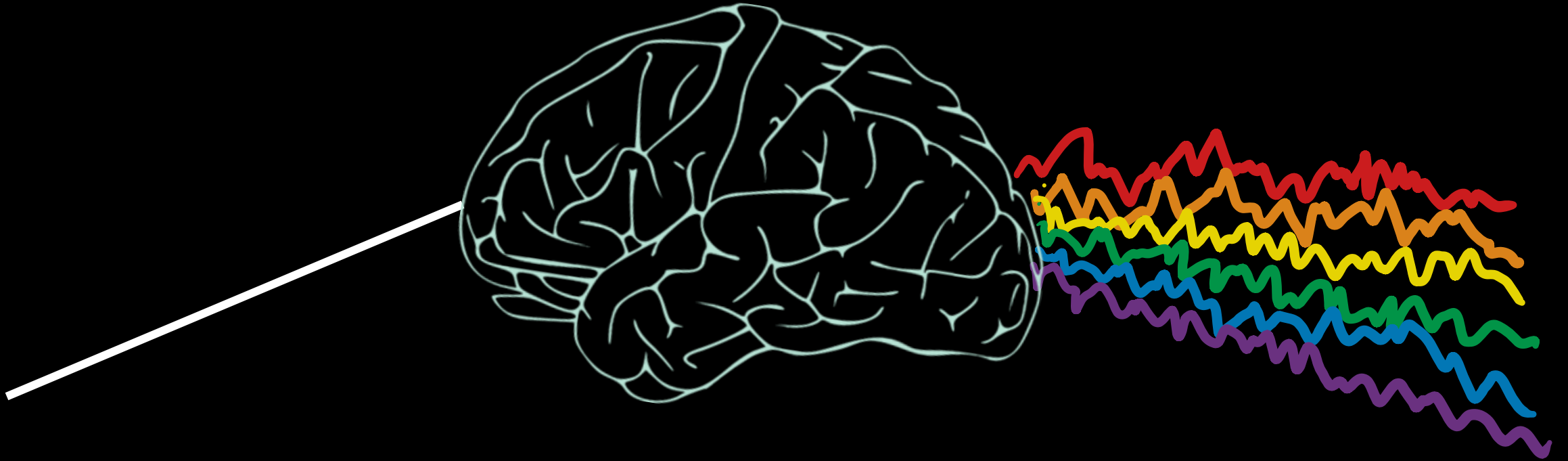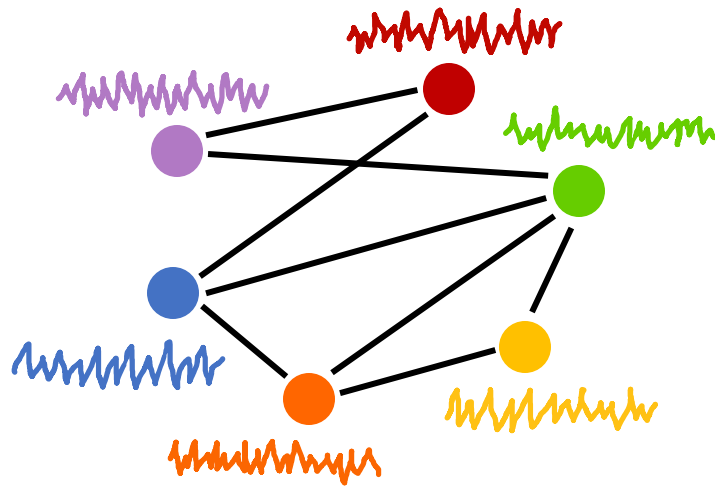# Complexity, Computation, and Criticality 2023

A **time-series** approach to understanding the **brain** as a **complex system**
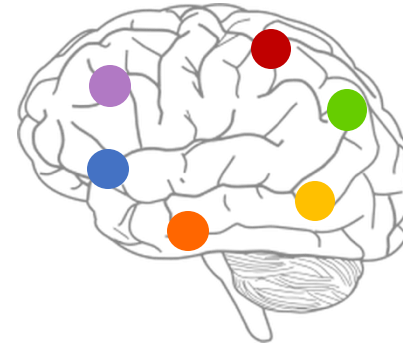
Presented by:
Annie G. Bryant
Dynamics and Neural Systems Lab
The University of Sydney

Representing **complex systems** through **time-series**

Example complex system

Multivariate time series (**MTS**) representation

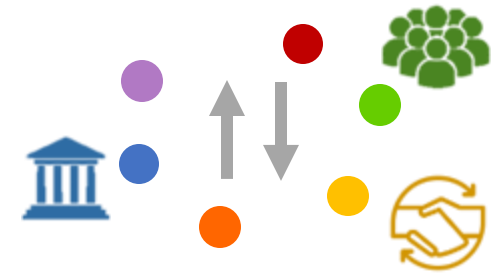Process

Timepoint

Biology

Brain function: perception, emotion, movement

Economics
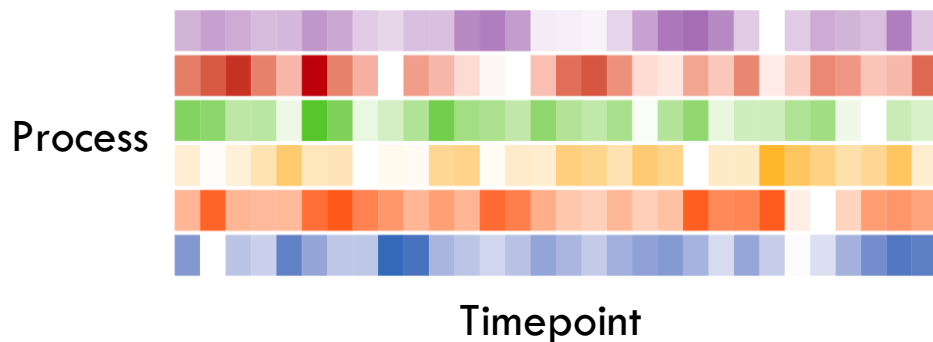
National economy: economic growth, recession

Physics
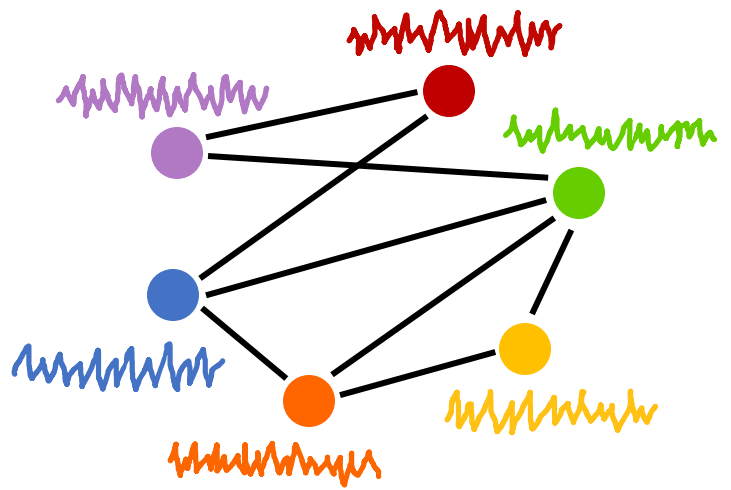
Fluid dynamics: vortices, turbulence

Social networks

Facebook friends: community formation

Representing **brain networks** through **time-series**

Example complex system

Multivariate time series (**MTS**) representation

Brain region

Timepoint

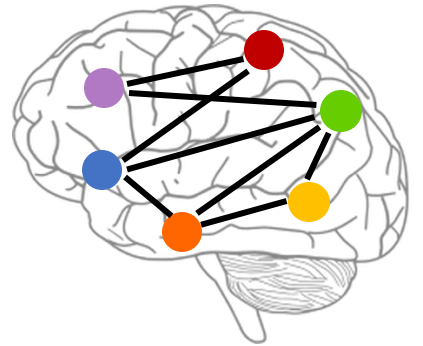Neuroimaging: blood oxygen level-dependent (**BOLD**) functional magnetic resonance imaging (**fMRI**)
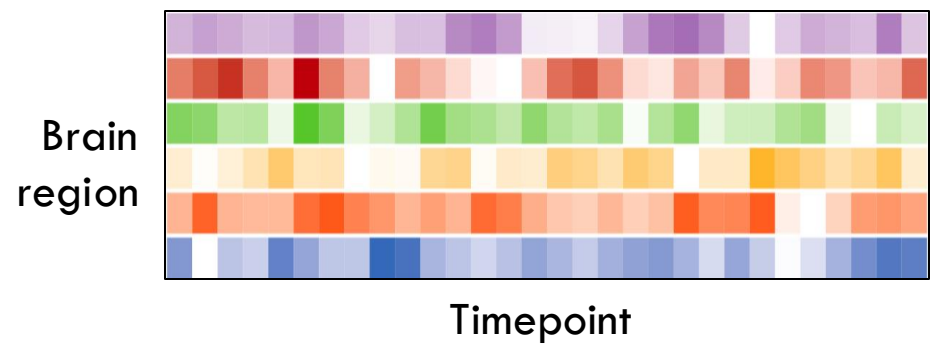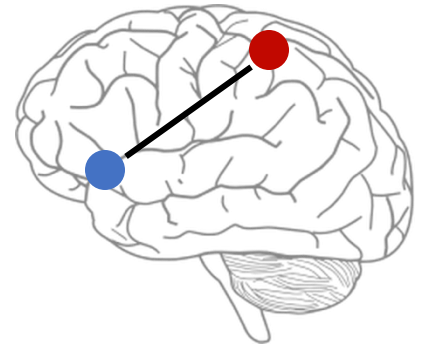
Local

Pairwise

Global

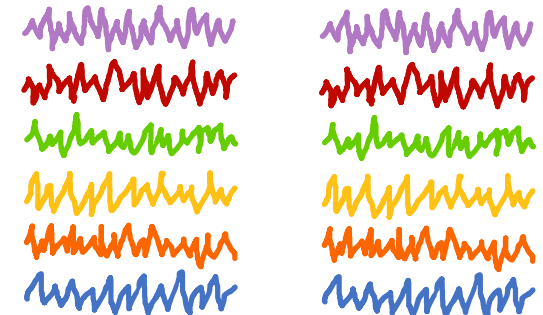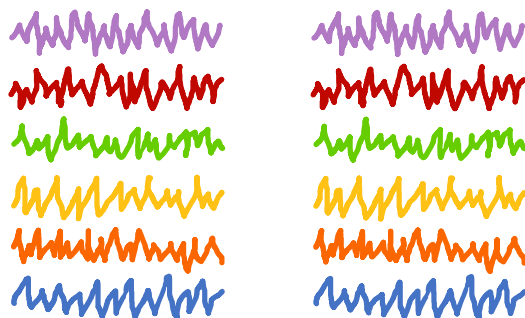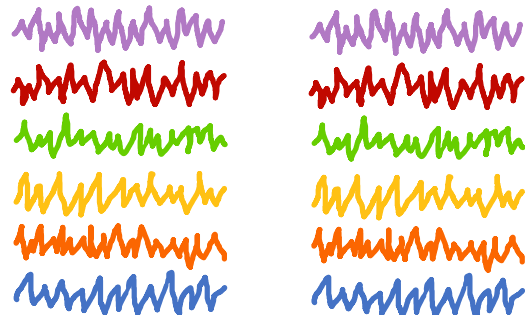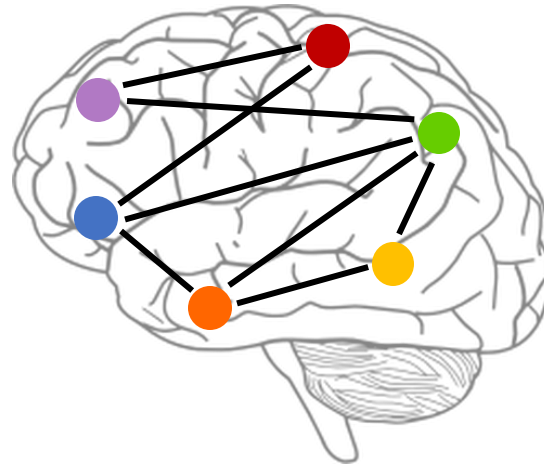# Example problem: use BOLD fMRI to classify individuals with versus without a given neurological disorder
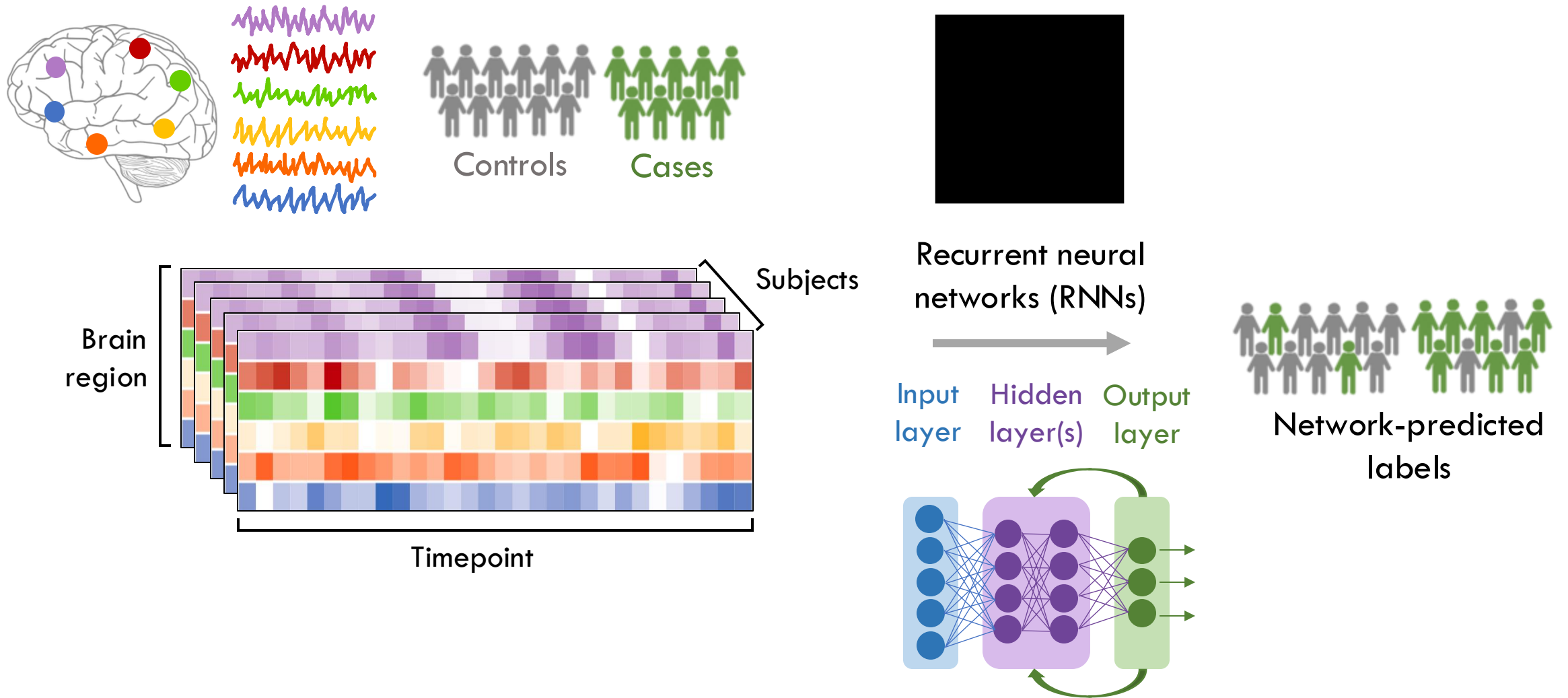

Healthy controls

Patients
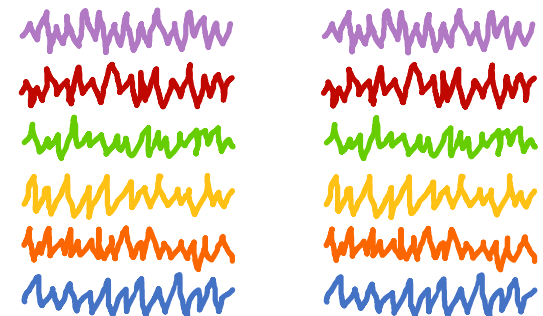
Local: aberrant neural activity in individual regions
Pairwise: disrupted communication between pairs of regions
Global: aberrant sensory perception, disordered thought

Direct from neuroimaging to a **deep learning** classifier pipeline

Controls   Cases

Subjects

Brain region

Timepoint

Recurrent neural networks (RNNs)

Input layer   Hidden layer(s)   Output layer

Network-predicted labels

Schizophrenia: Yan et al. *The Lancet* (2019)
Autism: Dvornek et al. *Machine Learning in Medical Imaging* (2017)

Feature-based representations of complex system temporal dynamics

Local

Amplitude of low-frequency fluctuations
Statistical properties
Sample entropy
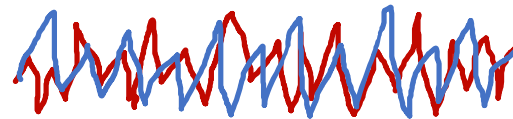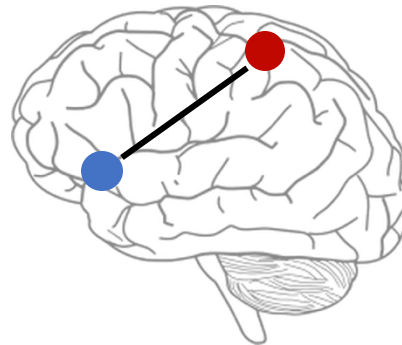Correlation structures
Stationarity
Power spectrum distributions

Pairwise

Pearson correlation coefficient
Directed information
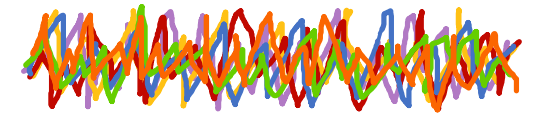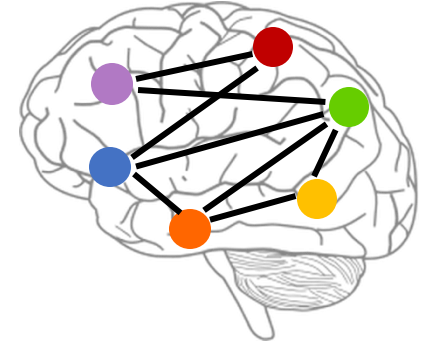Transfer entropy
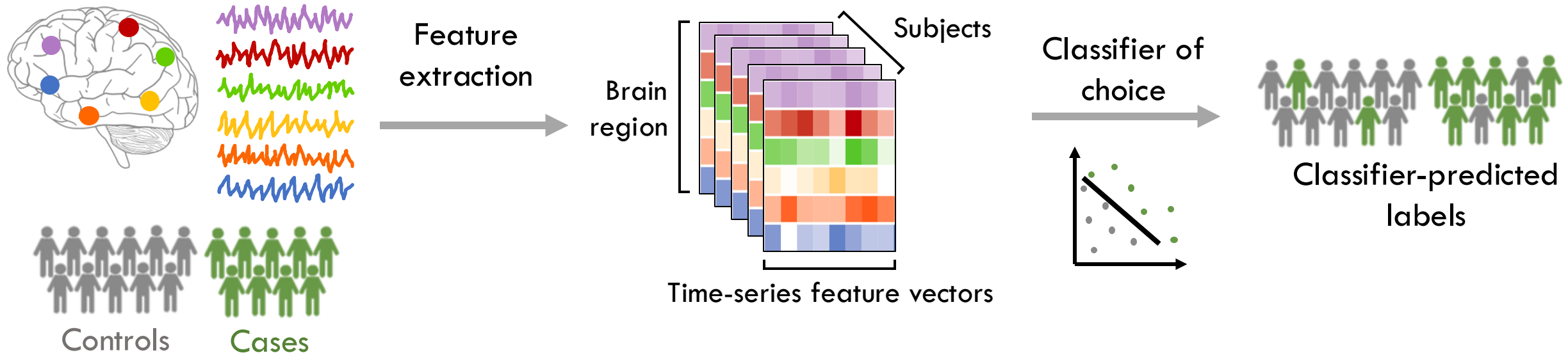Coherence magnitude
Distance metrics
Cointegration

Global

Φ (integrated information)

# Feature-based representations of complex system temporal dynamics

Handful of manually-curated
features
+
Complex deep learning method,
e.g. multi-layer convolutional
neural network

Comprehensive analysis of dozens
to hundreds of univariate and
pairwise TS features
+
Simple classifiers that emphasize
interpretability

Leveraging TS features for interpretable schizophrenia classification
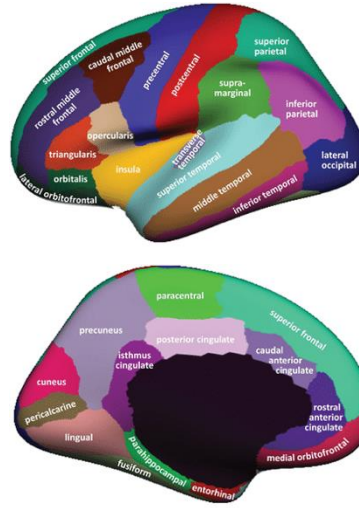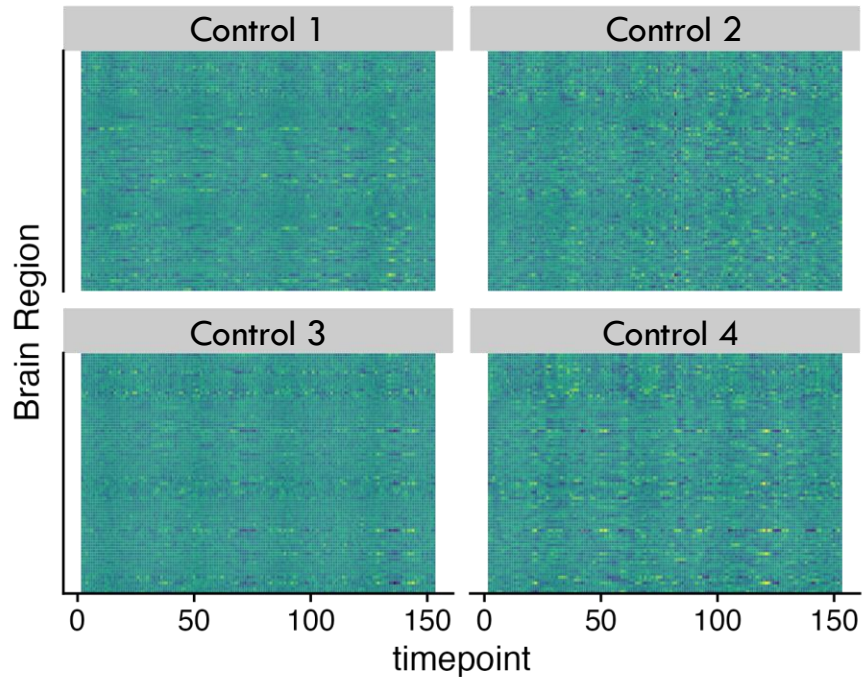
Time-series extracted from 82 cortical and subcortical brain regions
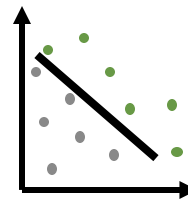(Image: Klein and Tourville 2012)

Measure of BOLD activity (a.u.)
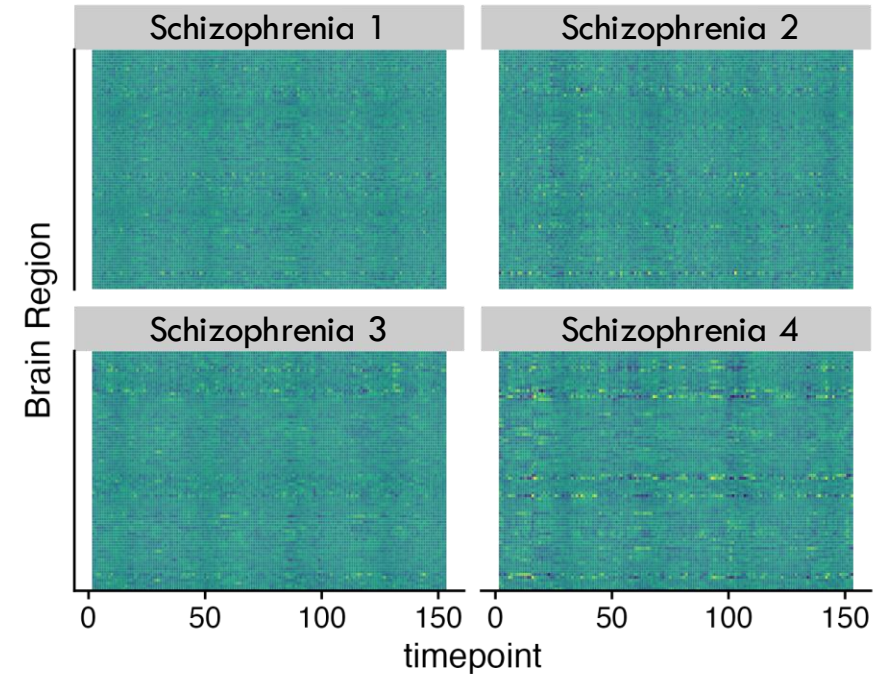
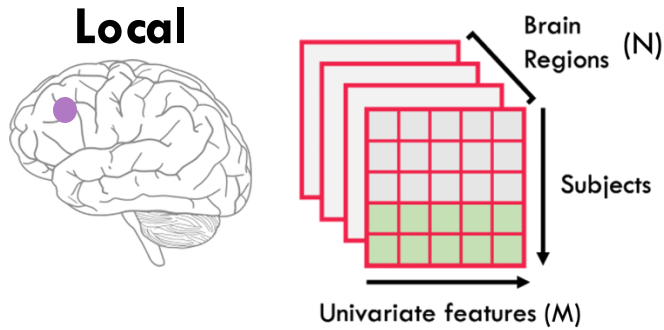theft — 22 univariate features per region

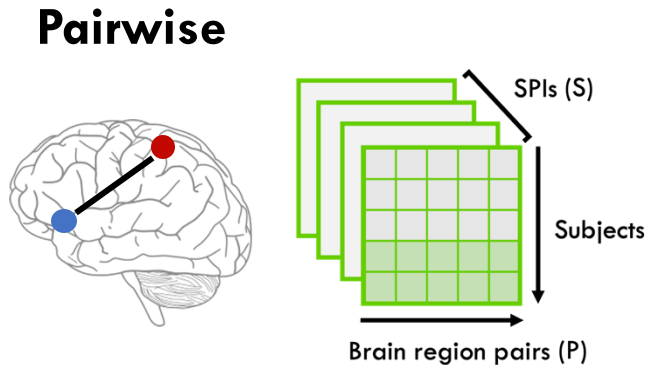pyspi — 14 pairwise features per region pair

Linear SVM with inverse probability weighting
10-fold cross-validation to measure balanced accuracy
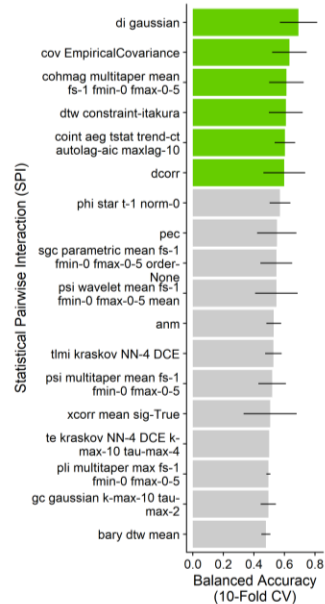10 repeats per CV analysis

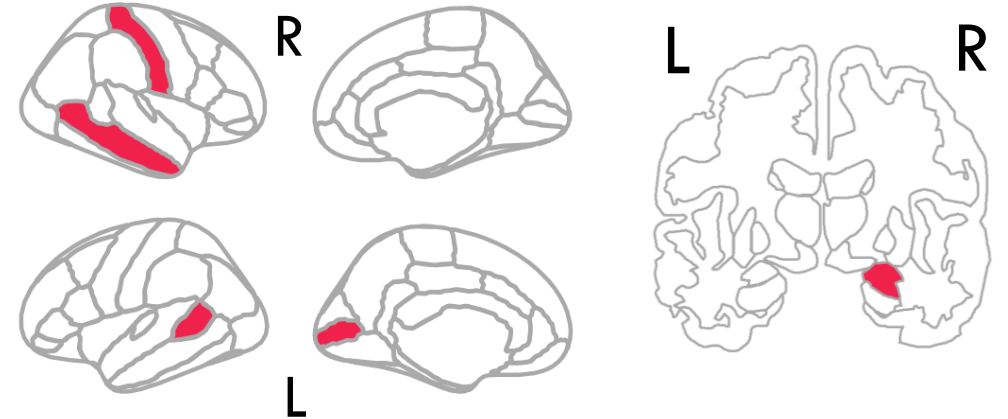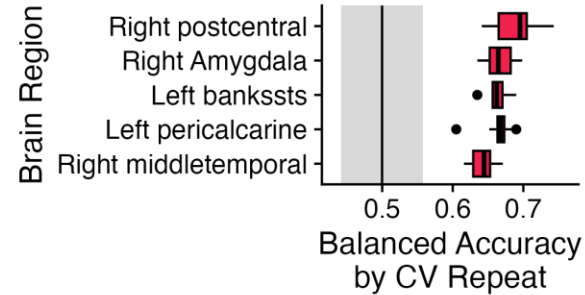# Identifying specific **brain regions** and **BOLD dynamics** **properties** that differentiate case vs controls
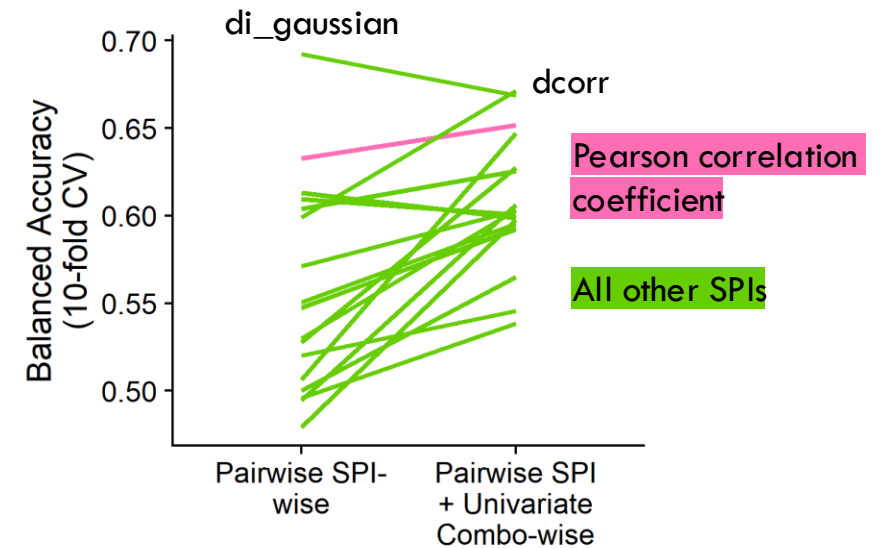
Challenges and future directions

Subjects

Brain region

Time-series feature vectors

"Curse of dimensionality"

↑ Feature space   ↑ Dataset size

Dimensionality reduction
(e.g. PCA, ICA)

Feature selection
(e.g. L1 regularization)
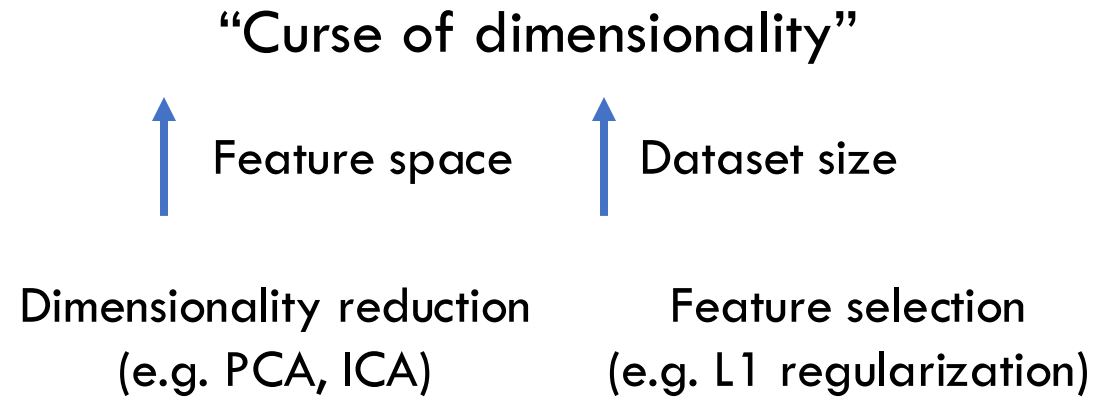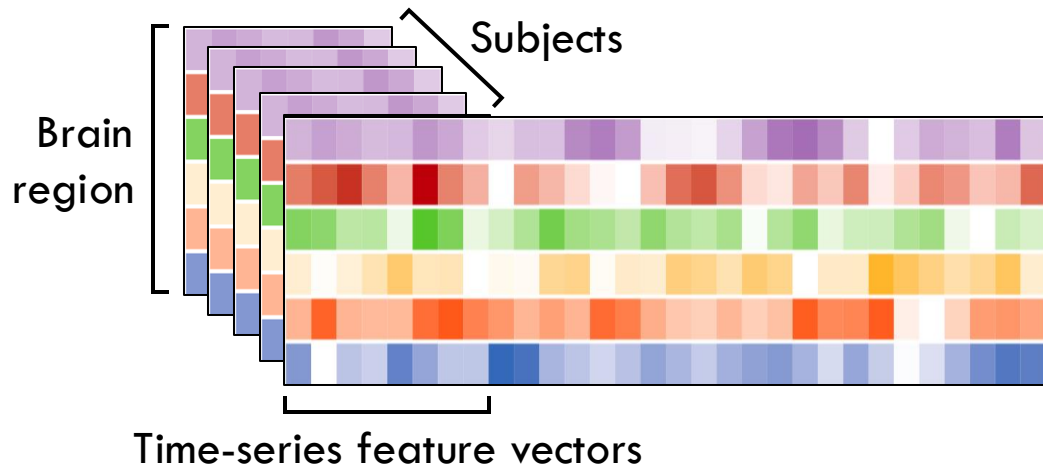
Next step: apply this framework to multimodal **Alzheimer's disease** neuroimaging data

Healthy brain

Alzheimer's brain

Amyloid-beta plaques

Image adapted from: NIH National
Institute on Aging

mean(vIFC)

SCD

residuals of SCD-MoCA
residuals of SCD-vIFC(R-G-temporal-middle)
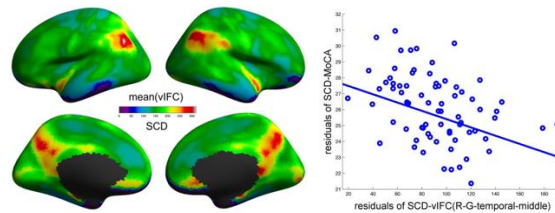
Jiang et al. *Sci Reports* (2018)

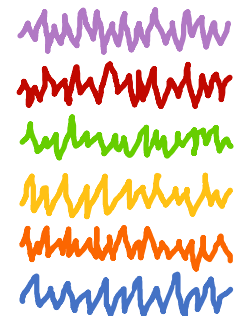AD   Control

0   0.2   0.4   0.6   0.8   1
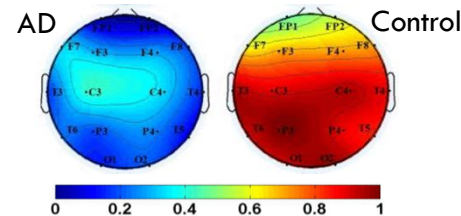
Average EEG signal entropy
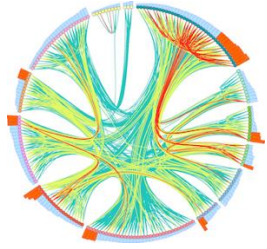
Cao et al. *Chaos* (2015)

Amyloid-beta
positron emission
tomography (PET)

BOLD fMRI

Thank you!

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