The topology of mental states.
Combining data science and graph theory to reveal neural networks for cognitive functions.

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November 1st, 2017

The problem

Characterization of brain networks underlying "mental" states using data science tools

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Characterization of brain networks underlying “mental” states using data science tools

- mental

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Characterization of brain networks underlying “mental” states using data science tools

- mental
- brain as a network

The problem

Characterization of brain networks underlying “mental” states using data science tools

- mental
- brain as a network
- data science

The problem

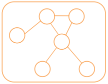
Example: brain network of Alzheimer desease.

The problem: example

The problem: example

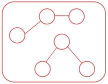
Non-pathological network

Subject 1

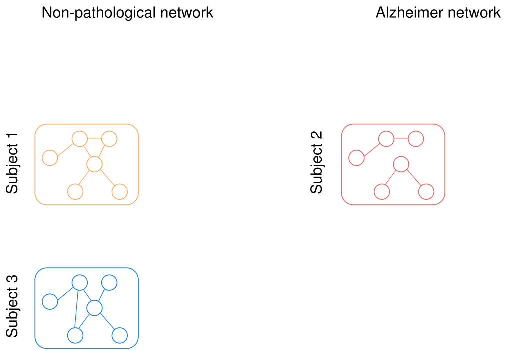


Alzheimer network

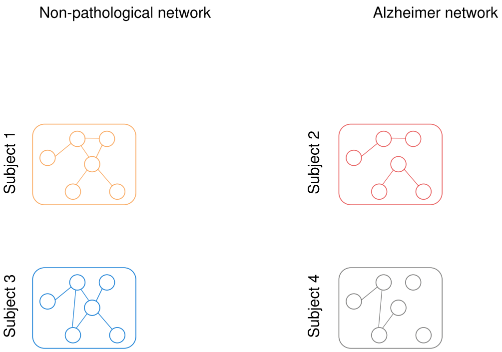
Subject 2



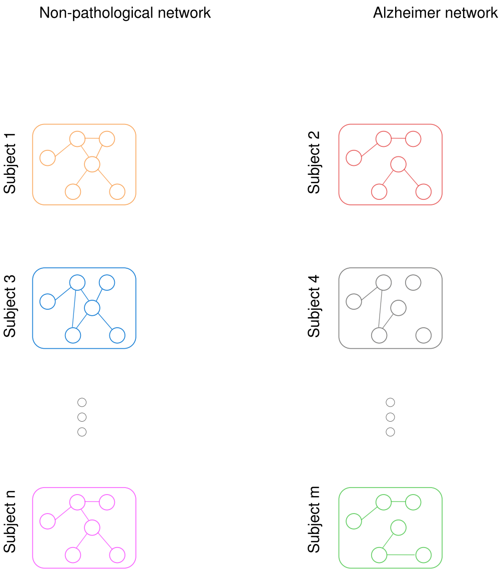
The problem: example



The problem: example



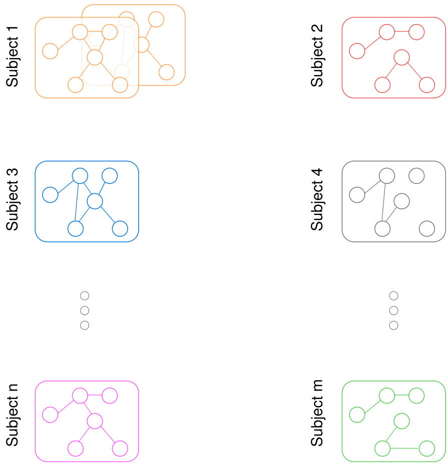
The problem: example



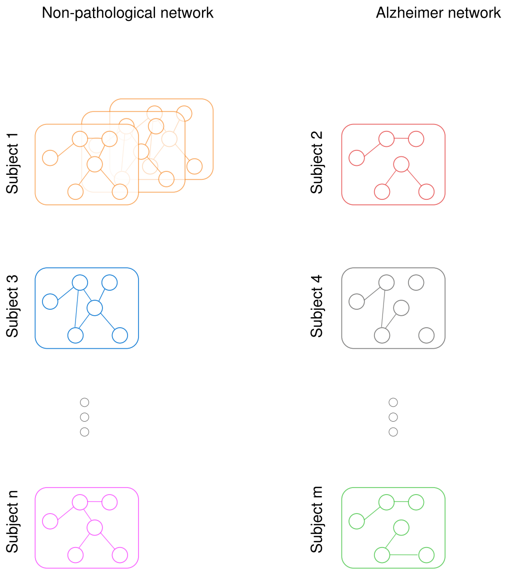
The problem: example

Non-pathological network

Alzheimer network



The problem: example



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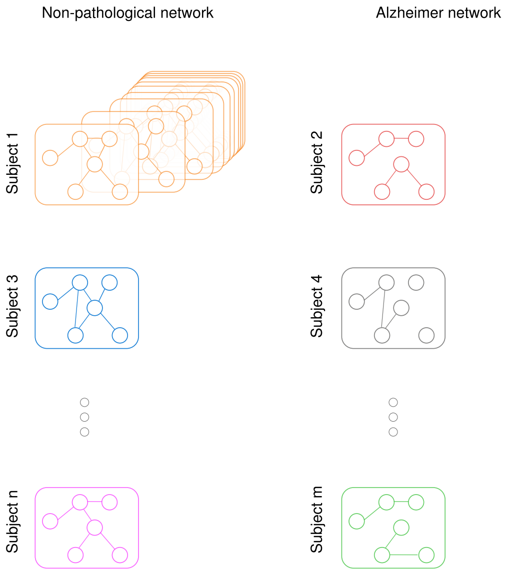

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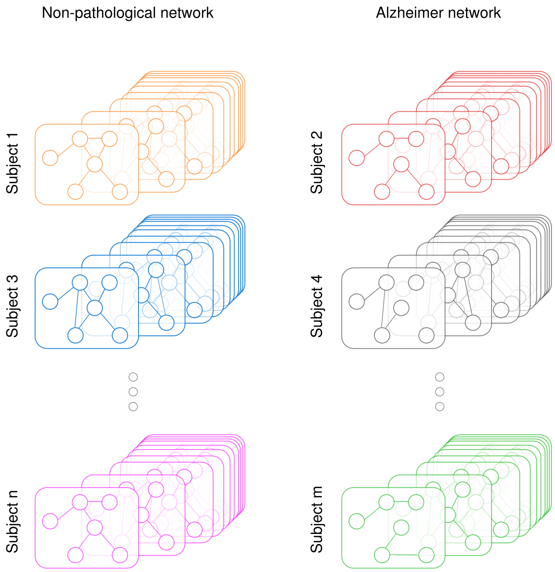

The problem and subproblems

- Characterization of brain networks underlying “mental” states using data science tools

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    - classify individuals

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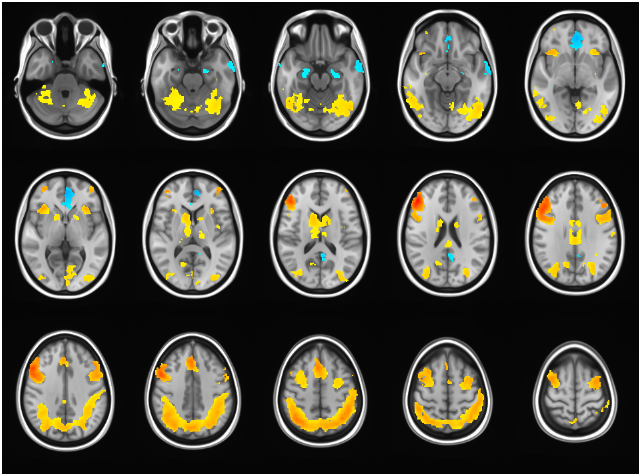
  - classify individuals
  - classify conditions

The problem and subproblems

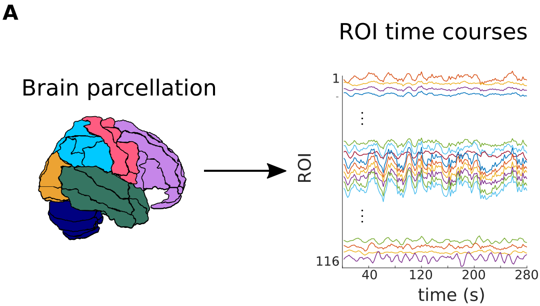
- Characterization of brain networks underlying "mental" states using data science tools
- Separate different sources of varibility/noise
  - classify individuals
  - classify conditions
  - extract networks underlying each classification

Data

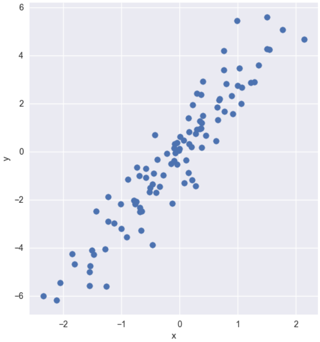
- fMRI
- BOLD signal

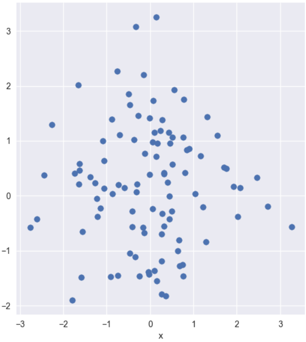


Data

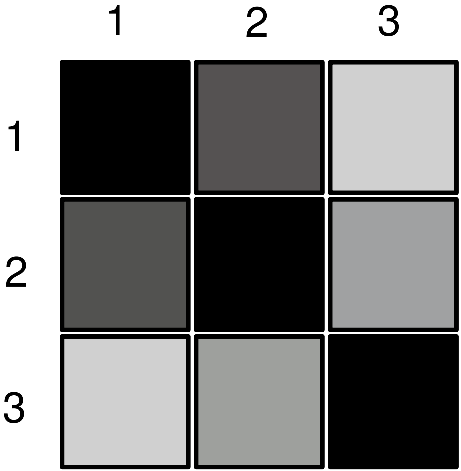

A
Brain parcellation
ROI time courses
1
ROI
116
40
120
200
280
time (s)

Statistical association: correlation

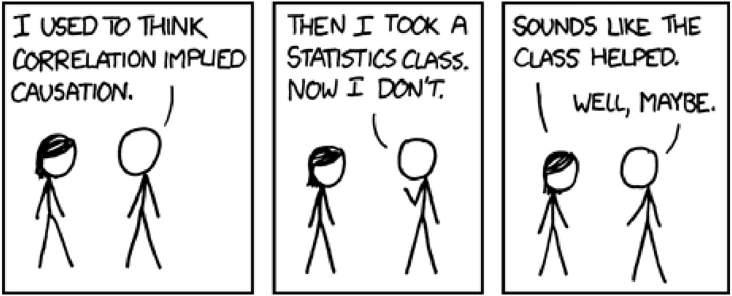




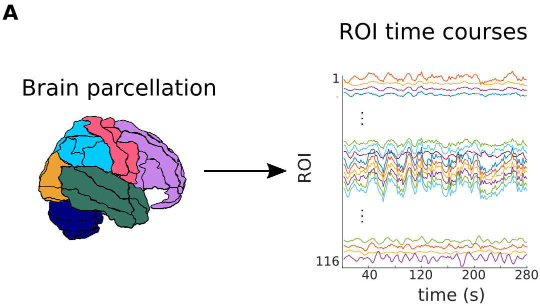
Statistical association: correlation



Statistical association: correlation



FC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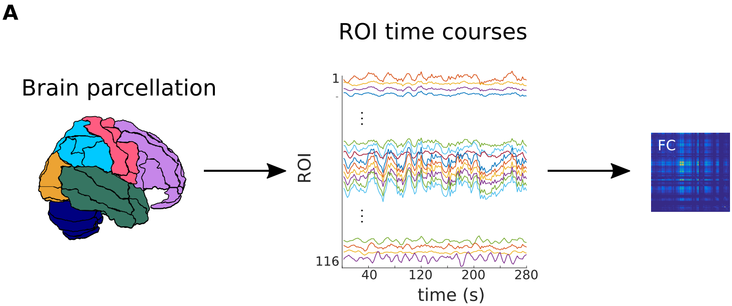
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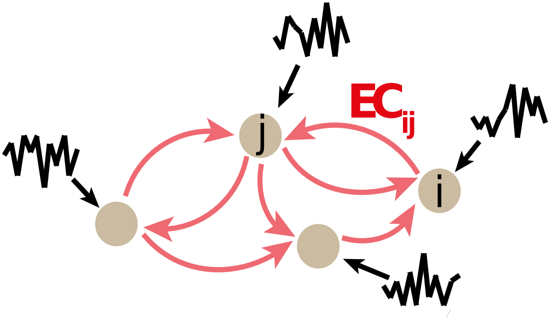
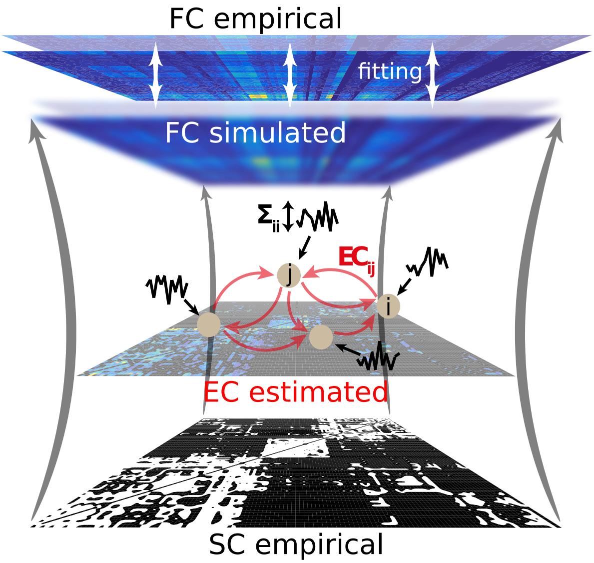
EC




FC empirical
fitting
FC simulated
Σii
ECij
j
i
EC estimated
SC empirical

Reduction of ANN to two-equations rate model

Wong & Wang (2006)

Reduction of ANN to two-equations rate model

Wong & Wang (2006)

Reduction of ANN to two-equations rate model

Wong & Wang (2006)

confidence in ANN

Insabato et al. (2010)

confidence in ANN

Insabato et al. (2010)

Vox populi

Galton visits a livestock fair

Vox populi

Galton visits a livestock fair

- 800 guesses

Vox populi

Galton visits a livestock fair

- 800 guesses
- mean of the guesses: 1198 pounds

Vox populi

Galton visits a livestock fair

- 800 guesses
- mean of the guesses: 1198 pounds
- weigth of the ox: 1198 pounds

An ensamble attractor model for decision and confidence

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Paz et al. (2016)

Dependence of model behavior on IC

Paz et al. (2016)

Estimation of σ_{dv}

Estimation of σ_{dv}

Paz et al. (2016)

Estimation of σ_{dv}

Lo & Wang (2006)

Estimation of σ_{dv}

Lo & Wang (2006)

Estimation of σ_{dv}

Paz et al. (2016)

Fixed duration experiment

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- Accuracy increases as a function of stimulus duration

Fixed duration experiment

- Accuracy increases as a function of stimulus duration
- Confidence increases as a function of stimulus duration

Fixed duration experiment

- Accuracy increases as a function of stimulus duration
- Confidence increases as a function of stimulus duration

Paz et al. (2016)

Asymmetric confidence kernels

Paz et al. (2016)

Asymmetric impact of fluctuations

Paz et al. (2016)

Reproduction of experimental findings

Paz et al. (2016)

Summary

1. Confidence can be estimated from the dispersion of modules in an ensamble network
2. Several experimental findings can be reproduced by this model:
   - Confidence is higher for easier stimuli
   - Confidence decreases as a function of RT
   - Choice accuracy and confidence are positively related
   - Confidence increases as a function of time in fixed duration experiments
   - Asymmetric confidence kernels

Acknowledgments

Luciano Paz

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Gustavo Deco

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