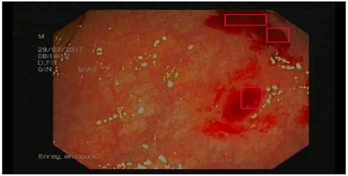
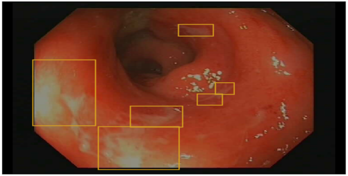
Automatic detection of ulcerative colitis lesions in colonoscopy videos

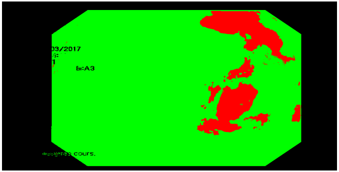
Objective : Detect bleeding and ulcers



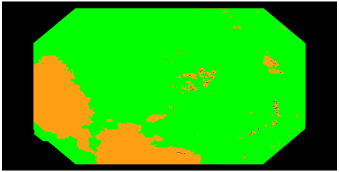
Bleeding annotations



Ulcer annotations



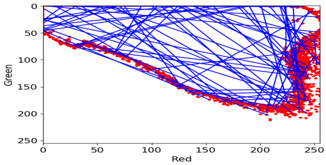
Detected bleeding



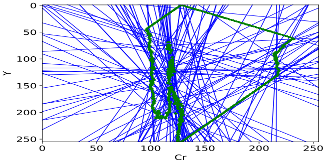
Detected ulcers

Find best linear classifier in RGB or YCbCr color space

- Sampling strategy to avoid trivial classifiers

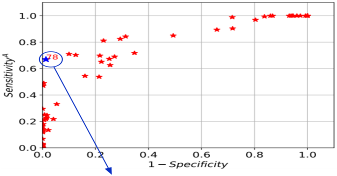


Classifiers for bleeding detection

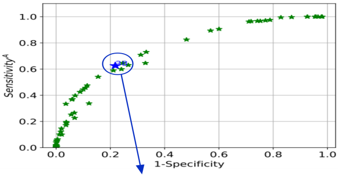


Classifiers for ulcer detection

- Modified **Sensitivity** does not penalise wrong pixels annotations



$G < 0.193R - 0.758$



$Y \geq 0.611Cr - 2.947$

Partial Matching in the space of Varifolds

Pierre-Louis Antonsanti, Irène Kaltenmark, Joan Glaunès.

$$\arg\min_v J(v) = \underbrace{\gamma . E(v)}_{\text{Deformation cost}} + \underbrace{A(\varphi^v(S), T)}_{\text{Data attachment}}$$

$v \in L^2([0,1], V)$
φ^v a C^1- diffeomorphism, solution at t=1 of the flow equation

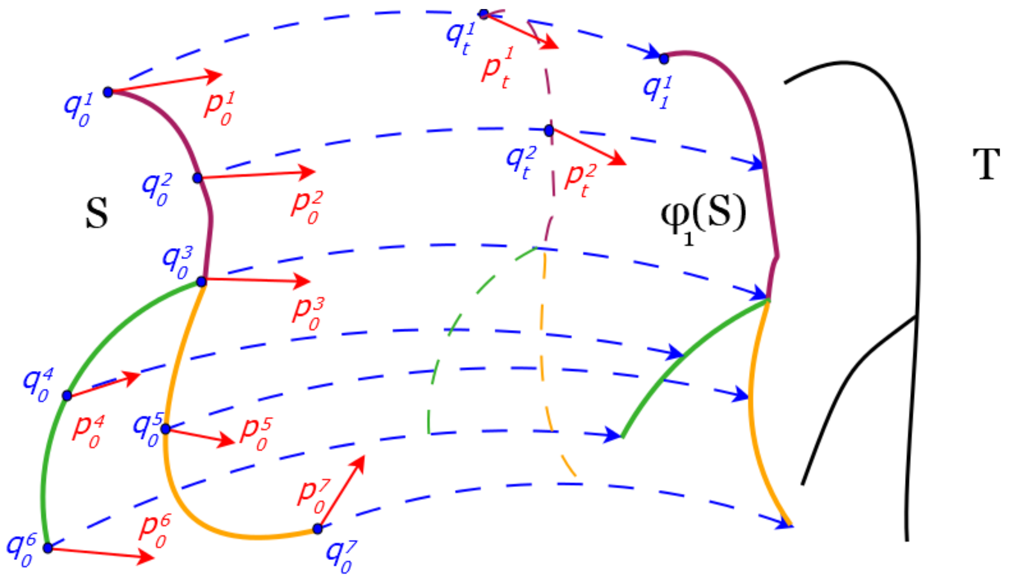
Varifold distance :

$$A(\varphi^v(S), T) = \|\mu_{\varphi^v(S)}\|^2_{W'} - 2.\langle \mu_{\varphi^v(S)} | \mu_T \rangle + \|\mu_T\|^2_{W'}$$

Partial matching dissimilarity function (first idea) :

$$A(\varphi^v(S), T) = (\|\mu_{\varphi^v(S)}\|^2_{W'} - \langle \mu_{\varphi^v(S)} | \mu_T \rangle)^2$$

$$= \langle \mu_{\varphi^v(S)} | \mu_{\varphi^v(S)} - \mu_T \rangle^2$$



GE Healthcare

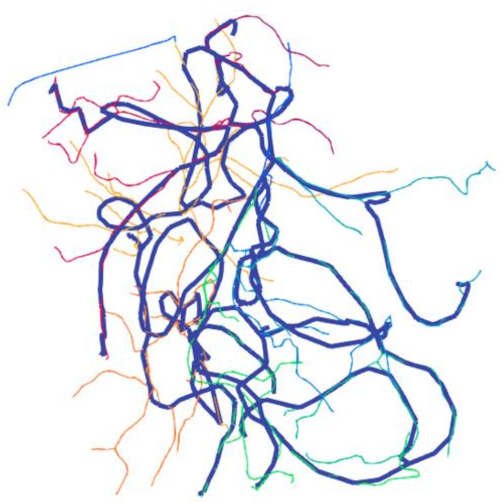
Partial Matching in the space of Varifolds

Université de Paris

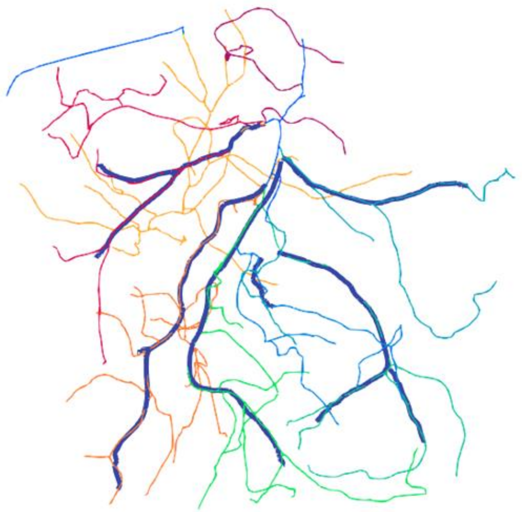
Pierre-Louis Antonsanti, Irène Kaltenmark, Joan Glaunès.

The partial dissimilarity : $\boldsymbol{\Delta(S,T) = \int_S g\big(\omega_S(x,\tau_x S) - \widetilde{\omega_T}(x,\tau_x S)\big)\, dx}$,

with $g(x) = \max(0,x)^2$ and $\widetilde{\omega_T}(x,\tau_x S) = \int_T \min\left(1, \frac{\omega_S(x,\tau_x S)}{\omega_T(y,\tau_y T)}\right) k_e(y,x).\, k_t(\tau_y T, \tau_x S) dy$.



Varifold registration



Partial dissimilarity registration

A general system of differential equations to model first order adaptive algorithms

André BELOTTO DA SILVA

Institut de Mathématiques de Marseille

Aix*Marseille université Initiative d'excellence

Mathematics, Signal Processing and Learning

CIRM, Aix-Marseille Université

25 of January, 2021

Optimization in deep learning

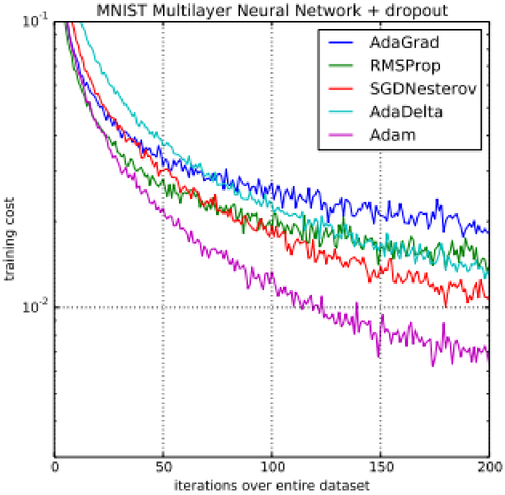


Figure: Training of multilayer neural networks on MNIST images. (Kingma et Ba, "ADAM: a method for stochastic optimization", 2014).

Project : Dynamical study of Adaptive methods, in collaboration with M. Gazeau, Borealis AI

Our intended goal :

- Help the practitioner to choose the initial conditions, the learning rate and the hyper-parameters
- Provide qualitative advice on when to use ADAM instead of SGD.

First step: Build a differential theory

- Provide a differential equation that describes the system;
- Study the convergence of the system.

Second step: Practical advice

- Find the appropriate intervals where to choose the hyper-parameters;
- Find specific situations where ADAM converges (or does not converge);
- Provide advice to improve the algorithm.

Bibliographic reference :

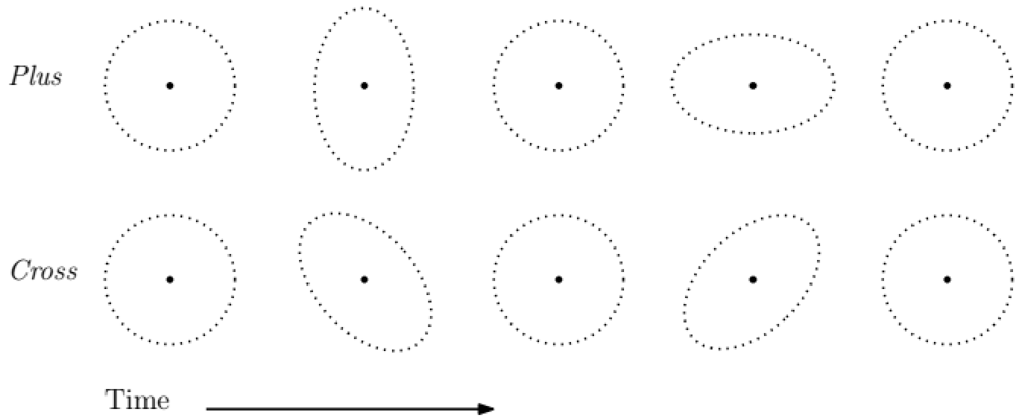
- A. Belotto da Silva et M. Gazeau, *A general system of differential equations to model first order adaptive algorithms*, Journal of Machine Learning Research, 21(129):1-42, 2020.

Thank you for your attention !

Cyril Cano (cyril.cano@gipsa-lab.fr) et al.

Gravitational-wave polarimetry with quaternions and application to precessing binaries

Gravitational waves are polarized

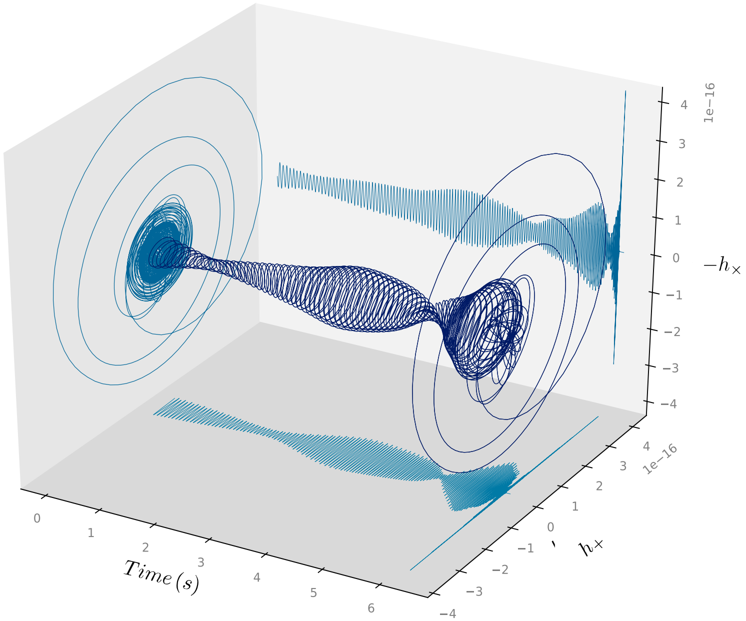


Each detector measures a linear combination

$$\frac{\Delta L(t)}{L} = h_+(t)F_+(\Theta) + h_\times(t)F_\times(\Theta)$$

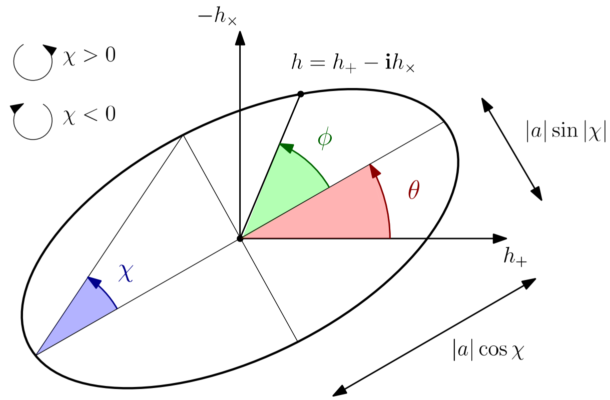
Cyril Cano (cyril.cano@gipsa-lab.fr) et al.

Gravitational-wave polarimetry with quaternions and application to precessing binaries



$$h = h_+ - \mathbf{i}h_\times$$

Quaternionic embedding



$$h_{\mathbb{H}} = a e^{\mathbf{i}\theta} e^{-\mathbf{k}\chi} e^{\mathbf{j}\phi}$$

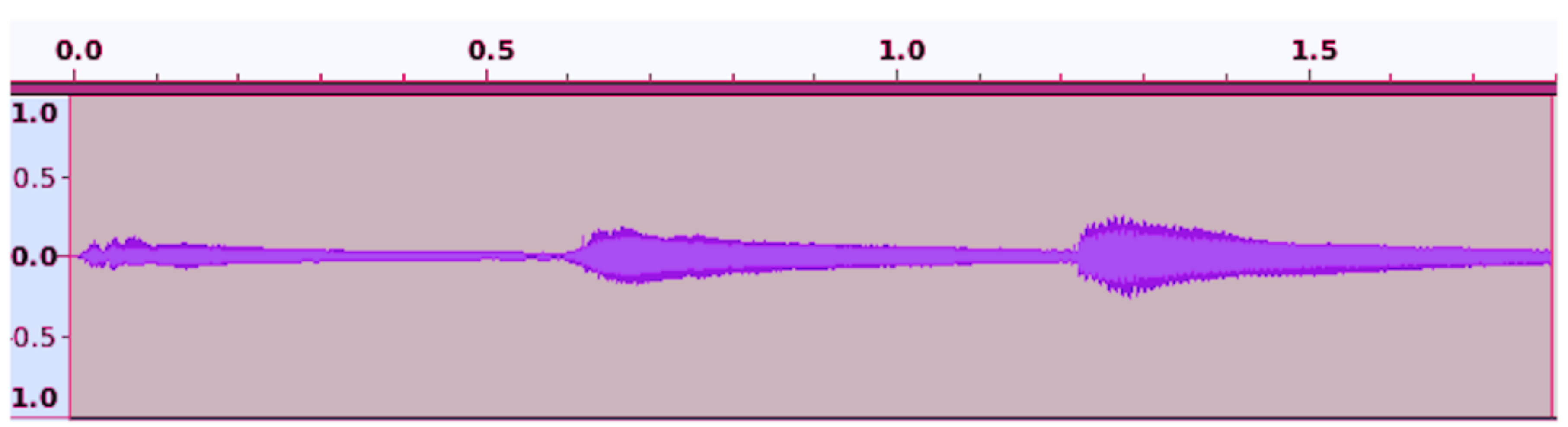
Take-home message

- Quaternionic time-frequency transform allows the ‘unmodelled’ characterization of the polarization state
- Offer a natural formalism for reconstruction of bivariate signals with polarization targetting priors
- Allows to build features to describe bivariate signals (Allows to learn a GW generative model)

Semi-Supervised Convolutive NMF for Automatic Music Transcription

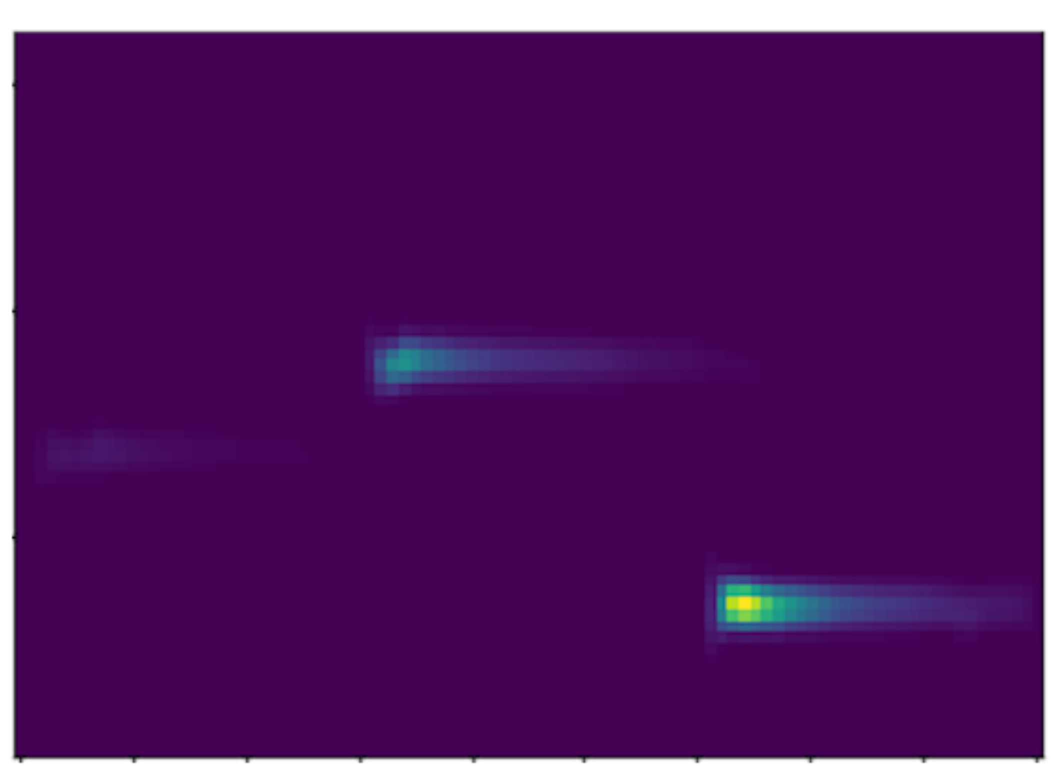
Haoran Wu, Axel Marmoret, Jeremy E. Cohen

Problem

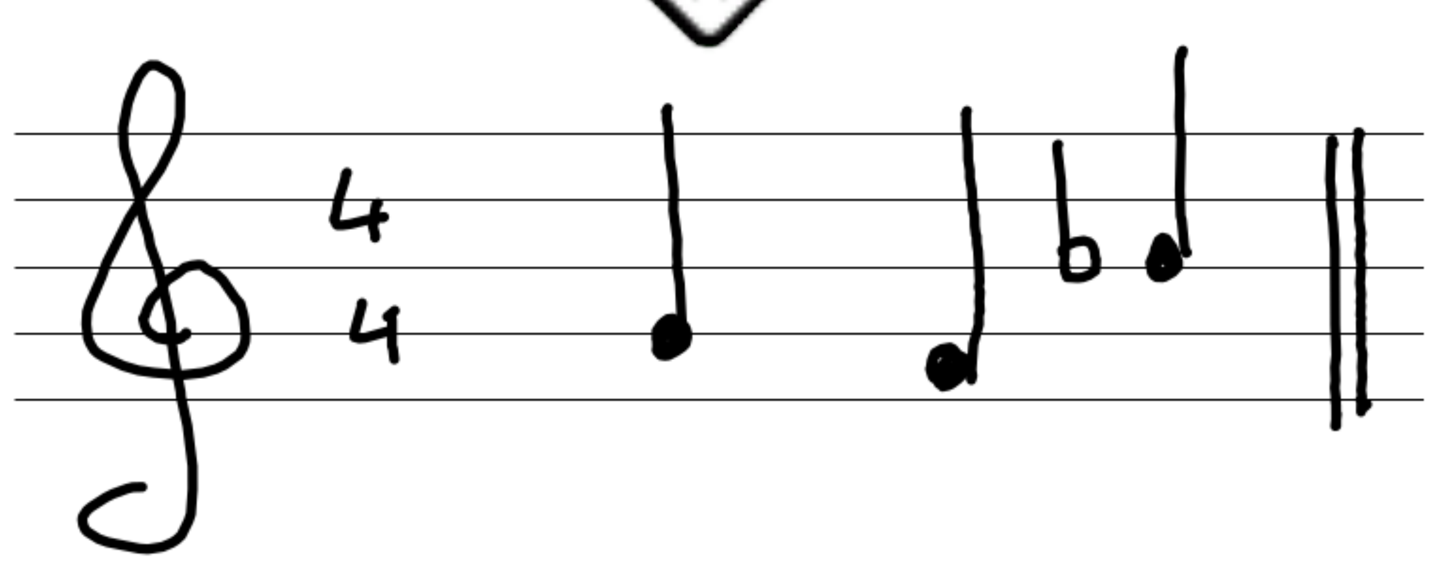


STFT

Frequency



Time

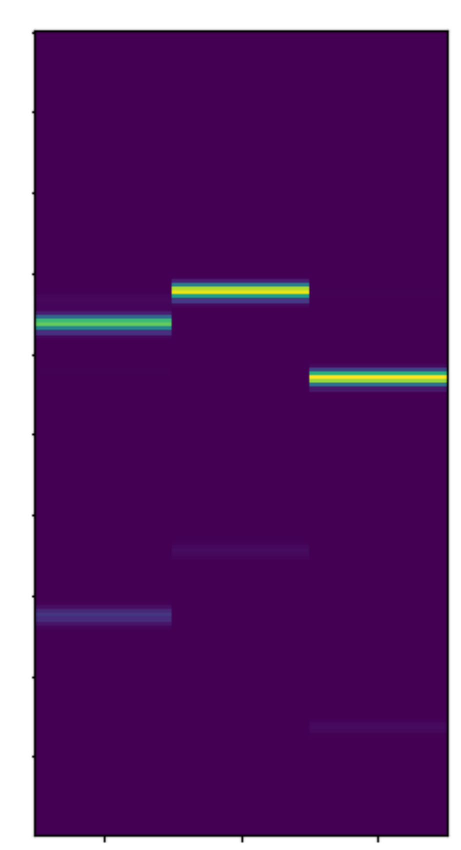


NMF

Post Processing

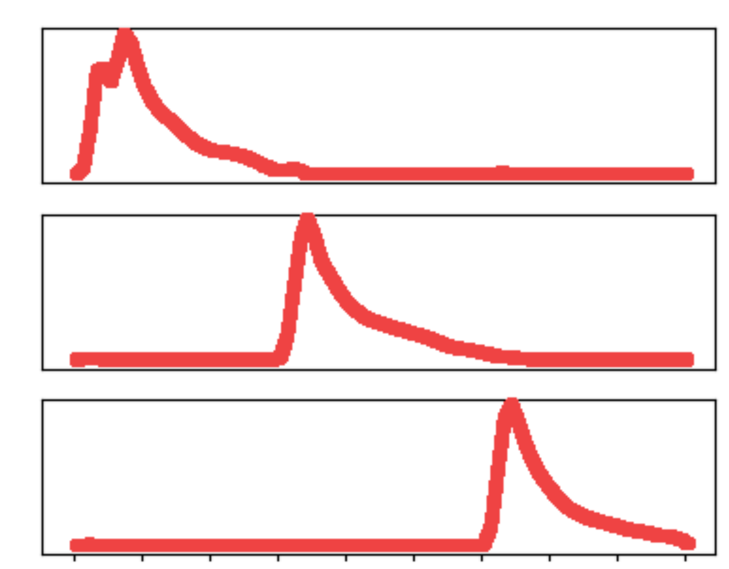
Nonnegative Matrix Factorization

W



Sol Fa Sib

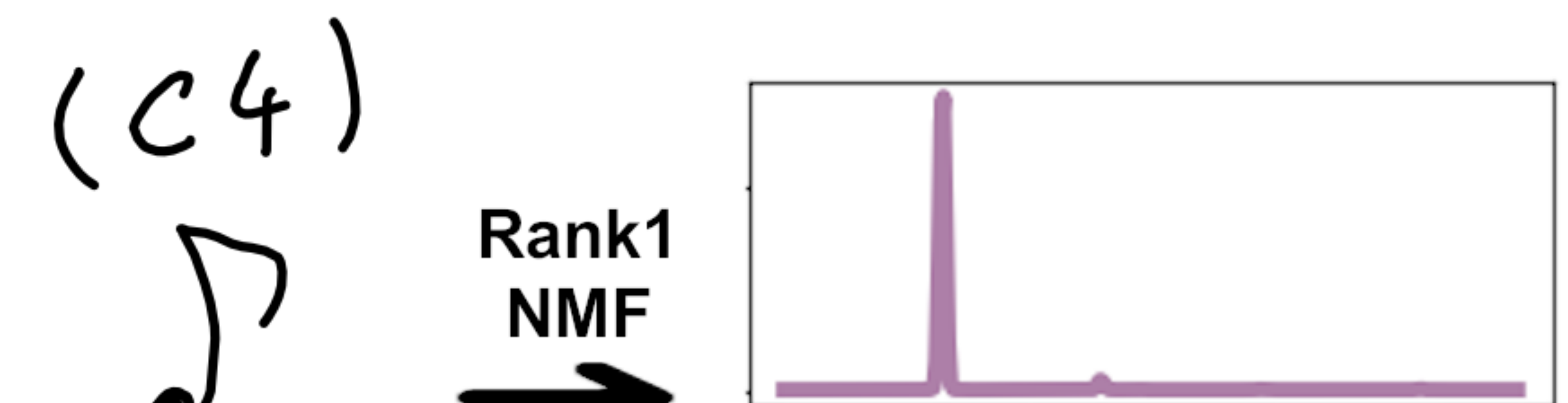
H



NMF is often not unique
W, H may not make sense

Semi-Supervision

1/ Learn W on individual notes

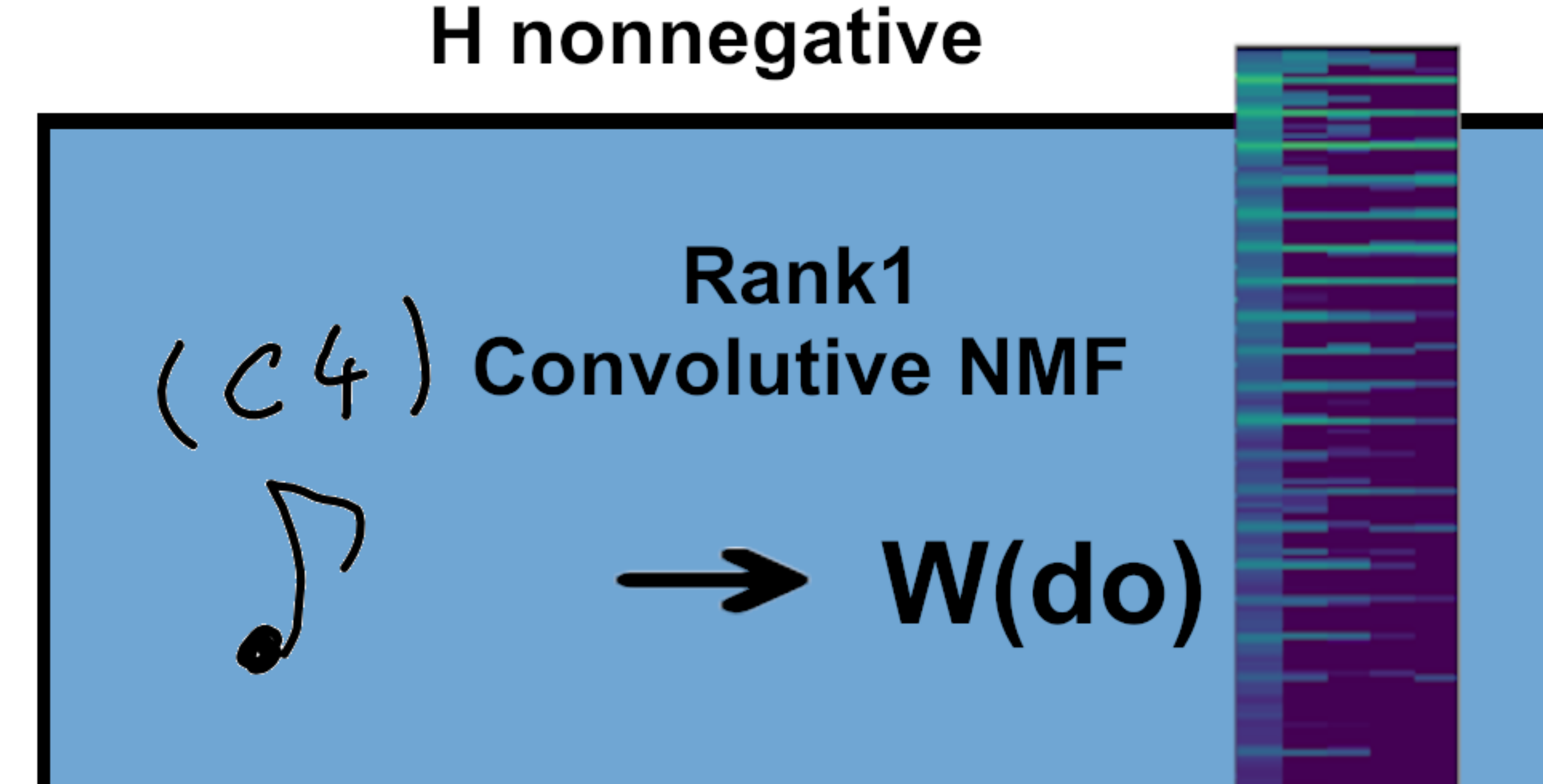


w(do)

2/ Learn only H from the song

$$H = \text{argmin } D(X,WH)$$

H nonnegative



Large dimensional analysis of LS-SVM transfer learning: Application to POLSAR classification

Cyprien DOZ
PhD 2nd year
SONDRA

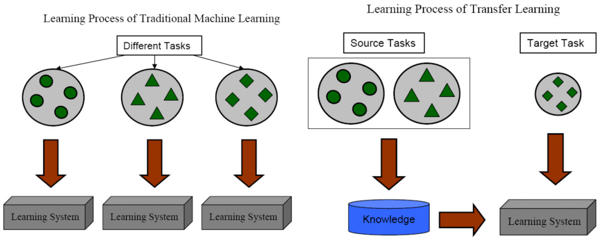
Romain COUILLET (GIPSA-lab), Chengfang REN (SONDRA), Jean-Philippe OVARLEZ (ONERA)

ONERA

THE FRENCH AEROSPACE LAB

Context and motivation

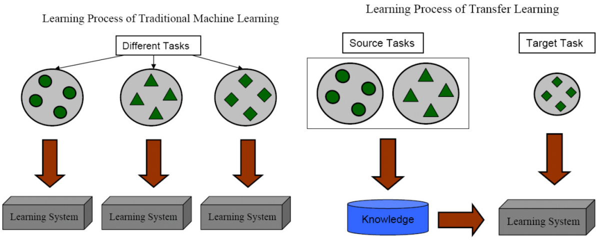
- Analysis, Interpretation and Improvement of transfer learning with Random Matrix Theory



(a) Traditional Machine Learning (b) Transfer Learning

Context and motivation

- Analysis, Interpretation and Improvement of transfer learning with Random Matrix Theory



(a) Traditional Machine Learning (b) Transfer Learning

1. $[\mathbf{x}_1^T, \ldots, \mathbf{x}_{n_T}^T]$: target data (annotated) **insufficient**.

Context and motivation

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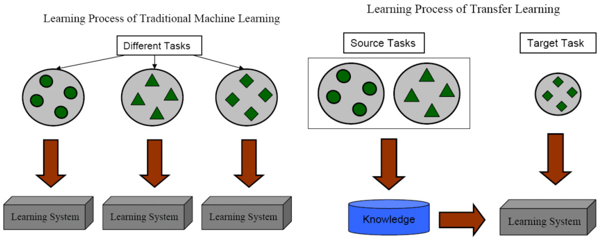

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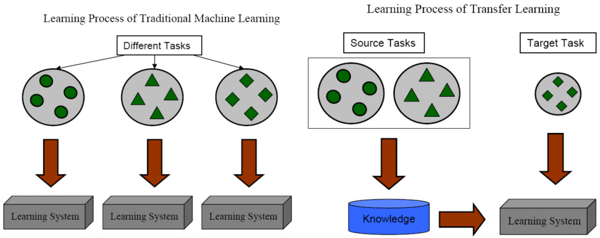

(a) Traditional Machine Learning (b) Transfer Learning

1. $[\mathbf{x}_1^T, \ldots, \mathbf{x}_{n_T}^T]$: target data (annotated) **insufficient**.
   ➥ failing supervised learning
2. $[\mathbf{x}_1^T, \ldots, \mathbf{x}_{n_T}^T] \leftarrow [\mathbf{x}_1^S, \quad \ldots \quad, \mathbf{x}_{n_S}^S]$: source data **"similar"**

Context and motivation

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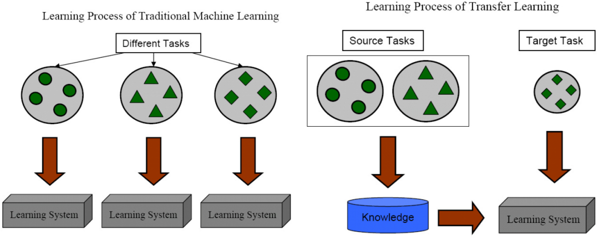

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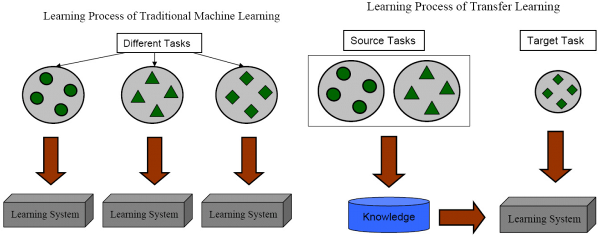
3. new learning set : $[\mathbf{x}_1, \quad \ldots \quad , \quad \ldots \quad \mathbf{x}_n]$, $n = n_S + n_T$

Context and motivation

- Analysis, Interpretation and Improvement of transfer learning with Random Matrix Theory



(a) Traditional Machine Learning (b) Transfer Learning

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3. new learning set : $[\mathbf{x}_1, \quad \ldots \quad , \quad \ldots \quad \mathbf{x}_n]$, $n = n_S + n_T$

- Application to **environmental monitoring** (few annotated data) : label optimization and performance guarantees in high dimension.

Large dimensional analysis of LS-SVM transfer learning :

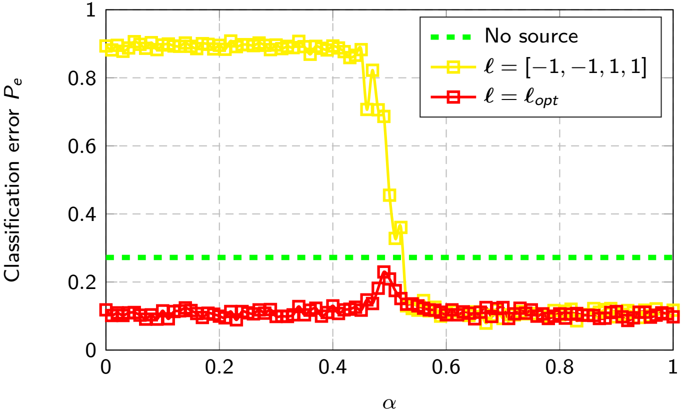

Figure – Classification performance for various label strategies ; $p = 512$, $n_{S_1} = n_{S_2} = 508$, $n_{T_1} = n_{T_2} = 4$, polynomial kernel f with $f(\tau) = 4$ and $f''(\tau) = 2$.

Weighted-CEL0 sparse regularisation for molecule localisation in Super-Resolution microscopy with Poisson data

Marta Lazzaretti
Joint work with Luca Calatroni and Claudio Estatico

Université Côte d'Azur
Università degli Studi di Genova

RESEARCH SCHOOL Mathematics, Signal Processing and Learning
CIRM, Luminy, Marseille 25 - 29 January 2021

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MORPHEME
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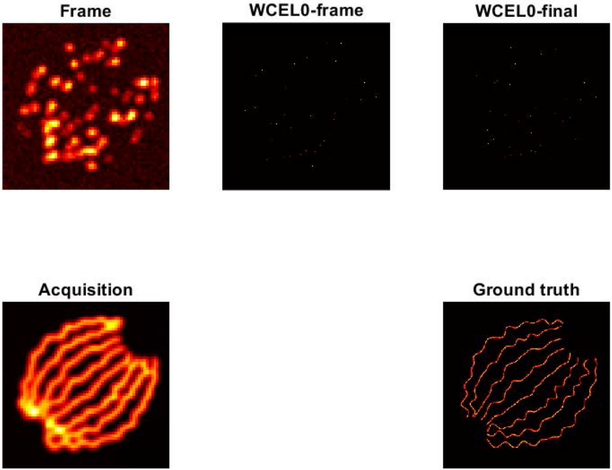
Single Molecule Localisation Microscopy

Light diffraction phenomena limits the spatial resolution.
SMLM idea: sequential activation/deactivation of molecules $\Longrightarrow$ **stack**.
Final reconstructed image=sum of singular frame reconstruction.

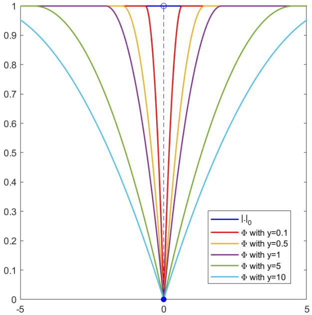


Weighted-CEL0 sparse regularisation

Sparsity-promoting weighted $\ell_2 - \ell_0$-type model, accounting for signal-dependent Poisson noise in SMLM data:

$$x^* \in \underset{x \in \mathbb{R}^{ML \times ML}}{\arg\min} \sum_{j=1}^{M^2} \frac{1}{2} \frac{\left((Ax)_j - y_j\right)^2}{y_j} + \lambda \|x\|_0$$

ℓ_0-norm $\Longrightarrow$ non-continuous, non-convex, NP-hard



Continuous non-convex relaxation of the ℓ_0-norm: weighted-CEL0 penalty

$$x^* \in \underset{x \in \mathbb{R}^{ML \times ML}}{\arg\min} \sum_{j=1}^{M^2} \frac{1}{2} \frac{\left((Ax)_j - y_j\right)^2}{y_j} + \Phi_{WCEL0}(x, \lambda, A, y)$$

Φ_{WCEL0} depends on the degradation matrix A and on the observed data y

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Graph Signal Smoothing via Random Spanning Forests

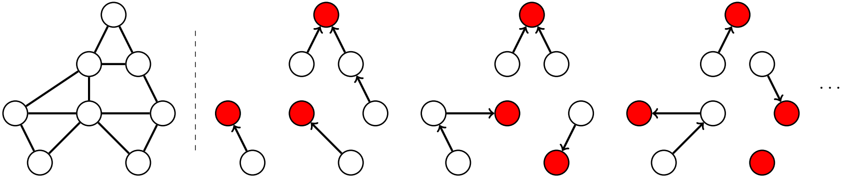
Yusuf Yigit Pilavci*
Pierre-Olivier Amblard
Simon Barthelmé
Nicolas Tremblay

25/01/2021

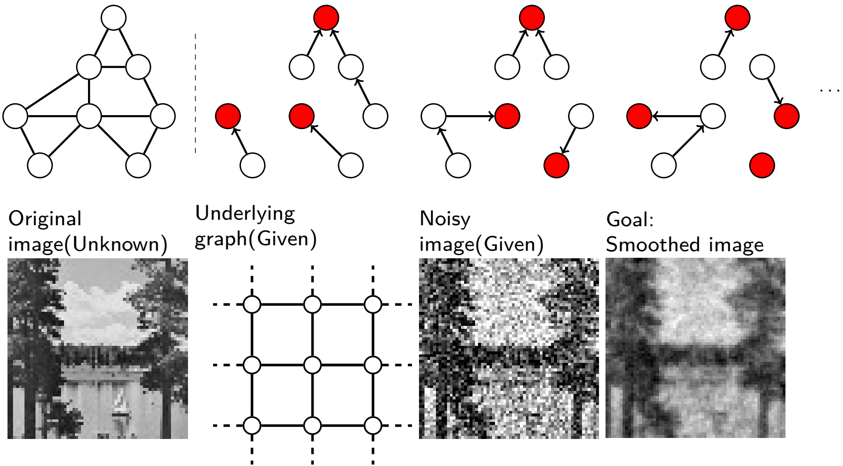
cnrs
Grenoble INP
UNIVERSITÉ Grenoble Alpes
UMR 5216

Graph Signal Smoothing via RSFs

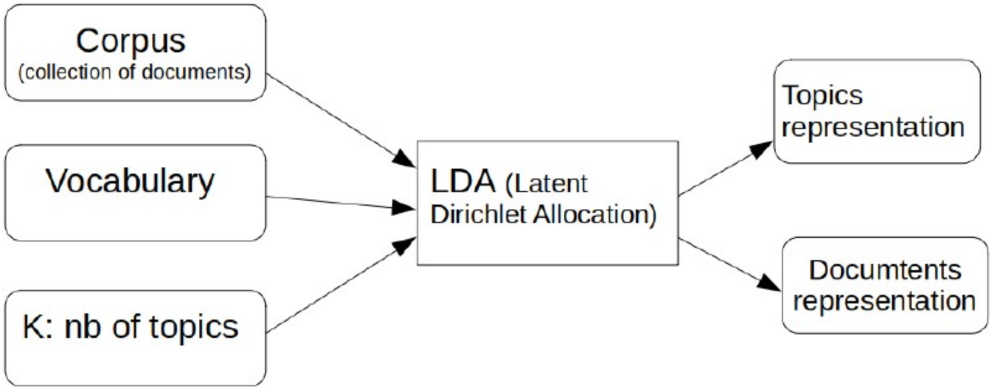
Graph Signal Smoothing via RSFs



Graph Signal Smoothing via RSFs



Topic models and the LDA algorithm



β: Topics representation θ: Documents representation

$$\beta = \begin{bmatrix} \beta_{11} & \beta_{12} & \dots & \beta_{1V} \\ \vdots & \ddots & & \\ \beta_{K1} & \beta_{K2} & \dots & \beta_{KV} \end{bmatrix}$$

$$\theta = \begin{bmatrix} \theta_{11} & \theta_{12} & \dots & \theta_{1V} \\ \vdots & \ddots & & \\ \theta_{K1} & \theta_{K2} & \dots & \theta_{KV} \end{bmatrix}$$

K: Number of topics

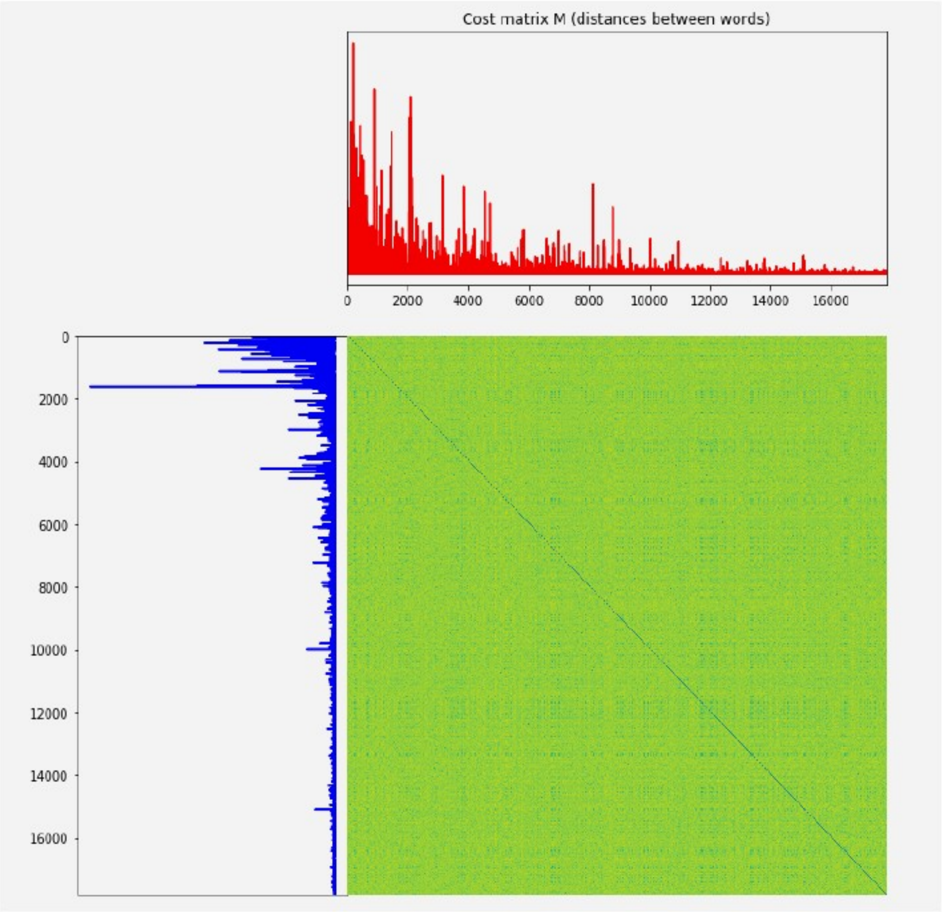
V: Number of words

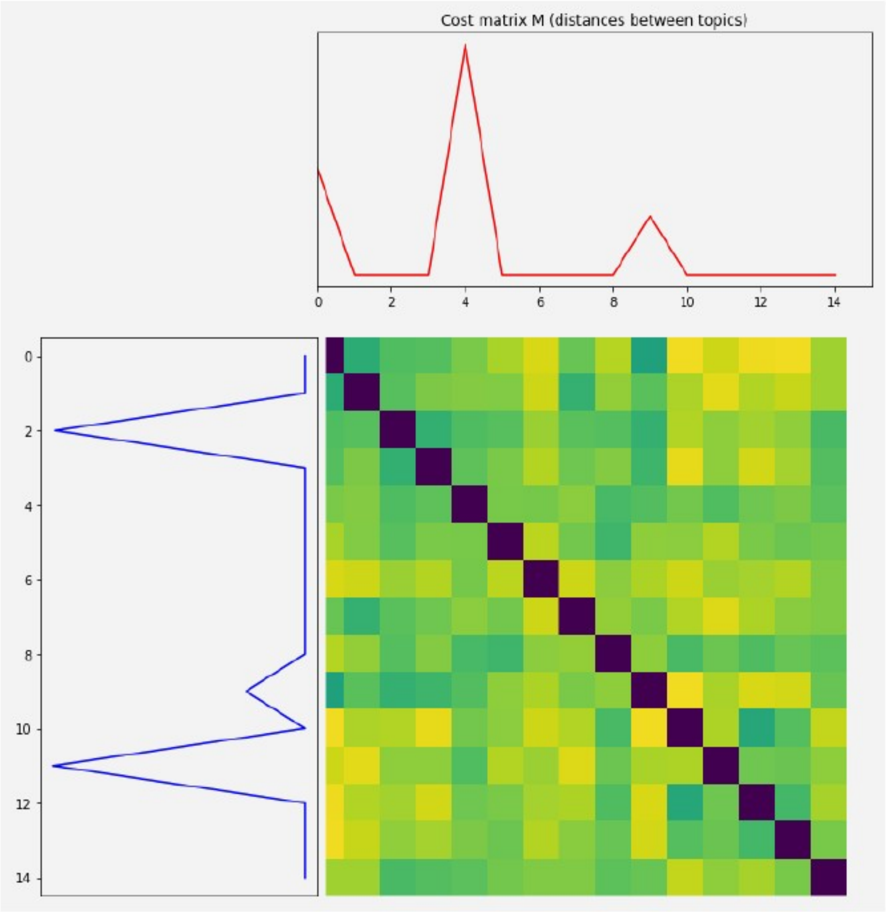
n: Number of documents

How could we use LDA decomposition to define documents similarities ?

Distances between words
Word embeddings.

Two stages Wasserstein distance approach





COℓ_0RME

COvariance-based ℓ_0 super-Resolution Microscopy with intensity Estimation

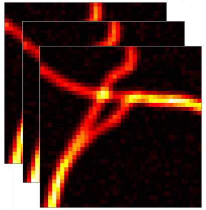
Vasiliki Stergiopoulou, José Henrique de Morais Goulart, Sébastien Schaub, Luca Calatroni, Laure Blanc-Féraud

Design a sparsity-promoting mathematical model for Super-Resolution in Fluorescence Microscopy.

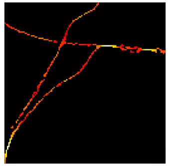
Features:

- ❖ Improved temporal/spatial resolution
- ❖ Harmless excitation levels
- ❖ Use of standard equipment
- ❖ Intensity estimation

Raw Data



COℓ_0RME



Acquire **short videos** with **high-density** of molecules per frame and use a reconstruction algorithm that codifies the assumption of the **temporal/spatial independence** between emitters and the **sparse distribution** of the fluorescent molecules

COℓ_0RME

Two steps:

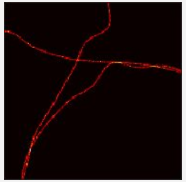
Support Estimation:

- Non-convex variational problem with a sparsity constraint formulated in the covariance domain
- Enforce Sparsity: Continuous Exact ℓ_0 Relaxation (CEL0)

$$\Phi_{\text{CEL0}}(\mathbf{r}_\mathbf{x};\lambda) = \sum_{i=1}^{L^2} \lambda - \frac{\|\mathbf{a}_i\|^2}{2}\left(|(\mathbf{r}_\mathbf{x})_i| - \frac{\sqrt{2\lambda}}{\|\mathbf{a}_i\|}\right)\mathbb{1}_{\{|(\mathbf{r}_\mathbf{x})_i| \leq \frac{\sqrt{2\lambda}}{\|\mathbf{a}_i\|}\}}$$

, where $\mathbf{a}_i = (\mathbf{\Psi} \odot \mathbf{\Psi})_i$

Intensity Estimation:



- Estimate intensity, only on the support, and background information
- Smoothness is promoted on intensity values

COℓ_0RME: Good localization and reconstruction results!

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MULTIVIEW CANONICAL CORRELATION ANALYSIS

CANONICAL CORRELATION ANALYSIS

- Given **N sources,** let be a dataset $\{X_m \in R^{D_m \times N}\}_{m=1}^{M}$ collected from M= 2 views.
- The goal of CCA is to find lower dimensional $d \ll D_m$ representation of these two views through a linear projection U_1 and U_2 while preserving cross information between two views.

$$[U_1^*,, U_2^*] = \boldsymbol{argmax}_{\{U_1,U_2\}} Corr(U_1X_1, U_2X_2)$$

- It has been shown that CCA can increase the quality of clustering and various machine learning tasks.
- CCA remains limited because it can only deal with two views and captures linear relationships.
- This original problem leads to various extensions more or less difficult to incorporate :

Multiviews M>2 / Non-linear extension /Awareness of potential geometric structure on sources etc.

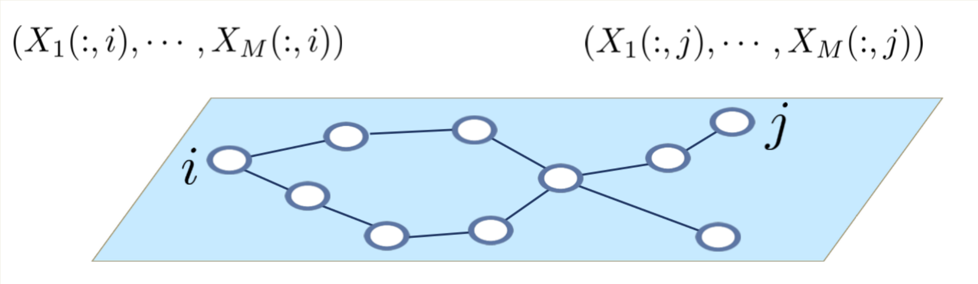
- These extensions can be caracterised by some key properties :

Method	Complexity	Non Linear	>2 views	Graph
CCA	$O(n)$	✗	✗	✗

MULTIVIEW CANONICAL CORRELATION ANALYSIS

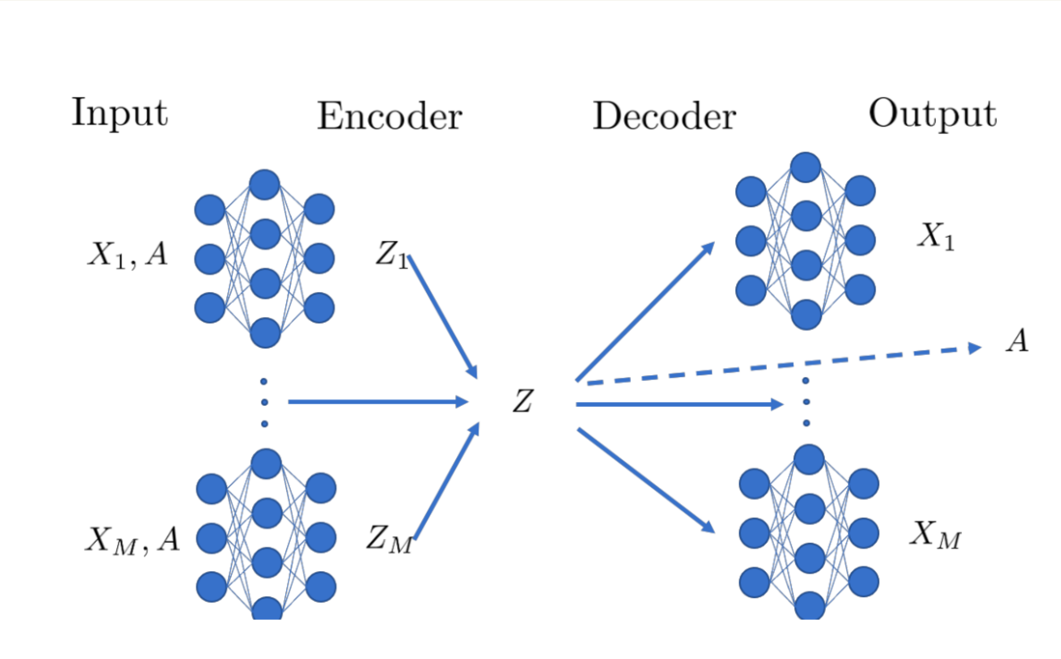
Multiview Varitional Graph CANONICAL CORRELATION ANALYSIS

- Sources can rely on a graph. **Taking care of this graph can improve results** but it's increase complexity.



- We propose a probabilistic model based on an existing **equivalence between original CCA and a bayesian problem** and **solved with a variational auto encoders.**

- $p(X_1, X_2, \dots, X_M, A) = \int P(X_1, A|Z) \dots P(X_M, A|Z)\, P(Z) dZ$



- This model is the only model which deals simultaneously with :
  - M > 2 views,
  - Non linear
  - Accounting for geometric structure
  - Scalable
  - Robust to missing views