Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals

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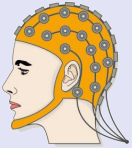
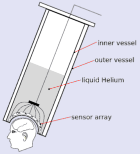
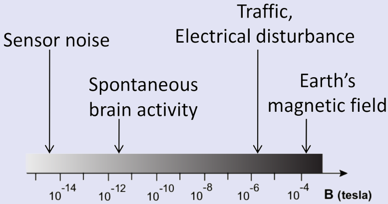
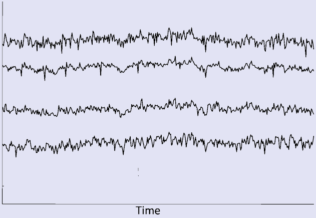
Studying brain activity through electromagnetic signals

- Brain (electrical) activity produces an electromagnetic field.
- This can be measured with EEG or MEG.









Goal: Study Oscillation in Neural Data

Oscillations are believed to play an important role in cognitive functions.

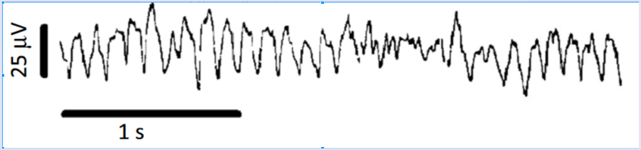
Many studies rely on Fourier or wavelet analyses:

- Easy interpretation,
- Standard analysis *e.g.* canonical bands alpha, beta or theta.

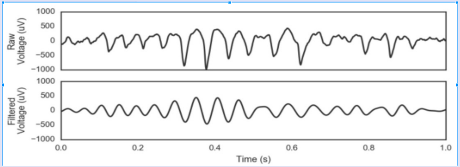
[Buzsáki, 2006]

Goal: Study Oscillation in Neural Data

However, some brain rhythms are not sinusoidal, *e.g.*mu-waves [Hari, 2006]



and filtering degrades waveforms

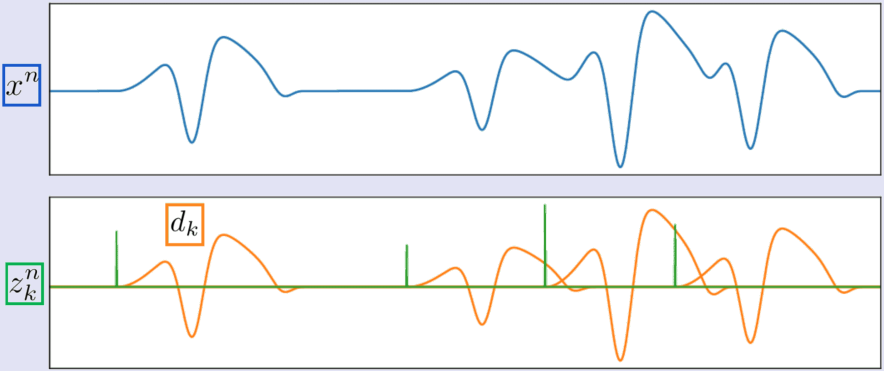


The shape of the waveform can be linked to the information flow between neurons.

$\Rightarrow$ Can extract them with an unsupervised data-driven approach?

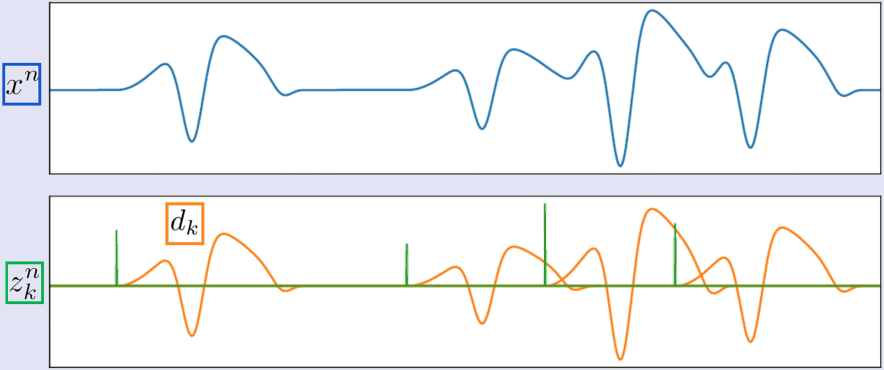
Extracting shift invariant patterns

Key idea: decouple the localization of the patterns and their shape



Extracting shift invariant patterns

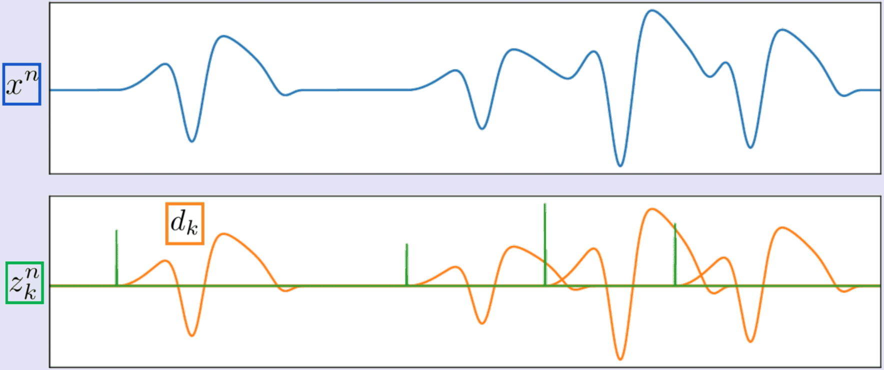
Key idea: decouple the localization of the patterns and their shape



Convolutional Representation:

$$\boxed{x^n}[t] = \sum_{k=1}^{K} (\boxed{z_k^n} * \boxed{d_k})[t] + \varepsilon[t]$$

Key idea: decouple the localization of the patterns and their shape



Convolutional Dictionary Learning:

$$\min_{d,z} \sum_{n=1}^{N} \frac{1}{2} \left\| \boxed{x^n} - \sum_{k=1}^{K} \boxed{z_k^n} * \boxed{d_k} \right\|_2^2 + \lambda \sum_{k=1}^{K} \|\boxed{z_k^n}\|_1,$$

$$\text{s.t.} \quad \|\boxed{d_k}\|_2^2 \leq 1$$

Shift-invariant Patterns in images

Images also have shift-invariant patterns that we might want to detect.

Convolutional Dictionary Learning (CDL) [Grosse et al., 2007]

For a set of N univariate signals x^n, solve

$$\min_{d_k, z_k^n} \sum_{n=1}^{N} \frac{1}{2} \|x^n - \sum_{k=1}^{K} z_k^n * d_k\|_2^2 + \lambda \sum_{k=1}^{K} \|z_k^n\|_1 \tag{1}$$

Hypothesis: patterns d_k are not present everywhere in the signal. They are localized in time.

$\Rightarrow$ Sparse activation signals z

Extra hypothesis: the patterns are in the ℓ_2-ball: $\|d_k\|_2^2 \leq 1$.

Optimization strategy

Bi-convex: The problem is not jointly convex in z_k^n, and d_k but it is convex in each block of coordinate.

Alternate minimization (*a.k.a.* Bloc Coordinate Descent):

- **Z-step:** given a fixed estimate of the atom, compute the activation signal z_k^n associated to each signal X^n.
- **D-step:** given a fixed estimate of the activation, update the atoms in the dictionary d_k.

Rank-1 constrained dictionary learning

References

- Dupré la Tour, T., Moreau, T., Jas, M., and Gramfort, A. (2018).

  Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals.

  In *Advances in Neural Information Processing Systems (NeurIPS)*, pages 3296–3306, Montreal, Canada

How to extend CSC to multivariate signals?

We can just use multivariate convolution,

$$\underbrace{X[t]}_{\in\mathbb{R}^P} = \sum_{k=1}^{K} \left(z_k * D_k\right)[t] = \sum_{k=1}^{K}\sum_{\tau=1}^{L} z_k[t-\tau]\,\underbrace{D_k[\tau]}_{\in\mathbb{R}^P}$$

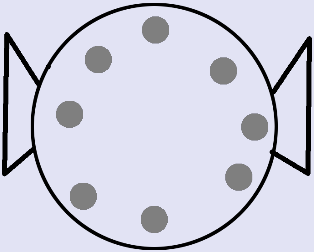
with:

- X a multivariate signal of length T in $\mathbb{R}^P$
- D_k a multivariate signal of length L in $\mathbb{R}^P$
- z_k a univariate activation signal of length $\widetilde{T} = T - L + 1$

However, this model does not account for the physics of the problem.

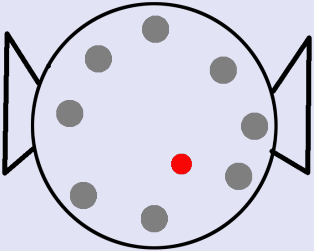
EM wave diffusion

- Recording here with 8 sensors



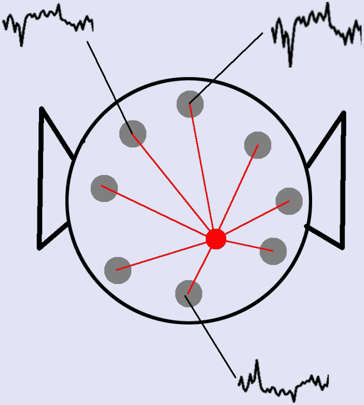
EM wave diffusion

- Recording here with 8 sensors
- EM activity in the brain



EM wave diffusion

- Recording here with 8 sensors
- EM activity in the brain
- The electric field is spread **linearly** and **instantaneously** over all sensors (Maxwell equations)



Multivariate CSC with rank-1 constraint

Idea: Impose a rank-1 constraint on the dictionary atoms D_k

To make the problem tractable, we decided to use auxiliary variables u_k and v_k *s.t.* $D_k = u_k v_k^\top$.

$$\min_{u_k, v_k, z_k^n} \sum_{n=1}^{N} \frac{1}{2} \left\| X^n - \sum_{k=1}^{K} z_k^n * (u_k v_k^\top) \right\|_2^2 + \lambda \sum_{k=1}^{K} \left\| z_k^n \right\|_1 , \quad (2)$$
$$\text{s.t.} \quad \|u_k\|_2^2 \leq 1 \ , \ \|v_k\|_2^2 \leq 1 \text{ and } z_k^n \geq 0 \ .$$

Here,

- $u_k \in \mathbb{R}^P$ is the spatial pattern of our atom
- $v_k \in \mathbb{R}^L$ is the temporal pattern of our atom

Optimization strategy

Tri-convex: The problem is not jointly convex in z_k^n, u_k and v_k but it is convex in each block of coordinate.

We can use a block coordinate descent, aka alternate minimization, to converge to a local minima of this problem. The 3 following steps are applied alternatively:

- **Z-step:** given a fixed estimate of the atom, compute the activation signal z_k^n associated to each signal X^n.
- **u-step:** given a fixed estimate of the activation and temporal pattern, update the spatial pattern u_k.
- **v-step:** given a fixed estimate of the activation and spatial pattern, update the temporal pattern v_k.

Z-step: Locally greedy coordinate descent (LGCD)

N independent problem such that

$$\min_{z_k^n \geq 0} \frac{1}{2} \left\| X^n - \sum_{k=1}^{K} z_k^n * D_k \right\|_2^2 + \lambda \sum_{k=1}^{K} \left\| z_k^n \right\|_1 \quad .$$

This problem is convex in z_k and can be solved with different techniques:

- Greedy CD [Kavukcuoglu et al., 2010]
- Fista [Chalasani et al., 2013]
- ADMM [Bristow et al., 2013]
- L-BFGS [Jas et al., 2017]

$\Rightarrow$ These methods can be slow for long signals as the complexity of each iteration is at least linear in the length of the signal.

Z-step: Locally greedy coordinate descent (LGCD)

For the Greedy Coordinate Descent, only 1 coordinate is updated at each iteration: [Kavukcuoglu et al., 2010]

1. The coordinate $z_{k_0}[t_0]$ is updated to its optimal value $z'_{k_0}[t_0]$ when all other coordinate are fixed.

$$z'_k[t] = \max\left(\frac{\beta_k[t] - \lambda}{\|D_k\|_2^2}, 0\right),$$

with $\beta_k[t] = \left[D_k^{\Lsh} * \left(X - \sum_{l=1}^K z_l * D_l + z_k[t]e_t * D_k\right)\right][t]$

For each coordinate update, it is possible to maintain the value of β with $\mathcal{O}(KL)$ operations.

Z-step: Locally greedy coordinate descent (LGCD)

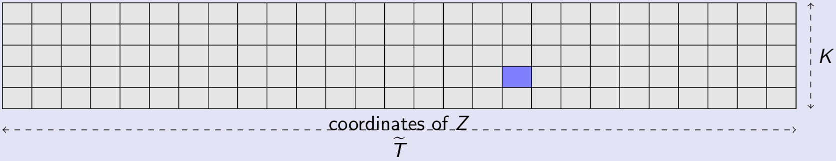
For the Greedy Coordinate Descent, only 1 coordinate is updated at each iteration: [Kavukcuoglu et al., 2010]

1. The coordinate $z_{k_0}[t_0]$ is updated to its optimal value $z'_{k_0}[t_0]$ when all other coordinate are fixed.

2. The updated coordinate is chosen

- Cyclic selection: $\mathcal{O}(1)$ [Friedman et al., 2007]
- Randomized selection: $\mathcal{O}(1)$ [Nesterov, 2010]
- Greedy selection: $\mathcal{O}(K\widetilde{T})$ [Osher and Li, 2009]
  by maximizing $|z_k[t] - z'_k[t]|$

We introduced the LGCD method which is an extension of GCD.



GCD has $\mathcal{O}(K\widetilde{T})$ computational complexity.

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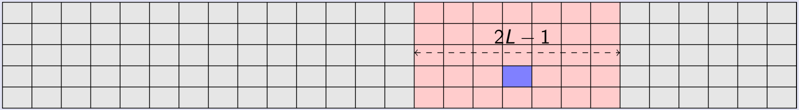
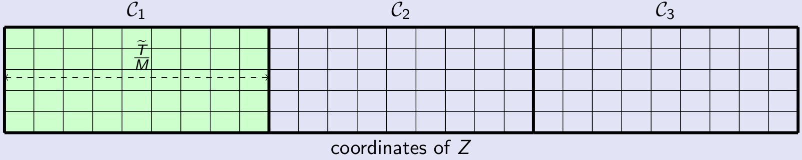


coordinates of Z

GCD has $\mathcal{O}(K\widetilde{T})$ computational complexity.

But the update itself has complexity $\mathcal{O}(KL)$

We introduced the LGCD method which is an extension of GCD.

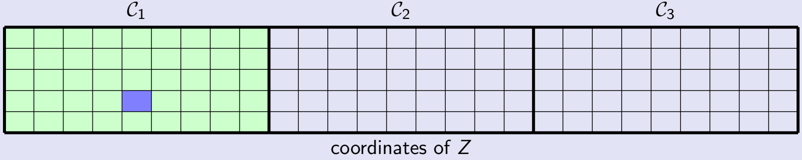


With a partition $\mathcal{C}_m$ of the signal domain $[1, K] \times [0, \widetilde{T}[$,

$$\mathcal{C}_m = [1, K] \times [\frac{(m-1)\widetilde{T}}{M}, \frac{m\widetilde{T}}{M}[$$

Locally Greedy Coordinate Descent [Moreau et al., 2018]

We introduced the LGCD method which is an extension of GCD.



With a partition $\mathcal{C}_m$ of the signal domain $[1, K] \times [0, \widetilde{T}[$,

$$\mathcal{C}_m = [1, K] \times [\frac{(m-1)\widetilde{T}}{M}, \frac{m\widetilde{T}}{M}[$$

The coordinate to update is chosen greedily on a sub-domain $\mathcal{C}_m$

$$\frac{\widetilde{T}}{M} = 2L - 1 \quad \Rightarrow \quad \mathcal{O}(\text{Coordinate selection}) = \mathcal{O}(\text{Coordinate Update})$$

The overall iteration complexity is $\mathcal{O}(KL)$ instead of $\mathcal{O}(K\widetilde{T})$.

$\Rightarrow$ Efficient for sparse Z

D-step: solving for the atoms

The dictionary update is performed by minimizing

$$\min_{\|D_k\|_2 \le 1} E(D) \triangleq \sum_{n=1}^{N} \frac{1}{2} \|X^n - \sum_{k=1}^{K} z_k^n * D_k\|_2^2 \quad . \tag{3}$$

Computing $\nabla_{d_k} E(\{d_k\}_k)$ can be done efficiently

$$\nabla_D E(D) = \sum_{n=1}^{N} (z_k^n)^{\urcorner} * \left(x^n - \sum_{l=1}^{K} z_l^n * D_l \right) = \Phi_k - \sum_{l=1}^{K} \Psi_{k,l} * D_l \ ,$$

$\Rightarrow$ Save with Projected Gradient Descent (PGD) with an Armijo backtracking line-search for the D-step [Wright and Nocedal, 1999].

D-step: solving for the atoms

We use the projected gradient descent with an Armijo backtracking line-search Wright and Nocedal [1999] for both u-step and v-step for

$$\min_{\substack{\|u_k\|_2 \leq 1 \\ \|v_k\|_2 \leq 1}} E(u_k, v_k) \overset{\Delta}{=} \sum_{n=1}^{N} \frac{1}{2} \|X^n - \sum_{k=1}^{K} z_k^n * (u_k v_k^\top)\|_2^2 \quad . \tag{4}$$

One important computation trick is for fast computation of the gradient.

$$\nabla_{u_k} E(u_k, v_k) = \nabla_{D_k} E(u_k, v_k) v_k \quad \in \mathbb{R}^P \ ,$$
$$\nabla_{v_k} E(u_k, v_k) = u_k^\top \nabla_{D_k} E(u_k, v_k) \quad \in \mathbb{R}^L \ ,$$

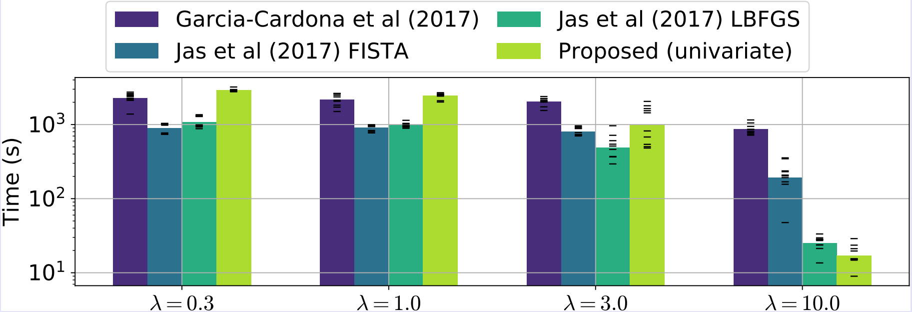
Computing $\nabla_{D_k} E(u_k, v_k)$ can be done efficiently

$$\nabla_{D_k} E(u_k, v_k) = \sum_{n=1}^{N} (z_k^n)^{\Lsh} * \left(X^n - \sum_{l=1}^{K} z_l^n * D_l \right) = \Phi_k - \sum_{l=1}^{K} \Psi_{k,l} * D_l \ ,$$

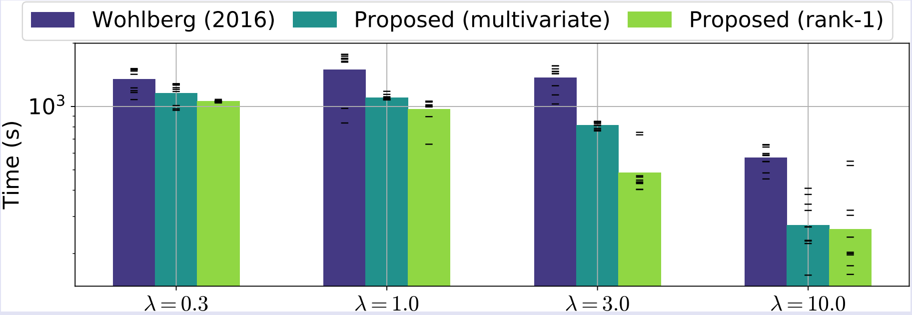
Experiments

Good time to wake-up if you got lost in the previous section!

Comparison with univariate methods on somato dataset with $T = 134,700$, $K = 8$ and $L = 128$

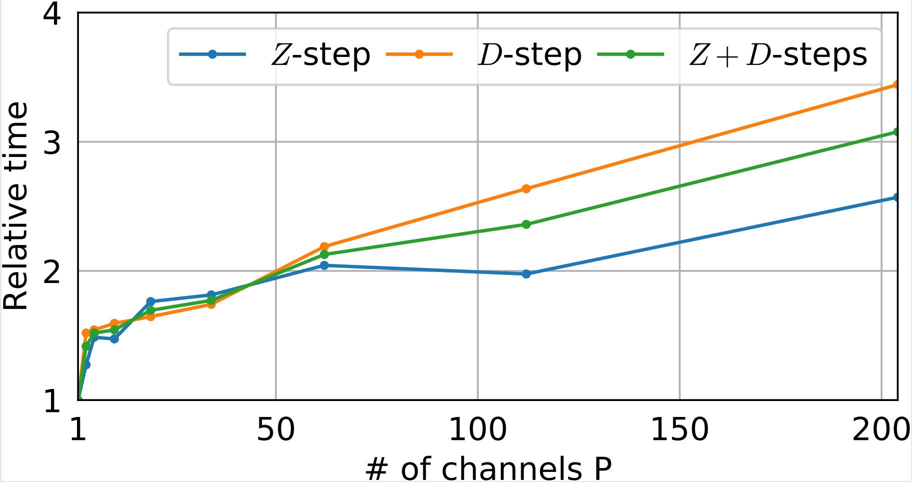


Comparison with multivariate methods on somato dataset with
$T = 134,700,\ K = 8,\ P = 5$ and $L = 128$



Good scaling in the number of channels P

Scaling relative to P on somato dataset with $T = 134,700$, $K = 2$, and $L = 128$



Pattern recovery

Test the pattern recovery capabilities of our method on simulated data,

$$X^n = \sum_{k=1}^{2} z_k * (u_k v_k^\top) + \mathcal{E}$$

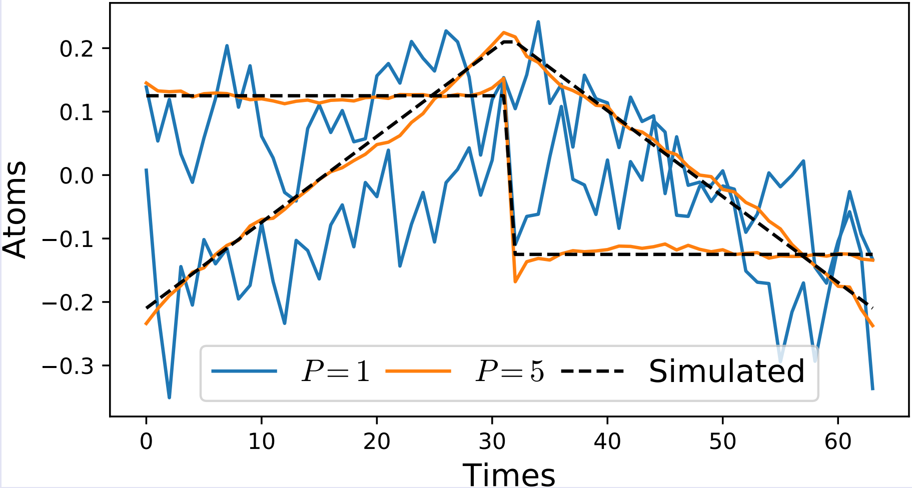
where (u_k, v_k) are chosen patterns of rank-1 and the activated coefficient $z_k^n[t]$ are drawn uniformly and their value are uniform in $[0, 1]$.

The noise $\mathcal{E}$ is generated as a gaussian white noise with variance σ.

We set $N = 100$, $L = 64$ and $\widetilde{T} = 640$

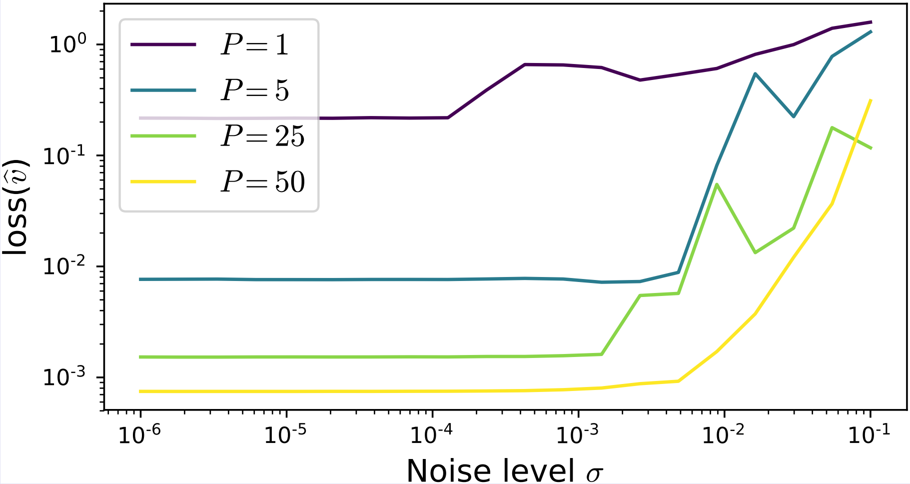
Pattern recovery

Patterns recovered with $P = 1$ and $P = 5$. The signals were generated with the two simulated temporal patterns and with $\sigma = 10^{-3}$.



Pattern recovery

Evolution of the recovery loss with σ for different values of P. Using more channels improves the recovery of the original patterns.

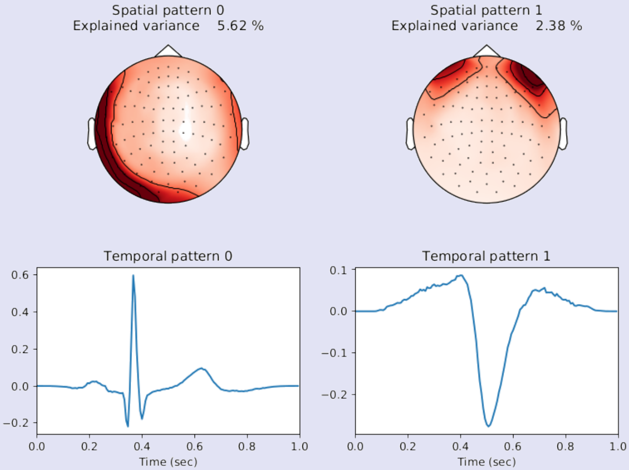


Experiments on MEG data

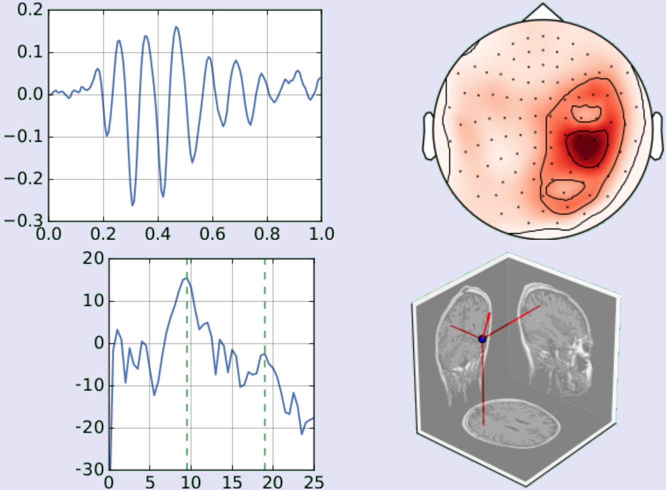
Even better time to wake-up!

MNE somatosensory data

A selection of temporal waveforms of the atoms learned on the MNE sample dataset.



Atoms revealed using the MNE somatosensory data. Note the non-sinusoidal comb shape of the mu rhythm.



Conclusion

- We proposed a model for multivariate CSC with rank-1 constraint. This model makes sense for different type of data.
- We proposed a fast algorithm to solve the optimization problem involved in this model.
- We demonstrated numerically the performance of our algorithm on both simulated and real datasets.
- We illustrated the benefit of such method to study electromagnetic signals form recorded from brain activity.

DiCoDiLe: Distributed Convolutional Dictionary Learning

References

- Moreau, T., Oudre, L., and Vayatis, N. (2018). DICOD: Distributed Convolutional Sparse Coding.

  In *International Conference on Machine Learning (ICML)*, pages 3626–3634, Stockohlm, Sweden. PMLR (80)

- Moreau, T. and Gramfort, A. (2019). Distributed Convolutional Dictionary Learning (DiCoDiLe): Pattern Discovery in Large Images and Signals.

  preprint ArXiv, 1901.09235

Weak dependence of the coordinate updates

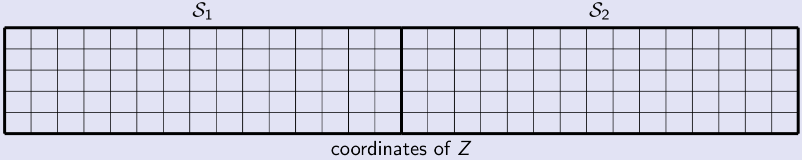
The update of the W coordinates $(k_w, \omega_w)_{w=1}^{W}$ with additive update $\Delta Z_{k_w}[\omega_w]$ changes the cost by:

$$\Delta E = \overbrace{\sum_{i=1}^{W} \Delta E_w}^{\text{iterative steps}} \underbrace{- \sum_{w \neq w'} (d_{k_w} * d^{\Lsh}_{k_{w'}})[\omega_{w'} - \omega_w] \Delta Z_{k_w}[\omega_w] \Delta Z_{k_{w'}}[\omega_{w'}]}_{\text{interference}},$$

$\Rightarrow$ If the updates are far enough, they can be considered as independent.

DICOD: Distributed Convolutional Coordinate Descent

[Moreau et al., 2018]



- Split the coordinates in continuous sub-segment $\mathcal{S}_w = \left[\frac{(w-1)T}{W}, \frac{wT}{W}\right[$.

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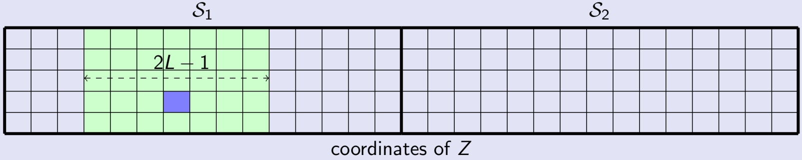

- Split the coordinates in continuous sub-segment $\mathcal{S}_w = \left[\frac{(w-1)T}{W}, \frac{wT}{W}\right[$.
- Use CD updates in parallel in each sub-segment.

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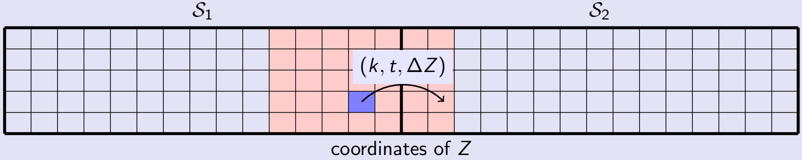
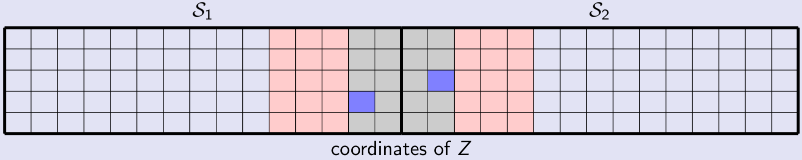


- Split the coordinates in continuous sub-segment $\mathcal{S}_w = \left[\frac{(w-1)T}{W}, \frac{wT}{W}\right[$.
- Use CD updates in parallel in each sub-segment.
- Notify neighbor workers when the update is on the border of $\mathcal{S}_w$.

DICOD: Distributed Convolutional Coordinate Descent

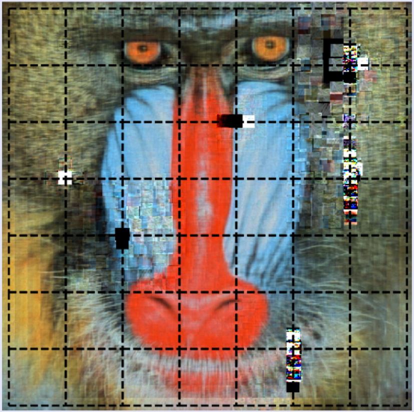
[Moreau et al., 2018]



- Split the coordinates in continuous sub-segment $\mathcal{S}_w = \left[\frac{(w-1)T}{W}, \frac{wT}{W}\right[$.
- Use CD updates in parallel in each sub-segment.
- Notify neighbor workers when the update is on the border of $\mathcal{S}_w$.
- What do we do when two updates are interfering?

Distributed Convolutional Dictionary Learning (DiCoDiLe-Z)

[Moreau and Gramfort, 2019]



- DICOD does not work for splits in dimension > 1.

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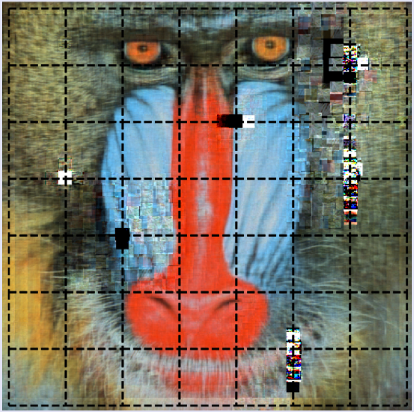

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- Extension require to control interferences.

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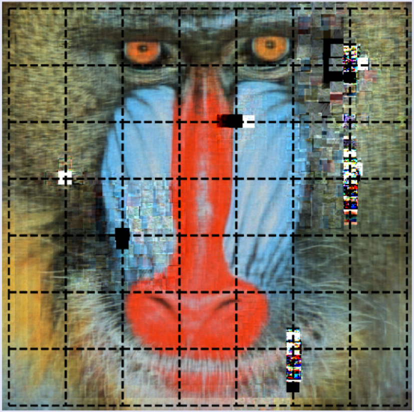
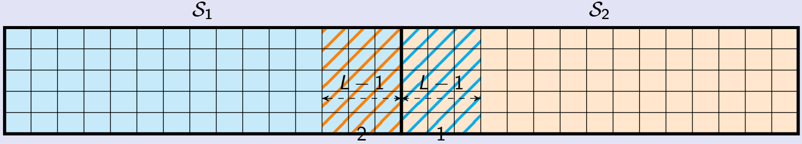
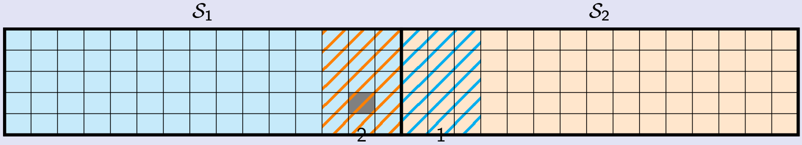


- DICOD does not work for splits in dimension > 1.
- Extension require to control interferences.
- Use asynchronous mechanism: Soft-lock.



- Keep track of the value of the optimal update in an extended zone of size $L-1$.



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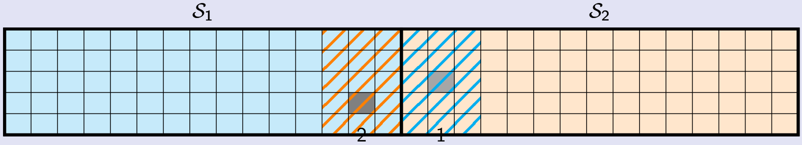
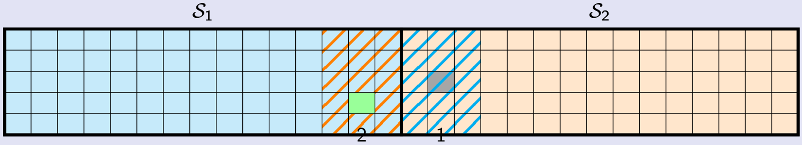
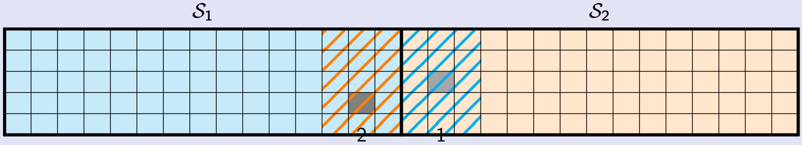
- Select an update candidate with LGCD.



- Keep track of the value of the optimal update in an extended zone of size $L - 1$.
- Select an update candidate with LGCD.
- If it is in the interfering zone, compare the value of the update with the value potential updates in the other worker.



- Keep track of the value of the optimal update in an extended zone of size $L - 1$.
- Select an update candidate with LGCD.
- If it is in the interfering zone, compare the value of the update with the value potential updates in the other worker.
- Only perform the udpate if it is larger than the other update.



- Keep track of the value of the optimal update in an extended zone of size $L-1$.
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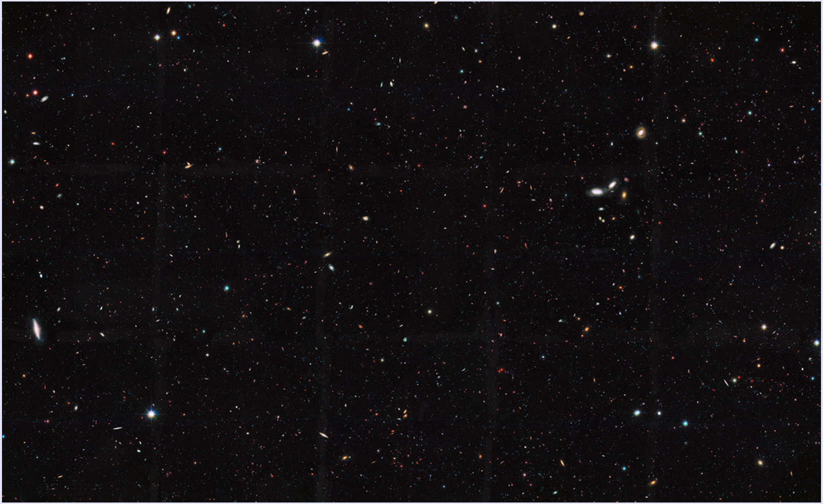
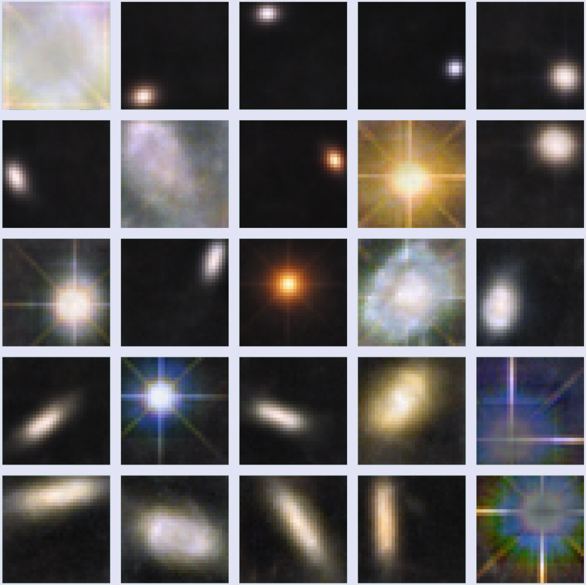
- If it is in the interfering zone, compare the value of the update with the value potential updates in the other worker.
- Only perform the udpate if it is larger than the other update.

$\Rightarrow$ Give an update order asynchronously.

Images from Hubble Space Telescope



Images from Hubble Space Telescope



Thanks for your attention!

Code available online:

alphacsc : alphacsc.github.io

DiCoDiLe : github.com/tommoral/dicodile

Slides are on my web page:

tommoral.github.io   @tomamoral

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