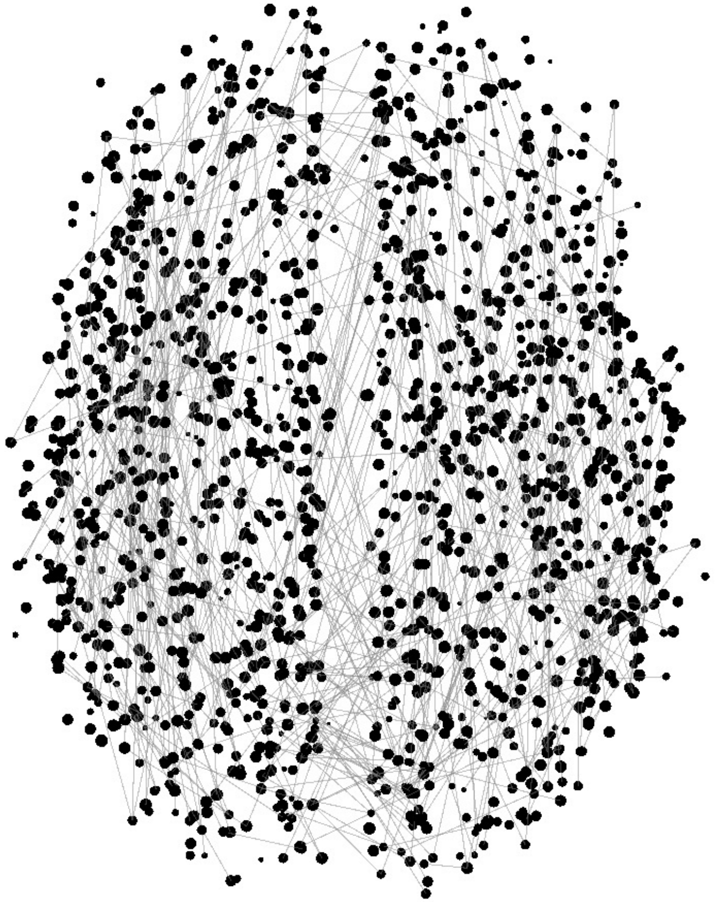


Lecture 2.3

Combining Structure and Function

David Pascucci, Ph.D.

Brain Mind Institute,
École Polytechnique Fédérale de Lausanne
Switzerland

david.pascucci@epfl.ch

@David__Pascucci

Brain Dynamics on the Connectome
Summer School 2021

EPFL

FNSNF
Swiss National Science Foundation

Outline

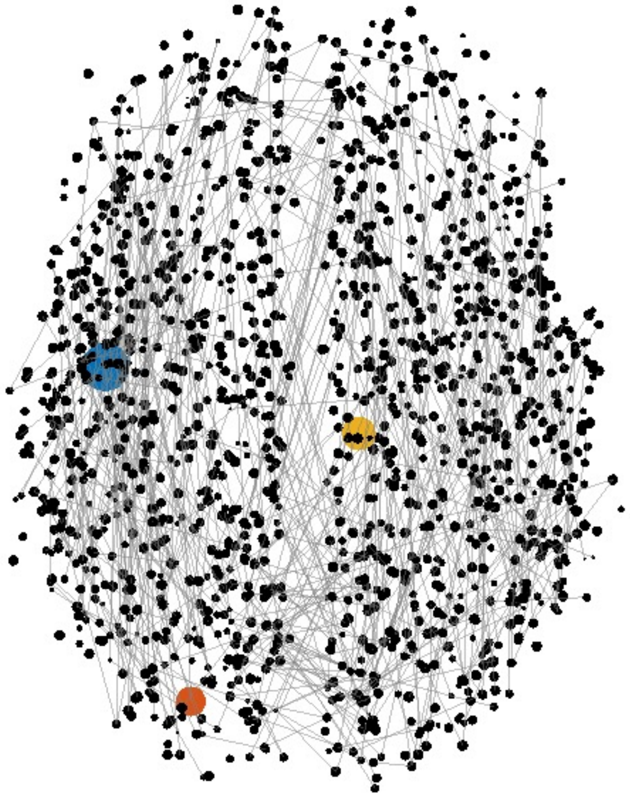
- Brain networks and dynamics
- Time-varying Autoregressive Model
- Adaptive filtering
- Structure-Function
- Structural priors in adaptive filtering

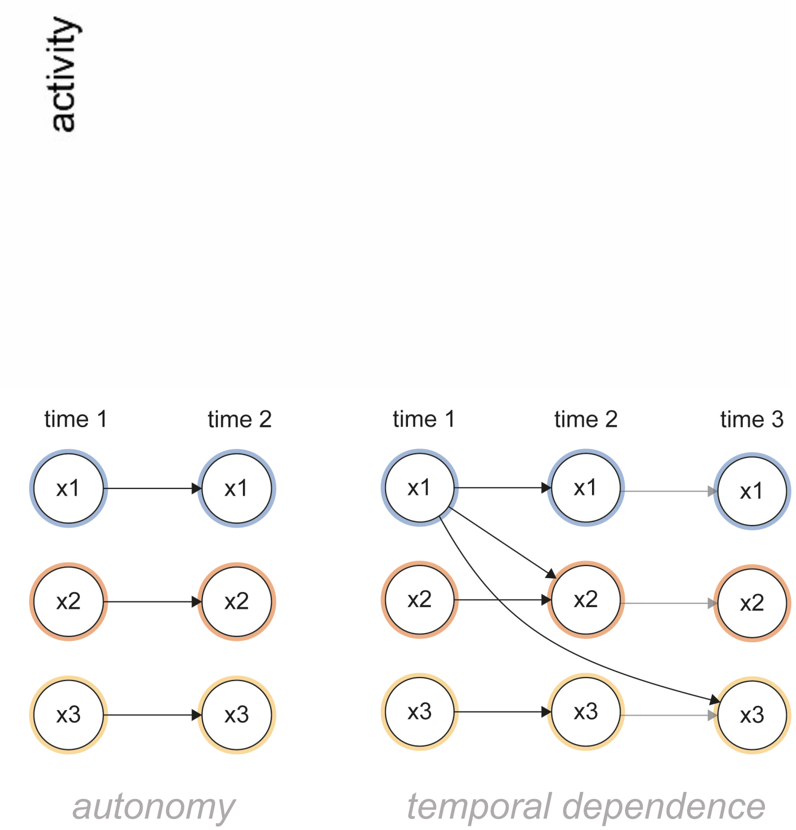
Brain Networks

Brain
- ~80 billion neurons
- trillions of connections

Recordings
- low spatial or temporal resolution
- noise

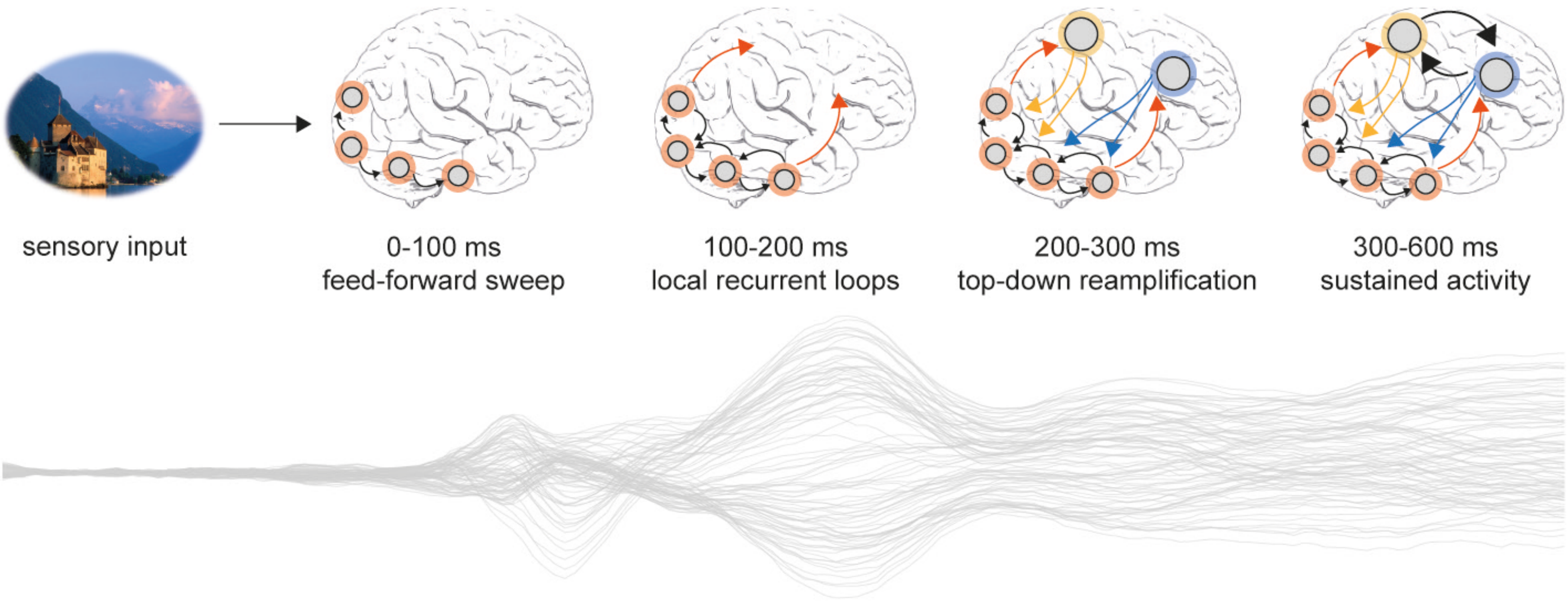
Dynamics
- distributed
- <u>*fast*</u>**! !**





Brain Networks

How fast?

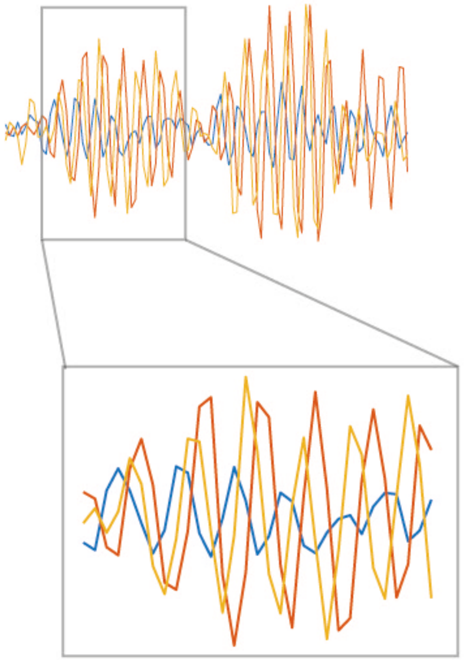


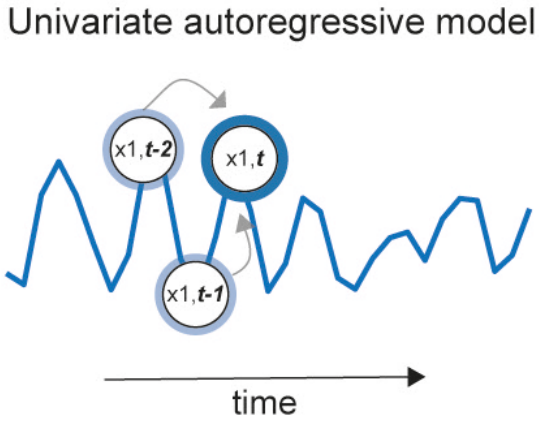
adapted from Sergent, C. (2018).

Wiener-Granger Causality

A quantity ... which measures the additional effectiveness of the past values of X2 in helping to determine the present values of X1

Wiener (1956). The theory of prediction.
Granger (1969). *Econometrica.*





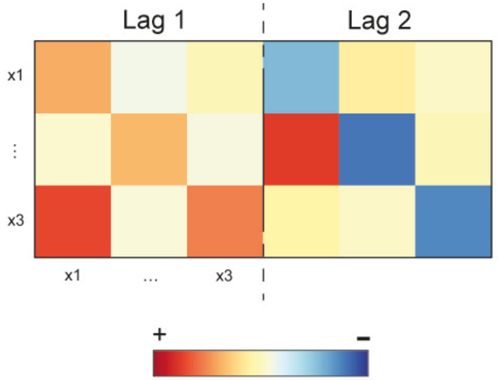
Time-varying Autoregressive Model

Lag 1

$$x_{1,t} = a_{11}x_{1,t-1} + a_{21}x_{2,t-1} + a_{31}x_{3,t-1} \dots$$

$$x_{2,t} = a_{12}x_{2,t-1} + a_{22}x_{2,t-1} + a_{32}x_{3,t-1} \dots$$

$$x_{3,t} = a_{13}x_{1,t-1} + a_{23}x_{2,t-1} + a_{33}x_{3,t-1} \dots$$



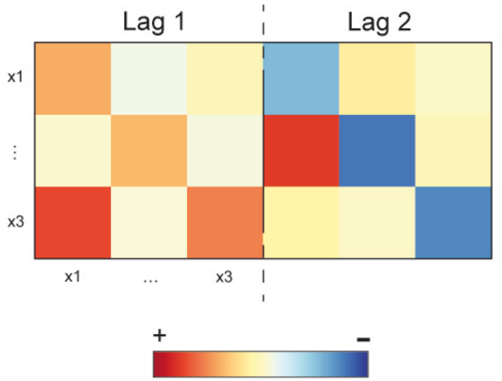
Time-varying Autoregressive Model

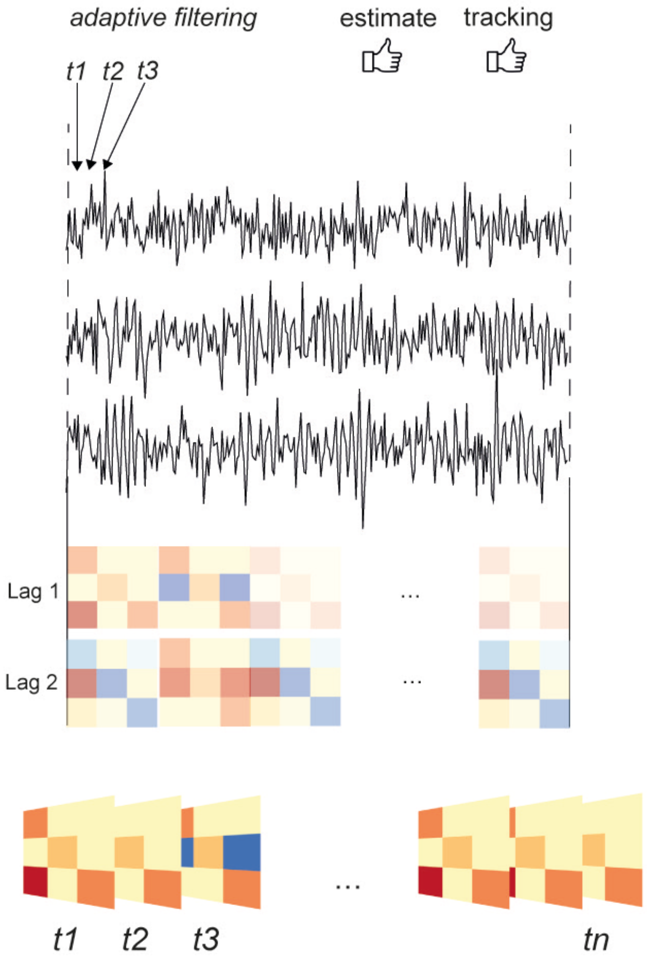
Lag 1

$$x_{1,t} = a_{11}x_{1,t-1} + a_{21}x_{2,t-1} + a_{31}x_{3,t-1} \dots$$

$$x_{2,t} = a_{12}x_{2,t-1} + a_{22}x_{2,t-1} + a_{32}x_{3,t-1} \dots$$

$$x_{3,t} = a_{13}x_{1,t-1} + a_{23}x_{2,t-1} + a_{33}x_{3,t-1} \dots$$

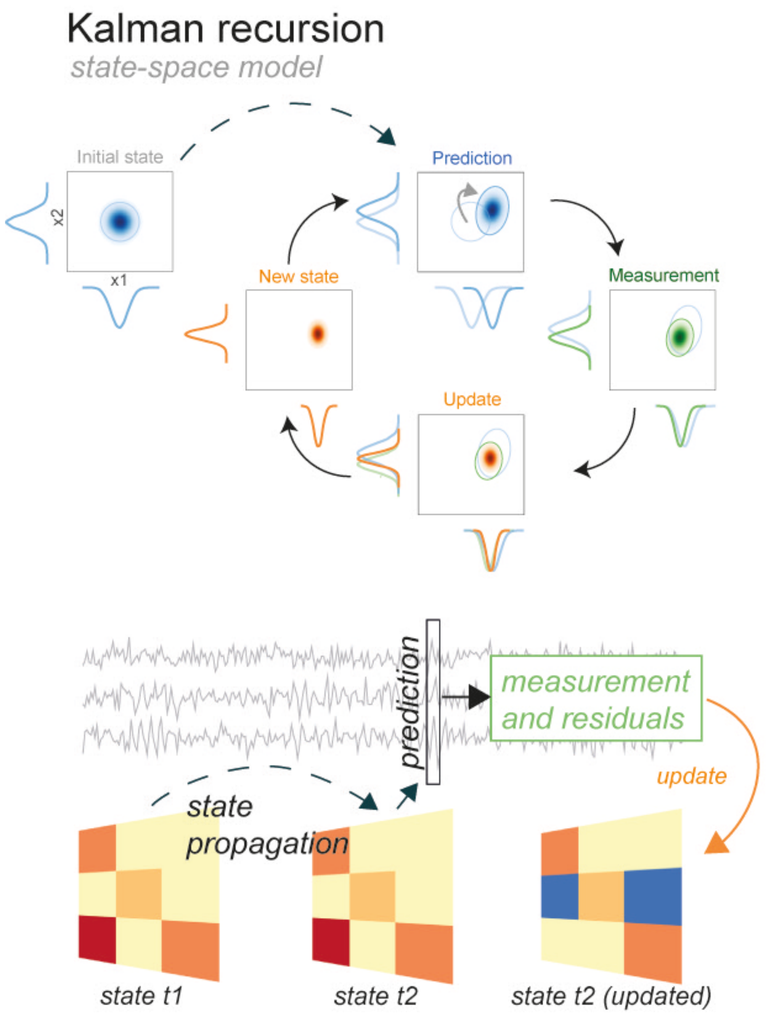




Adaptive filtering

The Kalman filter

Kalman (1960).
Milde et al. (2010). *NIMG.*



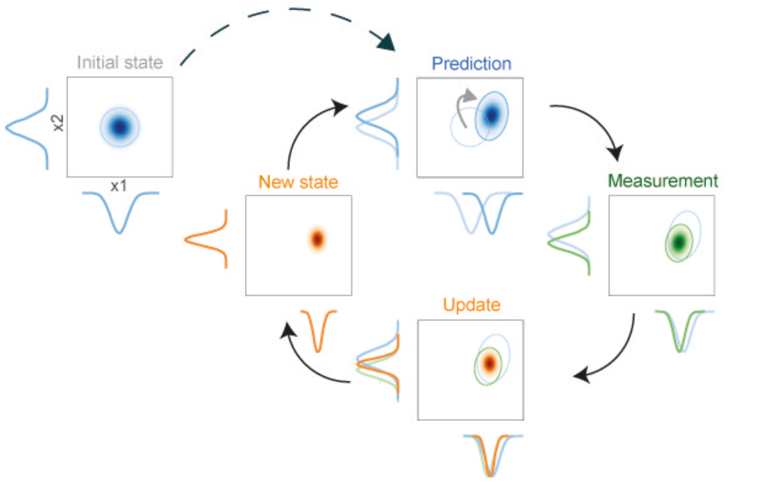
STOK

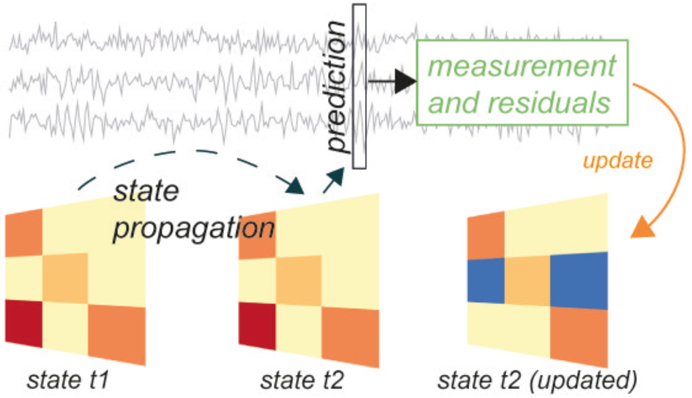
The Self-Tuning Optimized Kalman Filter

https://github.com/PscDavid/dynet_toolbox
https://github.com/joanrue/pydynet
Pascucci et al., (2020). PLoS Comput. Biol.

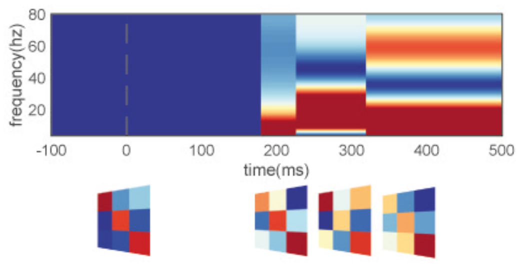
Kalman recursion

state-space model

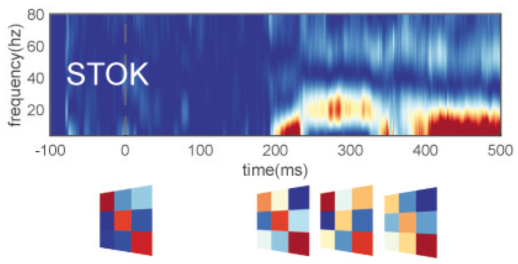




Target (ground truth)

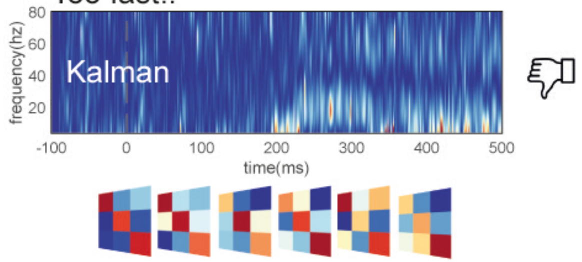


Self-tuning



More weight to measuremets

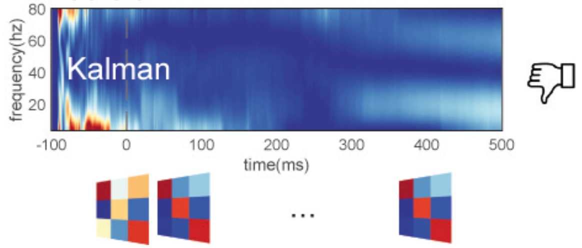
Too fast!!



$$\hat{x}_t^{(+)} = \frac{\hat{x}_t^{(-)} + c\tilde{H}_t^{+} z_t}{1 + c}$$

More weight to prior states

Too slow!!



$$b_t^{ols} = \tilde{H}_t^{+} z_t$$

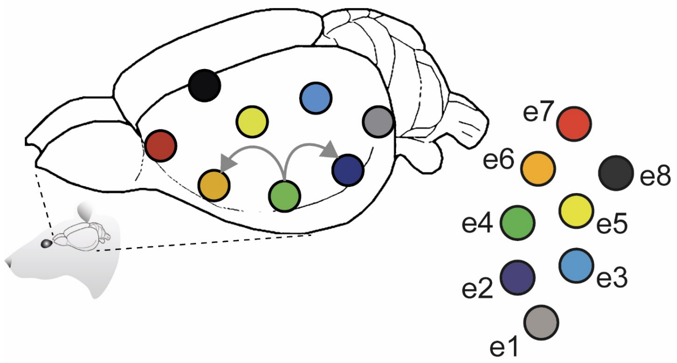
c = self-tuning memory

ols = ordinary least squares

STOK

Benchmark rat EEG data

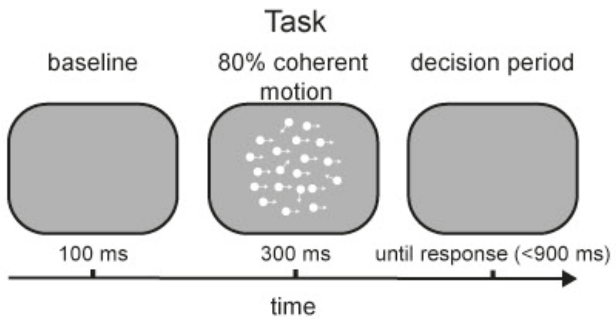
https://github.com/PscDavid/dynet_toolbox
https://github.com/joanrue/pydynet
Pascucci et al., (2020). PLoS Comput. Biol.

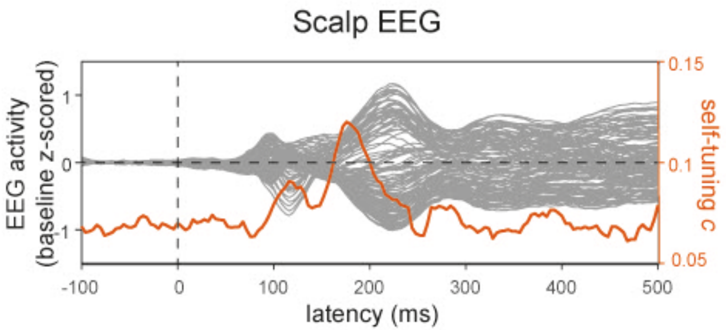


STOK

Human EEG source imaging data

https://github.com/PscDavid/dynet_toolbox
https://github.com/joanrue/pydynet
Pascucci et al., (2020). PLoS Comput. Biol.





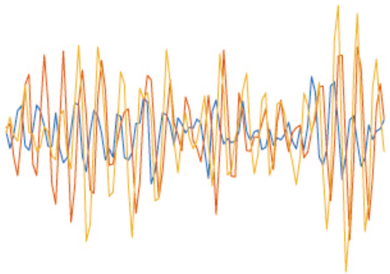
Adaptive filtering

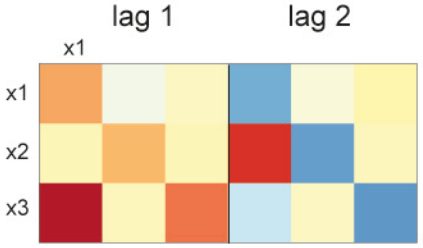
- Time-varying functional connectivity (FC) faces the challenge of non-stationary brain activity with unknown noise sources.

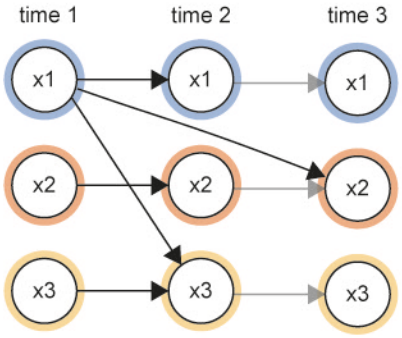
- Optimized adaptive filters (STOK) can overcome these problems, allowing the estimation of time-varying multivariate AR models with high temporal precision.

- Optimized adaptive filters are promising tools for dynamic FC at the sub-seconds time scale of perception, cognition and action.

Structural priors







Structural priors

Sources of 'structural priors':

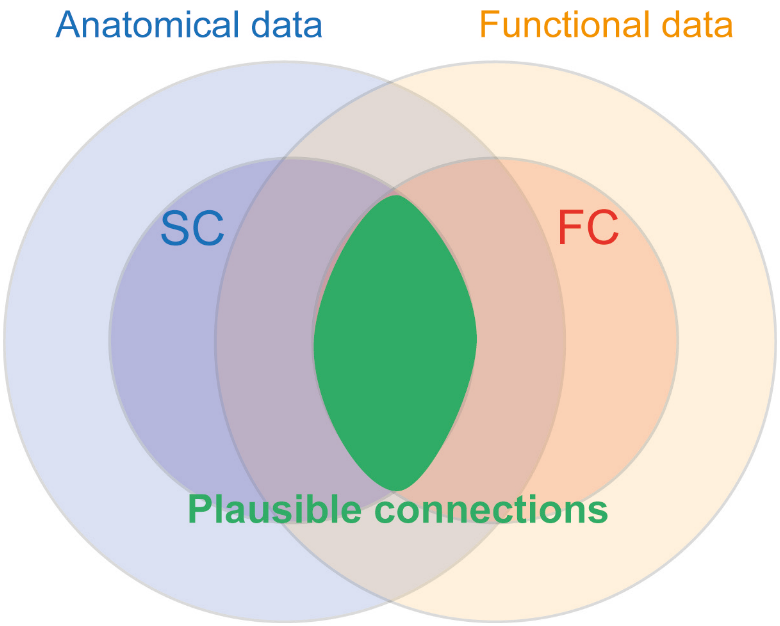
- *Prior studies;*
- *Meta-analysis data;*
- *FC from other modalities;*
- *Structural Connectivity (SC) (e.g., DTI metrics).*

Structure-function relationship:

- *SC = topological space for FC;*
- *FC + SC = more biologically plausible models.*

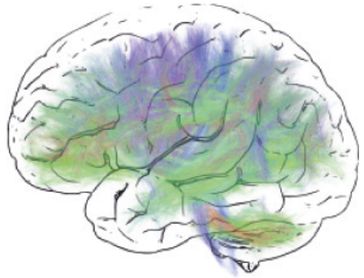
However, ...

- *SC-FC relationships varies markedly;*
- *A vast repertoire of dynamic neuronal interactions;*
- *A myriad of anatomical possibilities.*



adapted from Rykhlevskaia et al., (2008)

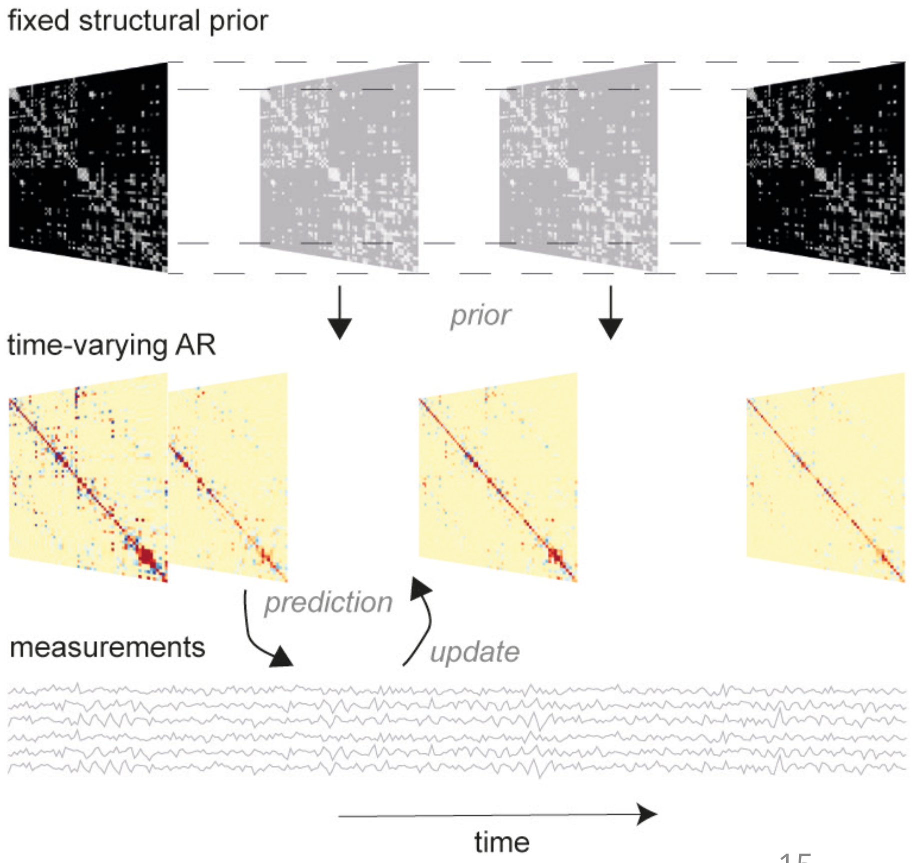
Structural priors



Structural Connectivity graphs as priors:

Undirected adjacency matrices:

- *Binary*
  - *Presence – Absence of physical links.*
- *Weighted*
  - *Strength (e.g., number of fibers).*



SC priors:

- *Improve model evidence in effective connectivity (DCM);*
- *Reduction of false positives.*

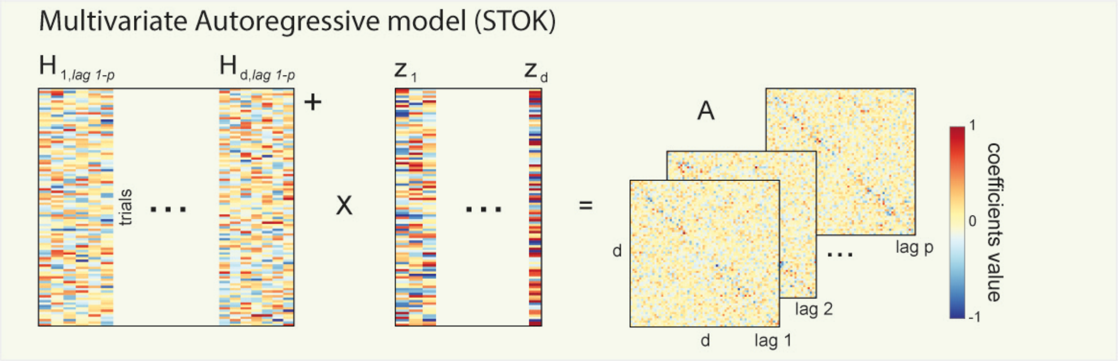
However, …

- *No one-to-one correspondence between SC and FC;*
- *Substantial number of false positives in SC.*

si-STOK

The structurally-informed Self-Tuning Optimized Kalman Filter

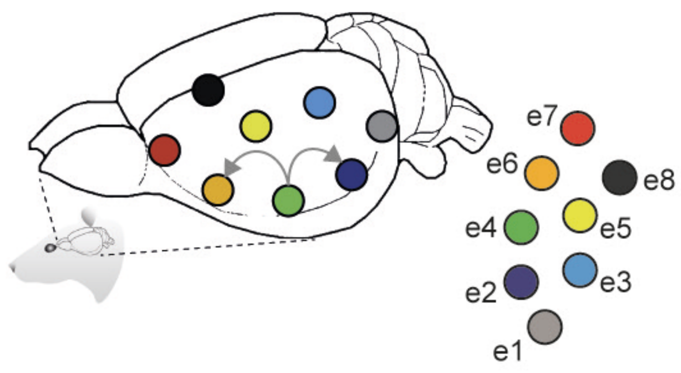
https://github.com/PscDavid/dynet_toolbox
https://github.com/joanrue/pydynet
Pascucci et al., (2021). BioRxiv.



si-STOK

Benchmark rat EEG data
SC from meta-analysis of histologically defined axonal connections

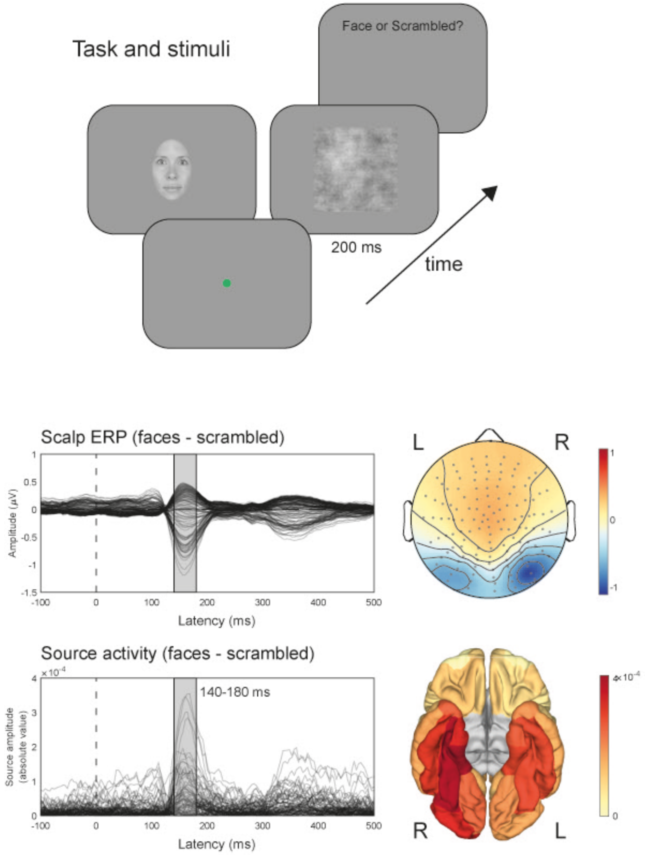
https://github.com/PscDavid/dynet_toolbox
https://github.com/joanrue/pydynet
Pascucci et al., (2021). BioRxiv.



si-STOK

Human EEG source imaging data
SC from diffusion tensor imaging (DTI), number of fibers

https://github.com/PscDavid/dynet_toolbox
https://github.com/joanrue/pydynet
Pascucci et al., (2021). BioRxiv.



Summary

- Dynamic and directed connectivity based on adaptive filtering can help to characterize large-scale rhythmic interactions in brain networks at the time scale of perception and cognition.

- Methods that allow the incorporation of structural priors from meta-analysis studies and other imaging modalities (e.g., DTI, fMRI), are promising tools for multimodal imaging.

- We present an algorithm for multimodal, high-temporal resolution and directed FC, optimized for tracking dynamic connectivity patterns during event-related activity.

REFS:

✓ Milde, T., et al. (2010). A new Kalman filter approach for the estimation of high-dimensional time-variant multivariate AR models and its application in analysis of laser-evoked brain potentials. Neuroimage.

✓ Pagnotta, M. F., & Plomp, G. (2018). Time-varying MVAR algorithms for directed connectivity analysis: Critical comparison in simulations and benchmark EEG data. PloS one.

✓ Pascucci, D., Rubega, M., & Plomp, G. (2020). Modeling time-varying brain networks with a self-tuning optimized Kalman filter. PLoS computational biology.

✓ Pascucci, D., Rubega, M., Rué-Queralt, J., Tourbier, S., Hagmann, P., & Plomp, G. (2021). Structure supports function: informing directed and dynamic functional connectivity with anatomical priors. bioRxiv.

david.pascucci@epfl.ch