gipsa-lab

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laboratoire

Current Topics in BCI Classification

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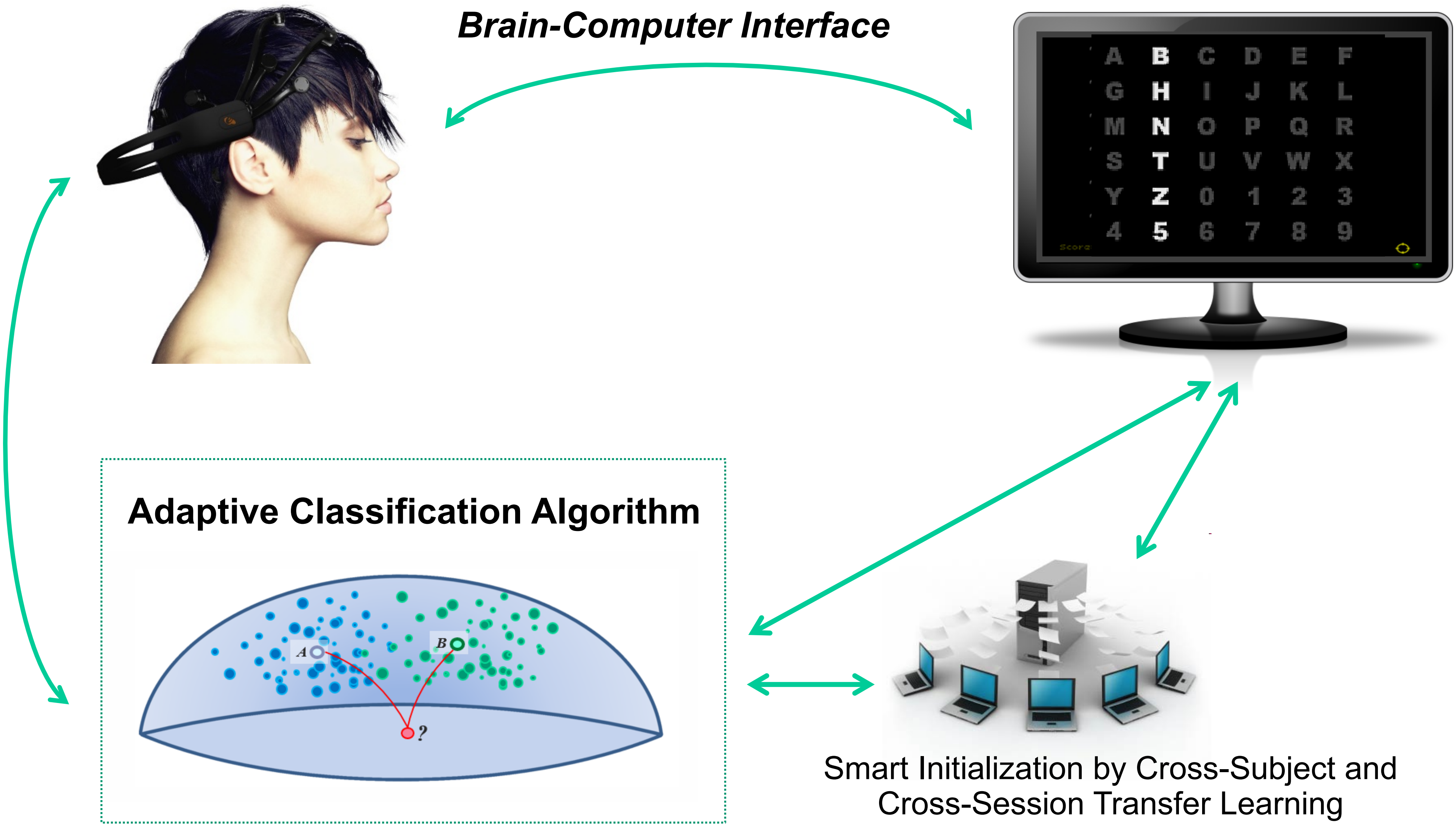
CNRS

University Grenoble Alpes

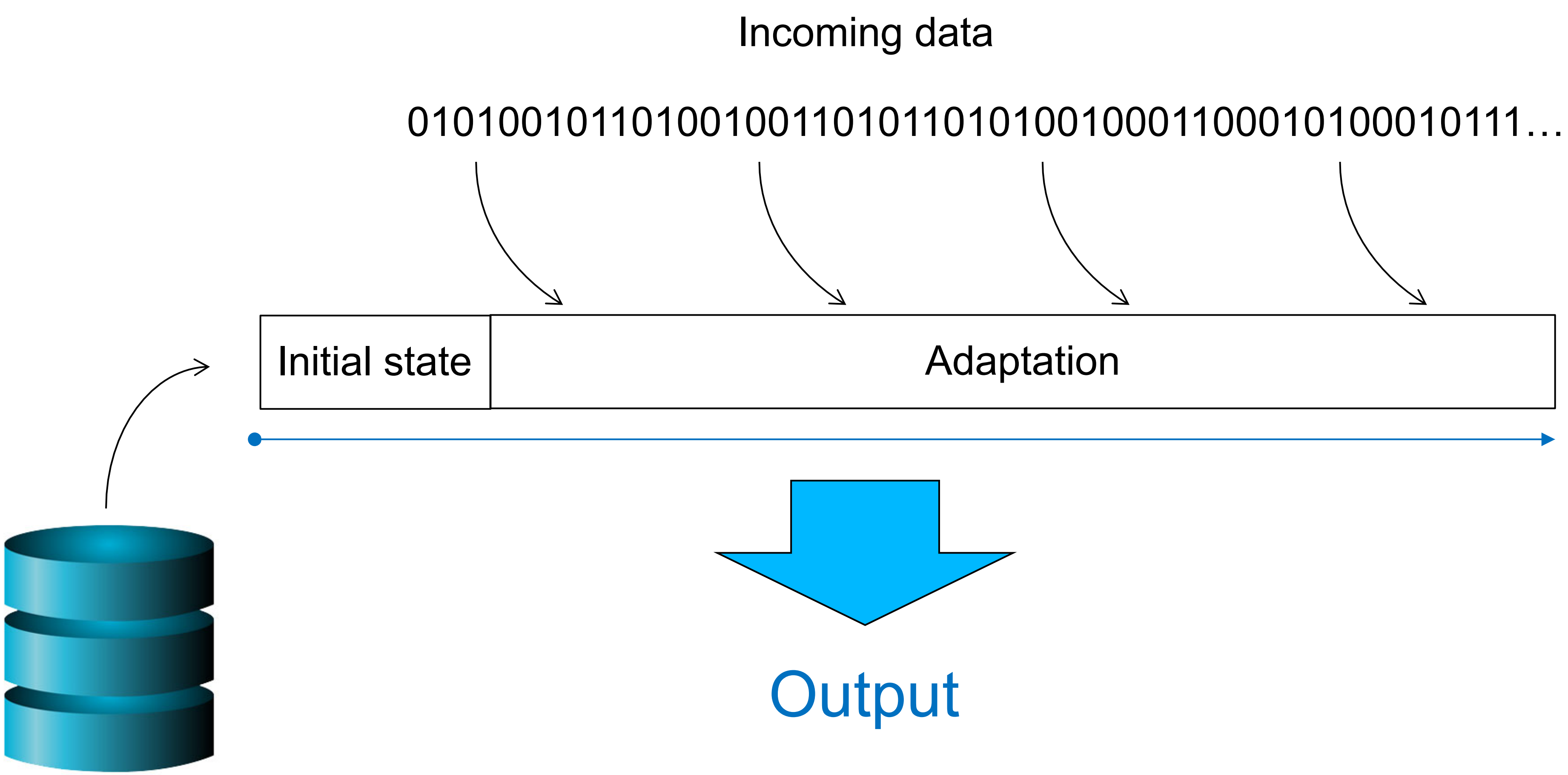
National Polytechnique Institute - Grenoble

UMR 5216

Second-Generation **Brain-Computer Interfaces**



Beyond the **Test-Training** Paradigm



Requested Characteristics of a BCI Decoder

a) ***High Accuracy*** (as compared to established state-of-the-art approaches)

Congedo, Bhatia & Barachant (2017)
Riemannian Geometry for EEG-based Brain-Computer Interfaces; a Primer and a Review.
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h) ***Generalization to the multi-user setting***

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Golden Standard: **on-line** (not always feasable and time consuming)

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- Use a great amount of real data featuring a large variability
- Employ objectives procedures

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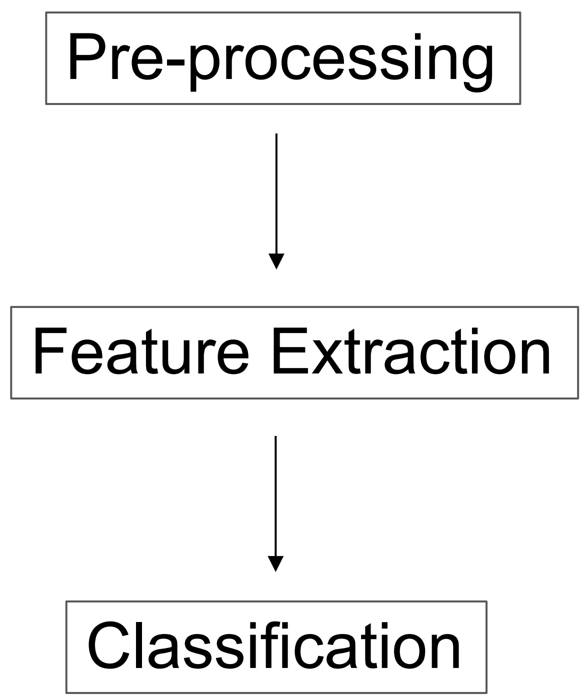
MOABB

Traditional Pipelines



Traditional Pipelines

Typical Pre-processing:

- Band-Pass Filtering
- Noise suppression
- Normalization
- Dimensionality Reduction
- …

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Typical Feature Extraction:

- Common Spatial Pattern (and all its variants, e.g., XDAWN)
- Spectral, Analytic Signal, Wavelet, Empirical-mode decomposition representation
- Indipendent component analysis / blind source separation
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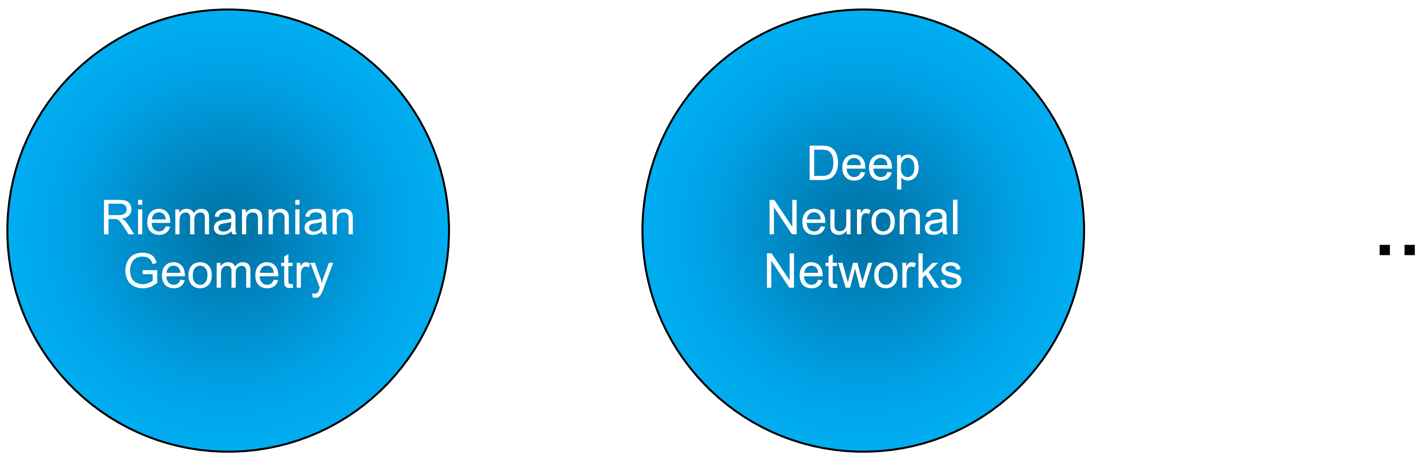
Typical Classification:

- LDA,
- Logistic Regression, Support-Vector Machine, …
- Random Forest
- …

Alternative Pipelines

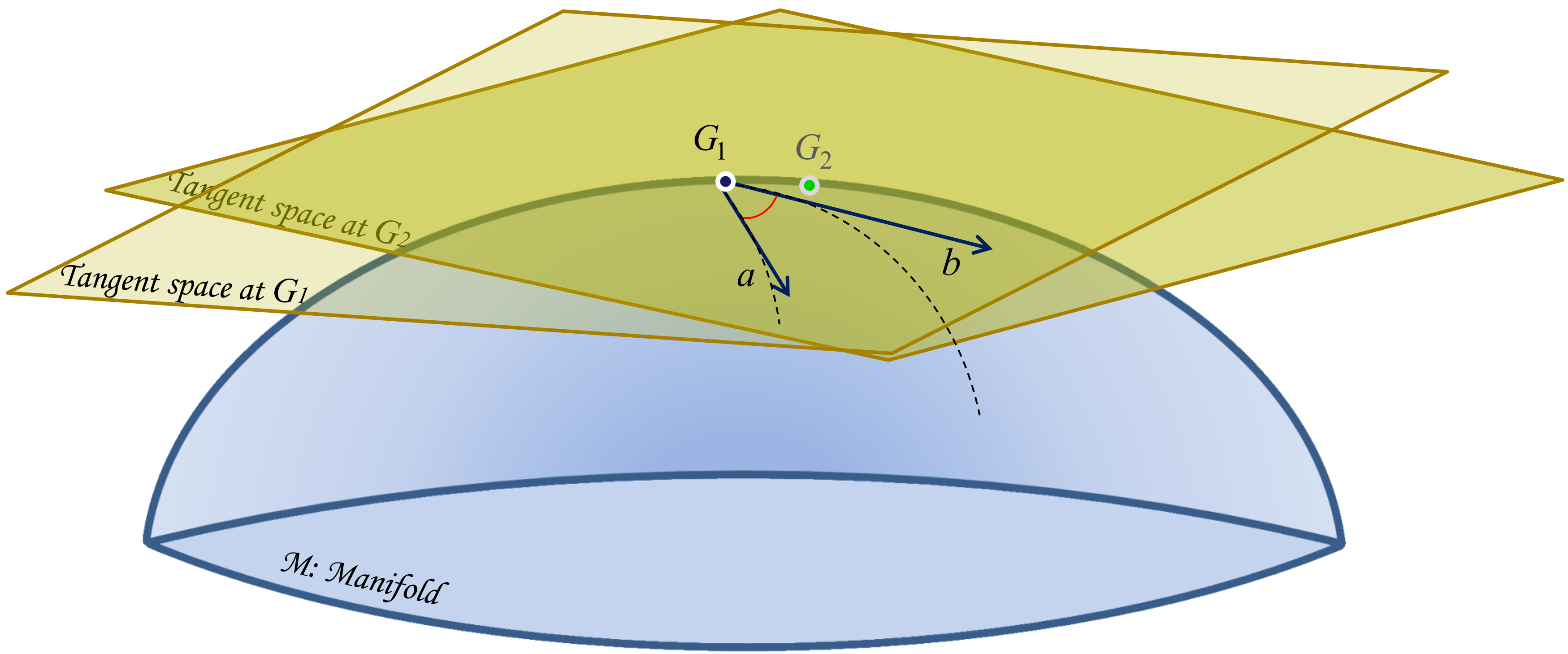


Riemannian Geometry: definition

A (smooth) *Riemannian manifold* $\mathcal{M}$ is a topological space that is locally similar to the Euclidean space with a globally defined differential structure.

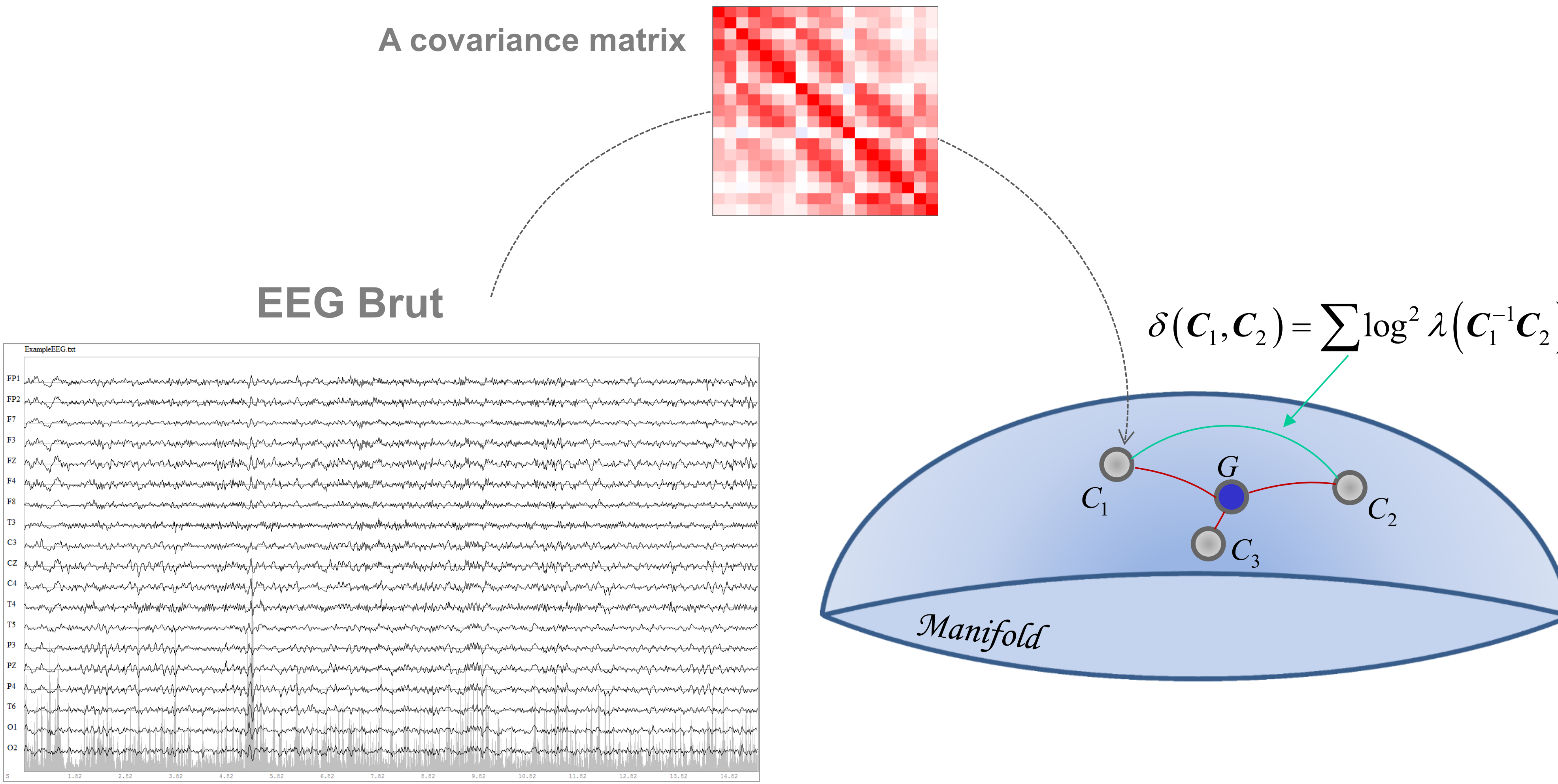
It is equipped with an *inner product* (metric) on the *tangent space* defined at each point and varying *smoothly* from point to point.

The tangent space $\mathcal{T}_G\mathcal{M}$ at point G is the Euclidean vector space containing the tangent vectors to all curves on $\mathcal{M}$ passing through G.



Inner product on tangent space (metric) → Riemannian Geometry

Representing the data on the Riemannian Manifold of Positive Definite Matrices



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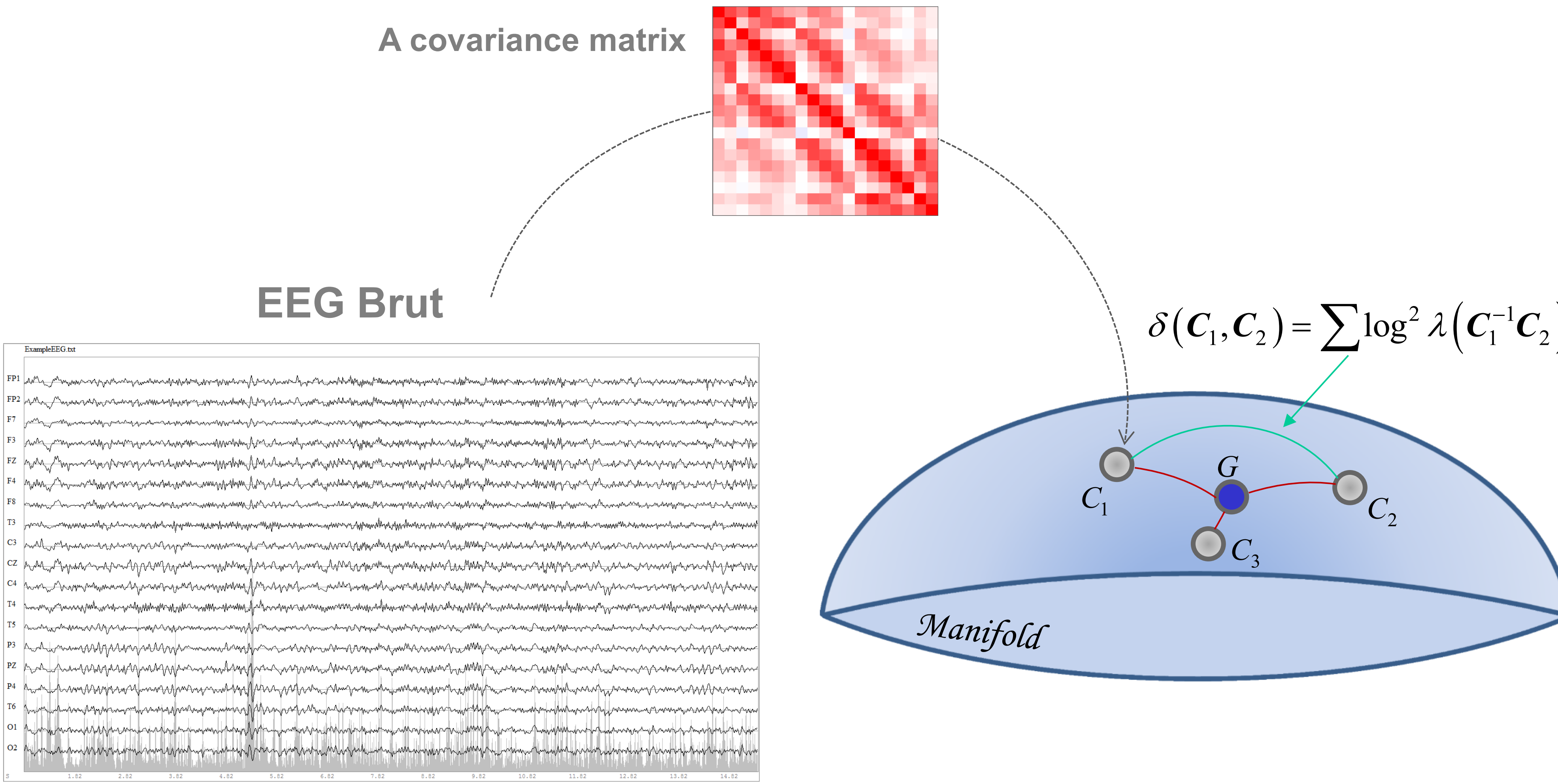


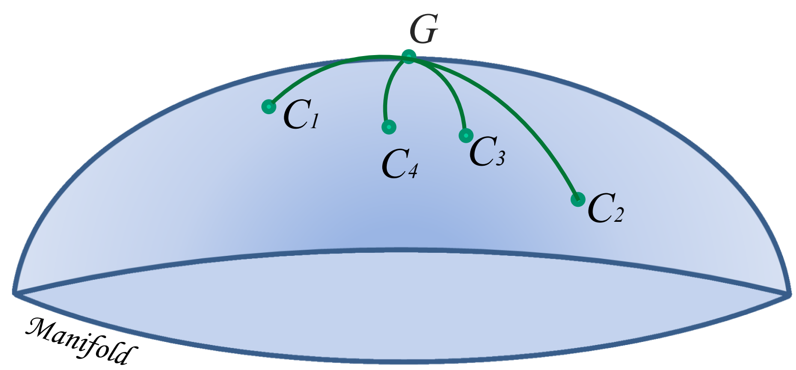
Invariances

$$\delta(\boldsymbol{C}_1, \boldsymbol{C}_2) = \delta\left(\boldsymbol{B}\boldsymbol{C}_1\boldsymbol{B}^T, \boldsymbol{B}\boldsymbol{C}_2\boldsymbol{B}^T\right)$$

$$\delta(\boldsymbol{C}_1, \boldsymbol{C}_2) = \delta\left(\boldsymbol{C}_1^{-1}, \boldsymbol{C}_2^{-1}\right)$$

Geometric Mean

$$\arg\min_{G} \sum_{k} \delta^{2}\left(G, C_{k}\right)$$



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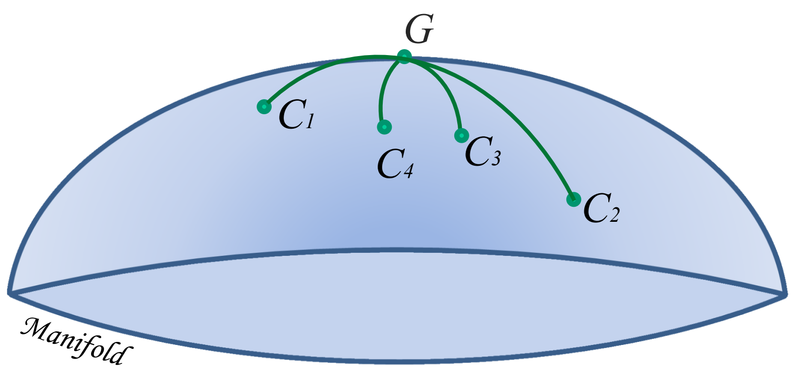


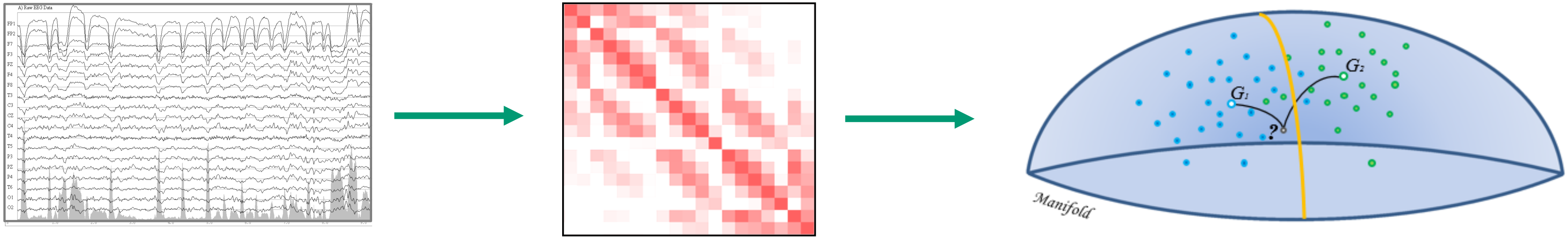
Always exixts, is unique and satisfies

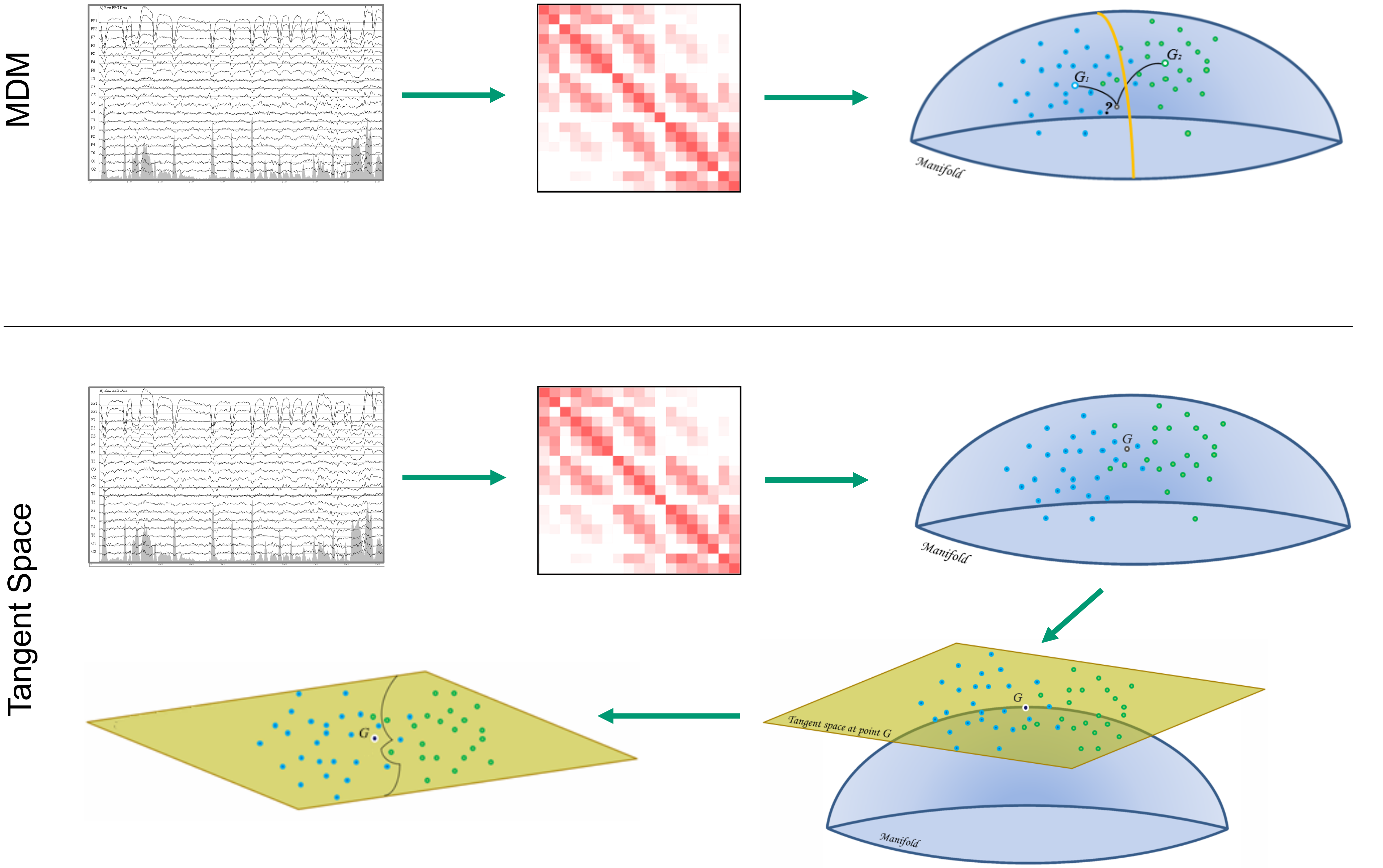
$$\sum_k \left[\mathrm{Log}\left(G^{-1/2} C_k G^{-1/2}\right)\right] = 0$$

First proved by Elie Cartan on Lie groups

Moakher M (2005) ***SIAM J Matrix Anal Appl,*** 26 (3), 735-747.

MDM





Pro

Performance Exceeds SoA
Allow using complex decision functions
Performs well in high dimension

Contra

More computationally involving
May be non-deterministic and may need hyperparameters

International BCI Decoding Competitions

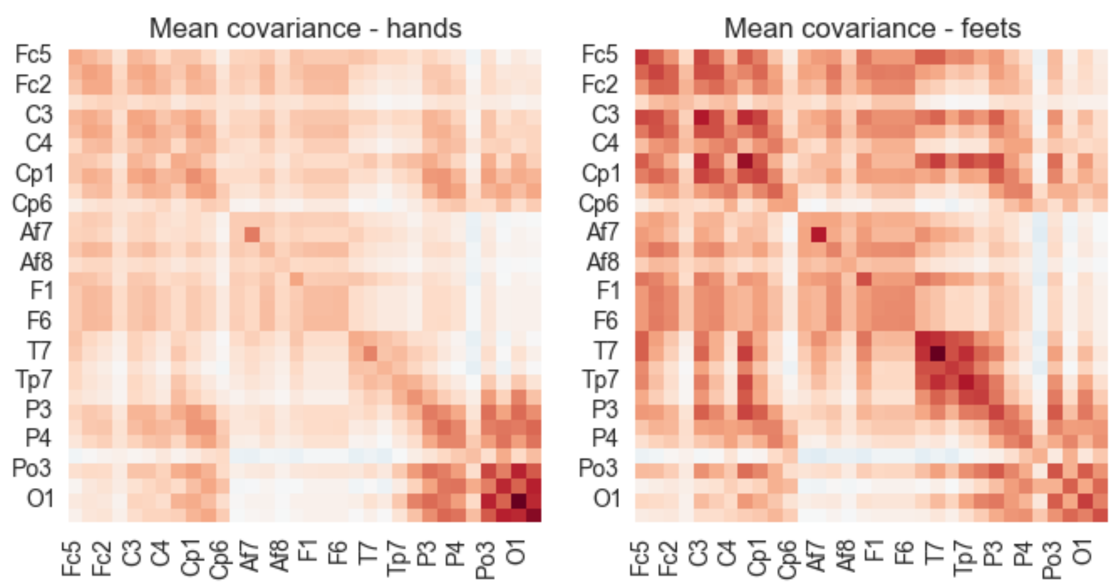
Nom de la Compétition	Événement ou Organisateur	Clôture	Participants	Score (%)
DecMeg 2014	BIOMAG 2014 Conference	27/07/2014	301	75.5
BCI Challenge	IEEE NER 2015 Conference	24/02/2015	311	87.2
Grasp&Lift EEG Challenge	WAY European Project	31/08/2015	452	98.1
Decoding Brain Signals	Microsoft	01/07/2016	688	93.7
Biomag2016 competition	BIOMAG 2016 Conference	25/09/2016	7	95.6

Feature Extraction as an **Encoding Step**

Induced Activity (e,g, Motor Imagery)

Z classes and K trials

$$\boldsymbol{X}_{\mathrm{zk}}^{MI} = \boldsymbol{X}_{\mathrm{zk}} \qquad\qquad \boldsymbol{C}_{\mathrm{zk}} = \frac{1}{T-1}\left(\boldsymbol{X}_{\mathrm{zk}}^{T}\boldsymbol{X}_{\mathrm{zk}}\right)$$

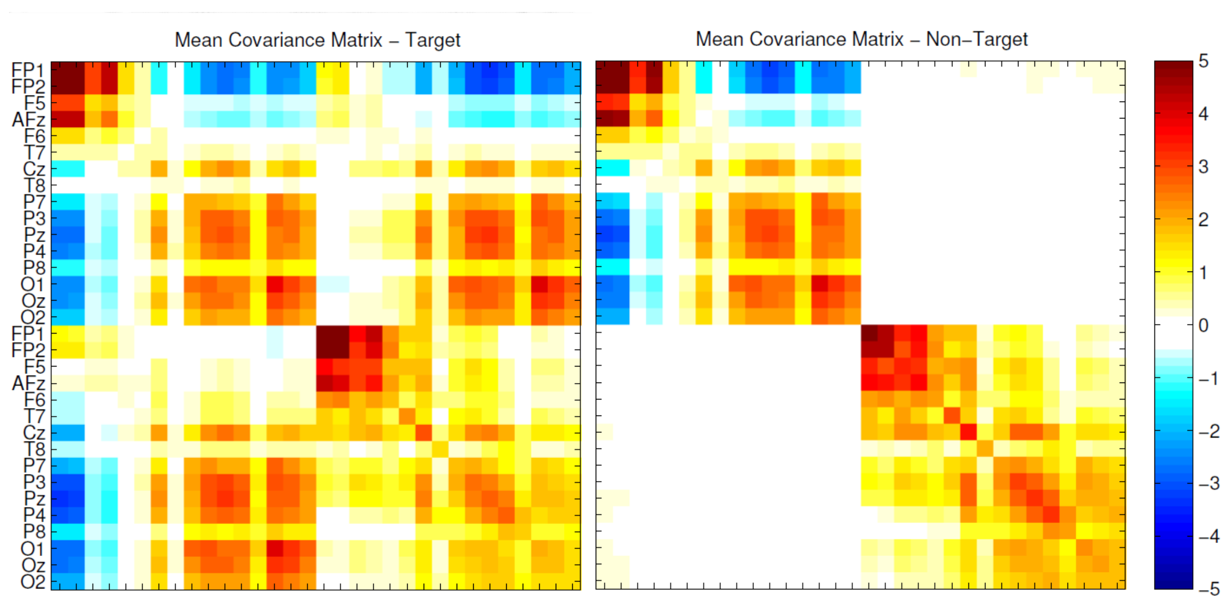


Evoked Activity (e.g., ERPs)

Z classes and K trials

$$\boldsymbol{X}_{\mathrm{zk}}^{P300} = \begin{pmatrix} \bar{\boldsymbol{X}}_{(+)} \\ \boldsymbol{X}_{\mathrm{zk}} \end{pmatrix} \qquad \boldsymbol{C}_{\mathrm{zk}} = \frac{1}{(T-1)}\left[\boldsymbol{X}_{\mathrm{zk}}^{P300}\left(\boldsymbol{X}_{\mathrm{zk}}^{P300}\right)^{T}\right] = \frac{1}{(T-1)}\begin{pmatrix} \bar{\boldsymbol{X}}_{(+)}\bar{\boldsymbol{X}}_{(+)}^{T} & \bar{\boldsymbol{X}}_{(+)}\boldsymbol{X}_{\mathrm{zk}}^{T} \\ \boldsymbol{X}_{\mathrm{zk}}\bar{\boldsymbol{X}}_{(+)}^{T} & \boldsymbol{X}_{\mathrm{zk}}\boldsymbol{X}_{\mathrm{zk}}^{T} \end{pmatrix}$$

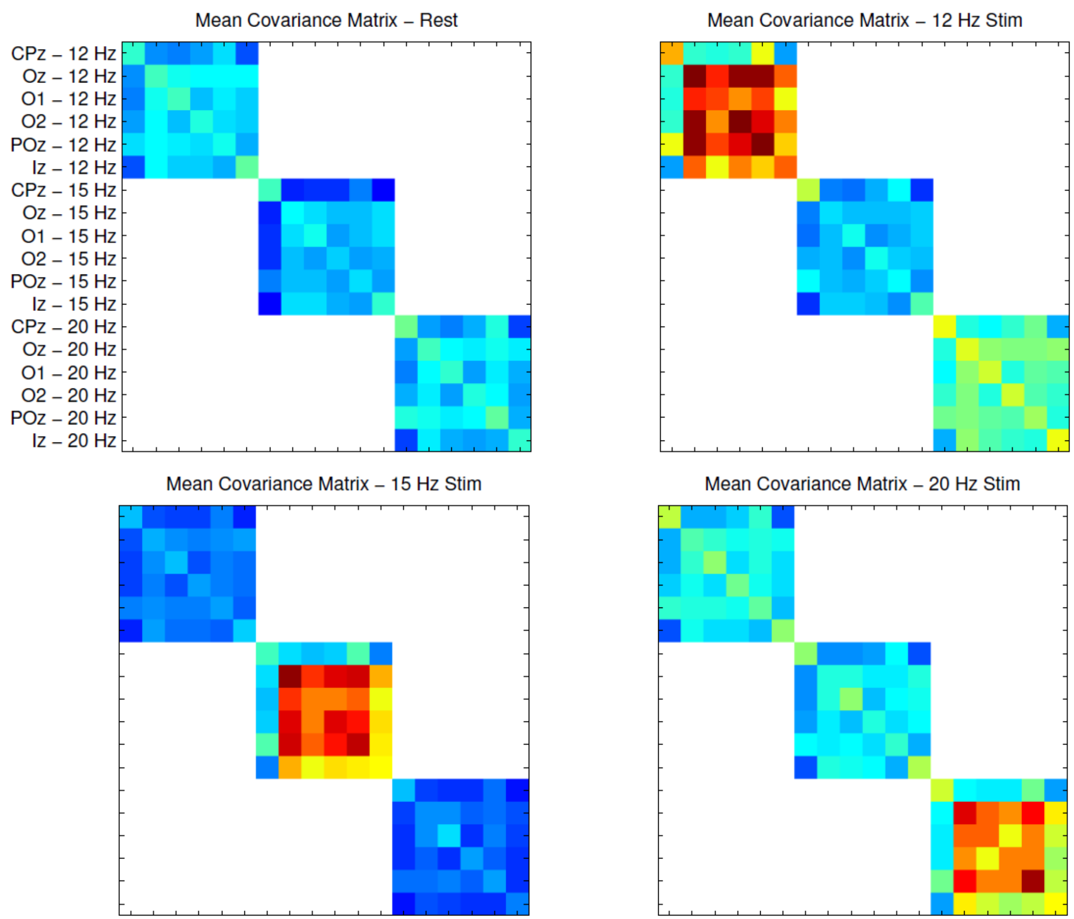
$$\boldsymbol{X}_{\mathrm{zk}}^{ERP} = \begin{pmatrix} \bar{\boldsymbol{X}}_{(1)} \\ \vdots \\ \bar{\boldsymbol{X}}_{(\mathrm{Z})} \\ \boldsymbol{X}_{\mathrm{zk}} \end{pmatrix} \qquad \boldsymbol{C}_{\mathrm{zk}} = \frac{1}{(T-1)}\left(\boldsymbol{X}_{\mathrm{zk}}^{ERP}\left(\boldsymbol{X}_{\mathrm{zk}}^{ERP}\right)^{T}\right) = \frac{1}{(T-1)}\begin{pmatrix} \bar{\boldsymbol{X}}.\bar{\boldsymbol{X}}.^{T} & \left(\boldsymbol{X}_{\mathrm{zk}}\bar{\boldsymbol{X}}.^{T}\right)^{T} \\ \boldsymbol{X}_{\mathrm{zk}}\bar{\boldsymbol{X}}.^{T} & \boldsymbol{X}_{\mathrm{zk}}\boldsymbol{X}_{\mathrm{zk}}^{T} \end{pmatrix}$$



SSVEP and Related Phenomena

Z classes and K trials

$$\boldsymbol{X}_{zk}^{SSEP} = \begin{pmatrix} \boldsymbol{X}_{1k} \\ \vdots \\ \boldsymbol{X}_{Zk} \end{pmatrix} \qquad \boldsymbol{C}_{zk} = \frac{1}{(T-1)} \begin{pmatrix} \boldsymbol{X}_{1k}\boldsymbol{X}_{1k}^{T} & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{X}_{Zk}\boldsymbol{X}_{Zk}^{T} \end{pmatrix}$$



Current Topic 1

Geometry-Aware Dimensionality Reduction

Unsupervised and Supervised methods

Geometry-Aware Dimensionality Reduction

As N grows, the accuracy of classification methods on Manifold decreases

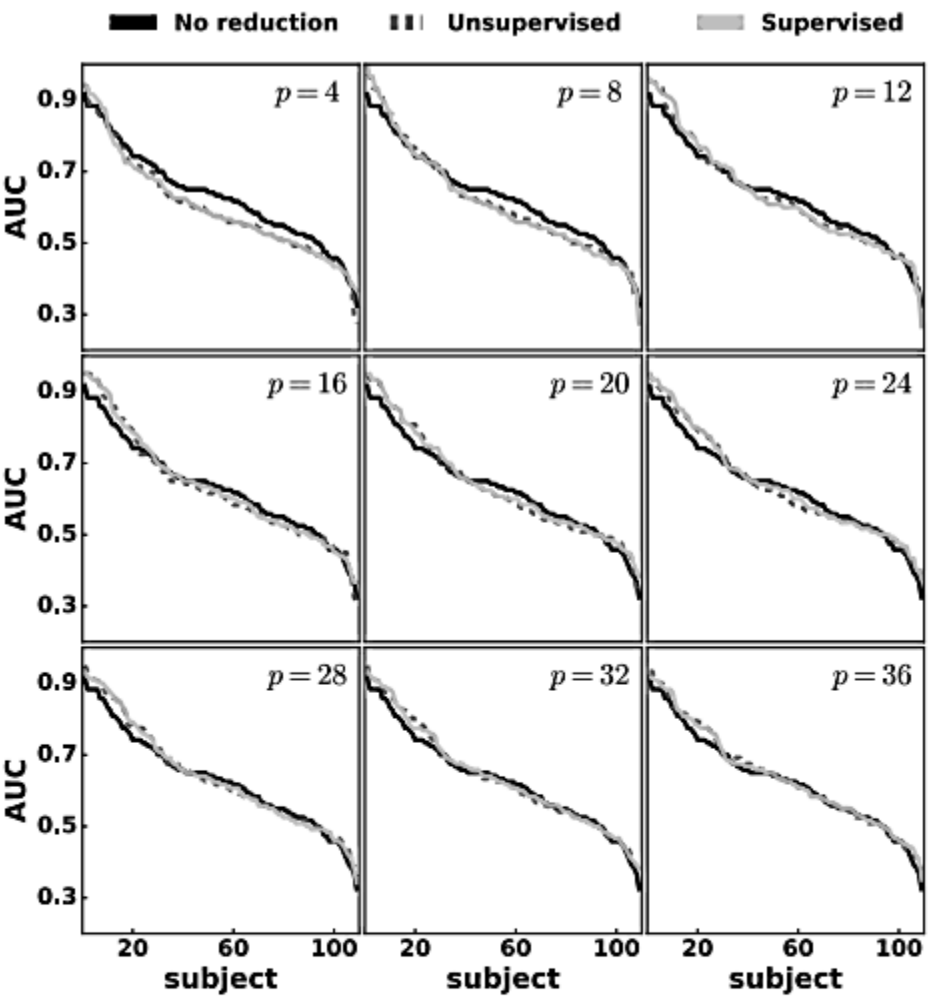
As N grows, the computational complexity grows cubically

Ex: unsupervised Approach: $$\underset{Z \in O_{P \cdot N}}{\arg\max} \sum_k \delta^2 \left(Z C_k Z^T, Z G Z^T \right)$$

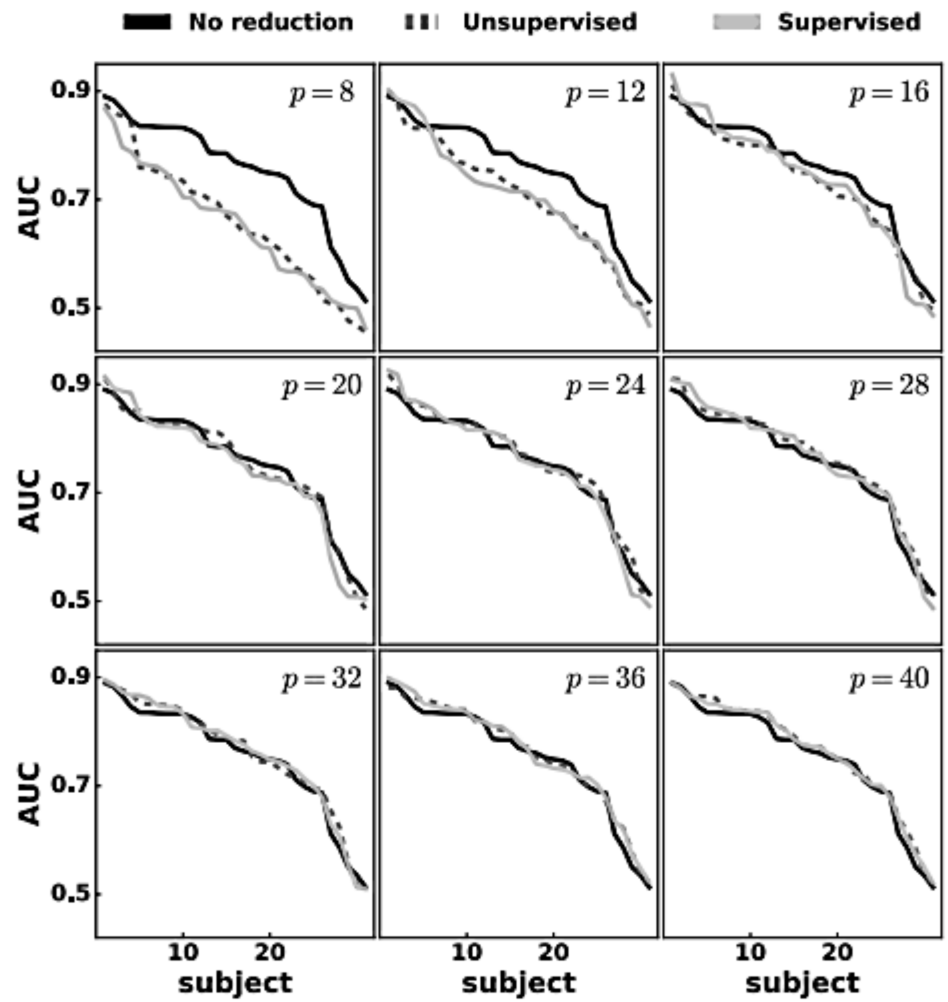
Rodrigues PLC, Bouchard F, Congedo M, Jutten C (2017)
Dimensionality Reduction for BCI classification using Riemannian geometry,
7th Graz ***Brain-Computer Interface Conf.***, Sep 2017, Graz, Austria.

Congedo M, Rodrigues PLC, Bouchard F, Barachant A, Jutten C (2017)
A Closed-Form Unsupervised Geometry-Aware Dim. Reduction Method in the Riemannian Manifold of SPD Matrices
Proc. of the 39th Int. ***Conf. of the IEEE EMBS***, Jeju Island, South Korea, July 11-15 2017, pp.3198-3201.

Physionet (MI, 109 ss, 64 elec.)



Brain Invaders (P300, 38 ss, 32 elec.)

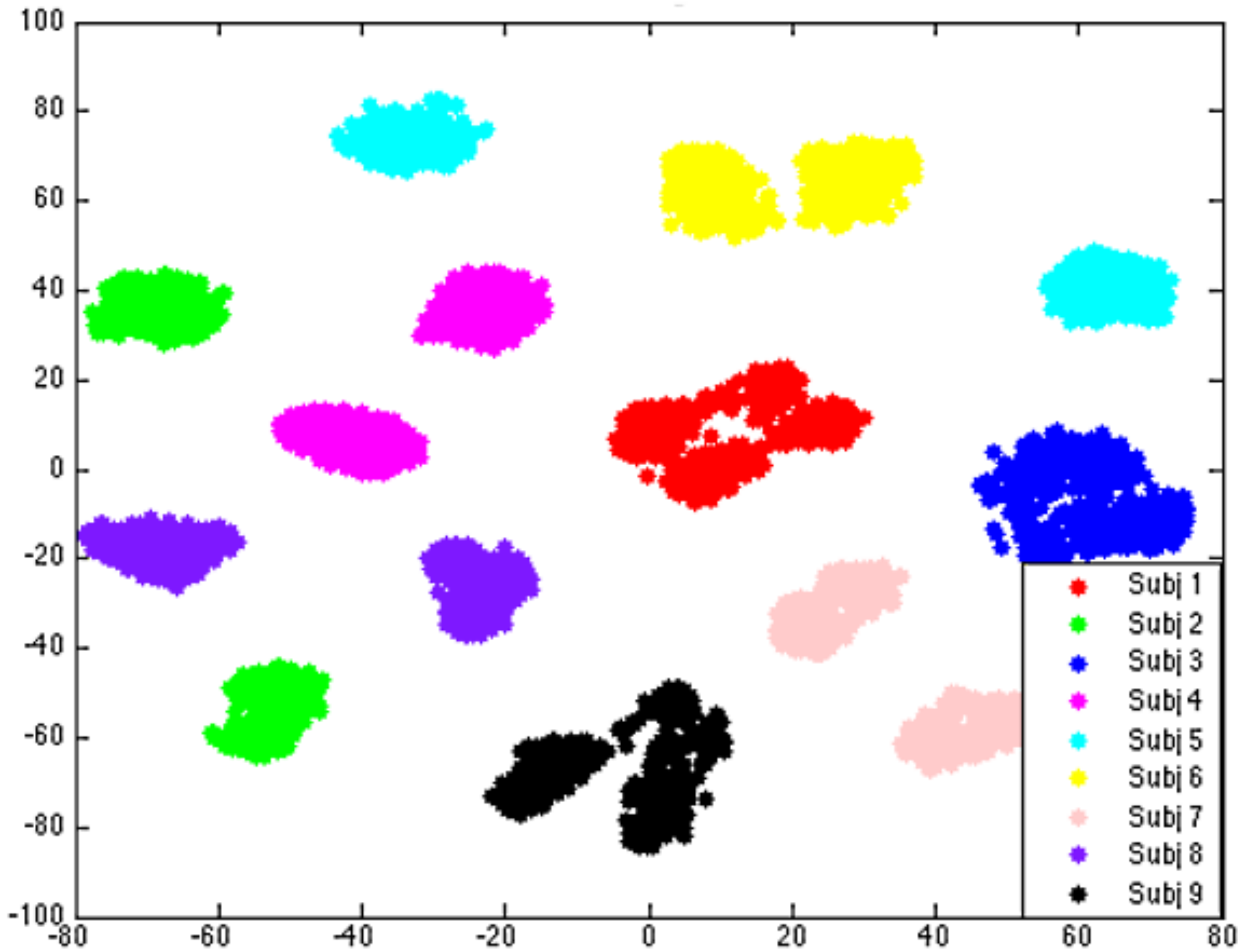


p=subspace dimension

Current Topic 2

Transfer Learning

Cross-Subject and Cross-Session Shift

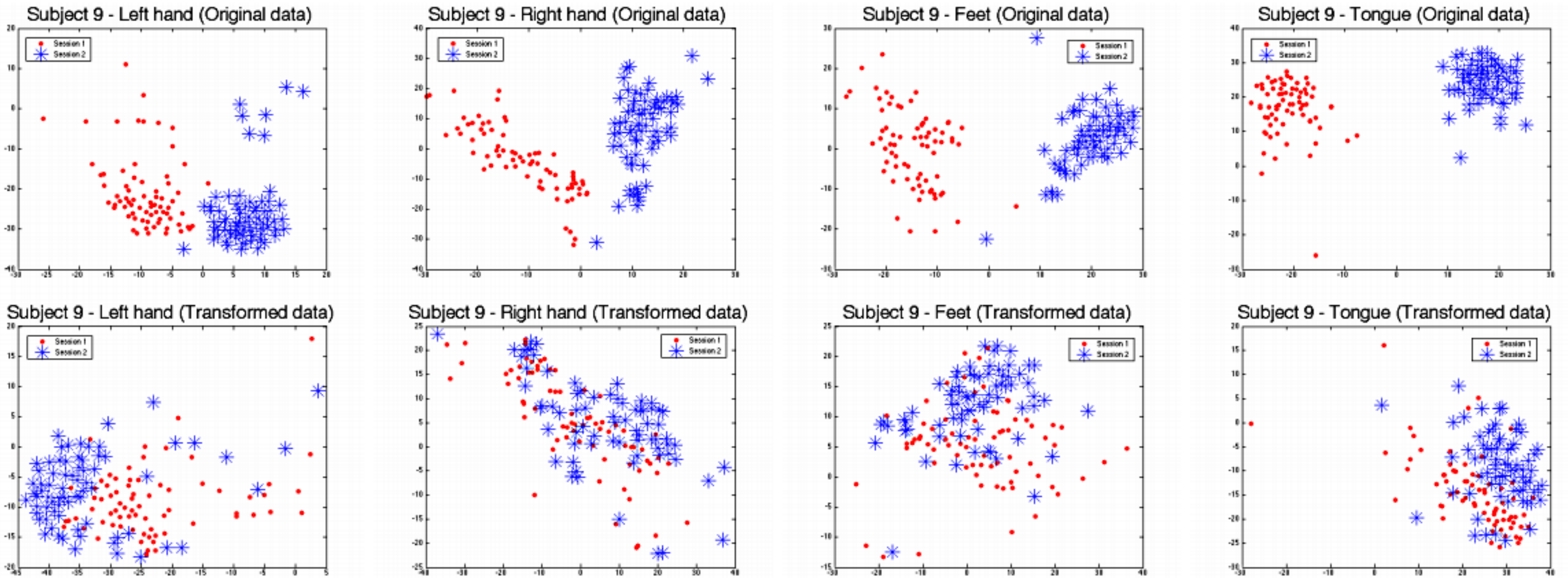


BCI Competition 2008, MI. 9 Ss, 2 sess, 22 ele, 4 Classes. Visualization: t-SNE

Recentering (Translation)

$$C_k \leftarrow G^{-1/2} C_k G^{-1/2}$$

Unsupervised Cross-Session Transfer Learning



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Zanini P, Congedo M, Jutten C, Said S, Berthoumieu Y (2018)
Transfer Learning: a Riemannian geometry framework with applications to Brain-Computer Interfaces
IEEE Trans Biomed Eng, 65(5), 1107-1116.

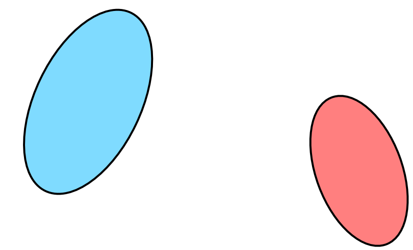
Current Topic

Transfer Learning by
Riemannian Procrustes Analysis
(semi-supervised)

Riemannian Procrustes Analysis (RPA)

Raw Data

C_k



Rodrigues PLC, Jutten C, Congedo M (2019)
Riemannian Procrustes Analysis : Transfer Learning for Brain-Computer Interfaces,
IEEE Tran Biomed Eng, *66(8), 2390-2401.*

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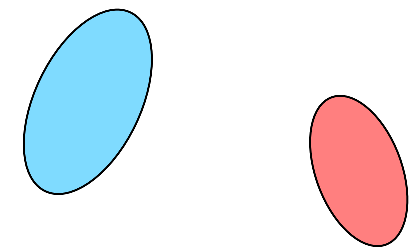
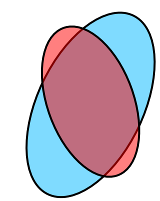


Recentering $C_k \leftarrow G^{-1/2} C_k G^{-1/2}$



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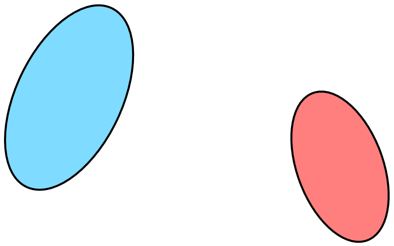
Riemannian Procrustes Analysis (RPA)

UNSUPERVISED

Raw Data C_k



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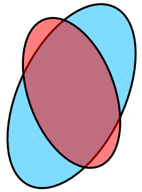
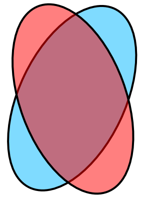


Stretching $C_k \leftarrow C_k^p$



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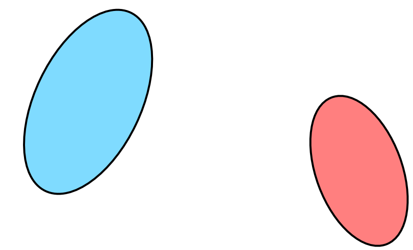
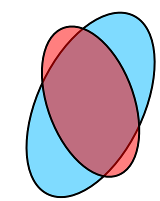
Riemannian Procrustes Analysis (RPA)

Raw Data C_k



UNSUPERVISED

Recentering $C_k \leftarrow G^{-1/2} C_k G^{-1/2}$



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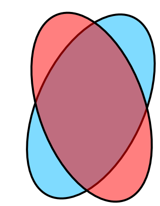
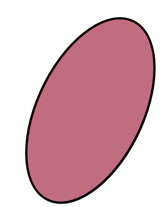


SUPERVISED

Rotation $C_k \leftarrow U C_k U^T$



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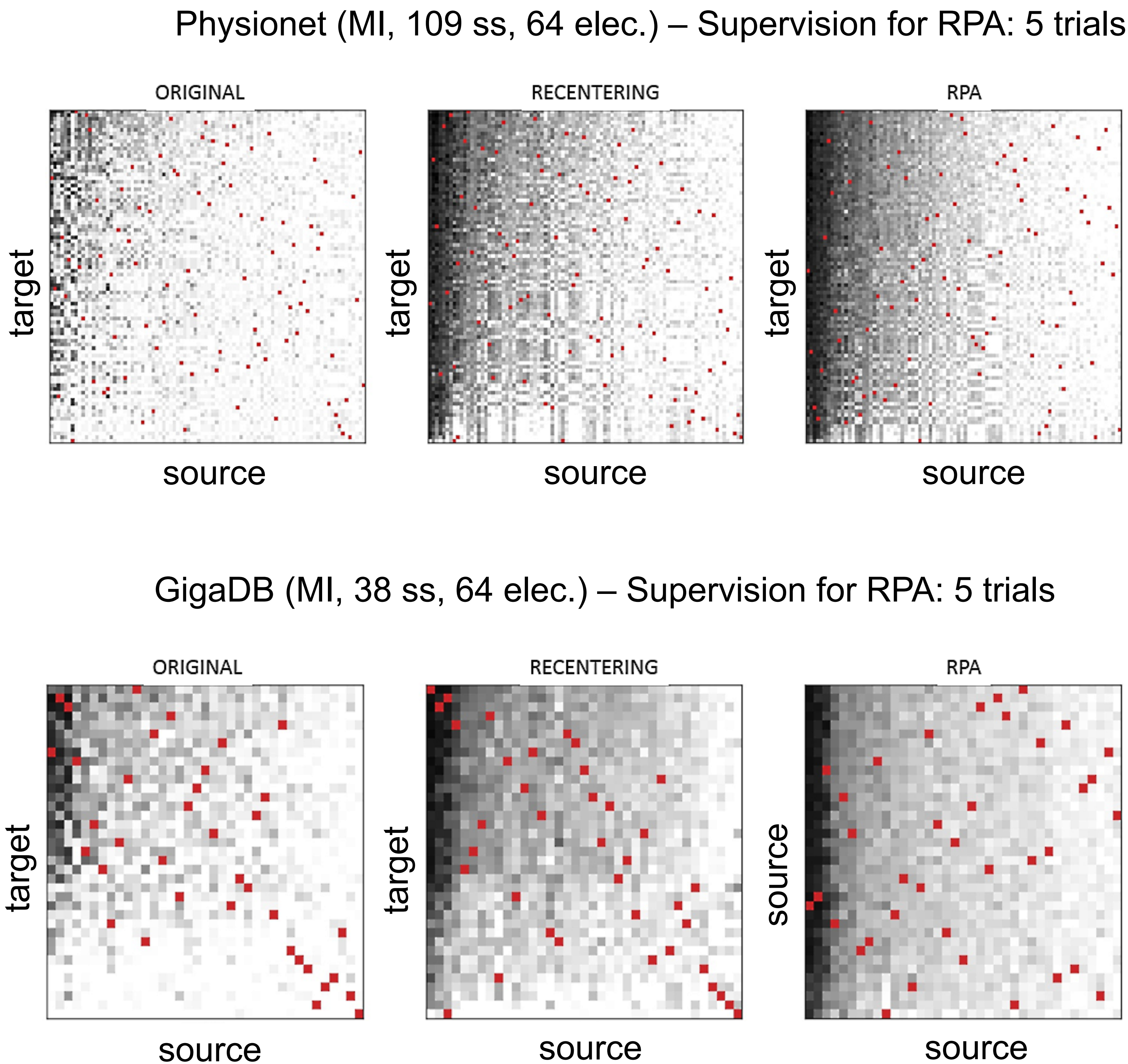
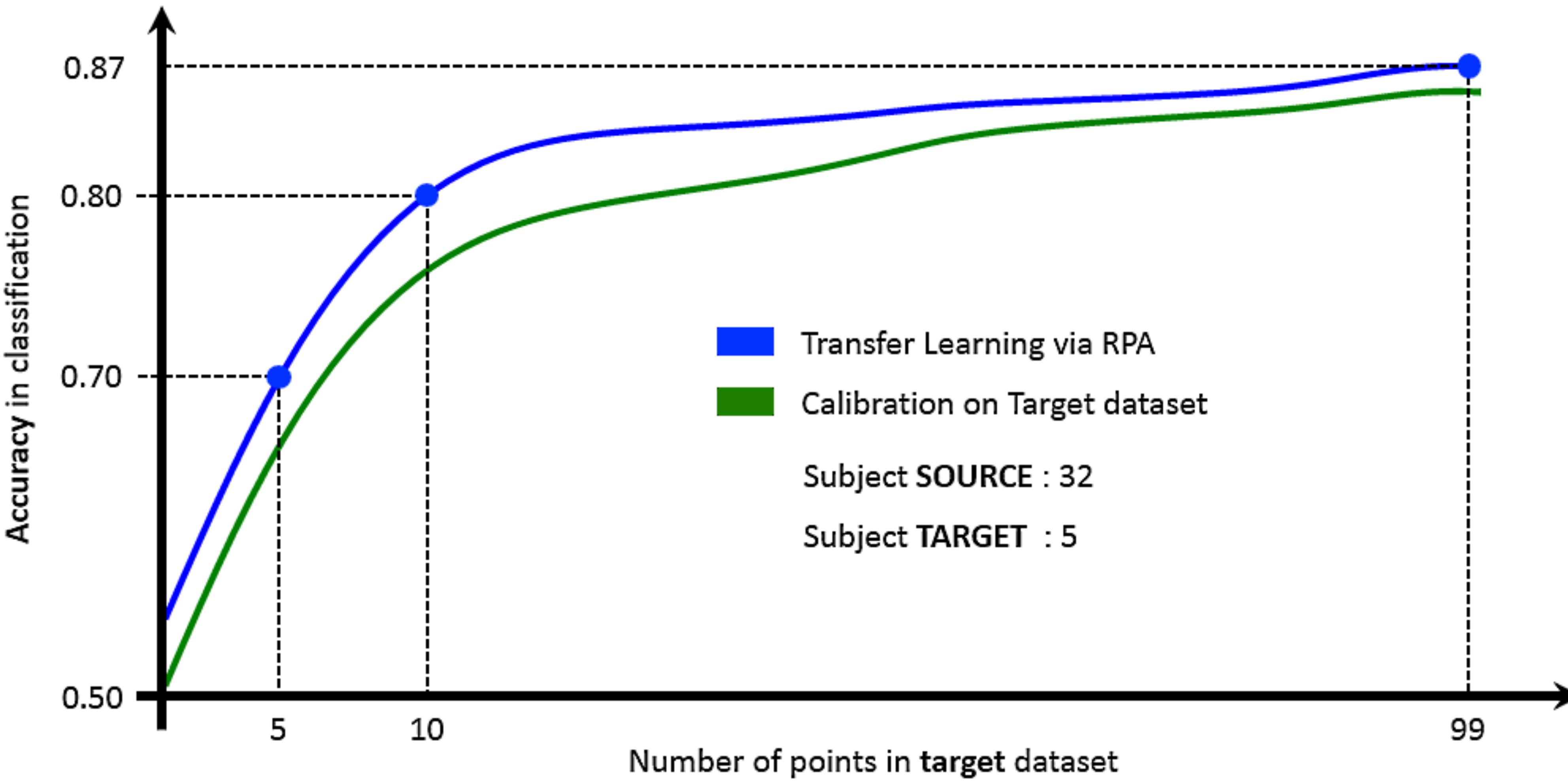


Physionet (MI, 109 ss, 64 elec.) – Supervision for RPA: 5 trials
ORIGINAL
RECENTERING
RPA
target
source
GigaDB (MI, 38 ss, 64 elec.) – Supervision for RPA: 5 trials
ORIGINAL
RECENTERING
RPA
target
source

What about just using calibration ?

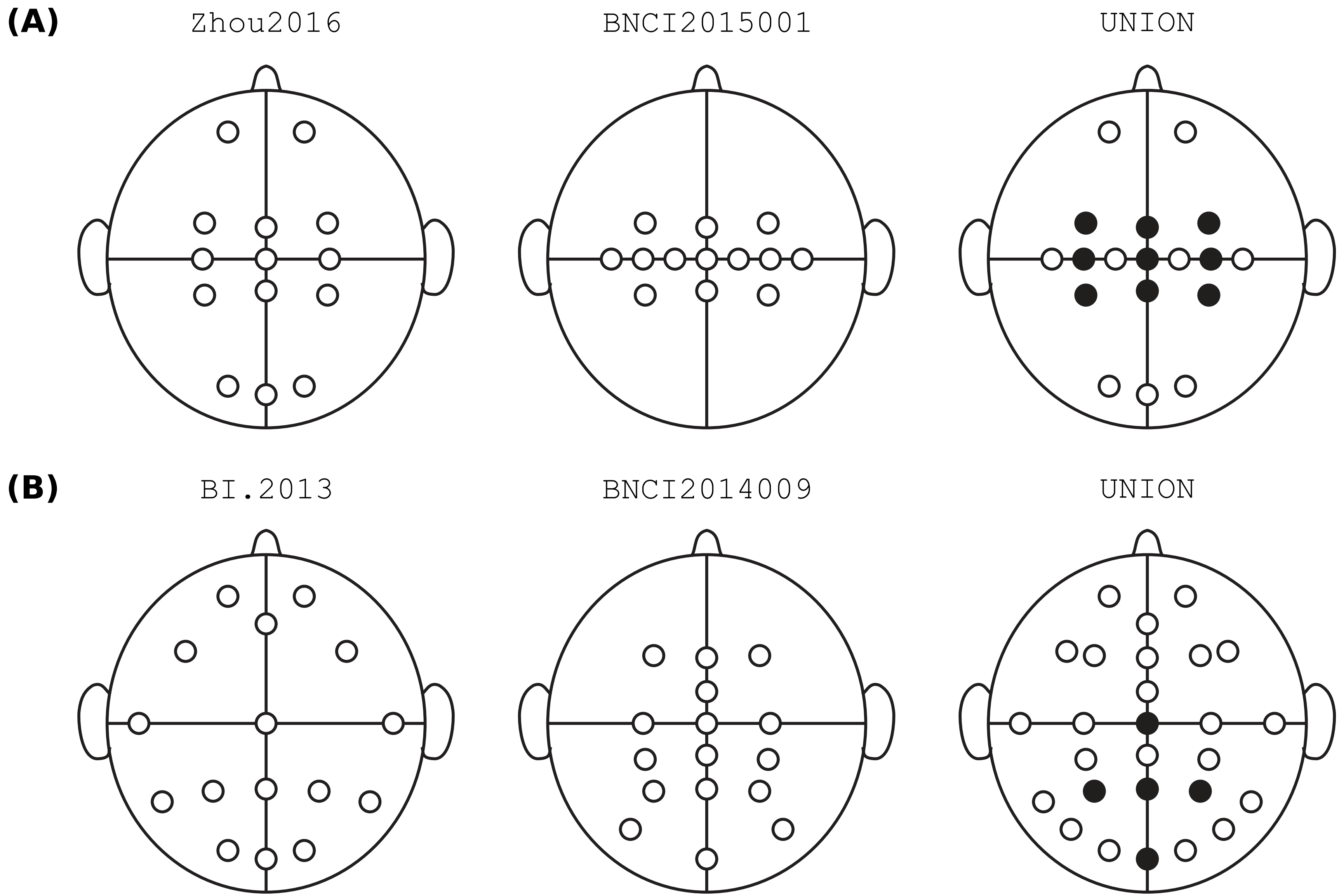


Data from GigaDB

Current Topic

Dimension Trascending

(semi-supervised)


(A)
Zhou2016
BNCI2015001
UNION
(B)
BI.2013
BNCI2014009
UNION

Two datasets with different **dimensionalities**

MATCH DIMENSIONALITIES (via matrix augmentation)

Two datasets with same **dimensionality**
but different **statistical** distributions

MATCH STATISTICAL DISTRIBUTIONS (via RPA)

Two datasets with same **dimensionality**
and similar **statistical** distributions

Rodrigues et al., "Dimensionality transcending: a method for merging datasets with different dimensions" . Work submitted to the IEEE TPAMI

Code for Riemannian geometry

(Julia, Python, R, Matlab, Delphi)

https://sites.google.com/site/marcocongedo/science/code-resources

P300 Data (7 databases, 273 subjects)

https://sites.google.com/site/marcocongedo/science/eeg-data

End