Laboratoire de Génie Informatique et d'Ingénierie de Production (LG2IP)
Nîmes

Data Mining and Machine Learning for Classification and Clustering of NIRS signals

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Laboratoire de Génie
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de Production (LG2IP)

Gérard Dray

Sami Dalhoumi

Aim and Outline

Interest of DM and ML for NIRS Data Analysis and BCI

What could be the contribution of Mines Alès in the French Community for functional NIRS ?

- **Machine Learning and Data Mining**
- **Brain Computer Interface (BCI)**
- **Main issues**
- **Applications**
  - Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs
  - Estimation of operator attentional state

Machine Learning

« Field of study that gives computers the ability to learn without being explicitly programmed »
Arthur Samuel 1959

« Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's ? If this were then subjected to an appropriate course of education one would obtain the adult brain. » Alan Turing 1963

Data Mining

« The non-trivial process of identifying valid, novel, potentially usefull and ultimately understandable patterns in data »

Fayyad, Shapiro et Smyth 1996

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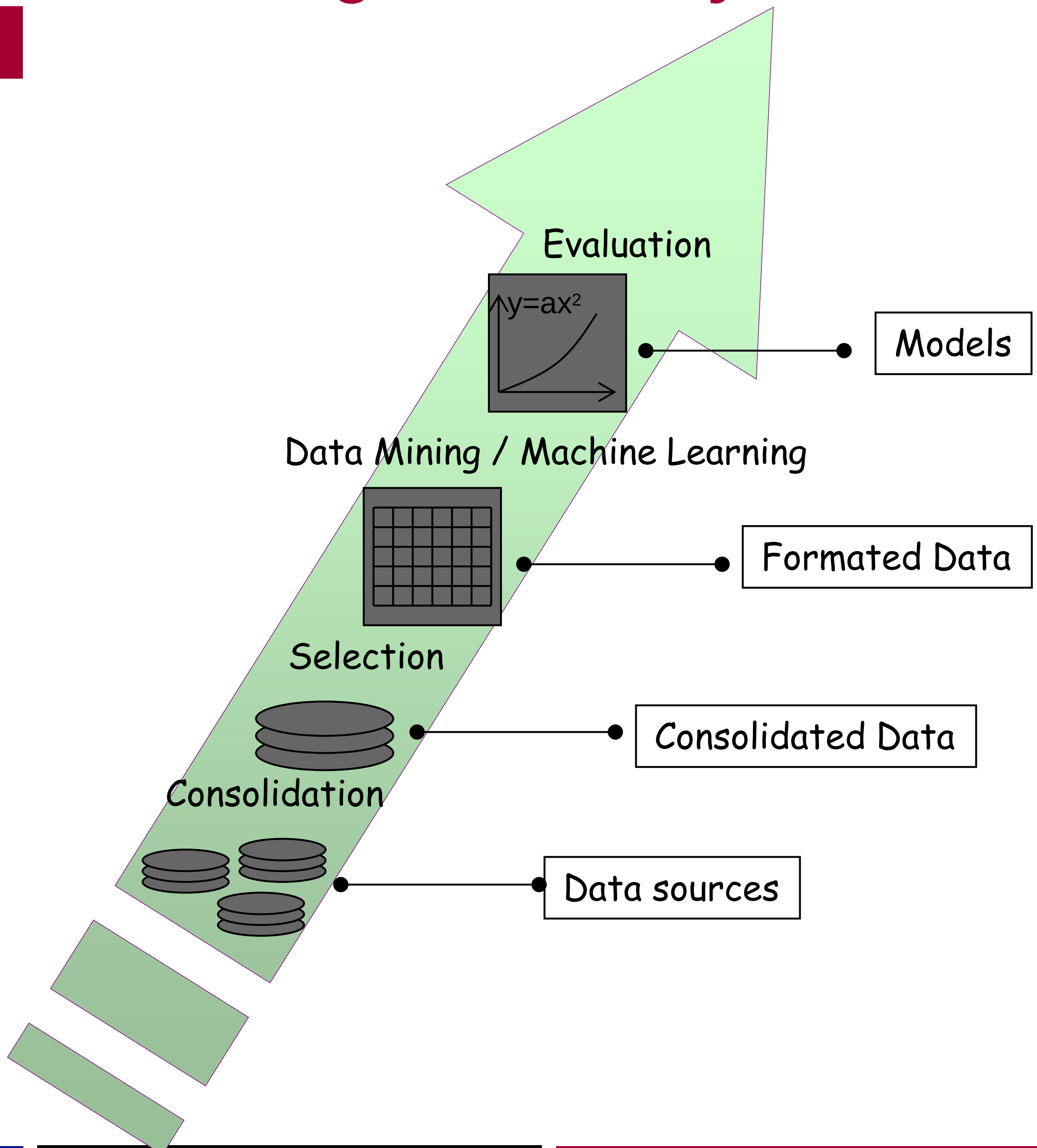
Knowledge Discovery from Data



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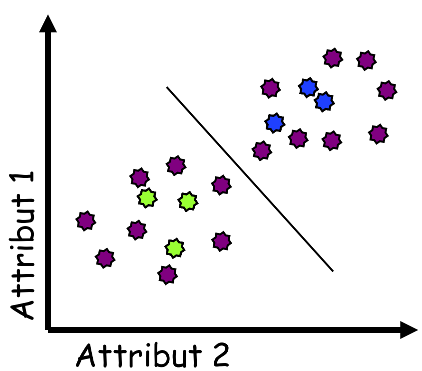
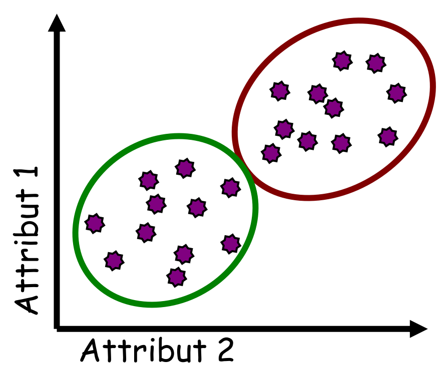
Classification / Clustering

		Attributs										
		Age	Revenu	Sexe		Situation Matrimoniale			...	Attributs j	...	Attributs p
				M	F	Marié	Célibataire	Veuf Divorcé				
		X^1	X^2	X^3	X^4	X^5	X^6	X^7	...	X^j	...	X^p
Individus	X_1	x_1^1	x_1^2	x_1^3	x_1^4	x_1^5	x_1^6	x_1^7	...	x_1^j	...	x_1^p
	X_2	x_2^1	x_2^2	x_2^3	x_2^4	x_2^5	x_2^6	x_2^7	...	x_2^j	...	x_2^p
	...	...	...	...	...	...	...	...	...	...	...	...
	X_i	x_i^1	x_i^2	x_i^3	x_i^4	x_i^5	x_i^6	x_i^7	...	x_i^j	...	x_i^p
	...	...	...	...	...	...	...	...	...	...	...	...
	X_n	x_n^1	x_n^2	x_n^3	x_n^4	x_n^5	x_n^6	x_n^7	...	x_n^j	...	x_n^p

Classification

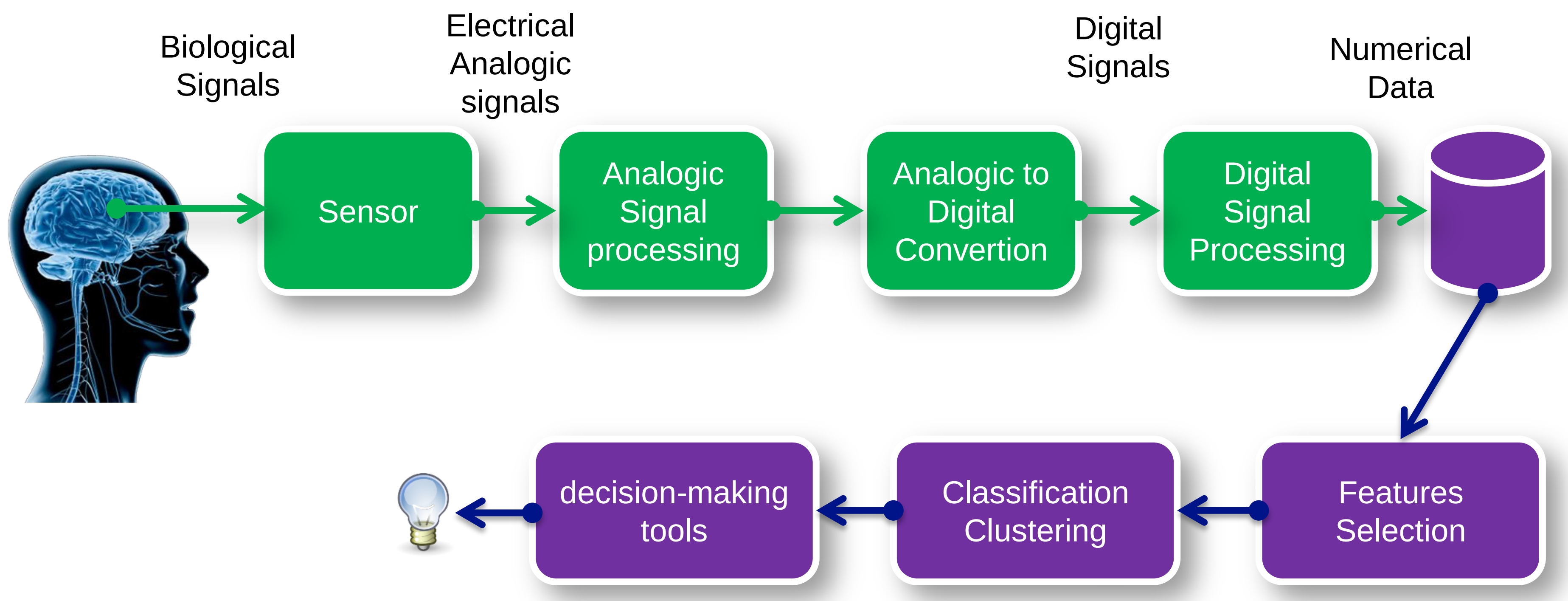


Clustering

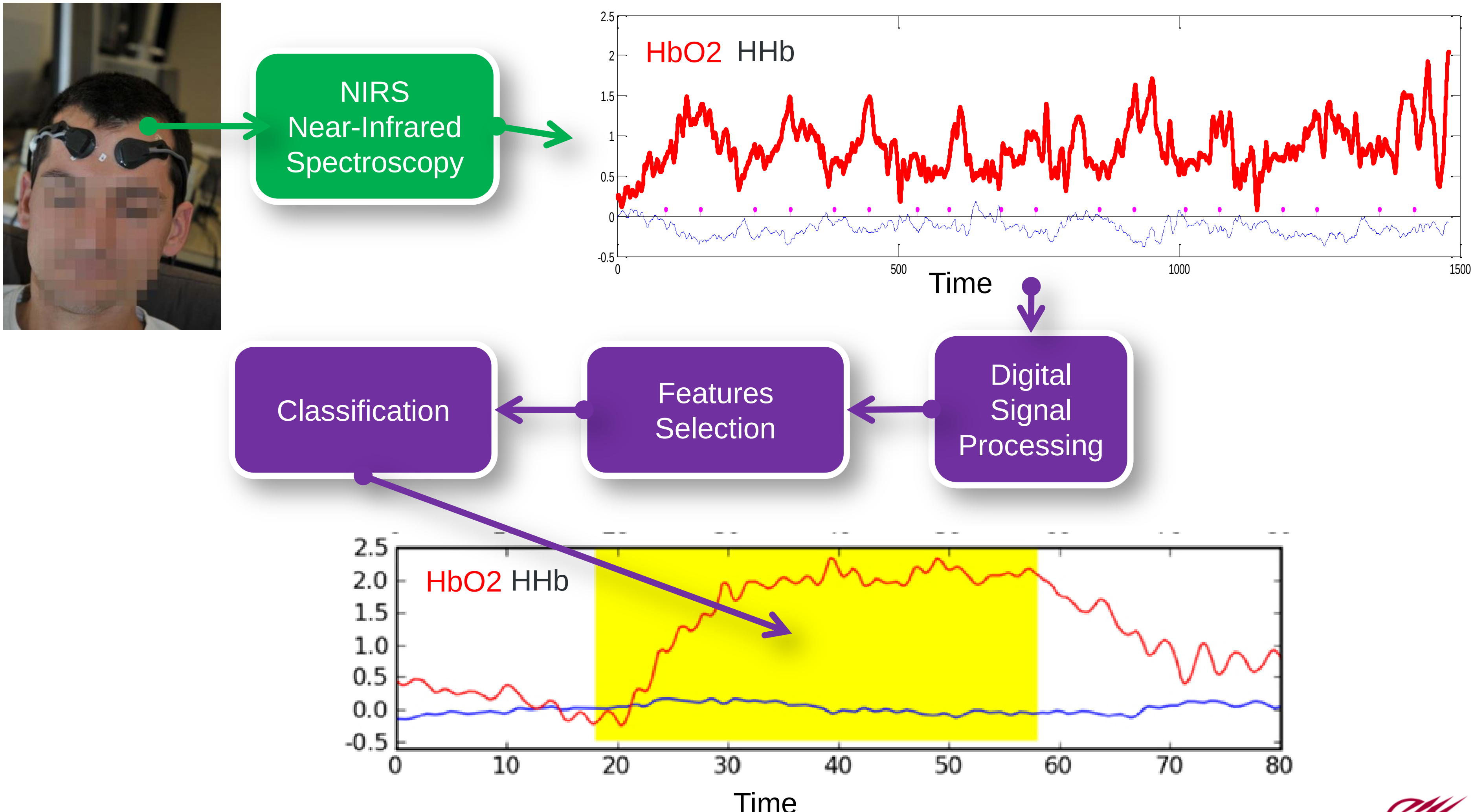


- SVM
- LDA
- K-means
- Decision trees
- Neural networks
- Fuzzy Logic clustering
- Regression
- Rules
- Case based reasoning
- Bayesian networks
- ...

General principles of BCI



NIRS based BCI



Main issues

- Variability Inter subjects and Inter sessions
- Long calibration time for BCI
- Choice of the ML / DM classification method
- Off line / On line approach
- Lack of data for benchmark

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Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs
Sami DALHOUMI, Gérard DEROSIERE, Gérard DRAY, Jacky MONTMAIN, Stéphane PERREY
IPMU 2014 (*International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems)*

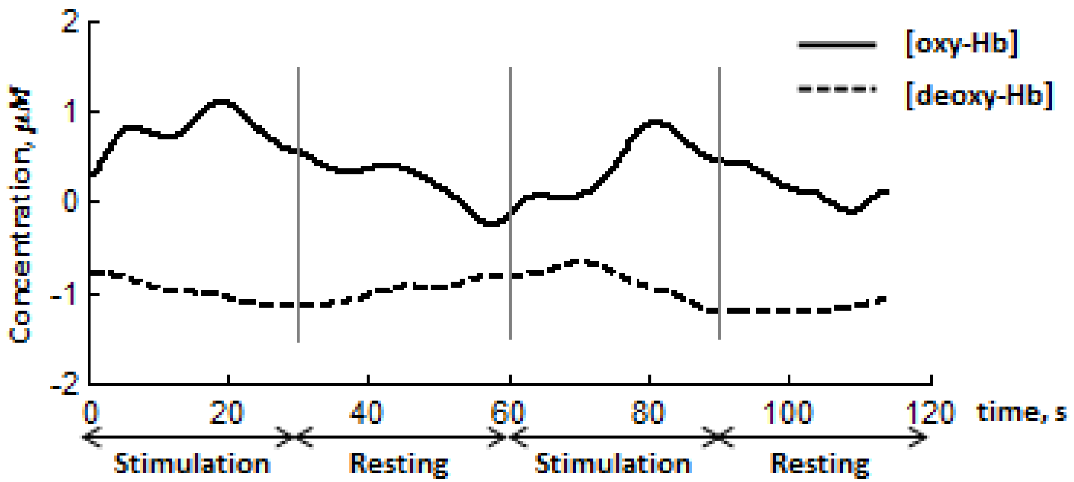
- **Long calibration time needed before every use in order to train a subject-specific classifier**
- **One way to reduce this calibration time is to use data collected from other users or from previous recording sessions of the same user as a training set.**
- **However, brain signals are highly variable and using heterogeneous data to train a single classifier may dramatically deteriorate classification performance.**
- **Transfer learning framework in which we model brain signals variability in the feature space using a bipartite graph.**

Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

- **Open Data provided by Abibullaev et al., 2013**
- **NIRS signals recorded from seven healthy subjects using 16 measurement channels on pre-frontal cortex**
- **Two experiments - four sessions:**
  - discern brain activation patterns related to imagery movement of right forearm from the activation patterns related to relaxed state
  - discern brain activation patterns related to imagery movement of left forearm from the activation patterns related to relaxed state.
- **During each session, participants performed three trials**

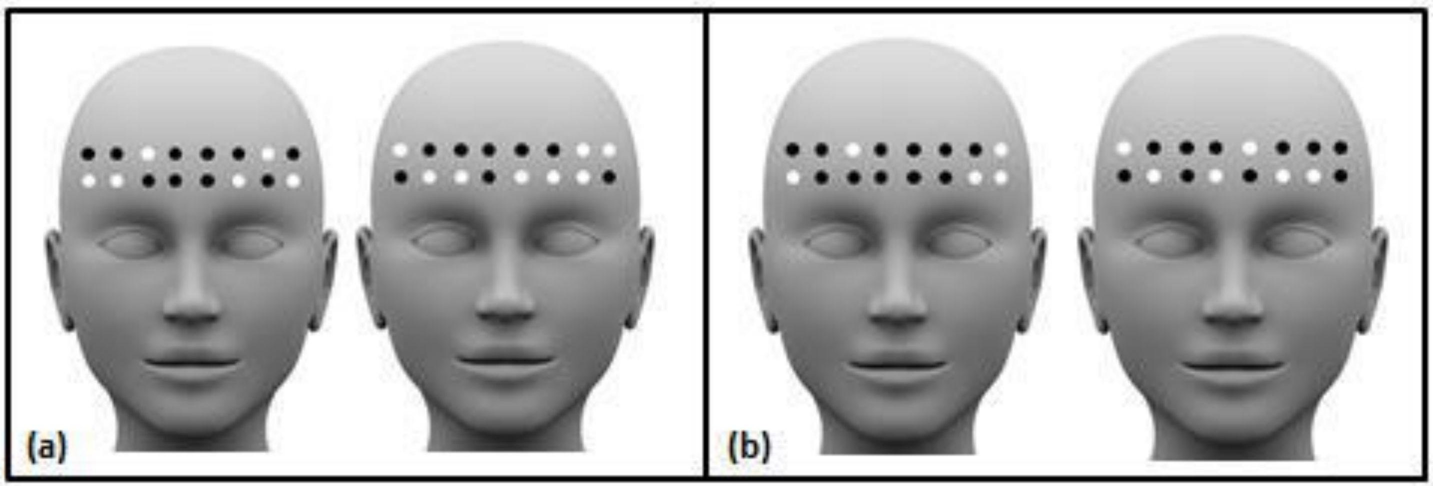
Abibullaev, B., An, J., Jin, S.H., Lee, S.H., Moon, J.I.: Minimizing Inter-Subject Variability in fNIRS-based Brain-Computer Interfaces via Multiple-Kernel Support Vector Learning. Medical Engineering and Physics, S1350-4533(13)00183-5 (2013)

Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs



Prototypical brain activity pattern using NIRS technology

Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs



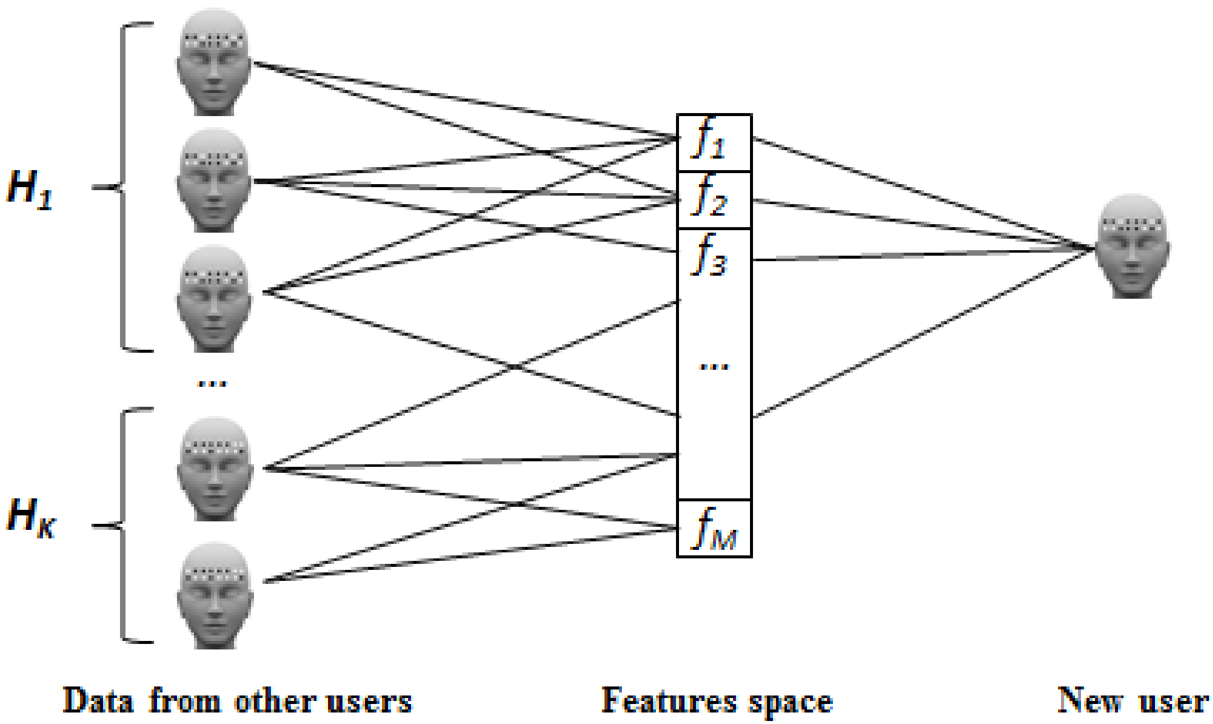
Brain signals variability in NIRS-based BCIs :

(a) Inter-sessions variability of explanatory channels for subject 5 in experiment 1.

(b) Inter-subjects variability of explanatory channels for subjects 3 and 4 in experiment 2.

White dots represent explanatory channels and black dots represent non-explanatory channels.

Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

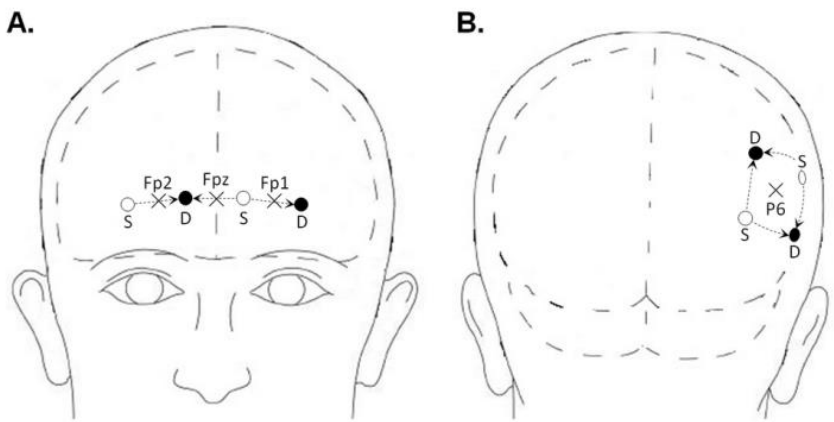


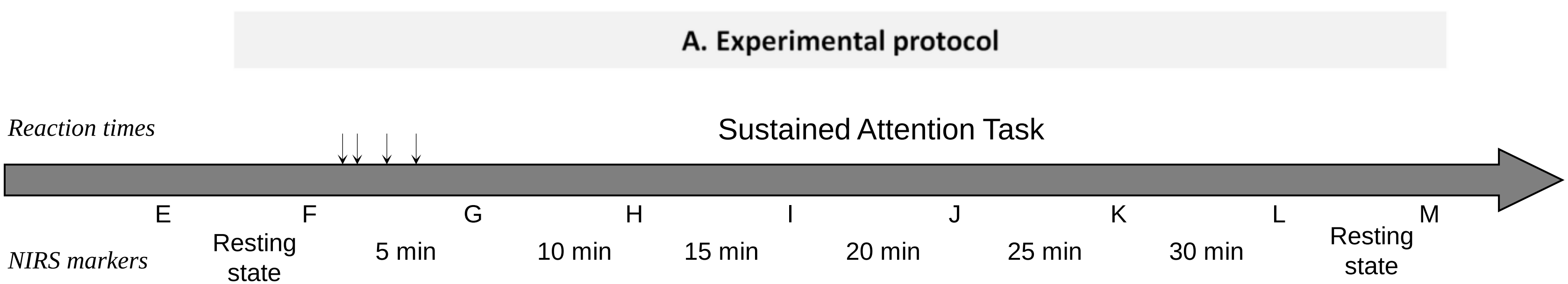
Bipartite graph model for characterizing brain signals variability in the features space between different users

Estimation of operator attentional state

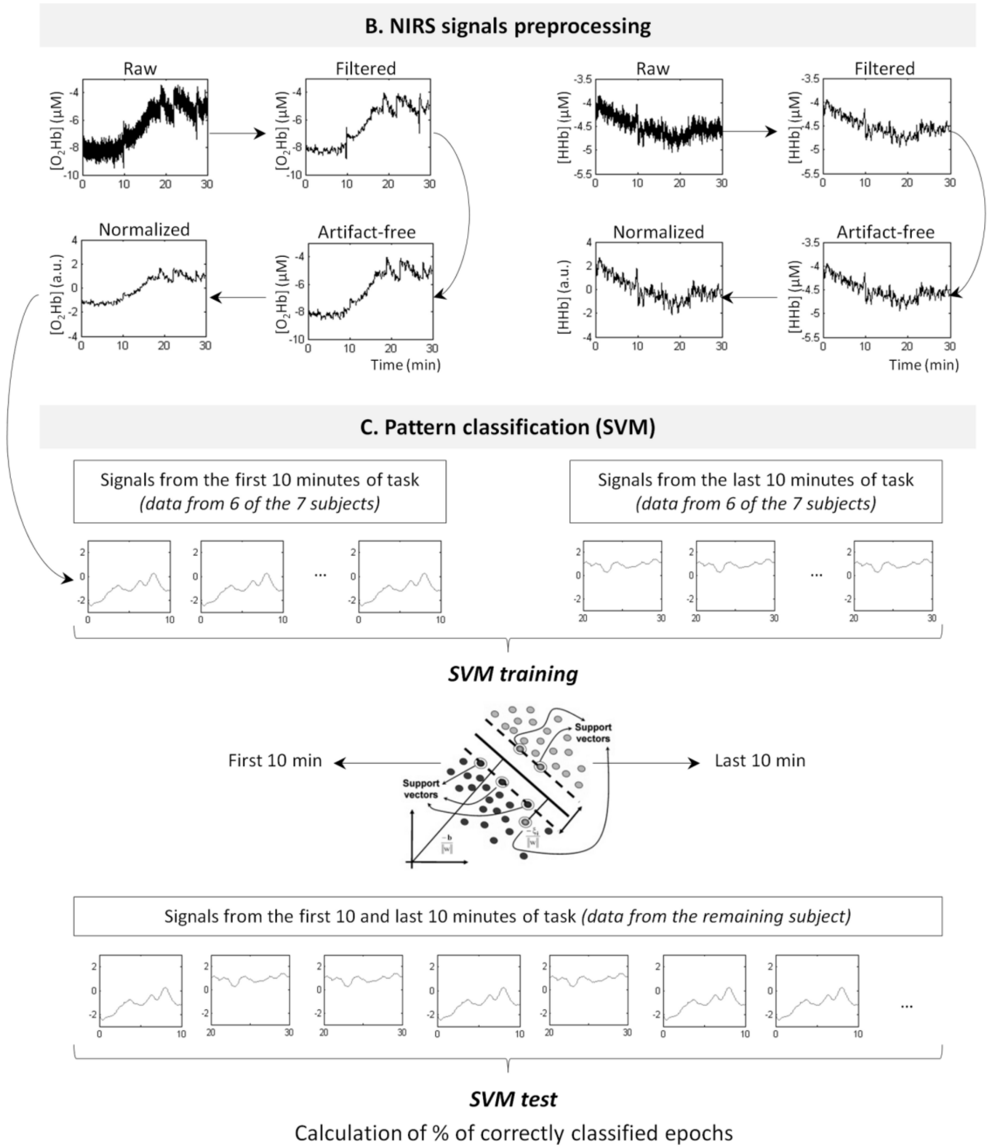
Towards a near infrared spectroscopy-based estimation of operator attentional state.
Gérard Derosière, Sami Dalhoumi, Stéphane Perrey, Gérard Dray, Tomas Ward
PLoS ONE 01/2014

7 subjects





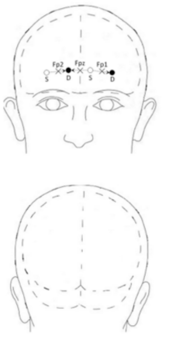
Estimation of operator attentional state



Estimation of operator attentional state

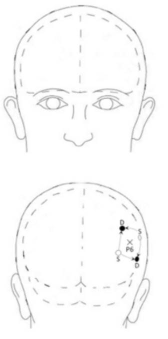
A.

Subject	[O2Hb]	[HHb]	[O2Hb] and [HHb]
1	44.5	87.8	88.8
2	73.5	94.2	89.1
3	49.2	28.4	32.1
4	95.1	90.4	90.6
5	98.4	80.6	76.5
6	82.5	21.2	68.3
7	100	60.8	96.7
Mean ± SD	**77.6 ± 23**	**66.2 ± 30.3**	**77.4 ± 22.2**



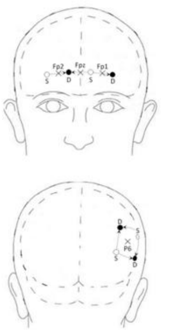
B.

Subject	[O2Hb]	[HHb]	[O2Hb] and [HHb]
1	94.9	94	99.6
2	85.4	81.6	97.9
3	91.7	22.6	77
4	100	26.4	91.3
5	83.8	45	72.2
6	76.3	86.1	100
7	96.4	100	97.2
Mean ± SD	**89.8 ± 8.3**	**65.1 ± 32.8**	**90.7 ± 11.5**



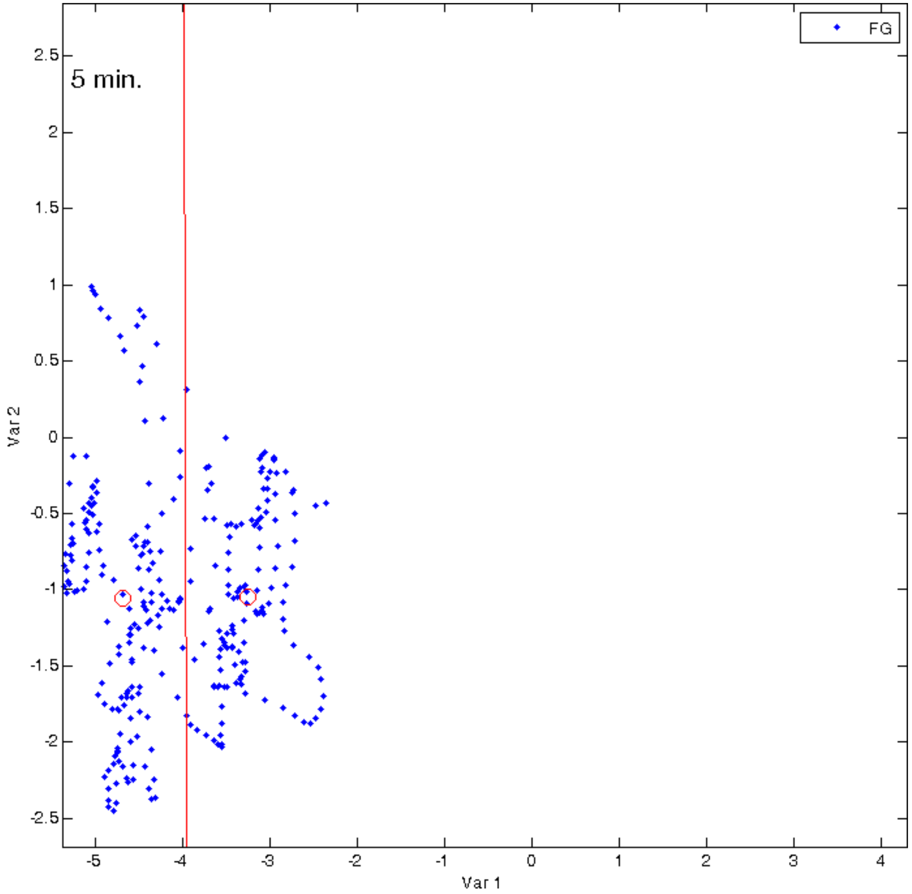
C.

Subject	[O2Hb]	[HHb]	[O2Hb] and [HHb]
1	60.8	100	91.8
2	85	96.5	96.3
3	39.8	6.6	34.2
4	92	34.5	96.7
5	94	61.4	74.7
6	75.5	70.7	93.9
7	92.2	93.9	96.8
Mean ± SD	**77 ± 20.2**	**66.2 ± 35.1**	**83.5 ± 23.1**



Estimation of operator attentional state

On line
K-means custering



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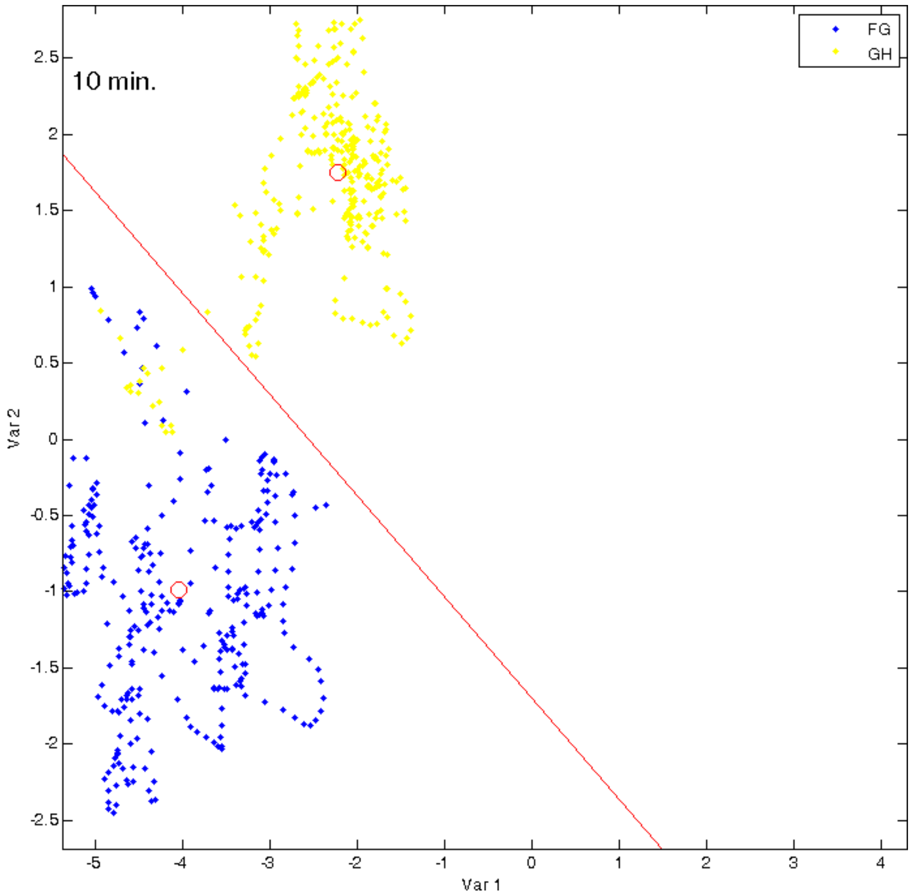
Estimation of operator attentional state

On line
K-means custering



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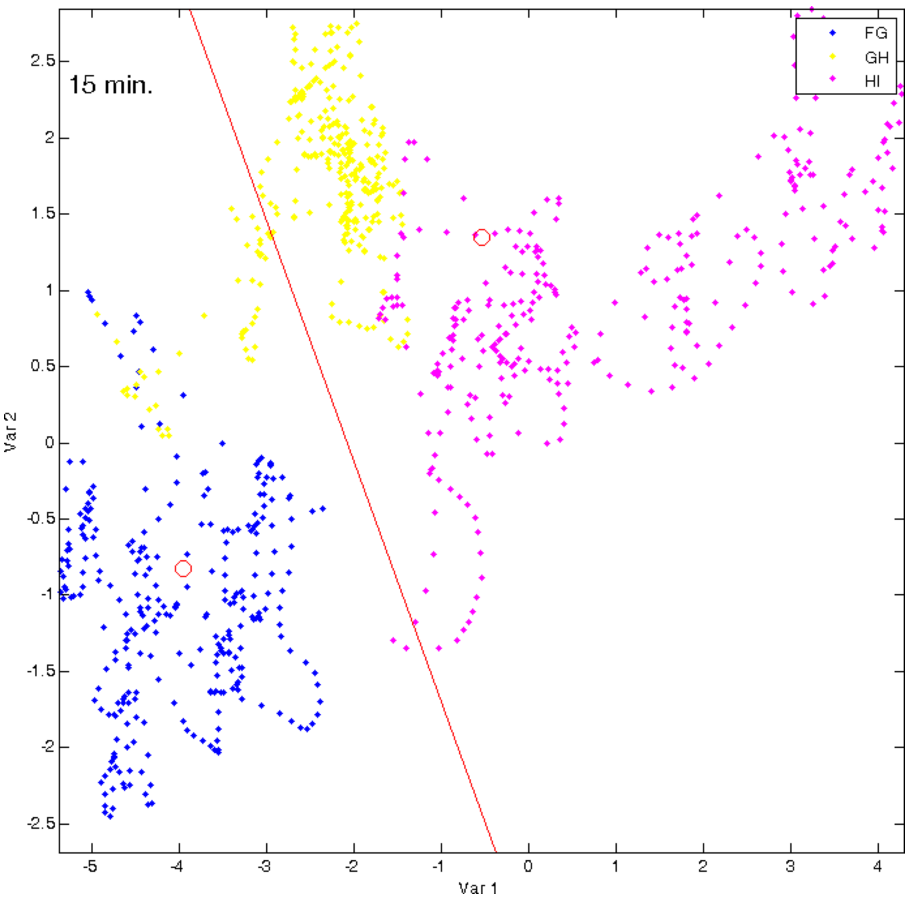
Estimation of operator attentional state

On line
K-means custering



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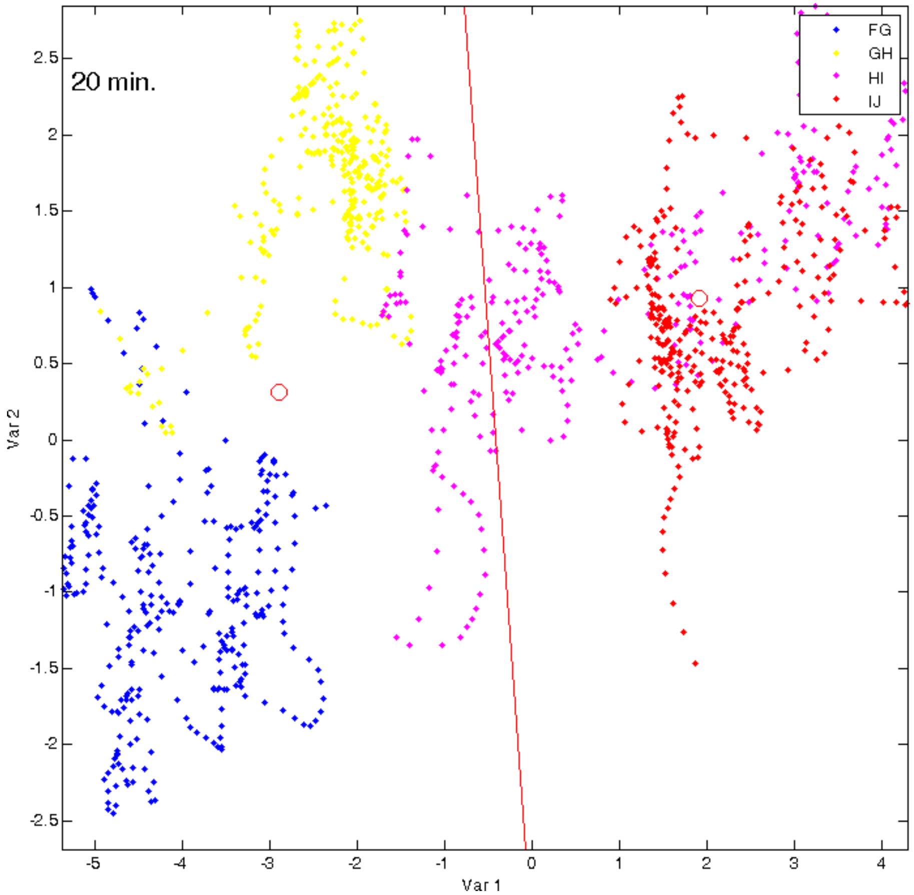
K-means custering



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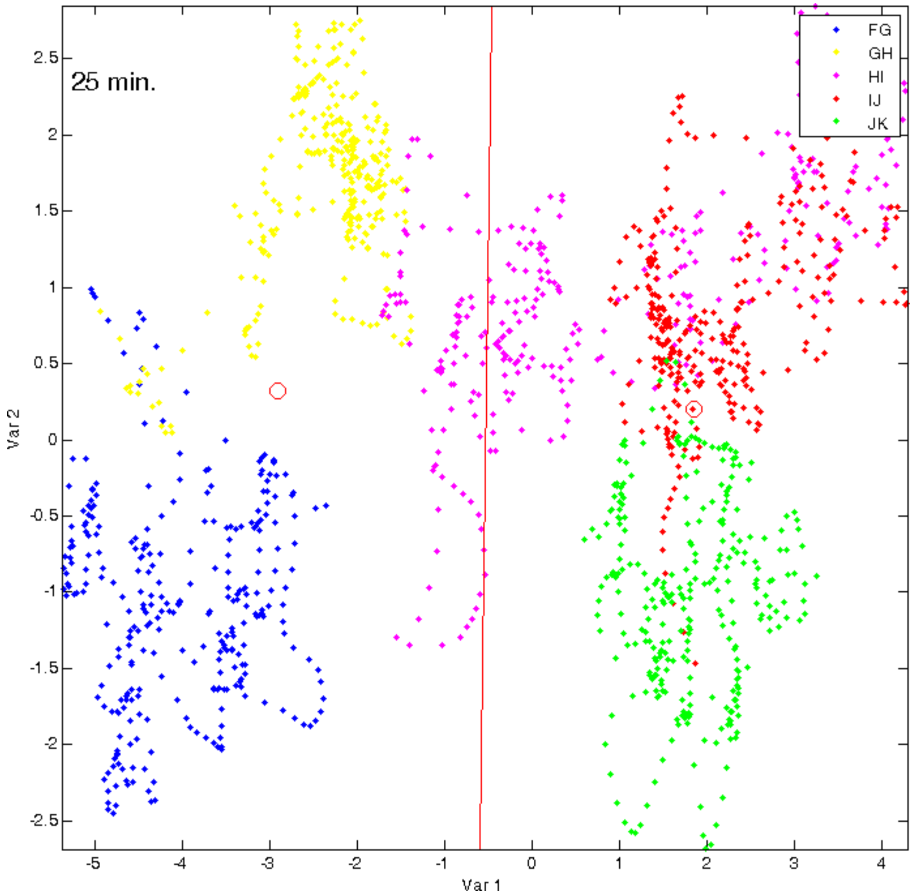

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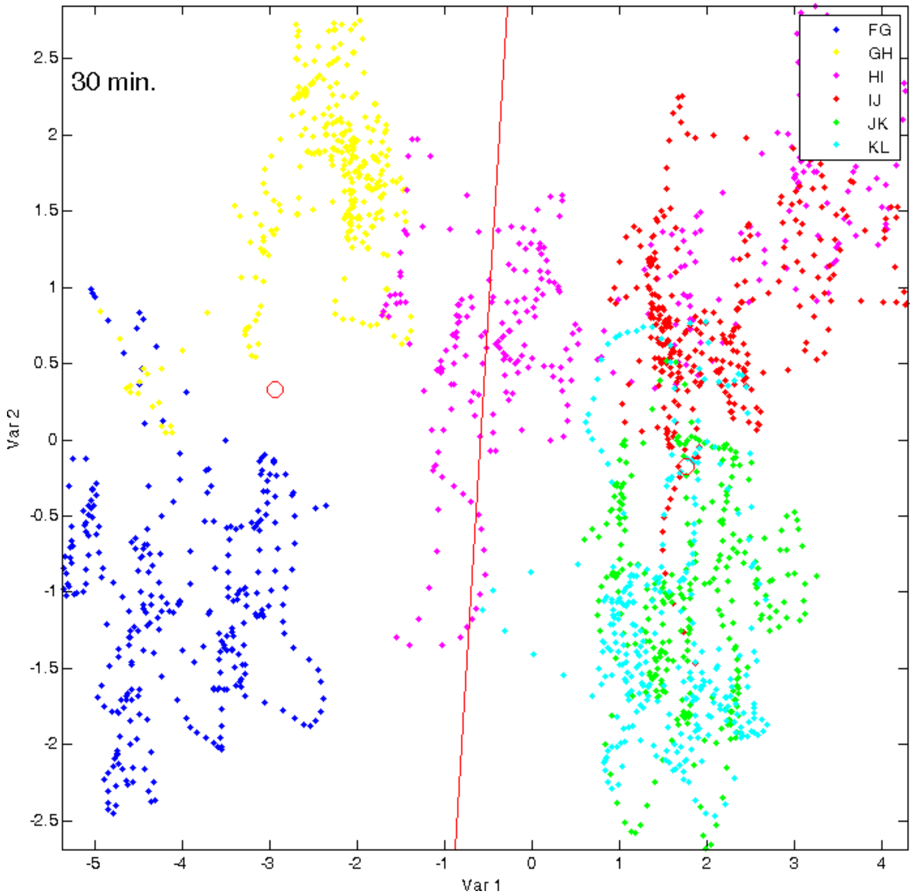

Future work

- On line data analysis
- Fuzzy clustering
- Multi Classifier aggregation

- NIRS Open Data Repository
- NIRS Open Data Analysis Software

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