

Elastic maps with applications in bioinformatics

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- Principal manifolds as surfaces of minimal elastic energy
- Elastic maps: construction and utilization
- Examples of use
- Microarray datasets
- Future development



Mean point





Principal "Object"





Principal Component Analysis





Principal manifold





Probability distribution: idea of self-consistency





Self-organizing maps





Metaphor of elasticity (energy function proposed by Gorban in 1996 at Russian national neuroinformatics workshop "Neuroinformatics and its applications - 1996")





Constructing elastic nets





Definition of elastic energy



Scaling rules

 $\lambda = \lambda_0 s \frac{\frac{2-d}{d}}{\frac{4-d}{d}}$ $\mu = \mu_0 r^{-\frac{d}{d}}$

For uniform d-dimensional net from the condition of constant energy density we obtain:

$$\lambda_1 = \lambda_2 = \ldots = \lambda_s = \lambda(s);$$

$$\mu_1 = \mu_2 = \dots = \mu_r = \mu(r)$$

s is number of edges, *r* is number of ribs in a given volume



Elastic manifolds





Global minimum and softening





Adaptive algorithms





Projection onto the manifold



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Mapping distortions



Two basic types of distortion:

O 1) Projecting distant points in the close ones (bad resolution)

2) Projecting close points in the distant ones (**bad topology compliance**)



Instability of projection



Best Matching Unit (BMU) for a data point is the closest node of the graph, BMU2 is the second-close node. If BMU and BMU2 are not adjacent on the graph, then the data point is *unstable*.

Gray polygons are the areas of instability. Numbers denote the degree of instability, how many nodes separate BMU from BMU2.



Dealing with missing values in data





Colorings: visualize any function





Density visualization





Various manifold topologies





Example 1: Approximating molecular surface



Approximating by 2D spherical grid

approximating by 2D spherical gri



Approximating by 1D curve





Example 2: Image skeletonization or clustering around curves



Example 3: Medical table

1700 patients with infarctus myocarde





Example 3: Medical table

1700 patients with infarctus myocarde



128 clinical variables



Age

Numberof infarctus in anamnesis

Stenocardia functional class



Example 4: Codon usage in all genes of one genome





Microarray technology and microarray datasets





One spot corresponds to a gene (mRNA concentration)

Table of numbers, characteristic size is 10000 genes x100 samples



Gene space: every point correspond to a gene characterized by its expression in m samples











2006

Bladder cancer dataset (Dataset II), 40 patients



102 healthy tissues (Dataset III)







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102 healthy tissues (Dataset III)



actin gamma 2

claudin 1





aldolase B



ERBB3



calgranulin B

Implementation of the idea: VidaExpert tool



http://bioinfo.curie.fr/projects/vidaexpert/



elmap C++ package

http://bioinfo.curie.fr/projects/elmap/

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VIMIDA: Java-applet for multidimensional data visualization

Part of PLATAN : Microarray data analysis pipeline developed In Institut Curie



http://bioinfo.curie.fr/projects/vimida/ (

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Anonce

Topological grammars: principal trees, cubic complexes, etc. in the talk of Professor Gorban (26 August)



Branching principal components for bioinformatics data: alternative for hierarchical clustering?





Papers



Prof. Misha Gromov (France)

Dr. Alexei Rossiev (Moscow)

Dr. Alexander Pitenko (Krasnoyarsk, Russia)

Neil Sumner (Leicester, UK)

Laboratory of neuroinformatics of Institute of computational Modeling, Russian Academy of Science

