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Relating Information Flow and Causal Effect in Neural Circuits

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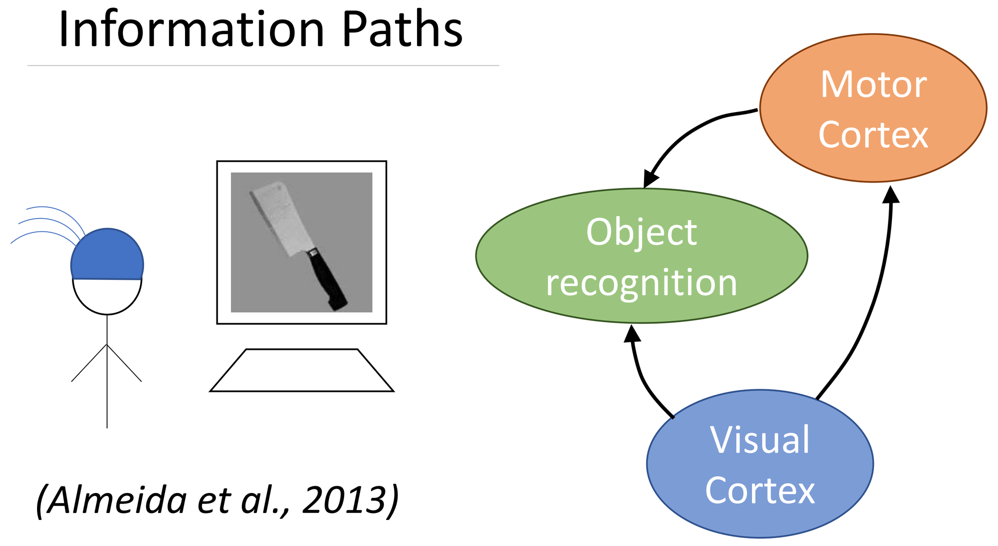
What do we want to measure?

Information Paths



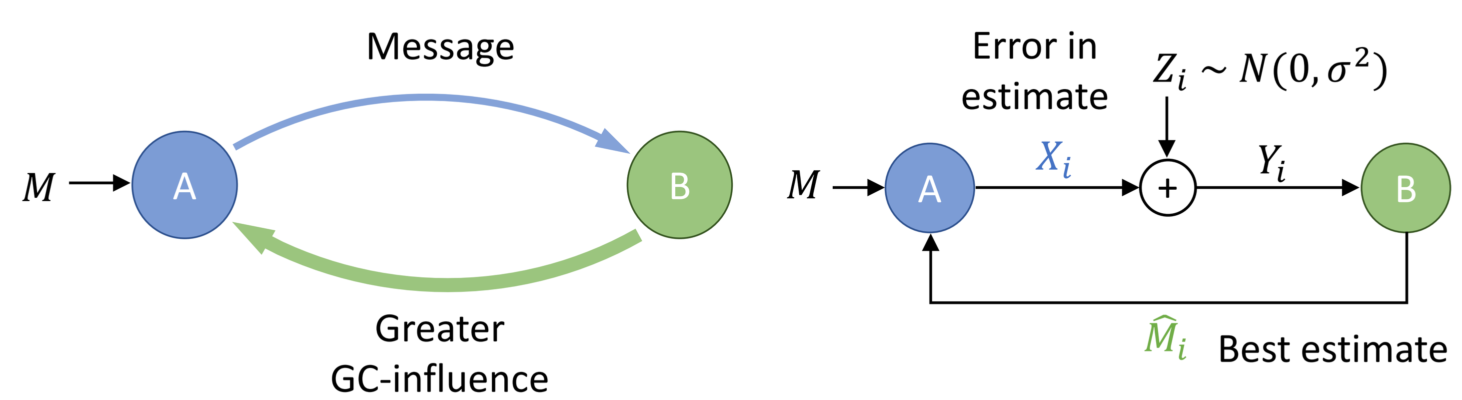
(Almeida et al., 2013)

- 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

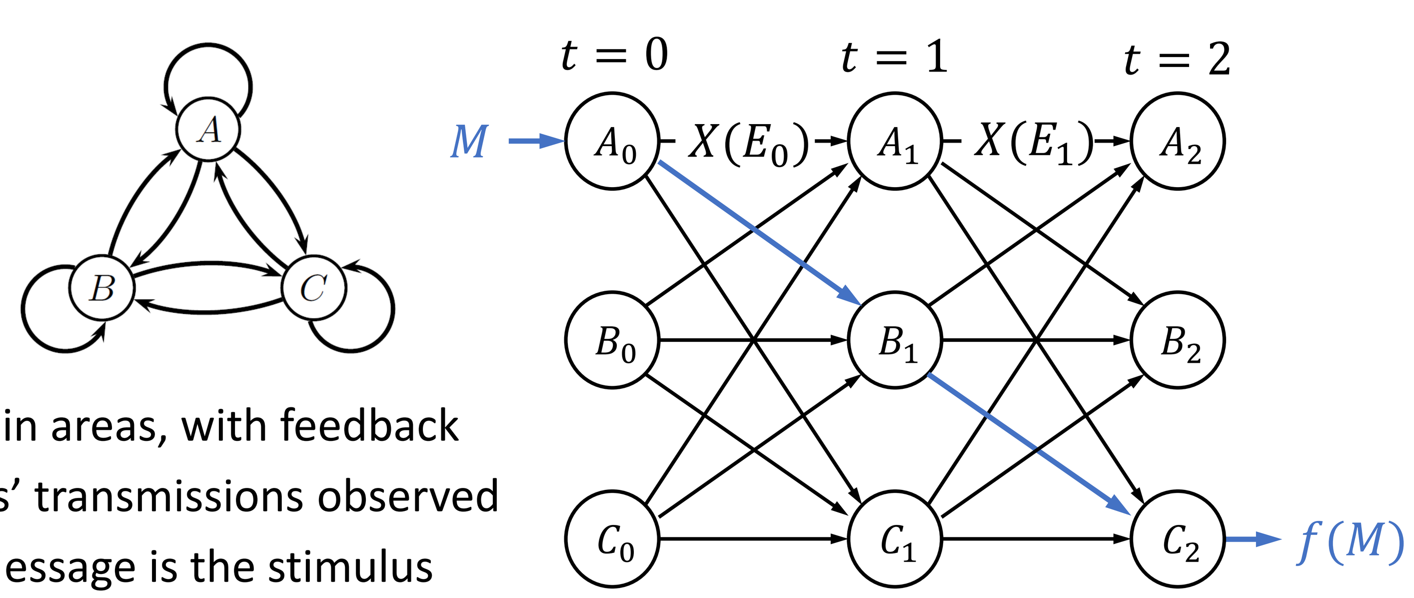
Granger Causality, Transfer Entropy, Directed Information



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

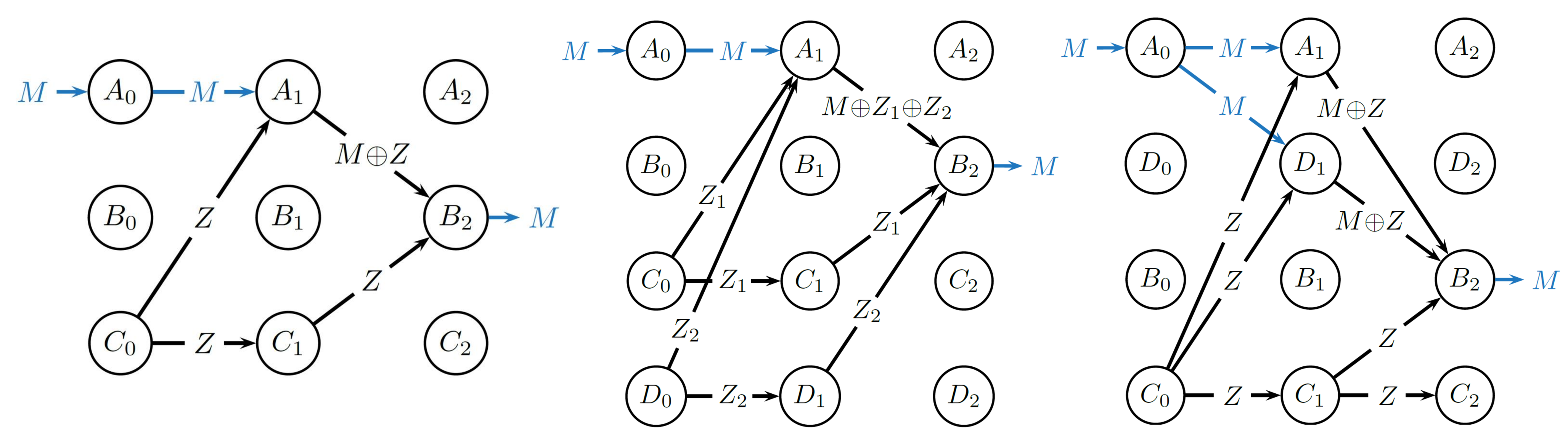


Brain areas, with feedback
Edges' transmissions observed
Message is the stimulus

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



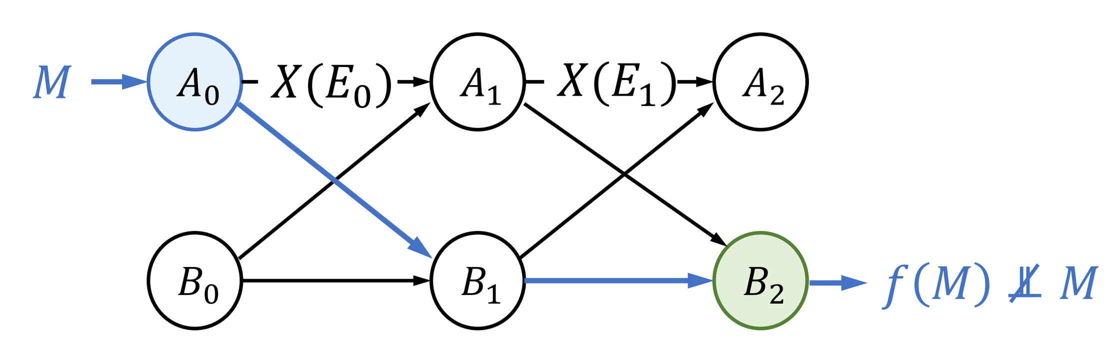
Final Definition: Condition on a *subset* of edges

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

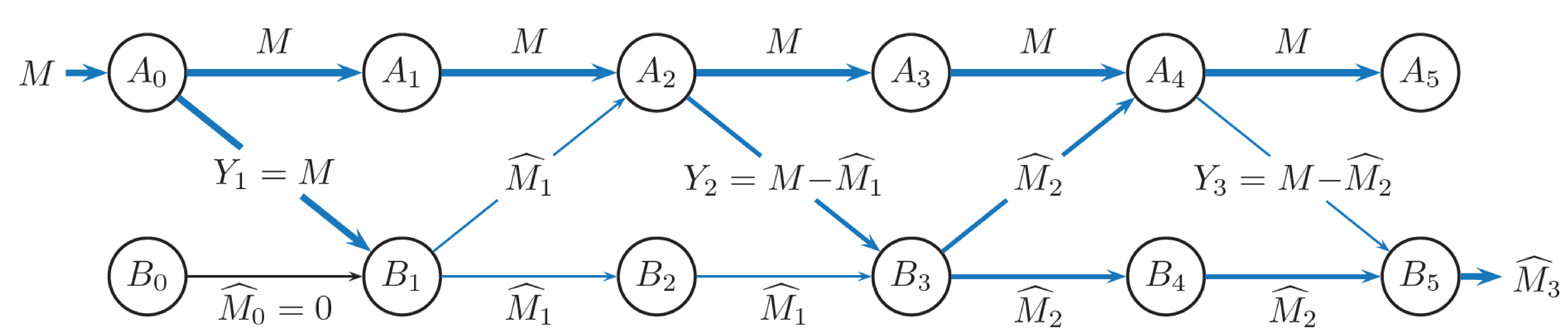
***M*-information path:**
Every edge has M-information flow

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

Quantifying information flow can reveal the asymmetry between the transmitter and the receiver

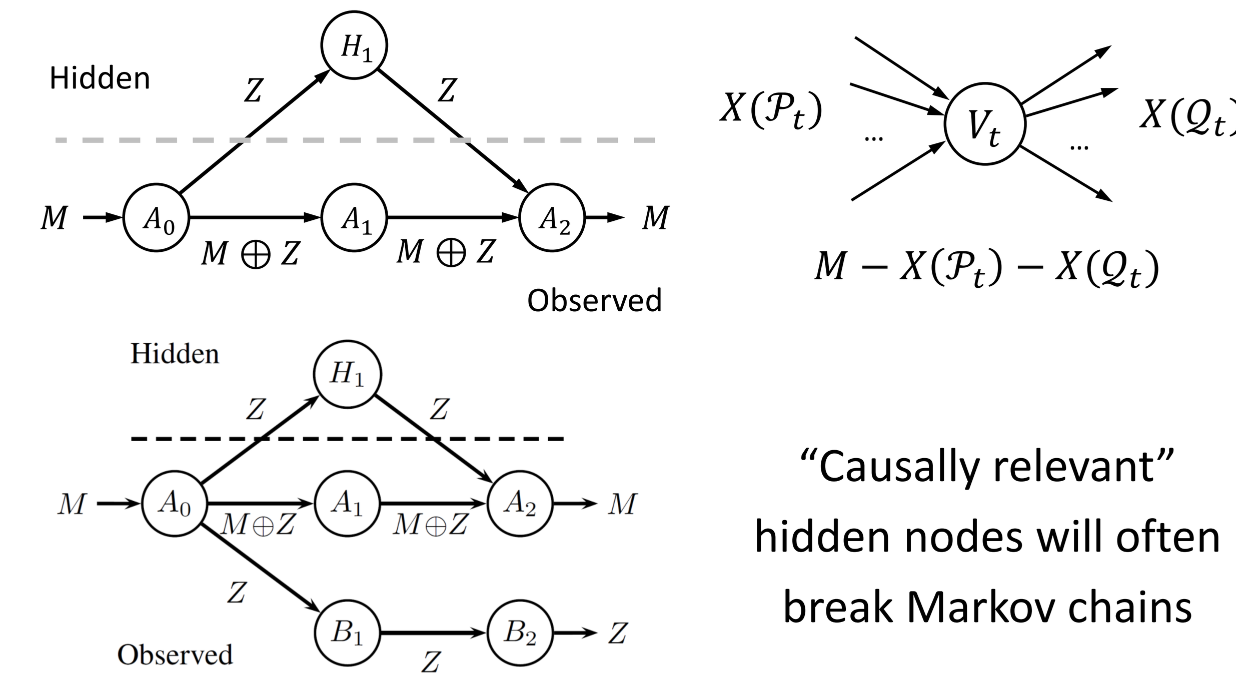


Bob's transmissions *are* M-derived from Alice's transmissions, but Alice's transmissions are *not* M-derived from Bob's transmissions

(Venkatesh et al. 2019)

✓ M—[M, $M - \widehat{M}_1$]—$\widehat{M}_2$ ✗ M—[$\widehat{M}_1$, $\widehat{M}_2$]—$M - \widehat{M}_2$

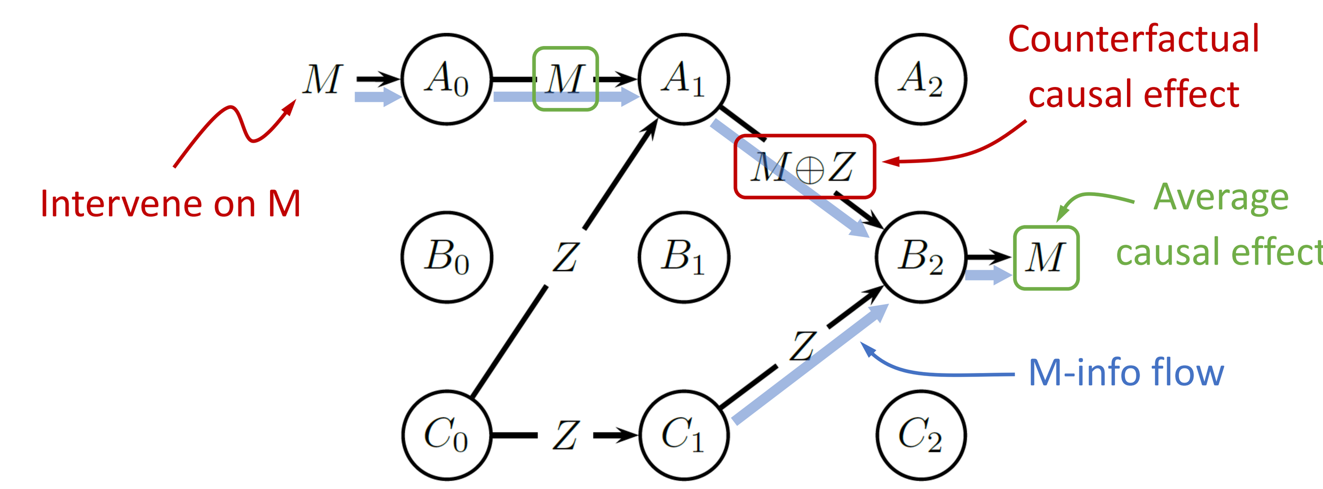
Discovering Hidden Nodes



"Causally relevant" hidden nodes will often break Markov chains

Causal Effect and Info Flow

Average causal effect at a node's output $\Rightarrow$ M-dependence $\Rightarrow$ M-information flow



Some *counterfactual* causal effects are captured by M-information flow: even if there is *no average causal effect*

Acknowledgments

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References

1. P. Venkatesh, S. Dutta and P. Grover, "Information Flow in Computational Systems", *arXiv:1902.02292 [cs.IT]*, February 2019.
2. P. Venkatesh, S. Dutta and P. Grover, "How should we define Information Flow in Neural Circuits?", *ISIT*, July 2019 *(accepted)*.
3. P. Venkatesh and P. Grover, "Is the direction of greater Granger causal influence the same as the direction of information flow?", *Allerton*, September 2015.
4. J. Almeida et al., "Tool manipulation knowledge is retrieved by way of the ventral visual object processing pathway", *Cortex*, 49 (9), 2334–2344, 2013.
5. M. I. Posner, "Orienting of Attention", *Quart. J. of Exp. Psychol.*, 32(1), 3–25, 1980.
6. S. Sreenivasan and I. Fiete, "Grid cells generate an analog error-correcting code for singularly precise neural computation", *Nature neuroscience*, 14.10: 1330, 2011.
7. E. Schneidman, W. Bialek and M. Berry, "Synergy, Redundancy and Independence in Population Codes", J. Neurosci., 23(37), 11539–11553, 2003.