Enabling tools to model information processing in brains

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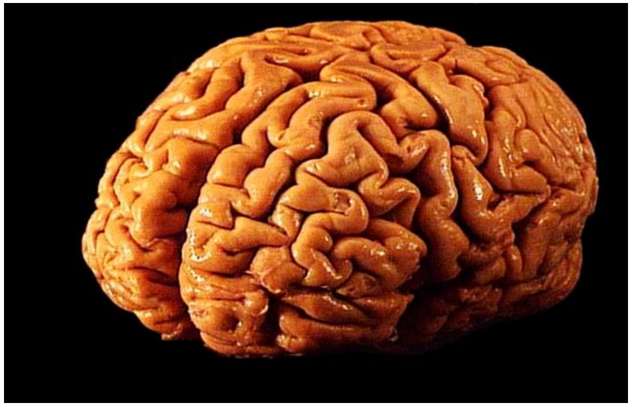
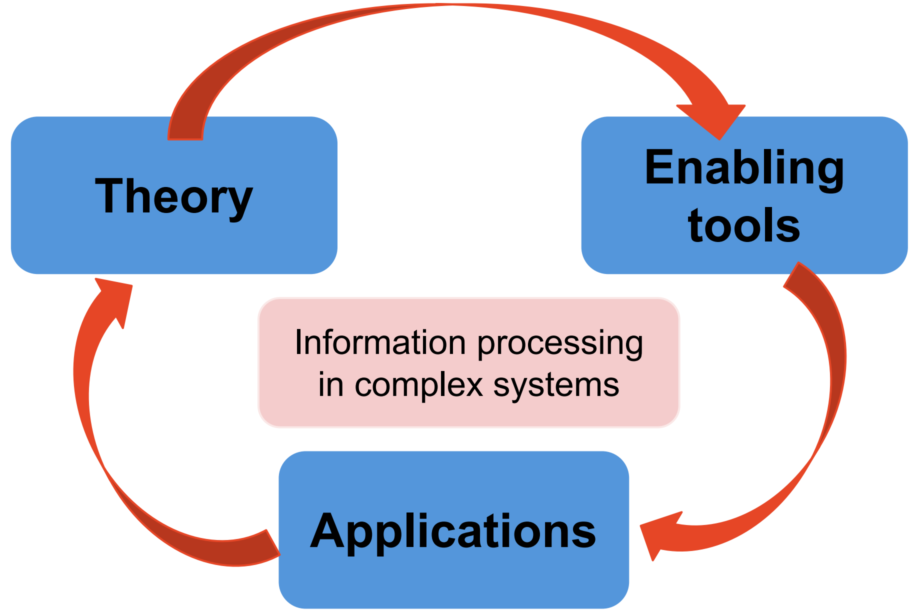
Neuroscience and me



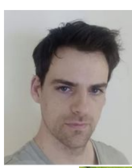


USyd

Mac Shine

Ben Fulcher

Richard Spinney



Oliver Cliff

Conor Finn

David Shorten

Leonardo Novelli

Mike Li

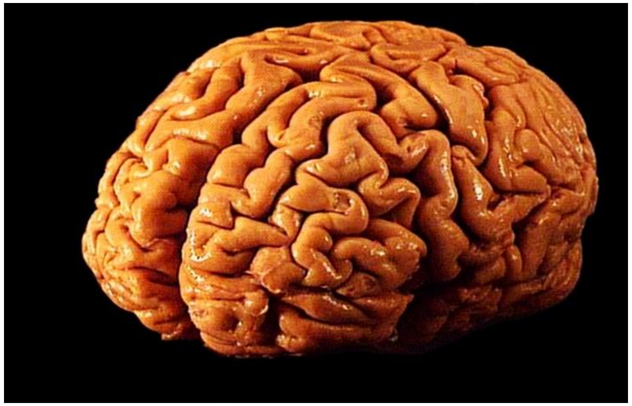
Michael Wibral

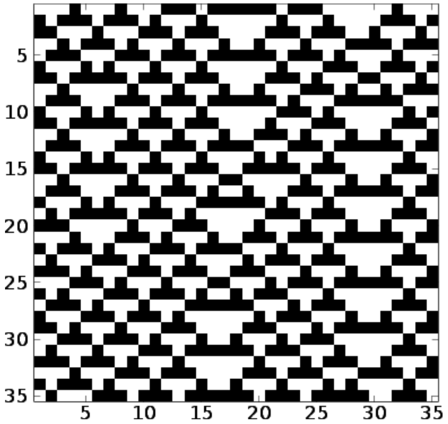
Viola Priesemann

Patricia Wollstadt

Pedro Mediano

Complex systems

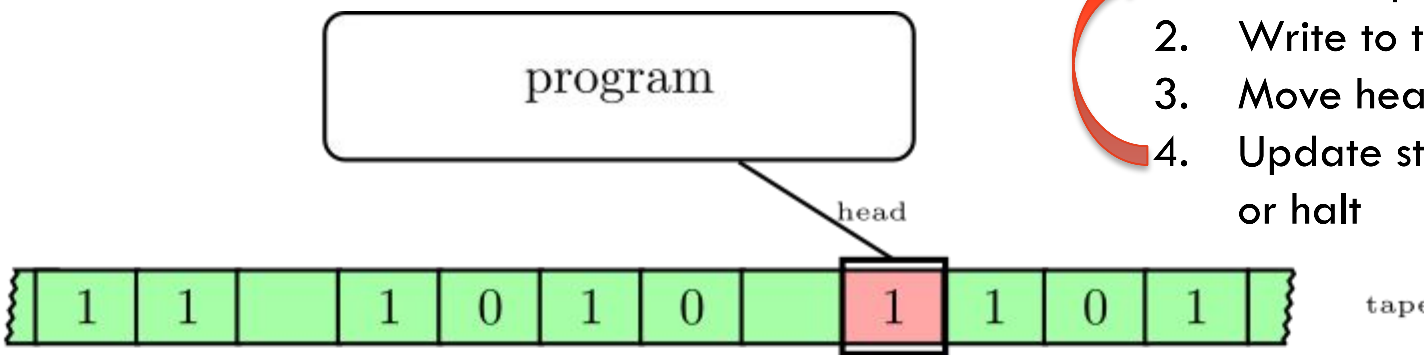




My research focus: how to model information processing in complex systems?

Computation

- How is computation approached in Computer Science?
  - Primary theoretical (abstract) model is a Turing Machine
  - A deterministic state machine operating on an infinite tape
  - Well-defined **inputs, outputs, algorithm/task, terminating condition**



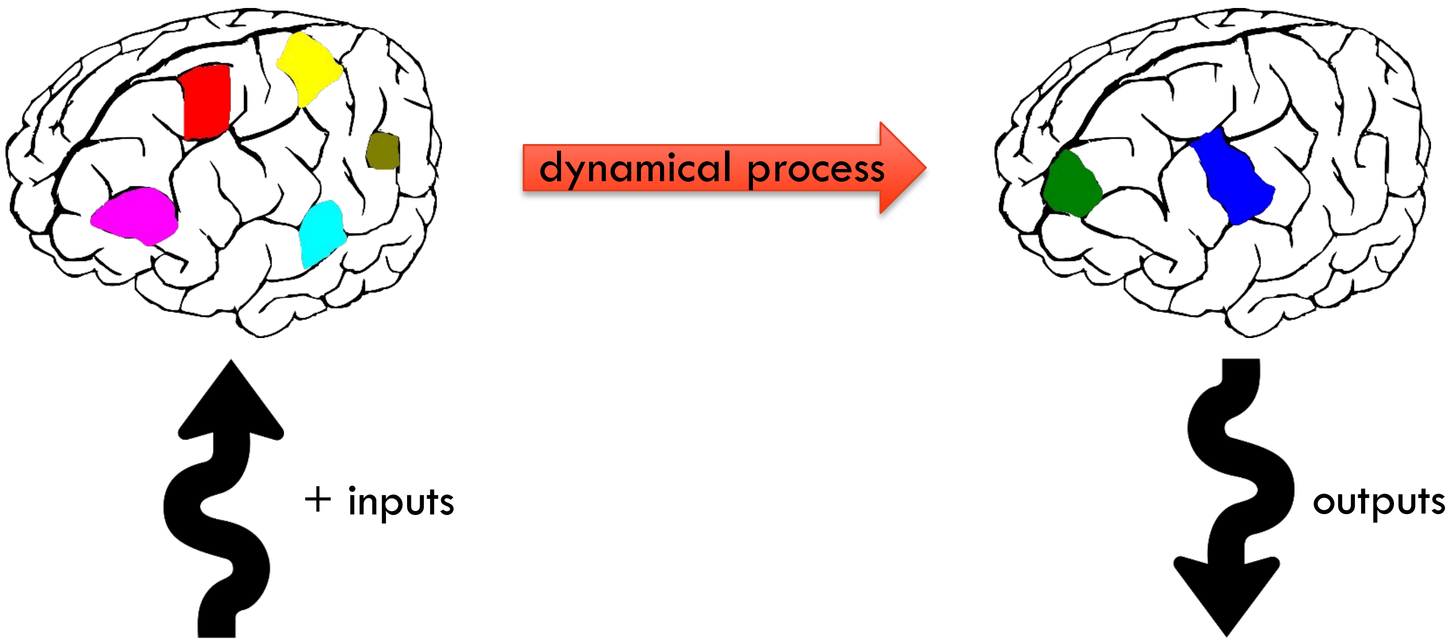
1. Read tape
2. Write to tape
3. Move head
4. Update state / instruction or halt

Mitchell: For complex systems, the "*Language of dynamical systems may be more useful than language of computation.*"

M. Sipser "Introduction to the Theory of Computation", PWS Publishing Company, Boston, 1997
Image by Wdvorak (Own work) [CC BY-SA 4.0], via Wikimedia Commons; Turing image (public domain) via Wikimedia Commons
M. Mitchell, "Introduction to Complexity", Lecture 7

Biological computation: we need a new perspective

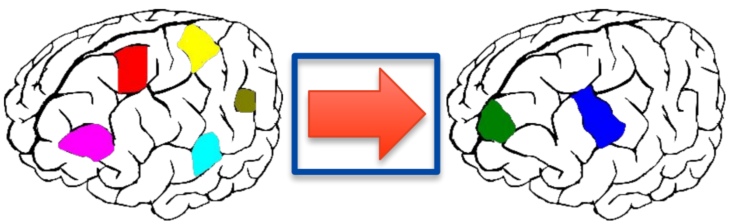
- Mitchell: For complex systems, the "*language of dynamical systems may be more useful than language of computation.*"



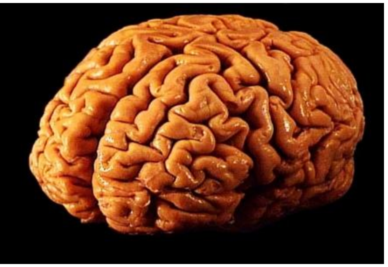
- Intrinsic information processing (Feldman et al., 2008) occurs whenever a system undergoes a dynamical process changing its initial state (+inputs) into some later state (+outputs)

D. P. Feldman, C. S. McTague, and J. P. Crutchfield. "The organization of intrinsic computation: Complexity-entropy diagrams and the diversity of natural information processing", Chaos, 18(4):043106, 2008.

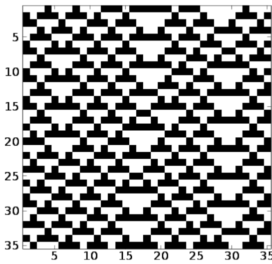
Intrinsic information processing



- We *talk* about computation as:
  - Memory
  - Signalling
  - Processing
- Intrinsic information processing is any process involving these features:

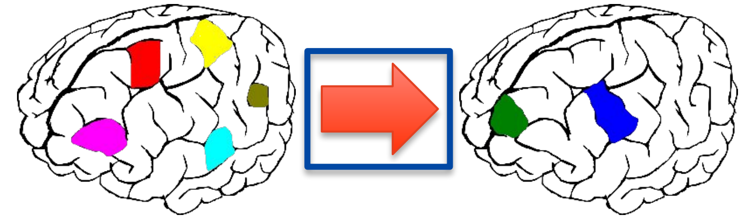






- How can we make these notions more precise?

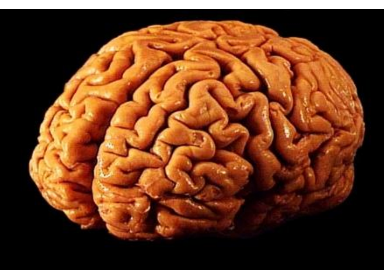
Intrinsic information processing



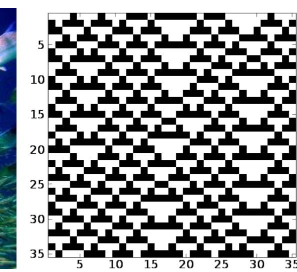
- We *talk* about computation as:
  - Memory
  - Signalling
  - Processing

- Idea: Model computation via:
  - Information storage
  - Information transfer
  - Information modification

- Intrinsic information processing is any process involving these features:







- Goal: by modelling intrinsic computation in the language it is normally described in, we can better understand e.g. neural information processing and its deficiencies.

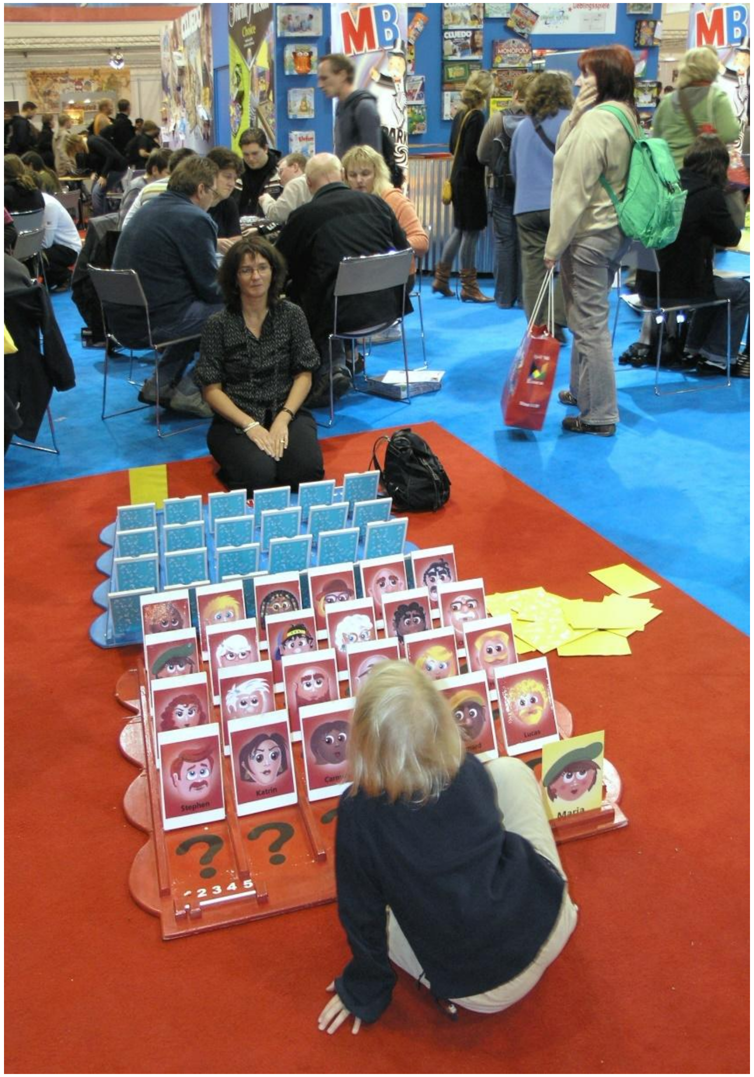
Contents

- What is information?
- How do we model information processing?
- What can this reveal about the brain?

A game about information: Guess Who? (Hasbro)

You can play online

What are the best/worst questions to ask?



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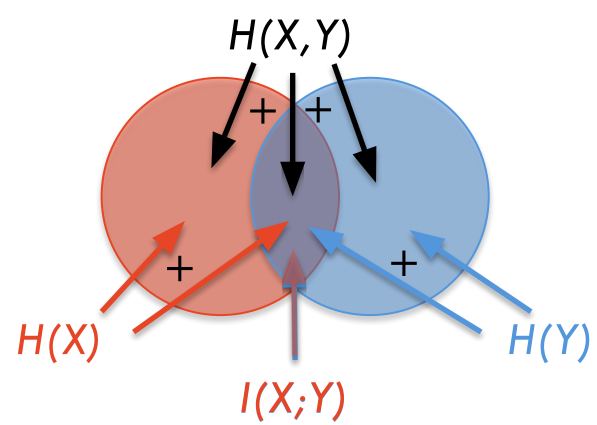
Defining information – first pass

- JL: "*Information is all about questions and answers*"

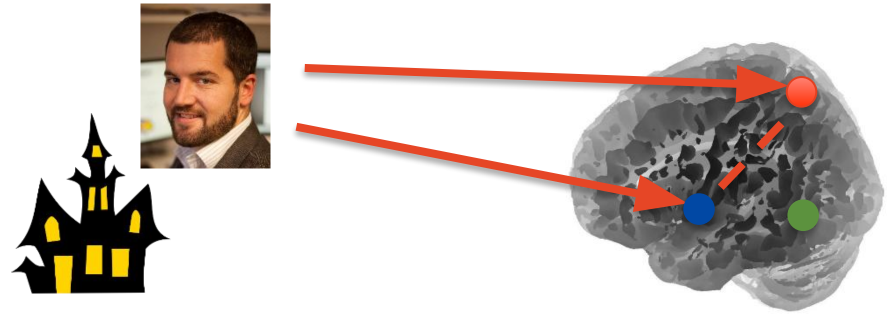
- Information is the amount by which
  - one variable (an answer/signal/measurement)
  - reduces our uncertainty or surprises us
  - about another variable.

- We need to quantify both:
  - Uncertainty (entropy)
  - Uncertainty reduction (information)



C. E. Shannon. A mathematical theory of communication. Bell System Technical Journal, 27(3–4):379–423, 623–656, 1948.
T. M. Cover and J. A. Thomas. Elements of Information Theory. Wiley-Interscience, New York, 1991.
D. J. C. MacKay. Information Theory, Inference, and Learning Algorithms. Cambridge University Press, Cambridge, 2003

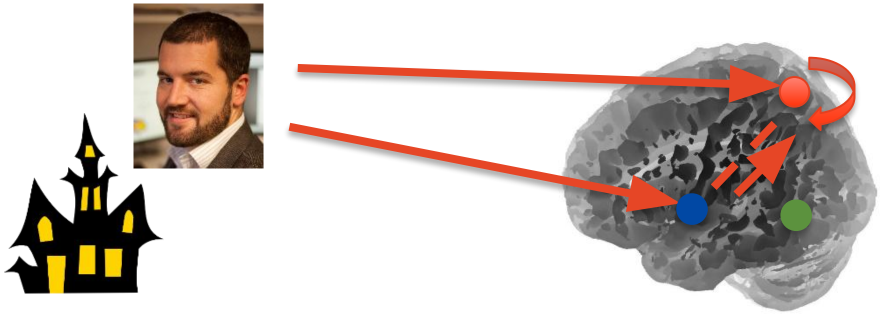
What can you measure with information theory?



- How surprising is `sex = F`?
- How much uncertainty is there about the `identity`?
- Uncertainty reduction about `identity` from `hair colour`?
- Information about `identity` from `hair = red`?
- Information about `sex = F` from `hair = red`?
- Information about `sex = F` from `hair = red` given `hat = yes`?

- How surprising is `object = face`?
- How much uncertainty is there about the `object`?
- Uncertainty reduction about `object` from `area-1`?
- Information about `object` from `area-1 = 0.8`?
- Information about `area-1 = 0.8` from `area-2 = 0.2`?
- Information about `area-1 = 0.8` from `area-2 = 0.2` given `area-3 = -0.2`?

Why use information theory for neural data analysis?



- Allows us to answer questions that are naturally phrased:
  - In a model-free way
  - Captures non-linearities
  - Estimators for different data types, and multivariates

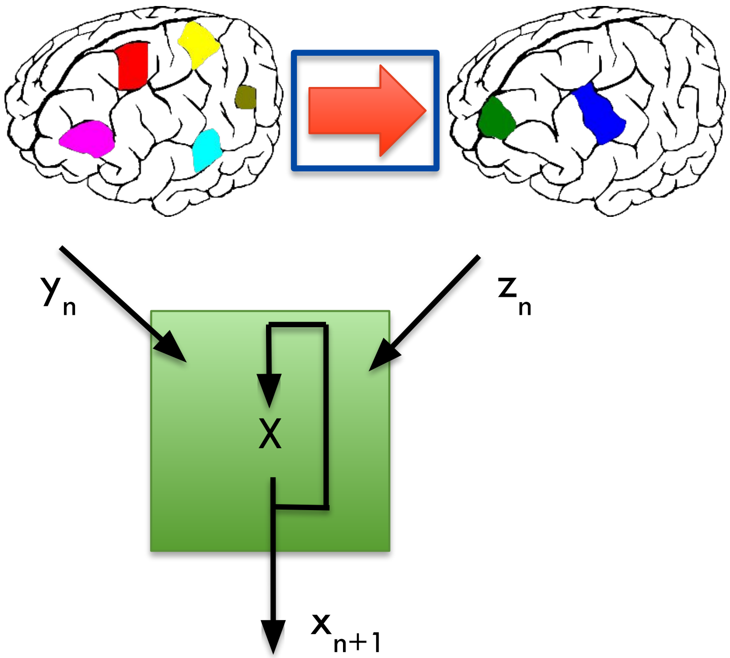
1. The nature of neural codes
   a. Bridging Marr's task and implementation levels
   b. Functional relationships
2. Modelling information processing dynamics

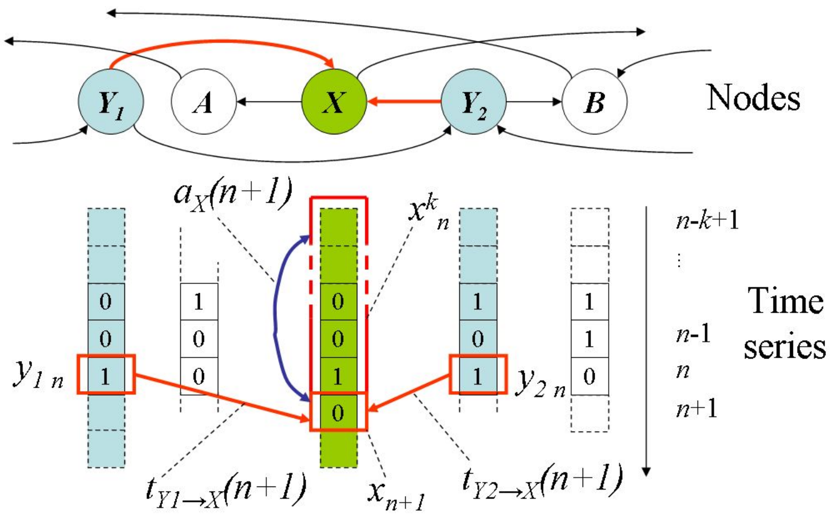
- How surprising is `object = face`?
- How much uncertainty is there about the `object`?
- Uncertainty reduction about `object` from `area-1`?
- Information about `object` from `area-1 = 0.8`?
- Information about `area-1 = 0.8` from `area-2 = 0.2`?
- Information about `area-1 = 0.8` from `area-2 = 0.2` given `area-3 = -0.2`?

M. Wibral, J.T. Lizier and V. Priesemann, "*Bits from Brains for Biologically-inspired Computing*", Frontiers in Robotics and AI, vol. 2, 5, 2015

Image modified from an original credited to dow_at_uoregon.edu, obtained here (distributed without restrictions)

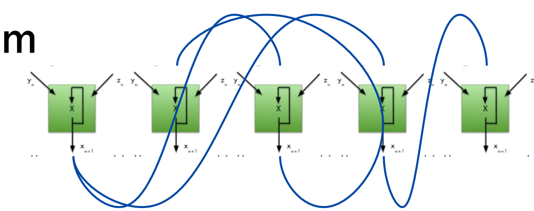
Modelling information processing dynamics





Complex system as a multivariate time-series of states
e.g. fMRI, MEG, EEG, etc.

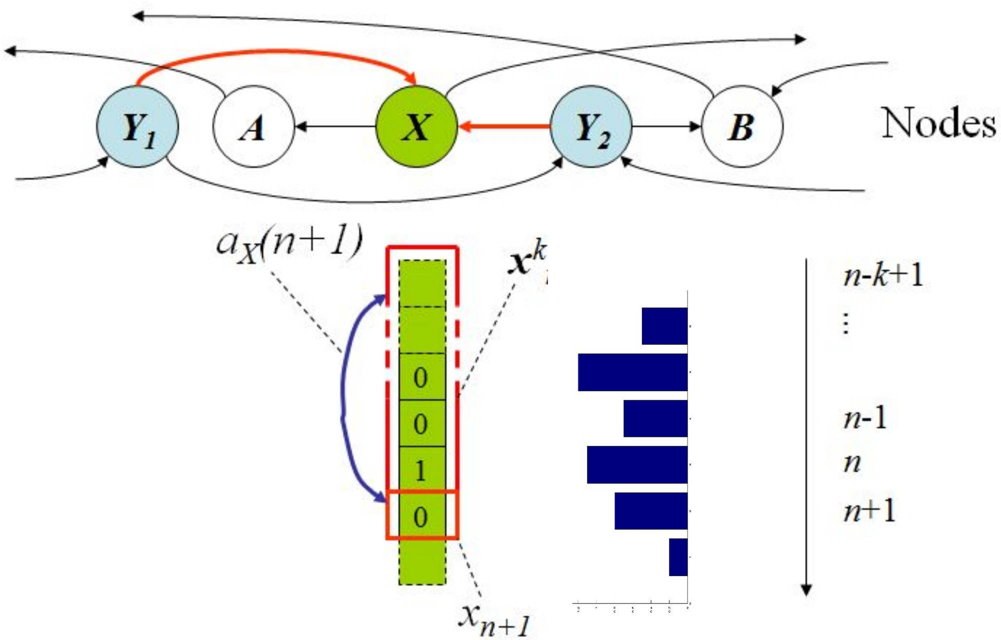
– How can we *model* neural information processing dynamics?
  – It is the output of a local computation within the system
    - Inputs, outputs, rules/algorithm, halt
  – Model in terms of information storage and transfer
  – Establishing an information-theoretic footprint



J.T. Lizier, "*The local information dynamics of distributed computation in complex systems*", Springer: Berlin/Heidelberg, 2013
M. Wibral, J.T. Lizier and V. Priesemann, "Bits from Brains for Biologically-inspired Computing", Frontiers in Robotics and AI, vol. 2, 5, 2015

Information storage

– How much information about the next observation X_n of process X can be found in its past state $\boldsymbol{X}_n^{(k)} = \{X_{n-k+1}, \dots, X_{n-1}, X_n\}$?



Active information storage (AIS)

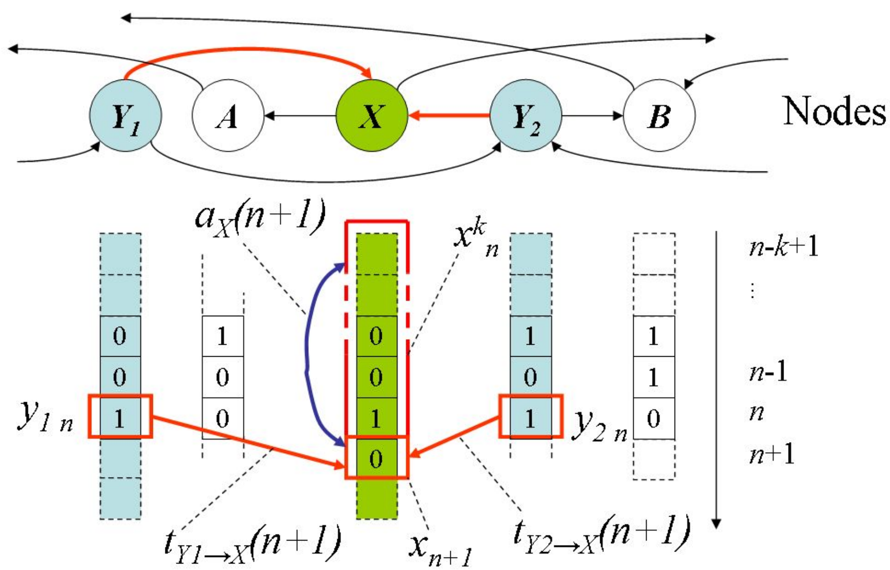
$$A_X(k) = I(\boldsymbol{X}_n^{(k)}; X_{n+1})$$

- Average information from past state that is in use in predicting the next value
- Storage underpins periodic behaviour, stability and concept of memory.
- Model captures: Internally stored, distributed storage, input driven storage

J.T. Lizier, M. Prokopenko, A.Y. Zomaya, "*Detecting Non-trivial Computation in Complex Dynamics*", Proc. ECAL, pp. 895-904 (2007).
J.T. Lizier, M. Prokopenko, & A.Y. Zomaya, "*Local measures of information storage in complex distributed computation*", Information Sciences 208, 39 (2012)
Obst, O., Boedecker, J., Schmidt, B., and Asada, M. (2013), "On active information storage in input-driven systems", arXiv:1303.5526

Information transfer

- How much information about the next observation X_n of process X can be found in observation Y_n of process Y, in the context of the past state $\boldsymbol{X}_n^{(k)} = \{X_{n-k+1}, \dots, X_{n-1}, X_n\}$?



Transfer entropy (TE)

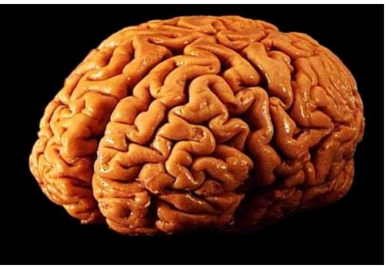
$$T_{Y\to X}(k) = I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right)$$

- Average info from source that helps predict next value in context of past.
- Granger-like
- Models strength of predictive effect or statistical dependence.

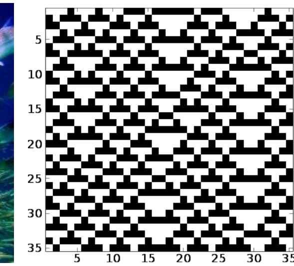
Total information: $H_X = A_X + T_{Y1\to X} + T_{Y2\to X|Y1} + H_{X|X^k,Y1,Y2}$

T. Schreiber, "*Measuring Information Transfer*", Physical Review Letters, 85(2), pp. 461-4, 2000.
Bossomaier T, Barnett L, Harré M, Lizier JT. 2016 An introduction to transfer entropy. Cham, Switzerland: Springer

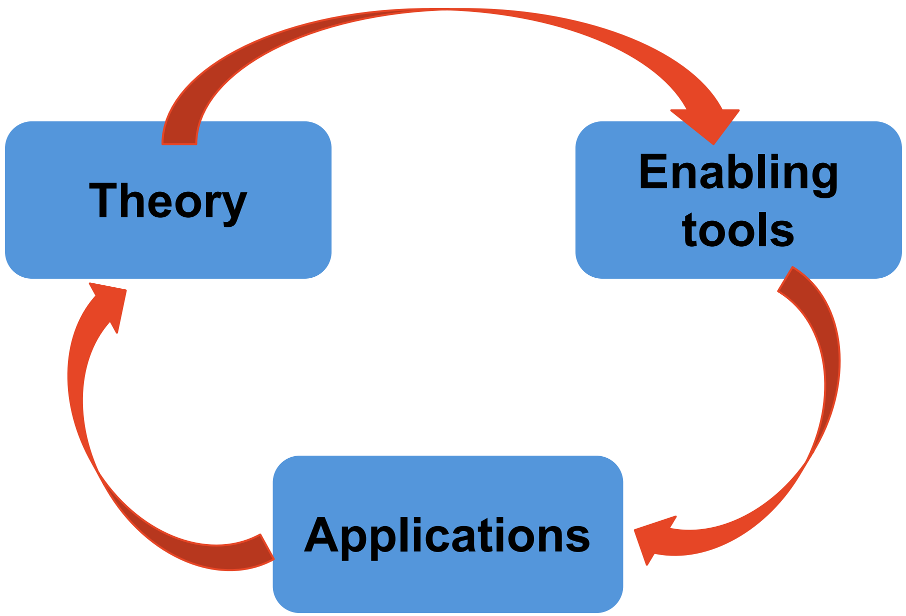
Studying information processing in complex systems

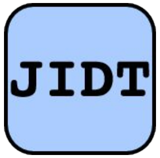




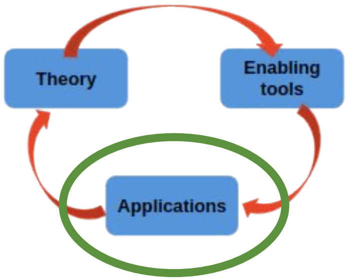


Also see:
Wibral / Priesemann / Wollstadt
Mediano / Rosas
Marinazzo
Battaglia
Faes
Stramaglia
Beggs
Barnett / Seth
Shimono
…





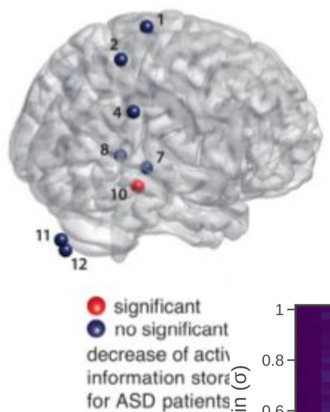
Open source tools: JIDT and IDTxl

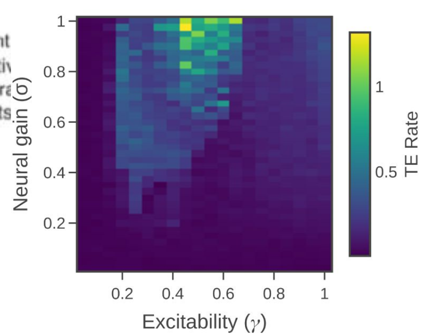


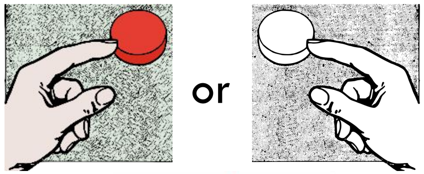
Analysing neural information processing

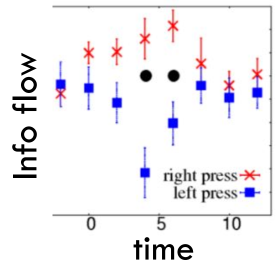
Key question: What does such modelling tell us about neural information processing?

1. Characterising different regimes of behavior

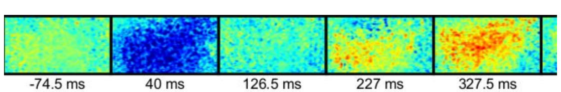




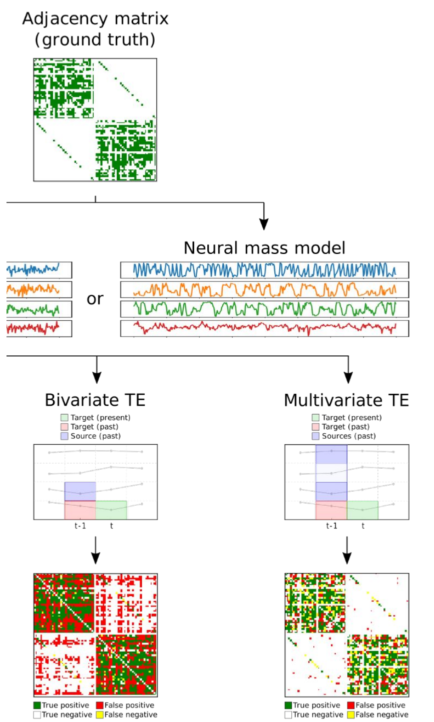


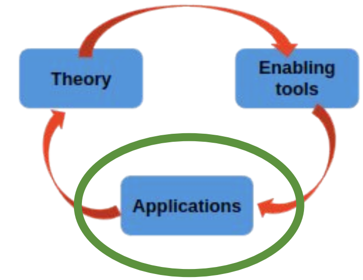


2. Space-time dynamics



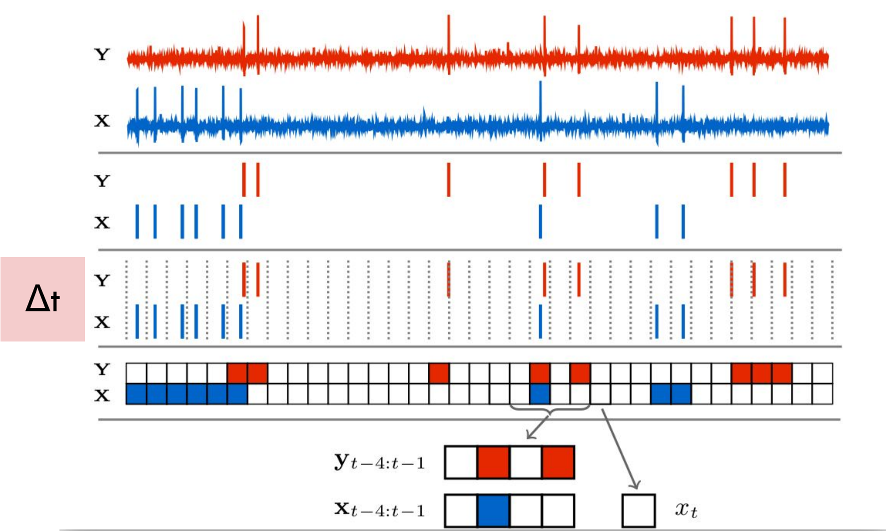
3. Functional and effective network modelling

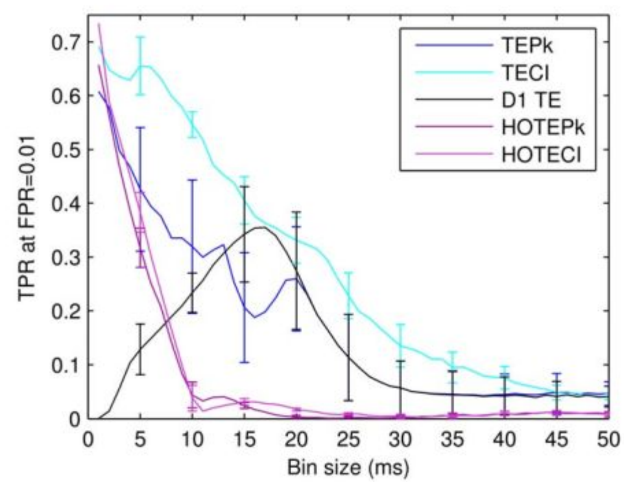




1. Information flow between spike trains

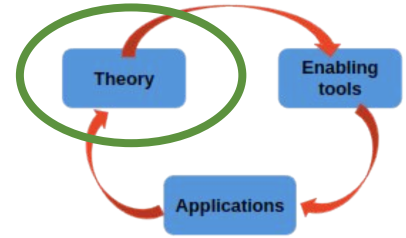
- Promise of high spatial / temporal precision recordings to facilitate study of information flows at the neural level
- Prior use of discrete-time TE estimator to infer directed functional networks and study their properties:
  - Long-tailed degree distribution
  - Rich club
  - Relation of hubs to specific time-scales





But TE is highly sensitive to discrete bin size Δt (Ito et al 2011)

Shimono M, Beggs JM. Cerebral Cortex, 25:3743–3757, 2015
Nigam S, et al. Journal of Neuroscience 36:670–684, 2016
Timme N, et al.,. PLOS ONE 9:e115764, 2014
Timme NM et al., PLOS Computational Biology 12:e1004858, 2016
Wibral M, et al.. Entropy 19:494, 2017
Ito S et al., PLoS One 6(11):e27431, 2011



1. Information flow between spike trains

Established theoretical formulation for TE between spike trains:

- Properly formulated in terms of **rates** and **path integrals**
- If a limiting rate exists, a consistent discrete-time estimate of should scale with Δt:

$$\dot{T}_{y\to x}(t) = \lim_{\Delta t\to 0} \frac{1}{\Delta t} T^{\Delta t}_{y\to x}(t)$$

- Only interactions at target spikes contribute to the average rate.

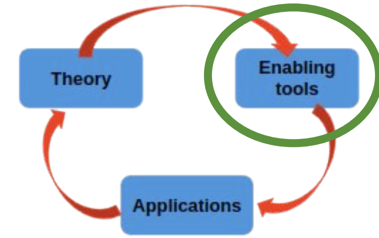
$$\dot{\mathbf{T}}_{Y\to X} = \lim_{\tau\to\infty}\frac{1}{\tau}\sum_{i=1}^{N_X}\ln\frac{\lambda_{x|\mathbf{x}_{<t},\mathbf{y}_{<t}}\left[\mathbf{x}_{<x_i},\mathbf{y}_{<x_i}\right]}{\lambda_{x|\mathbf{x}_{<t}}\left[\mathbf{x}_{<x_i}\right]}$$

Expected target spike rate, given source and target past

Expected target spike rate, given target past

Sampling time

Spinney RE, Prokopenko M, Lizier JT. Transfer entropy in continuous time, with applications to jump and neural spiking processes. *Physical Review E*, 95:032319, 2017

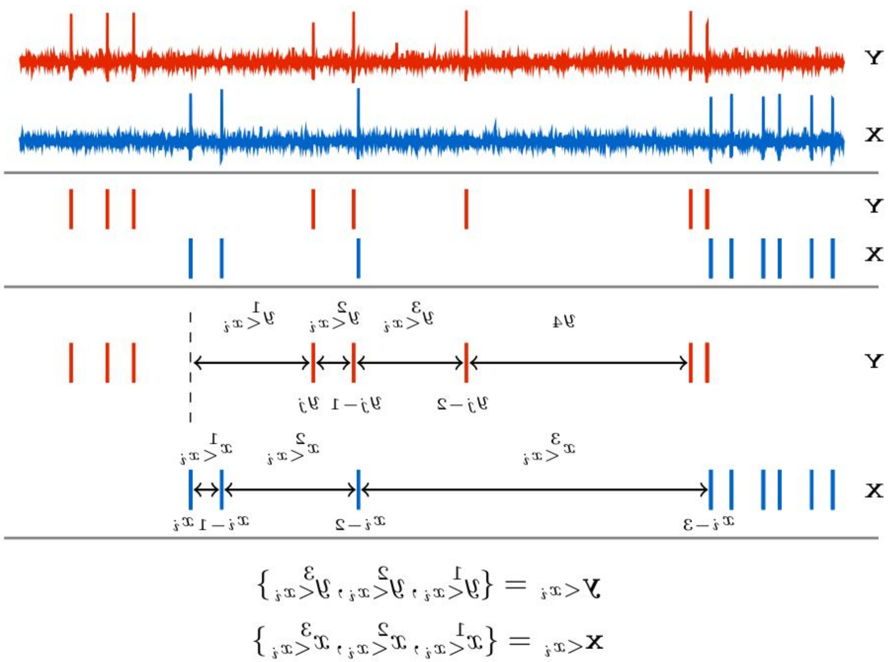


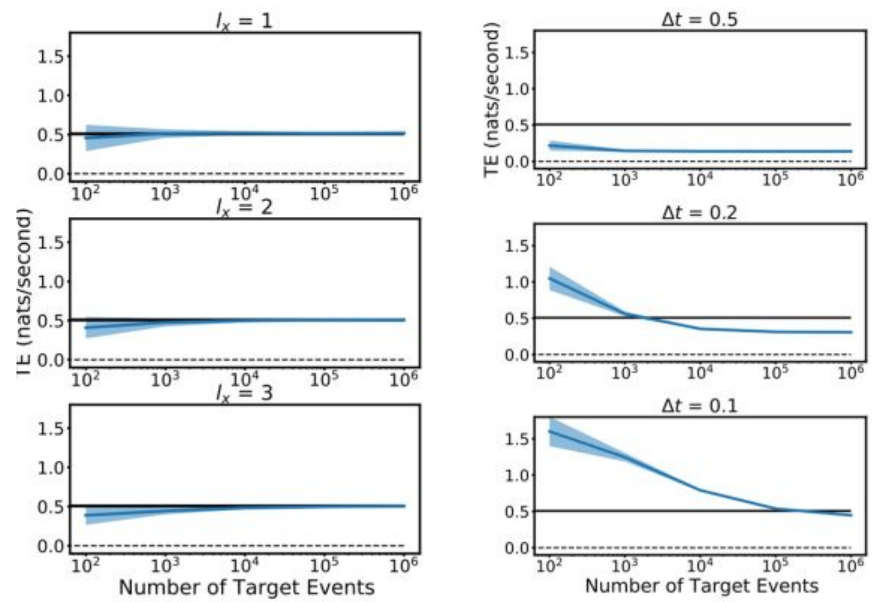
1. Information flow between spike trains

Translated theoretical formulation into estimation algorithm:

- Utilised nearest-neighbour matching on source-target ISI vectors to provide an efficient estimator, which:

is consistent, not sensitive to parameters



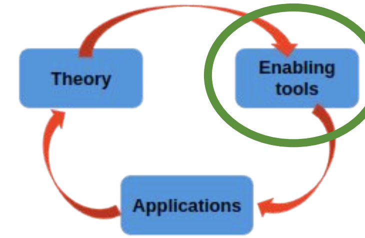


(B) Continuous-time estimator

(C) Discrete-time estimator

D. P. Shorten, R. E. Spinney, and J. T. Lizier, Estimating transfer entropy in continuous time …, *PLoS Computational Biology 17*, e1008054 (2021)

1. Information flow between spike trains

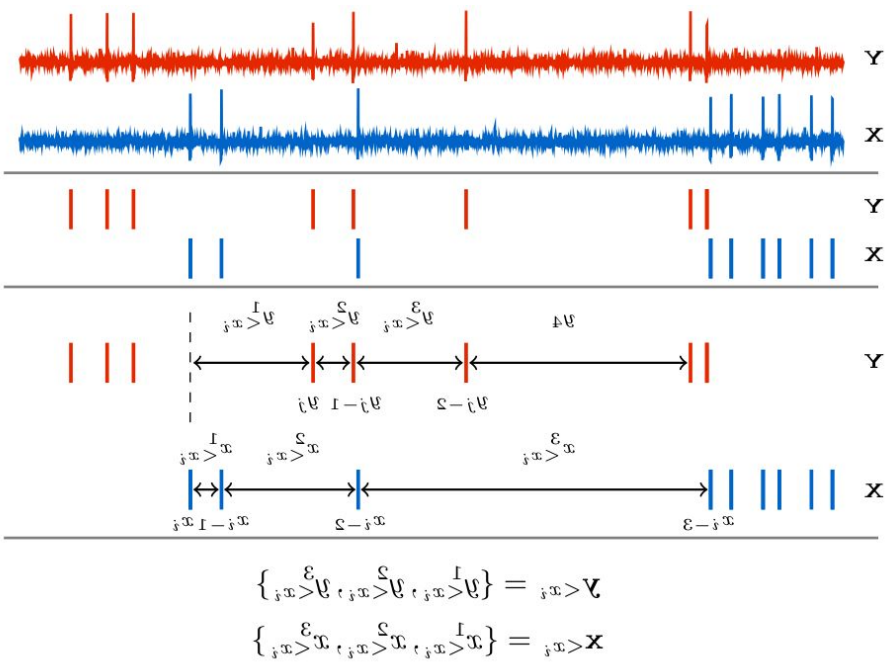


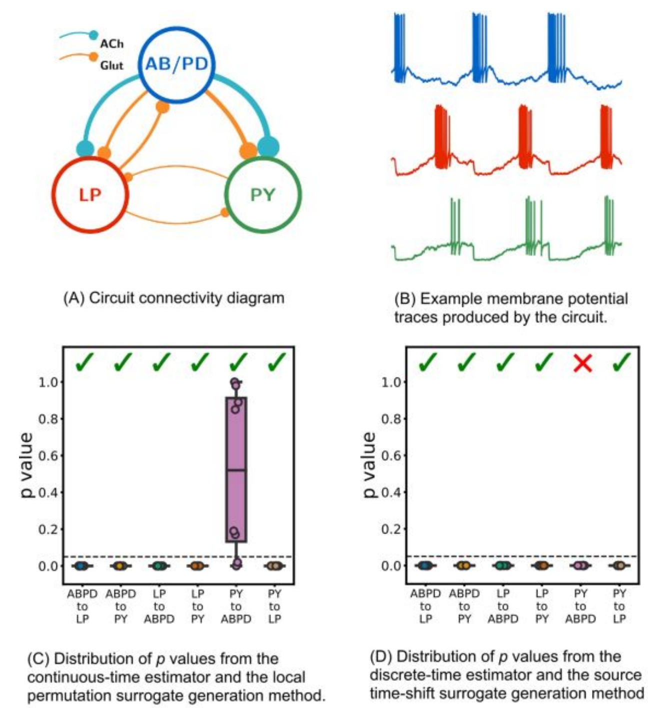
JIDT

Translated theoretical formulation into estimation algorithm:

– Utilised nearest-neighbour matching on source-target ISI vectors to provide an efficient estimator, which:

reliably distinguishes conditional in/dependence





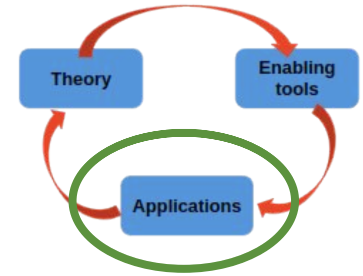
(A) Circuit connectivity diagram

(B) Example membrane potential traces produced by the circuit.

(C) Distribution of *p* values from the continuous-time estimator and the local permutation surrogate generation method.

(D) Distribution of *p* values from the discrete-time estimator and the source time-shift surrogate generation method

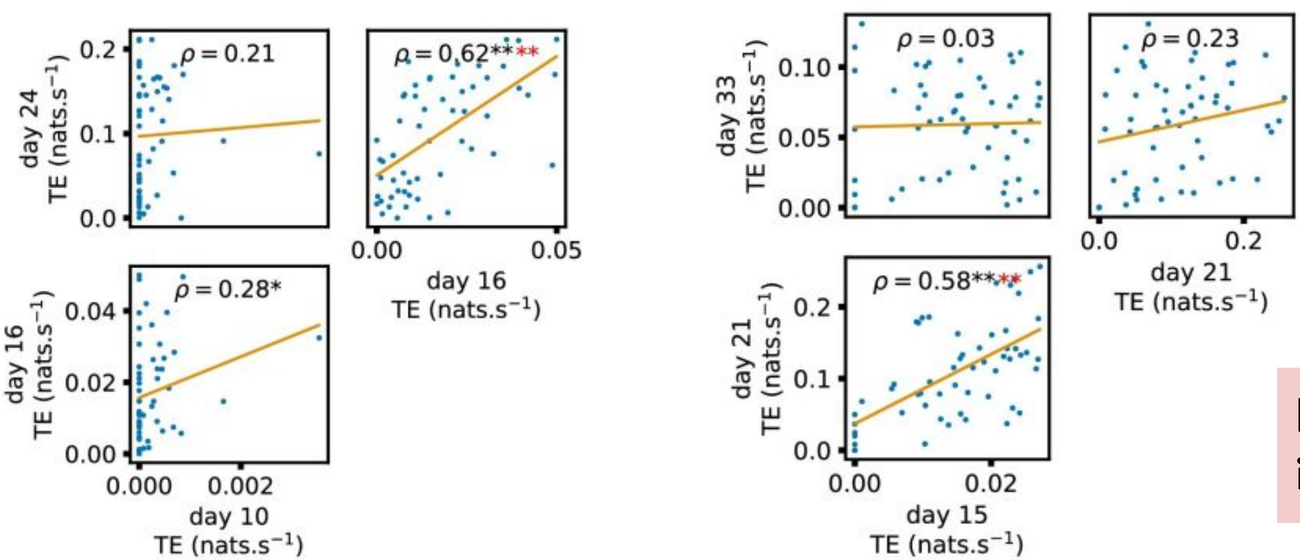
D. P. Shorten, R. E. Spinney, and J. T. Lizier, Estimating transfer entropy in continuous time …, *PLoS Computational Biology 17*, e1008054 (2021)



1. Information flow between spike trains

Studied changes in TE during development of neural cell cultures:

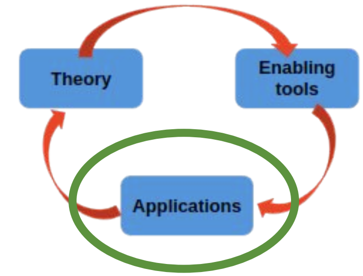
- Examined all pairs directed functional network, as function of culture age (DIV)



(a) Culture 1-3 (b) Culture 2-2

Information flows lock in early in development

D.P Shorten, V. Priesemann, M. Wibral, J. T Lizier. Early lock-in of structured and specialised information flows during neural development. *eLife*, 11:e74651, 2022
D. A Wagenaar, J. Pine, S.M Potter. An extremely rich repertoire of bursting patterns during the development of cortical cultures. *BMC Neuroscience*, 7(1):11, 2006



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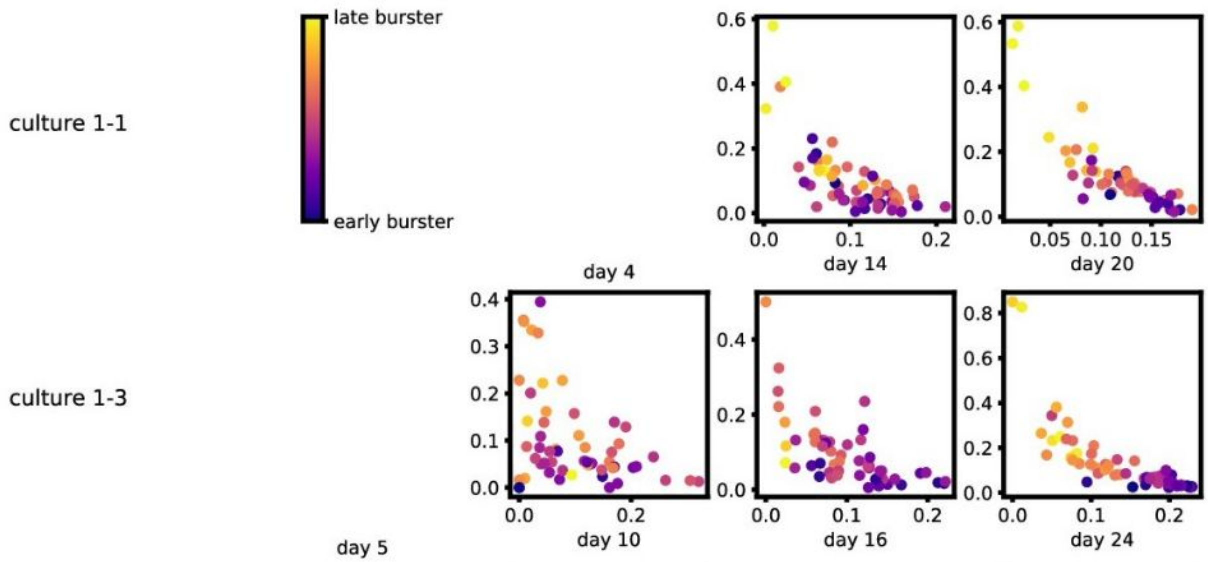
Studied changes in TE during development of neural cell cultures:

- Examined all pairs directed functional network, as function of culture age (DIV)

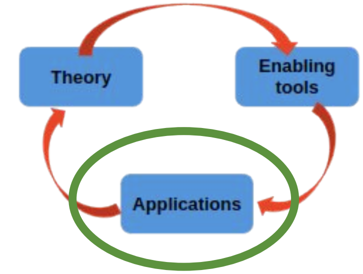


Nodes take on different computational roles during burts

Similar results observed in synthetic model with STDP

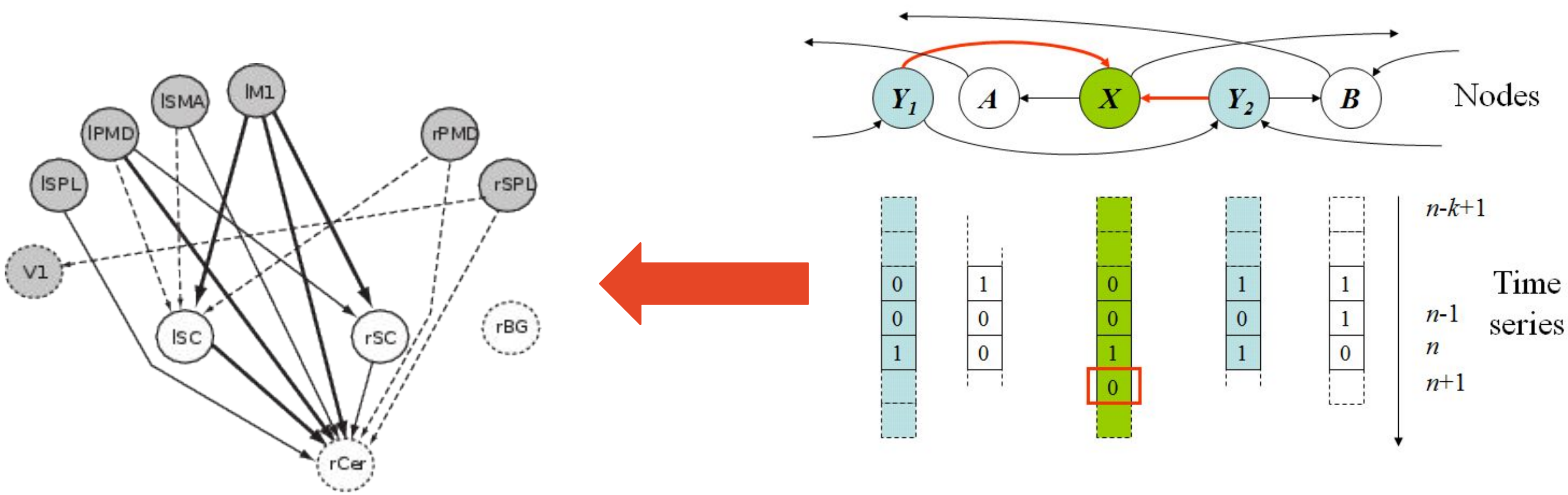
D.P Shorten, V. Priesemann, M. Wibral, J. T Lizier. Early lock-in of structured and specialised information flows during neural development. *eLife*, 11:e74651, 2022

D. A Wagenaar, J. Pine, S.M Potter. An extremely rich repertoire of bursting patterns during the development of cortical cultures. *BMC Neuroscience*, 7(1):11, 2006



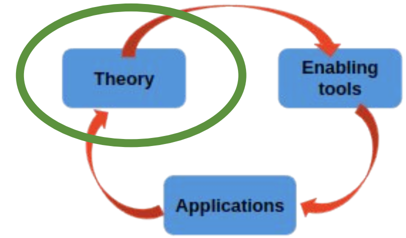
2. Effective network modelling

- Information transfer is ideally placed for the "*inverse problem*" – effective connectivity analysis – inferring a "*minimal circuit model*" that can explain observed dynamics
  - Aim: **Model** the computation taking place in the system, revealing emergent computational structure.



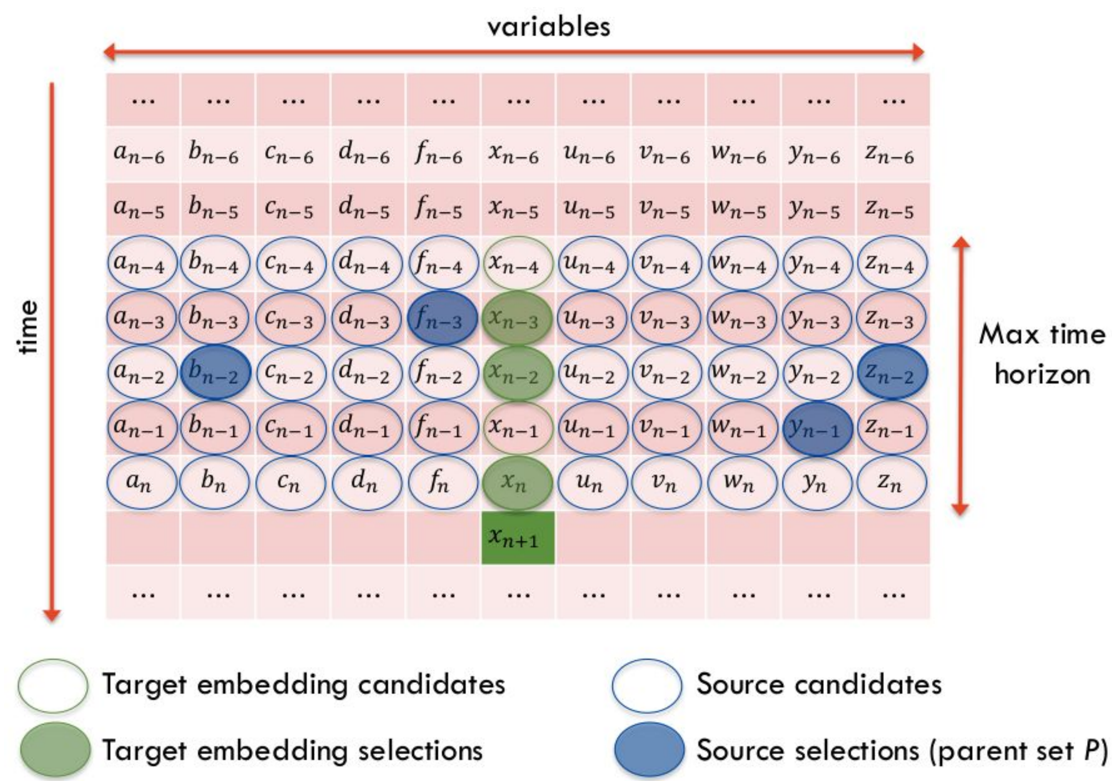
Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 7.2

2. Effective network modelling



Real goal here: to infer this parent set $\{Y, Z\}$ for X

$$H(X_{n+1}) = I\left(\boldsymbol{X}_n^{(k)}; X_{n+1}\right) + I\left(Y_n, Z_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right) + H\left(X_{n+1} \middle| \boldsymbol{X}_n^{(k)}, Y_n, Z_n\right)$$



Vlachos, I., & Kugiumtzis, D., Physical Review E, 82(1), 016207, 2010

Faes, L., Nollo, G., & Porta, A., Physical Review E, 83(5), 051112, 2011

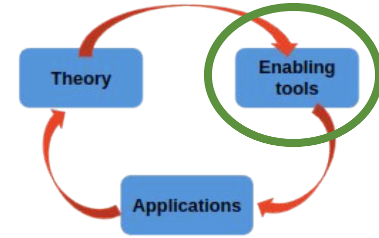
J. T. Lizier and M. Rubinov. Technical Report 25/2012, Max Planck Institute for Mathematics in the Sciences, 2012.

S. Stramaglia, G.-R. Wu, M. Pellicoro, and D. Marinazzo, Physical Review E, 86(6):066211+, 2012

Montalto, A., Faes, L., & Marinazzo, D., PLoS ONE, 9(10), e109462, 2014

Sun, J., Taylor, D., & Bollt, E. M., SIAM Journal on Applied Dynamical Systems, 14(1), 73–106, 2015

L. Novelli, P. Wollstadt, P. Mediano, M. Wibral, J.T. Lizier, Network Neuroscience, 3(3), 827-847, 2019



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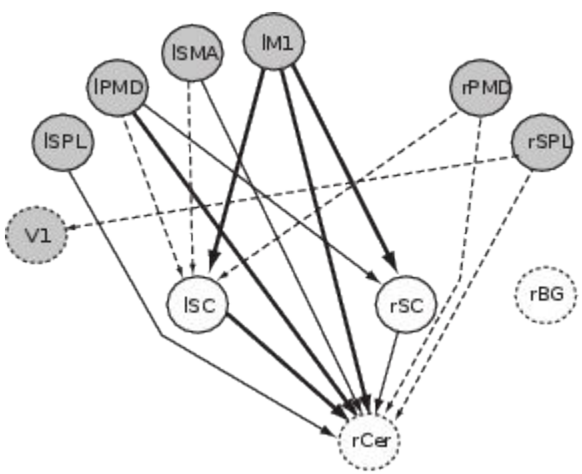


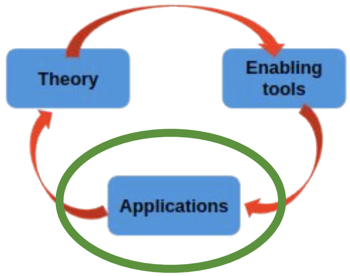
TRENTOOL

\+ JIDT

\+ Multivariate extensions, GPU & efficiencies

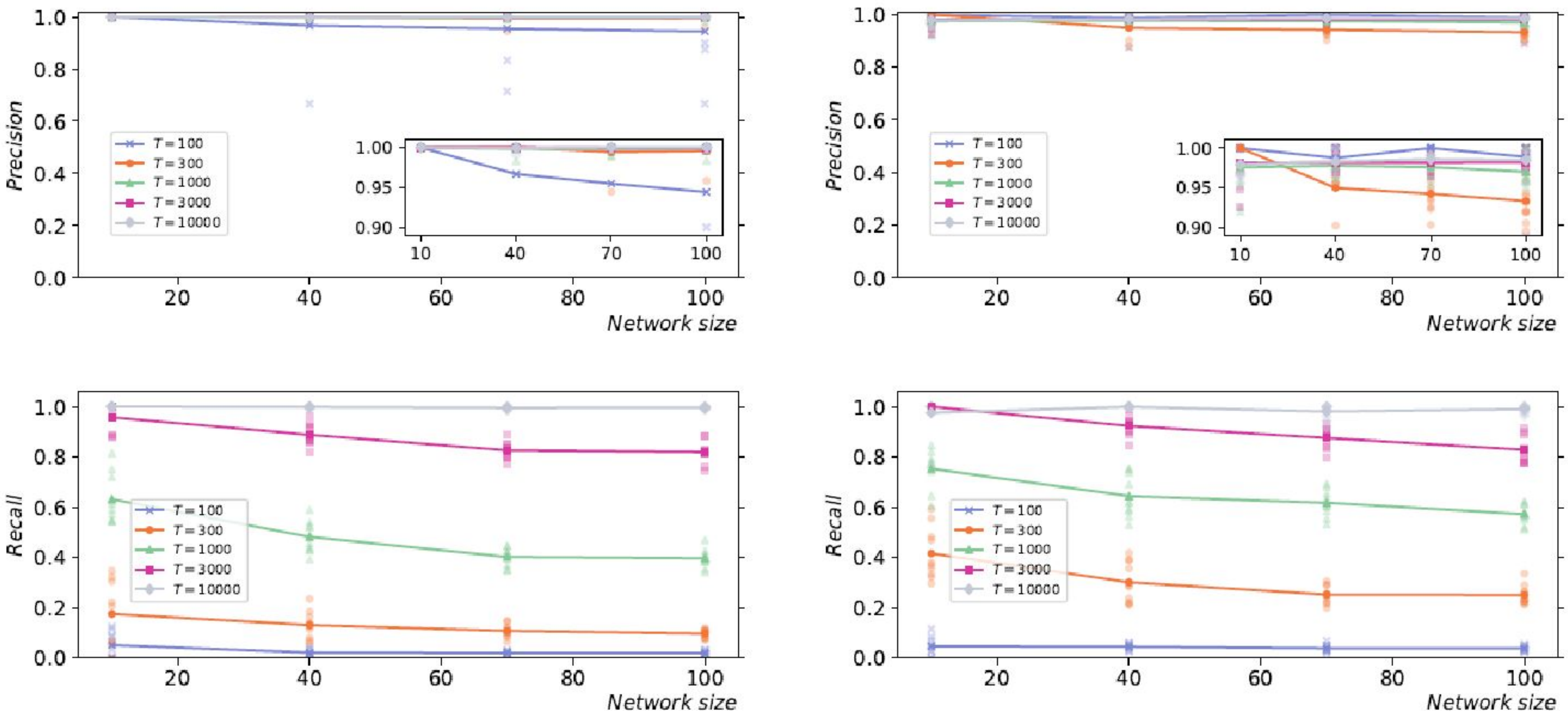
= https://github.com/pwollstadt/IDTxl

P. Wollstadt, J.T. Lizier, R. Vicente, C. Finn, M. Martinez-Zarzuela, P. Mediano, L. Novelli and M. Wibral, "IDTxl: The Information Dynamics Toolkit xl: a Python package for the efficient analysis of multivariate information dynamics in networks", Journal of Open Source Software, 4(3), 1081, 2019
L. Novelli, P. Wollstadt, P. Mediano, M. Wibral, J.T. Lizier, Network Neuroscience, 3(3), 827-847, 2019



2. Effective network modelling

Vector auto-regressive　　　　Coupled logistic maps

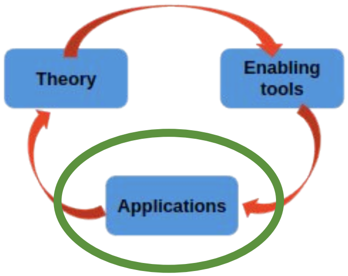


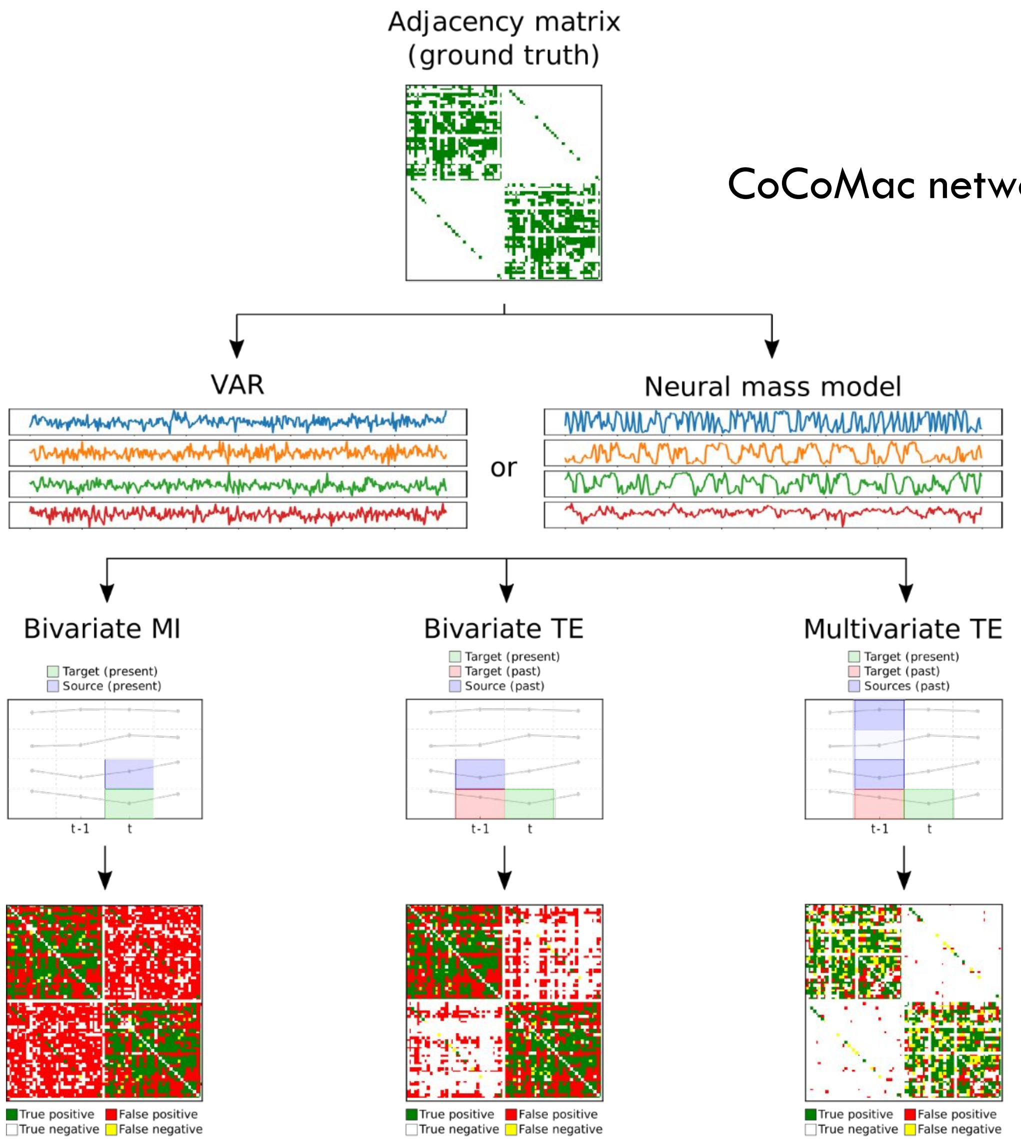
First time test of realistic size data sets with non-linear estimator

α_{max}=0.001, S=1000 surrogates, max δ_x = 5

L. Novelli, P. Wollstadt, P. Mediano, M. Wibral, J.T. Lizier, Network Neuroscience, 3(3), 827-847, 2019

2. Effective network modelling

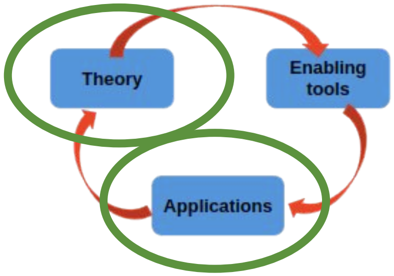


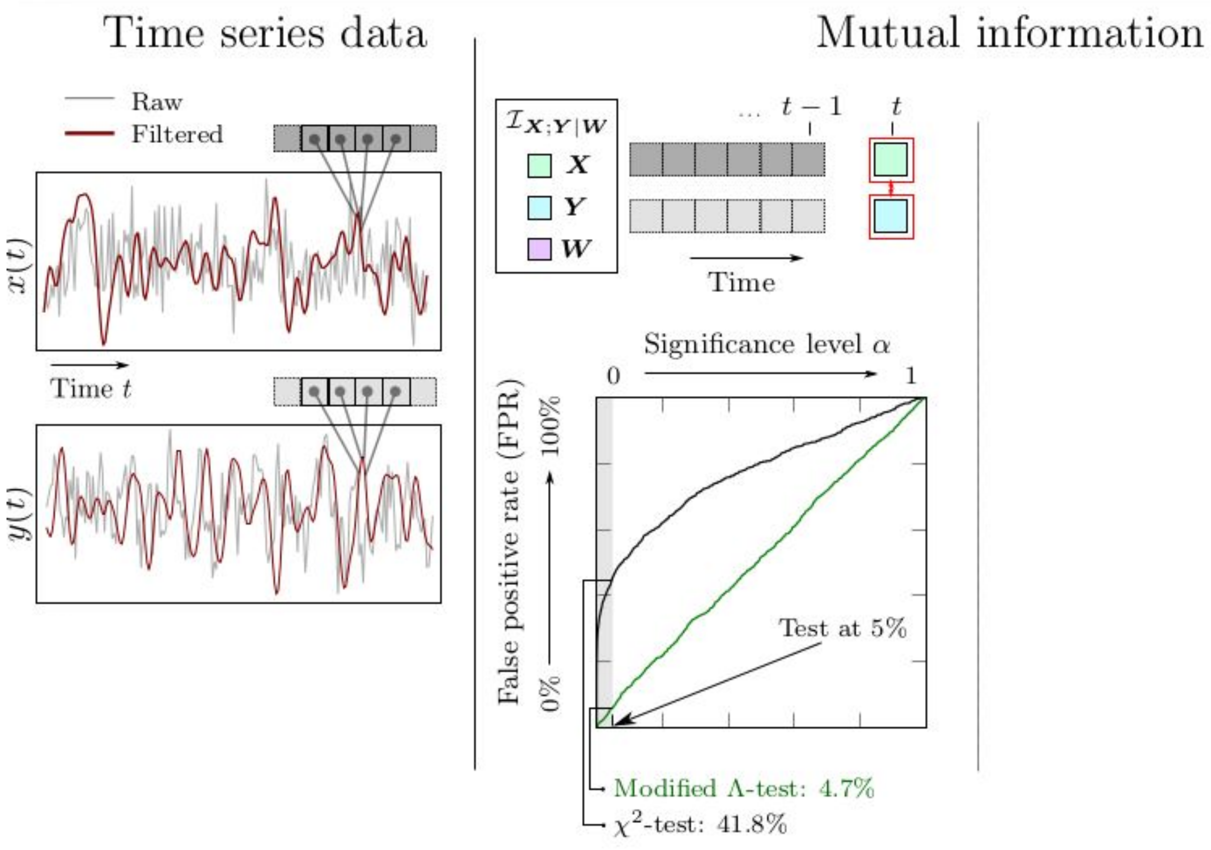


CoCoMac network

Novelli, L., & Lizier, J. T. (2021). Network Neuroscience, 5(2), 373–404

2. Effective network modelling



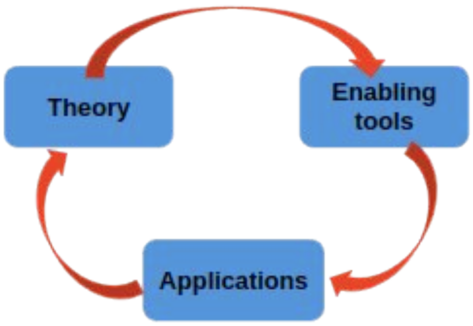


E. Florin, J. Gross, J. Pfeifer, G. R. Fink, and L. Timmermann, NeuroImage 50, 577 (2010).
L. Barnett and A. K. Seth, J. Neurosci. Methods 201, 404 (2011).
C. E. Davey, D. B. Grayden, G. F. Egan, and L. A. Johnston, NeuroImage 64, 728 (2013).
S. Afyouni, S. M. Smith, and T. E. Nichols, NeuroImage 199, 609 (2019).
M. S. Bartlett, J. R. Stat. Soc. 98, 536 (1935).

Cliff, O. M., Novelli, L., Fulcher, B. D., Shine, J. M., & Lizier, J. T.. *Phys. Rev. Research* 3, 013145 (2021)

Summary

- How to model information processing in complex systems
- How this is naturally applied to answer meaningful questions in a neuroscience setting
- The integration between theory, empirical enablers and applications is helping forge the path

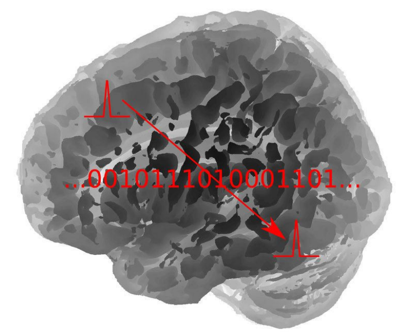


- What can it do for us in a neuroscience setting?
  - Characterising different regimes of behaviour;
  - Space-time characterisation of information processing dynamics;
  - Effective network inference;
  - etc. …

Plugs

- JIDT / IDTxl

- Info Theory workshop on Tuesday / Wednesday
  → https://bit.ly/cns2022itw



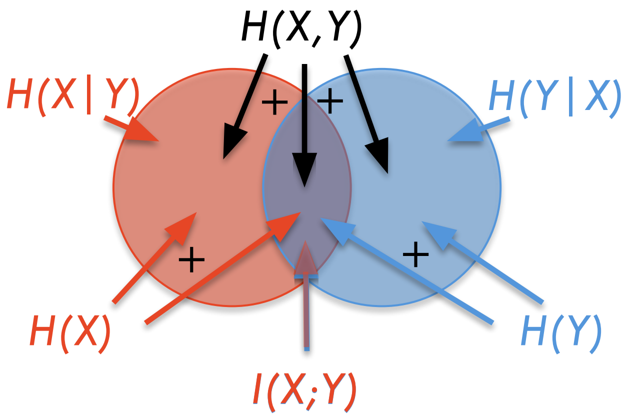
- Come study with me!

- Slides:

Questions

Fundamental measures

	Entropy (uncertainty)	Mutual information
Average		
Pointwise/local		



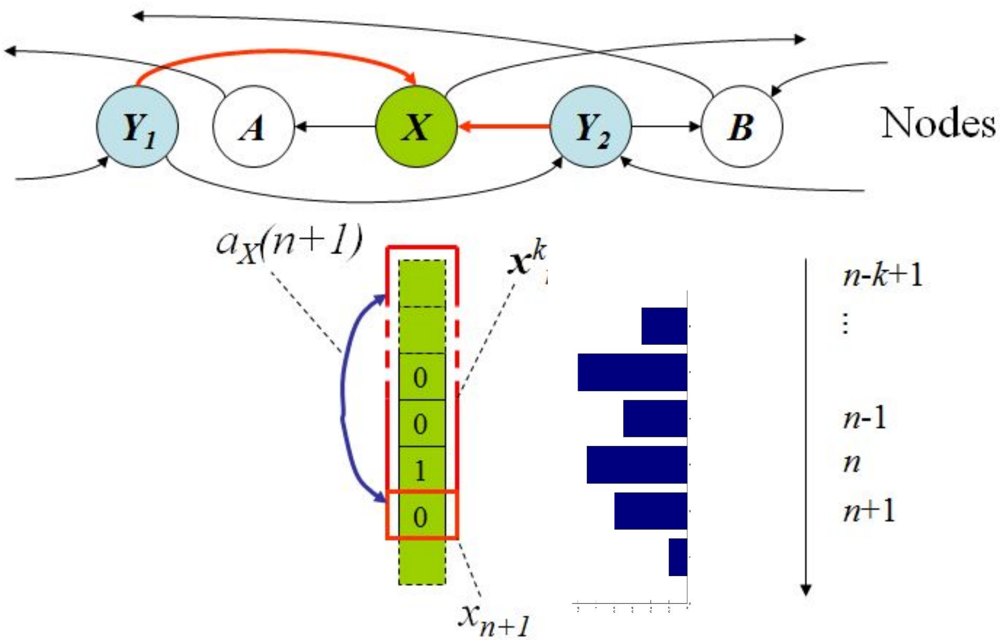
Can define:

- Joint versions,
  - e.g. $H(X,Y)$ or $H(\mathbf{X})$; and
- Conditional versions,
  - e.g. $H(X|Y)$, $I(X;Y|Z)$

Uncertainties and information in Guess Who?

Active information storage

- How much information about the next observation X_n of process X can be found in its past state $\boldsymbol{X}_n^{(k)} = \{X_{n-k+1}, \dots, X_{n-1}, X_n\}$?



Active information storage (AIS)

$$A_X(k) = I(\boldsymbol{X}_n^{(k)}; X_{n+1})$$

- Average information from past state that is in use in predicting the next value

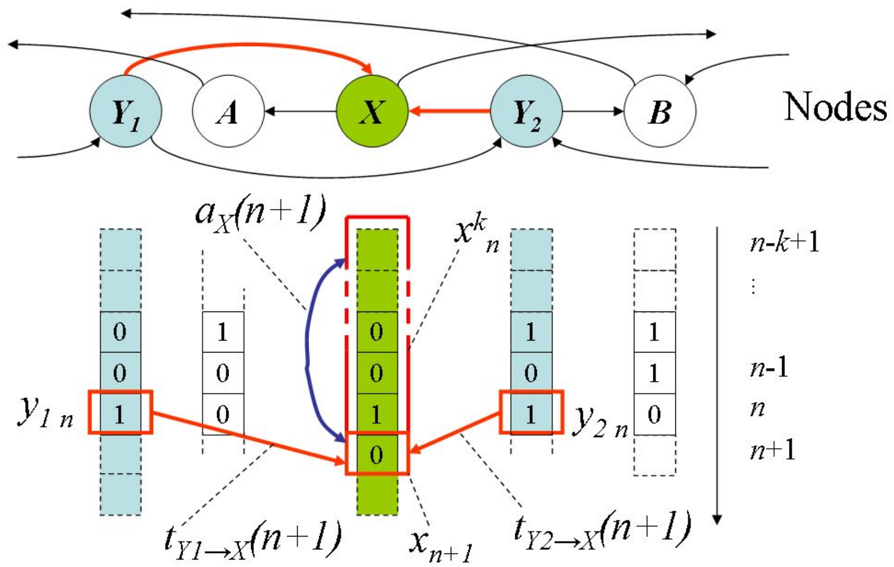
Local AIS

- Information from a specific past state in use in predicting specific next value

J.T. Lizier, M. Prokopenko, A.Y. Zomaya, "*Detecting Non-trivial Computation in Complex Dynamics*", Proc. ECAL, pp. 895-904 (2007).
J.T. Lizier, M. Prokopenko, & A.Y. Zomaya, "*Local measures of information storage in complex distributed computation*", Information Sciences 208, 39 (2012)

Transfer entropy

- How much information about the next observation X_n of process X can be found in observation Y_n of process Y, in the context of the past state $\boldsymbol{X}_n^{(k)} = \{X_{n-k+1}, \dots, X_{n-1}, X_n\}$?



Transfer entropy (TE)

$$T_{Y\to X}(k) = I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right)$$

- Average info from source that helps predict next value in context of past.
- Granger-like

Local TE

- Local TE: info from a specific source value to predict specific next value in context of past.

T. Schreiber, "*Measuring Information Transfer*", Physical Review Letters, 85(2), pp. 461-4, 2000.

J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "*Local information transfer as a spatiotemporal filter for complex systems*". Physical Review E, 77(2):026110, 2008.

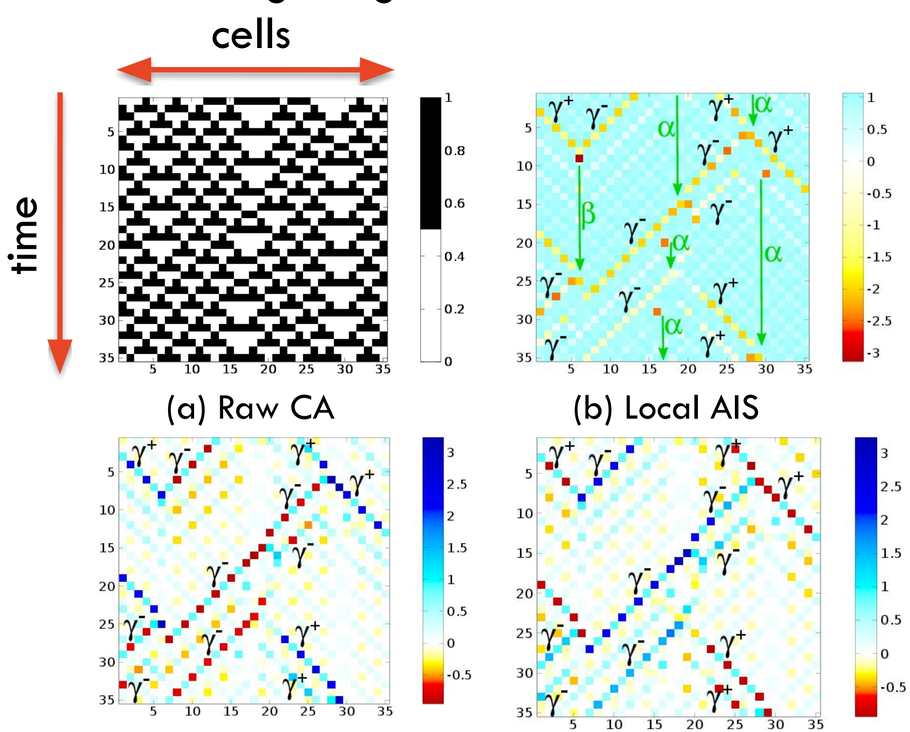
A critique of a critique of transfer entropies

- James et al. (2016) criticise 3 aspects of transfer entropies:
  1. It is not causal;
  2. Includes synergies as well as unique information; and changes on conditioning.
  3. "Shoehorns" dyadic relationships into network representation
- Resolution: It is a **model** of information flow, in juxtaposition to information storage. Responses:
  1. Known (Ay and Polani, 2008; Chicharro and Ledberg, 2012; Lizier and Prokopenko, 2010): but only this modelling perspective aligns with how we describe information processing.
  2. Known (Lizier et al., 2010; Williams and Beer, 2011): Synergies are an important part of how we describe information flow (e.g. gliders). Different models (pairwise and conditional) of flow are important components of a wholistic view of information processing; they are complementary.
  3. Disagree on interpretation (Bossomaier et al., 2016; Lizier and Rubinov, 2012): More later …

R. G. James, N. Barnett, and J. P. Crutchfield. "Information flows? a critique of transfer entropies". Physical Review Letters, 116:238701+, 2016

Example: modelling information processing in CAs

- Transfer entropy perspective aligns with how we describe complex systems
  - Emergent glider structures have strongest information transfer values.



(a) Raw CA

(b) Local AIS

(c) Local TE right

(d) Local TE left

Blinkers and background domains are dominant storage entities!

Links algorithmic and implementation levels

Gliders are dominant transfer entities!

J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "*Local information transfer as a spatiotemporal filter for complex systems*". Physical Review E, 77(2):026110, 2008.

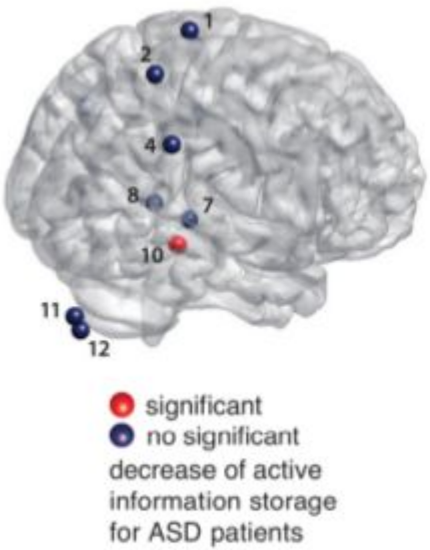
J.T. Lizier, "JIDT: An Information-Theoretic toolkit for studying the dynamics of complex systems". Frontiers in Robotics and AI, 1:11, 2014.

1. Characterising different regimes of behaviour

Aim: to characterise behaviour and responses in terms of information processing

- For example:

W.r.t neural conditions:
ASD vs controls



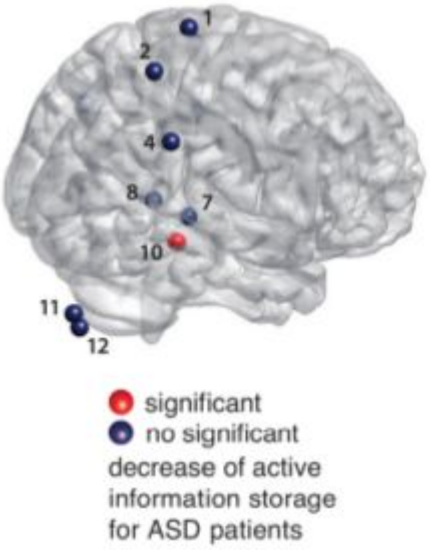
W.r.t different stimuli

Regarding critical dynamics

Does information storage use change in ASD?

Two MEG studies contrasting active information storage in resting state activity of ASD subjects vs controls:

- [1] 10x14, 12 sources;
- [2] 19x19, 478 sources.



Lower information storage overall and in:

- hippocampus [1],
- precuneus, posterior cingulate cortex, supramarginal gyrus (all DMN) [2].

of Autism Spectrum Disorder subjects.

[1] C. Gómez, et al., "Reduced predictable information in brain signals in autism spectrum disorder", Frontiers in Neuroinformatics, 8:9+, 2014.
[2] A. Brodski-Guerniero, et al., "Predictable information in neural signals during resting state is reduced in autism spectrum disorder", Human Brain Mapping, 39(8):3227–3240, 2018

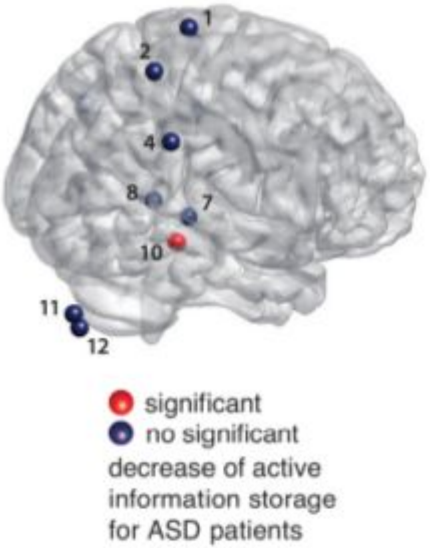
Does information storage use change in ASD?

– Lower information storage overall and in particular areas for ASD subjects.

→ Use/precision of prior reduced at source level

– Decrease correlates with symptom severity (ADI-R rit) for cerebellum and precuneus.

– No significant changes for α power, ACT nor signal entropy.



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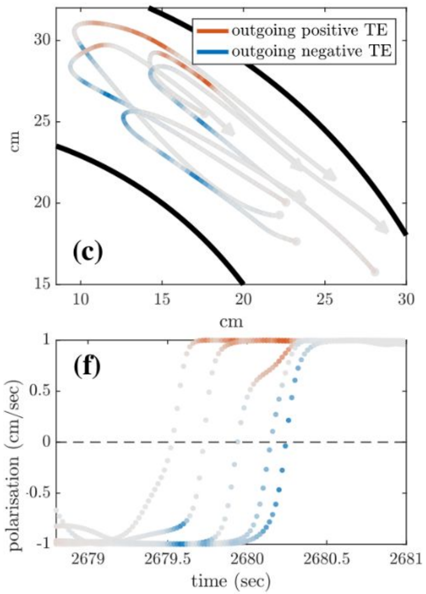
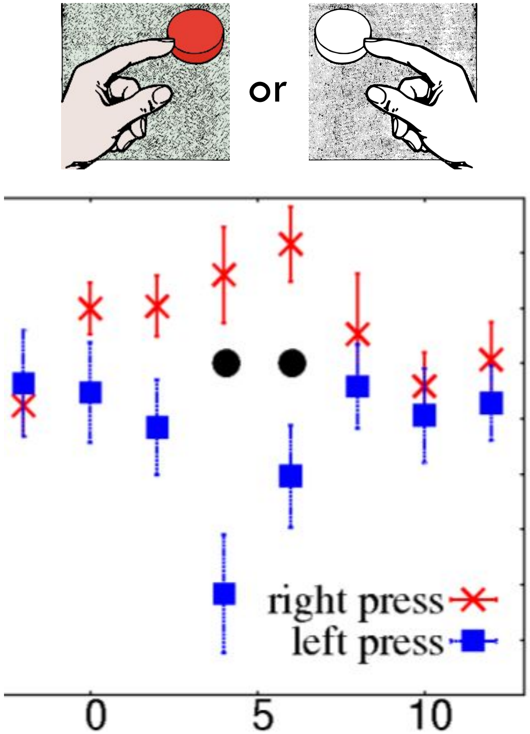
[2] A. Brodski-Guerniero, et al., "Predictable information in neural signals during resting state is reduced in autism spectrum disorder", Human Brain Mapping, 39(8):3227–3240, 2018

2. Space-time characterization of info processing

Aim:

– Highlight info processing hot-spots;
– Use info processing to explain dynamics;
– Validate conjectures on neural information processing.





E. Crosato *et al.*, "*Informative and misinformative interactions in a school of fish*", Swarm Intelligence, 12(4), pp.283-305, 2018
J.T. Lizier *et al.*, "Spatiotemporal information transfer pattern differences in motor selection", BMC Neuroscience 12 (Suppl. 1): P261, 2011

2. Space-time characterization of info processing

Predictive coding makes conjectures regarding when and where information should be stored and transferred in layered structure.

In our MEG recordings from a Mooney face/house detection experiment (52 subjects, 960 trials), suggests that when priming for a face:

Top — Face-specific area 1

Transfer ↑ ✔, {aIT, PPC} → FFA

Transfer $\propto \alpha/\beta$ ✔

Bottom — Face-specific area 2

Storage ↑ ✔

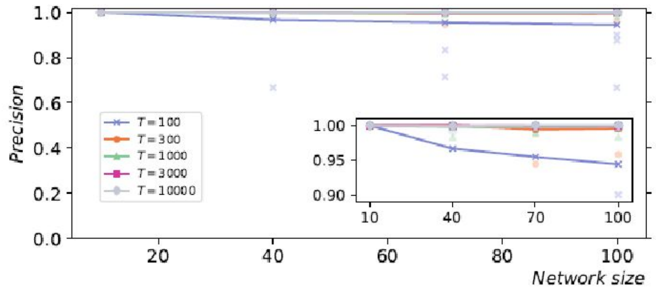
Storage $\propto \alpha/\beta$ ✔

Storage $\propto$ performance ✔

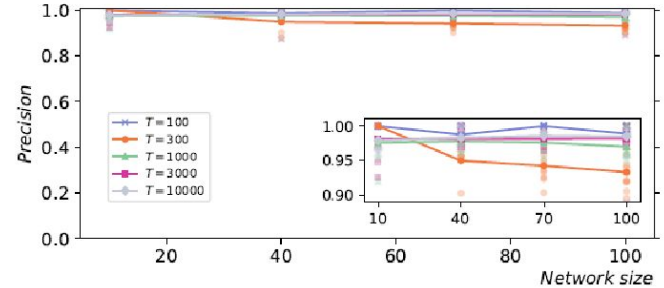
A. Brodski-Guerniero, et al., "Information theoretic evidence for predictive coding in the face processing system". J. Neuroscience, 37(34):8273–8283, 2017

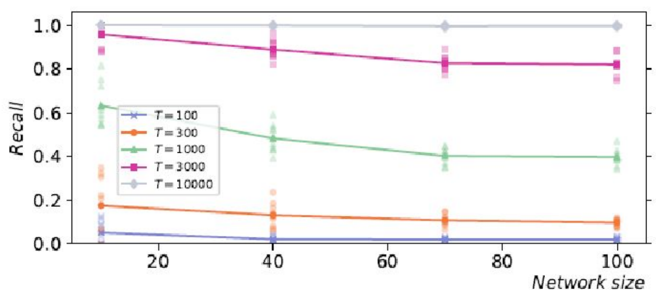
2. Effective network modelling

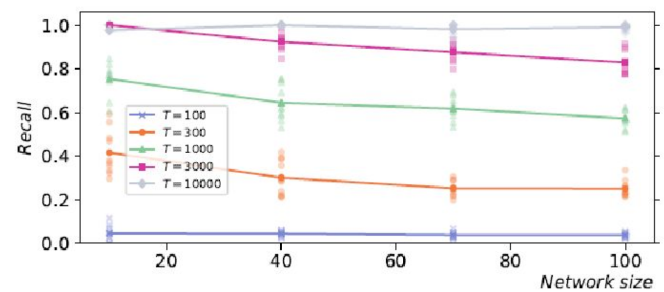
Vector auto-regressive



Coupled logistic maps







Group differences