HILL
Different Standard Interpolation Methods

- **Nearest-neighbor (proximal) interpolation** is to select the value of the nearest point, and does not consider the values of other neighboring points at all, yielding a piecewise-constant interpolant.
- **Bilinear interpolation** determines the grey level value from the weighted average of the four closest pixels to the specified input coordinates.
- **Bicubic interpolation** determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates.

\[
\begin{align*}
Q_1 &= (x_1, f(x_1)), \ldots, Q_n = (x_n, f(x_n)) \\
g(x) &= \sum_{k=1}^{n} w_k U(|x - x_k|) \\
g(x_i) &= f(x_i)
\end{align*}
\]
Image Inpainting

$Q_1 = (x_1, f(x_1))$

$Q_2 = (x_2, f(x_2))$

$P = (x, g(x))$

$g(x) = f(x_1)(x - x_1)/(x_2 - x_1) + f(x_2)(x_2 - x)/(x_2 - x_1)$
Image Inpainting

1D

\( Q_0 = (x_1, f(x_1)) \quad \dot{f}(x_1) \)

\( Q_1 = (x_2, f(x_2)) \quad \dot{f}(x_2) \)

Let \( P = (x, g(x)) \) and \( t = (x - x_1)/(x_2 - x_1) \),

\[ g(x) = h_{00}(t)f(x_1) + h_{10}(t)\dot{f}(x_1)(x_2 - x_1) + h_{01}(t)f(x_2) + h_{11}(t)\dot{f}(x_2)(x_2 - x_1) \]

\( h_{00}(t) = 2t^3 - 3t^2 + 1 \quad (1 + 2t)(1 - t)^2 \)

\( h_{10}(t) = t^3 - 2t^2 + t \quad t(1 - t)^2 \)

\( h_{01}(t) = -2t^3 + 3t^2 \quad t^2(3 - 2t) \)

\( h_{11}(t) = t^3 - t^2 \quad t^2(t - 1) \)

Bernstein

\( B_0(t) + B_1(t) \)

\( B_1(t)/3 \)

\( B_3(t) + B_2(t) \)

\( -B_2(t)/3 \)

Finite difference

\[ \dot{f}(x_1) \approx \frac{f(x_2) - f(x_0)}{2(x_2 - x_1)} + \frac{f(x_1) - f(x_0)}{2(x_1 - x_0)} \]

Catmull-Rom spline

\[ \dot{f}(x_1) \approx \frac{f(x_2)}{x_2} - \frac{f(x_0)}{x_0} \]
Example 1.3. Different Interpolation

```
B = imsize(A, 0.1, 'nearest');
```
Image Interpolation

Spline interpolation for 1D Data

\[
(x) = \text{spline}(x) = \sum_{l=1}^{m} c_l b^l(x)
\]

\[
\mathcal{S}(x_j) = \text{DataT}(x_j) = \sum_{l=1}^{m} c_l b^l(x_j) \quad \text{for } j = 1, \cdots, n
\]

\[
\text{DataT} = [b^1(x_c), \cdots, b^m(x_c)](c_1, \cdots, c_m)^T = B_m \tilde{c}
\]
Image Interpolation

Spline interpolation for d-D Data

\[ \mathcal{I}(x) = \mathcal{I}_{\text{spline}}(x) = \sum_{l_1=1}^{m_1} \cdots \sum_{l_d=1}^{m_d} c_{l_1,\ldots,l_d} b_{l_1}(x^1) \cdots b_{l_d}(x^d) \]

\[ \mathcal{I}(x_j) = \text{DataT}(x_j) = \sum_{l_1=1}^{m_1} \cdots \sum_{l_d=1}^{m_d} c_{l_1,\ldots,l_d} b_{l_1}(x^1_j) \cdots b_{l_d}(x^d_j) \quad \text{for} \ j = 1, \ldots, n \]

\[ \text{DataT} = B_{m} \tilde{c} = B_{m^d} \otimes \cdots \otimes B_{m^1} \tilde{c} \]

\[ \partial_{x^q} \mathcal{I}(x) = \mathcal{I}_{\text{spline}}(x) = \sum_{l_1=1}^{m_1} \cdots \sum_{l_d=1}^{m_d} c_{l_1,\ldots,l_d} b_{l_1}(x^1) \cdots \partial_{x^q}[b_{l_q}(x^q)] \cdots b_{l_d}(x^d) \]
The objective is to find a function

\[ \text{Data}_T(x_j) = \mathcal{I}(x_j) + \varepsilon(x_j) \quad \text{for} \quad j = 1, \ldots, n \]

\[ \mathcal{I}(x) = \text{inter}(T, , xc) \]

\[ (\square) = \arg\min \{ ||\text{Data}_T(\text{xc})||^2 + ( ) \} \]

\[ = 0 \text{ yields the interpolation problem.} \]

\[ \rightarrow \infty \text{ yields a very smooth solution.} \]

Example on spline

\[ (x) = \text{spline} (x) = \sum_{l=1}^{m} c_l b^l(x) \]

\[ \rho(\mathcal{I}) = \int \{ d^2 \mathcal{I}(x) \}^2 dx = \tilde{c}^T M\tilde{c} \]
\[(B^T B + \lambda W)\tilde{c} = B^T \text{DataT}\]

Spline: \( W = M \)

Tychonoff regularization: \( W = I \)

Tychonoff-Phillips regularization: \( W = D^T D \)

- E3_MS_splineInterpolation2D
- E3_US_getMultilevel
- E3_splineInterpolation2D
Image Representation

= 0

= 1000

= 10

The UNIVERSITY of NORTH CAROLINA at CHAPEL HILL
A multilevel approach is to use a finite number of interpolants $\ell$ based on data $(x_{c\ell}, T_{\ell})$, where the discrete parameter $\ell$ ranges from a coarse to a fine level.

**Example** Let $m = 2^L, L \in N$ and $\text{dataT} \in R^m$. A multilevel representation of the data is $\{T_{\ell} : \ell = 0, \cdots, L\}$, where $T^L = \text{dataT}$ and for all $\ell = L : 1 : 1$, we have

$$T_{\ell-1} = (T_{\ell} (1 : 2 : m - 1) + T_{\ell} (2 : 2 : m)) / 2$$
Imaging Denoising/Filter

- An image may be “dirty” (with dots, speckles, stains)
- Noise removal:
  - To remove speckles/dots on an image
  - Dots can be modeled as impulses (salt-and-pepper or speckle) or continuously varying (Gaussian noise)
  - Can be removed by taking mean or median values of neighboring pixels (e.g. 3x3 window)
  - Equivalent to low-pass filtering
- Problem with low-pass filtering
  - May blur edges
  - More advanced techniques: adaptive, edge preserving

Thanks Yao Wang
A 2D point spreading function (PSF) $K(x, y)$ is a smooth function satisfying
(preserve low frequency)
• $\int_{\mathbb{R}^2} K(x, y) \, dx \, dy = 1$ or $\hat{K}(0, 0) = 1$
(suppress high frequency)
• $\hat{K}(w_1, w_2)$ decays sufficiently fast as $|\omega| \to \infty$

2D Fourier transform
\[
\hat{K}(w_1, w_2) = \int_{\mathbb{R}^2} K(x, y) e^{-i(w_1 x + w_2 y)} \, dx \, dy
\]

Lowpass condition

**Figure 1.5** (a) Point spread function (PSF). (b) Corresponding modulation transfer function (MTF). The MTF is the amplitude of the optical transfer function (OTF), which is the Fourier transform (FT) of the PSF.
• A *radially* symmetric PSF $K$ is *isotropic*

$$K(x,y) = k(x^2 + y^2)$$

PSF is *orientation selective or polarized*, if

$$K(x,y) = k((x,y)A(x,y)^T)$$

• A nonnegative PSF $K(x,y) \geq 0$ is a PDF.

• Convolution is given by

$$\tilde{f}(x,y) = K \ast f(x,y) = \int_{\Omega} K(x-p,y-q) f(p,q) dp dq.$$
Weighted Averaging Filter

• Instead of averaging all the pixel values in the window, give the closer-by pixels higher weighting, and far-away pixels lower weighting.

\[ \tilde{f}(x,y) = K \ast f(x,y) = \int_{\Omega} K(x-p,y-q)f(p,q)dpdq. \]

• This type of operation for arbitrary weighting matrices is generally called “2-D convolution or filtering”. When all the weights are positive, it corresponds to weighted average.

• Weighted average filter retains low frequency and suppresses high frequency = low-pass filter
Weighted Averaging Filter
Median Filter

- **Problem with Averaging Filter**
  - Blur edges and details in an image
  - Not effective for impulse noise (Salt-and-pepper)

- **Median filter:**
  - Taking the median value instead of the average or weighted average of pixels in the window
    - Median: sort all the pixels in an increasing order, take the middle one
  - The window shape does not need to be a square
  - Special shapes can preserve line structures

- **Order-statistics filter**
  - Instead of taking the mean, rank all pixel values in the window, take the n-th order value.
  - E.g. max or min

Matlab command: medfilt2(A,[3 3])
Median Filter

**FIGURE 3.37** (a) X-ray image of circuit board corrupted by salt-and-pepper noise. (b) Noise reduction with a $3 \times 3$ averaging mask. (c) Noise reduction with a $3 \times 3$ median filter. (Original image courtesy of Mr. Joseph E. Pascente, Lixi, Inc.)
Highpass Filters

- Spatial operation: taking difference between current and averaging (weighted averaging) of nearby pixels
  - Can be interpreted as weighted averaging = linear convolution
  - Can be used for edge detection
- Example filters

\[
\begin{bmatrix}
0 & 1 & 0 \\
1 & -4 & 1 \\
0 & 1 & 0
\end{bmatrix}; 
\begin{bmatrix}
0 & -1 & 0 \\
-1 & 4 & -1 \\
0 & -1 & 0
\end{bmatrix};
\begin{bmatrix}
1 & 1 & 1 \\
1 & -8 & 1 \\
1 & 1 & 1
\end{bmatrix};
\begin{bmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1
\end{bmatrix};
\]

- All coefficients sum to 0!
Highpass Filters

\[
\begin{bmatrix}
0 & -1 & 0 \\
-1 & 4 & -1 \\
0 & -1 & 0
\end{bmatrix}
\]

Original image

Isotropic edge detection
Image Segmentation:
Subdivision of image data
Into “meaningful” entities
(objects, regions, boundaries).

= partitioning into disjoint object sets
(based on region properties)

There are other objects worthwhile
segmenting (e.g., graphs to analyze
social networks), but I won’t talk
about this today.

Slide: G. Gerig
Image Segmentation bridges between low-level vision/image processing and high-level vision. Its goal is to cluster a given image into a collection of ‘objects’, and then other high-level tasks such as object detection, recognition, and tracking can be performed.

**Definition:** \( I : \Omega \rightarrow M \quad \Omega \subseteq R^2 \text{ or } R^3 \)

\( \{ \Omega_i : i = 1, \ldots, N \} \) such that

(i) \( \Omega_i \cap \Omega_j = \emptyset \) for \( i \neq j \);

(ii) \( \Omega = \Omega_1 \cup \Omega_2 \cup \cdots \cup \Omega_N \cup \Gamma \) with \( \Gamma = \bigcup_{i=1}^{N} \partial \Omega_i \)
Examples

Example: Airway Segmentation from CT

Example: Automatic Segmentation of the Brain

structural MRI of the brain  Subcortical structures
Statistical Image Segmentation

Observed Image/features

\[ Y = \{ y(w) : w \in W \} \]

Likelihood Function

\[ p(Y \mid X) \]

Bayesian Rule

\[ p(X \mid Y) = \frac{p(Y \mid X)p(X)}{p(Y)} \]

Inference

\[ \hat{X} = \{ \hat{x}(w) : w \in W \} \Rightarrow \bigcup_{i=1}^{N} i \]

Classification Image

\[ X = \{ x(w) : w \in W \} \]

Prior (local smooth)

\[ p(X) \]
Example: Gaussian Mixture Normal

\[ p(Y \mid X) = \sum_{k=1}^{K} p_k \cdot N(y(d); \mu_k, \sigma_k^2) \]

\[ p(X) = \prod_{d} \prod_{D} \prod_{k=1}^{K} 1(\text{x(d)}=k) \]

Initial CT chest slice

Ground truth (hand-drawn lungs)
Deformable models are curves or surfaces, for segmentation in the image domain, or hyper-surfaces, for the segmentation of higher dimensional images.

\[
\Gamma = \bigcup_{i=1}^{N} \partial \Omega_i, \\
\quad p(Y \mid X; ) p(X; ) \quad \rightarrow \quad \hat{\Gamma} = \bigcup_{i=1}^{N} \partial \hat{\Omega}_i
\]

Parametric Active Contours (Kass et al 1987)

\[
C(s) = [x(s), y(s)]
\]

\[
E = \int_{0}^{1} \frac{1}{2} (\alpha |C'(s)|^2 + \beta |C''(s)|^2) ds + \int_{0}^{1} E_{ext}(C(s)) ds
\]

\[
E_{ext}(x, y) = -|\nabla (G_{\sigma} \ast I(x, y))|^2
\]
Neural Network

\[
\sigma \left( \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right) = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}
\]
Design a method to promote automatic segmentation algorithms on the 6-months infant brain MRI into white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) by utilizing T1- and T2-weighted brain MRI scans. The 6-month infant brain, which is also named by the isointense-phase infant brain, has the major difficulty to segment for its overlapping of GM and WM and the lowest tissue contrast.

**Example: U-net based Segmentation**

![Brain MRI images showing development from 2 weeks to 12 months](image)

![3D GlassesNet architecture](image)

**Table 2: The average Dice's coefficient over 13 testing samples**

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team</th>
<th>WM (p=1.9e-6)</th>
<th>GM (p=3.5e-7)</th>
<th>CSF (p=1.3e-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BigS2 (GlassesNet)</td>
<td>0.909</td>
<td>0.928</td>
<td>0.961</td>
</tr>
<tr>
<td>2</td>
<td>MSL SKKU</td>
<td>0.904</td>
<td>0.923</td>
<td>0.958</td>
</tr>
<tr>
<td>3</td>
<td>LIVIA</td>
<td>0.897</td>
<td>0.919</td>
<td>0.957</td>
</tr>
<tr>
<td>4+</td>
<td>Bern IPMI</td>
<td>0.896</td>
<td>0.916</td>
<td>0.954</td>
</tr>
<tr>
<td>5+</td>
<td>BigS2 (LFA-CNN)</td>
<td>0.867</td>
<td>0.892</td>
<td>0.948</td>
</tr>
</tbody>
</table>

Dice's coefficient $= \frac{2|X \cap Y|}{|X| + |Y|}$
Image registration is the process of transforming different sets of data into **one coordinate system**. Data may be multiple photographs, data from different sensors, from different times, or from different viewpoints.
Recall Contrast Enhancements

\[ \tilde{f}(i, j) = T[f(i, j)] \]

\[ \tilde{f}(\tilde{x}) = T[f(\tilde{x})], \quad \text{for all } \tilde{x} \in \Omega \]

when \( T[\tilde{y}] \) is a monotonic function of \( \tilde{y} \).

Deformation

\[ \tilde{f}(\tilde{x}) = f(T(\tilde{x})), \quad \text{for all } x \in \Omega \]

when \( \tilde{x}' = T(\tilde{x}) \) is a one-to-one transformation of \( \tilde{x} \).
Image Registration

Given two images $\mathcal{I}, \mathcal{R} : \subset \mathbb{R}^d \rightarrow \mathbb{R}$, find a transformation $T : \mathbb{R}^d \rightarrow \mathbb{R}^d$ such that

$$\hat{T} = \arg\min_T D(\mathcal{I}[T], \mathcal{R}) + S[T]$$

$\mathcal{I}, \mathcal{R} : \subset \mathbb{R}^d \rightarrow \mathbb{R}$ denote template and reference images

$[T](x) = (T(x))$

$D(\quad, \quad)$ denotes a prefixed distance measure

$S[T]$ is a regularizer of $T$
Parameterized Transformations

Examples of $\tilde{x}' = T(\tilde{x})$

- **Scaling**: $\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$
- **Translation**: $\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$
- **Shear**: $\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & u_x & 0 \\ u_y & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$
- **Rotation**: $\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$

**Linear (Affine) Transformation**

General affine $\begin{pmatrix} x' \\ y' \\ z' \\ 1 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & t_x \\ a_{21} & a_{22} & a_{23} & t_y \\ a_{31} & a_{32} & a_{33} & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}$.

**Nonlinear Transformation**
Parameterized Transformations

- Interpolated data, m=[192 128]
- Translation
- Interpolated data, m=[192 128]
- Scale

- Interpolated data, m=[192 128]
- Translation x1
- Interpolated data, m=[192 128]
- Non-linear

- Interpolated data, m=[192 128]
- Rotation
- Interpolated data, m=[192 128]
- Spline
The basic idea of landmark-based registration is to determine the transformation such that for a finite number of features, any feature of the template image is mapped onto the corresponding feature of the reference image.

Given two images $\mathcal{I}, \mathcal{R} : \subset R^d \to R$, find a transformation $T : R^d \to R^d$ such that

$$\hat{T} = \text{argmin}_T D(\mathcal{I}[T], \mathcal{R}) + S[T]$$

$t_j = (t_j^1, \cdots, t_j^d)^T \in \Omega$ template image;

$r_j = (r_j^1, \cdots, r_j^d)^T \in \Omega$ reference image

$T(r_j) \approx t_j$ for $j = 1, \cdots, m$. 
Landmark-based Registration

\[ D^{LM}(\{T\}, \cdot) = \sum_{j=1}^{m} \|T(r_j) - t_j\|_f^2 \]

Regression: \( T(r) = \sum_{j=1}^{m} j(r) \) and \( S[T] = 0 \) e.g.,

\{ \( j(.) \) \} can be set as the basis functions of affine transformation

RKHS: \( T(r) = \langle f, (r) \rangle_H \) and \( S[T] = \|f\|_H^2 \) e.g.,

\{ \( (.) \) \} denotes a feature map
Landmark-based Registration

BigTutorialLandmarks
Part 4. Challenges
Major Challenges

- Annotation datasets
- Complex objects
- Complex spatial and/or temporal structures
- Extremely high dimensionality

- Complicated causal pathways
- Complex missing patterns
- Heterogeneity across subjects, studies, and populations
- High dimensional variables across different domains
- Sampling bias
Data Challenges

- Over 15M labeled high resolution images
- Roughly 80K categories
- Collected from web and labeled by Amazon Mechanical Turk

Lack of a large number of annotated data with high-quality
Heterogeneity Challenges

Heterogeneity at the subject, group, and study levels

Subject

Group

Study


Davatzikos (2018) Neuroimage
Integration Challenges

Source: 滴滴AI Labs, 滴滴战略部

Healthcare
- Genetics
- Imaging
- Clinical

Shallow Information
- Speech Recognition
- NLP
- Computer Vision
- Prediction and Decision
- IOT

A hypothetical model of AD pathogenesis by Jack Jr et al. (2010).

Directed acyclic graph (DAG) of hippocampal exposure on dementia behavior.