(Some) Challenges in Tensor Mining

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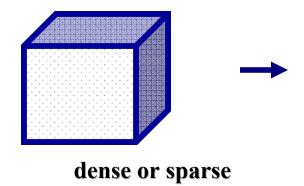
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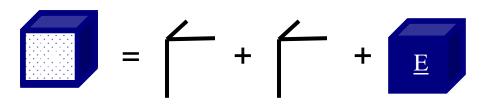


Tensor Mining

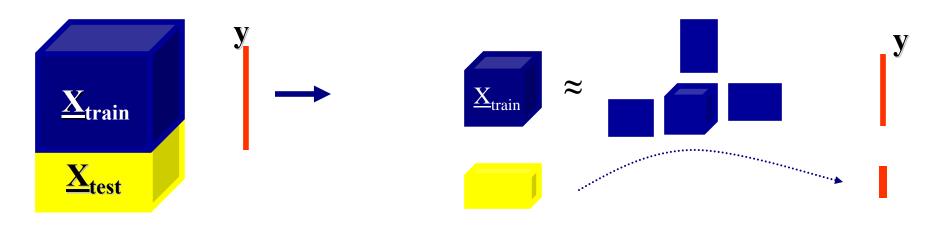
unsupervised



Parafac



supervised

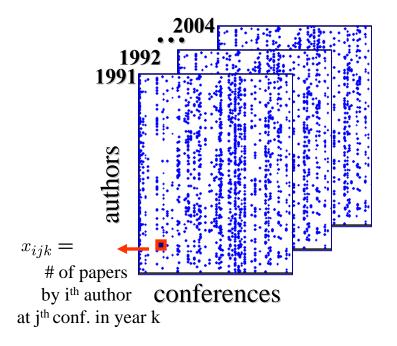




App I: Social Networks Analysis

Joint work with T.G. Kolda and D. M. Dunlavy

- In social networks, we are interested in modeling relationships (links) evolving over time.
- Example:
 - DBLP dataset: Authors x Conferences x Years (10K x 2K x 14: ~0.1% dense)



Q1: Can we use tensor decompositions to model the data and extract meaningful underlying factors?

Q2: Can we predict who is going to publish at which conferences in future?

(Link Prediction in time) SIAM CS&E March 2-6, 2009



Modeling DBLP using PARAFAC

$$\underline{\mathbf{X}} \in \mathbb{R}^{I \times J \times K} \quad \text{we start the problem of the problem} \approx \begin{bmatrix} \mathbf{c}_1 \\ \mathbf{b}_1 \\ \mathbf{a}_1 \end{bmatrix} + \begin{bmatrix} \mathbf{c}_2 \\ \mathbf{b}_2 \end{bmatrix} \cdots \begin{bmatrix} \mathbf{c}_R \\ \mathbf{b}_R \\ \mathbf{a}_R \end{bmatrix} \times \begin{bmatrix} \mathbf{c}_R \\ \mathbf{a}_R \end{bmatrix} \times \begin{bmatrix} \mathbf{c}_R \\ \mathbf{c}_R \end{bmatrix}$$

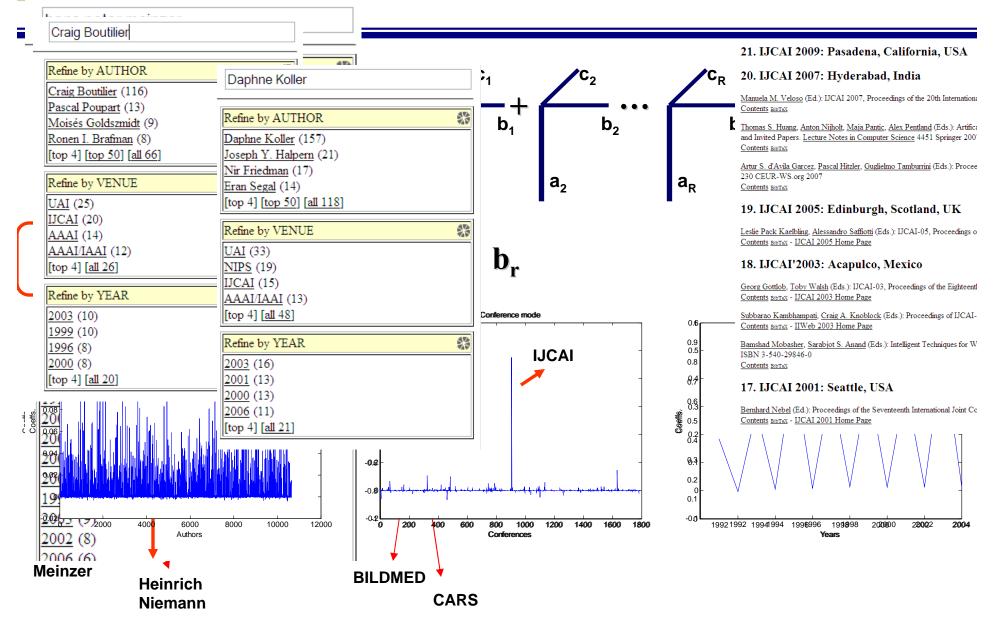
$$\min_{\mathbf{A},\mathbf{B},\mathbf{C}} \left\| \underline{\mathbf{X}} - (\sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r) \right\|^2$$

$$\|\underline{\mathbf{X}}\| = \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{i=1}^{I} x_{ijk}^2$$

- Solve using a gradient-based optimization approach
- Initialization:
 - first two modes using svd, $R \leq I, J$
 - last mode: random, R > K



Components make sense!





What if data is a **Sparse** tensor with Missing entries?

Sparse Data:
$$\min_{\mathbf{A},\mathbf{B},\mathbf{C}} \left\| \underline{\mathbf{X}} - (\sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r) \right\|^2 \qquad \mathbf{A} \in \mathbb{R}^{I \times R} = [\mathbf{a}_1 \cdots \mathbf{a}_R]$$
$$\mathbf{B} \in \mathbb{R}^{J \times R} = [\mathbf{b}_1 \cdots \mathbf{b}_R]$$

$$\mathbf{A} \in \mathbb{R}^{I \times R} = \left[\mathbf{a}_1 \cdots \mathbf{a}_R \right]$$

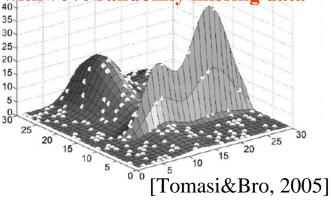
$$\mathbf{B} \in \mathbb{R}^{J \times R} = \left[\mathbf{b}_1 \cdots \mathbf{b}_R \right]$$

Success with 70% randomly missing data

Missing Data [Kiers, 1997; Tomasi & Bro, 2005]:

$$\min_{\mathbf{A},\mathbf{B},\mathbf{C}} \left\| \underline{\mathbf{W}} * (\underline{\mathbf{X}} - (\sum_{r=1}^R \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r)) \right\|_{\frac{15}{30}}^{\frac{15}{10}}$$

 $w_{ijk} = egin{cases} 1, & \text{if } x_{ijk} \text{ not missing,} \\ 0, & \text{if } x_{ijk} \text{ missing.} \end{cases}$



Sparse & Missing:

$$\min_{\mathbf{A},\mathbf{B},\mathbf{C}} \left\| \underline{\mathbf{W}} * (\underline{\mathbf{X}} - (\sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r)) \right\|^2 + ???$$

$$w_{ijk} = \begin{cases} 1, & \text{if } x_{ijk} \text{ not missing,} \\ 0, & \text{if } x_{ijk} \text{ missing.} \end{cases}$$

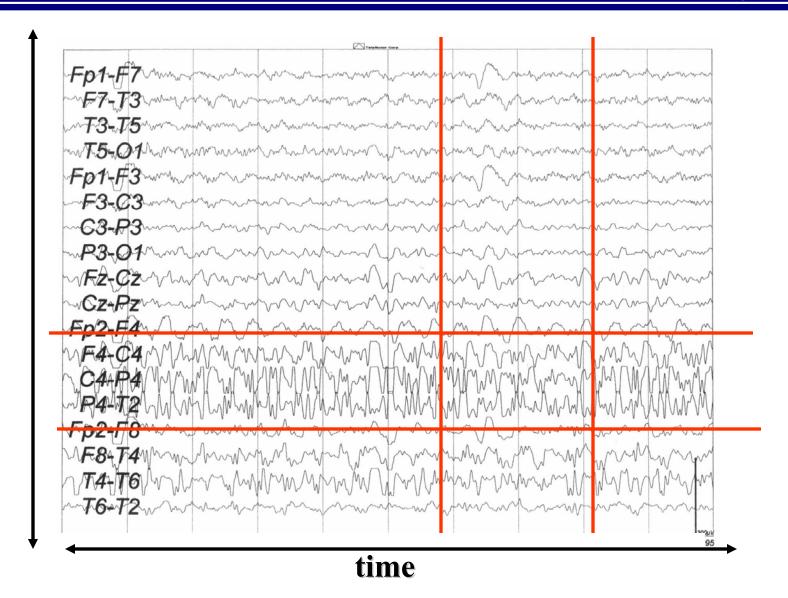


App II: Understanding Epileptic

Seizures

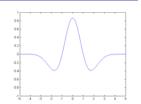
Joint work with R. Bro, B. Yener, C. A. Bingol. H. Bingol

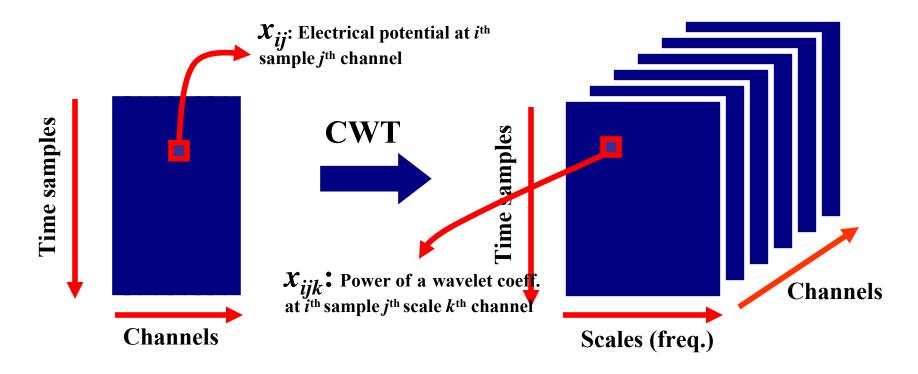






Epilepsy Tensors

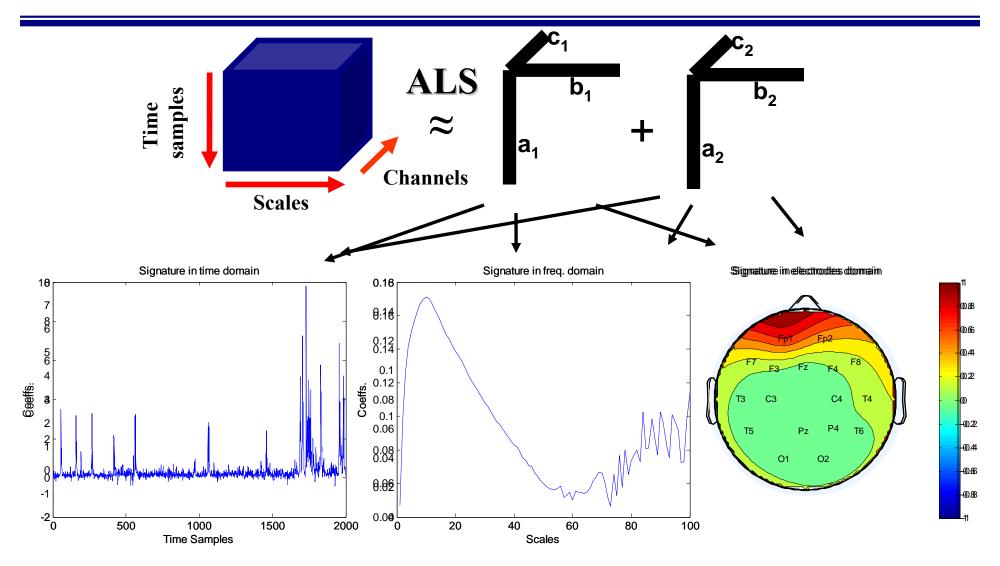




- Data rearranged as a three-way array using continuous wavelet transform (CWT):
 - •Let c_{ijk} be the wavelet coefficient at time sample i at scale j for the k^{th} channel.
 - An Epilepsy Tensor is a three-way array, \underline{X} , where each entry x_{ijk} is computed as: $x_{ijk} = |c_{ijk}|^2$



Epilepsy Focus Localization



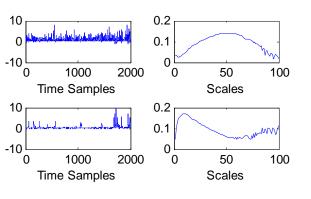


How many components?

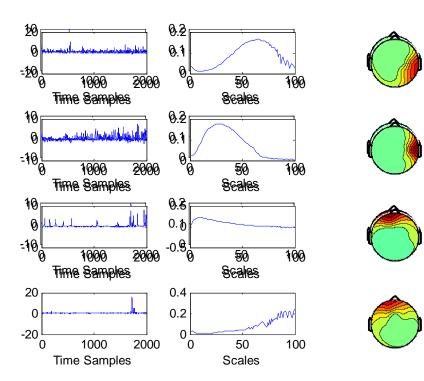
$$\underline{\mathbf{X}} \approx \sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r$$

$$R = 2$$









R = 4



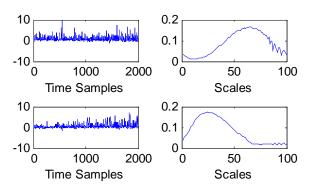
How to initialize?

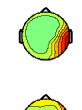
$$\underline{\mathbf{X}} \approx \sum_{r=1}^{2} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r$$

HOSVD

0.2 0.1 0 L 1000 2000 50 100 Time Samples Scales 10 0.2 0.1 0 1000 2000 50 100 Time Samples Scales

RANDOM

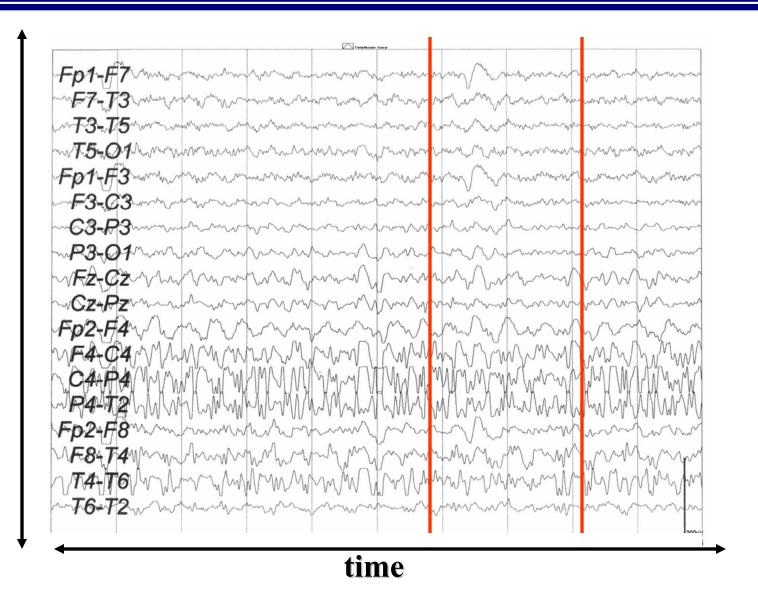






Understanding Epileptic Seizures

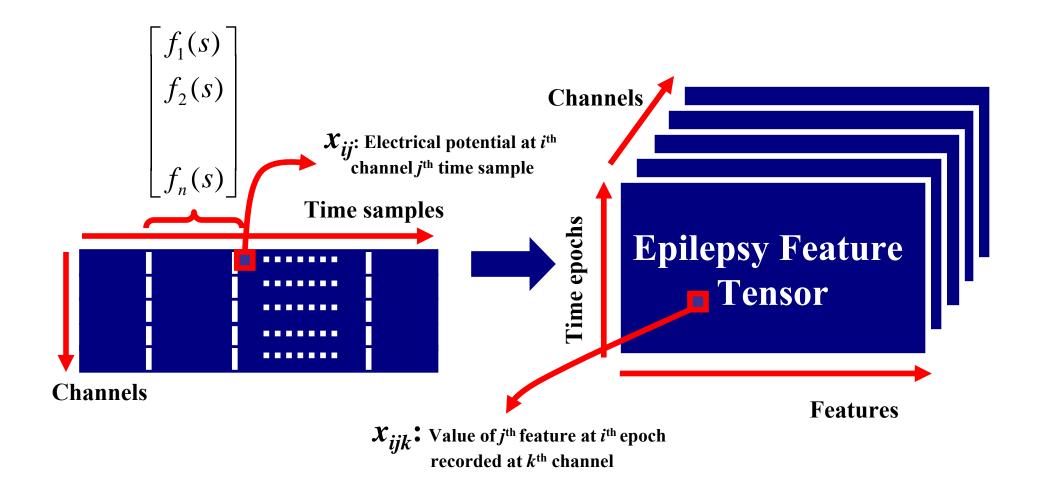






Epilepsy Feature Tensor

Construction of an Epilepsy Feature Tensor from multi-channel EEG





Seizure Recognition

Training Set

• Build a model using the training set $\underline{\mathbf{X}}$ and the labels \mathbf{y} .

Ytrain Pre₁ Seizure₁ seizure Post₁ Time epochs Pre₂ Seizure₂ Post₂ non-seizure Pre₃ Seizure₃ Post₃

Test Set

• Predict the labels of new recordings.

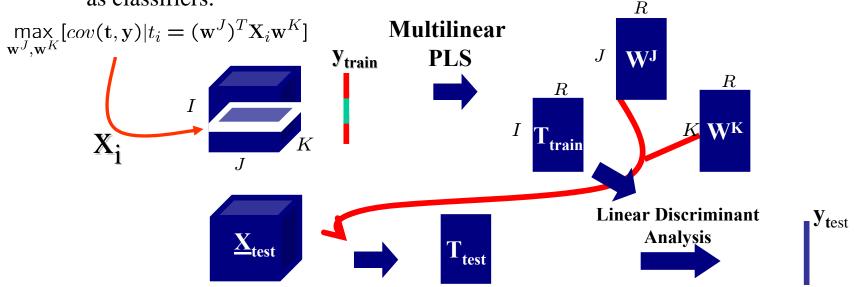




Multiway Classification(?)

• Potential Approaches

Modify multiway regression models, e.g., multilinear PLS [Bro, 1996; Bro et al., 2001],
 as classifiers.



Unfold the data and apply two-way classification, e.g., SVM.





Some challenges are ...

Handling Sparse Data with Missing Entries:

 We need models to capture the underlying sparse factors in sparse tensors with missing entries.

Determining the Rank:

Important also in practice.

• Initialization:

 Algorithms suffer from the local minima problem. In practice, we may end up interpreting our results differently.

Supervised learning on tensors:

 We need classification models for tensors as good as the state-of-the-art twoway classification approaches such as SVMs.



Thank you!

• References:

- Social Networks Analysis: [Tensor toolbox & Poblano toolbox (by Sandia)]
 - Acar, Kolda and Dunlavy, An Optimization Approach for Fitting Canonical Tensor Decompositions, SAND2009-0857, Feb. 2009.
- Understanding Epileptic Seizures: [PLS toolbox (by Eigenvector Research)]
 - Acar, Bingol, Bingol, Bro and Yener, Multiway Analysis of Epilepsy Tensors, *Bioinformatics*, 23(13): i10-i18, 2007.
 - Acar, Bingol, Bingol, Bro and Yener, Seizure Recognition on Epilepsy Feature Tensor, *Proc.* 29th Int. Conf. IEEE Engineering in Medicine and Biology Society, 2007.

– Survey:

• Acar and Yener, Unsupervised Multiway Data Analysis: A Literature Survey, *IEEE Transactions on Knowledge and Data Engineering*, 21(1): 6-20, 2009.

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