Connectivity

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IMC INTERACTING MINDS CENTRE

CFIN

Contents

Comments on paper_1

Paper_1 comments

7 pages of 2400 characters (including spaces and references) = 16.800 characters

Paper_1 comments

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- This includes everything:
  - Abstract
  - Main text
  - Footnote/endnotes
  - etc.

Paper_1 comments

7 pages of 2400 characters (including spaces and references) = 16.800 characters

- This includes everything:
  - Abstract
  - Main text
  - Footnote/endnotes
  - etc.

From lecture_1:

- A selection of three papers with an introduction and discussion/conclusion is to be handed in as one joint submission.
- A paper can be maximum 7 normal pages
  - code goes in an appendix
  - Figures does not count.
- Introduction and discussion/conclusion is combined maximum of 7 normal pages.
- A normal page is 2400 characters *including* spaces and in-text references.
- The reference list does *not* count for the pages limits.
- Citation style is APA7

Connectivity

What is connectivity?

Connectivity

The study of connections between to brain sites

What is connectivity?

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The study of connections between to brain sites

Two main questions:

What is connectivity?

Connectivity

The study of connections between to brain sites

Two main questions:

- What is a brain site?

What is connectivity?

Connectivity

The study of connections between to brain sites

Two main questions:

- What is a brain site?
- What is a connection?

What is connectivity?

Connectivity

The study of connections between to brain sites

Two main questions:

- What is a brain site?
  - Anatomically defined
  - Functionally defined
- What is a connection?

What is connectivity?

Connectivity

The study of connections between to brain sites

Two main questions:

- What is a <u>brain site</u>?
  - Anatomically defined
  - Functionally defined
- What is a <u>connection</u>?
  - Anatomical measure (e.g. fiber track)
  - Functional measure (i.e. statistical)

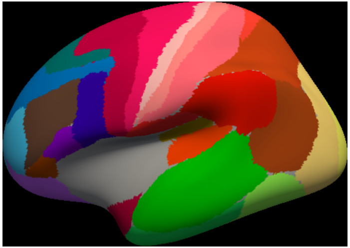
Brain areas

A priori defined:

Brain areas

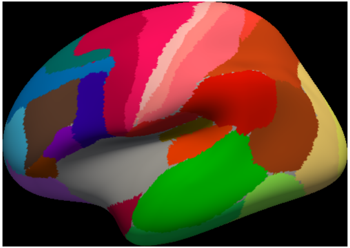
A priori defined:

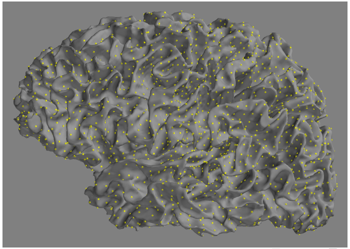
- Parcelations



A priori defined:

- Parcelations
- Source space points

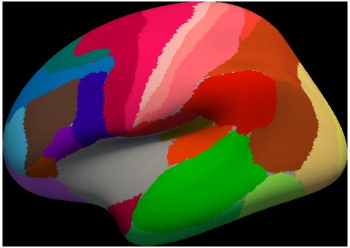


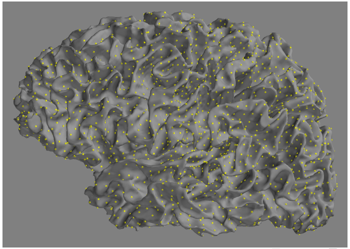


Brain areas

A priori defined:

- Parcelations
- Source space points
- Voxels



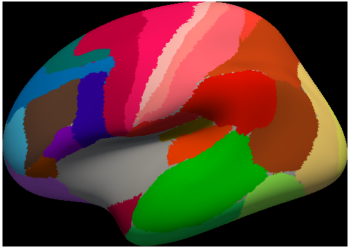


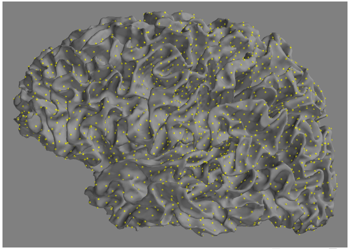
Brain areas

A priori defined:

- Parcelations
- Source space points
- Voxels

Functionally defined:





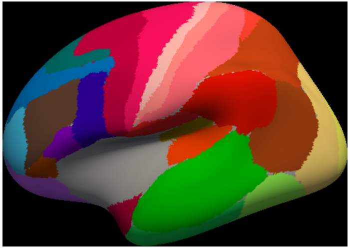
Brain areas

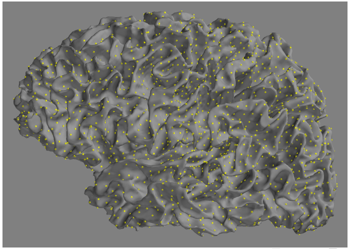
A priori defined:

- Parcelations
- Source space points
- Voxels

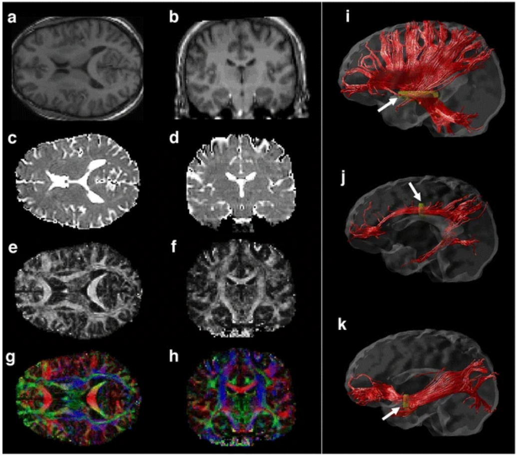
Functionally defined:

- From previous studies
  - Meta-analyses
  - Previous data from similar study/studies

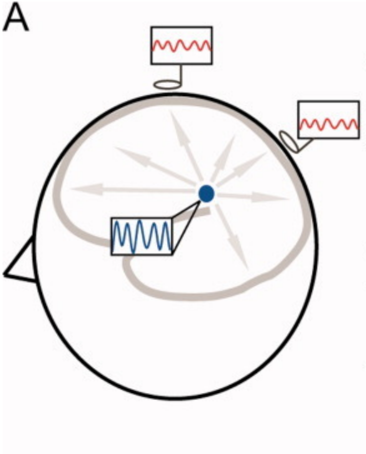




Measuring connectivity: anatomical measures

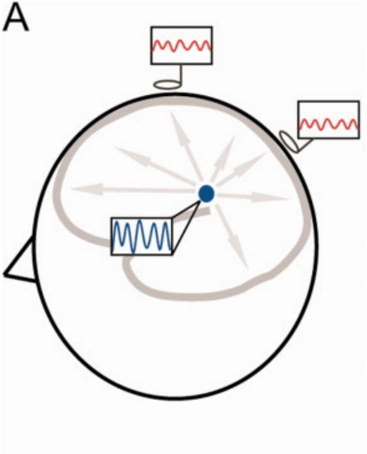


(Figure from Assaf & Pasternak, 2008)



(Figure from Schoffelen & Gross, 2009)

Measuring connectivity: statistical measures

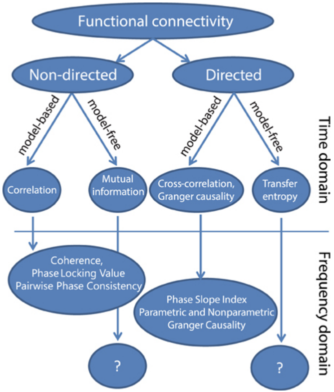


(Figure from Schoffelen & Gross, 2009)

Options in MNE-python:

- Coherence
- Coherency
- Imaginary coherence
- Phase-Locking Value (PLV)
- Corrected imaginary PLV (icPLV)
- Pairwise Phase Consistency (PPC)
- Phase Lag Index (PLI)
- Unbiased estimator of squared PLI
- Weighted Phase Lag Index (WPLI)
- Debiased estimator of squared WPLI
- Mutual information

Taxomony of functional connectivity analysis method



(Figure from Bastos & Schoffelen, 2016)

Granger causality

[A] variable X is said to G[ranger]-cause a variable Y if the past of X contains information that helps predict the future of Y over and above information already in the past of Y.[1]

(Barnett & Seth, 2014, p. 51)

[1] See also Granger (1969) for the original article.

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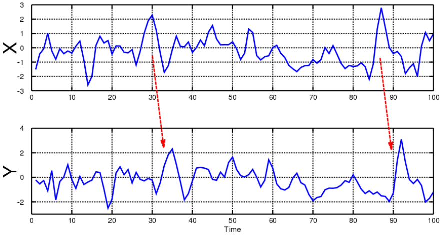

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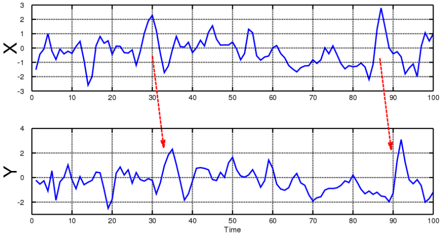

Granger causality assumes stationarity!

[1] See also Granger (1969) for the original article.

What is information?

Shannon entropy:

$$\mathrm{H}(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

"[Shannon entropy] is the amount of information, or "surprise," a variable has" (Cohen, 2014, p. 389)

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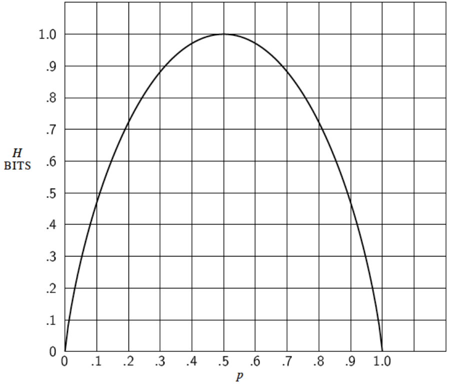
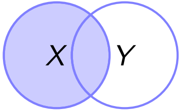


(Figure from Shannon, 1948)

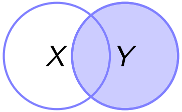
What is information?

$\mathrm{H}(X)$

Entropy X

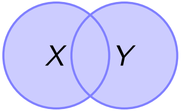


$\mathrm{H}(Y)$

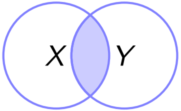


$H(X, Y)$

(Joint entropy)



Mutual information

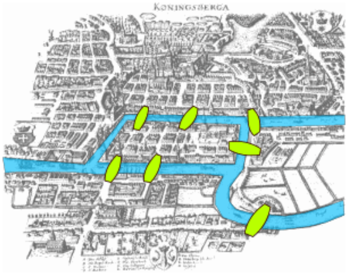


What is information?

> [T]he difference that makes a difference.
>
> (Chalmers, 1996, p. 238)

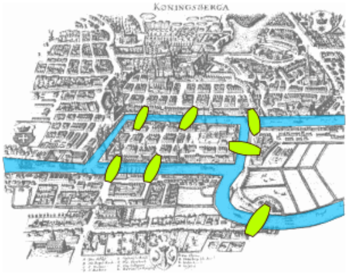
Graph theory

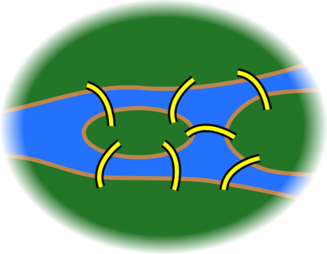
Graph theory



(Figure from https://en.wikipedia.org/wiki/Seven_Bridges_of_Konigsberg)

Graph theory





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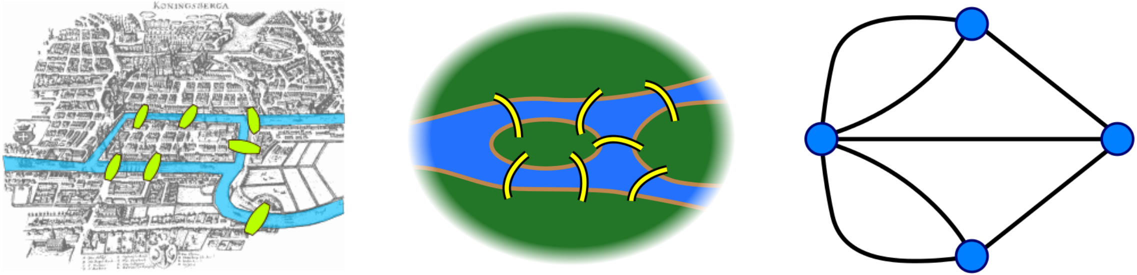

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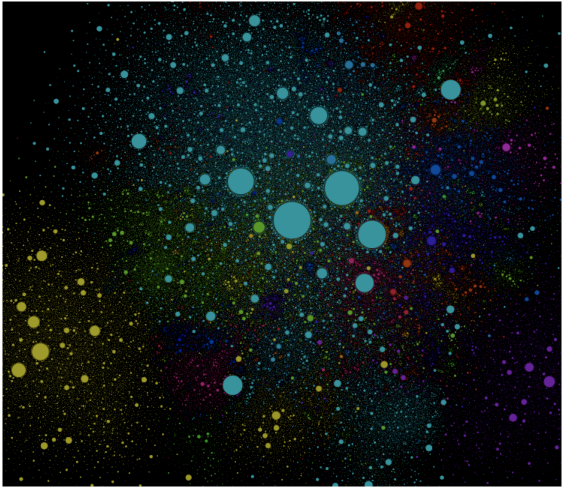
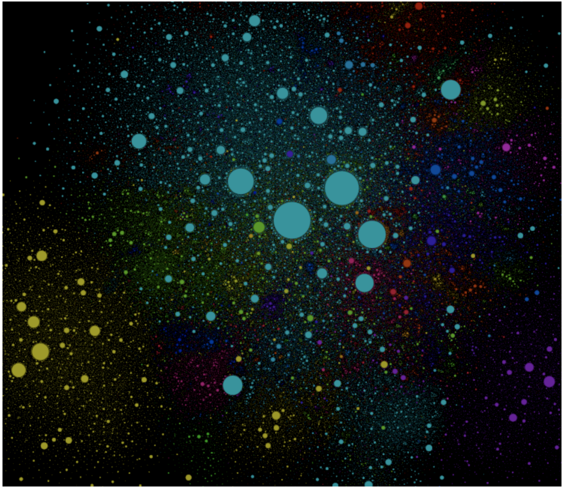
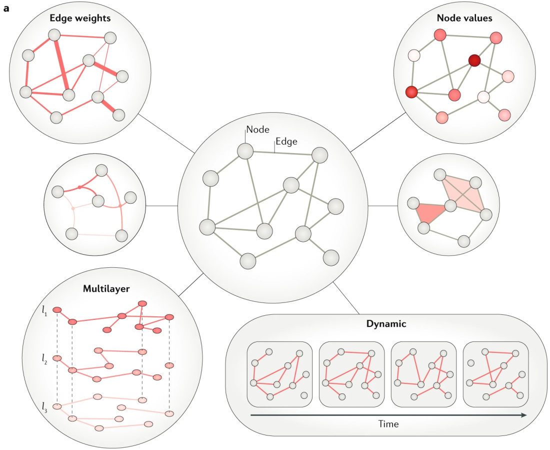


Graph theory



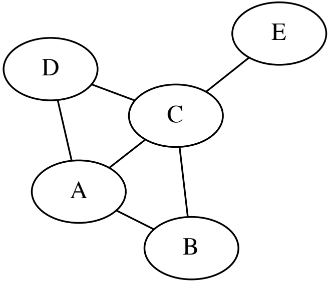
(**https://internet-map.net/**)

Graph theory measures



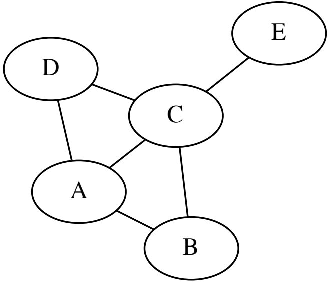
(Figure from Bassett et al., 2018)

Graph

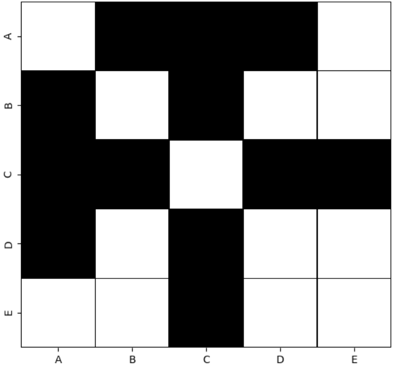


Representation of graphs

Graph



Adjacency matrix



Measures of functional segregation

"Functional segregation in the brain is the ability for specialized processing to occur within densely interconnected groups of brain regions. Measures of segregation primarily quantify the presence of such groups, known as clusters or modules, within the network." (Rubinov & Sporns, 2010, p. 1061)

Graph theory measures

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Measures of functional integration
"Functional integration in the brain is the ability to rapidly combine specialized information from distributed brain regions. Measures of integration characterize this concept by estimating the ease with which brain regions communicate and are commonly based on the concept of a path." (Rubinov & Sporns, 2010, p. 1061)

Graph theory measures

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Measures of centrality

"Important brain regions (hubs) often interact with many other regions, facilitate functional integration, and play a key role in network resilience to insult. Measures of node centrality variously assess importance of individual nodes on the above criteria." (Rubinov & Sporns, 2010, p. 1064)

Graph theory measures

Measures of functional segregation

Measures of functional integration

Measures of centrality

Graph theory measures

Measures of functional segregation

- Clustering coefficient
- Transitivty

Measures of functional integration

Measures of centrality

Measures of functional segregation

- Clustering coefficient
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Measures of functional integration

- Characteristic path length
- Global efficiency

Measures of centrality

Graph theory measures

Measures of functional segregation

- Clustering coefficient
- Transitivty

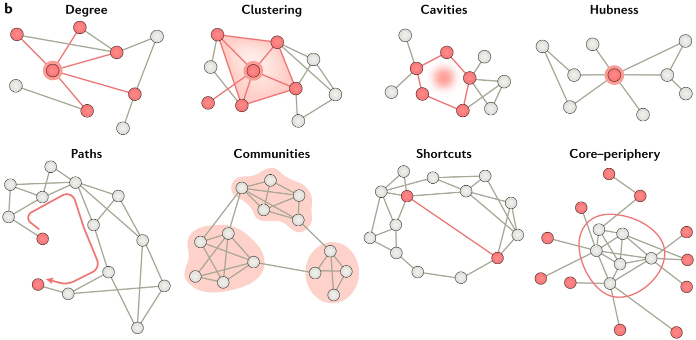
Measures of functional integration

- Characteristic path length
- Global efficiency

Measures of centrality

- Degree
- Closeness centrality
- PageRank

Graph theory measures



(Figure from Bassett et al., 2018)

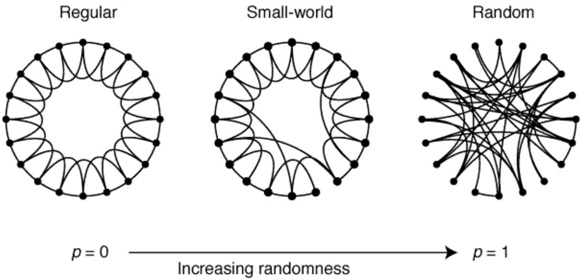
Small-world networks

Collective dynamics of 'small-world' networks

Duncan J. Watts* & Steven H. Strogatz

Department of Theoretical and Applied Mechanics, Kimball Hall, Cornell University, Ithaca, New York 14853, USA

Small-world networks



(Figure from Watts & Strogatz, 1998)

Small-world networks

$$swn = \frac{\frac{C}{C_r}}{\frac{L}{L_r}}$$

C is the clustering coefficient, L is the characteristic path length, subscript r refer to a random network.

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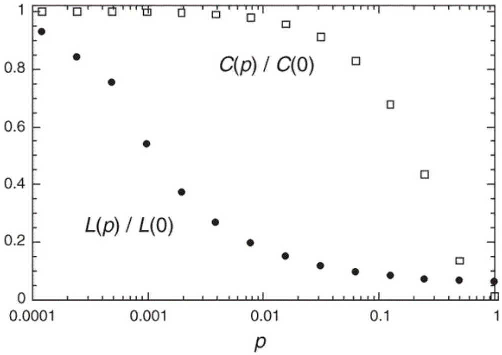
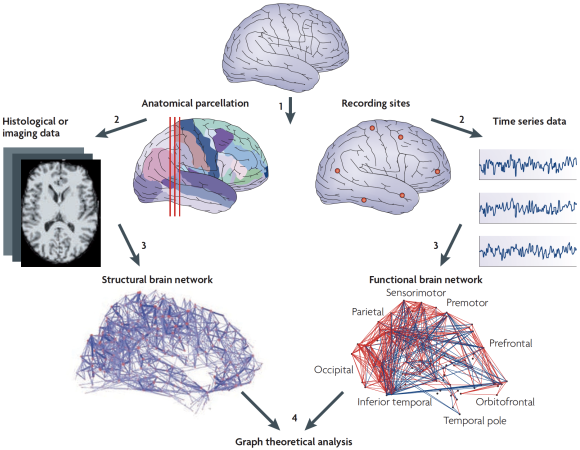


(Figure from Watts & Strogatz, 1998)

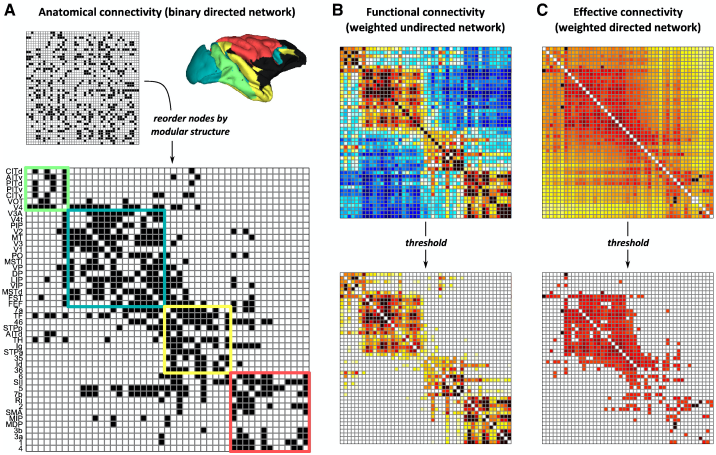
Graph theory and brain data

Graph theory and brain data

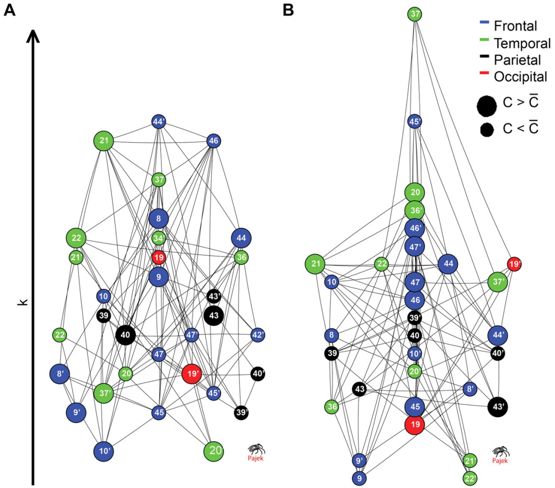


(Figure from Bullmore & Sporns, 2009)

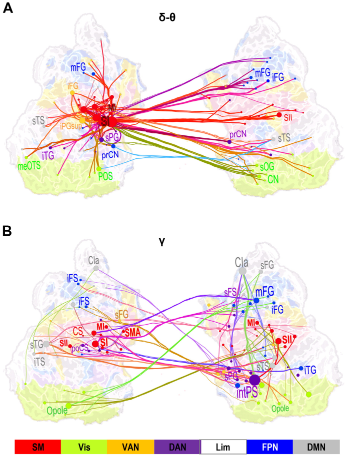
Graph theory and brain data



(Figure from Rubinov & Sporns, 2010)

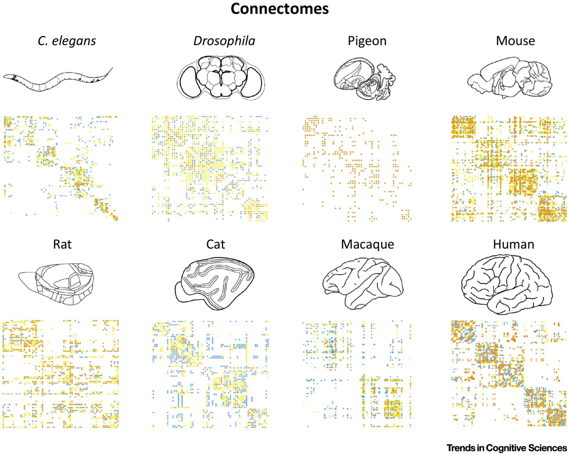


(Figure from Bassett et al., 2008)



(Figure from Hirvonen et al., 2018)

Connectome across species



(Figure from van den Heuvel et al., 2016)

Dynamic representations in networked neural systems

Dynamic representations in networked neural systems

"Our goal is to offer a holistic framework for understanding and describing neural information representation and transmission while revealing exciting frontiers for future research."

(Ju & Bassett, 2020, p. 908)

Neural representation

"In studying neural representations, an important recent step has been to measure how a population of neurons or voxels (i.e., volumes of brain tissue) can represent variables by activating in a specific spatial pattern in response to a particular stimulus pattern."

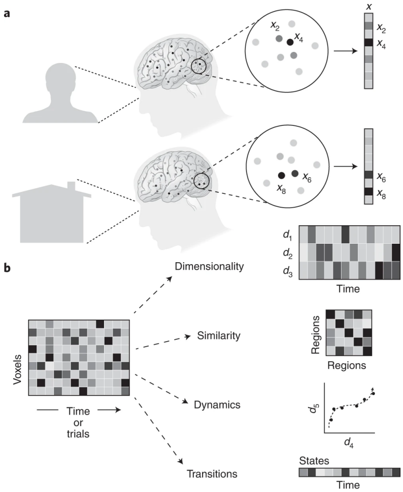
(Ju & Bassett, 2020, p. 908)

Neural representation

"In studying neural representations, an important recent step has been to measure how a population of neurons or voxels (i.e., volumes of brain tissue) can represent variables by activating in a specific spatial pattern in response to a particular stimulus pattern."

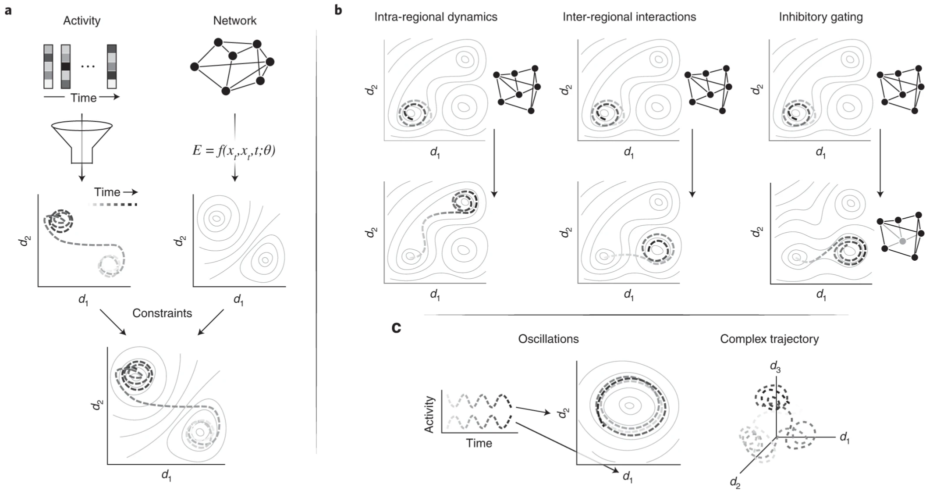
"The encoding of representations in neural populations offers a computational advantage over encoding in individual neurons, especially in complex cognitive tasks"

(Ju & Bassett, 2020, p. 908)



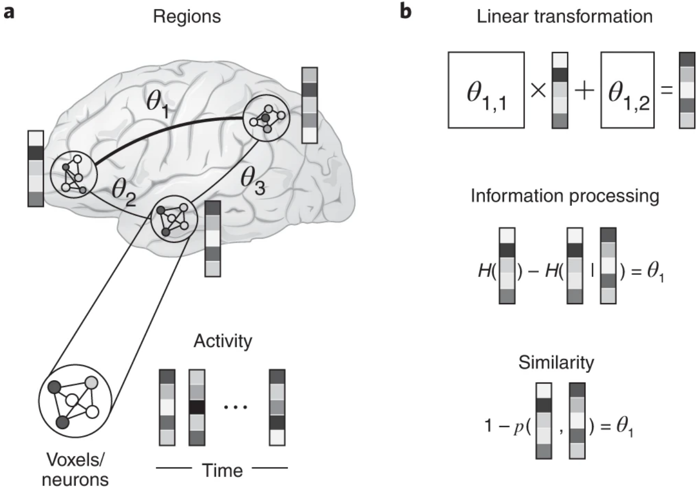
(Figure from Ju & Bassett, 2020)

Network models abstract neural systems



(Figure from Ju & Bassett, 2020)

Integrating network models and neural representations



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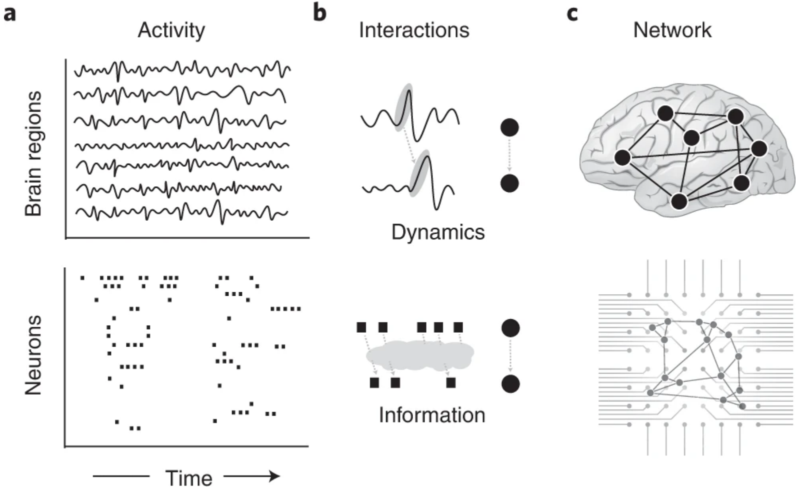
Dynamic representations in networked neural systems



(Figure from Ju & Bassett, 2020)

Summary: Dynamic representations in networked neural systems

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