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Modeling of Epileptic Seizures using Tensor Analysis

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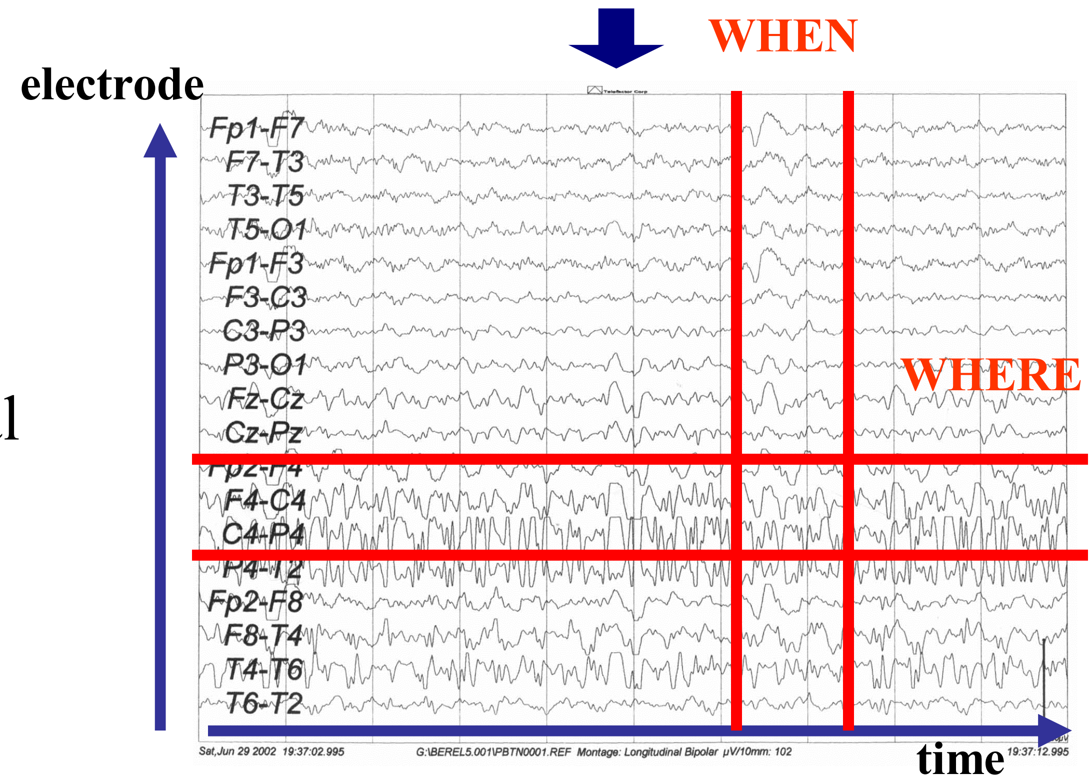
Problem Definition

- **Epilepsy:** neurological disorder characterized by recurrent, abrupt seizures.

- WHO: over 50 million people!

- Diagnosis techniques
  – Physical and neurological exams
  – Neuroimaging
  – Video-EEG monitoring



Problem Definition (Cont.)

Motivation:

– Visual analysis is time-consuming

>> saving manpower

– Visual analysis is subjective and error-prone

>> objective/robust analysis

Goal: Developing mathematical models that can capture a seizure structure automatically.

– Seizure recognition **(when)**

– Seizure localization **(where)**

Overview

- **Part I: Tensor Basics**
- **Part II: Epileptic Seizure Recognition**
  - Related Work (e.g., feature extraction from epileptic EEG)
  - Methodology:
    - Construction of a third-order **Epilepsy Feature Tensor**
    - Seizure recognition using Multilinear PLS
- **Part III: Discussions**
  - Future Research Directions
  - Other studies on epileptic EEG signals

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Why tensors?

Two-way data	Higher-order data

- **Social networks:**

  <user, keyword> <user, keyword, time>

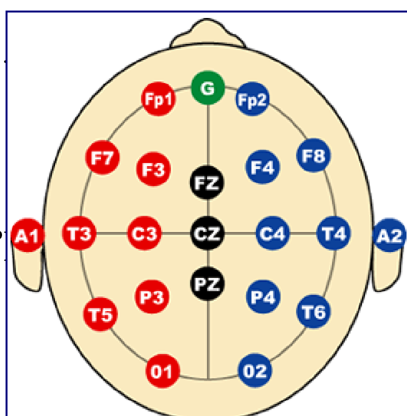
- **Text mining:**

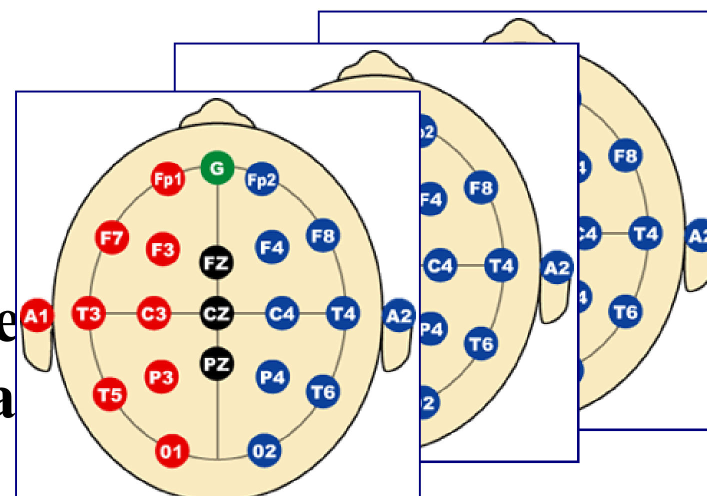
  <document, term> < document, term, author>

- **Face recognition:**

  <person, pixel> < person, pixel, viewpoint>

- **Neuroscience:**





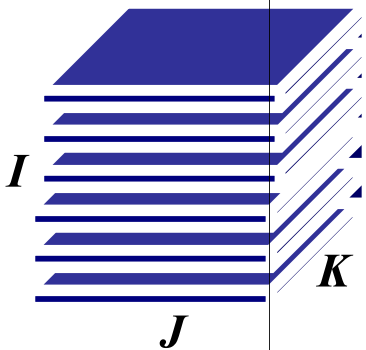
Matr ugh to represe t

he data from a

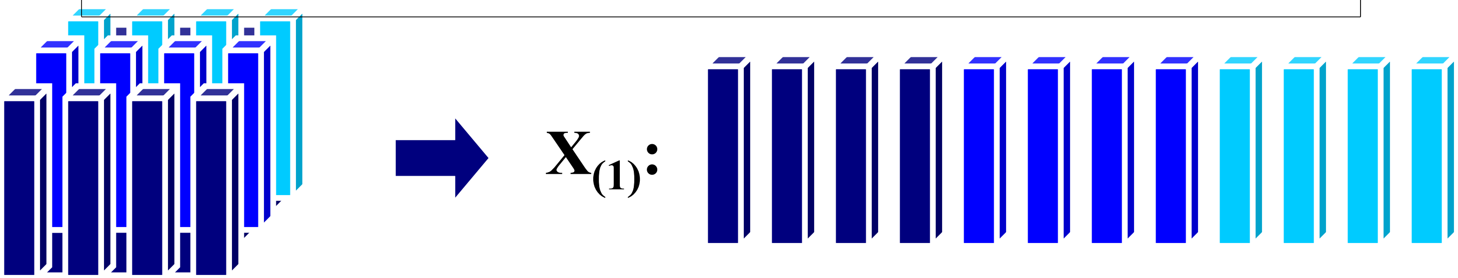
What is a tensor?

- A tensor is a higher-order generalization of a matrix.

Example: A third-order tensor $\underline{X} \in R^{I \times J \times K}$



- Matricization (unfolding/flattening)
  - rearranging a tensor as a matrix.
  - The mode-n matricization of a higher-order dataset, e.g., $\underline{X}$, denoted by $X_{(n)}$ unfolds the data in the n^{th} mode.



Tensor times a matrix

- The mode-n product of a tensor $\underline{X} \in \mathbb{R}^{I_1 \times I_2 \ldots \times I_n \times \ldots I_N}$ with a matrix $M \in \mathbb{R}^{P \times I_n}$ is denoted by

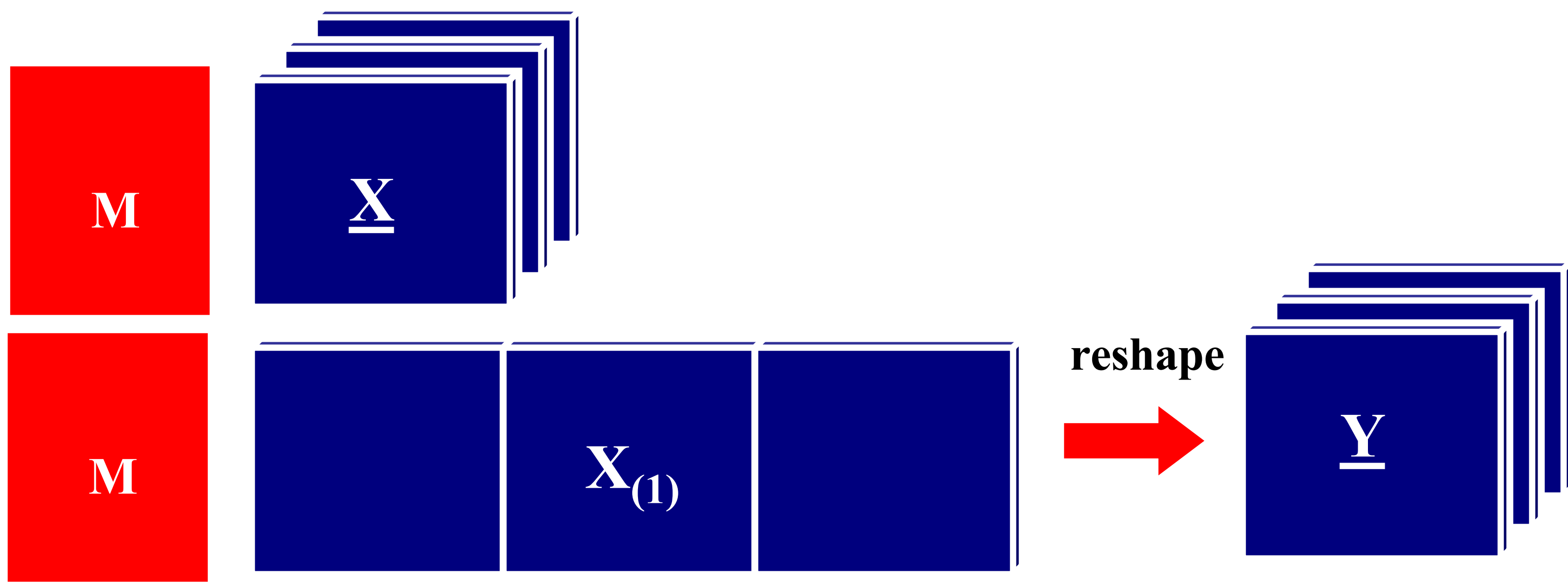
$$\underline{Y} = \underline{X} \times_n M$$

where $\underline{Y} \in \mathbb{R}^{I_1 \times I_2 \ldots I_{n-1} \times P \times I_{n+1} \ldots I_N}$

Example:

$\underline{X} \times_1 M =$

$=$



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Related Work

Common Approach: Divide an EEG recording into time epochs and extract features that can distinguish between seizures and other brain dynamics.

Analysis of the performance of multiple features on **single channel** EEG data

Time Epochs
i=1,2,…I

Features
j=1,2,…J

Analysis of the performance of a **single feature** on multi-channel EEG data

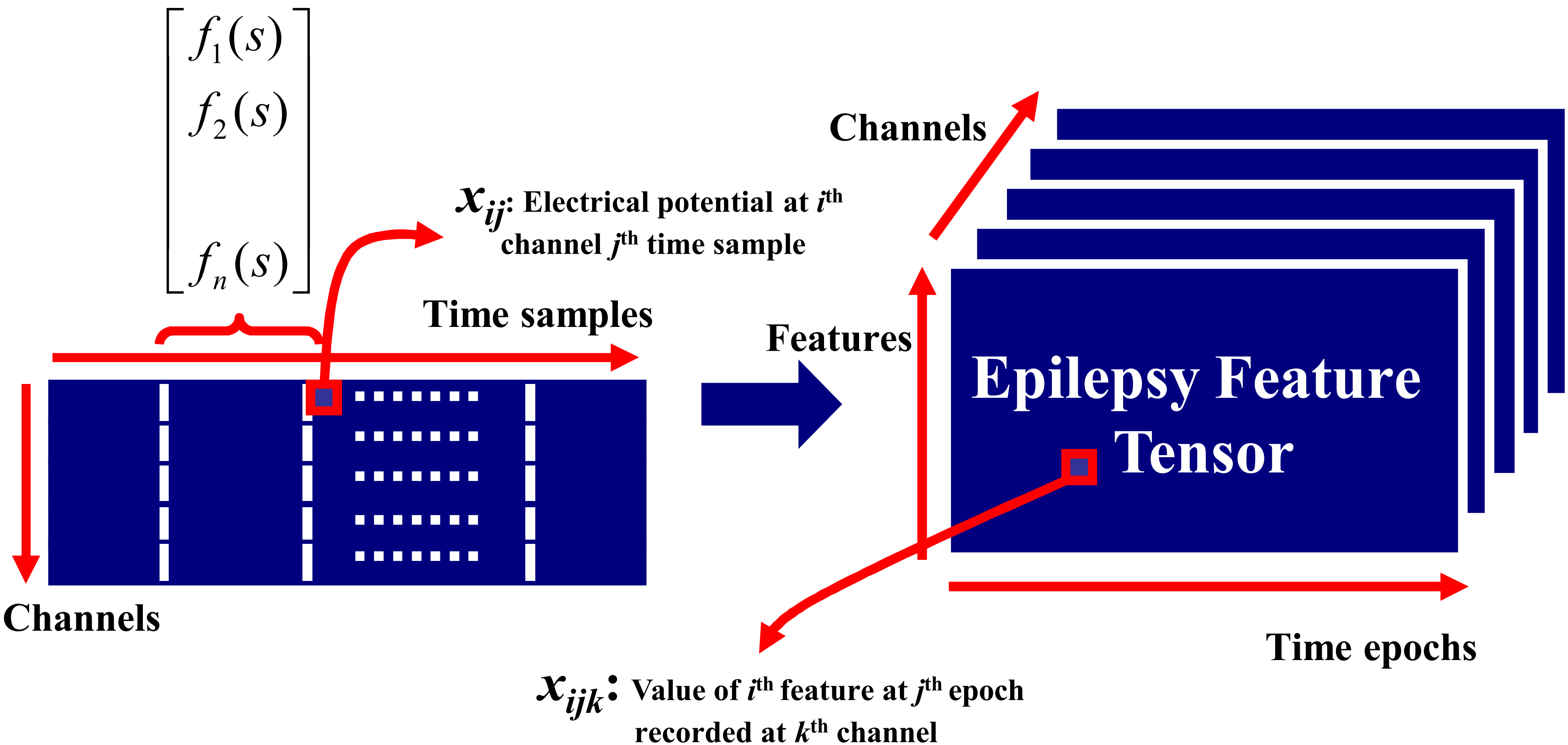
Time Epochs
i=1,2,…I

Channels
k=1,2,…K

Our Approach: Analysis of **multiple features** from different domains on **multi-channel** EEG data

STEP1: Epilepsy Feature Tensor

- Construction of an Epilepsy Feature Tensor from multi-channel EEG



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Features from Multiple Domains

Time domain

Let s ={s(1), s(2),…s(N)} be the time sequence for a particular epoch of length N.

- Activity: $f_1(s) = \sigma_s^2$
- Mobility: $f_2(s) = \frac{\sigma_{s'}}{\sigma_s}$
- Complexity

$$f_3(s) = \frac{(\sigma_{s''} / \sigma_{s'})}{(\sigma_{s'} / \sigma_s)}$$

- Mean Absolute Slope: f_4(s)

Frequency domain

Take the first difference and then compute the Fourier coefficients to construct the amplitude spectrum

- Median Frequency: f_5(s)

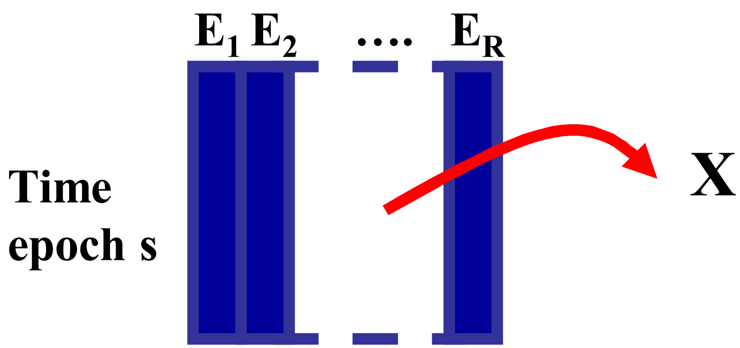
Compute the energy spread across different EEG bands, i.e., δ (0.5-3.5Hz), θ (3.5-7.5Hz), α (7.5-12.5Hz), β(12.5-30Hz) and γ(>30Hz)

- Spectral Entropy: f_6(s)
- Relative Energy in each freq. band:

f_7(s)- f_{10}(s)

More features

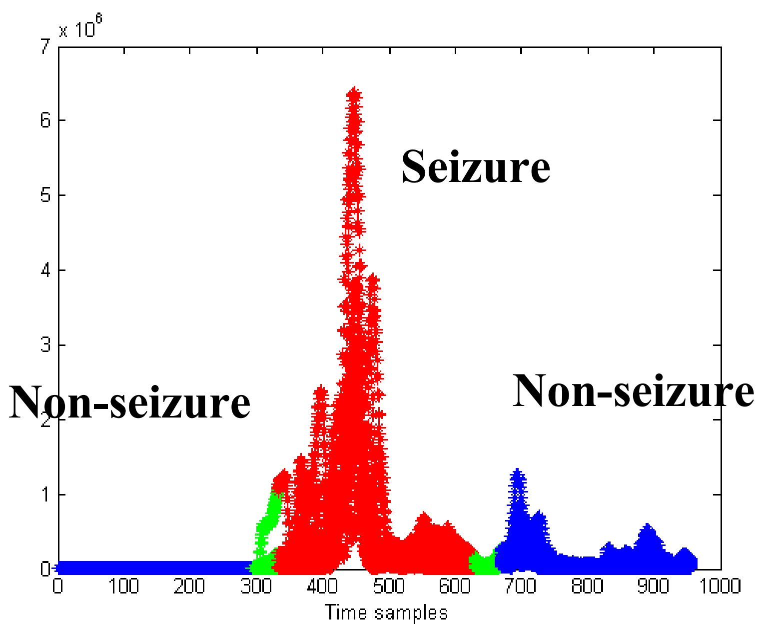
- To quantify the synchronization among channels, especially among neighboring channels as the seizure starts.



$$f_{11}(s,i) = \sum_{j \in NEIGH_i} \left|(X^T X)_{ij}\right|$$

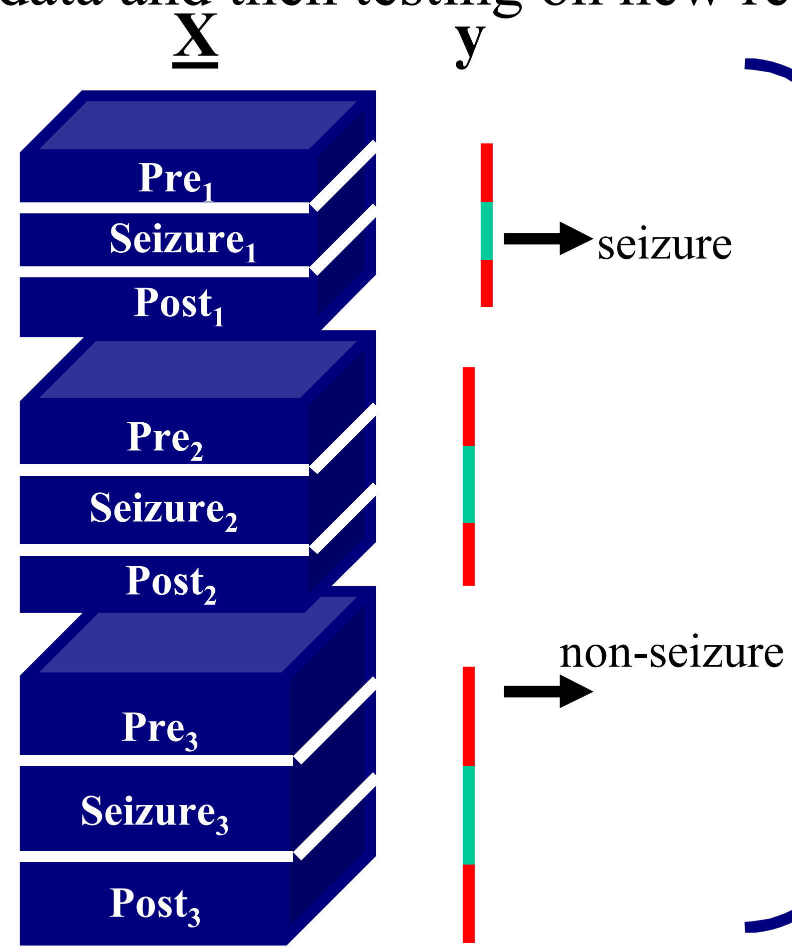
where $NEIGH_i$ contains the neighbors of electrode ***i***.

<u>Example:</u>



STEP2: Seizure Recognition

- Building a mathematical model based on Multilinear PLS on available data and then testing on new recordings

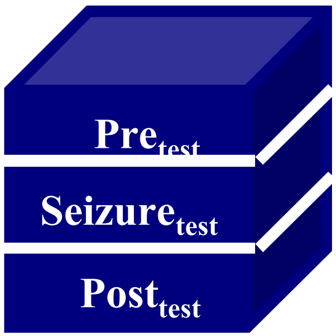


Training Set

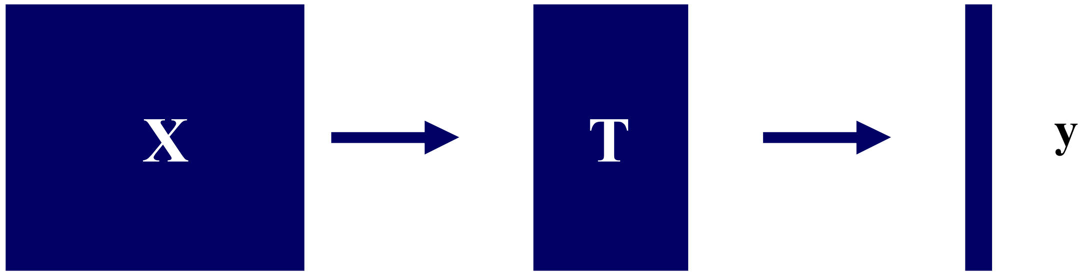
- Build a model based on N-PLS using the training set **X** and the labels **y**.

Test Set

- Predict the labels of new recordings.



Partial Least Squares (PLS)



Let $\mathrm{X} \in \mathrm{R}^{I \times J}$ and $\mathrm{y} \in \mathrm{R}^{I}$ be the independent and dependent (response) variables, respectively

- Map X to a low-dimensional space and regress onto y

$$\mathrm{y} = \mathrm{Tb} + \mathrm{e}$$

- Determine the columns of $\mathrm{T} \in \mathrm{R}^{I \times K}$ (where $\mathrm{K} < \mathrm{J}$), such that

$$\max_{\mathrm{w}} \quad \mathrm{cov}(\mathrm{Xw}, \mathrm{y})$$

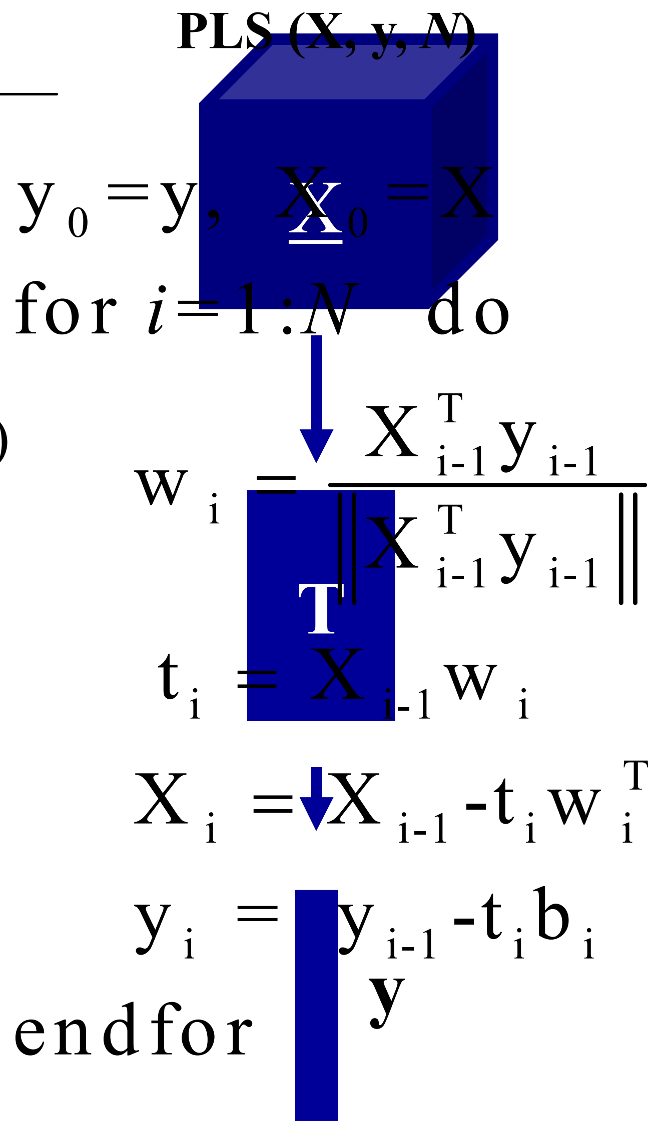
where **t**= **Xw** is a column of matrix **T**.

Multilinear PLS (N-PLS) (by Bro'96)

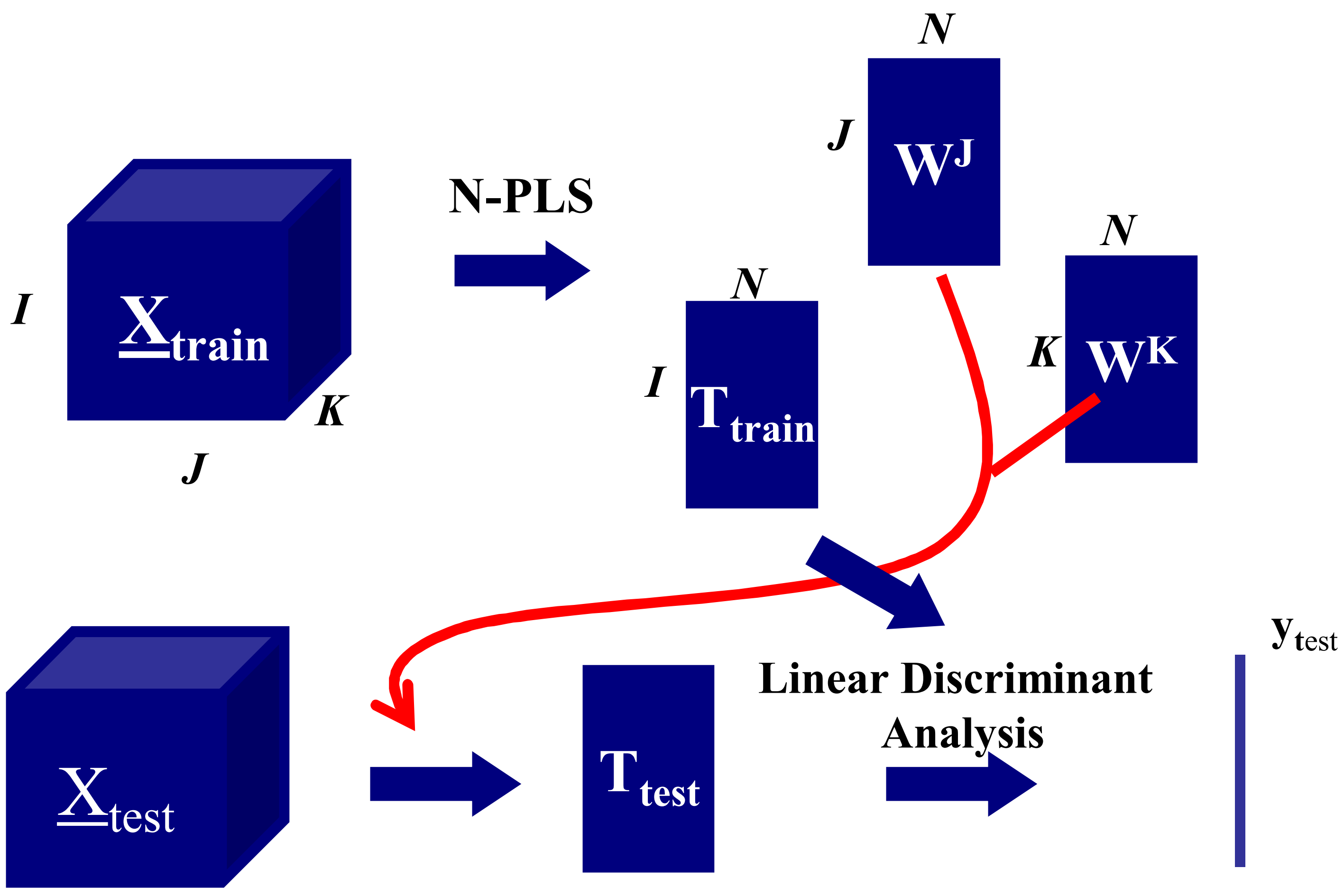
Multilinear PLS $(\underline{X}, y, N)$

1. $y_0 = y, X_0 = X_{(1)}$
2. for $i = 1$ to N do
3. $\quad z = y_{i-1}^T X_{i-1}$
4. $\quad Z = USV^T$, where $Z(m,n) = z(m + J(n-1))$
5. $\quad w^J = U(:,1), \quad w^K = V(:,1)$

   $\quad W^J(:,i) = w^J, W^K(:,i) = w^K$
6. $\quad T(:,i) = X_{i-1}(w^K \otimes w^J)$
7. $\quad X_i = X_{i-1} - T(:,i)(w^K \otimes w^J)^T$
8. $\quad b_i = (T^T T)^{-1} T^T y_{i-1} = T^+ y_{i-1}$
9. $\quad y_i = y_{i-1} - Tb_i$
10. endfor



To predict y_{test}: Combine N-PLS and LDA



Feature Selection: Generalization of VIP to 3-way

- **Goal:** Eliminate the features that are not very relevant with the classification of non-seizure and seizure epochs.
- **Approach:**

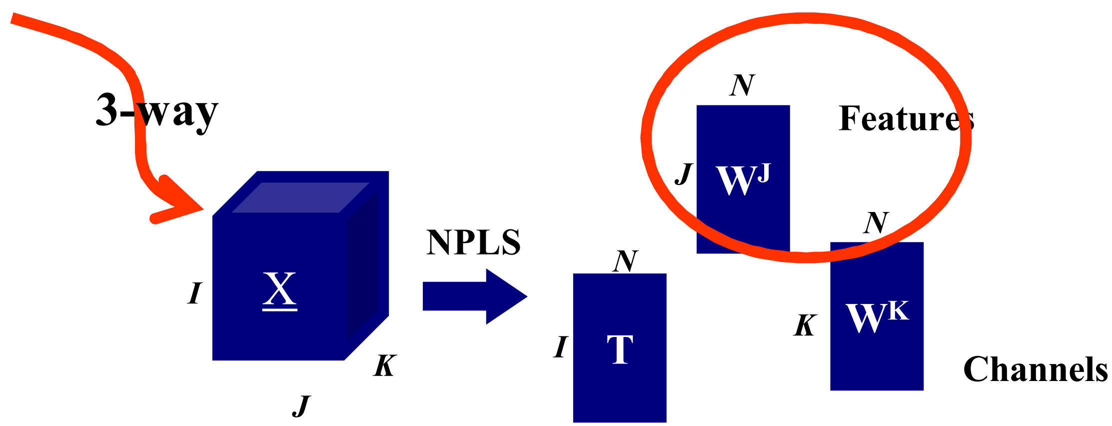
  Use the loadings to determine which variables are important (Variable Importance in Projection (VIP) (Word et *al.*'93))

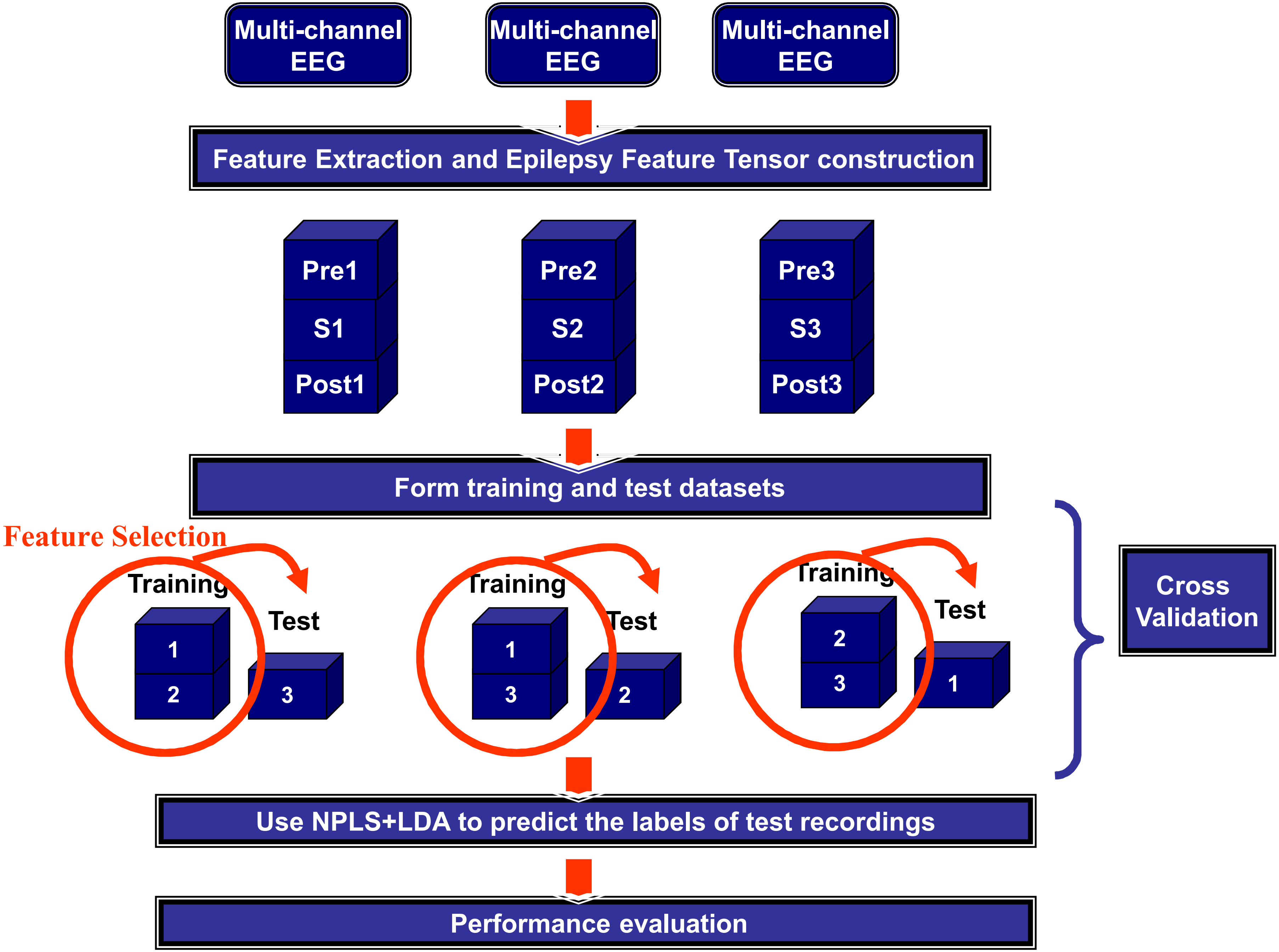
$$\mathbf{VIP}_j = \sqrt{J \times \frac{\sum_{k=1}^{N} b_k^2 t_k^T t_k \left(\frac{w_{jk}}{\|w_k\|}\right)^2}{\sum_{k=1}^{N} b_k^2 t_k^T t_k}}$$

2-way

$$\mathbf{X} = \mathbf{T}\mathbf{W}^{\mathrm{T}} + \mathbf{E}$$

$$\mathbf{y} = \mathbf{T}\mathbf{b} + \mathbf{e}$$




Multi-channel EEG
Multi-channel EEG
Multi-channel EEG
Feature Extraction and Epilepsy Feature Tensor construction
Pre1
S1
Post1
Pre2
S2
Post2
Pre3
S3
Post3
Form training and test datasets
Feature Selection
Training
1
2
Test
3
Training
1
3
Test
2
Training
2
3
Test
1
Cross Validation
Use NPLS+LDA to predict the labels of test recordings
Performance evaluation

DATA (Patient-Specific Seizure Recognition)

- Collected in the epilepsy monitoring unit of
  - Yeditepe University Hospital (Istanbul, Turkey)
  - Albany Medical College (NY, USA)
- 32 seizures from 9 patients with different seizure origins (at least 3 seizures/patient)
- Seven Features: Activity, Complexity, Mobility, Mean Absolute Slope, Spatial Information, Spectral Entropy, Median Frequency.
- Preprocessing:
  - Filter at 50Hz/60Hz
  - Scaling within features mode

Patient Id	Seizure Id	Size of an Epilepsy Feature Tensor
1	1	302 x 7 x 18
	2	386 x 7 x 18
	3	320 x 7 x 18
	4	398 x 7 x 18
	5	444 x 7 x 18
2	1	878 x 7 x 18
	2	866 x 7 x 18
	3	902 x 7 x 18
	4	986 x 7 x 18
	5	998 x 7 x 18
3	1	790 x 7 x 18
	2	746 x 7 x 18
	3	1034 x 7 x 18
4	1	1174 x 7 x 18
	2	1346 x 7 x 18
	3	1170 x 7 x 18

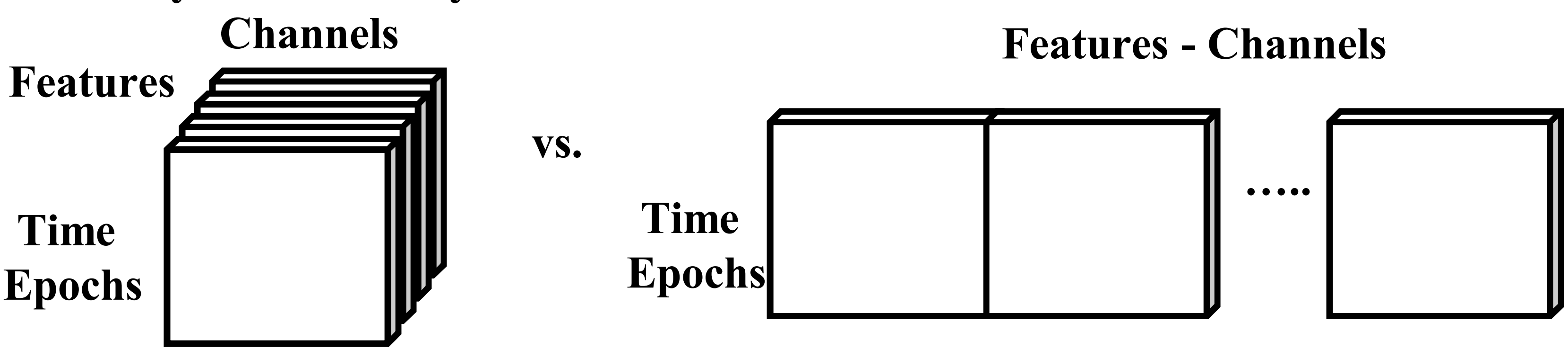
⋮

Performance Evaluation

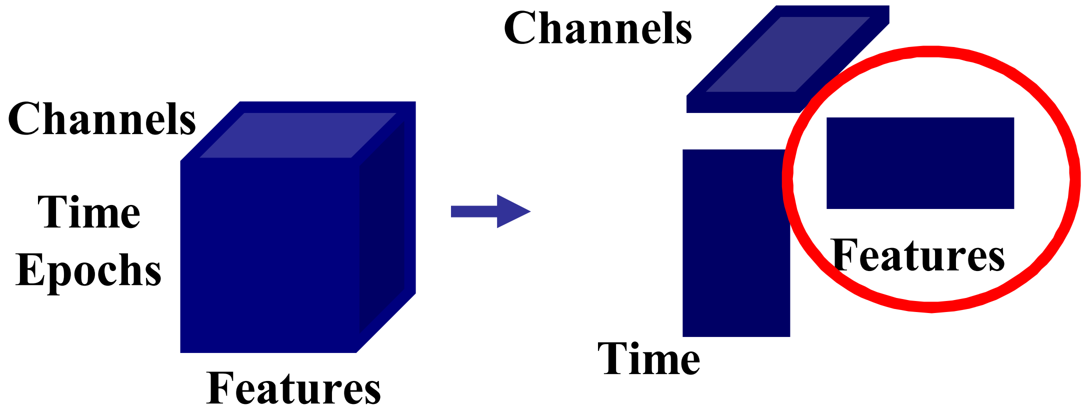
- **G-means:** $\sqrt{Sensitivity \times Specificity}$

	NPLS+LDA	NPLS+LDA (FS)
Patient1	85.3%	86.6%
Patient2	97.6%	96.7%
Patient3	91.3%	91.1%
Patient4	75.0%	**77.3%**
Patient5	28.6%	**83.1%**
Patient6	72.3%	**89.3%**
Patient7	97.0%	92.1%
Patient8	86.0%	78.4%
Patient9	84.5%	77.4%

- **Three-way vs. Two-way:**



Features

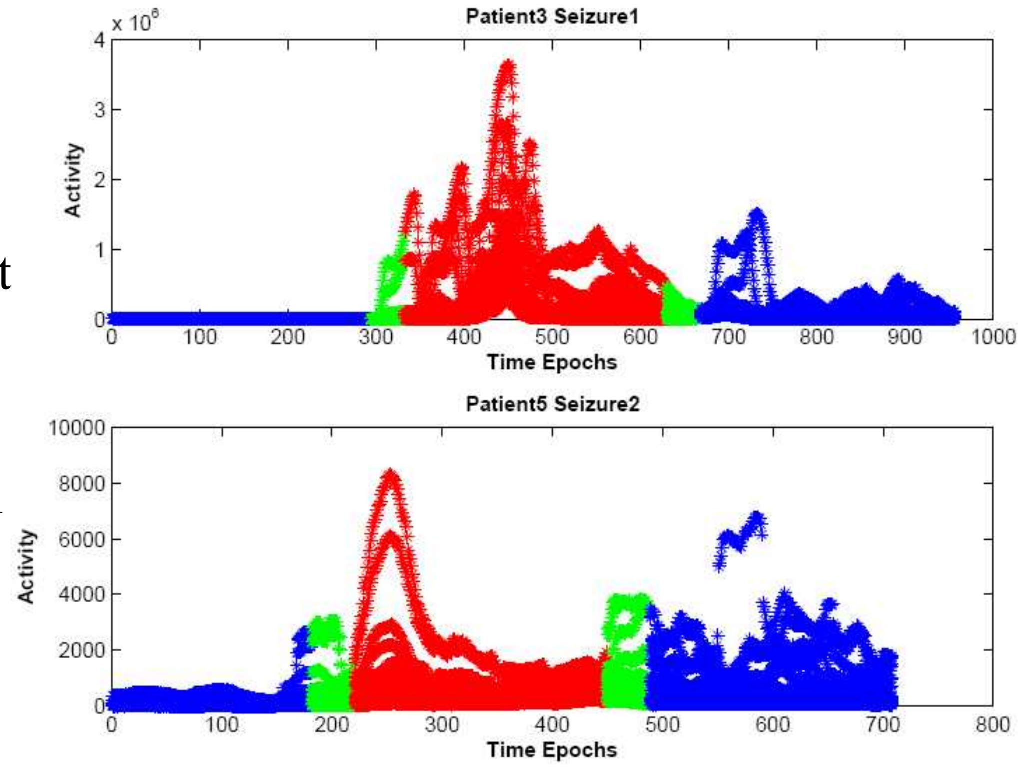


PID	Activity	Mobility	Complexity	Mean Abs. Slope	Spatial Info	Median Freq.	Spectral Entropy
1	✓	✓	✓	✓	✓	×	✓
2	✓	✓	✓	✓	✓	×	✓
3	✓	✓	✓	×	✓	×	✓
4	✓	✓	✓	×	✓	×	✓
5	✓	✓	✓	×	×	×	✓
6	✓	✓	✓	×	✓	×	×
7	✓	✓	✓	✓	✓	×	✓
8	✓	✓	✓	✓	✓	×	×
9	✓	✓	×	×	✓	×	×

DATA (Patient Non-Specific Seizure Recognition)

- Collected in the epilepsy monitoring unit of
  - Yeditepe University Hospital (Istanbul, Turkey)
  - Albany Medical College (NY, USA)
- 26 seizures from 9 patients (left or right temporal)
- Eleven Features: Activity, Complexity, Mobility, Mean Absolute Slope, Spatial Information, Spectral Entropy, Median Frequency, **Relative Energy**.
- Preprocessing:
  - Filter at 50Hz/60Hz
  - Scaling within features mode
  - **Log transform**

Patient Seizure Size of an Epilepsy



⋮

Performance Evaluation

- **G-means:** $\sqrt{Sensitivity \times Specificity}$

Patient ID	NPLS+LDA (v1)	NPLS+LDA (v2)	NPLS+LDA (v1+heuristic)
1	87.7%	81.4%	89.0%
2	88.8%	87.0%	90.2%
3	83.7%	88.1%	85.2%
4	41.9%	84.7%	39.8%
5	95.6%	94.9%	96.9%
6	95.6%	92.6%	95.6%
7	94.5%	88.1%	95.6%
8	69.6%	71.1%	69.3%
9	68.1%	72.8%	68.6%
MEAN	80.6%	84.5%	81.1%

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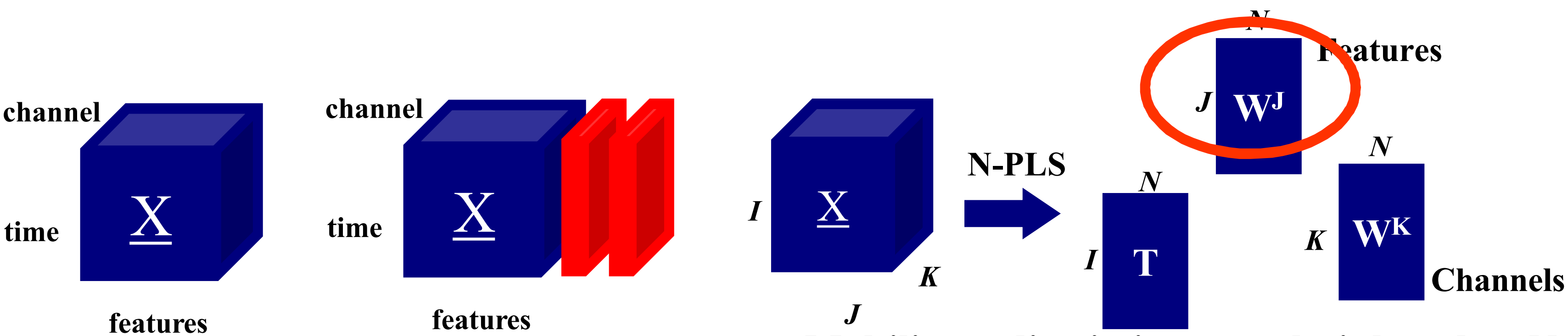
Results

- Average performance of patient-specific seizure recognition over 9 patients (32 seizures) is **85.8%.**
  - better performance using feature selection
  - performance comparable with SVMs and easier interpretation
  - feature selection may improve the understanding of epileptic seizures

- Average performance of patient non-specific seizure recognition over 9 patients (26 seizures) is **80.6%**.
  - heuristics to handle false-positives may improve the performance.

Summary

- **Epileptic Seizure Recognition:**



Epilepsy feature tensor

More features e.g., spatial information

- **Multilinear discriminant analysis based on N-PLS and LDA**
- **VIP extended to three-way**
- **Comparison with SVMs**
- **Patient specific and non-specific seizure recognition**

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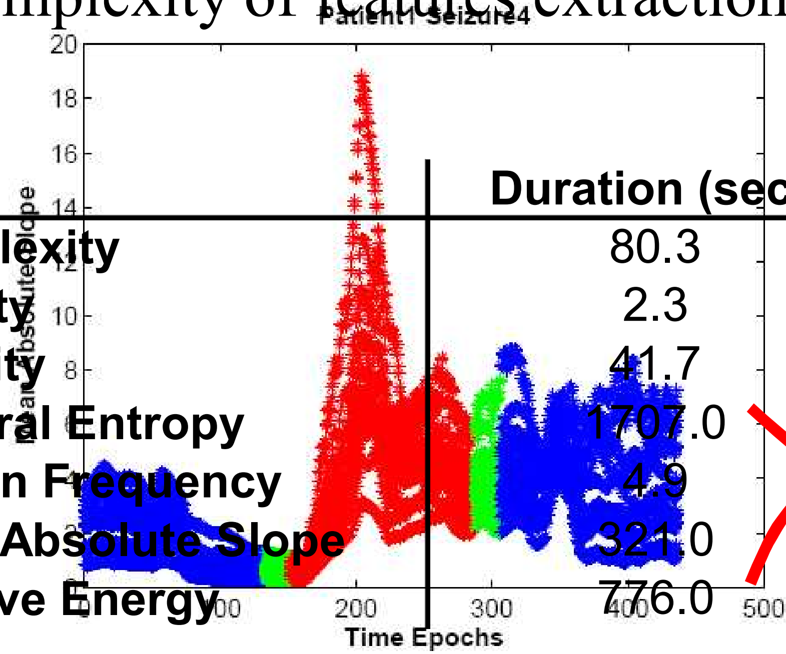
Epilepsy Feature Tensor Construction

- Features can distinguish between pre-seizure and post-seizure.
- Computational complexity of features extraction

Example:



	Duration (sec.)
Complexity	80.3
Activity	2.3
Mobility	41.7
Spectral Entropy	1707.0
Median Frequency	4.9
Mean Absolute Slope	321.0
Relative Energy	776.0

O(nlogn)/scale

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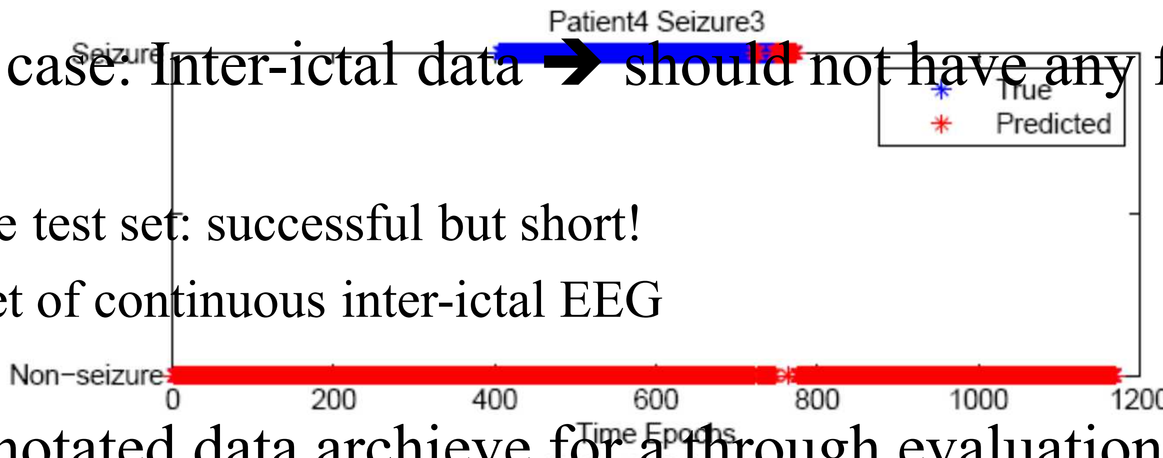
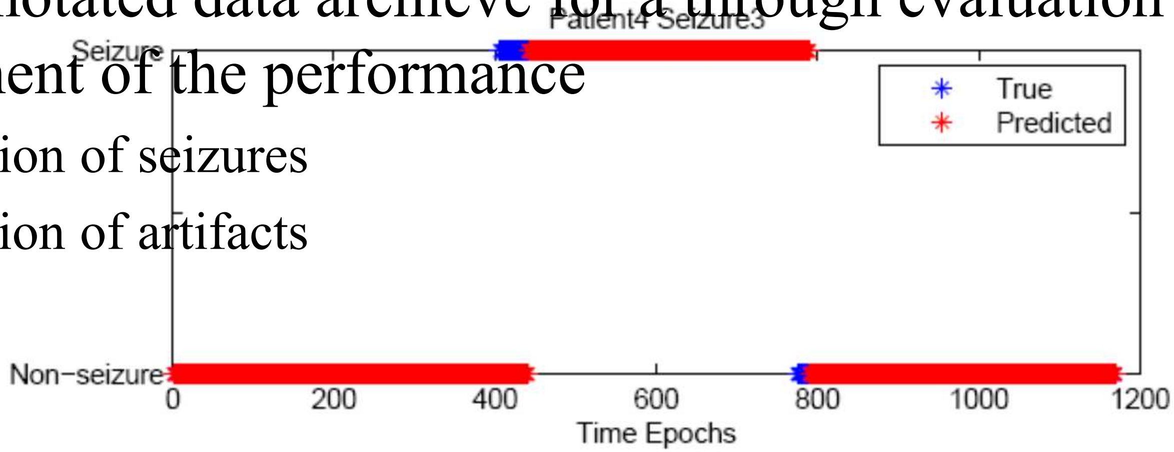
Seizure Recognition

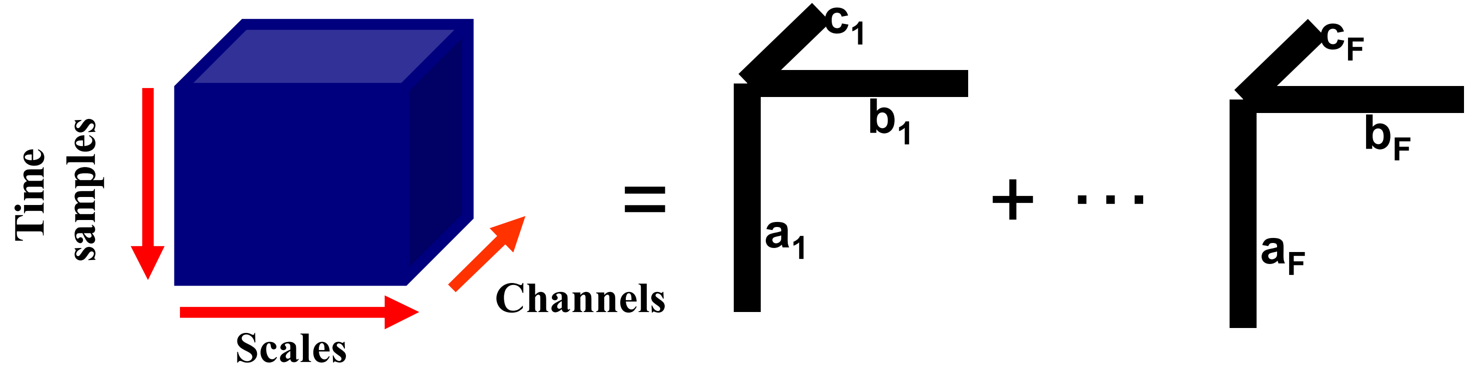
- Log transform to handle inter-patient variation not enough!
- Good test case: Inter-ictal data ➔ should not have any false positives!
  - 4-minute test set: successful but short!
  - Large set of continuous inter-ictal EEG



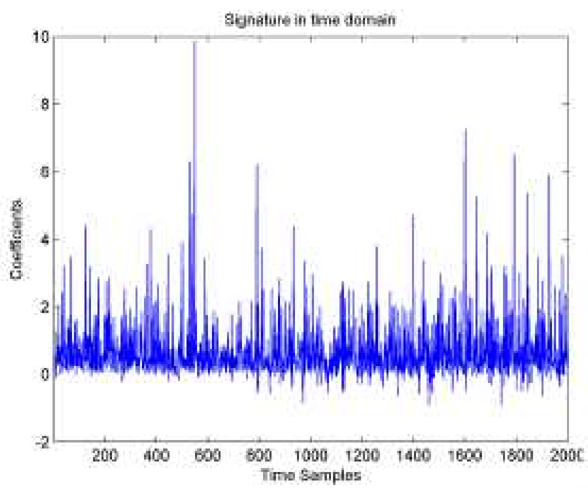
- Larger annotated data archieve for a through evaluation and improvement of the performance
  - Annotation of seizures
  - Annotation of artifacts

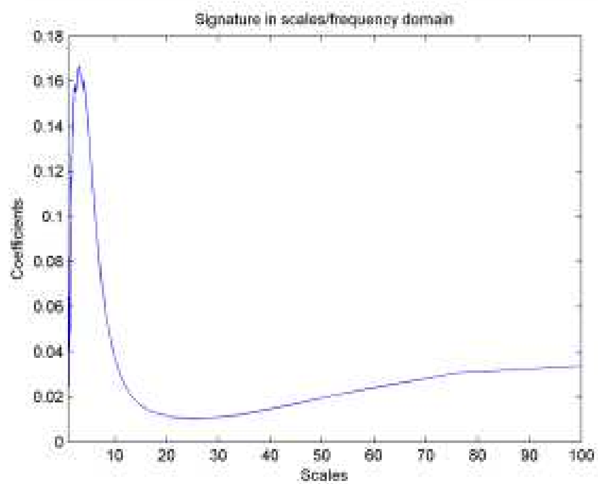


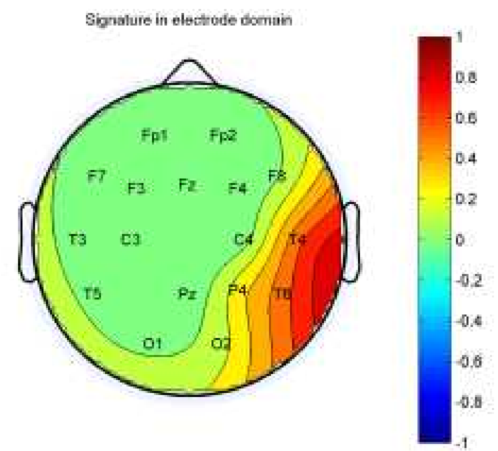
Epilepsy Focus Localization



$$\underline{X} = a_1 \circ b_1 \circ c_1 + a_2 \circ b_2 \circ c_2 + \underline{E}$$







Evrim Acar, Canan A. Bingol, Haluk Bingol, Rasmus Bro and Bulent Yener, **Multiway Analysis of Epilepsy Tensors,** *Bioinformatics*, 2007, 23(13): i10-i18.

Thank you!

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MATLAB scripts: www.cs.rpi.edu/~acare/Epilepsy