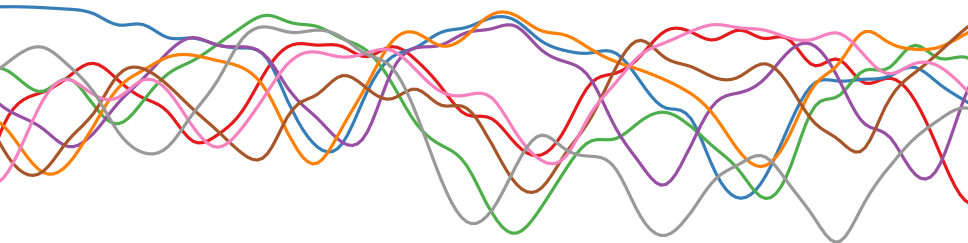


RECONCILING EMERGENCES

AN INFORMATION-THEORETIC APPROACH TO IDENTIFY
CAUSAL EMERGENCE IN MULTIVARIATE DATA



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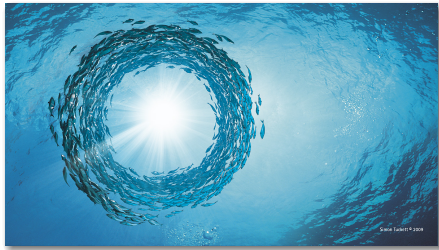
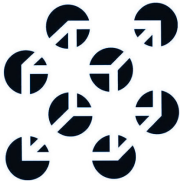
Thanks to:

- ▶ Anil Seth
- ▶ Henrik Jensen
- ▶ Robin Carhart-Harris

EMERGENCE: WHAT IT IS, AND WHY IT MATTERS

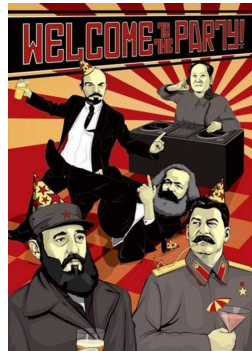
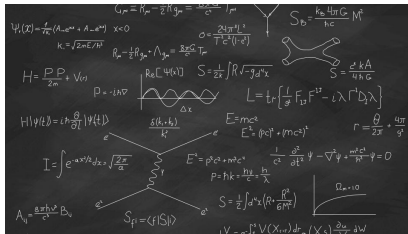


Informally: “the whole is more than the sum of its parts.”



THEORIES OF EMERGENCE

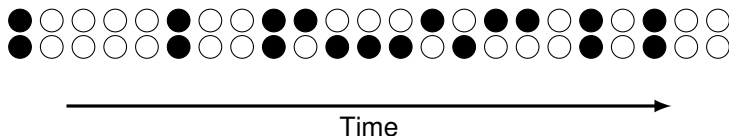
1. **Reductionism:** There's only physics. Laplace's demon rocks.
2. **Emergentism:** Some things can't be explained by "microstates."
 - 2A *Strong:* true emergence possible in principle.
 - 2B *Weak:* true emergence only apparent in practice.



CAUSAL EMERGENCE

MINIMAL EXAMPLE

- ▶ Example system with two binary variables:
 - With probability γ , the future has the same parity as the past.
 - Otherwise, they have the opposite parity.



- ▶ The dynamics are not visible in *any subset* of the system.



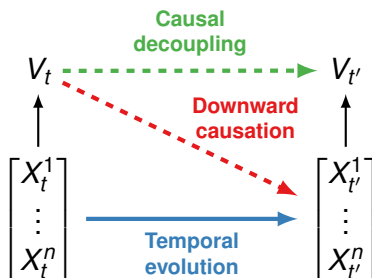
Many measures can't pick this up: $TE = MI = \Phi = 0$.



This is a minimal example of **causal emergence**.

CAUSAL EMERGENCE

OUTLINE



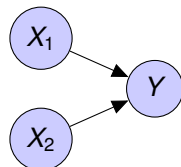
1. Provide a formal definition of causal emergence.
2. Distinguish between two different *kinds* of emergence.
3. Propose a practical criterion and show it in action.

INFORMATION DECOMPOSITION

PARTIAL INFORMATION DECOMPOSITION

Two predictors X_1, X_2 and one target Y .

- ▶ Joint predictability: $I(X_1 X_2; Y)$
- ▶ Marginal predictability: $I(X_1; Y), I(X_2; Y)$



However, sometimes:

$$\underbrace{I(X_1 X_2; Y)}_{\text{"the whole"}} > \underbrace{I(X_1; Y) + I(X_2; Y)}_{\text{"the parts"}}$$

The *Partial Information Decomposition* (PID) postulate:

$$I(X_1 X_2; Y) = \underbrace{I_{\partial}^{\{1\}\{2\}}}_{\text{redundancy}} + \underbrace{I_{\partial}^{\{1\}} + I_{\partial}^{\{2\}}}_{\text{unique info}} + \underbrace{I_{\partial}^{\{12\}}}_{\text{synergy}}$$

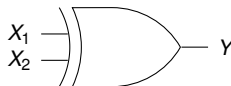
(Williams & Beer, 2010)

EXAMPLE: XOR LOGIC GATE



Perfect example of synergy: XOR.

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0



- Knowing one input tells you nothing:

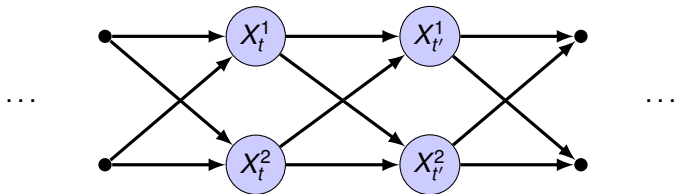
$$I(X_1; Y) = I(X_2; Y) = 0$$

- Knowing both inputs tells you everything:

$$I(X_1 X_2; Y) = 1$$

INFORMATION AND DYNAMICAL SYSTEMS

- ▶ PID decomposes information many sources have about one target.
- ▶ **BUT** we care about multivariate systems evolving *jointly* over time.



Problem: PID cannot deal with multiple targets!

INFORMATION DECOMPOSITION



Can we extend PID to multivariate time series?




Yes! With *Integrated Information Decomposition*, Φ ID.

$$I(\mathbf{X}_t; \mathbf{X}_{t'}) = \sum_{\alpha, \beta \in \mathcal{A}} I_{\partial}^{\alpha \rightarrow \beta}$$


Beyond integrated information: A taxonomy of information dynamics phenomena

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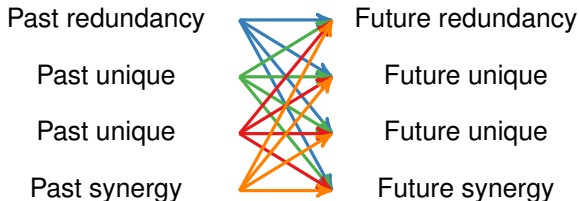
⁶The Data Intensive Science Centre, Department of Physics and Astronomy, University of Sussex, Brighton BN1 9QH, UK

INTEGRATED INFORMATION DECOMPOSITION

- In PID there are 4 terms: redundancy, unique (2x), and synergy:

$$\underbrace{I_{\partial}^{\{1\}\{2\}}}_{\text{redundancy}}, \underbrace{I_{\partial}^{\{1\}}, I_{\partial}^{\{2\}}}_{\text{unique info}}, \underbrace{I_{\partial}^{\{12\}}}_{\text{synergy}}$$

- In Φ ID, we have all combinations of past and future PID:



- In total, $4 \times 4 = 16$ terms.

INTEGRATED INFORMATION DECOMPOSITION

Examples:

- ▶ $I_{\partial}^{\{1\}\{2\} \rightarrow \{1\}\{2\}}$: redundant stored information
- ▶ $I_{\partial}^{\{1\} \rightarrow \{2\}}$: unique transferred information
- ▶ $I_{\partial}^{\{1\} \rightarrow \{1\}\{2\}}$: “duplicated” information
- ▶ ...

DEFINING EMERGENCE

PID NOTATION

- ▶ We need to define a *coarse-grained* PID:
 - $\mathbf{Un}(X \rightarrow Y|\mathbf{Z})$: unique information that X has about Y that no individual variable Z^i has.
 - $\mathbf{Syn}(\mathbf{X} \rightarrow Y)$: information about Y that no individual X^i has (but \mathbf{X} as a whole does).

DEFINING EMERGENCE

► Setting:

- System with n components $\mathbf{X}_t = (X_t^1, X_t^2, \dots, X_t^n)$
- Candidate emergent feature $V_t = F(\mathbf{X}_t)$

► Informal definition: A feature V_t that says something about the future that individual micro elements don't.

► Formal definition:

Definition (causal emergence):

A supervenient feature $V_t = F(X_t)$ exhibits causal emergence if $\text{Un}(V_t \rightarrow \mathbf{X}_{t'} | \mathbf{X}_t) > 0$.

DEFINING EMERGENCE



To compute $\mathbf{un}(V_t \rightarrow \mathbf{X}_{t'} | \mathbf{X}_t)$ we need to know V_t in advance.



Solution: use more PID!

Result:

A system has causally emergent features
if and only if $\mathbf{syn}(\mathbf{X}_t \rightarrow \mathbf{X}_{t'}) > 0$.

- Synergy quantifies the *emergence capacity* of a system.

A TAXONOMY OF EMERGENCE

- ▶ Previous definition tells us *whether* there is emergence, but not *what kind* of emergence it is.
- ▶ We introduce two types of emergence:
 - **Downward causation:** macroscopic features affect individual elements.
 - **Causal decoupling:** macroscopic features affect other macroscopic features.

A TAXONOMY OF EMERGENCE

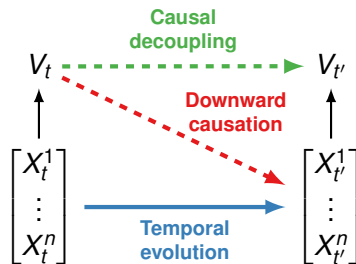
► Formal definitions:

Downward causation:

$$\text{Un}(V_t \rightarrow X_{t'}^i | \mathbf{X}_t) > 0$$

Causal decoupling:

$$\text{Un}(V_t \rightarrow V_{t'} | \mathbf{X}_t, \mathbf{X}_{t'}) > 0$$



A TAXONOMY OF EMERGENCE

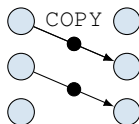


We can decompose causal emergence using Φ ID:

$$\underbrace{\mathbf{Syn}(\mathbf{X}_t \rightarrow \mathbf{X}_{t'})}_{\substack{\text{total emergence} \\ \text{capacity}}} = \underbrace{\mathcal{G}(\mathbf{X}_t)}_{\substack{\text{causal} \\ \text{decoupling}}} + \underbrace{\mathcal{D}(\mathbf{X}_t)}_{\substack{\text{downward} \\ \text{causation}}}$$

SIMPLE EXAMPLES

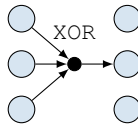
- Example: as feature, take V_t as the parity of \mathbf{X}_t .



$$\text{Un}(V_t \rightarrow \mathbf{X}_{t'} | \mathbf{X}_t) = 0$$

$$\mathcal{D}(\mathbf{X}_t) = \mathcal{G}(\mathbf{X}_t) = 0$$

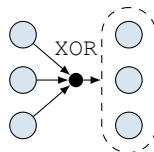
✗ Not emergent



$$\text{Un}(V_t \rightarrow \mathbf{X}_{t'} | \mathbf{X}_t) = 1$$

$$\mathcal{D}(\mathbf{X}_t) = 1$$

✓ Emergent



$$\text{Un}(V_t \rightarrow \mathbf{X}_{t'} | \mathbf{X}_t) = 1$$

$$\mathcal{G}(\mathbf{X}_t) = 1$$

✓ Emergent

PRACTICAL TOOLS



A feature V_t is causally emergent **if** $\Psi > 0$.

$$\Psi_{t,t'}^{(k)}(V) := I(V_t; V_{t'}) - \sum_{j=1}^n I(X_t^j; V_{t'})$$

Pros:

- ✓ Uses only standard mutual information.
- ✓ Uses only pairwise marginals (no curse of dimensionality).
- ✓ No false positives.

Cons:

- ✗ Needs a candidate feature V_t .
- ✗ Double-counts redundancy (which reduces sensitivity).
- ✗ Inconclusive if $\Psi \leq 0$.

INTERIM SUMMARY

CAUSAL EMERGENCE

► So far, we have:

1. Formulated a rigorous definition of causal emergence.
2. Provided an intrinsic criterion of CE based on synergy.
3. Decomposed emergence into \mathcal{D} and \mathcal{G} .
4. Provided practical tools to test for emergence in data.

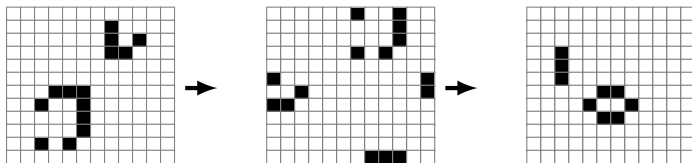
CASE STUDIES

CAUSAL EMERGENCE

RESULTS



Canonical example of emergence: the **Game of Life**.



- **Micro variable:** cell states, $\mathbf{X}_t \in \{0, 1\}^n$.
- **Macro variable:** particle type, $V_t \in \{\text{blinker}, \text{glider}, \dots\}$.

→

$$\Psi_{t,t'}(V) = 0.58 \text{ bit}$$

CAUSAL EMERGENCE

RESULTS



Example of emergence: **flocking behaviour**.

- **Micro variable:** bird position, $\mathbf{X}_t \in \mathbb{R}^{2n}$.
- **Macro variable:** center of flock, $\mathbf{V}_t \in \mathbb{R}^2$.

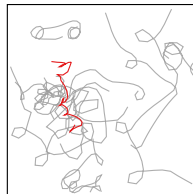
$a_2 = 0.00$



$a_2 = 0.05$



$a_2 = 0.20$



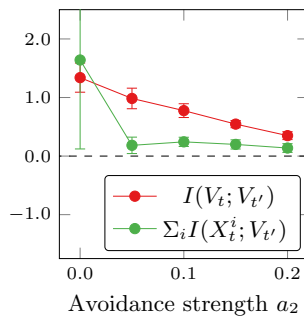
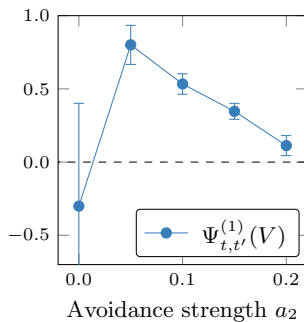
CAUSAL EMERGENCE

RESULTS



Example of emergence: **flocking behaviour**.

- **Micro variable:** bird position, $\mathbf{X}_t \in \mathbb{R}^{2n}$.
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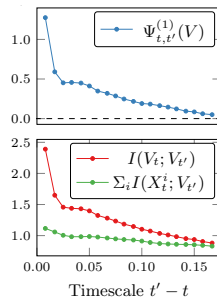
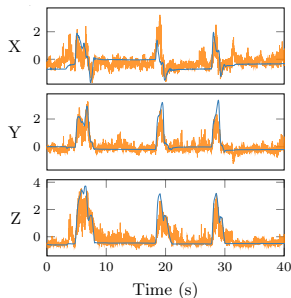
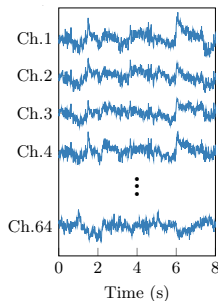
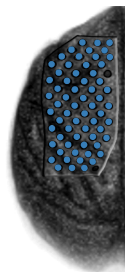
CAUSAL EMERGENCE

RESULTS



Example of emergence: **neural activity** during motor control.

- **Micro variable:** ECoG channels, $\mathbf{X}_t \in \mathbb{R}^{64}$.
- **Macro variable:** decoded hand motion, $\mathbf{V}_t \in \mathbb{R}^3$.



WRAP-UP

WRAP-UP

- ✓ We proposed a quantitative, rigorous theory of causal emergence.
- ✓ Our theory agrees with intuition in paradigmatic examples of emergence (e.g. Game of Life).
- ✓ New family of information metrics to analyse neural (or other) data.
→ www.github.com/pmediano/ReconcilingEmergences

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Thank you for listening!