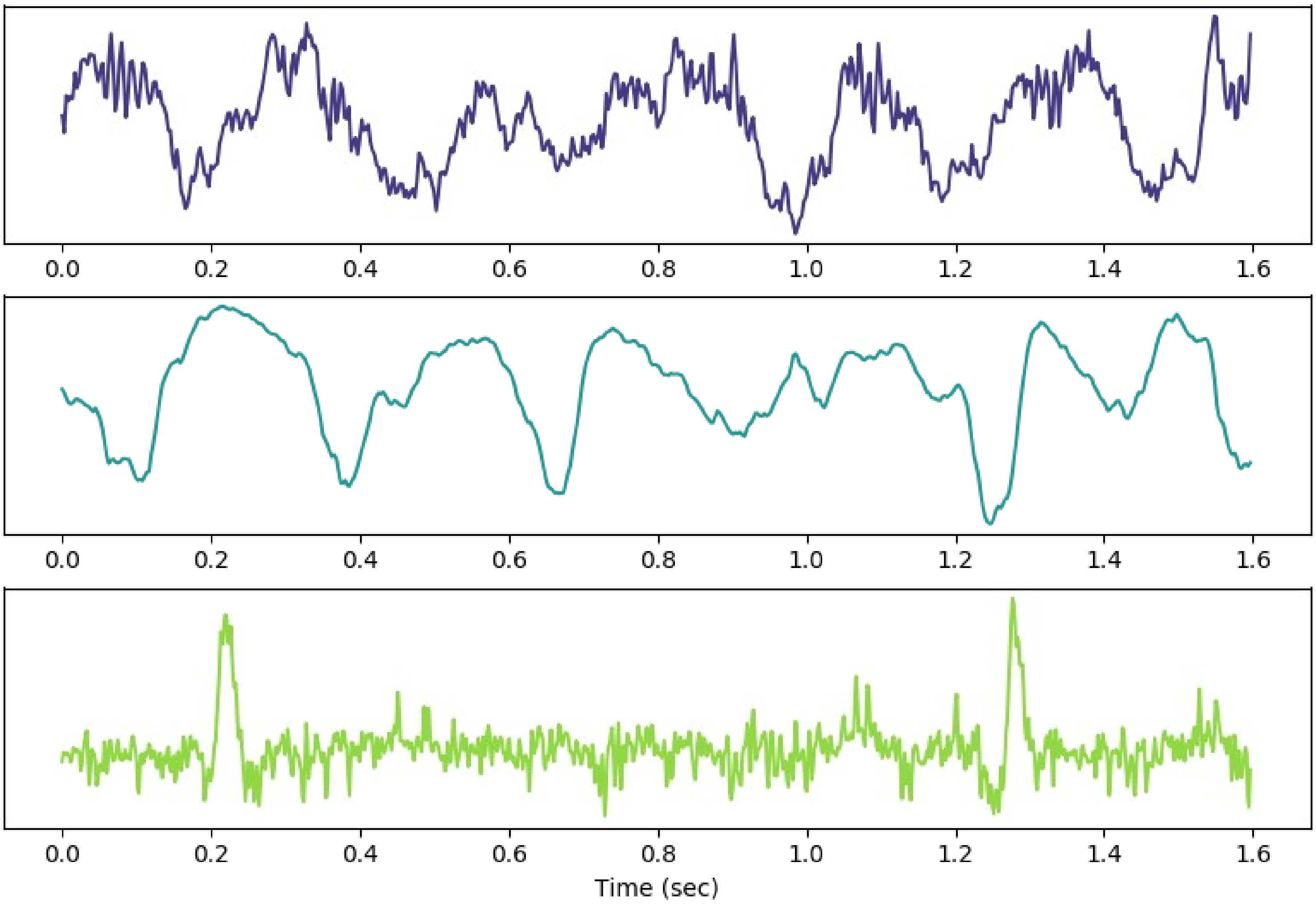
NON-LINEAR MODELS FOR NEUROPHYSIOLOGICAL TIME SERIES

Tom Dupré la Tour

Prix de thèse “Signal, Images, Vision”

Club EEA – GdR Isis – GRETSI

Neurophysiological time series



Outline

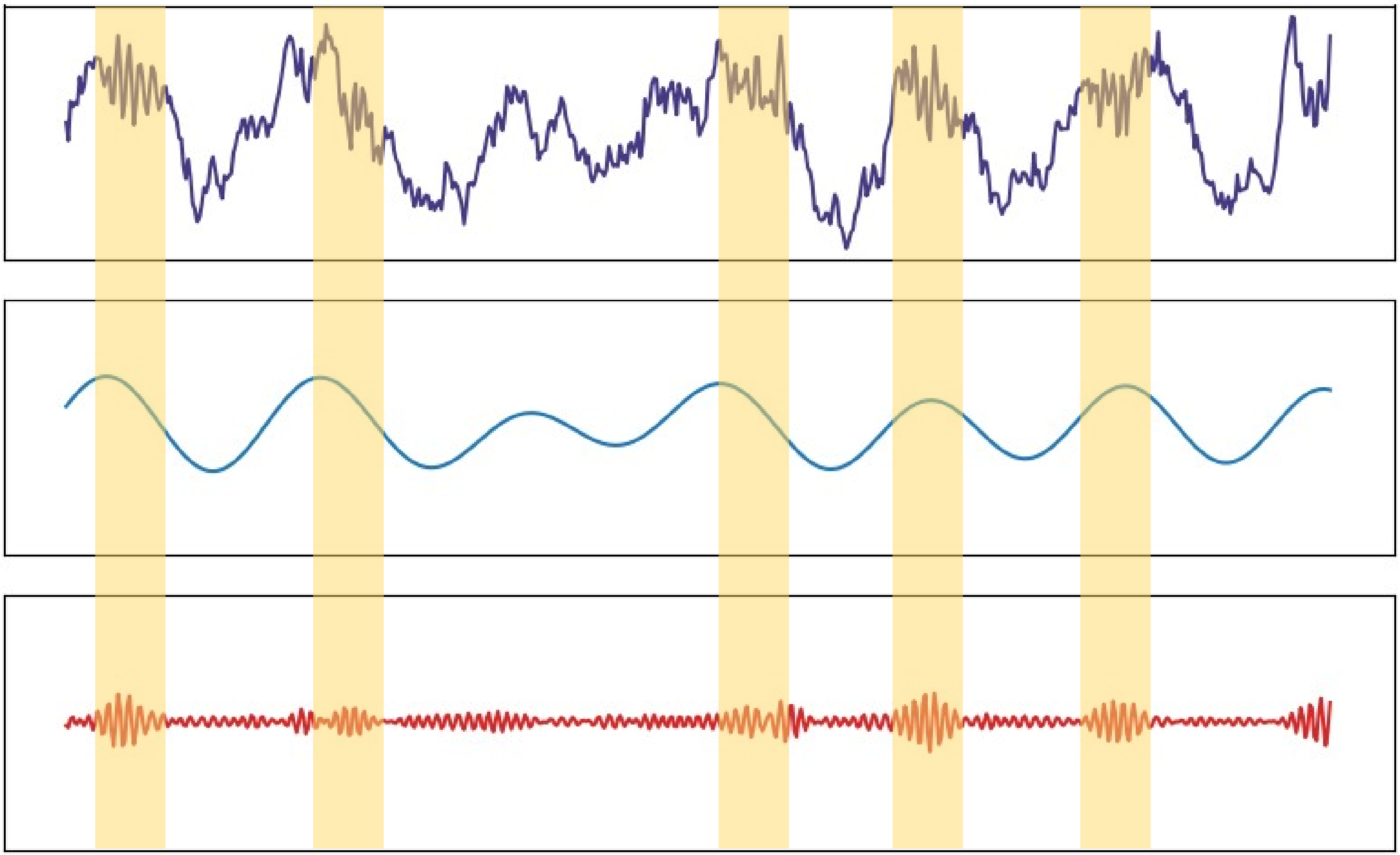
1. Cross-frequency coupling analysis
   with driven autoregressive models

2. Temporal waveform analysis
   with convolutional sparse coding models

1. Cross-frequency coupling

Low-frequency phase and high-frequency amplitude

(Bragin et al 1995, Canolty et al, 2006)



1. Driven auto-regressive model

Auto-regressive (AR) model

(Makhoul, 1975)

$$y(t) + \sum_{i=1}^{p} a_i y(t-i) = \varepsilon(t) \qquad \varepsilon(t) \sim \mathcal{N}(0, \sigma^2)$$

Driven AR (DAR) model

(Grenier, 1983, 2013)

$$a_i(t) = \sum_{j=0}^{m} a_{ij} x(t)^j \qquad \log(\sigma(t)) = \sum_{j=0}^{m} b_j x(t)^j$$

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A different parametrization ensuring DAR model stability :

Parametric estimation of spectrum driven by an exogenous signal
T. Dupré la Tour, Y. Grenier, A. Gramfort, *ICASSP 2017*

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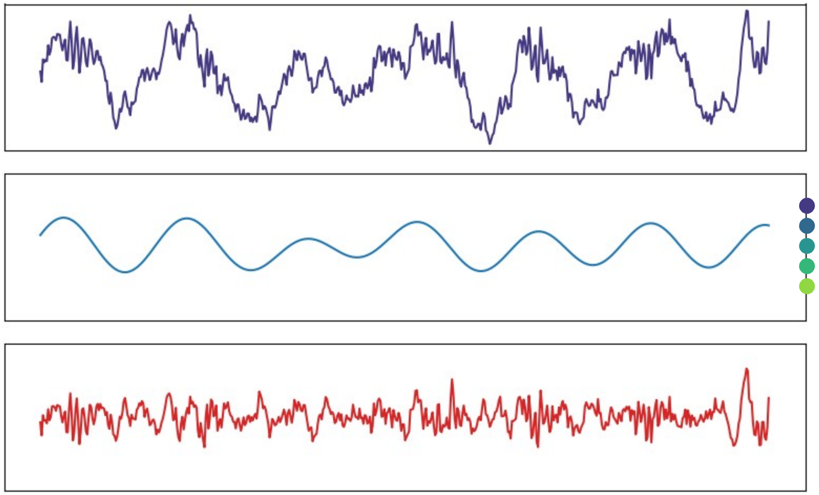
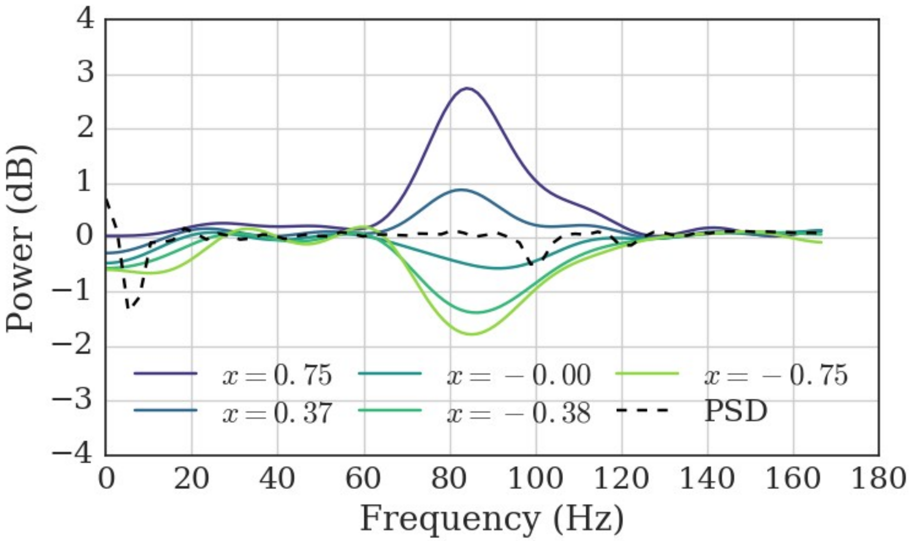
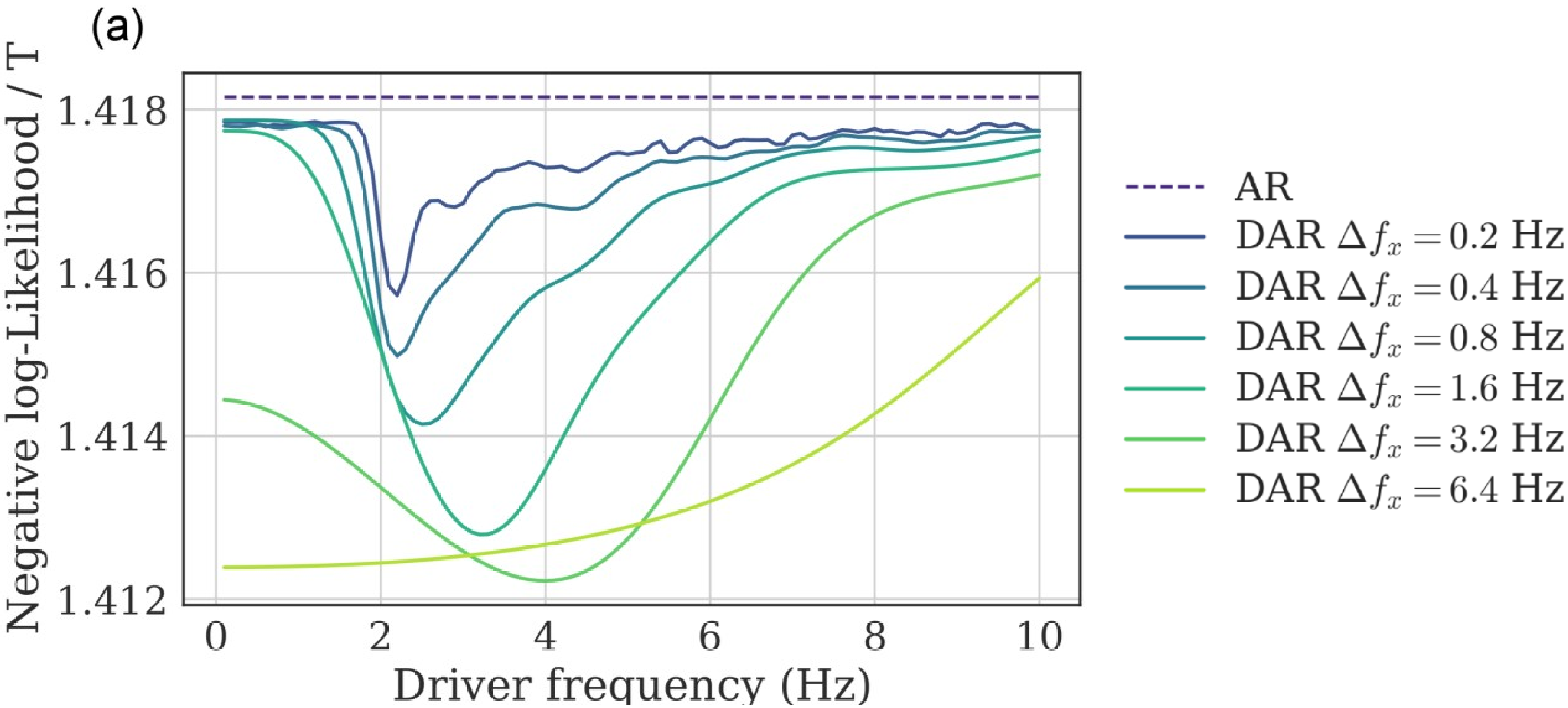




1. Driver selection



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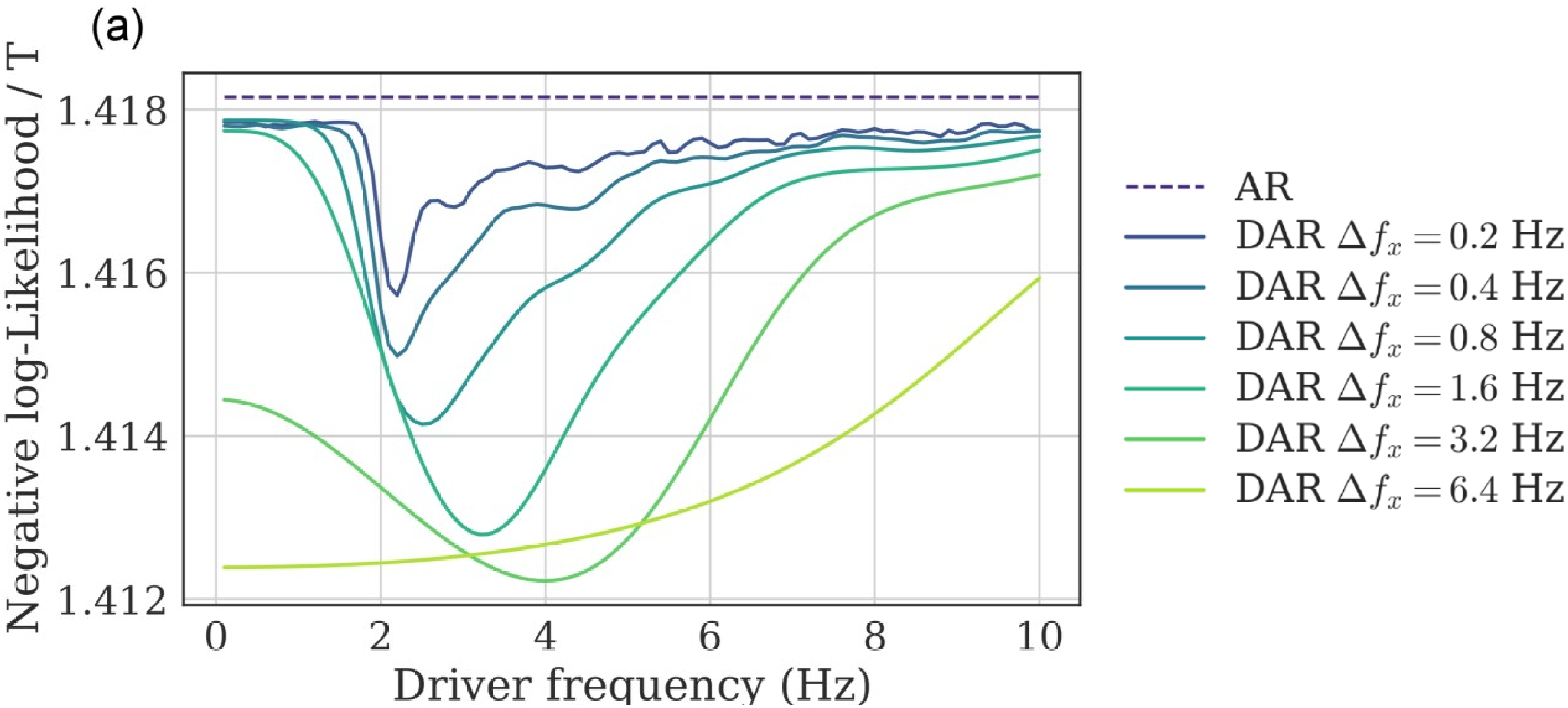
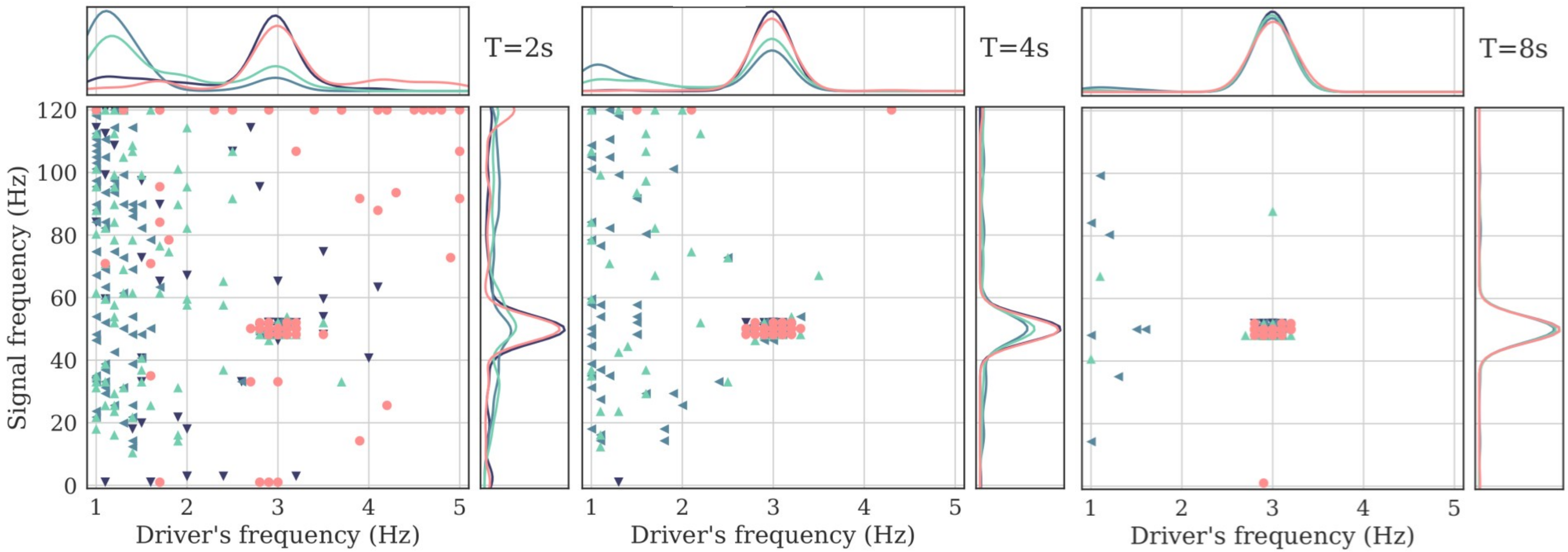


A finer optimization of the driver filter :

Driver estimation in non-linear autoregressive models
T. Dupré la Tour, Y. Grenier, A. Gramfort, *ICASSP 2018*

1. Robustness to short signals

(Penny et al, 2008) (Ozkurt et al, 2011)
(Tort et al, 2009) (Dupré la Tour et al, 2017)



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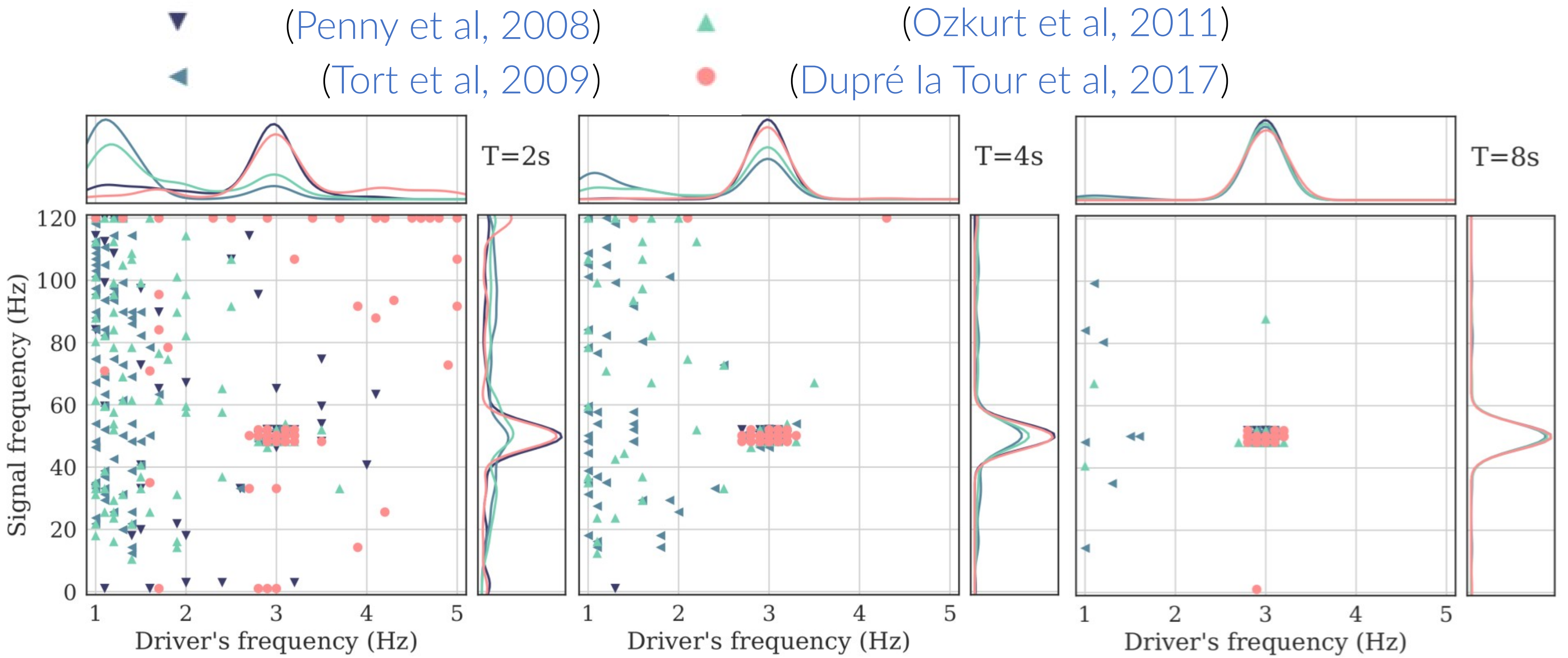
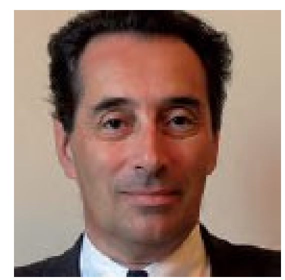


Non-linear auto-regressive models for cross-frequency coupling in neural time series
T. Dupré la Tour, L. Tallot, L. Grabot, V. Doyère, V. van Wassenhove, Y. Grenier, A. Gramfort, *PLOS Computational Biology 2017*

1. Cross-frequency coupling analysis
with driven auto-regressive models








`https://pactools.github.io`

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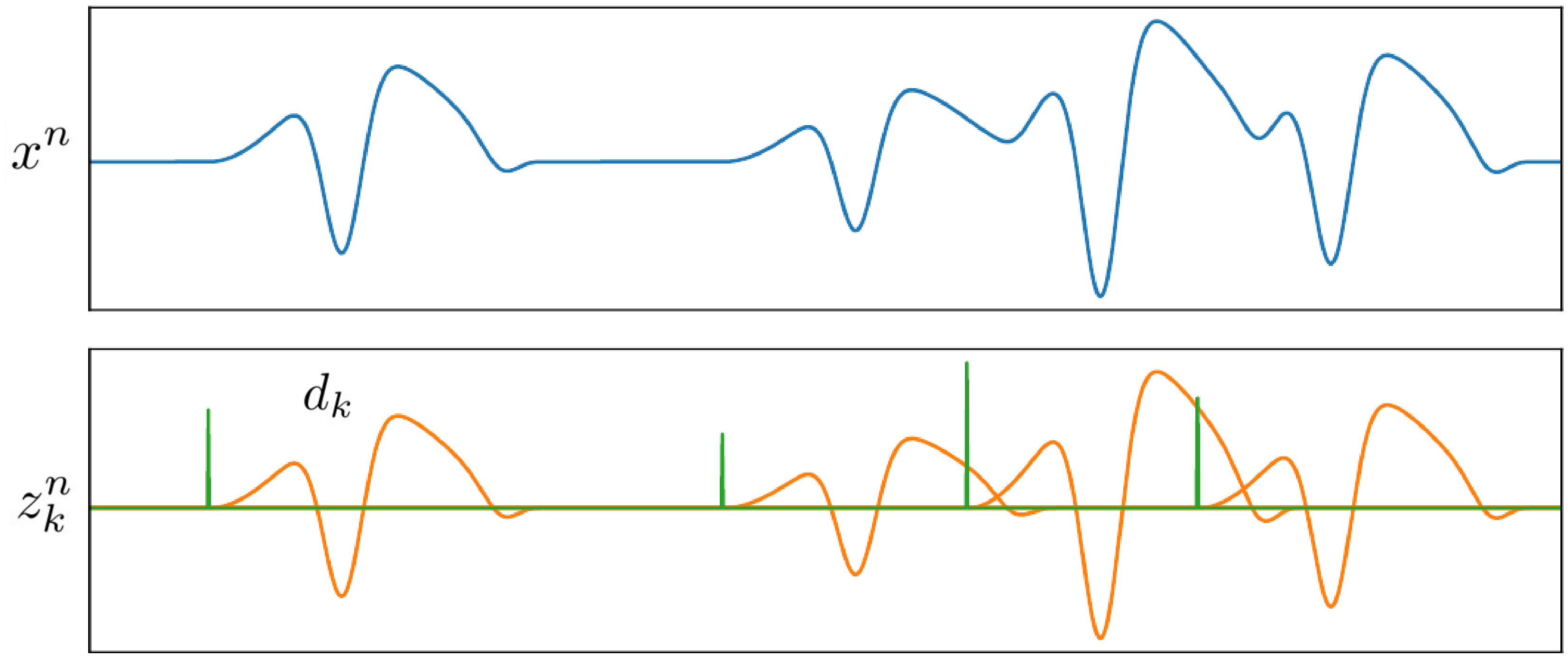
with driven autoregressive models

2. Temporal waveform analysis

with convolutional sparse coding models

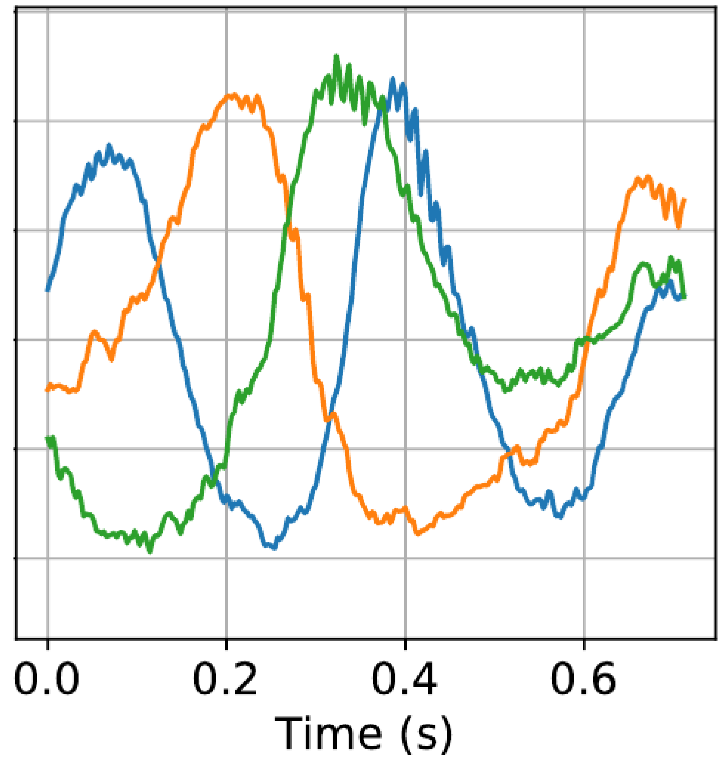
2. Convolutional sparse coding

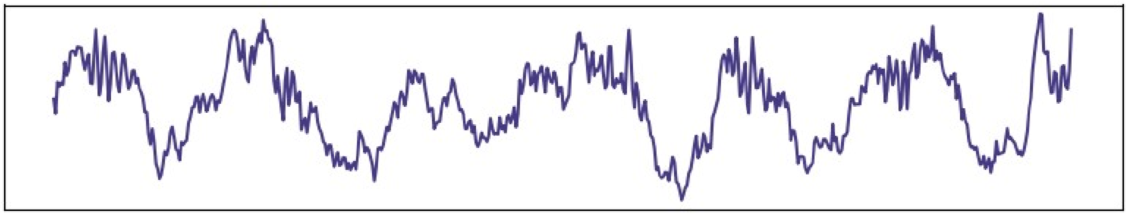


$$x^n[t] = \sum_{k=1}^{K} (z_k^n * d_k)[t] + \varepsilon[t]$$

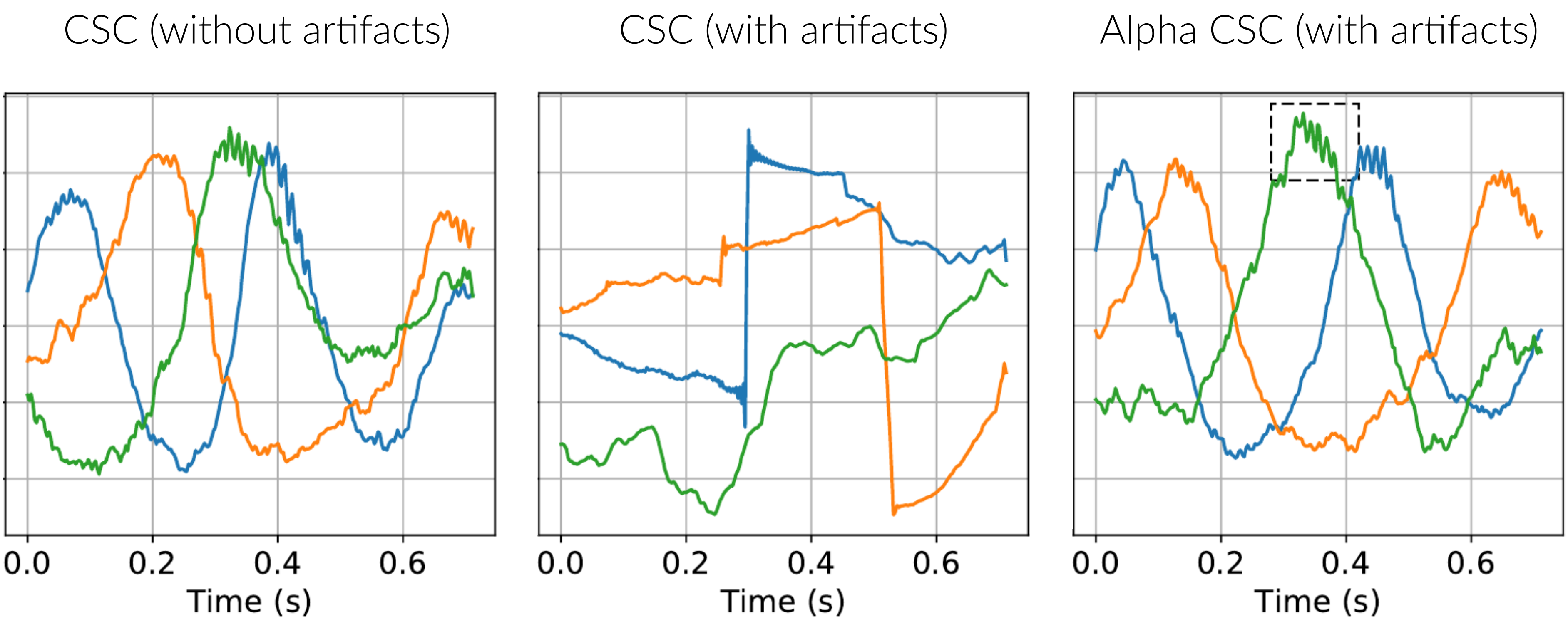
(Grosse et al, 2007)

2. Univariate model





2. Alpha-stable univariate model



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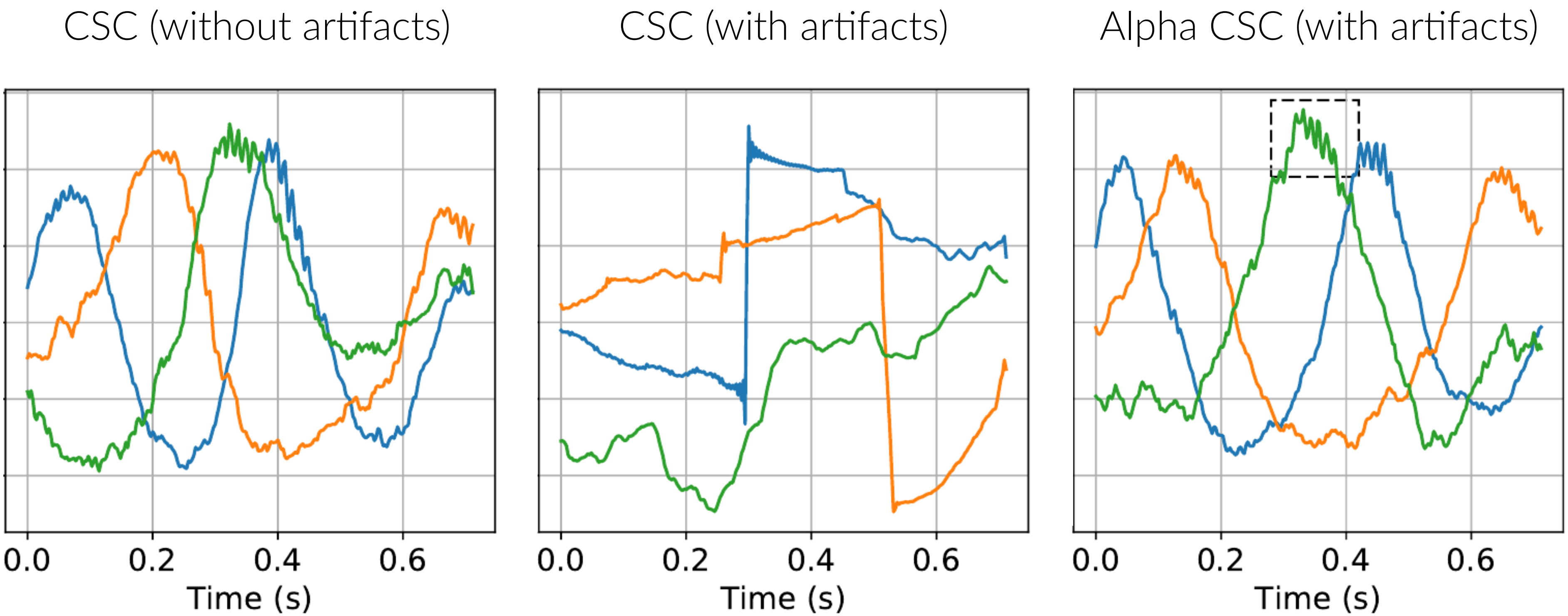
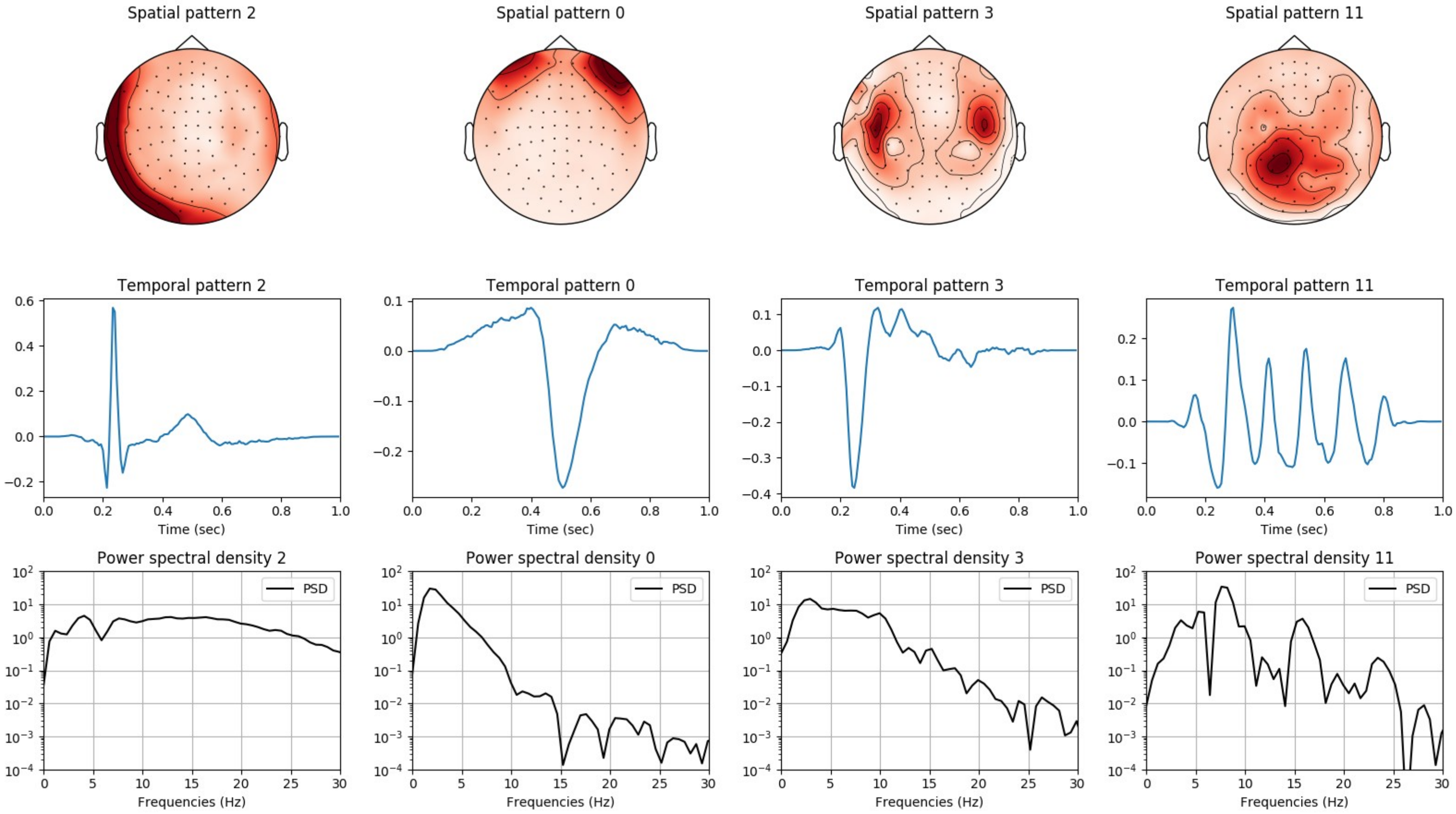
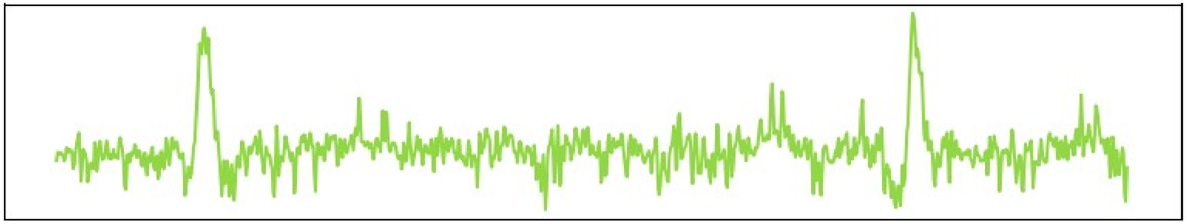


Learning the morphology of brain signals using alpha-stable convolutional sparse coding
M. Jas*, T. Dupré la Tour*, U. Şimşekli, A. Gramfort, *NeurIPS 2017*

2. Rank-1 multivariate model





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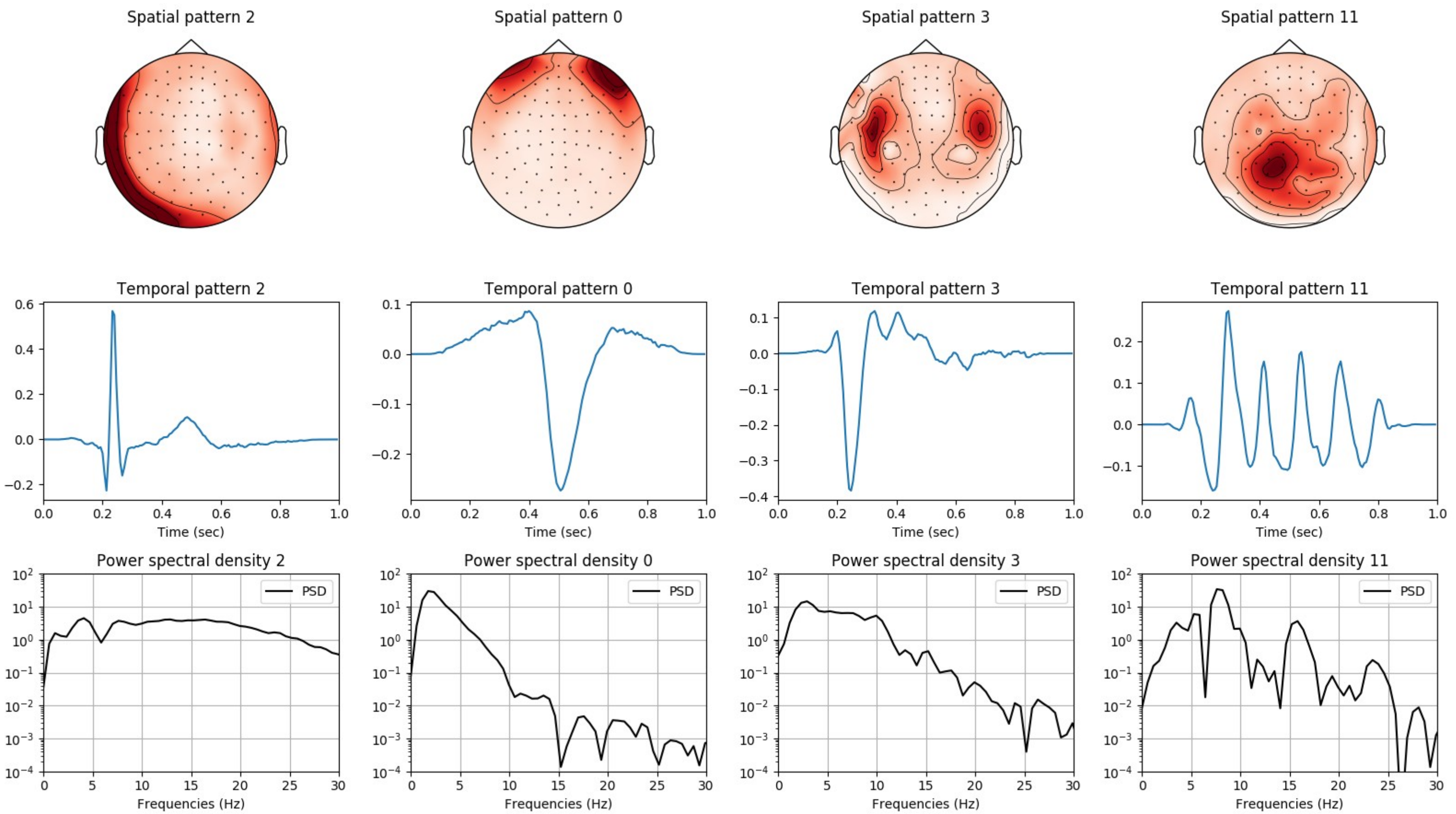

Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals
T. Dupré la Tour*, T. Moreau*, M. Jas, A. Gramfort, *NeurIPS 2018*

TELECOM ParisTech

Inria — inventors for the digital world

université PARIS-SACLAY

2. Temporal waveform analysis

with convolutional sparse coding models




https://alphacsc.github.io

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