What information dynamics can tell us about ... brains

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Computation

Computer science view:

- Primary theoretical (abstract) model is a Turing Machine
- A deterministic state machine operating on an infinite tape
- Well-defined inputs, outputs, algorithm (update rules), terminating condition

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Computation

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

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M. Mitchell, “Introduction to Complexity”, Lecture 7
Intrinsic computation

+ inputs
Intrinsic computation

The dynamical process involves inputs and outputs:

+ inputs

$\rightarrow$

dynamical process

$\rightarrow$

+ outputs
Intrinsic computation

Intrinsic information processing occurs whenever a system undergoes a dynamical process changing its initial state (+inputs) into some later state (+outputs)
Information dynamics and computation

Intrinsic computation

- Information processing in the brain
- Time evolution of cellular automata
- Gene regulatory networks computing cell behaviours
- Flocks computing their collective heading
- Ant colonies computing the most efficient routes to food
- The universe is computing its own future!
Information dynamics and computation

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Information dynamics and computation

We *talk* about computation as:

- Memory
- Signalling
- Processing

**Intrinsic computation** is any process involving these features:

- Information processing in the brain
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Idea: quantify computation via:

- Information storage
- Information transfer
- Information modification

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General idea: by quantifying intrinsic computation in the language it is normally described in, we can understand how nature computes and why it is complex.
Information dynamics
  Measures of information dynamics

Application areas
  Characterising different regimes of behaviour
  Space-time characterisation of information processing
  Relating complex network structure to function

Wrap-up
Information dynamics

Key question: how is the next state of a variable in a complex system **computed**?
It is the output of a local computation within the system.

**Q:** Where does the information in $x_{n+1}$ come from (inputs), and how can we measure it?

**Q:** How much was stored, how much was transferred, can we partition them or do they overlap?

Complex system as a multivariate **time-series** of states
Information dynamics

Models computation of the next state of a target variable in terms of information storage, transfer and modification: (Lizier et al., 2008, 2010, 2012b)

The measures examine:

- State updates of a target variable;
- Dynamics of the measures in space and time.
Information-theoretic quantities

Shannon entropy

\[ H(X) = - \sum_x p(x) \log_2 p(x) \]

\[ = \langle - \log_2 p(x) \rangle \]

Conditional entropy

\[ H(X|Y) = - \sum_{x,y} p(x, y) \log_2 p(x|y) \]

Mutual information (MI)

\[ I(X; Y) = H(X) + H(Y) - H(X, Y) \]

\[ = \sum_{x,y} p(x, y) \log_2 \frac{p(x|y)}{p(x)} \]

\[ = \langle \log_2 \frac{p(x|y)}{p(x)} \rangle \]

Conditional MI

\[ I(X; Y|Z) = H(X|Z) + H(Y|Z) - H(X, Y|Z) \]

\[ = \langle \log_2 \frac{p(x|y, z)}{p(x|z)} \rangle \]
Active information storage (Lizier et al., 2012b)

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

Active information storage:

Nodes $A_X = I(X_{n+1}; X_n^{(k)})$

$= \left\langle \log_2 \frac{p(x_{n+1}|x_n^{(k)})}{p(x_{n+1})} \right\rangle$

Average information from past state that is in use in predicting the next value.
Active information storage (Lizier et al., 2012b)

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

**Active information storage:**

$$A_X = I(X_{n+1}; X^{(k)}_n) = \langle \log_2 \frac{p(x_{n+1}|x^{(k)}_n)}{p(x_{n+1})} \rangle$$

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

**Local active information storage:**

$$a_X(n) = \log_2 \frac{p(x_{n+1}|x^{(k)}_n)}{p(x_{n+1})}$$

Information from a specific past state that is in use in predicting the specific next value.
Interpreting local active information storage

Cellular automata example:

Informative storage during regular patterns (domains and blinkers);
Misinformative storage at gliders, with change in phase or pattern of activity
(Lizier et al., 2007-2012)

JIDT Toolkit on github
Information transfer

How much information about the state transition $X_n^{(k)} \rightarrow X_{n+1}$ of $X$ can be found in the past state $Y_n^{(l)}$ of a source process $Y$?

Transfer entropy: (Schreiber, 2000)

$$T_{Y \rightarrow X} = I(Y_n^{(l)} ; X_{n+1} | X_n^{(k)})$$

$$= \left\langle \log_2 \frac{p(x_{n+1} | x_n^{(k)}, y_n^{(l)})}{p(x_{n+1} | x_n^{(k)})} \right\rangle$$

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

Storage and transfer are complementary:

$$H_X = A_X + T_{Y \rightarrow X} + \text{higher order terms}$$
Information transfer

How much information about the state transition $X_n^{(k)} \rightarrow X_{n+1}$ of $X$ can be found in the past state $Y_n^{(1)}$ of a source process $Y$?

Transfer entropy: (Schreiber, 2000)

$$T_{Y \rightarrow X} = I(Y_n^{(1)} ; X_{n+1} \mid X_n^{(k)}) = \left\langle \log_2 \frac{p(x_{n+1} \mid x_n^{(k)}, y_n^{(1)})}{p(x_{n+1} \mid x_n^{(k)})} \right\rangle$$

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

Local transfer entropy: (Lizier et al., 2008)

$$t_{Y \rightarrow X}(n) = \log_2 \frac{p(x_{n+1} \mid x_n^{(k)}, y_n^{(1)})}{p(x_{n+1} \mid x_n^{(k)})}$$

Information from a specific observation about the specific next value.
Information dynamics in CAs

Gliders are the dominant information transfer entities.

Misinformative transfer in opposite direction

Lizier et al. (2007-2012) JIDT Toolkit
Information dynamics

We talk about computation as:

- Memory
- Signalling
- Processing

Key properties of the information dynamics approach:

- A focus on individual operations of computation rather than overall complexity;
- Alignment with descriptions of dynamics in specific domains;
- A focus on the local scale of info dynamics in space-time;
- Information-theoretic basis directly measures computational quantities:
  - Captures non-linearities;
  - Is applicable to, and comparable between, any type of time-series.
Application areas of information dynamics

Key question: what can it tell us about neural information processing?
Application areas of information dynamics

Key question: what can it tell us about neural information processing?

1. Characterising different regimes of behaviour;
2. Space-time characterisation of information processing;
3. Relating network structure to function;
4. ...
1. Characterising different regimes of behaviour

Idea:

- Characterise behaviour and responses in terms of information processing;
- e.g. different neural conditions.

Lower AIS in hippocampus of Autism Spectrum Disorder subjects (Gómez et al., 2014)
2. Space-time characterisation of info processing

Idea:

- Highlight information processing hot-spots;
- Use information processing to explain dynamics.

Classic example: cellular automata

(Wibral et al., 2015)
2. Space-time characterisation of info processing

Idea:

- Highlight information processing hot-spots locally;
- Use information processing to explain dynamics.

Local TE reveals coherent information cascades in flocking dynamics (Wang et al., 2012).
2. Space-time characterisation of info processing

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Computational neuroscience examples:

- High local TE to motor control during button pushes (Lizier et al., 2011a)
2. Space-time characterisation of info processing

Idea:

- Highlight information processing hot-spots locally;
- Use information processing to explain dynamics.

Computational neuroscience examples:

- High local TE to motor control during button pushes (Lizier et al., 2011a)
- Local AIS reveals stimulus preferences and surprise on stimulus change in visual cortex (Wibral et al., 2014):
2. Space-time characterisation of info processing

Idea:

- Validate conjectures on neural information processing.

**Predictive coding** suggests that in a Mooney face detection experiment (Brodski-Guerniero et al., 2017):

- TE $\uparrow$
- TE $\propto \alpha/\beta$
- AIS $\uparrow$
- AIS $\propto \alpha/\beta$
- AIS $\propto$ performance
2. Space-time characterisation of info processing

Idea:

- Validate conjectures on neural information processing.

Predictive coding suggests that in a Mooney face detection experiment (Brodski-Guerniero et al., 2017):

Top

Content-specific area 1

TE \uparrow, \{aIT, PPC\} \rightarrow FFA

TE \propto \alpha/\beta

Bottom

Content-specific area 2

AIS \uparrow

AIS \propto \alpha/\beta

AIS \propto \text{performance}
2. Space-time characterisation of info processing

Idea:
- Highlight information processing hot-spots locally;
- Use information processing to explain dynamics.

How to compute transfer entropy between spike trains (Spinney et al., 2017):

![Diagram showing spike trains and transfer entropy calculations.]
3. Relating network structure to function

Idea:

- Diversity of network processes is a road-block to a unified view of the structure-function question;
- Information dynamics can address this and aligns with description of dynamics on complex networks.
- Transfer entropy is an ideal tool for effective network inference.
3.a Theoretical results

In a small-world network transition: (Lizier et al., 2011b)

Random Boolean dynamics, $\bar{K} = 4$, $r = 0.36$, $N = 264$
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In a small-world network transition: (Lizier et al., 2011b)

1. Info storage dominates dynamics of regular networks

Info storage is supported by clustered structure – contributions of feedback and forward motifs identified (Lizier et al., 2012a).
3. a Theoretical results

In a small-world network transition: (Lizier et al., 2011b)

1. Info storage dominates dynamics of regular networks →

![Diagrams](a) $w_{i,2}^{cyc}$ (b) $w_{i,3}^{cyc}$ (c) $w_{i,3}^{fwd}$

Info storage is supported by clustered structure – contributions of feedback and forward motifs identified (Lizier et al., 2012a).

Info transfer is promoted by long links as network is randomised. In-degree and betweeness centrality correlated to higher transfer capability (Ceguerra et al., 2011; Lizier et al., 2009).

2. Info transfer dominates dynamics of random networks ←

Random Boolean dynamics, $\bar{K} = 4$, $r = 0.36$, $N = 264$
3.a Theoretical results
In a small-world network transition: (Lizier et al., 2011b)

1. Info storage dominates dynamics of regular networks

2. Info transfer dominates dynamics of random networks

3. Balance near small-world regime

Info storage is supported by clustered structure – contributions of feedback and forward motifs identified (Lizier et al., 2012a).
Info transfer is promoted by long links as network is randomised.
In-degree and betweenness centrality correlated to higher transfer capability (Ceguerra et al., 2011; Lizier et al., 2009).
3.b Effective network analysis

Transfer entropy is ideally placed for the “inverse problem” — effective connectivity analysis — inferring a “minimal neuronal circuit model” that can explain the observed dynamics

(Lizier et al., 2011b)
3.b Effective network analysis

Transfer entropy is ideally placed for the “inverse problem” – effective connectivity analysis – inferring a “minimal neuronal circuit model” that can explain the observed dynamics

- TRENTOOL etc. from Lindner et al. (2011); Vicente et al. (2011); Wibral et al. (2011)
- Multivariate, iterative extensions to eliminate redundancies and incorporate synergies in a computationally feasible fashion (Lizier and Rubinov, 2012)
- New (python-based) IDTxl toolkit – https://github.com/pwollstadt/IDTxl
- Can examine, e.g. differences in networks between groups of subjects, or with experimental conditions (Wibral et al., 2011).
3.b Effective network analysis

IDTxl results:
Summary

Information dynamics delivers measures for operations on information, on a local scale in space and time, in complex systems. → We no longer have to rely on conjecture on computational properties.

What can it do for us in a neuroscience setting?

- Characterising different regimes of behaviour;
- Space-time characterisation of information processing;
- Relating network structure to function;
- etc. . .
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Advertisements!

- Java Information Dynamics Toolkit (JIDT) – http://jlizier.github.io/jidt/
- PhD scholarships available
References I


References II


