An Information-theoretic Framework for Examining Information Flow in the Brain

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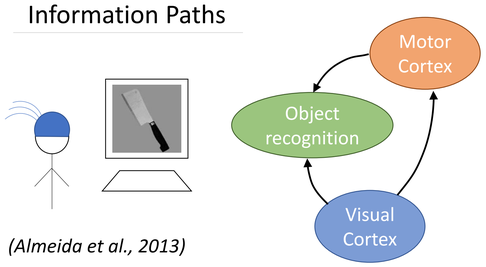
What do we want to measure?

Information Paths



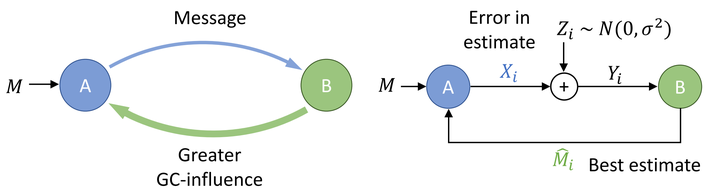
(Almeida et al., 2013)

- Info flow *between* **brain regions**
- Information is *about* a **stimulus**
- **Feedback** info-flow possible
- **Synergistic** info-flow possible

(M.I. Posner, 1980) *(Sreenivasan and Fiete, 2011)* *(Schneidman et al., 2003)*

Previous Approaches

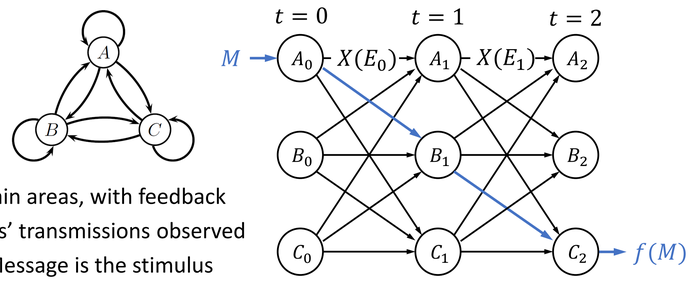
Granger Causality, Transfer Entropy, Directed Information



The direction of greater Granger causal influence can be opposite to the direction of information flow

(Venkatesh and Grover, Allerton & SfN, 2015)

A Computational Model



Brain areas, with feedback

Edges' transmissions observed

Message is the stimulus

(Thompson, 1980; Ahlswede et al., 2000; Peters et al., 2016)

In Search of a Definition

Candidate Definition I: Mutual Information

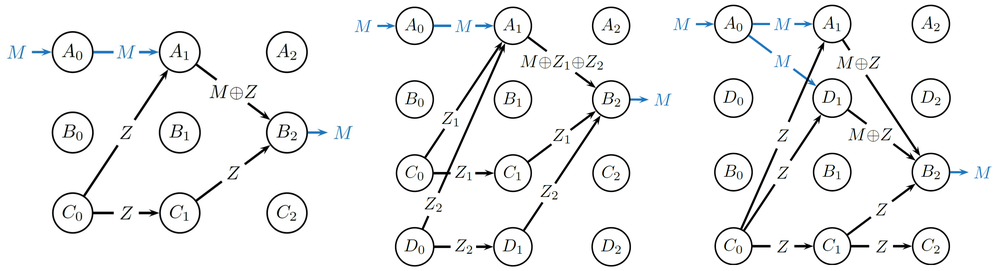
Information flows on an edge E_t if its transmission depends on M

$I(M; X(E_t)) > 0$

Candidate Definition II: Conditional Mutual Info

Conditioning on the other edge (Z) reveals the information flow!

$I(M; X(E_t)) > 0$ or $I(M; X(E_t) \mid X(E_t')) > 0$



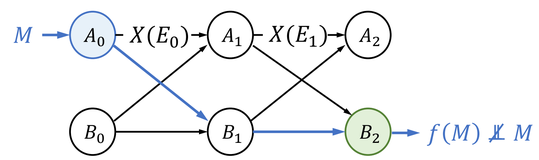
Final Definition: Condition on a *subset* of edges

Information flows on an edge E_t if $\exists\ \mathcal{E}_t' \subseteq \mathcal{E}_t$ s.t. $I(M; X(E_t) \mid X(\mathcal{E}_t')) > 0$.

Information Paths

***M*-information path:**
Every edge has M-information flow

If the transmissions of an "output" node V_t^{op} *depend* on M, then there is an M-information path leading from the input nodes to V_t^{op}.

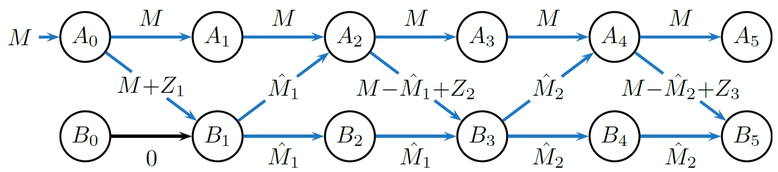


Information Flow and Feedback

Derived Information can reveal the asymmetry between the transmitter and the receiver

(Venkatesh and Grover, 2015)

M—$X(P_t')$—$X(Q_t)$

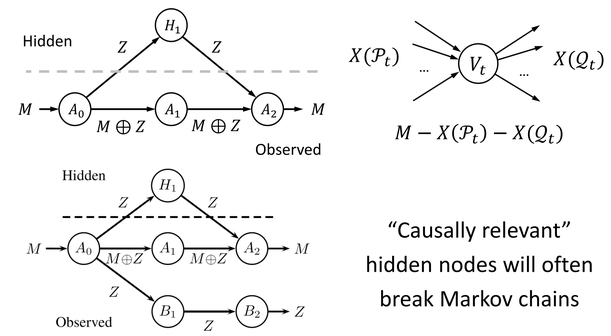


Bob's transmissions *are* M-derived from Alice's transmissions, but Alice's transmissions are *not* M-derived from Bob's transmissions

✓ M—$[M+Z,\ M-\hat{M}_1+Z_2]$—$\hat{M}_2$

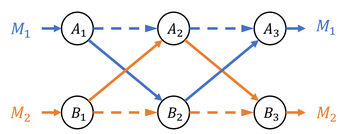
✗ M—$[\hat{M}_1, \hat{M}_2]$—$M-\hat{M}_2+Z_3$

Discovering Hidden Nodes



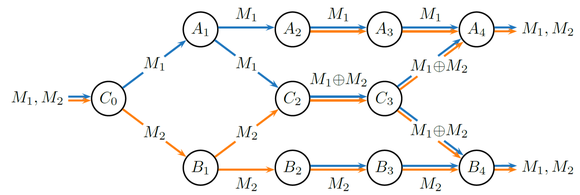
"Causally relevant" hidden nodes will often break Markov chains

Information Flow in ANNs



We can distinguish how information flows in small toy neural networks, which have known ground truth

Multiple Messages



(Ahlswede et al., 2000)

Acknowledgments

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