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What Kind of Network is the Brain?

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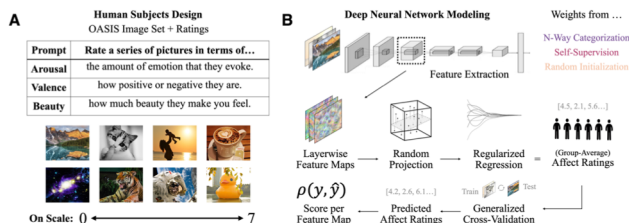
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Background

Deep neural network models appear to capture key *representational* strategies of brain networks because both systems share foundational “tricks” such as hierarchical architecture, learning from natural inputs, gradient descent, and sparse activation. For example, we recently showed that generic deep neural network computer vision models can achieve higher level cognitive abilities “for free,” and without retraining.

EXAMPLE: Visually-evoked Affect (Conwell, Graham, Boccagno & Vessel, 2024)



Results: Across a “model zoo” of 180 deep nets, model features predict an average of >50% of explainable variance in human arousal, valence, and beauty ratings of natural images—without any retraining for visually-evoked affect. Accuracy also increases with layer depth.

To the extent that brains and perceptual machines are similar, these results support the idea that **brains are networks that achieve efficient representations by employing similar basic principles as deep nets**. The predictivity of stimulus responses in visual neurons using deep net vision networks also supports this notion (e.g., Yamins et al., 2014).

But to understand brains as networks, we need to go beyond their representational properties. We need to consider brain network communication (Graham et al., 2020), which undergirds multisystem integration. Specifically, how brains achieve **routing** on networks is not understood. Little is known about basic properties of message propagation in brains such as how many “hops” (synapses) messages traverse, how much redundancy is employed, and how message-passing varies across species.

Approach

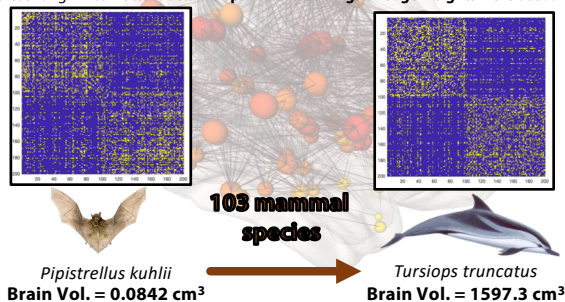
- We model message-passing on brain networks using “first principles” of network communication, and we simulate message propagation on a large collection of mammal anatomical connectomes.
- A basic design specification for any communication network is how many “hops” messages typically take traveling across the network. To investigate this in the brain, we measure message survival distance (hop count) using an “**information spreading**” model.
- Message-message interactions (**collisions**) are difficult to study analytically, requiring simulations, and are ignored in most network communication models (Seguin et al., 2023; Hao & Graham, 2020; Mišić et al., 2014). In our model, colliding messages are deleted.

Research Questions

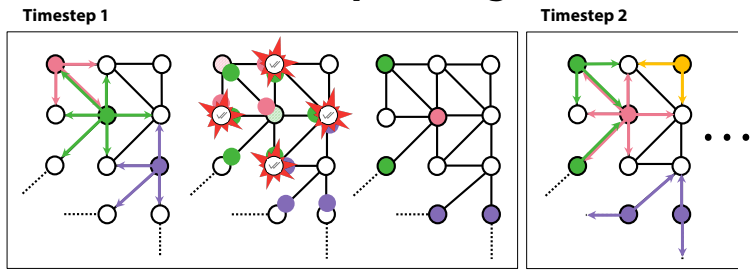
1. How far do messages typically travel on mammal brain networks in the presence of collisions?
2. How does brain size affect message survival distance?

Mammal Connectome Dataset

We generated adjacency matrices from diffusion tensor imaging-based connectomes of 190 brains from 103 mammal species in the MaMI database (Assaf et al., 2020). All are normalized to have 200 edges representing brain regions (100 per hemisphere) and 2985 bidirectional edges representing white matter tracts. **No spatial embeddings or edge weights were used.**



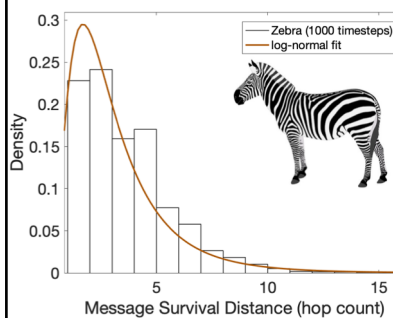
Information Spreading Model



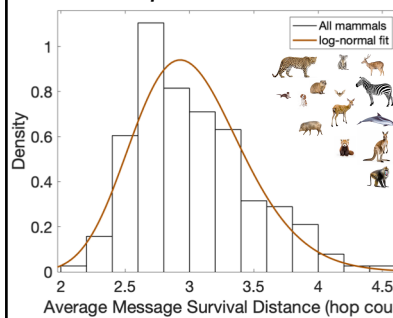
We propose a synchronous-time model of brain network communication that captures two basic principles of message-passing:

1. **Nodes spread messages to share information across the network.**
 - Nodes receiving a message then pass copies of those messages to all nearest network neighbors. New messages are injected at a fraction of randomly-chosen open nodes each time step.
 - Accords with long-range axons’ behavior of passing essentially the same excitatory message to all partners.
2. **Simultaneous arrival at nodes indicates successful completion of message-passing.**
 - Delivery success is indicated by removing simultaneously-arriving messages from the network.
 - Captures neurons’ general requirement of coincident signals from multiple inputs to become activated.

Message survival distance is log-normally distributed within a species...



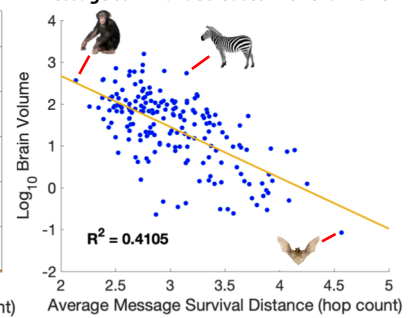
...and across species:



Results

1. Message survival distance is log-normal within species. This is an emergent effect (not dependent on spatial embedding or edge weights) and it **mirrors empirical log-normal distributions of white matter edge weights and interareal distances in mammal brains** (Horvát et al., 2016). Average message survival distance across species is also log-normal.
2. On connectomes of fixed edge and node count, **average message survival time is strongly anti-correlated with log brain volume**. Brain volume thus constrains network distance traveled independent of physical distance between regions and edge weight.

Message survival decreases with brain size



TAKE-HOME IDEAS

- Independent of physical distances and connection strengths between brain regions, simulated messages that are subject to collisions travel a range of network distances, which are distributed log-normally within species and across species.
- Not only are long-range axonal connections increasingly constrained with brain size (Zhang & Sejnowski, 2003), the network distance messages can propagate in the presence of message-message interactions is also increasingly constrained with size.
- This evidence supports the notion that **brains are networks that implement abstract principles of representation and abstract principles of routing**, and do so over a common neuronal network substrate (Graham, 2023).

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