

An Engine for Comparative Time-Series Analysis

“the taming of the zoo”



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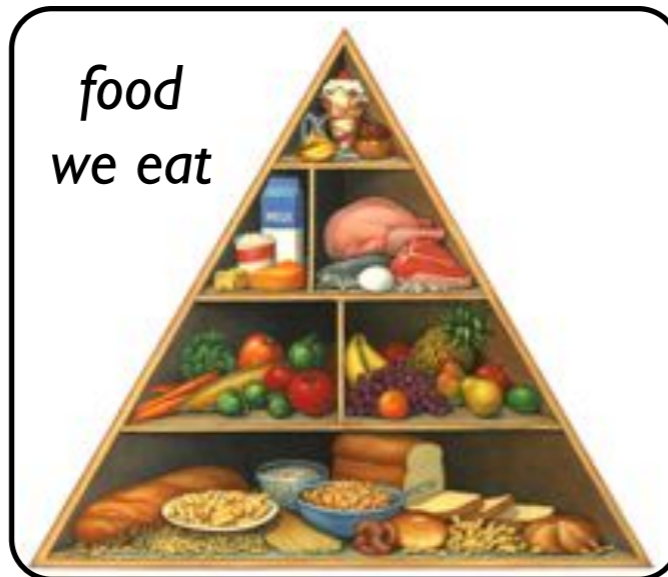


Organizing

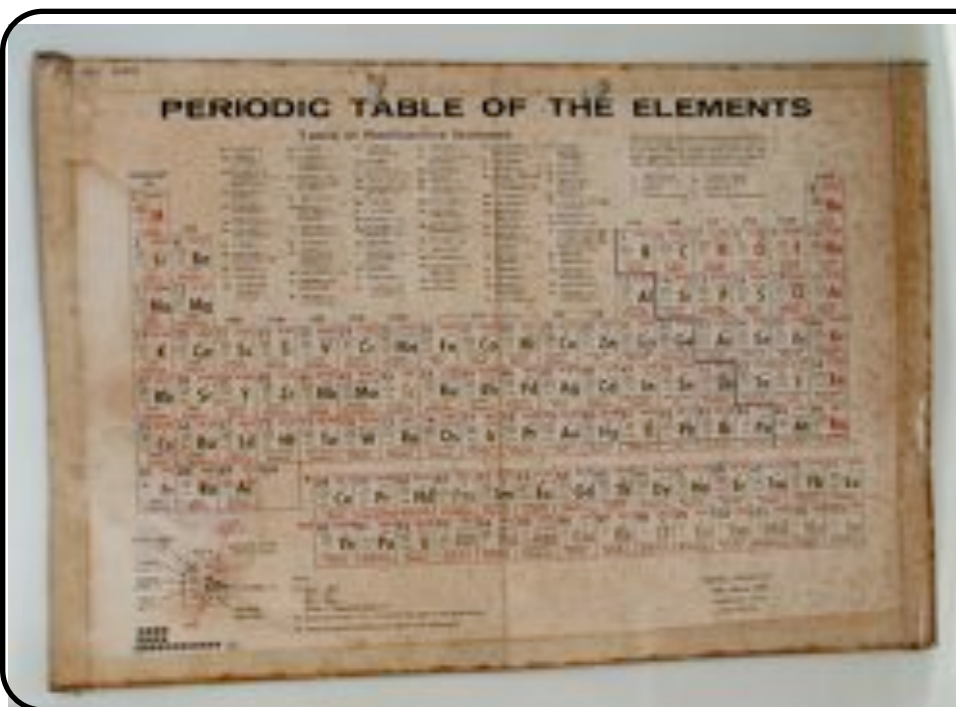
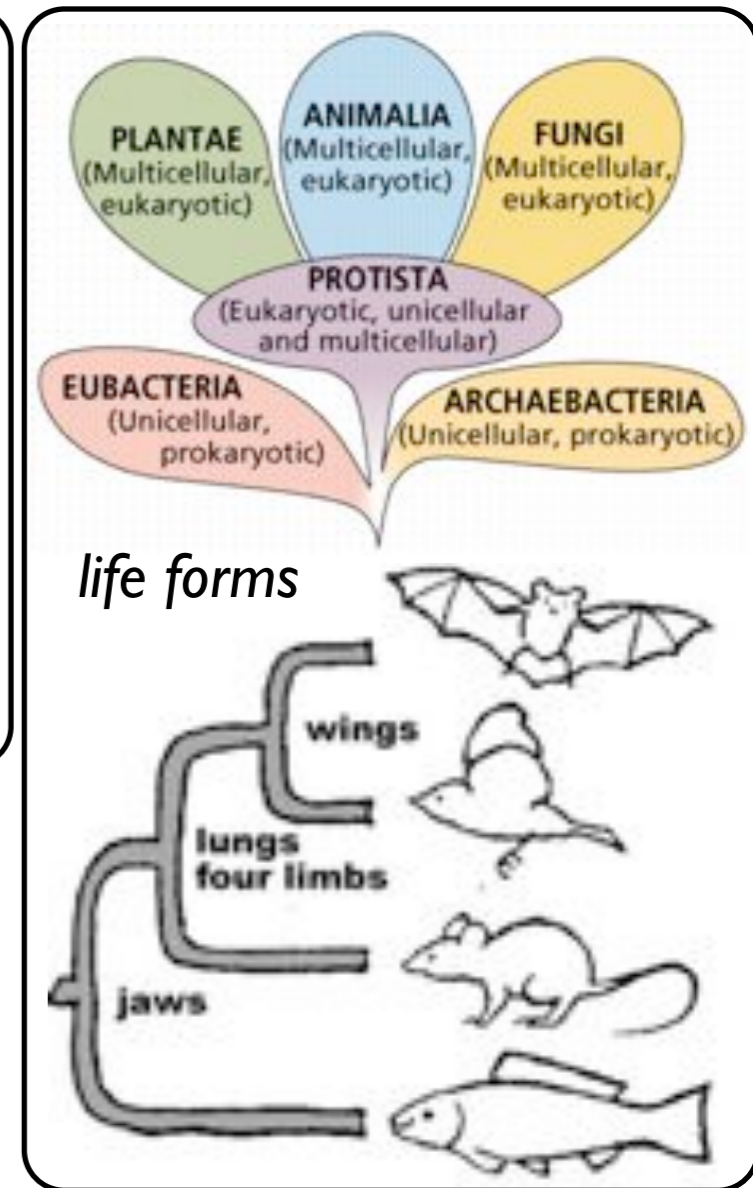
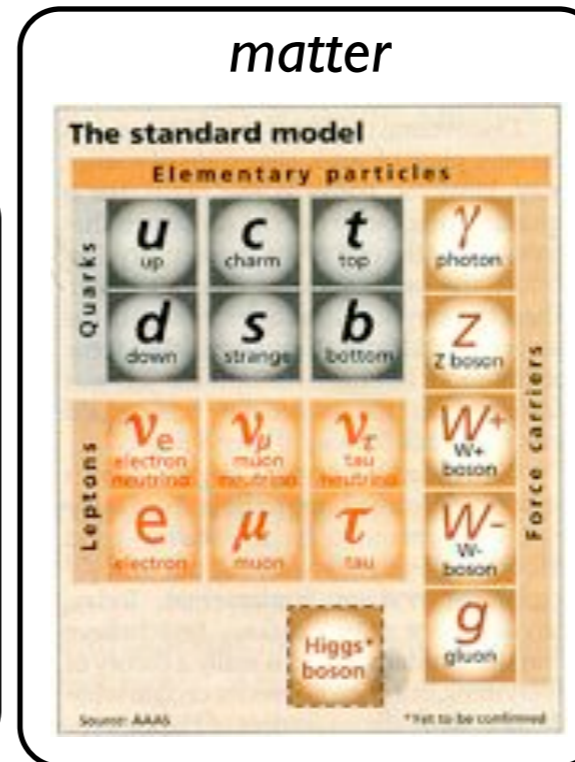
Scientific endeavors often focus on structuring libraries of collected information.



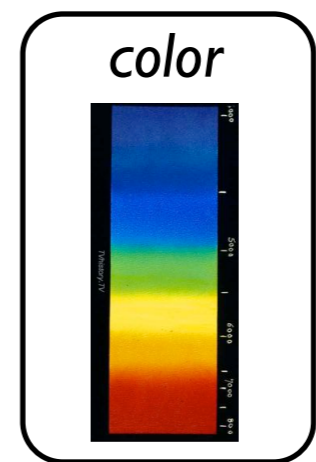
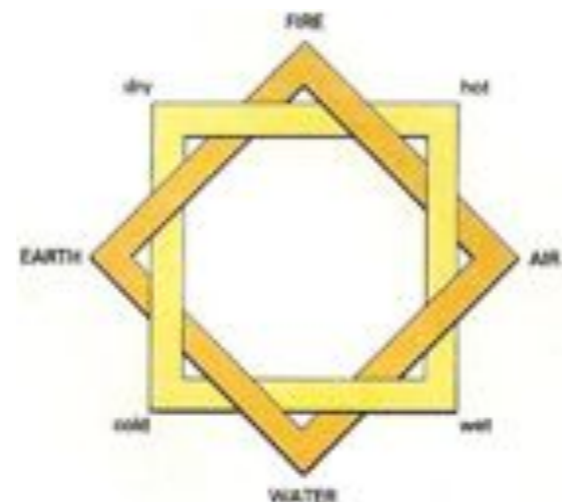
personalities



food we eat



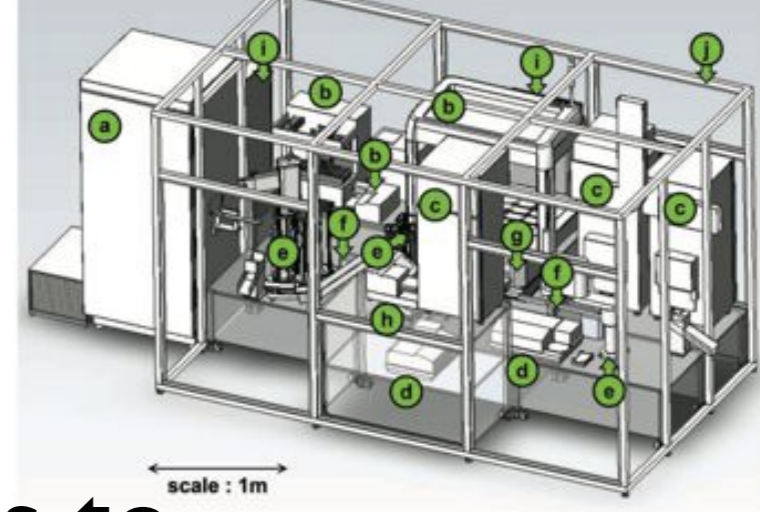
macroscopic substances we encounter



color

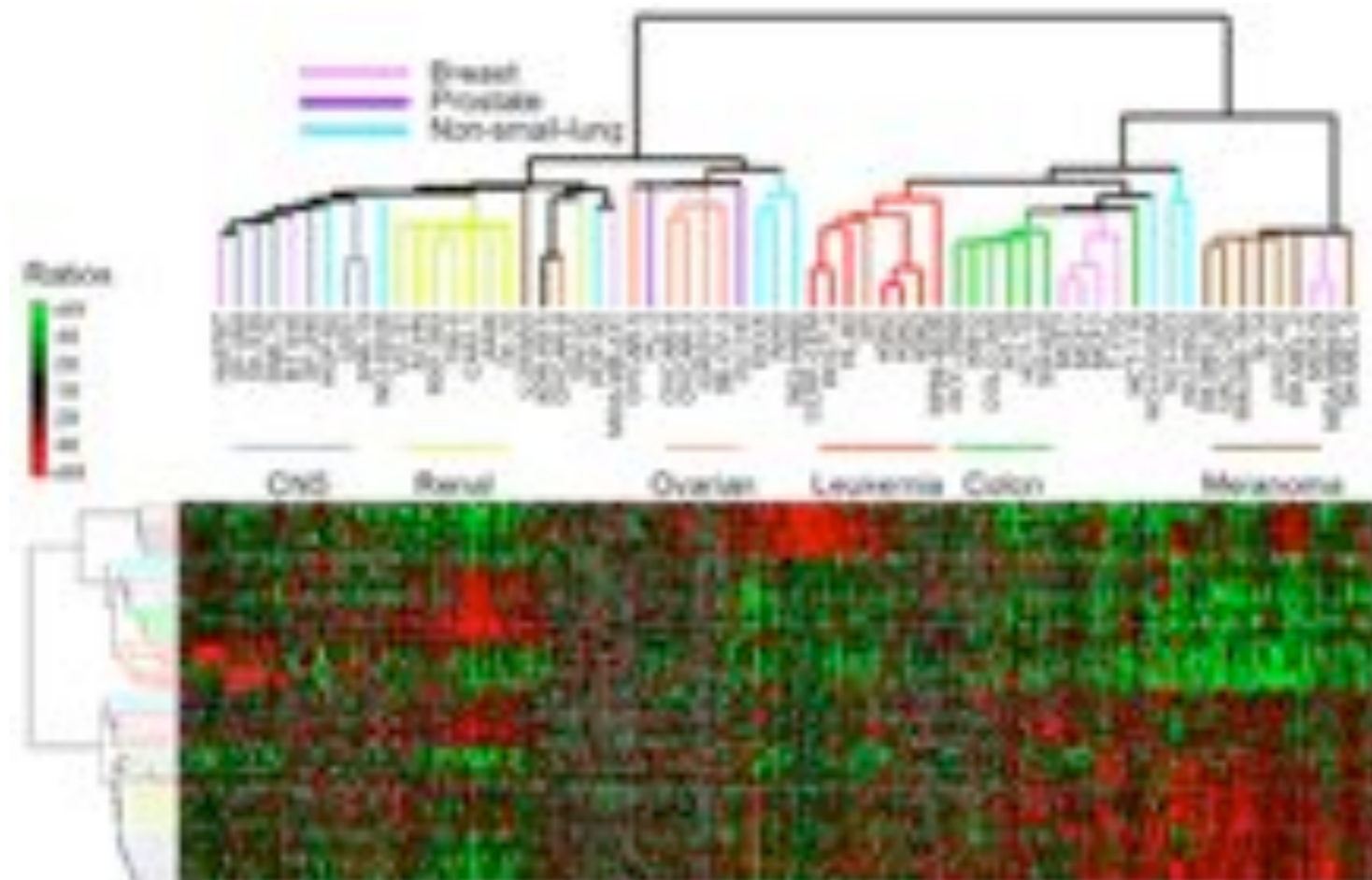
this helps us understand the complexity in the world

Organizing



Statistical learning techniques allow us to organize and understand things on a greater scale than ever before.

e.g., the genetic microarray



Organizing Science

- Our data and our methods are also objects that require organization.
- How do we make sense of the time-series data that we observe in the world?

We construct a comparative framework for time-series analysis





Challenges



Time Series Analysis:

- Pervasive importance in science
- Huge quantities of data
- Vast and growing quantity of methods
- Interdisciplinary boundaries



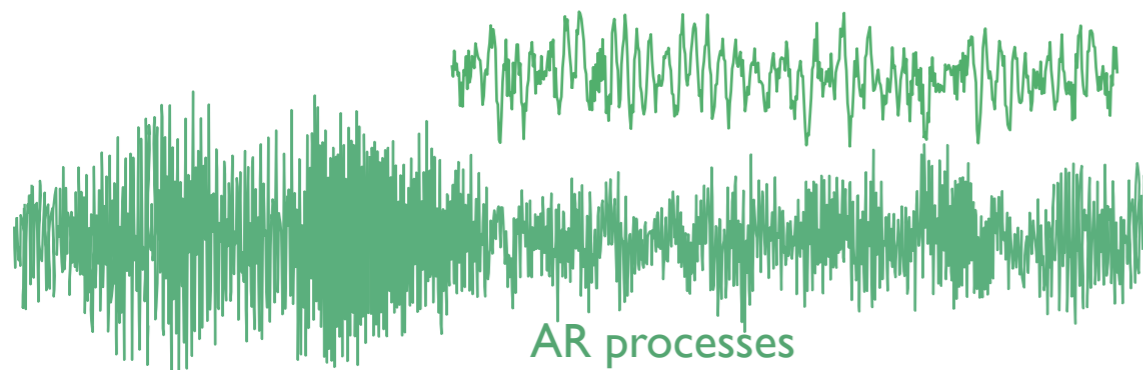
Structure

- Framework
- Structure of methods for time-series analysis
- Structure of empirical time series
- Utility for specific applications
- Constrained time-series datasets

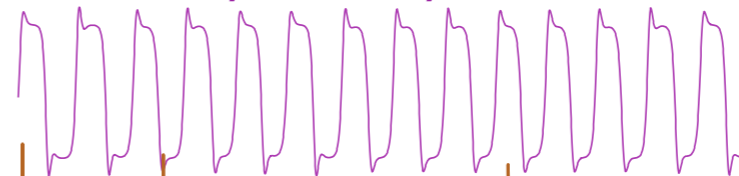
medical CO₂ fluctuations

> 30 000

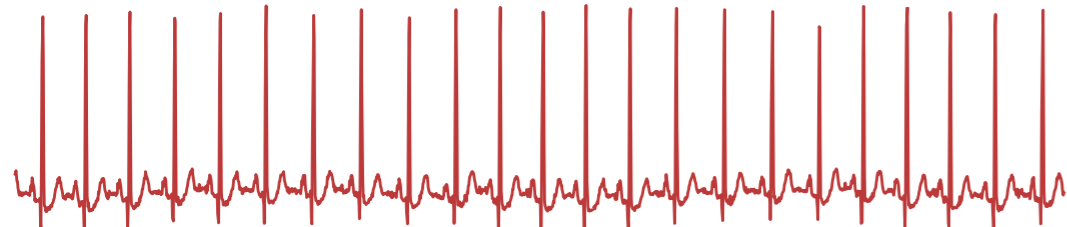
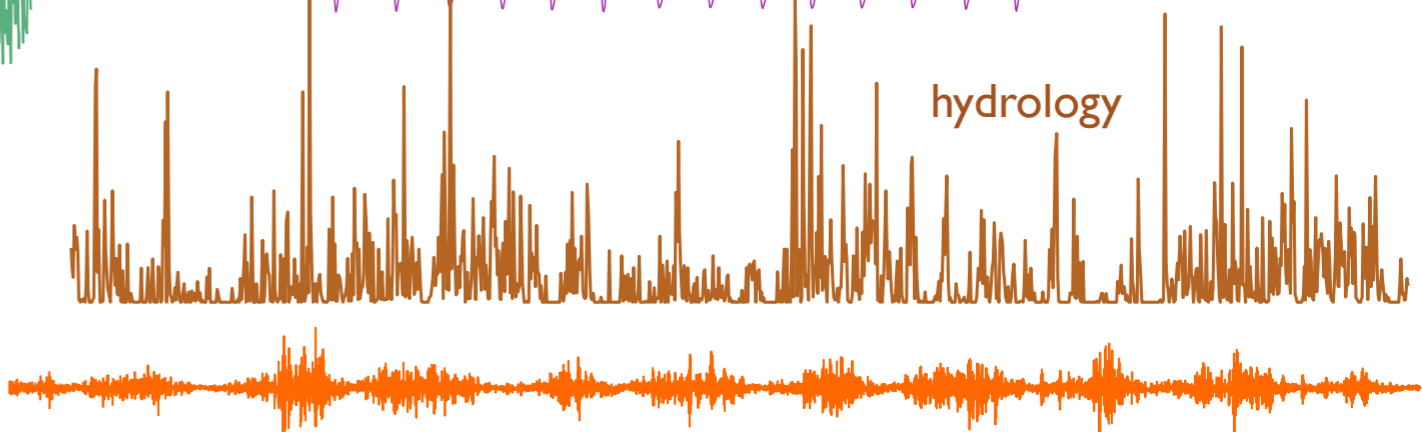
What time series?



dynamical systems



hydrology

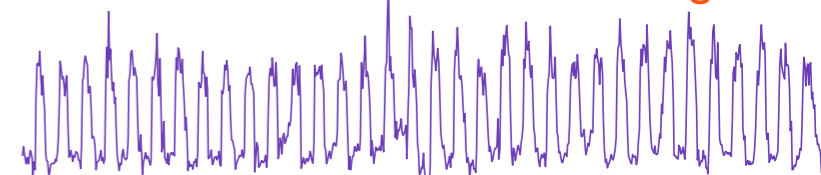


medical: normal sinus rhythm

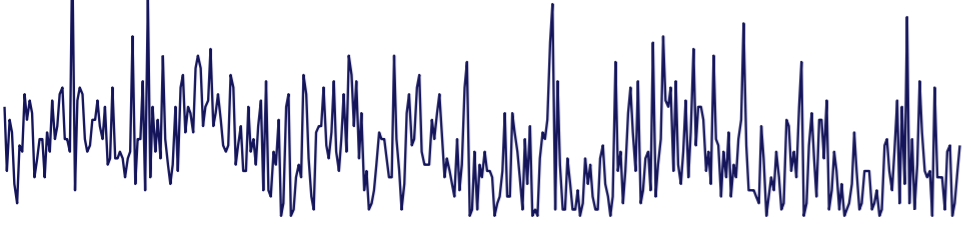
finance: oil prices



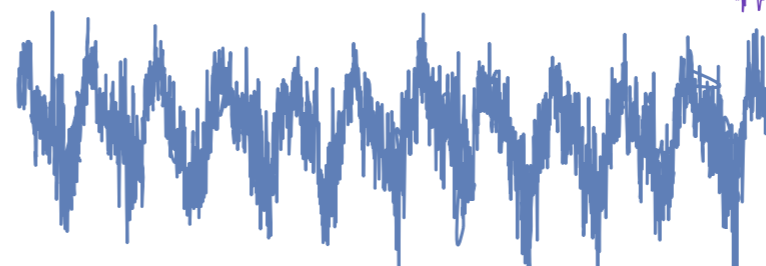
audio: brushing teeth



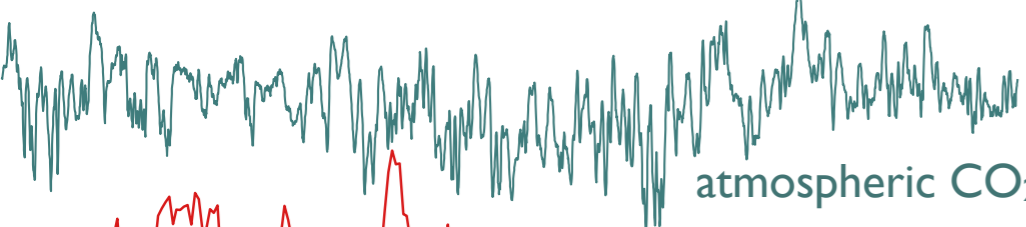
text: sentence lengths



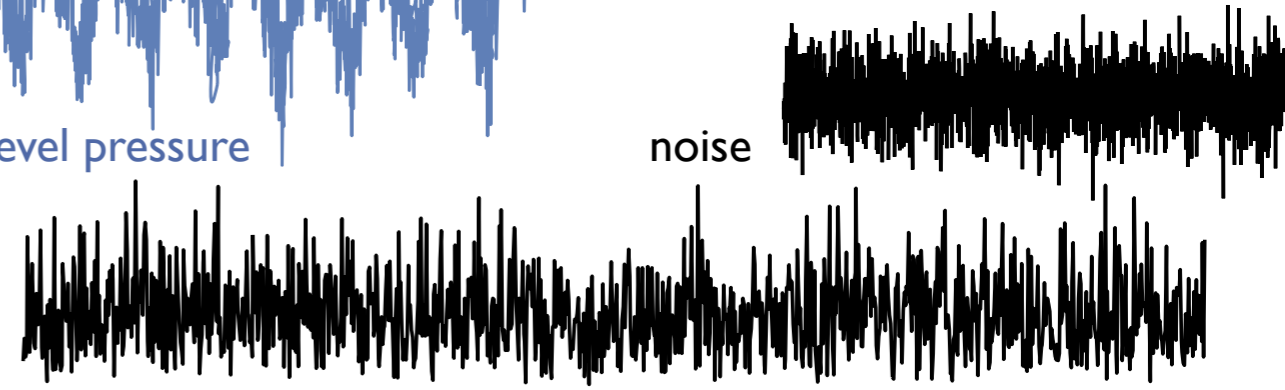
satellite position



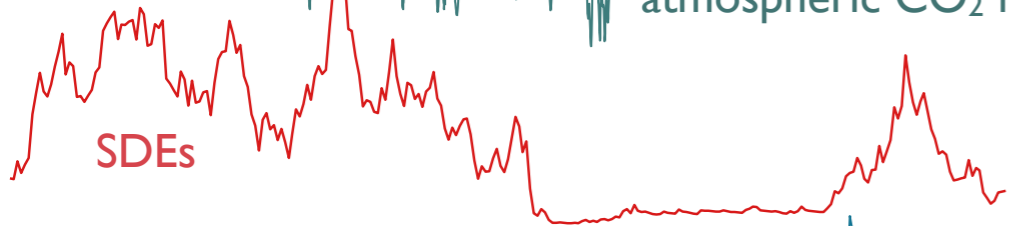
climatology: sea level pressure



noise



atmospheric CO₂ fluctuations



SDEs

zooplankton growth



What operations?

Basic statistics

trimmed means zero crossings
standard deviation
outliers local extrema

Stationarity

StatAv sliding windows
bootstraps
distribution comparisons

Static distribution

quantiles moments
fits to standard distributions
hypothesis tests

Basis Functions

wavelet transform
spectral measures power spectrum peaks
low frequency power

Correlation

linear autocorrelations decay properties
automutual information
dependence on additive noise
nonlinear autocorrelations
time reversal asymmetry
generalized self-correlation function
recurrence structure
autocorrelation robustness
fluctuation analysis: scaling
randomization robustness
recurrence plots
seasonality testing

Model fits

primitive forecasting
Fourier fits GARCH modeling
step-ahead dependence
exponential smoothing AR models
state space models
hidden Markov models
piecewise splines 'walker' statistics
ARMA modeling Gaussian Processes

Nonlinear

2D embedding structure TSTOOL
TISEAN fractal dimension
correlation dimension Taken's estimator
Poincaré sections surrogate data
nonlinear prediction error
Lyapunov exponent
false nearest neighbours

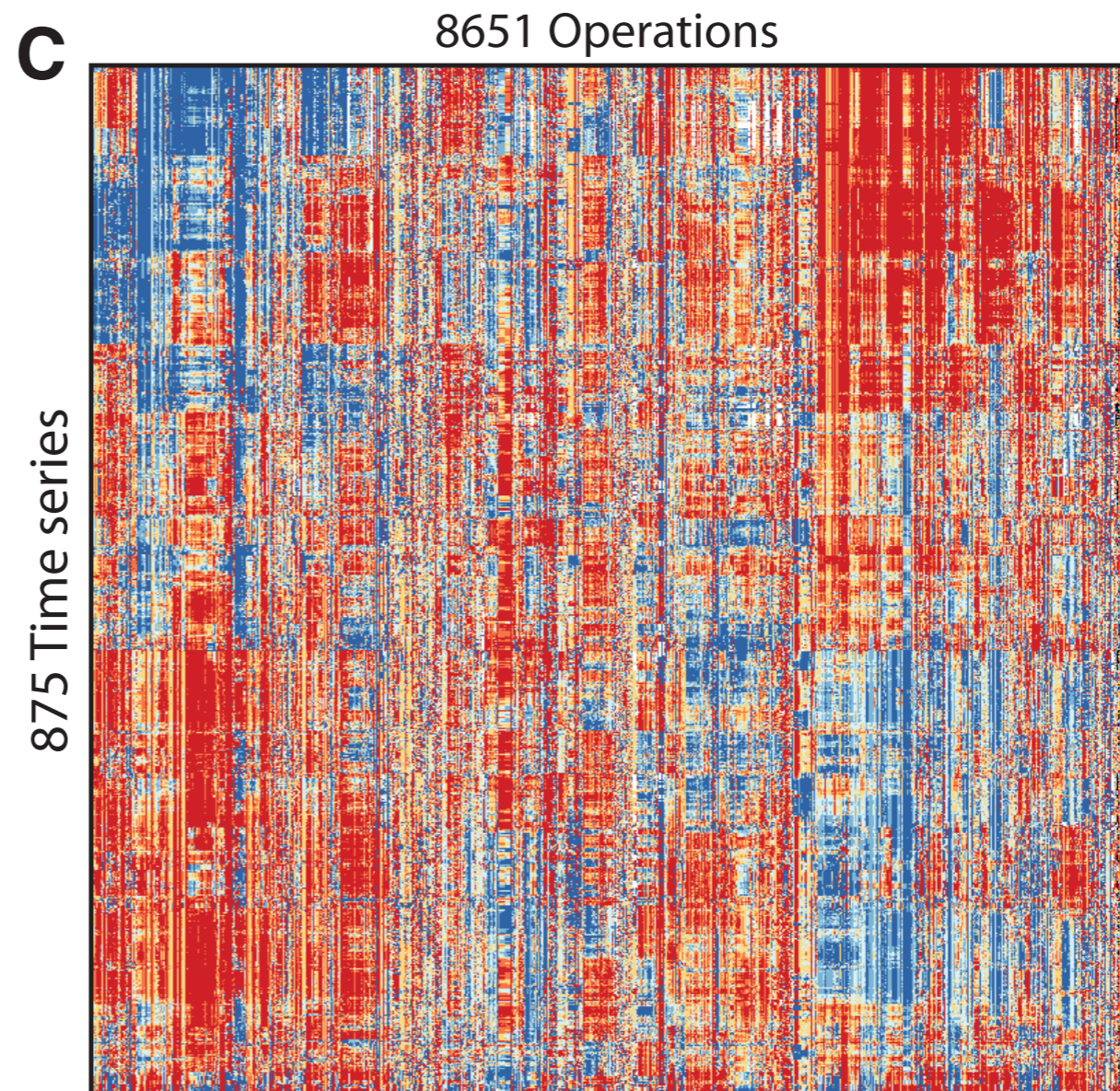
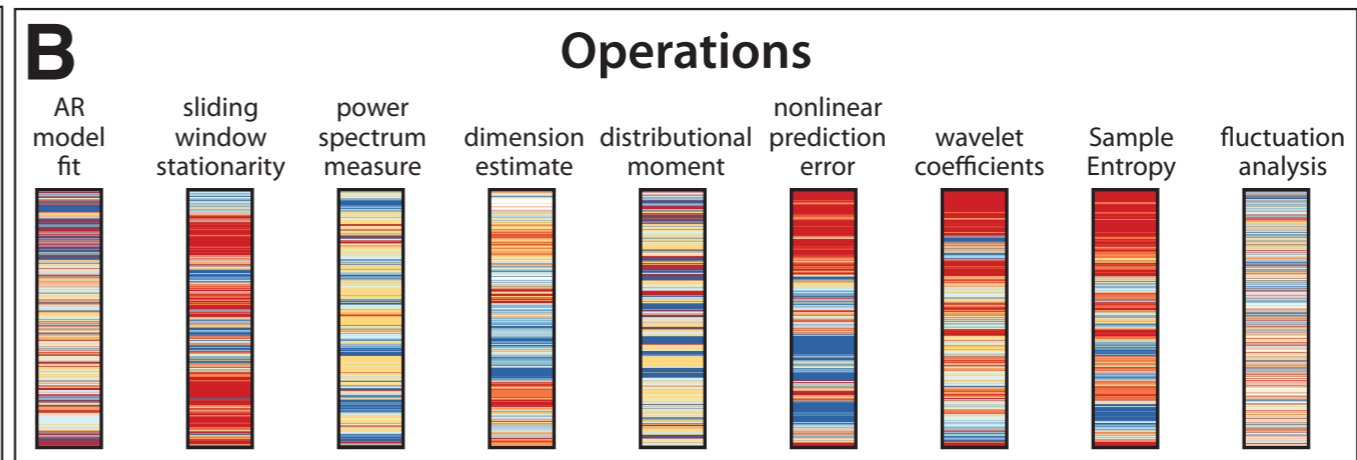
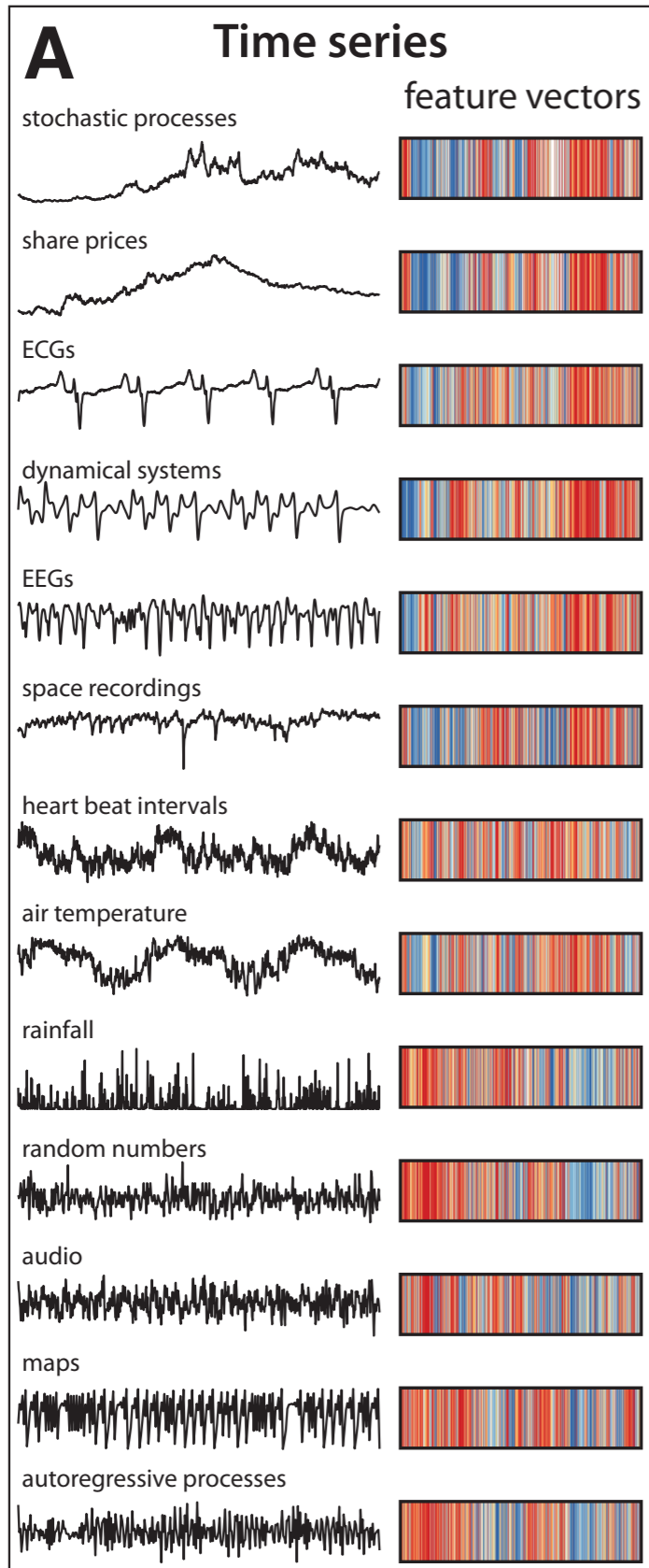
Others

course-grained transition matrices
motif distributions
couple to dynamical systems
visibility graph stick angle distribution
step detection algorithms
extreme events drifting mean tests
PCA of embedded signal
domain-specific standard metrics

Information Theory

SampEn distributional entropies
conditional entropies binned entropies
kernel smoothed entropies
Tsallis entropies ApEn

Design Matrix



Organizing Our Methods

- We organize operations using their outputs on a diverse range of empirical time series.
- Clustering allows us to form reduced sets of operations that capture the dominant types of behavior in our database.
- Gives structure to an interdisciplinary field.



long-range scaling

*power spectral
density*

linear models

stationarity

variance

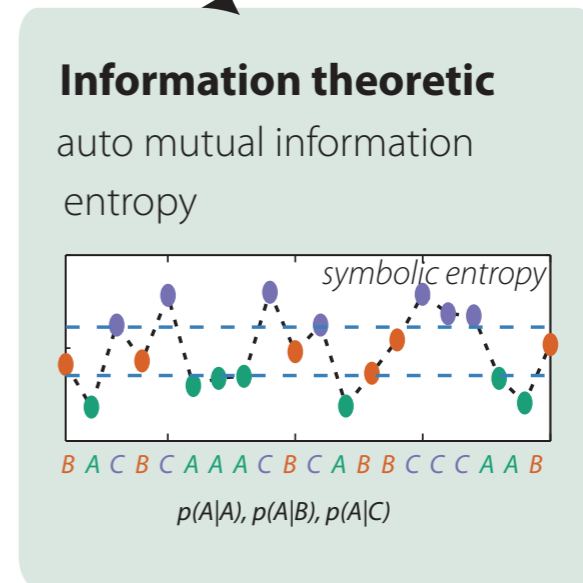
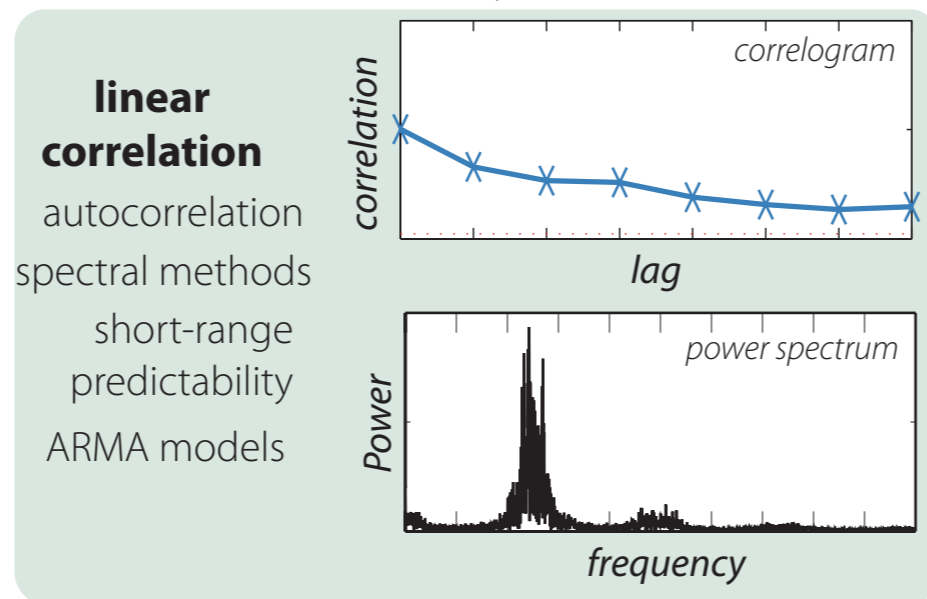
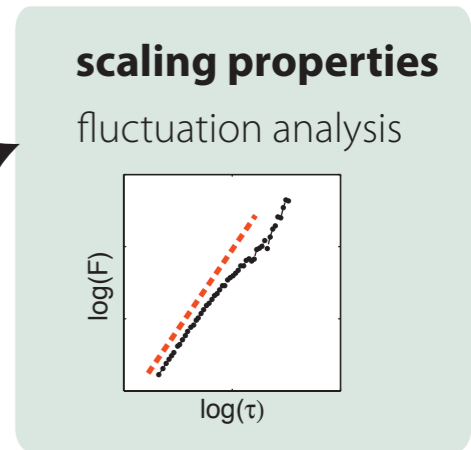
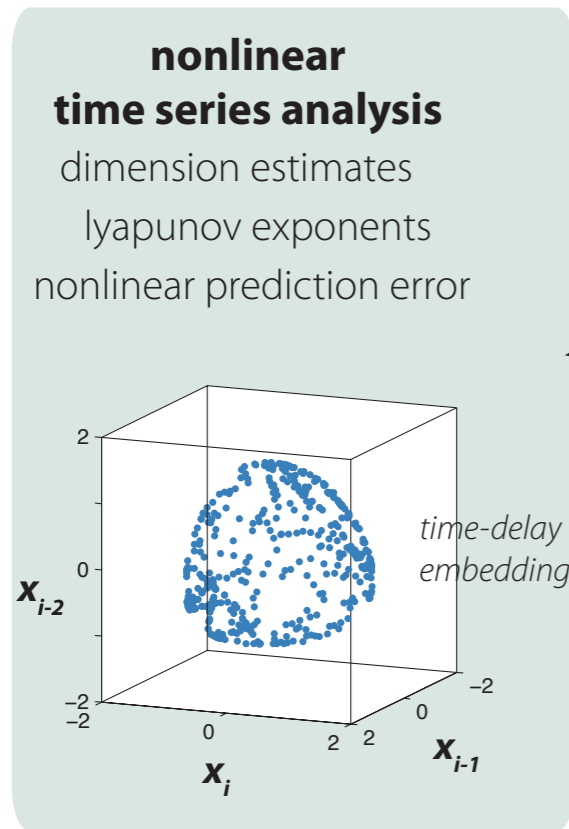
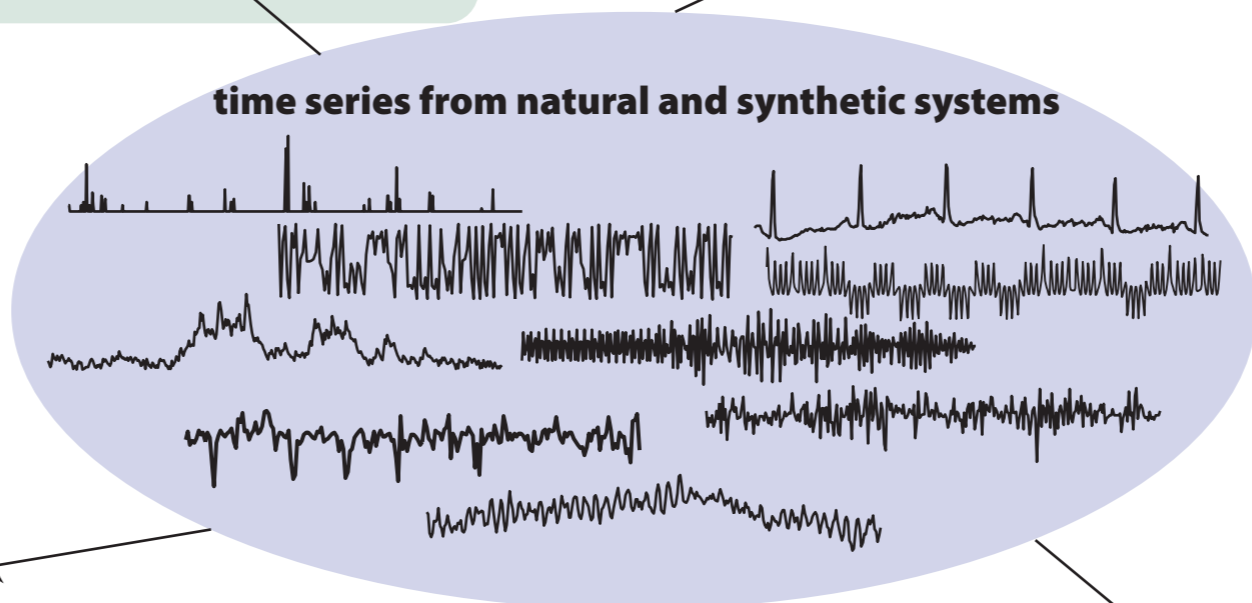
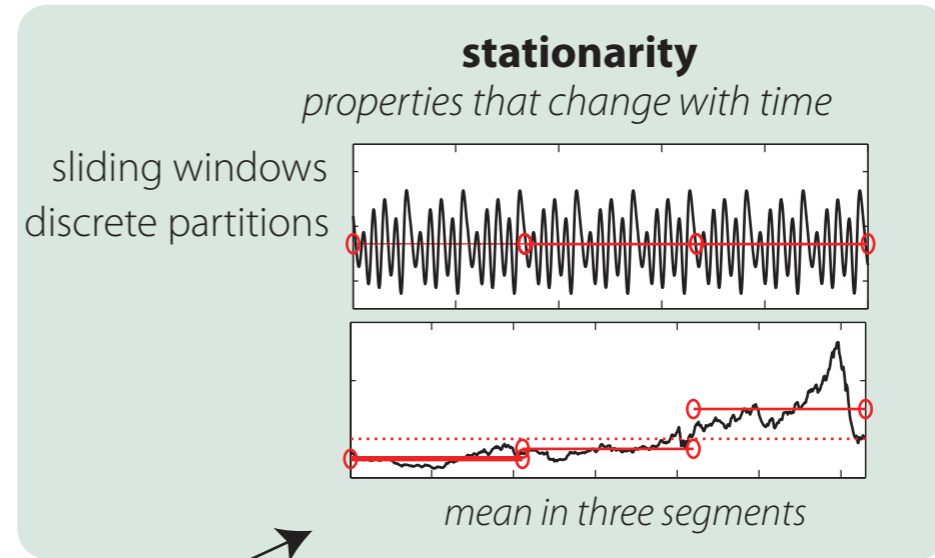
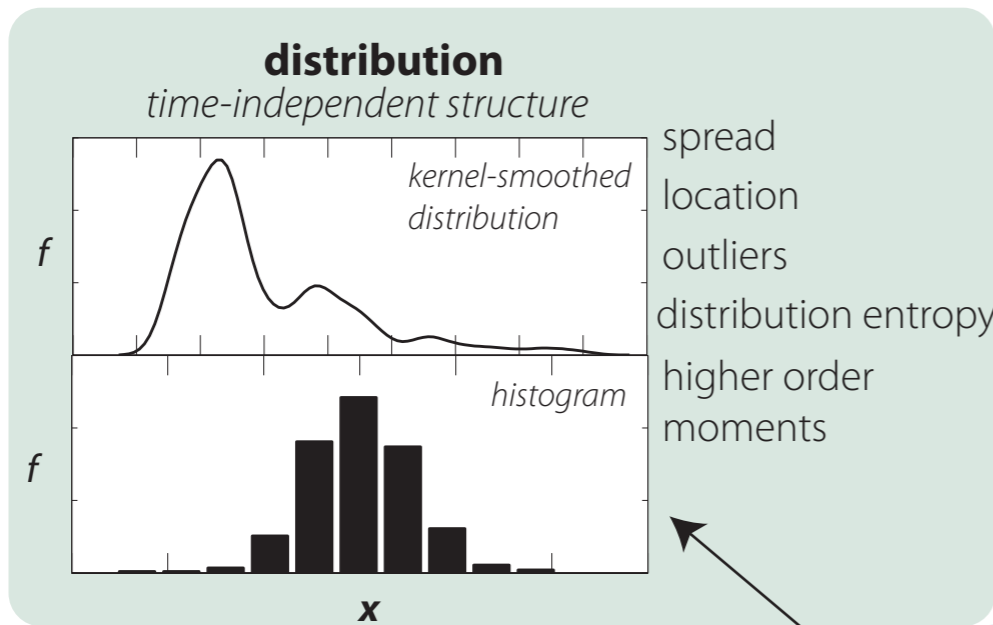
entropy

correlation dimension

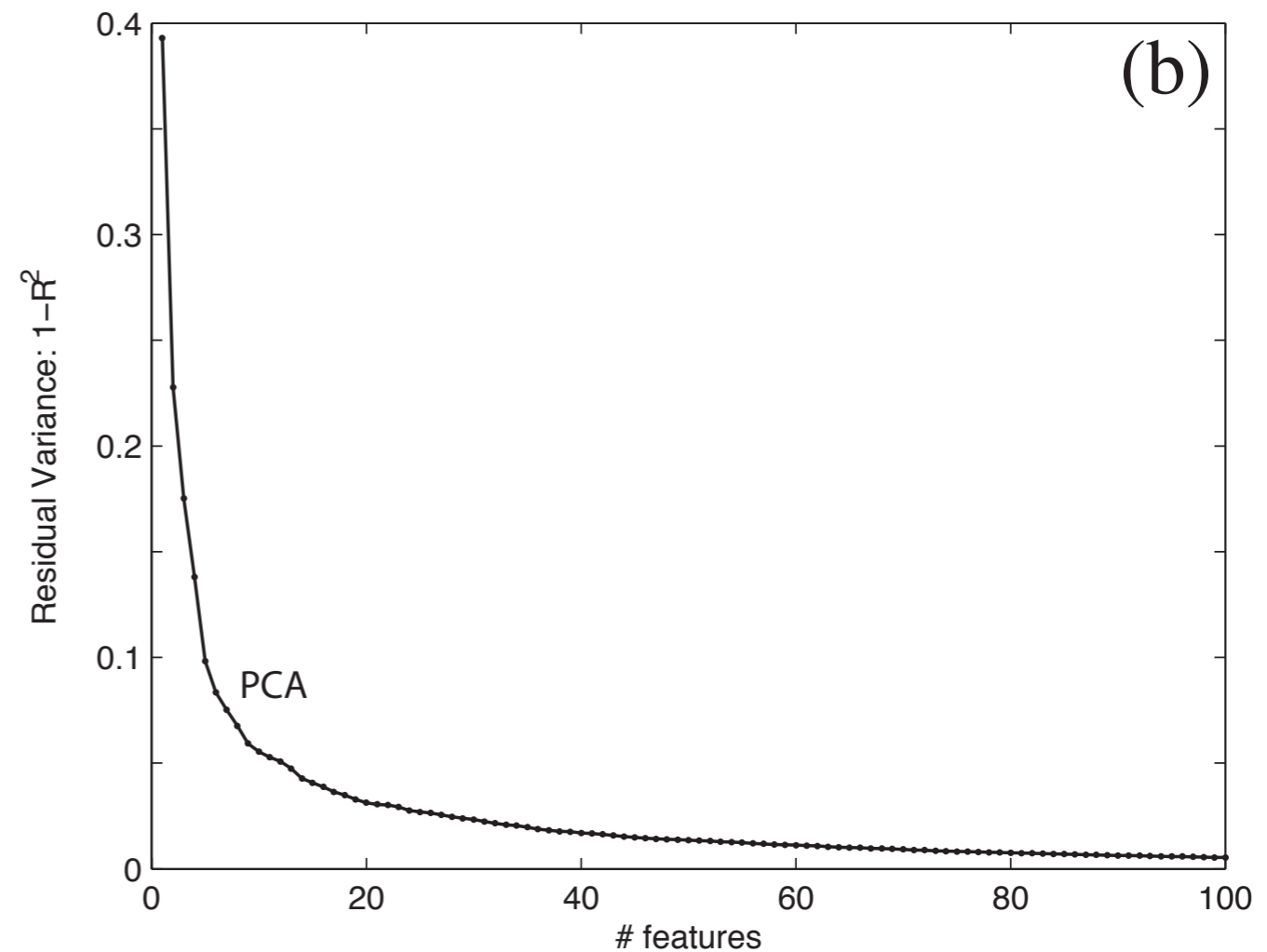
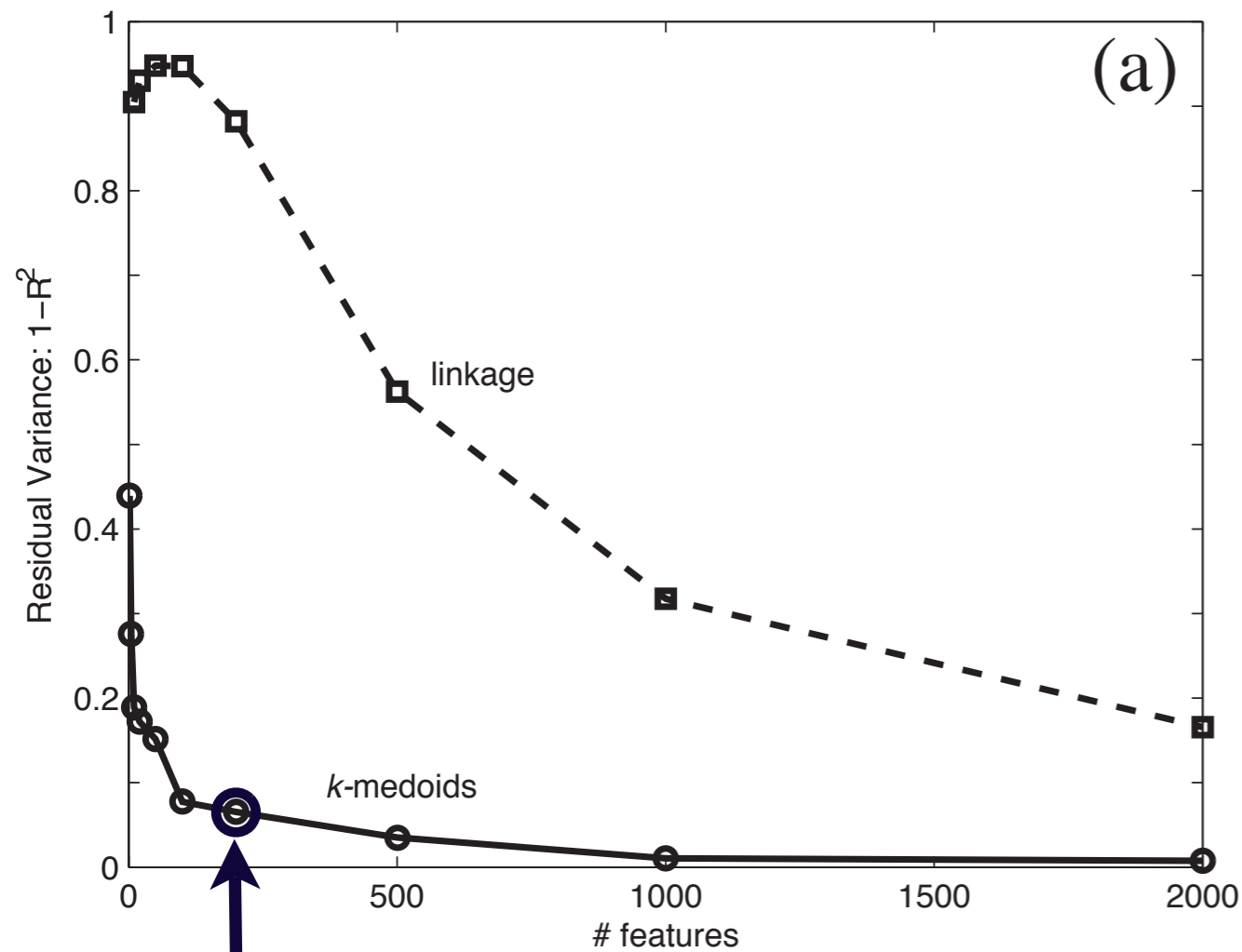
complexity

information theory

BIG PICTURE



How many operations are needed to efficiently summarize the structure we observe in empirical signals?



200 operations provide an efficient and interpretable summary

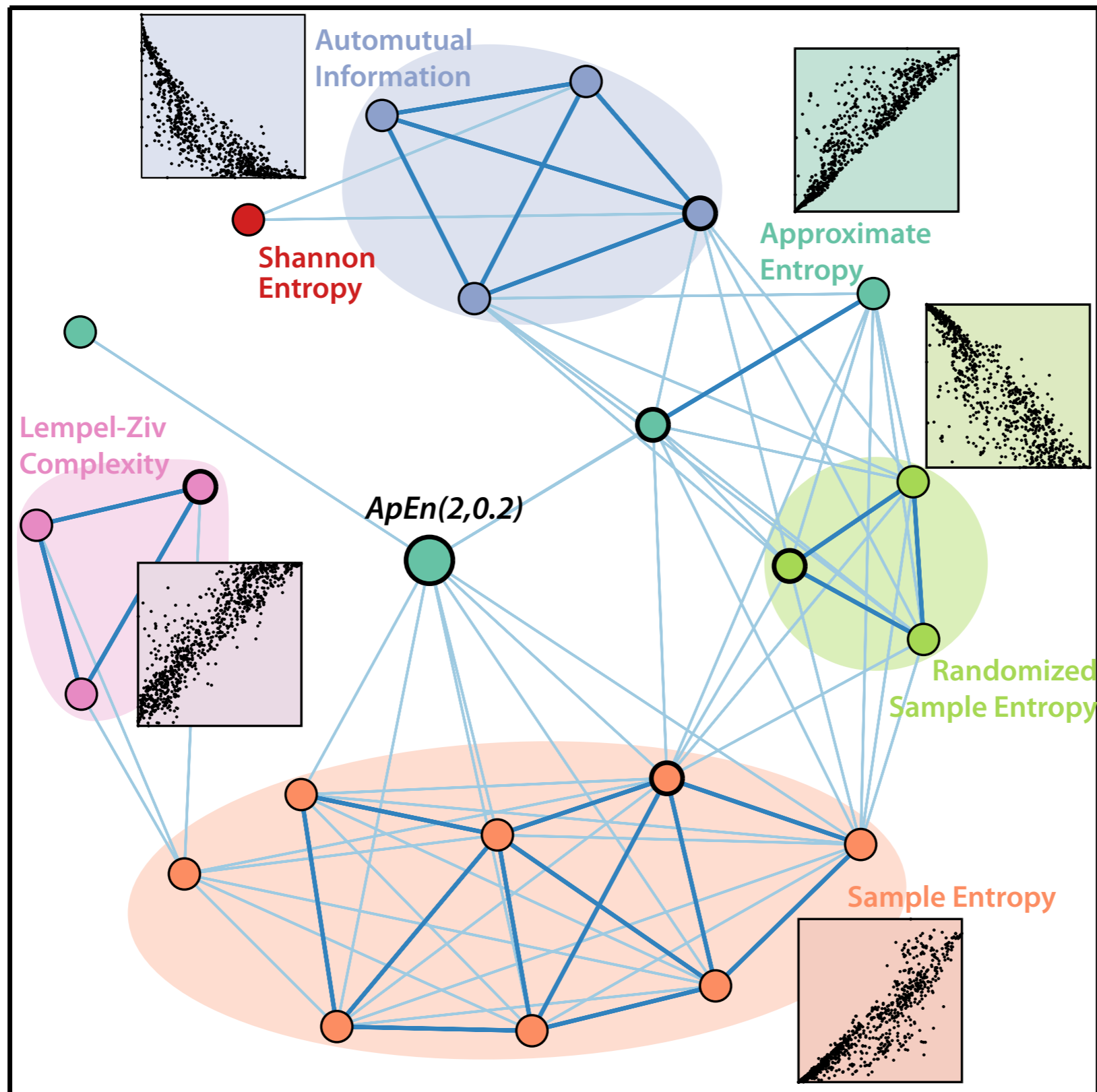
“i’m an
AR(3) coefficient”

“hello,
what are
you?”



ZOOMING IN

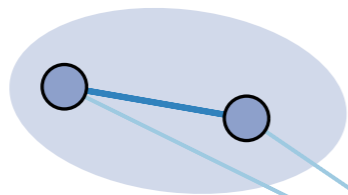
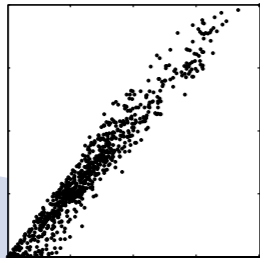
Local Neighborhoods



*Organize
our methods
for time-series
analysis*

Local Neighborhoods

fluctuation analysis

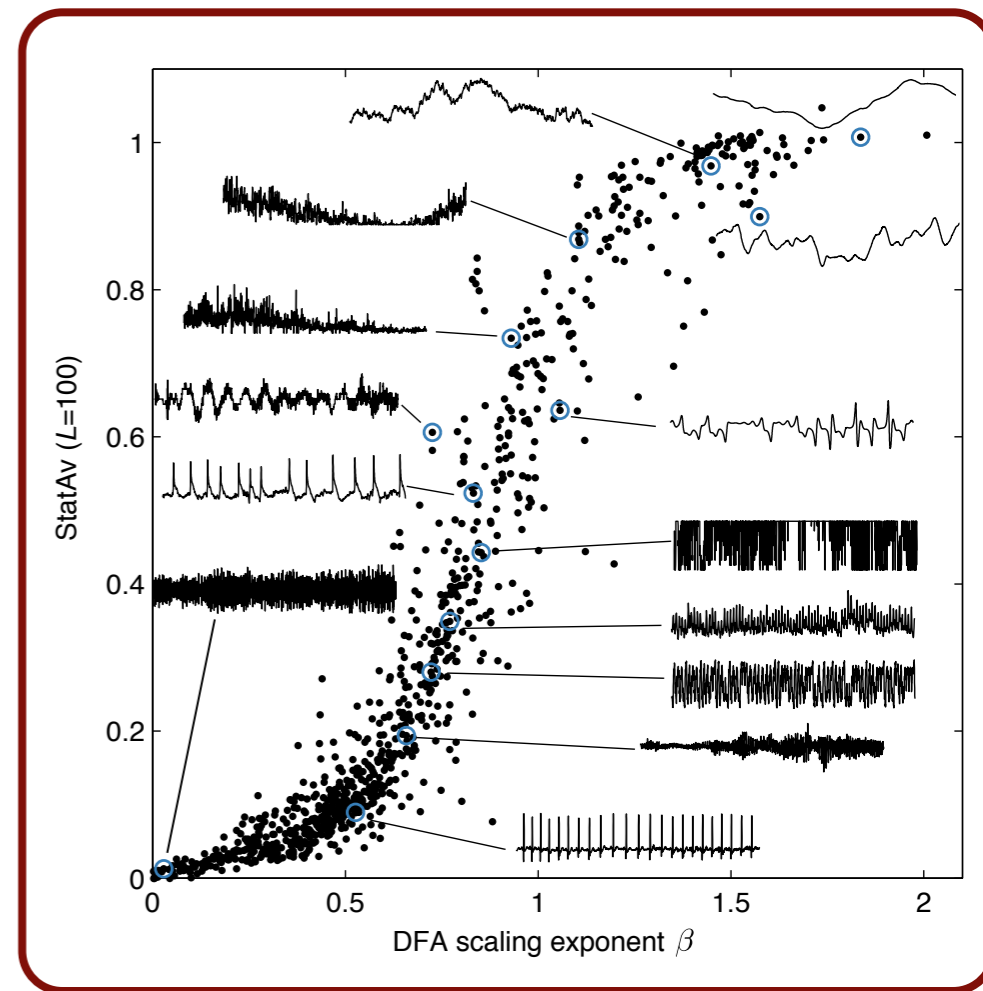
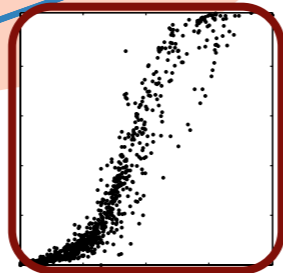


low frequency power

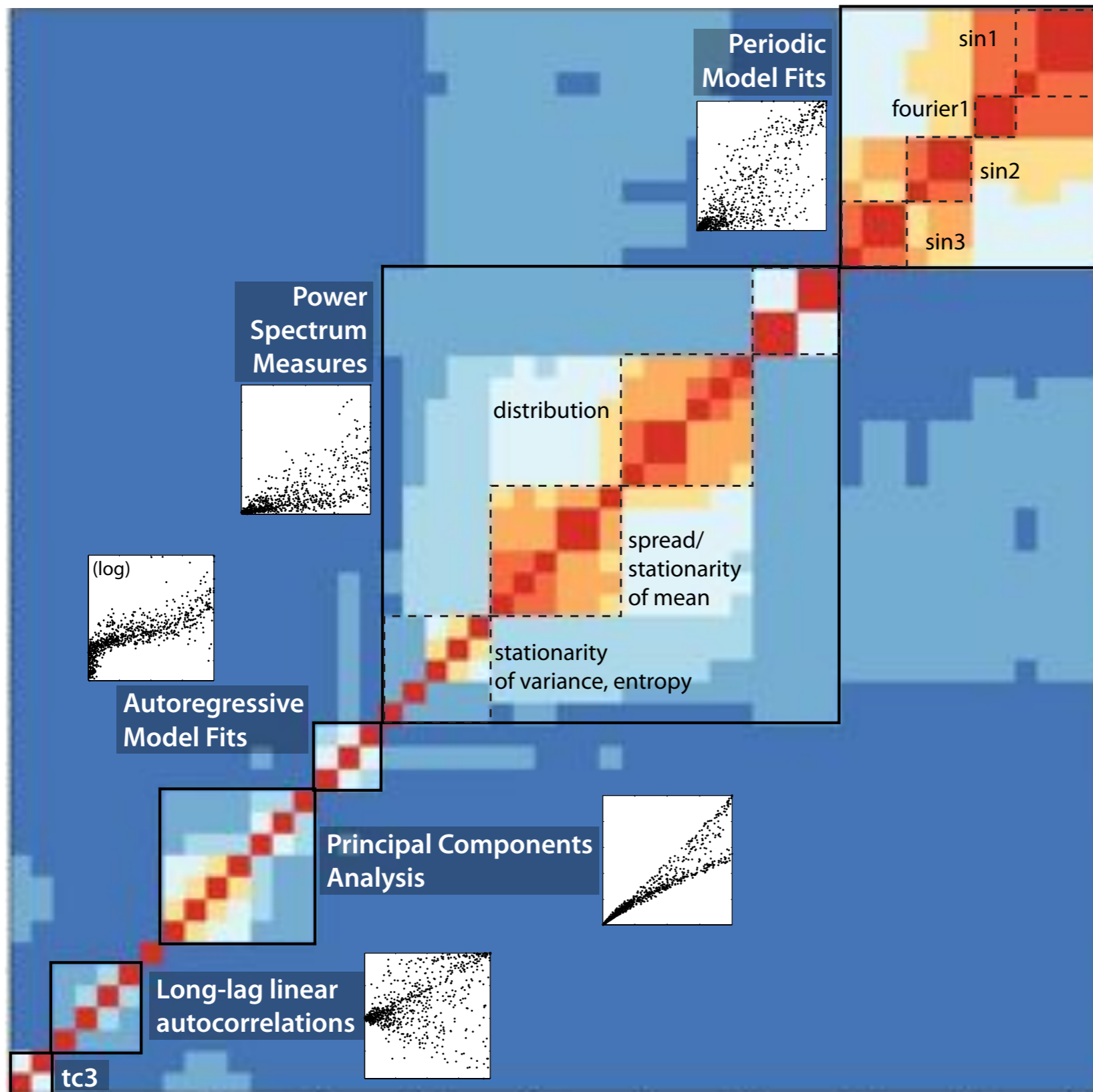
DFA

stationarity measures

step detection

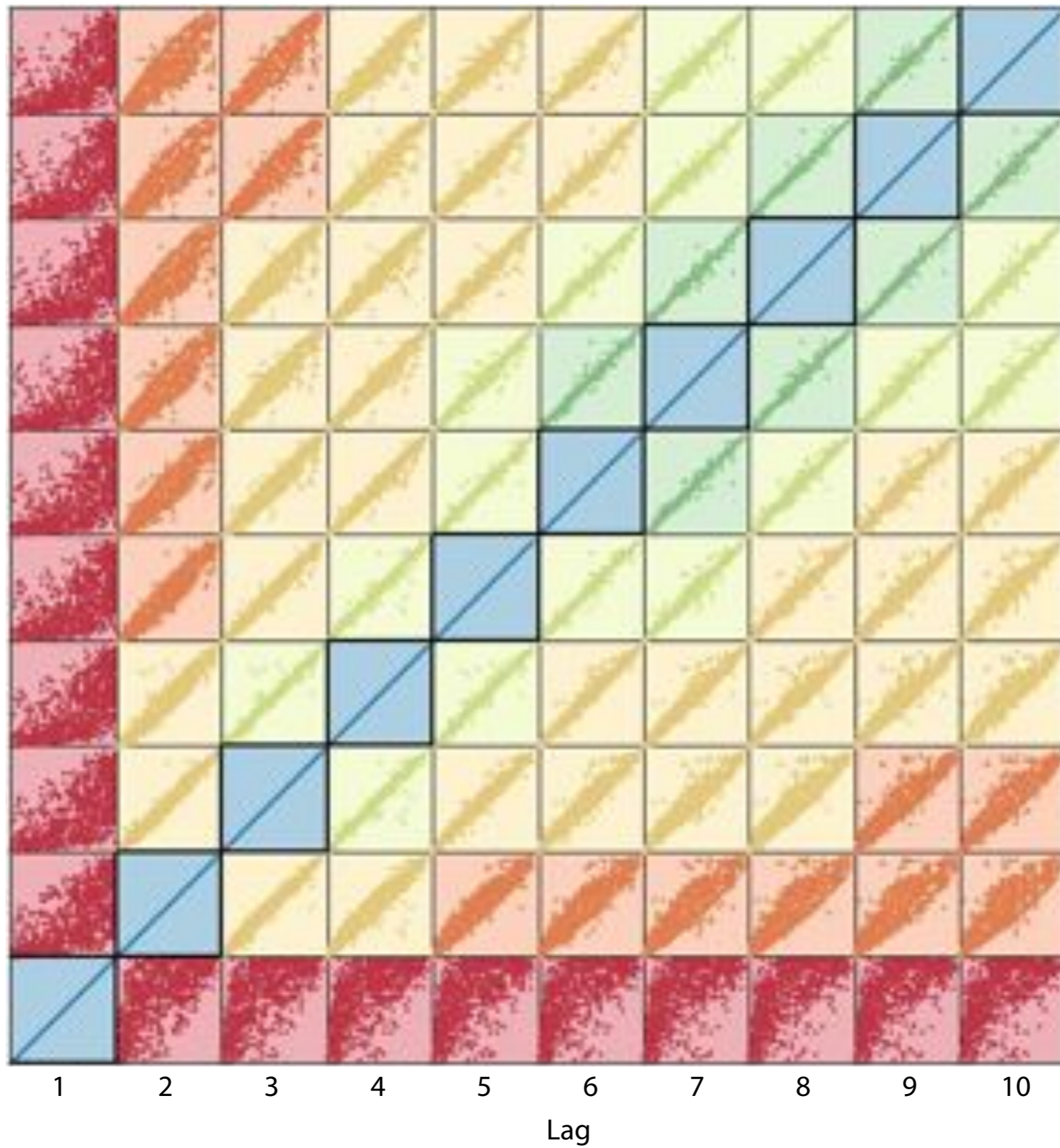


Local Neighborhoods

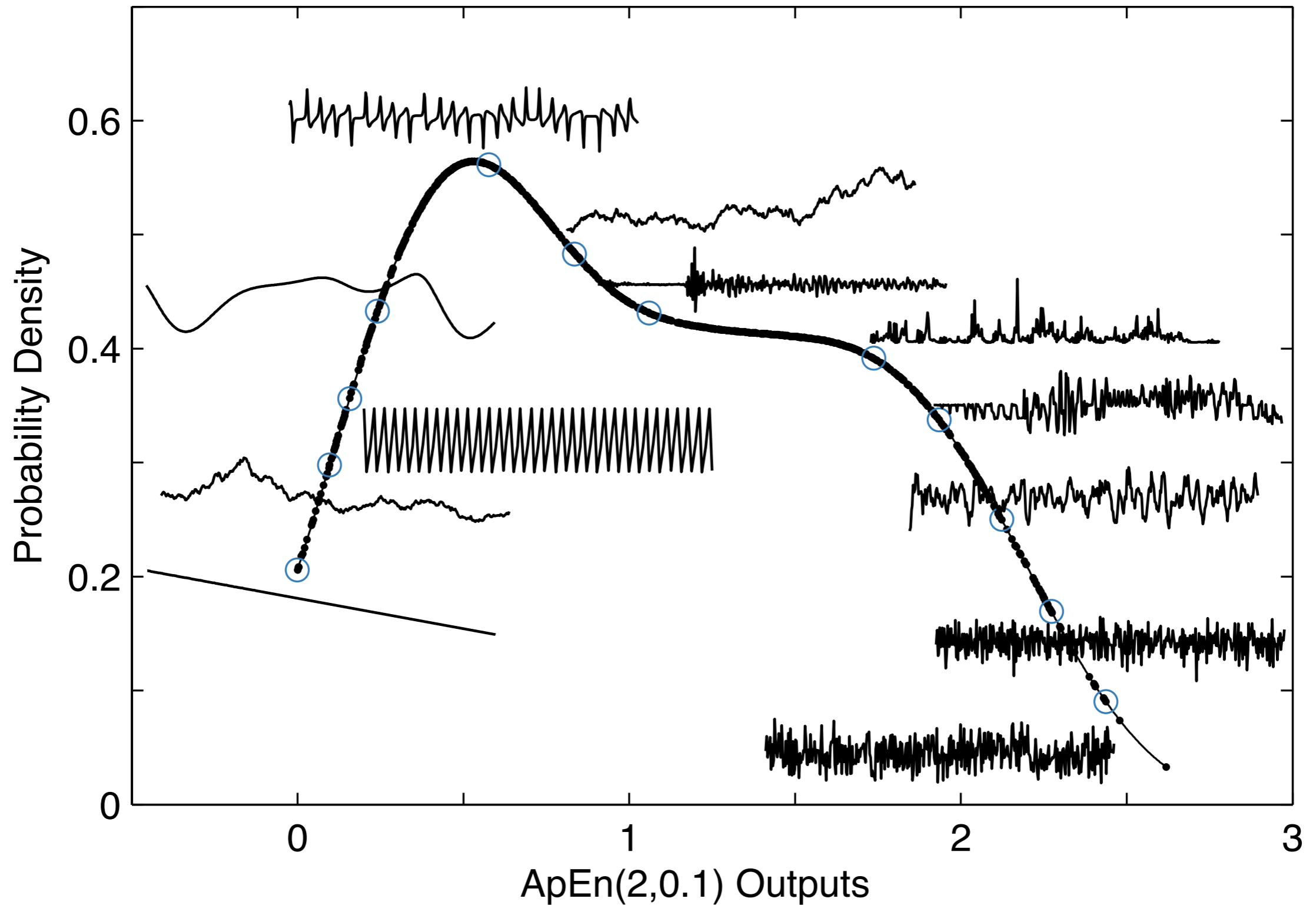


*Organize
our methods
for time-series
analysis*

Automutual Information Measures



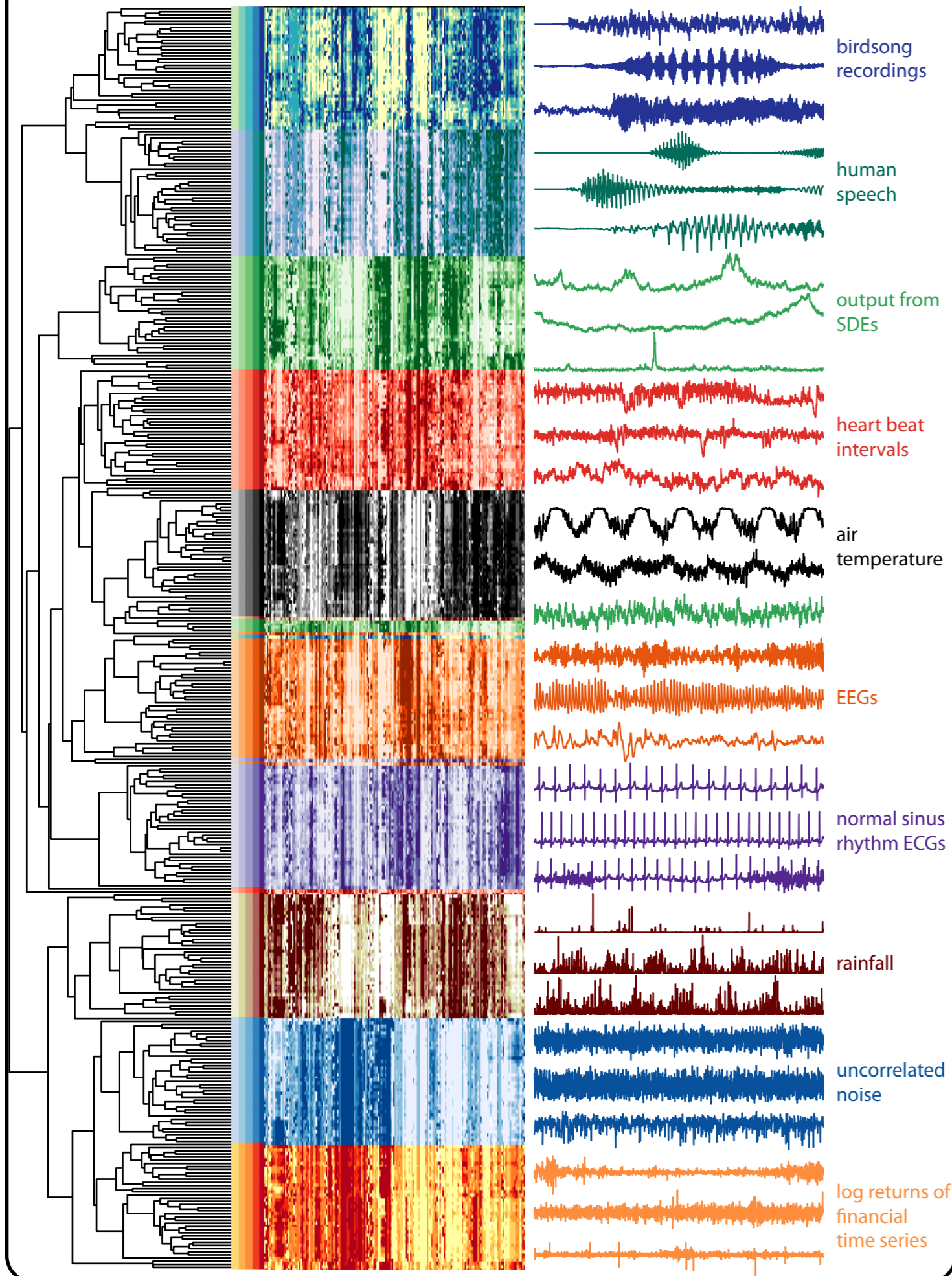
Visualize behavior



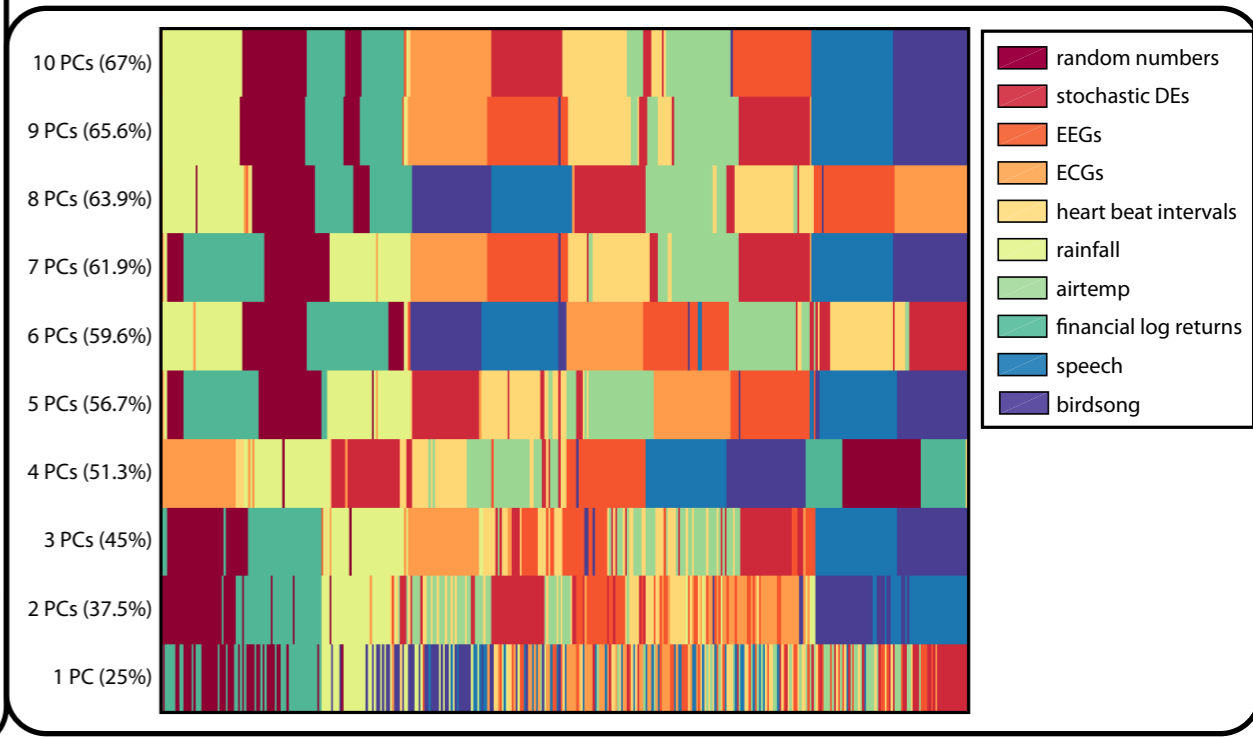
Organizing Our Data

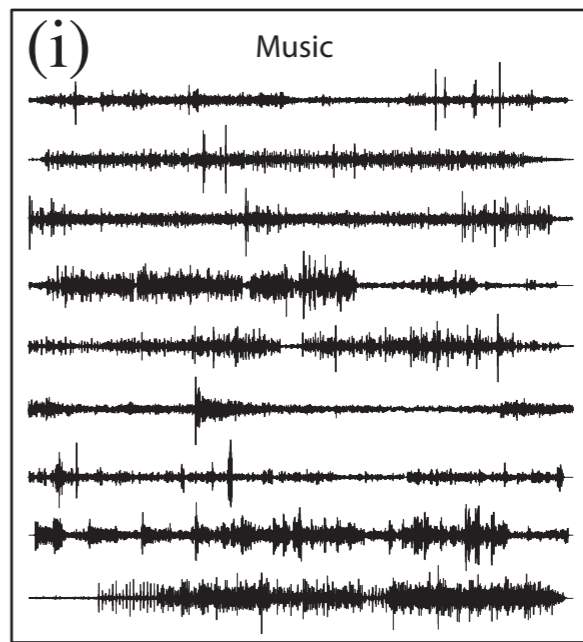
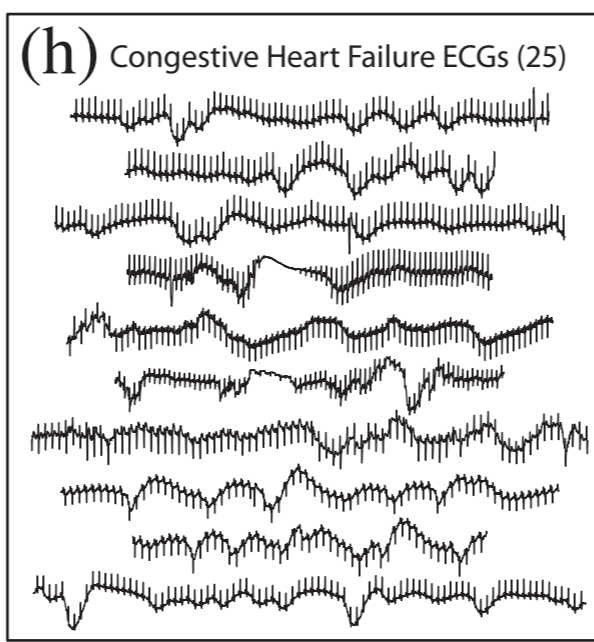
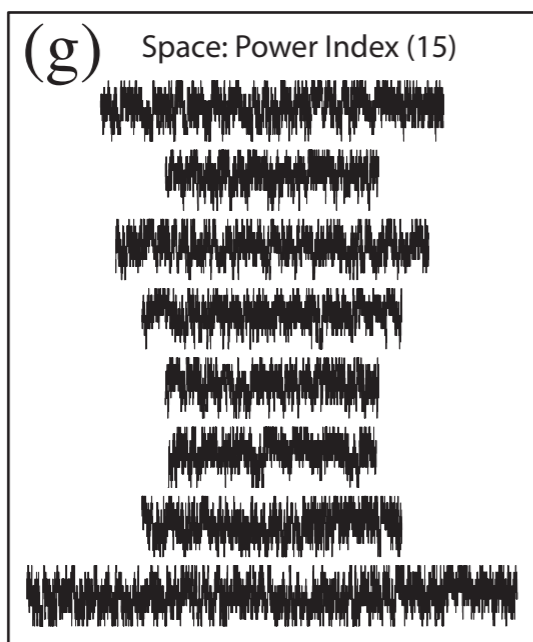
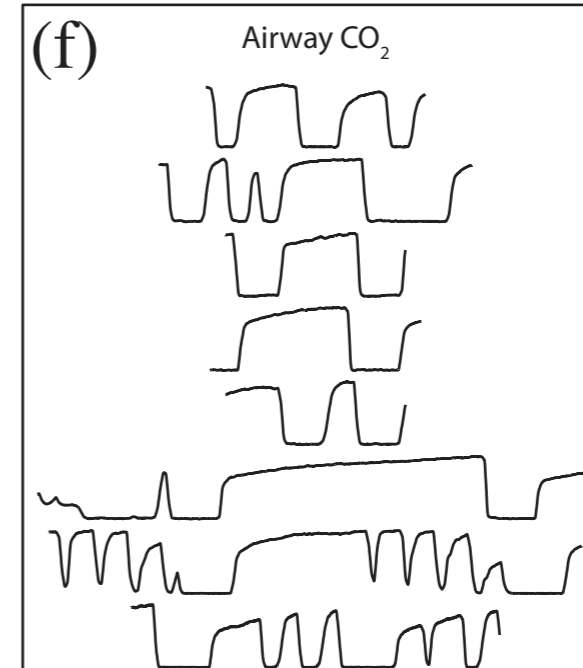
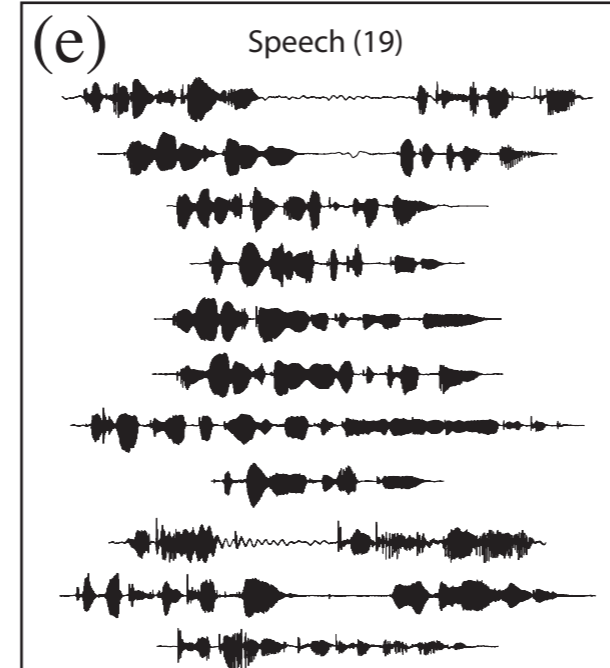
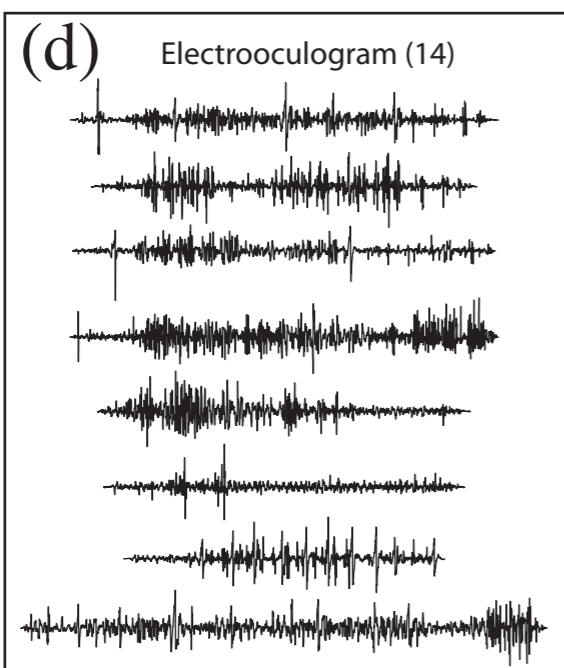
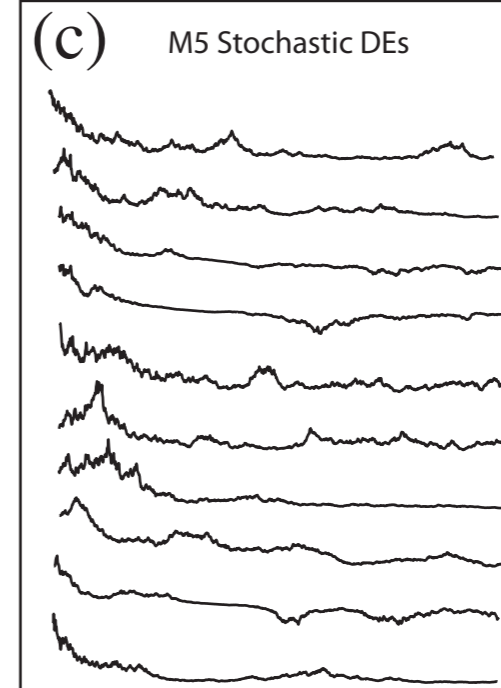
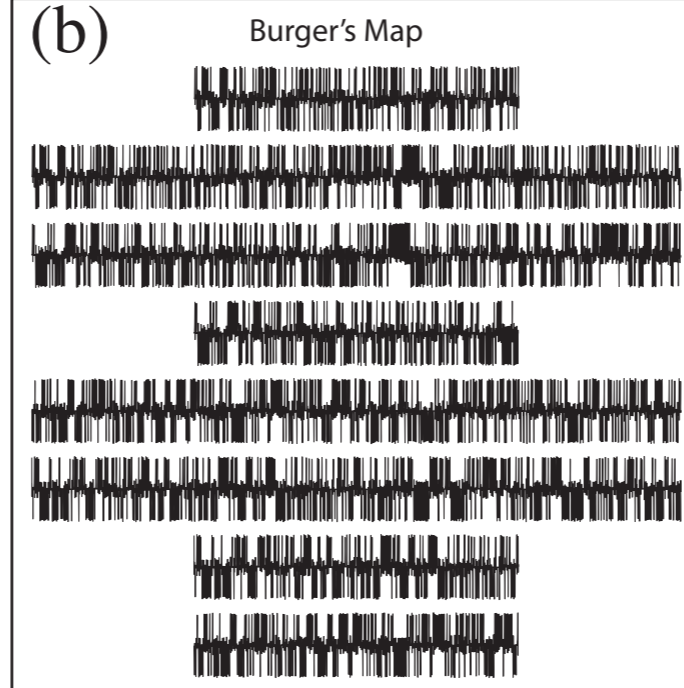
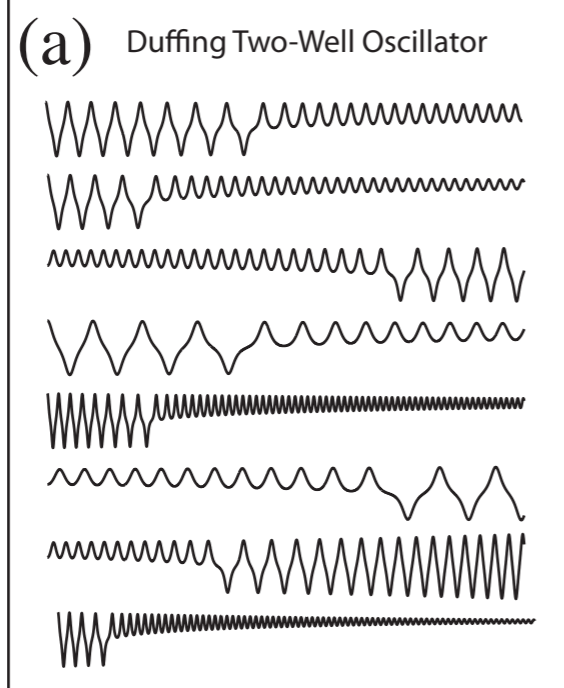
- Our reduced interdisciplinary set of operations is a powerful summary of the structure in empirical time series
- Links between real-world and synthetically-generated time series encourage a unified, collaborative framework for understanding the dynamics in time series

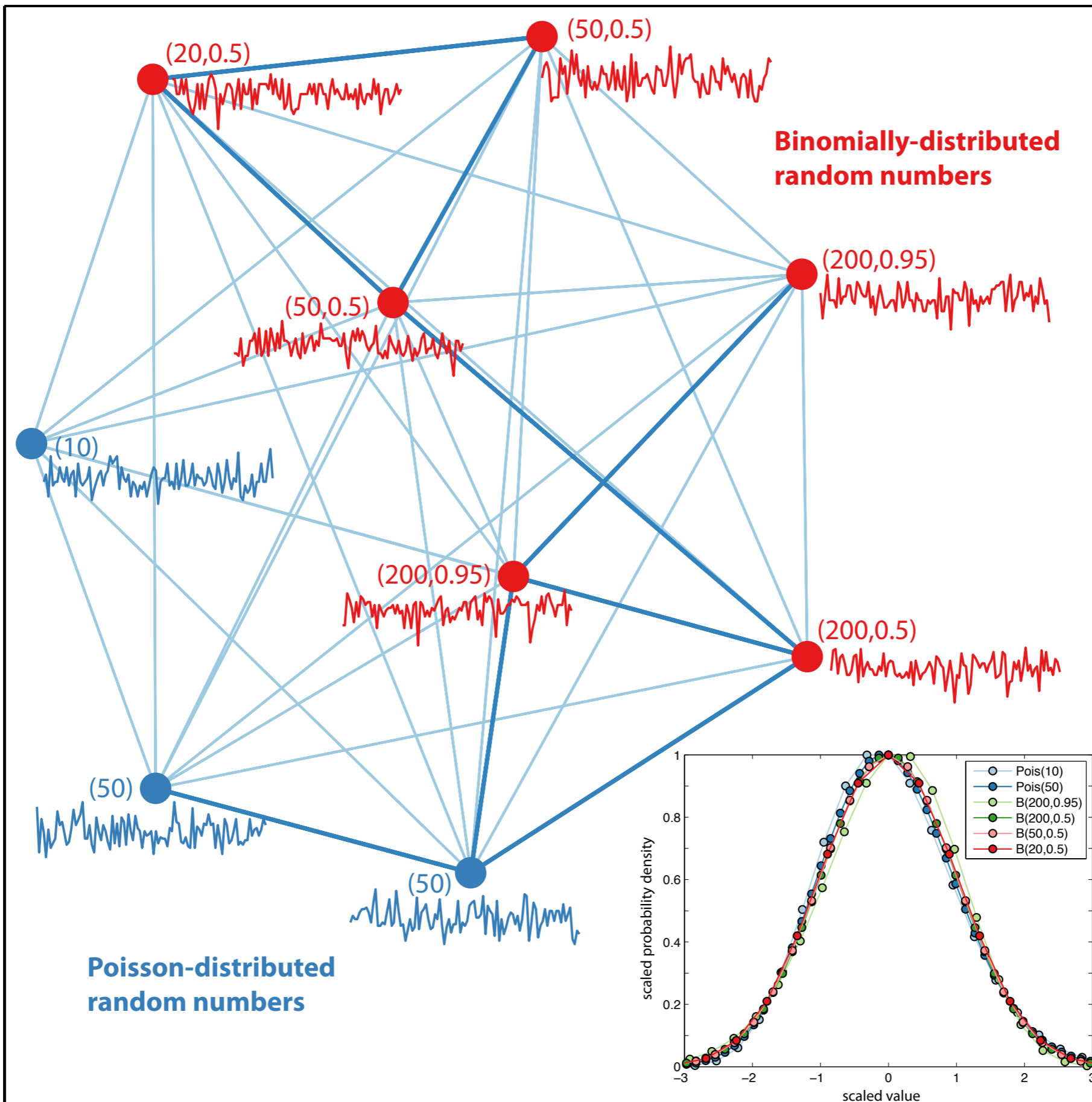
194 operations

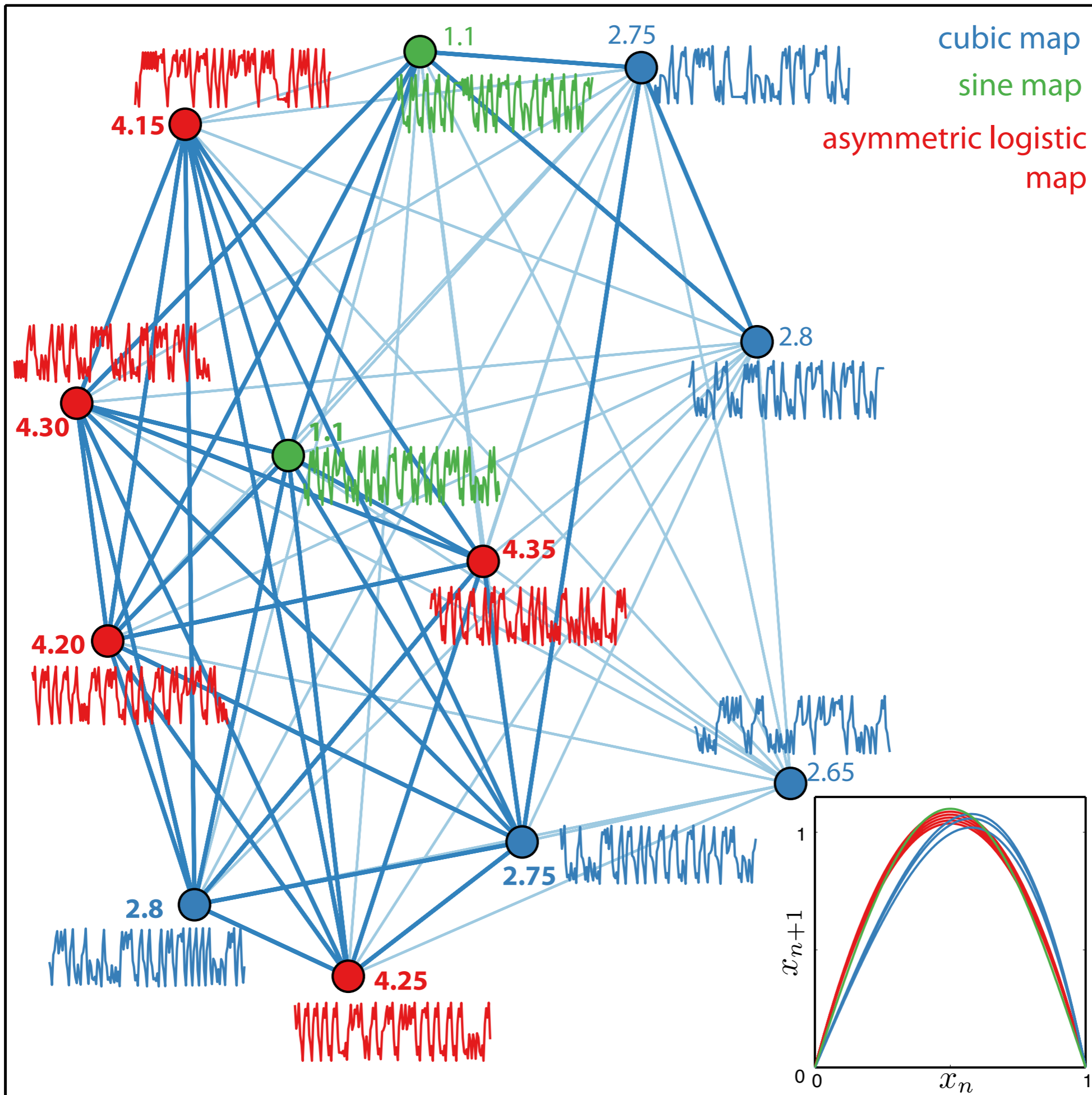


broad classes of dynamics are distinguished





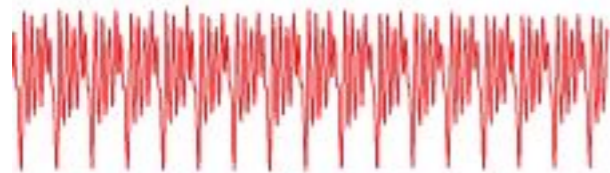




Time-series models?

- Real data are recordings of dynamics
- Time-series models generate dynamics with a known mechanism

speech recording



“he did it”



$$dx/dt = y$$

$$dy/dt = z$$

$$dz/dt = -z - (T - R + Rx^2)y - Tx$$

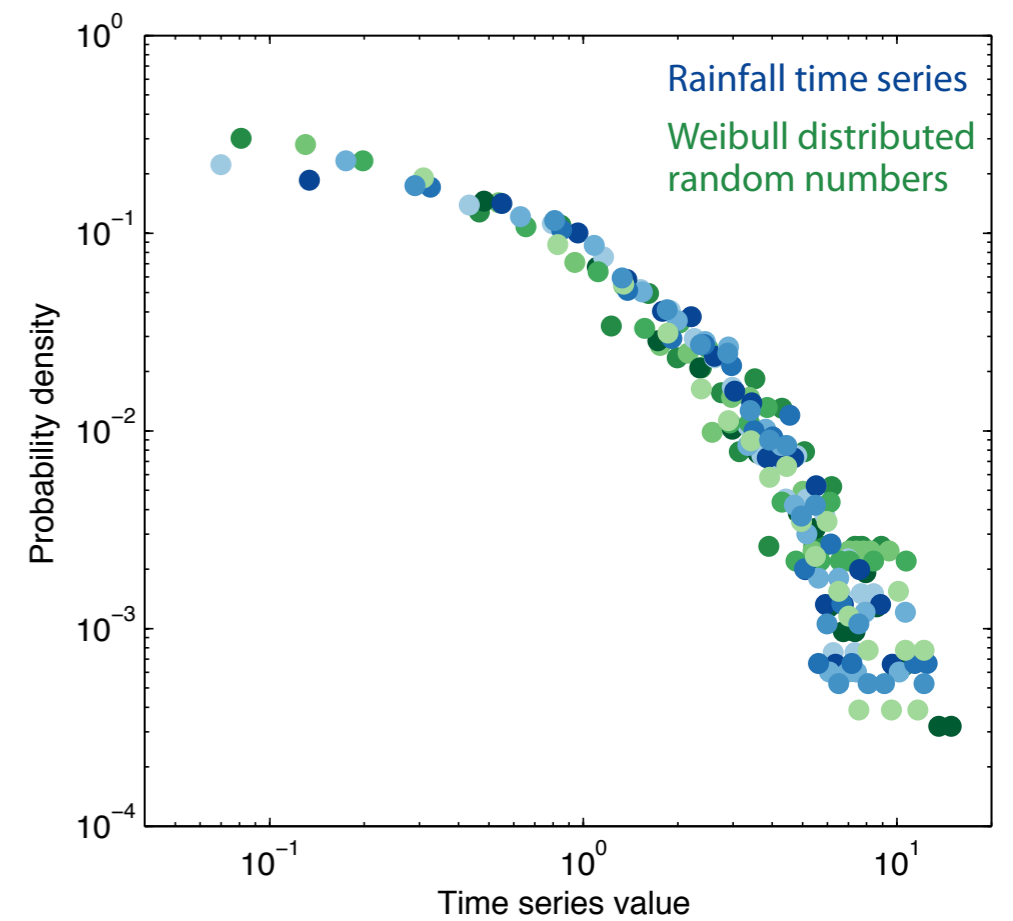
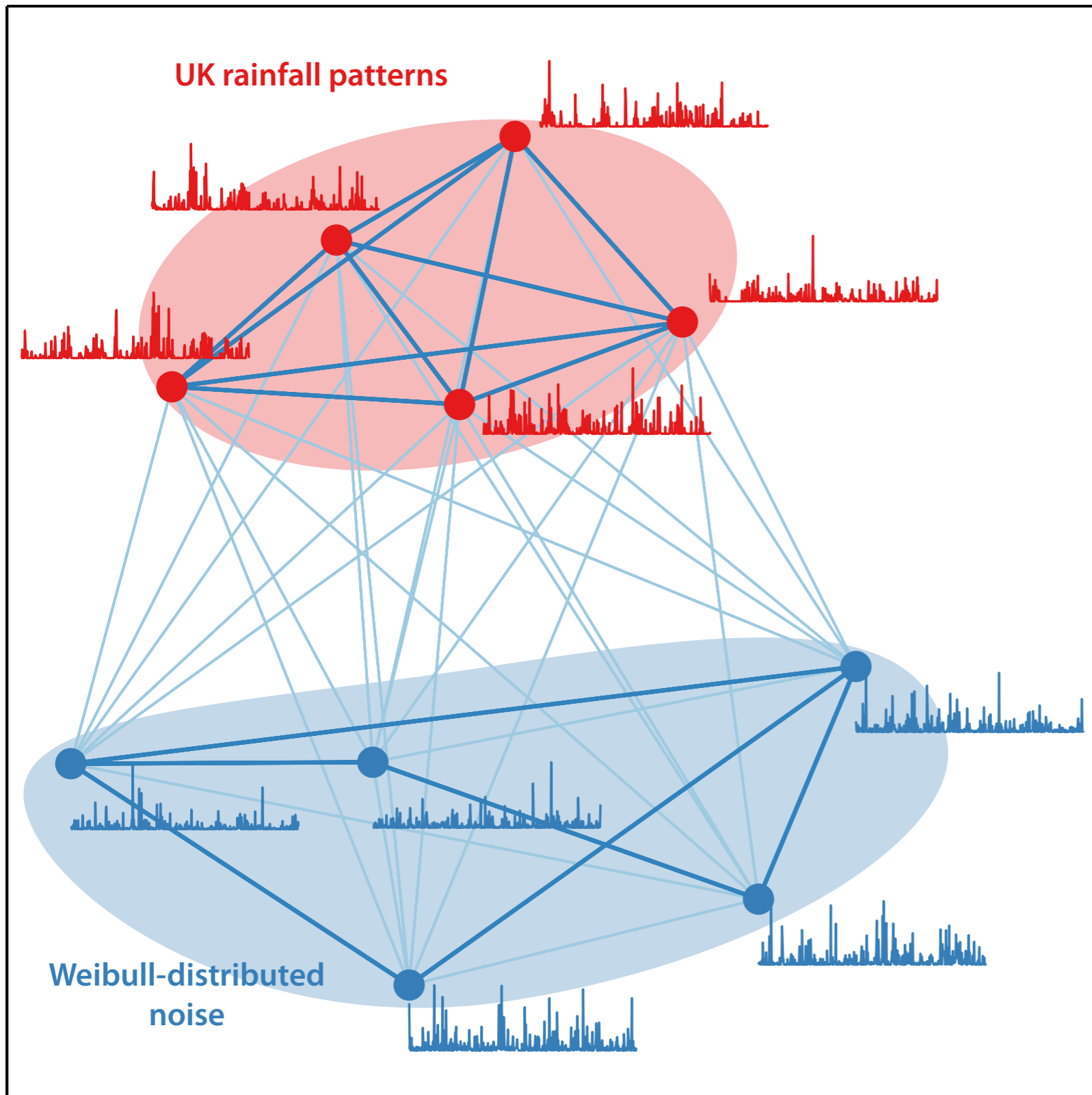


“he did it”



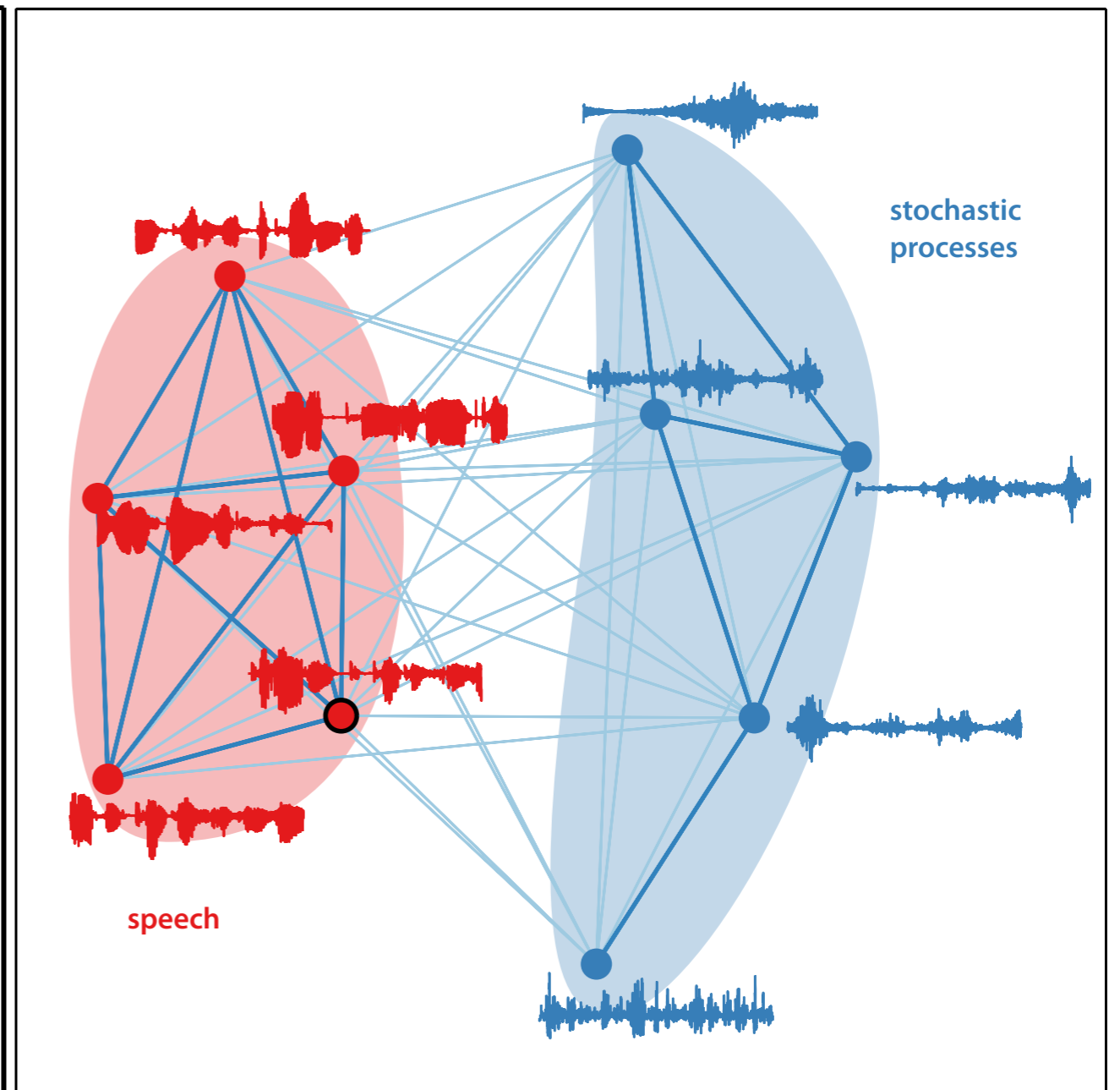
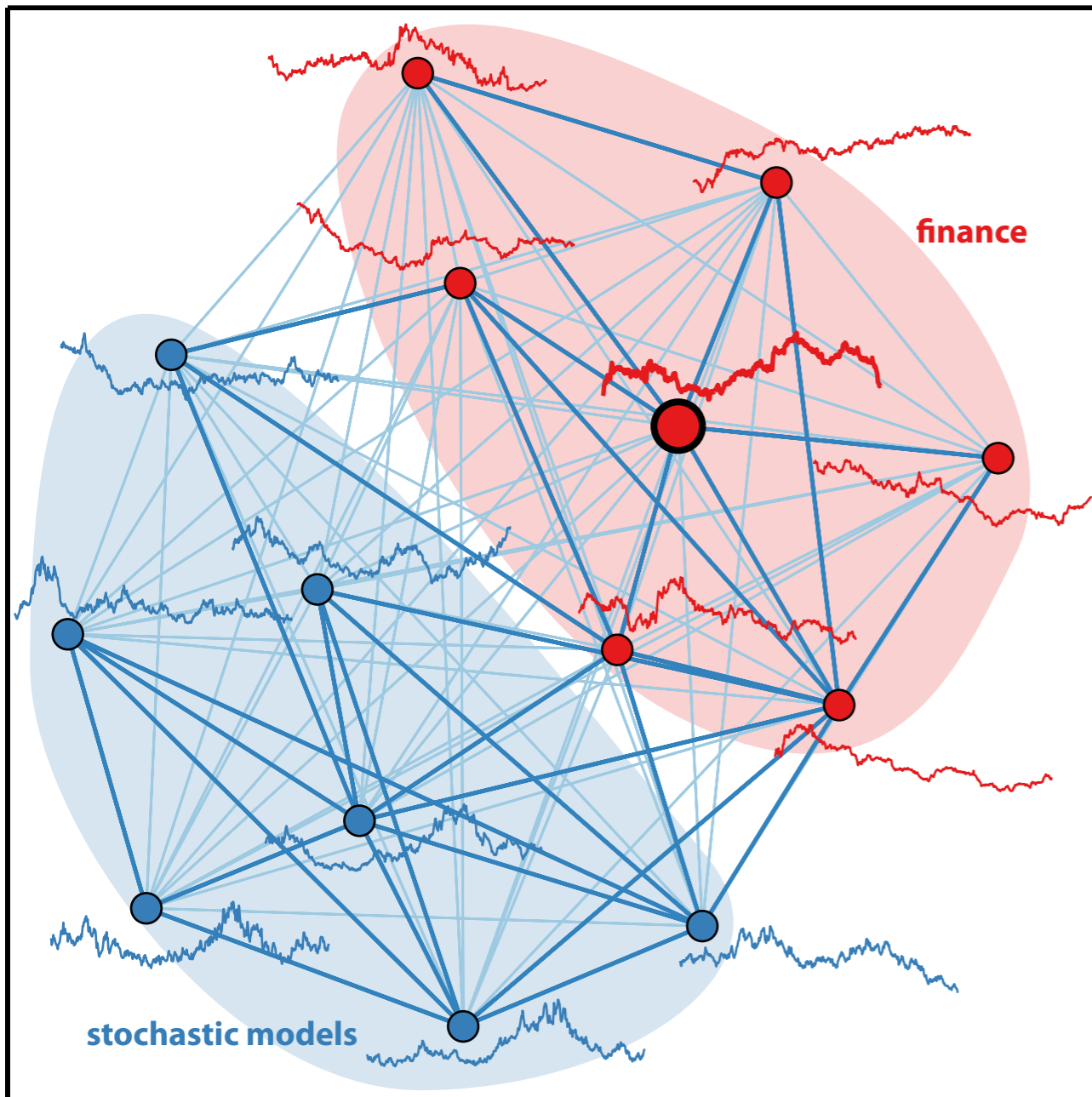
Pointing the finger

Similarity Search

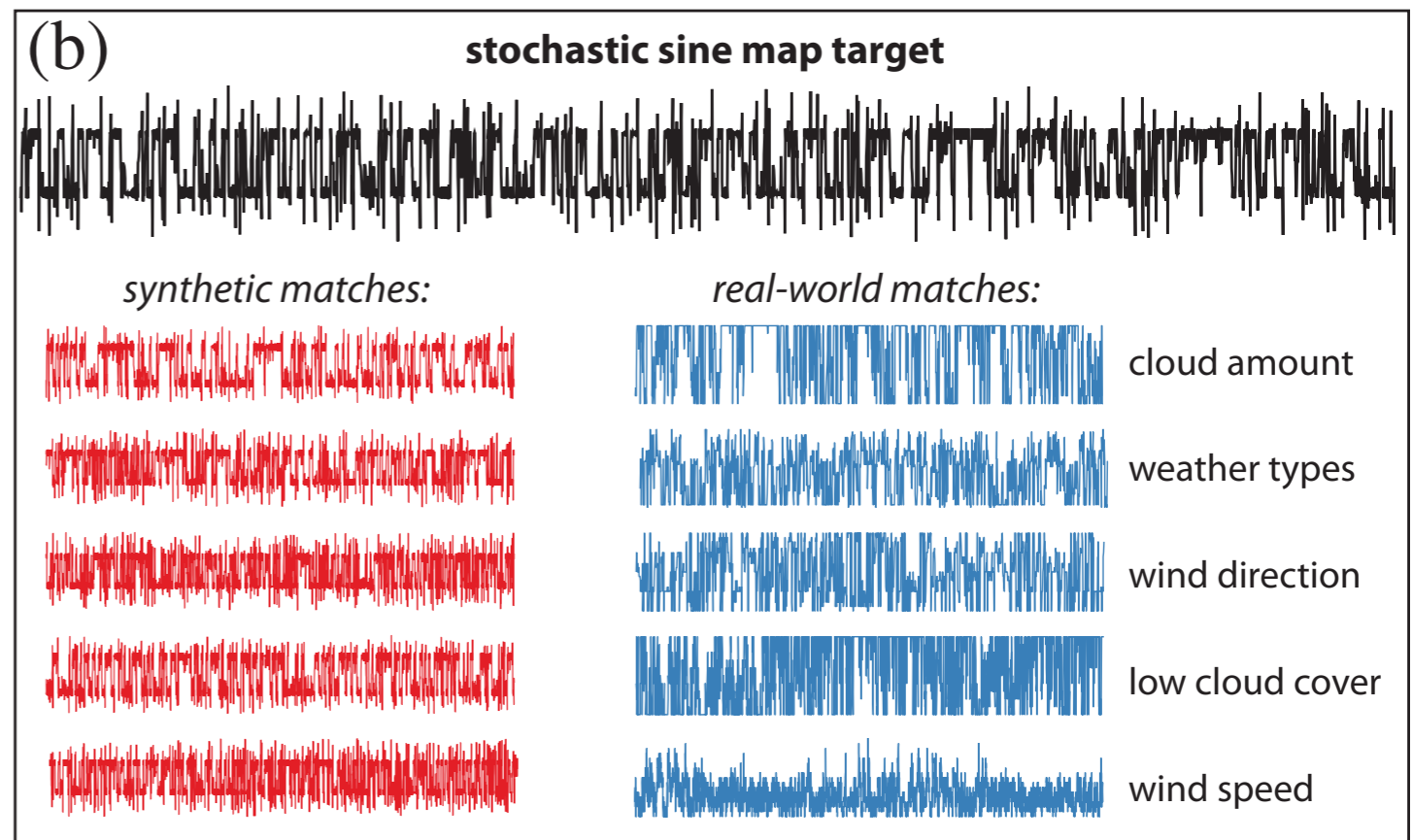
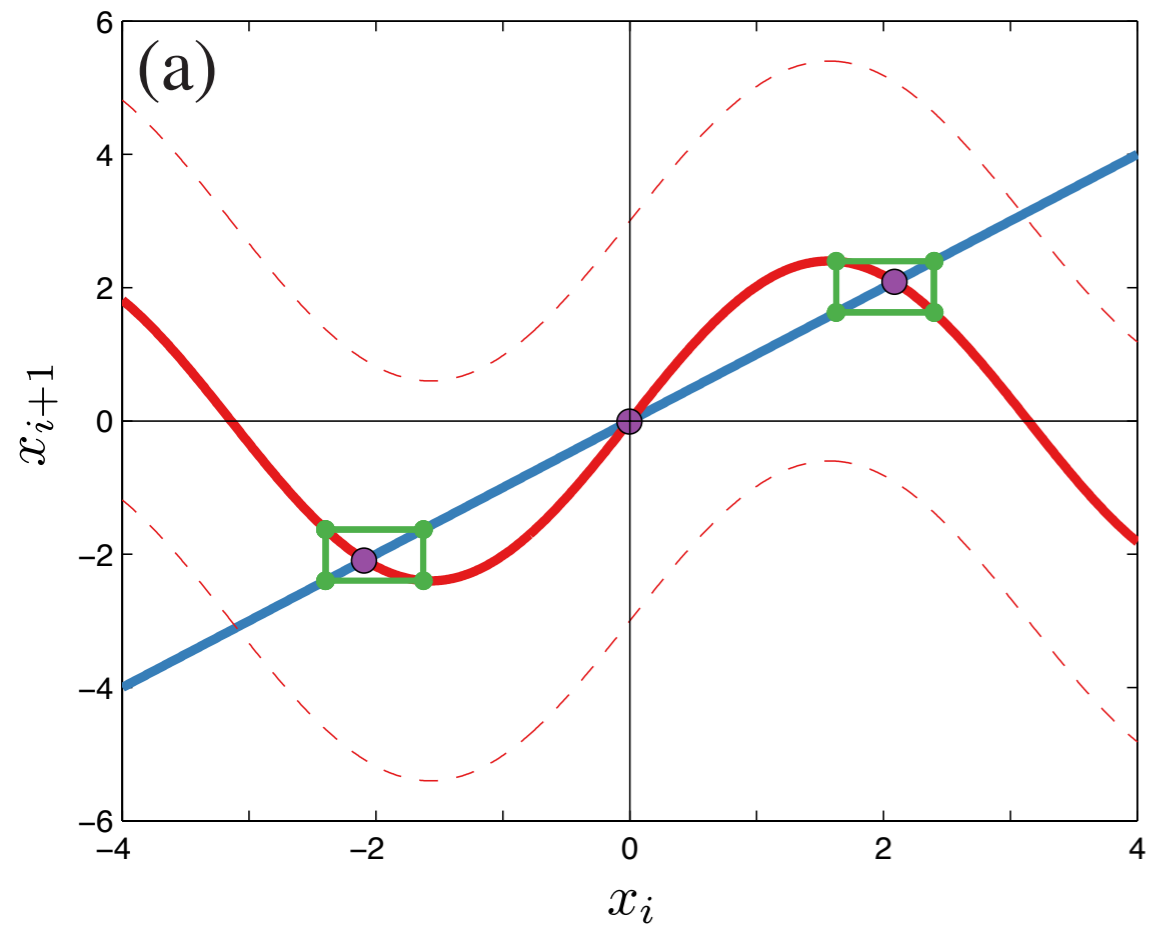


*suggest models
for our data*

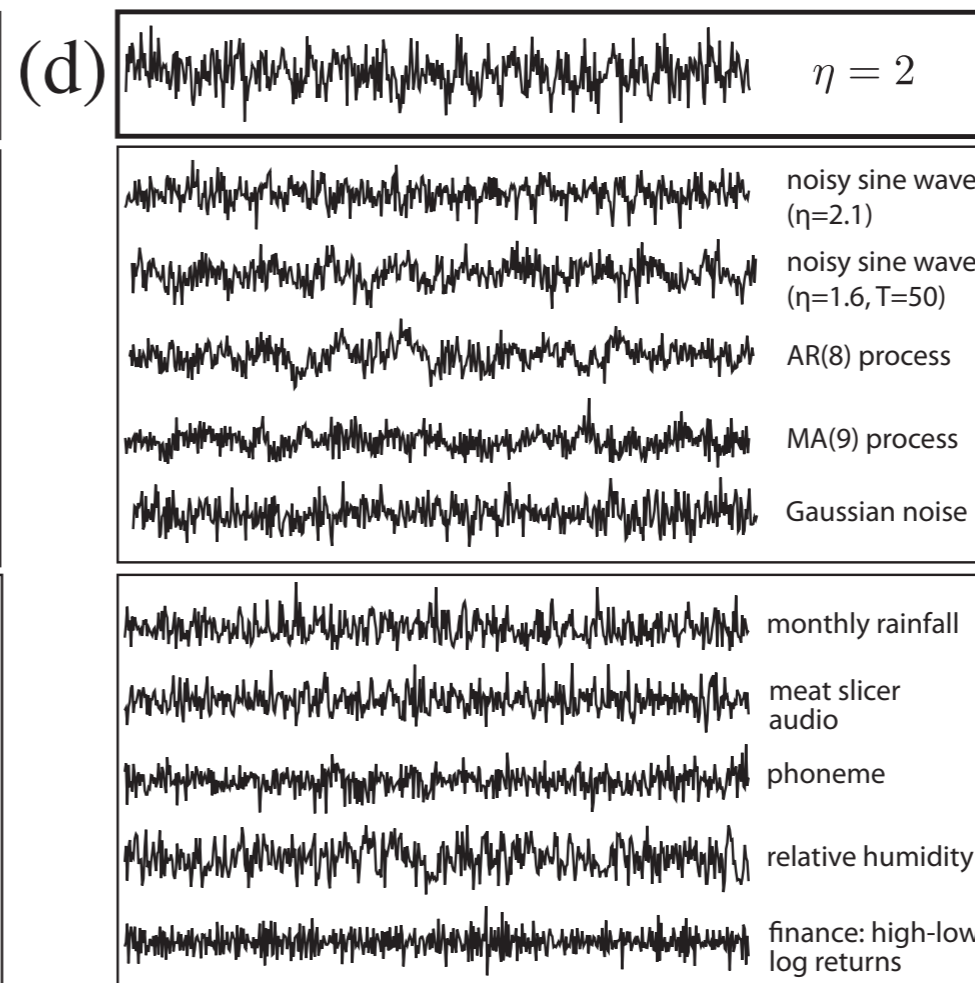
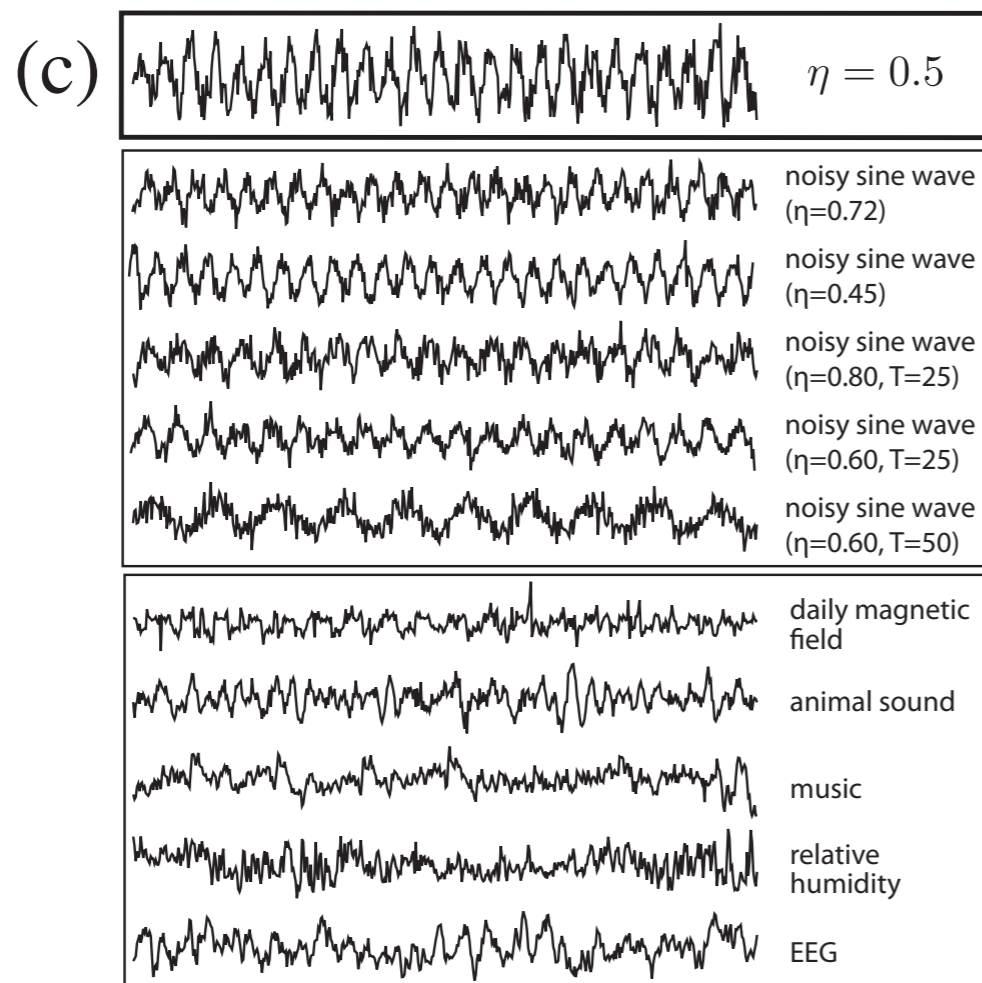
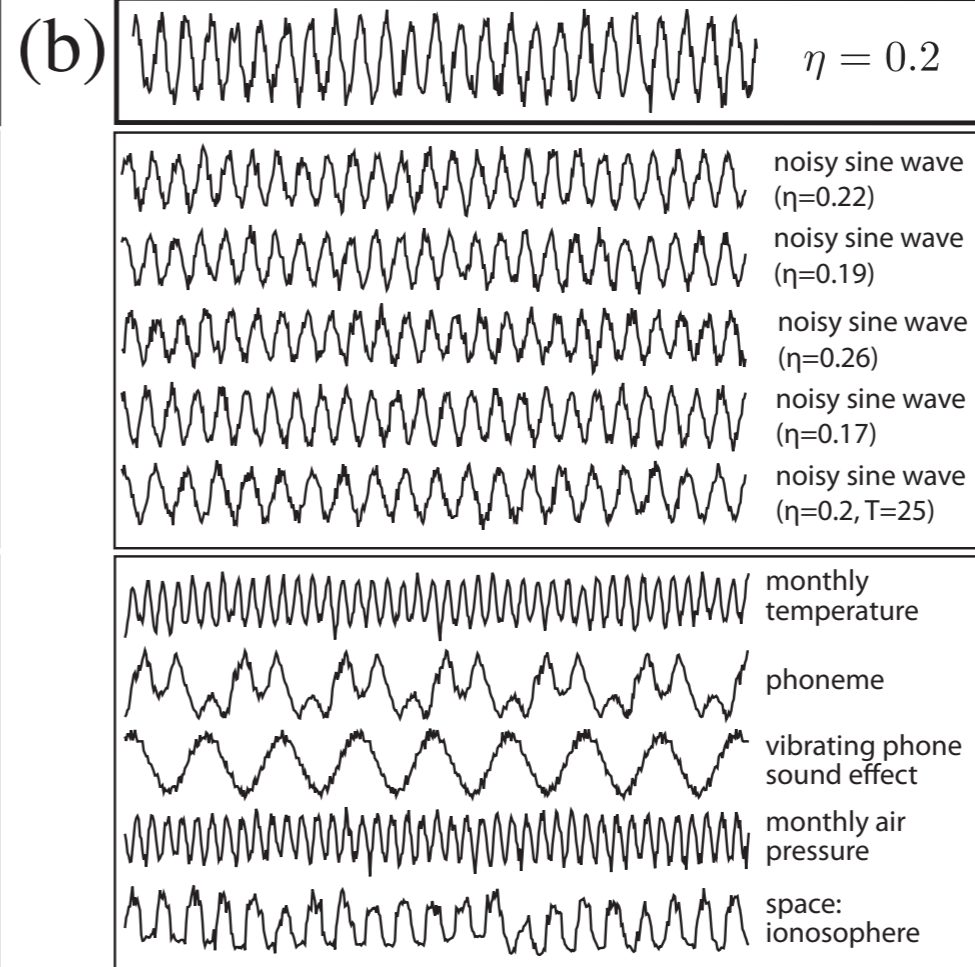
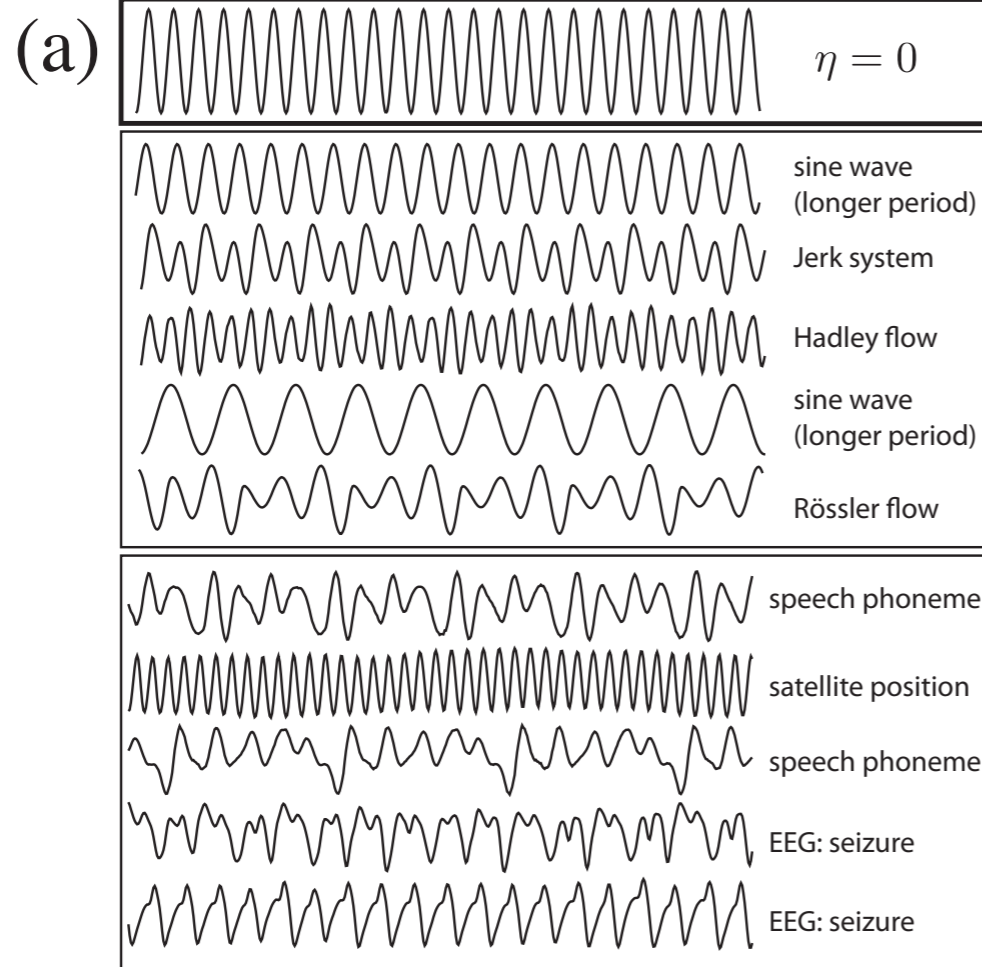
Similarity Search



*suggest models
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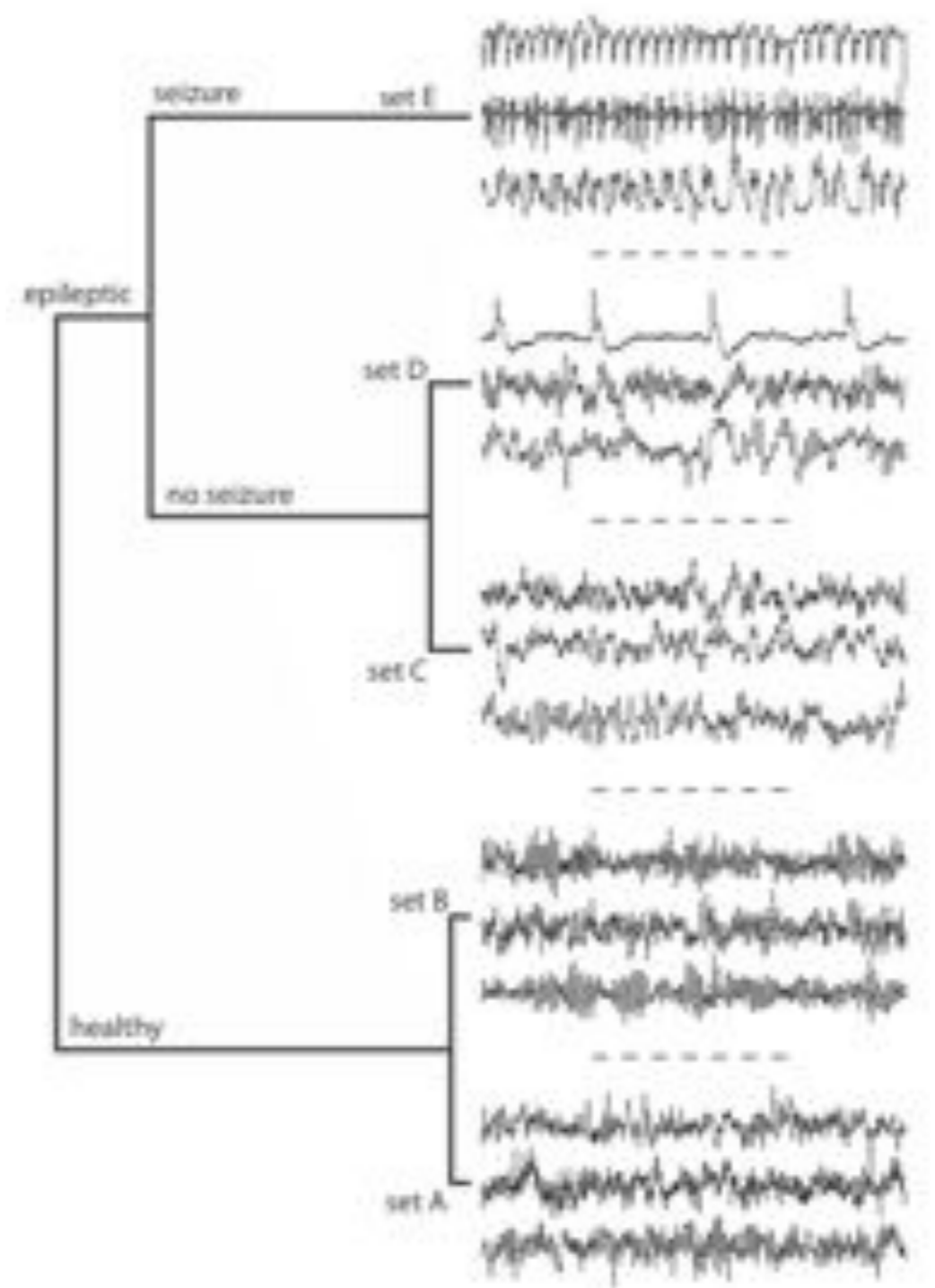
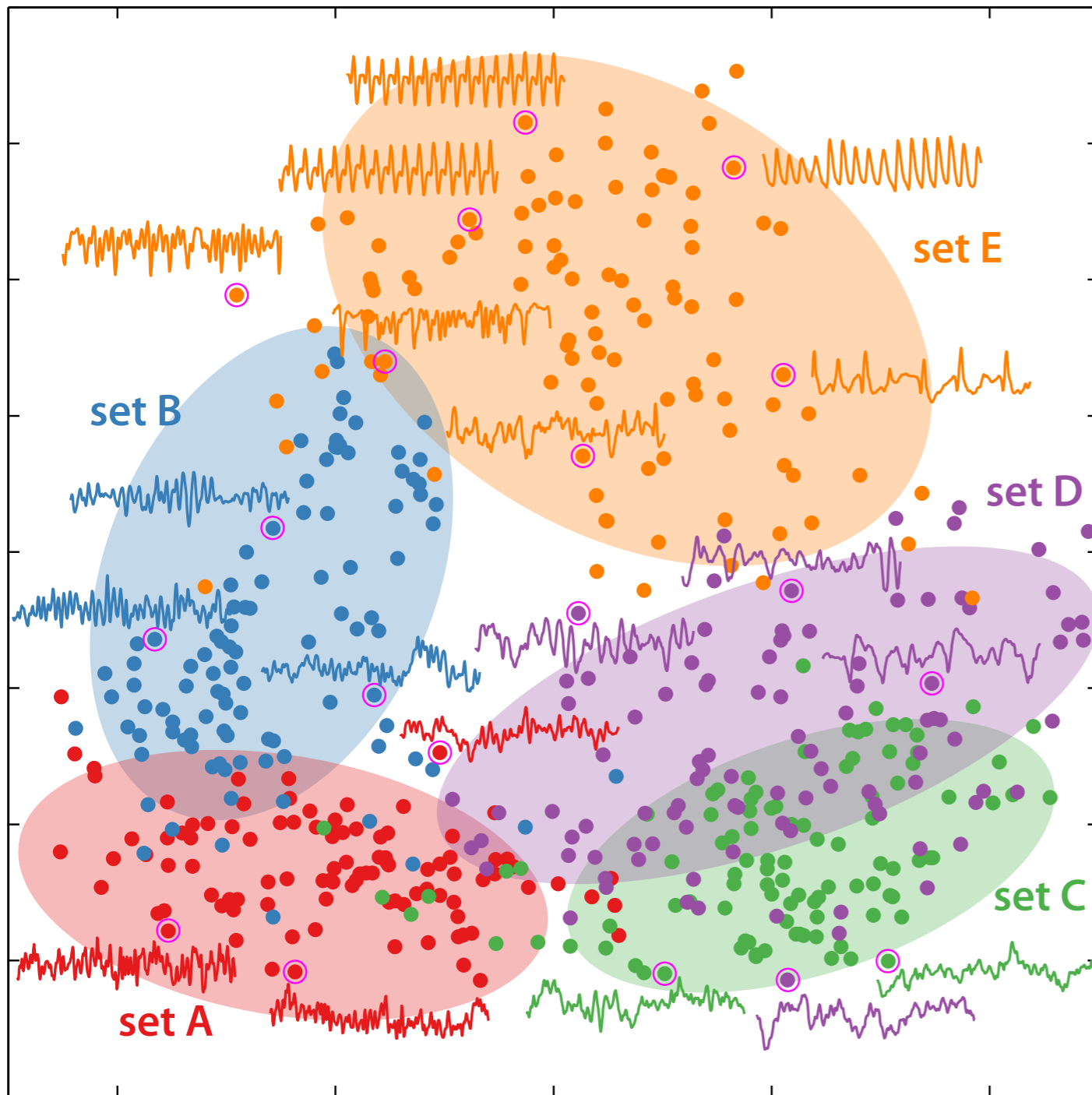
*suggest data for
our models*



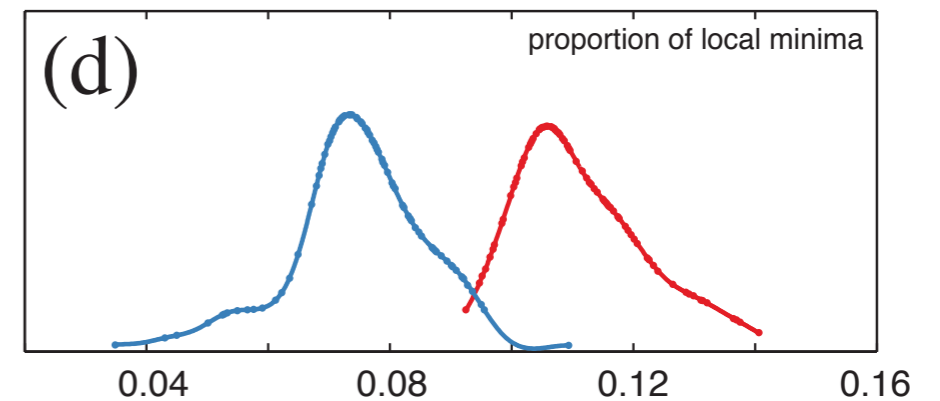
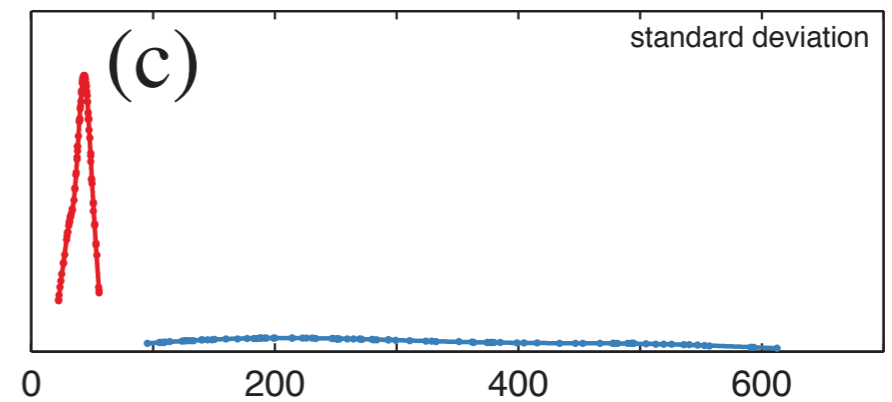
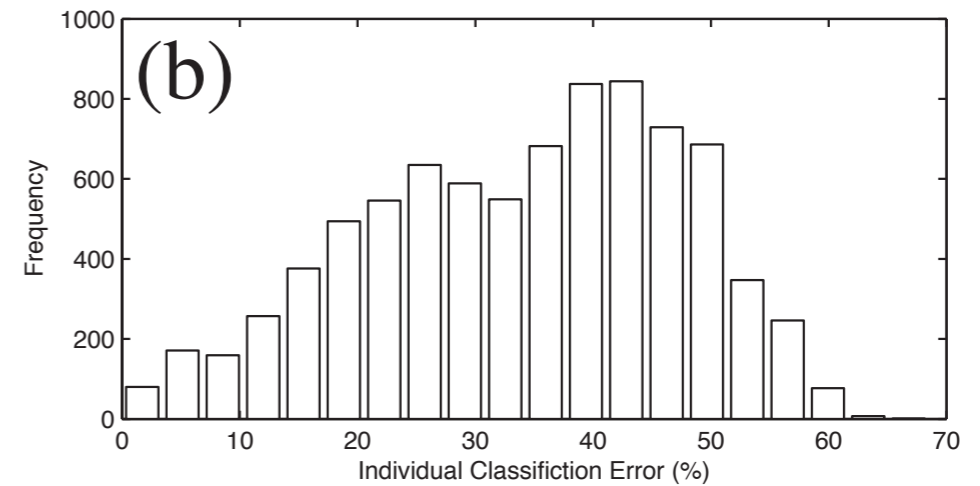
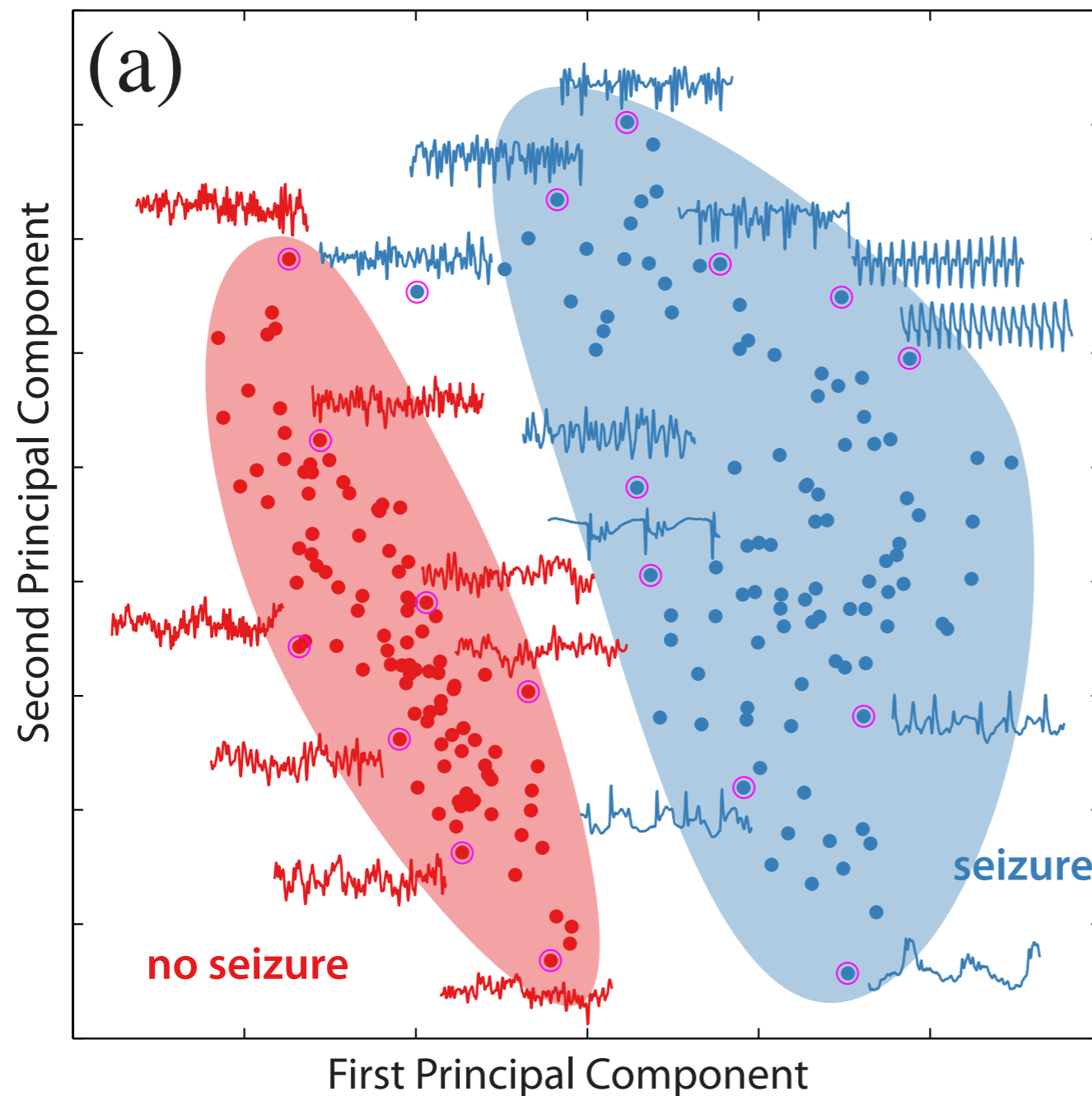
Applications

- Drawing on a rich, interdisciplinary database of methods for time-series analysis allows datasets to be analyzed in new ways
- Reveal structure using PCA
- Select interpretable families of useful methods for a given classification/regression task

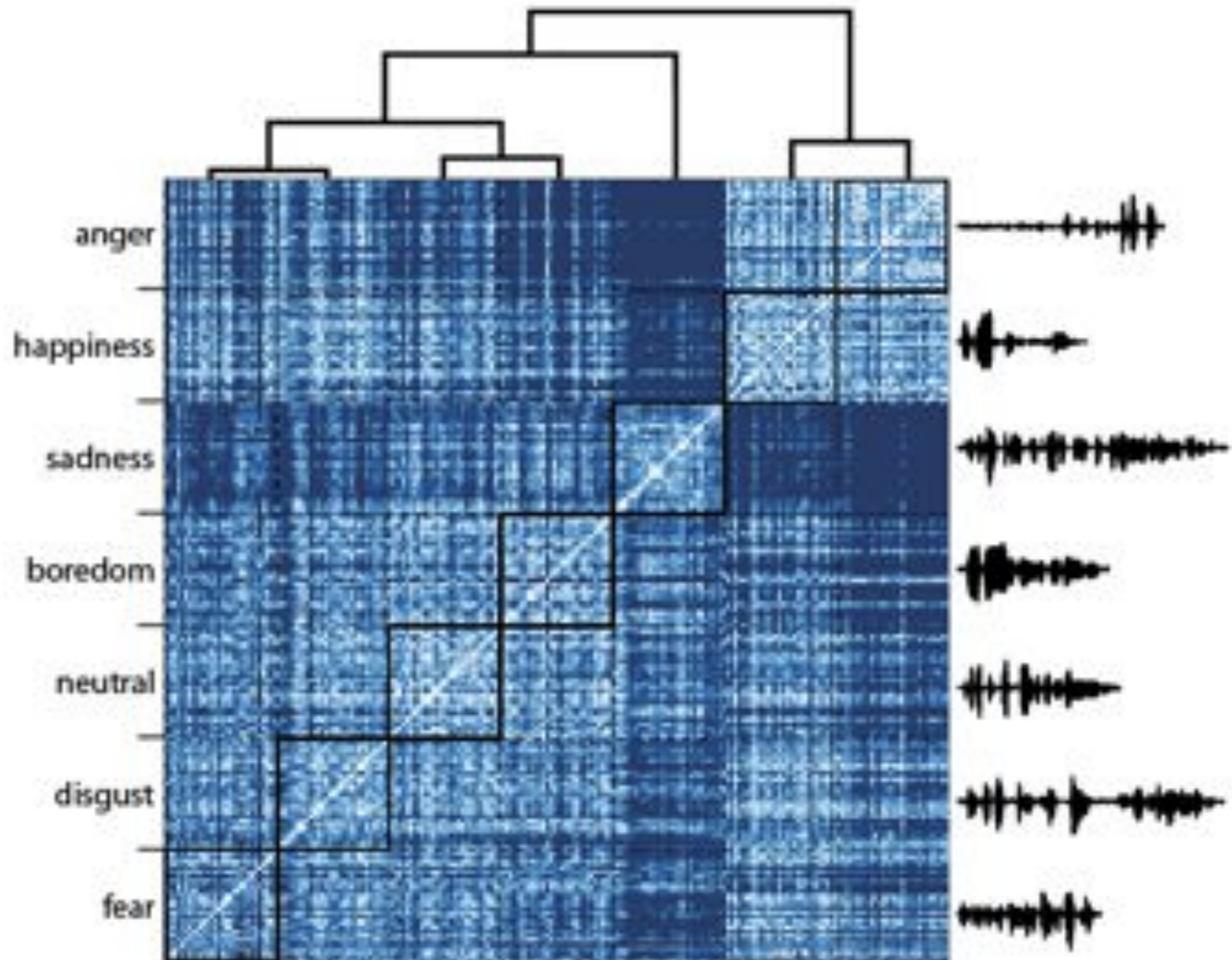
EEGs



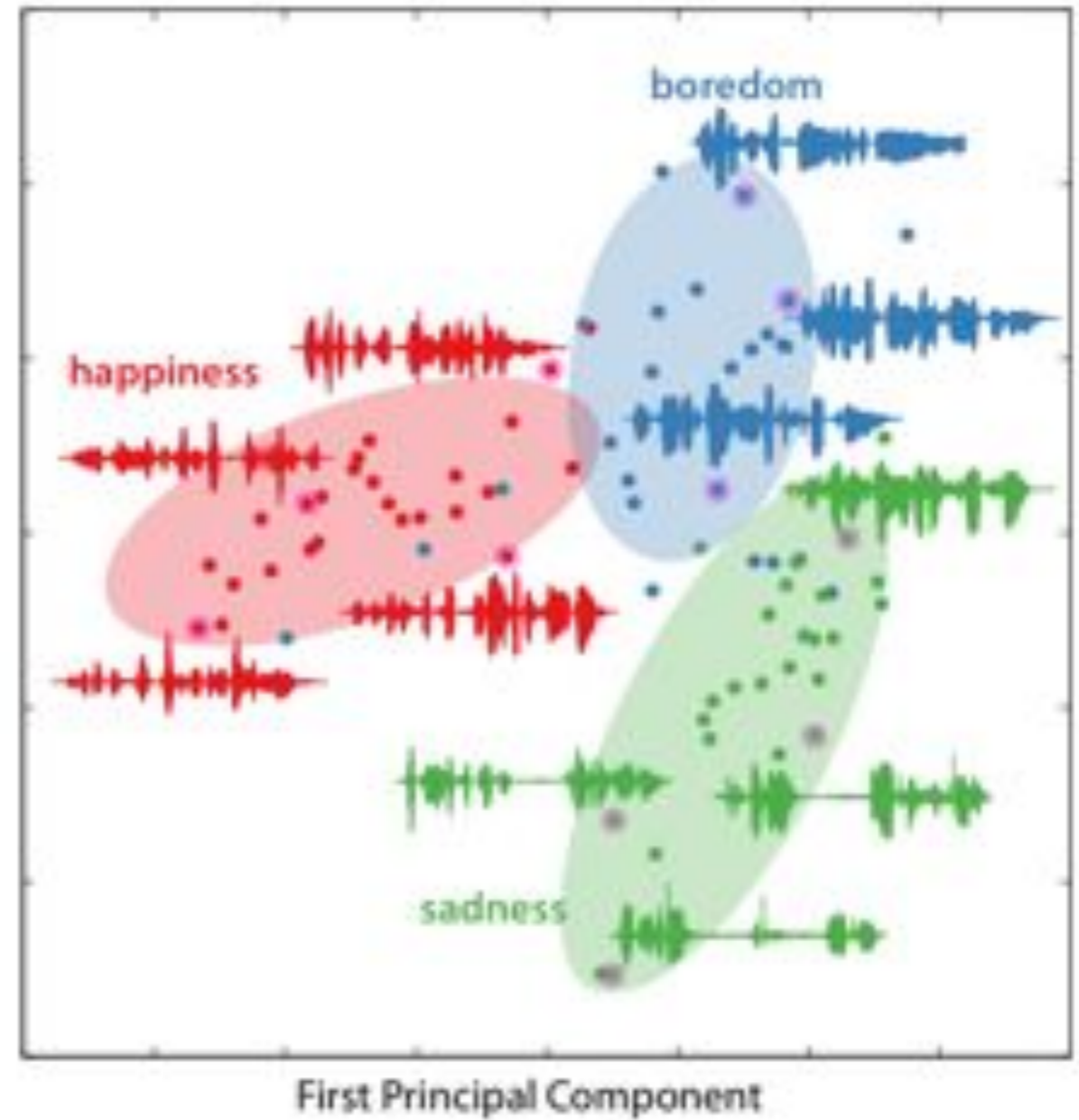
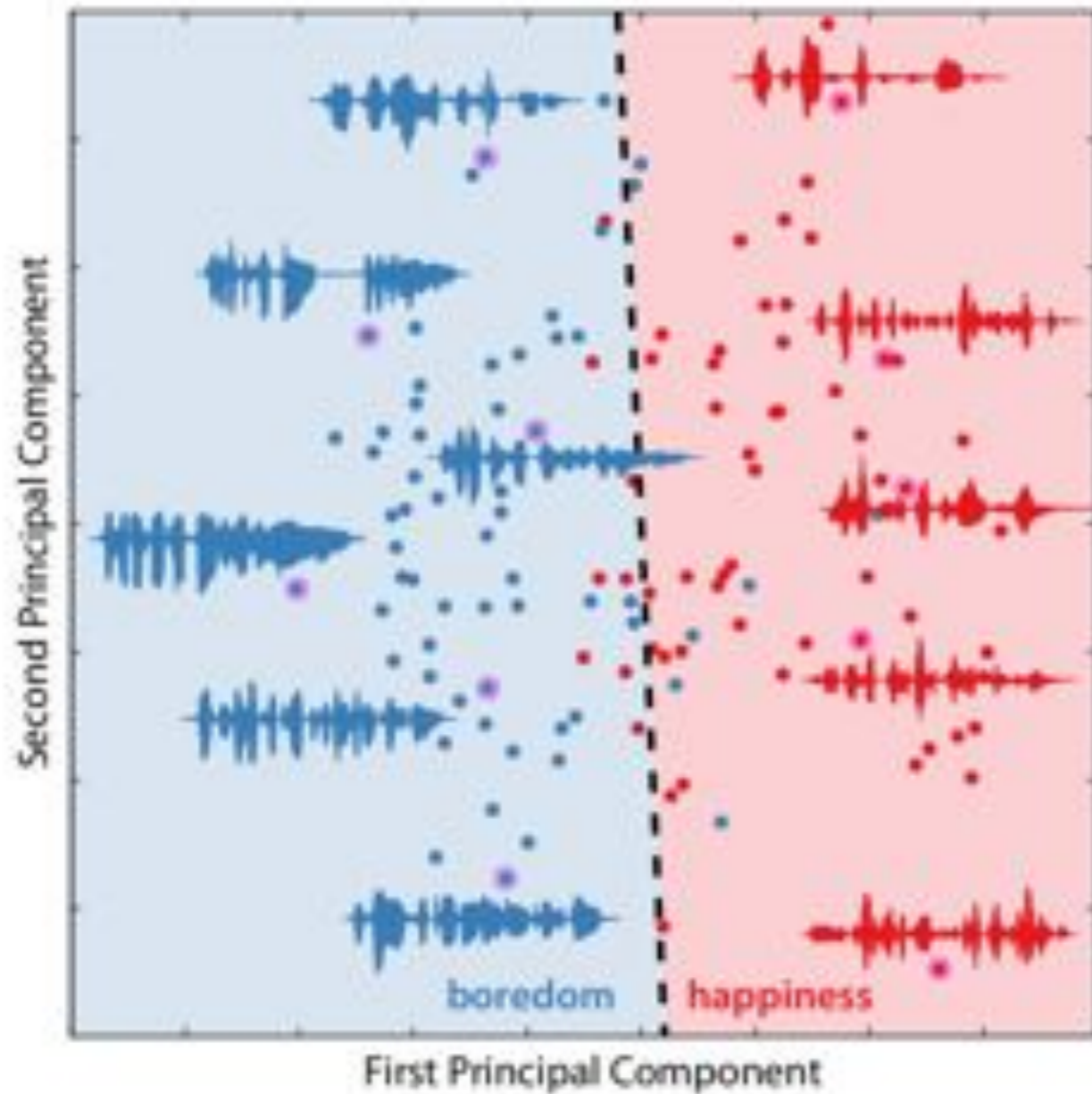
Distinguishing seizures



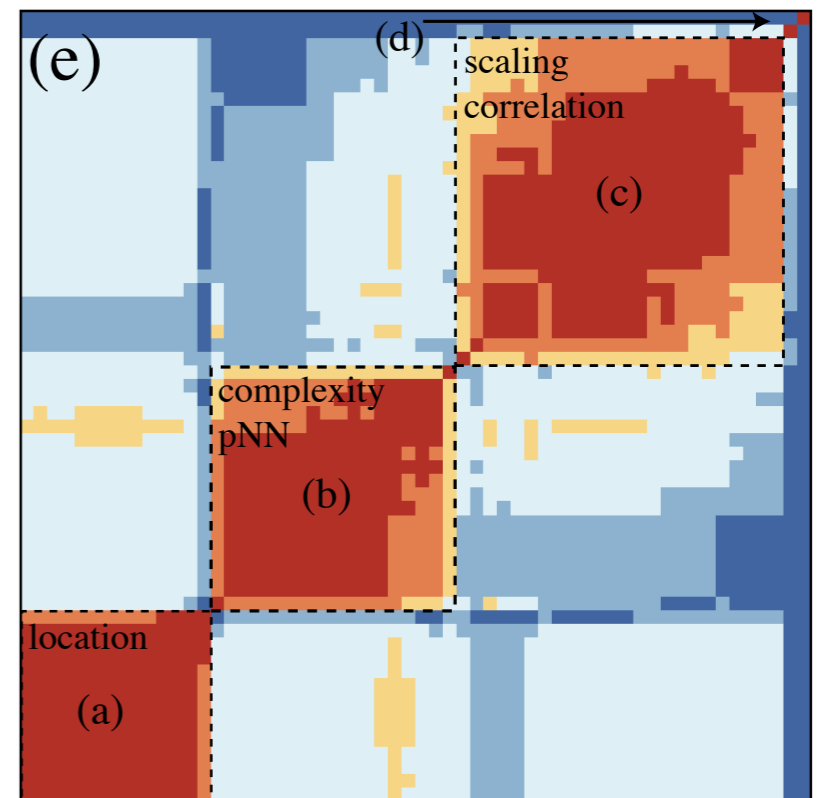
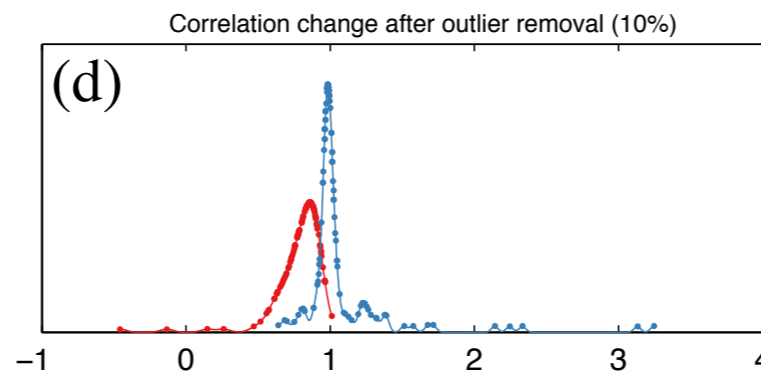
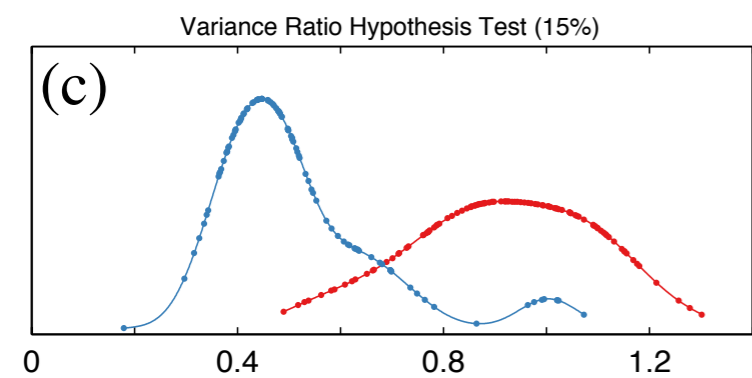
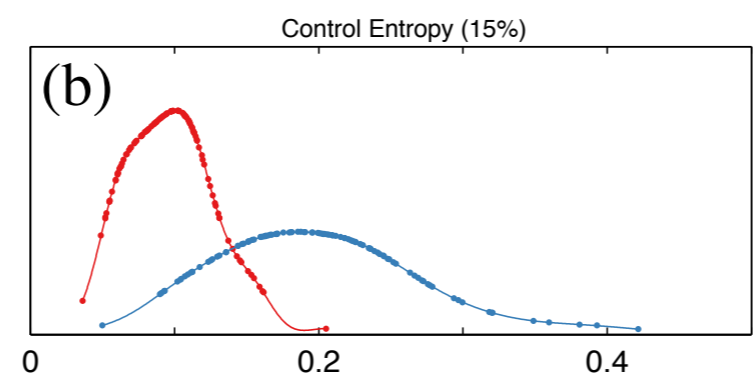
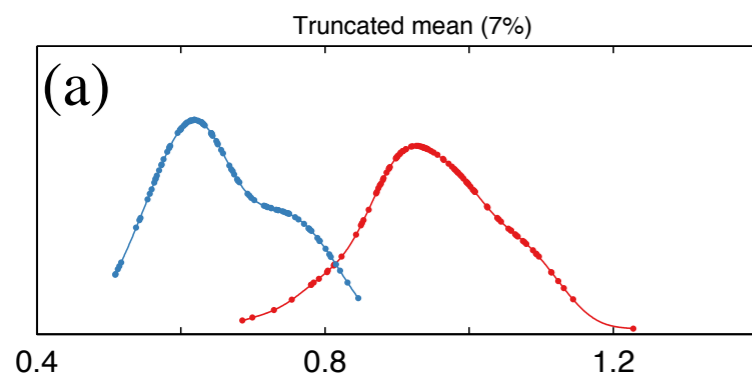
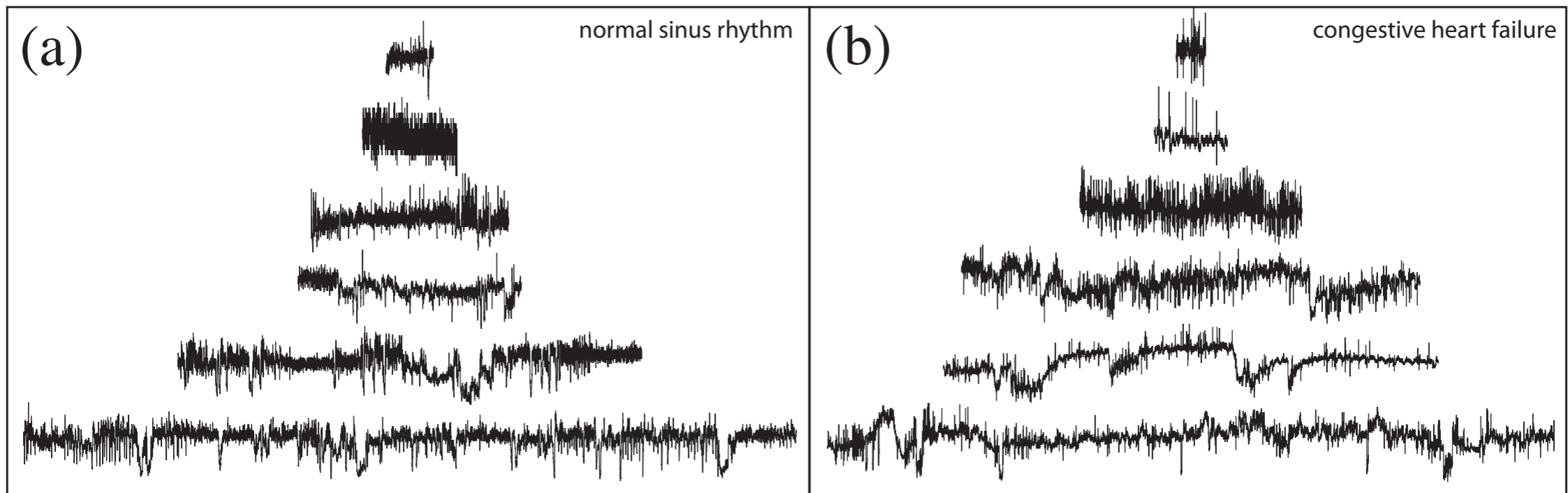
Emotional Speech



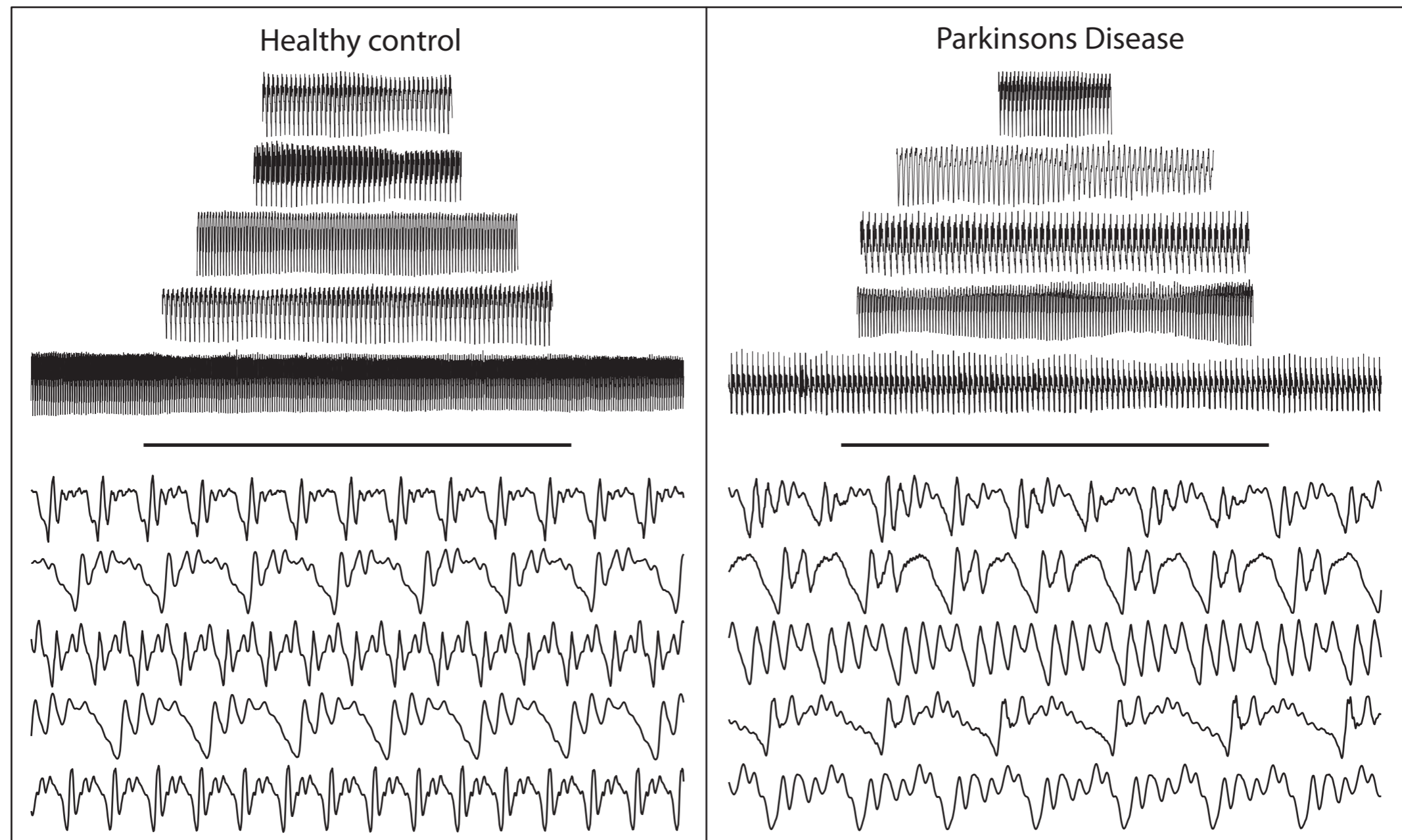
Emotional Speech



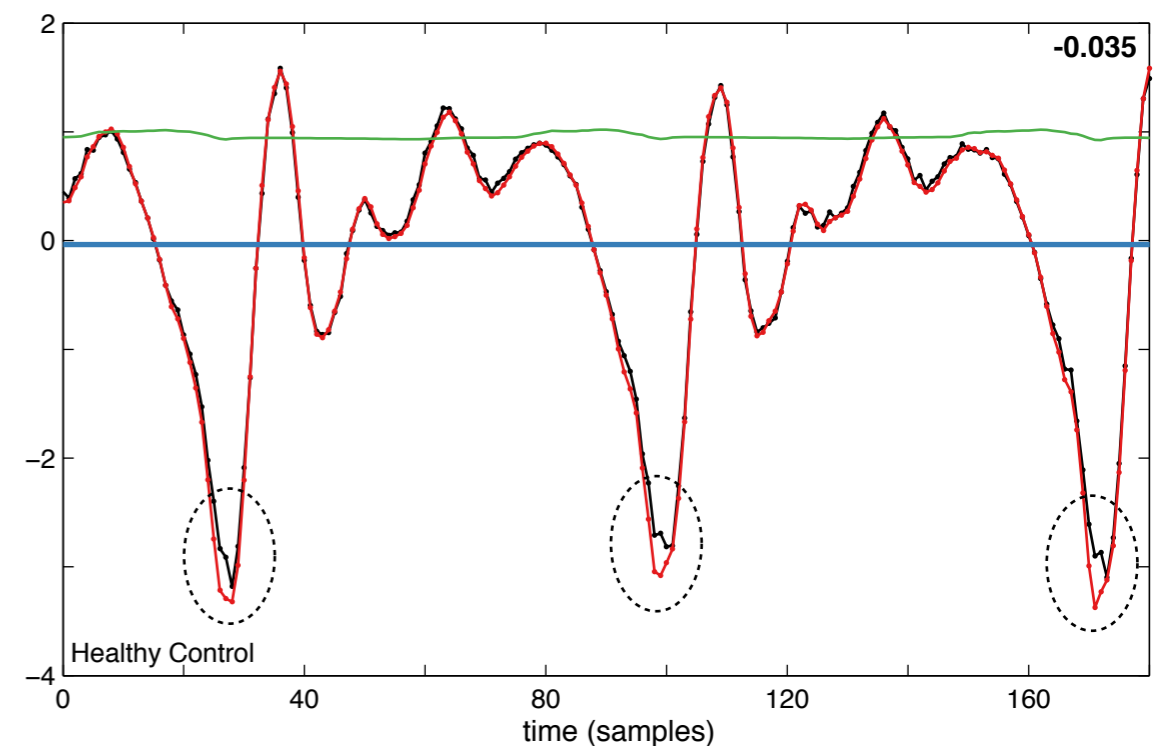
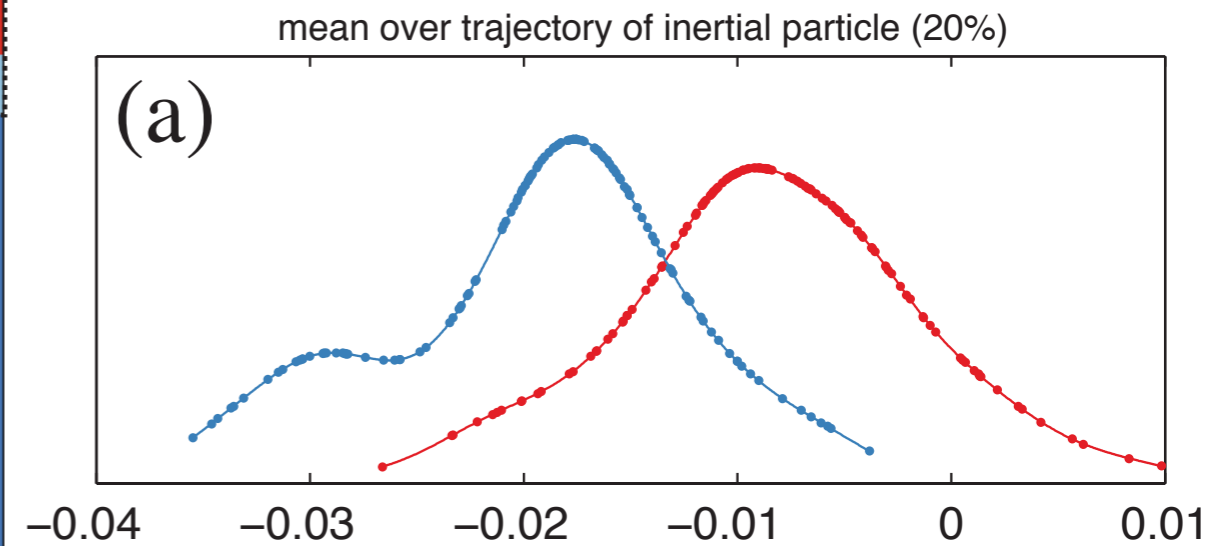
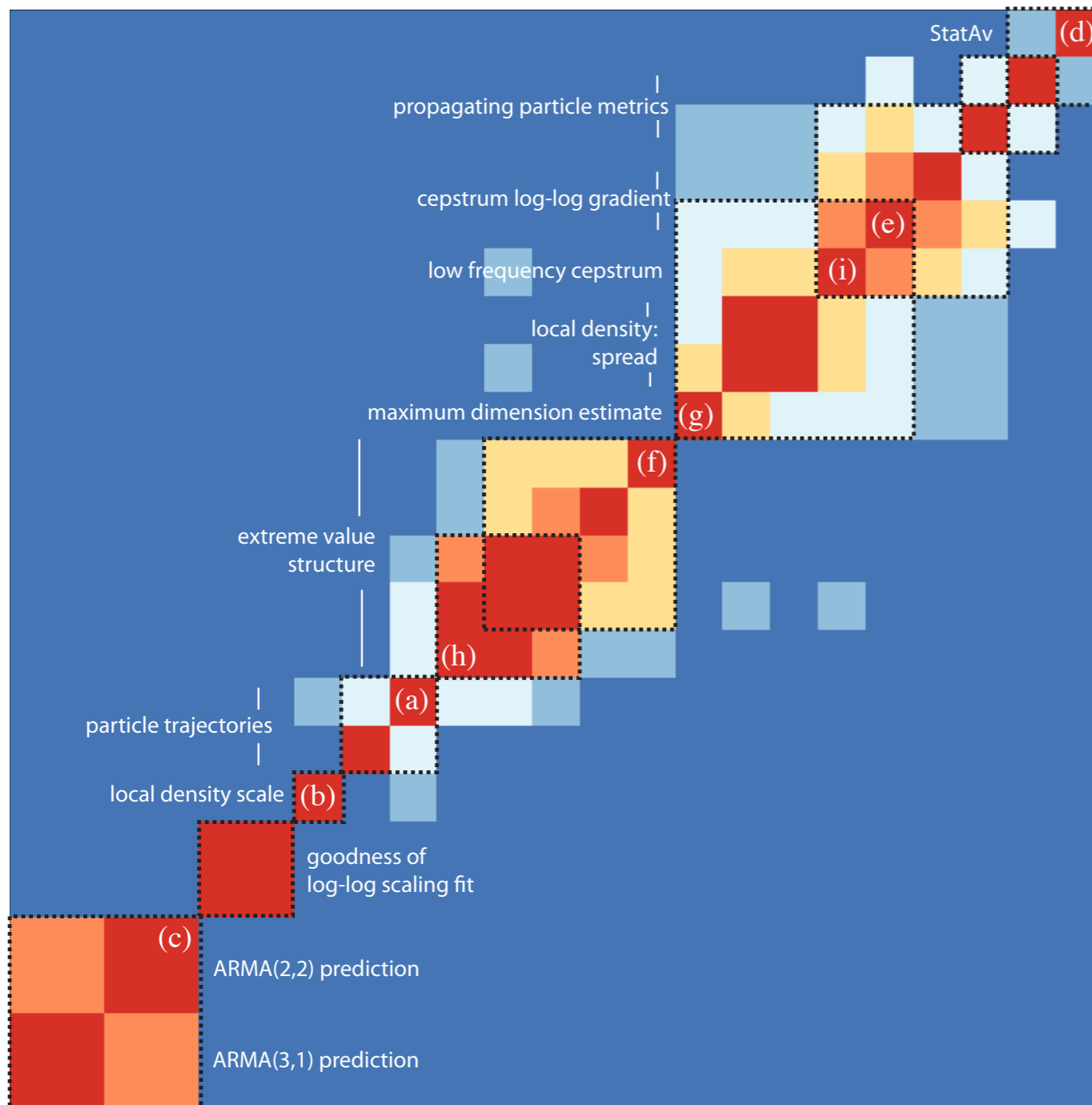
Heart Rate Variability



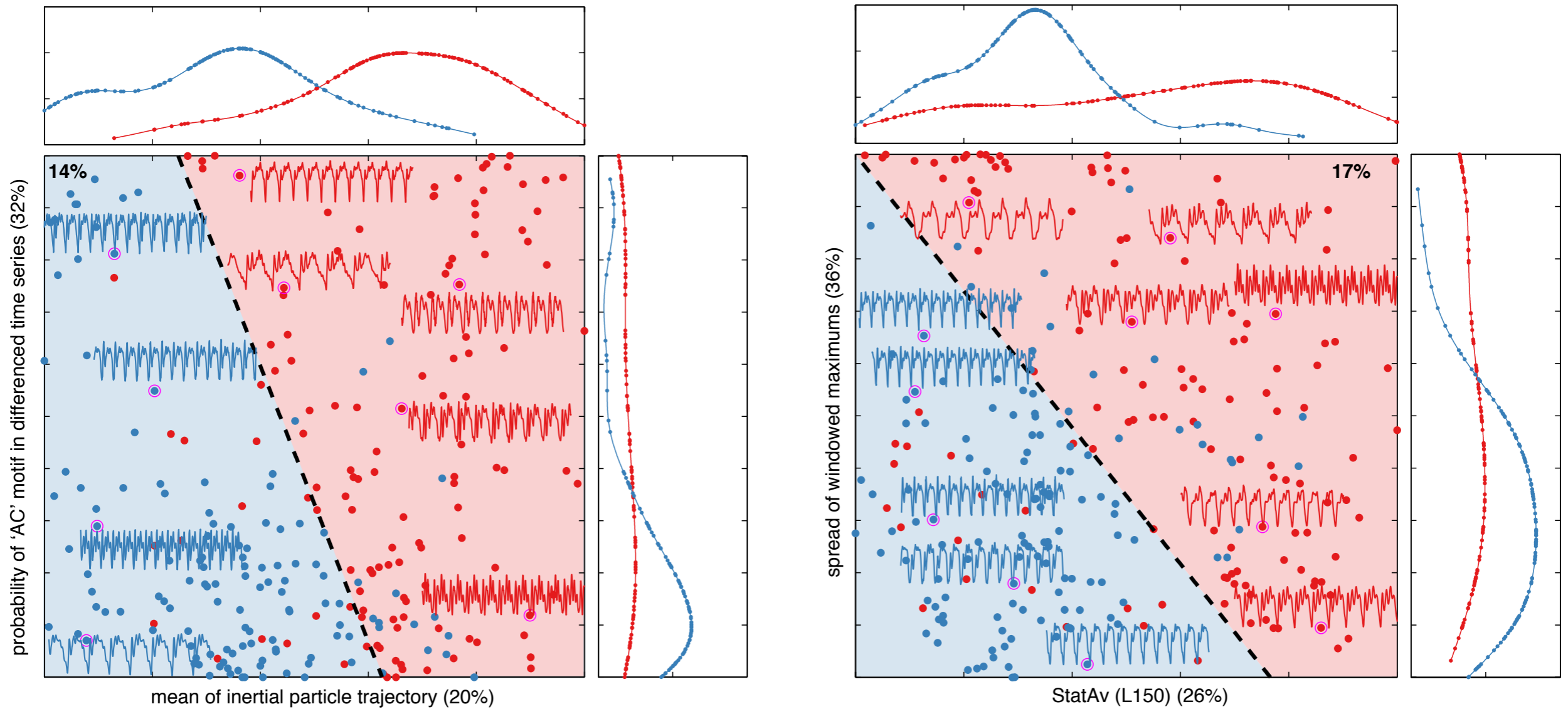
Parkinson's Disease Speech



Parkinsonian Speech

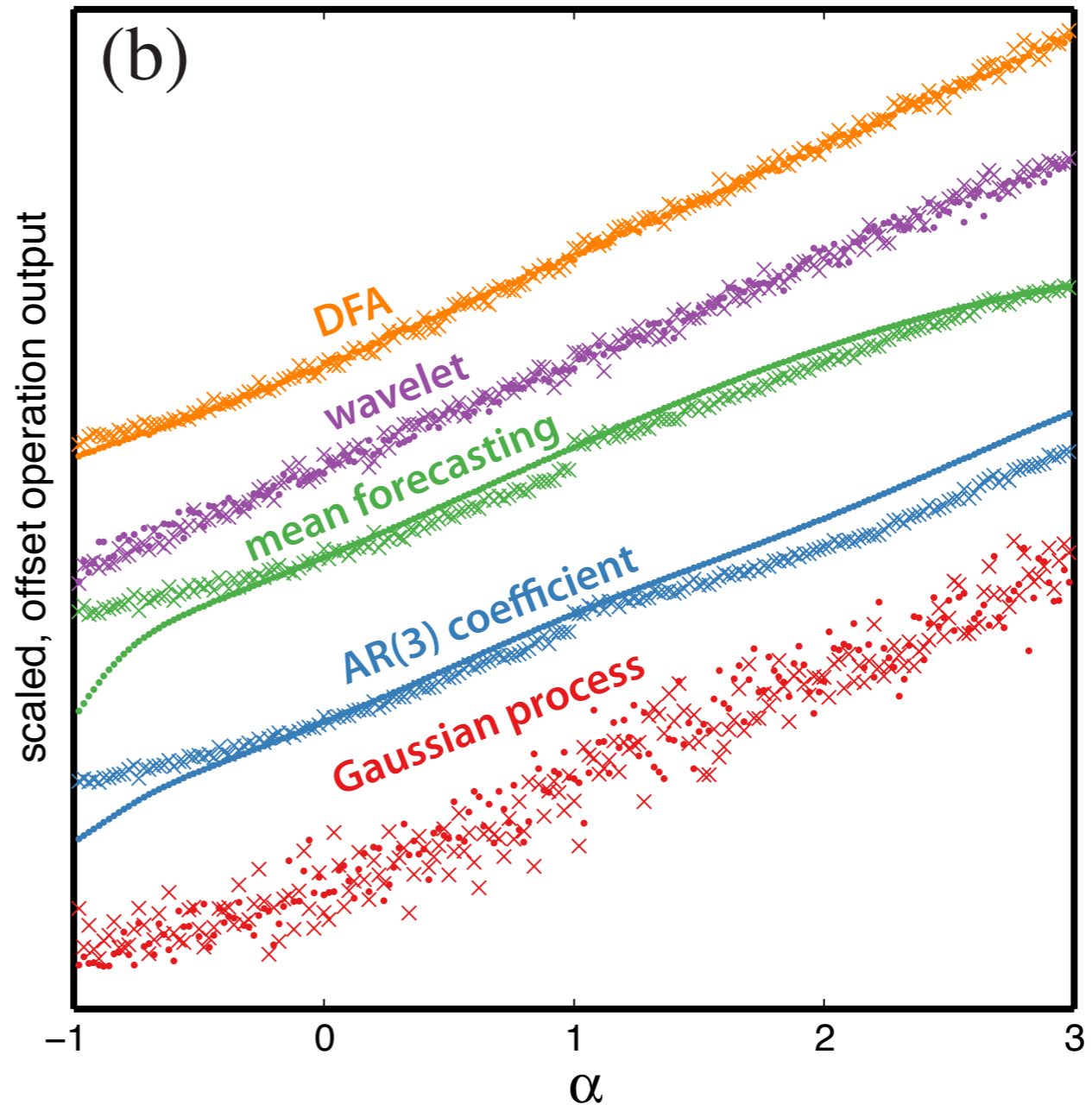
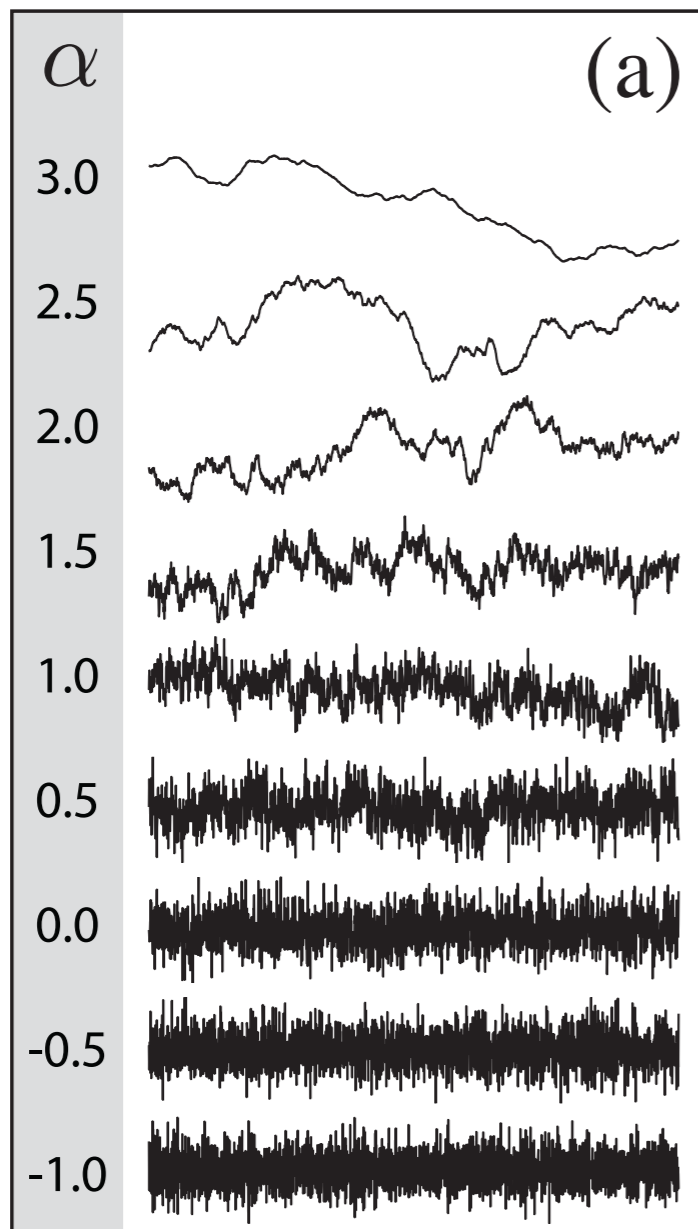


Parkinsonian Speech

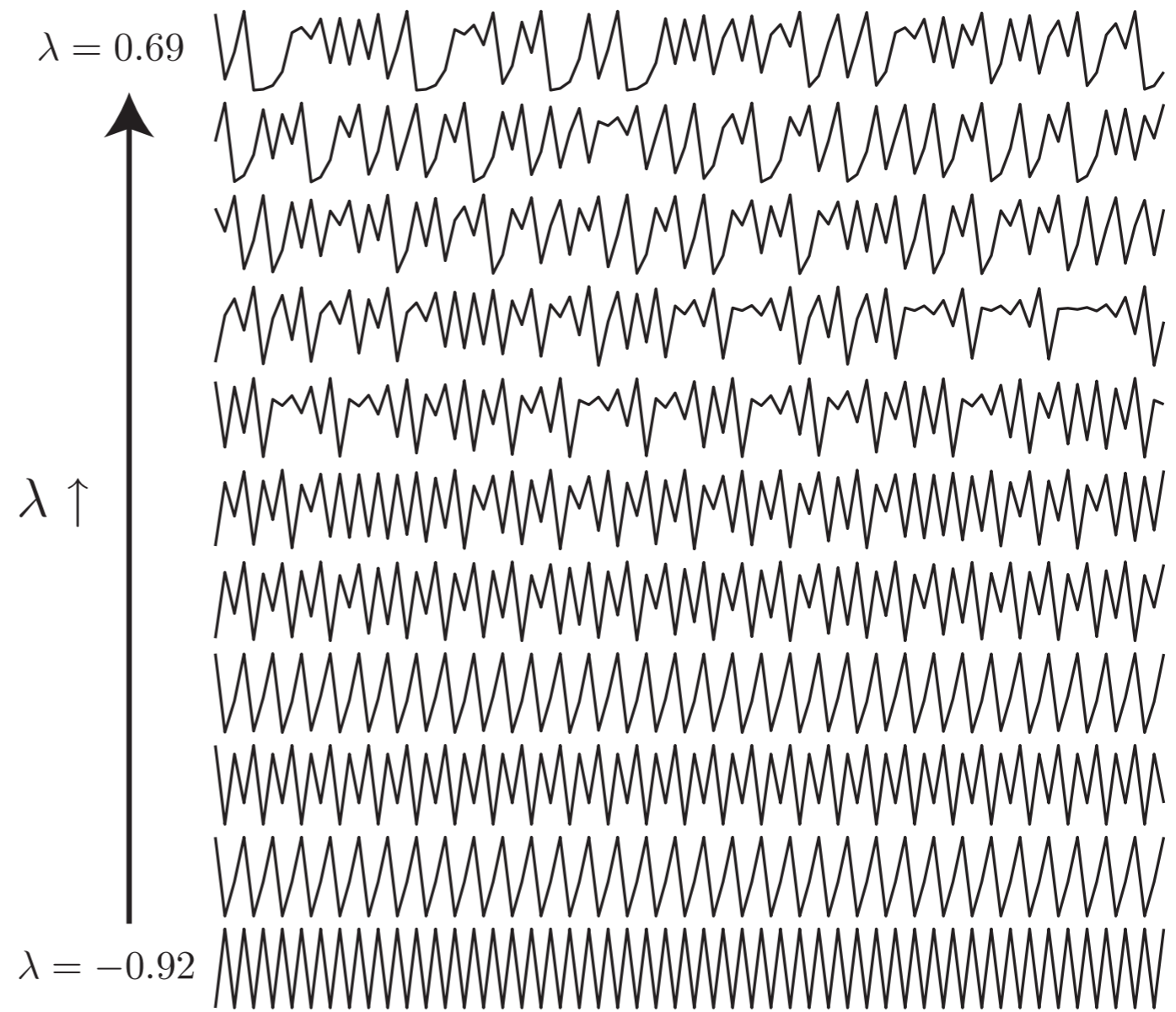
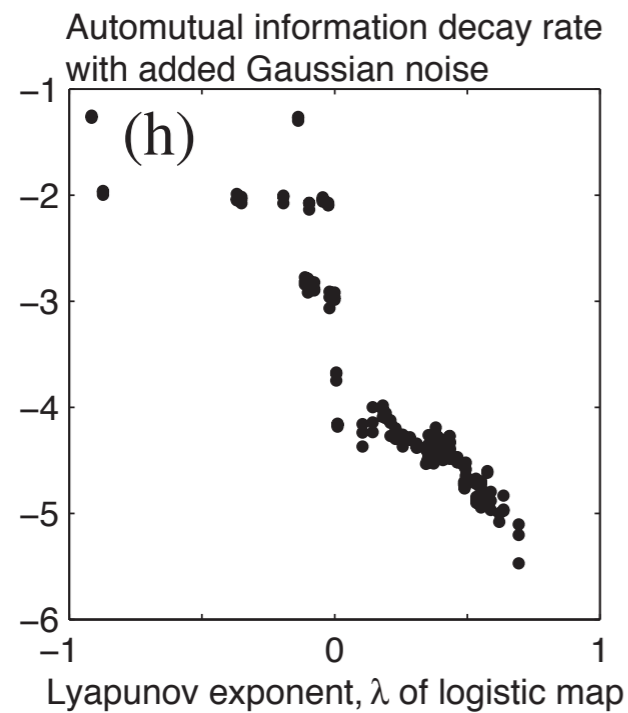
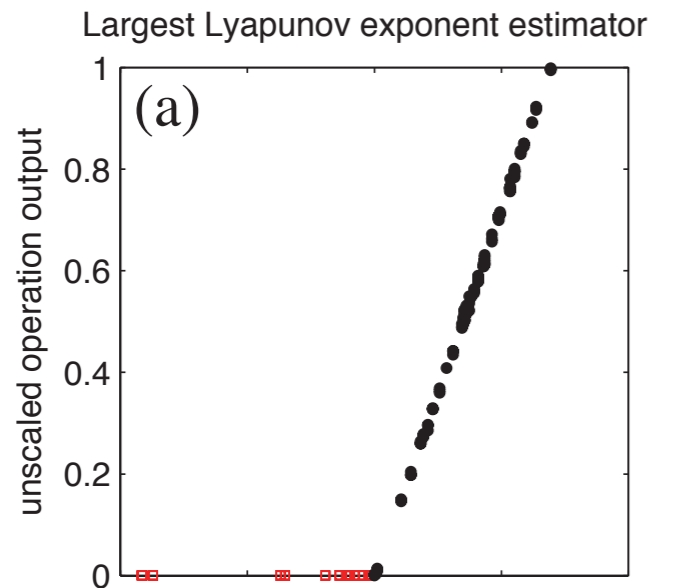


classifiers mix methods developed in different disciplines

Self-Affine Time Series

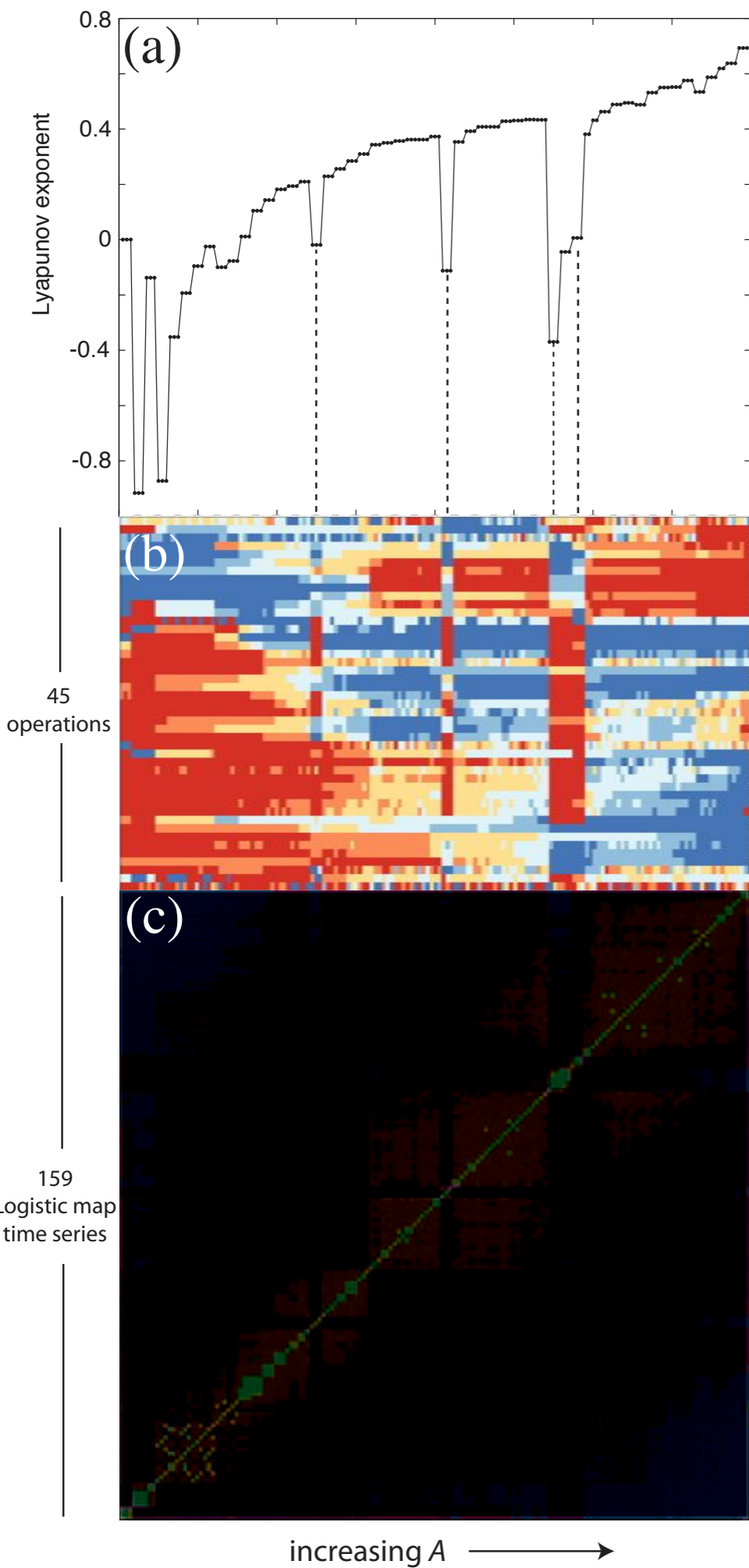


Logistic Map Regression



logistic maps: $x_{n+1} = Ax_n(1 - x_n)$

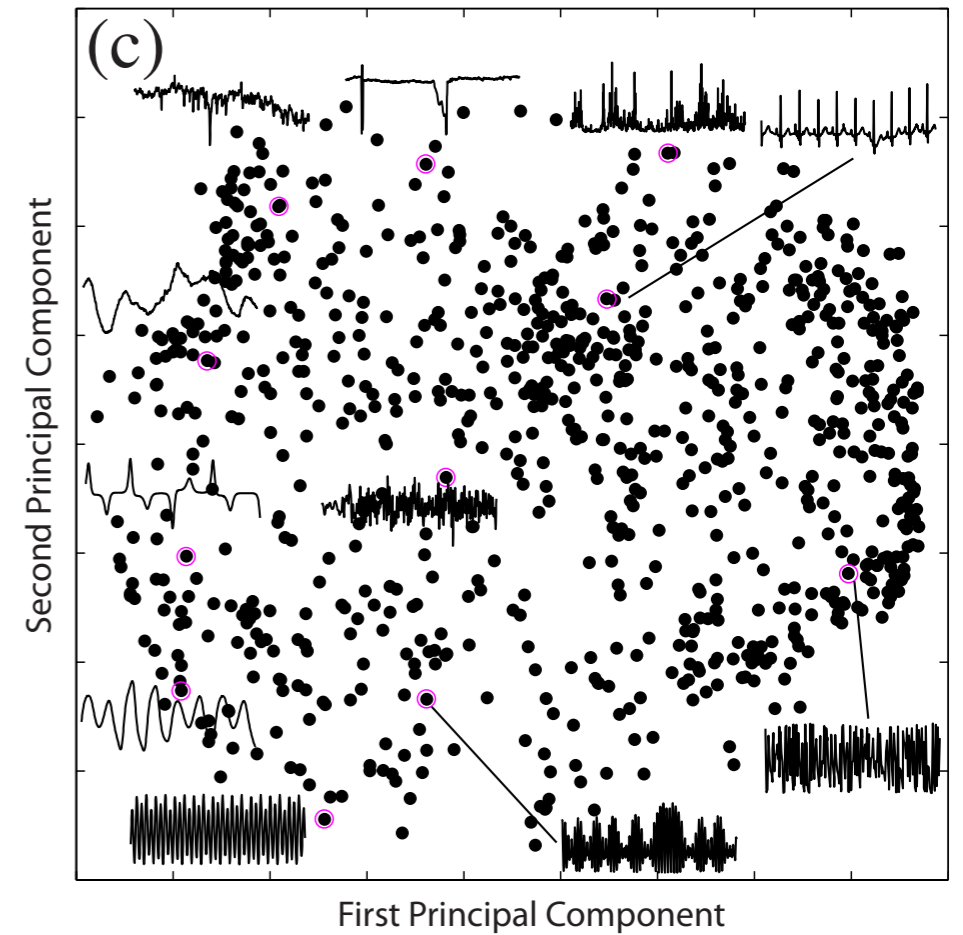
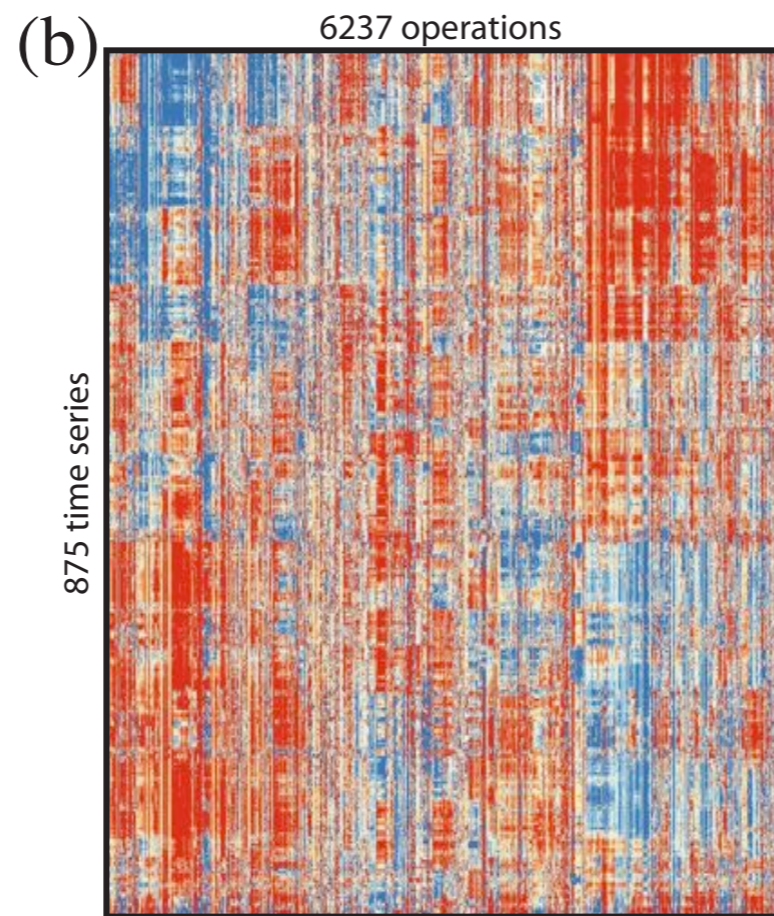
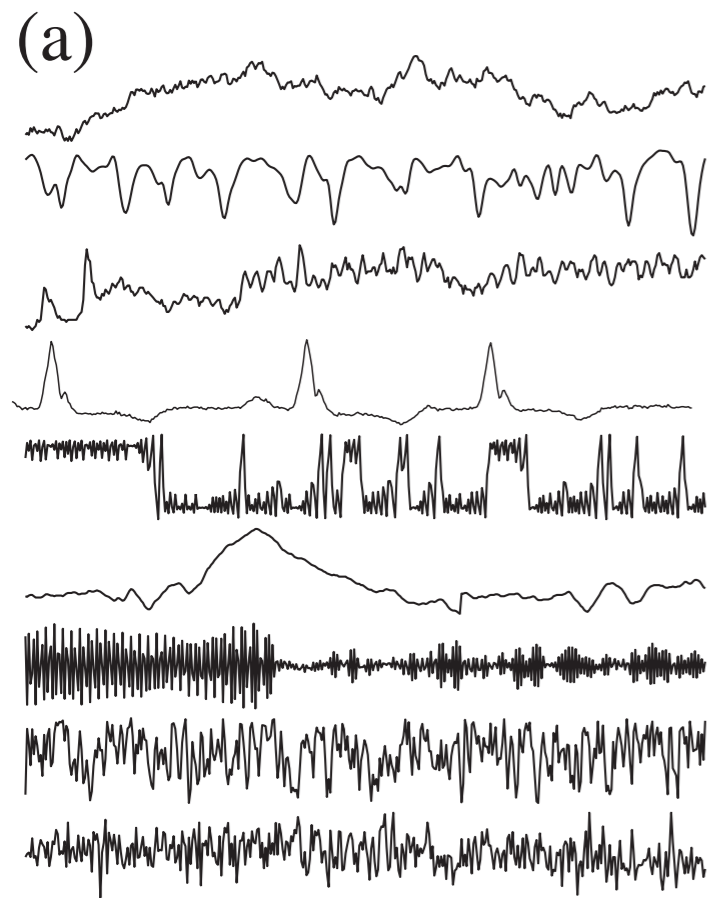
Logistic Map



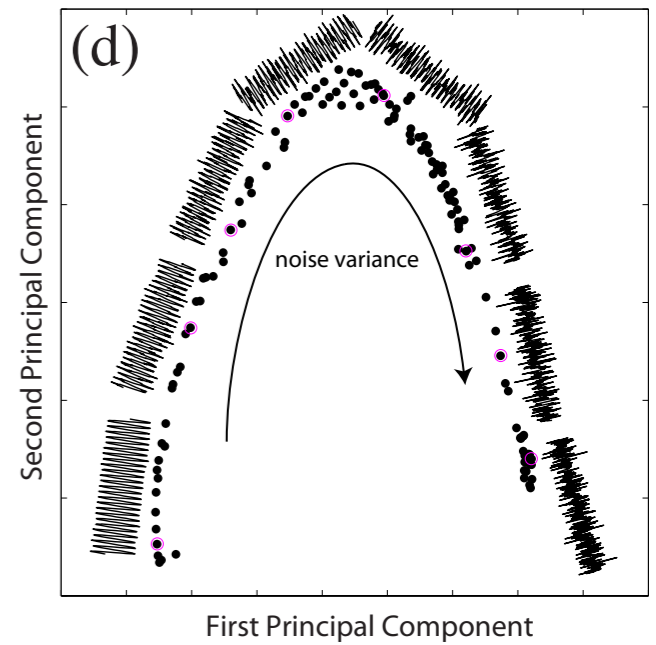
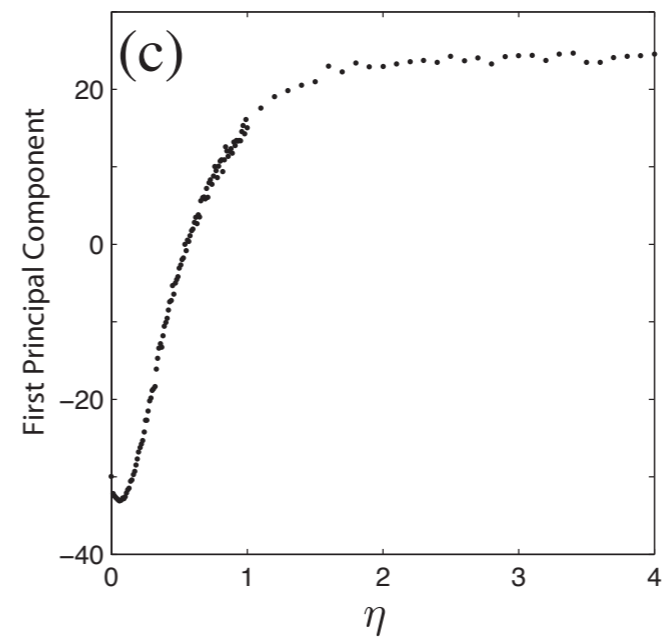
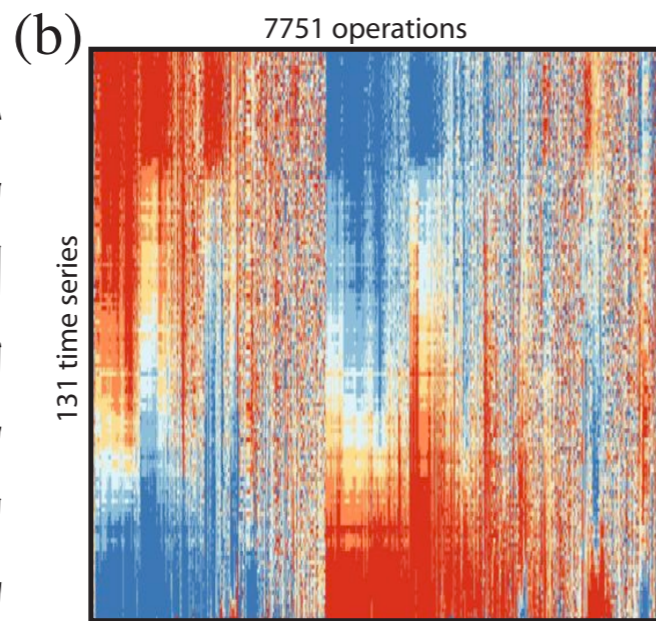
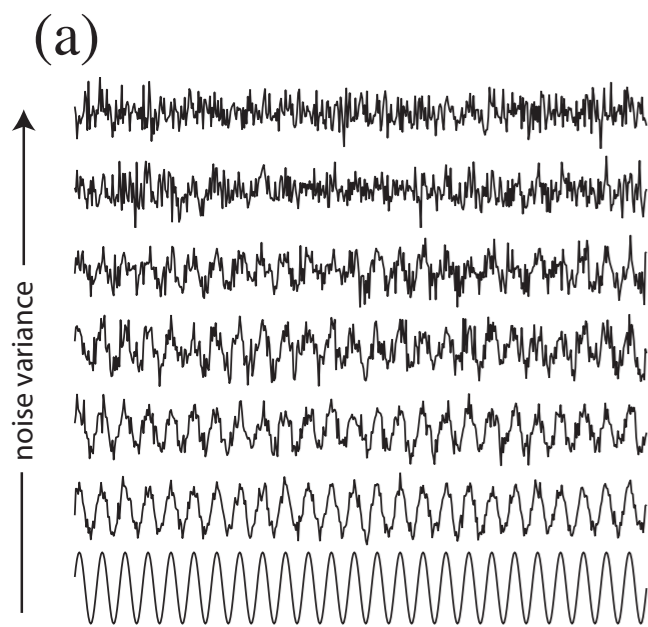
Constrained systems

- We've seen redundancy in set of methods for natural signals.
- What about systems that can be fully described by a small number of parameters?
- The structure of our database can hint at this.

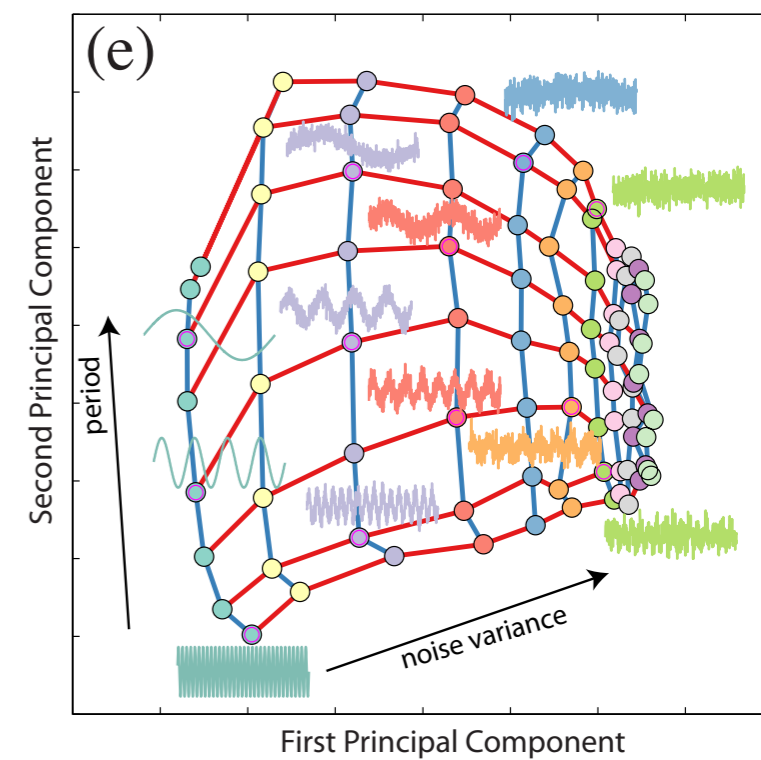
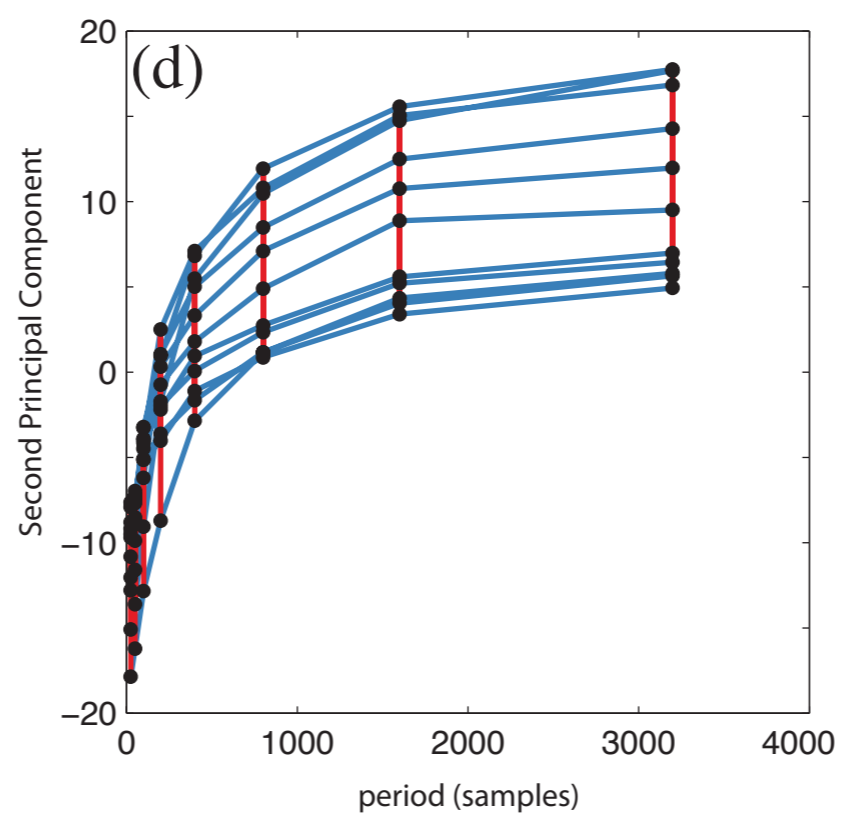
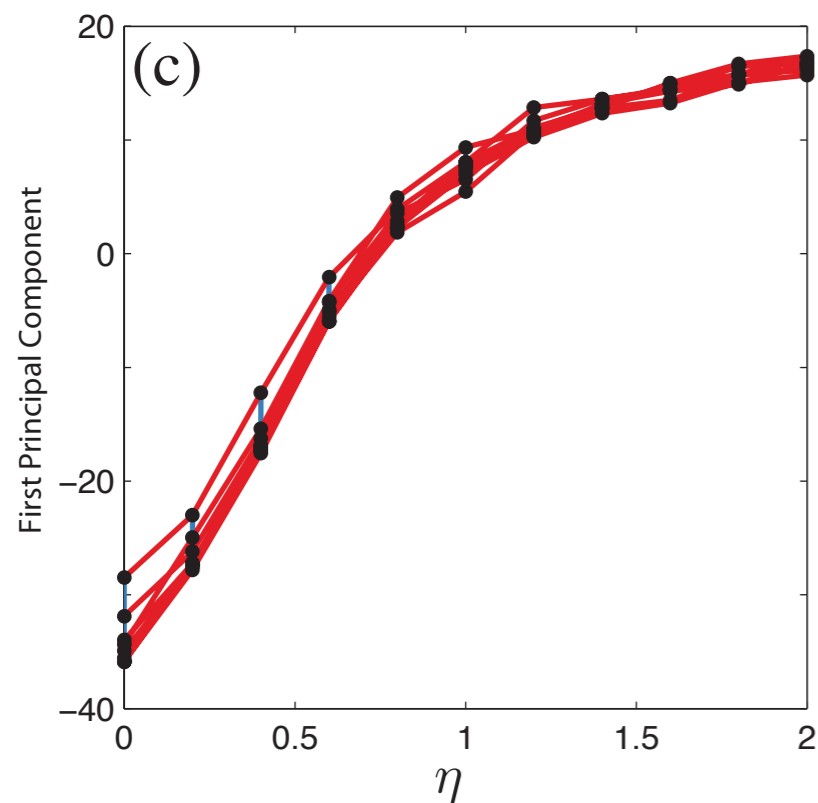
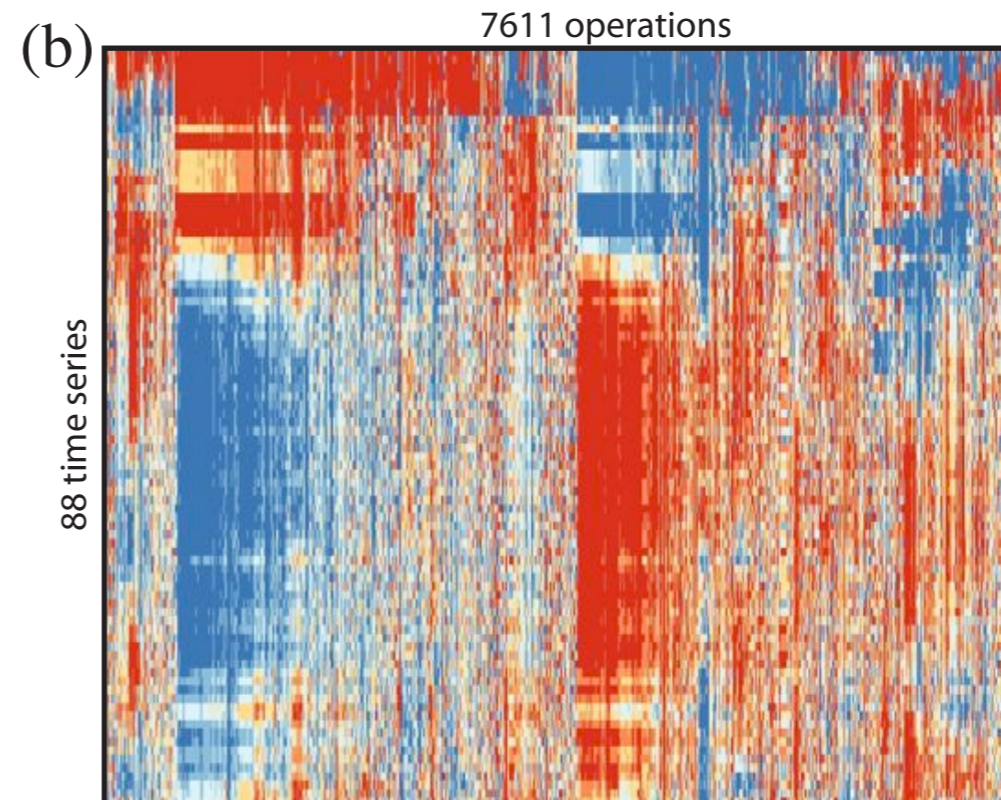
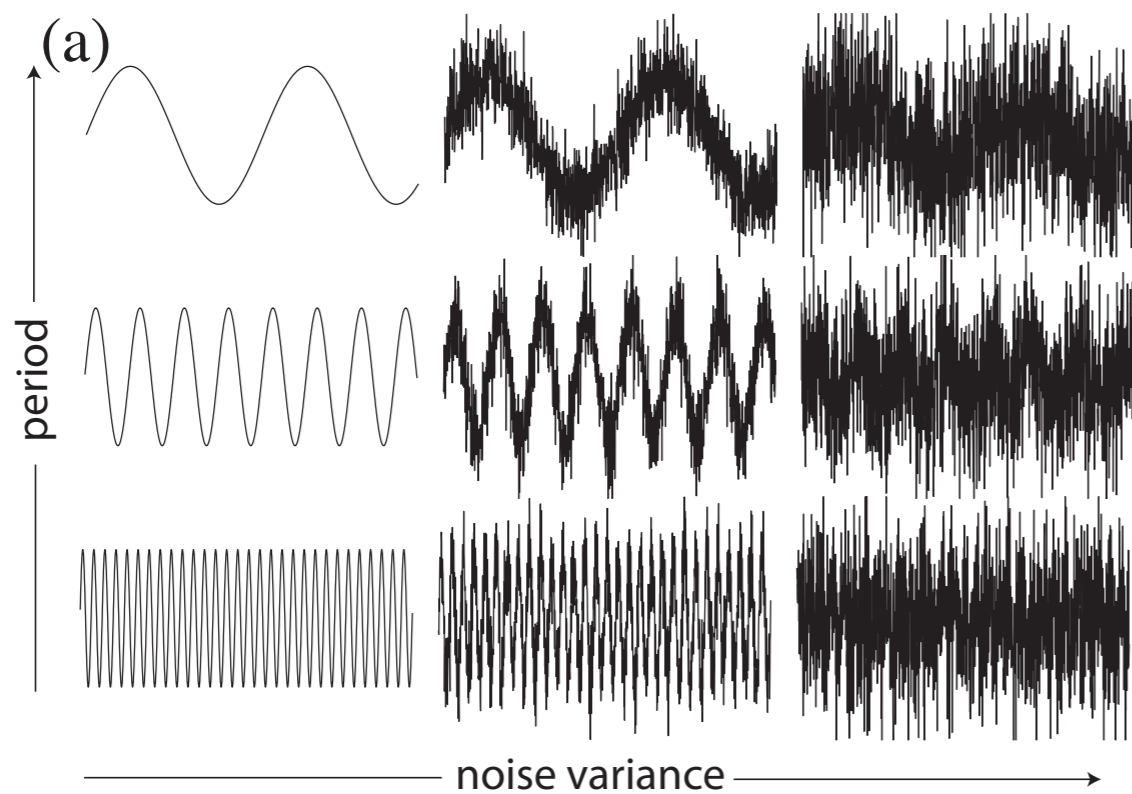
Many parameters



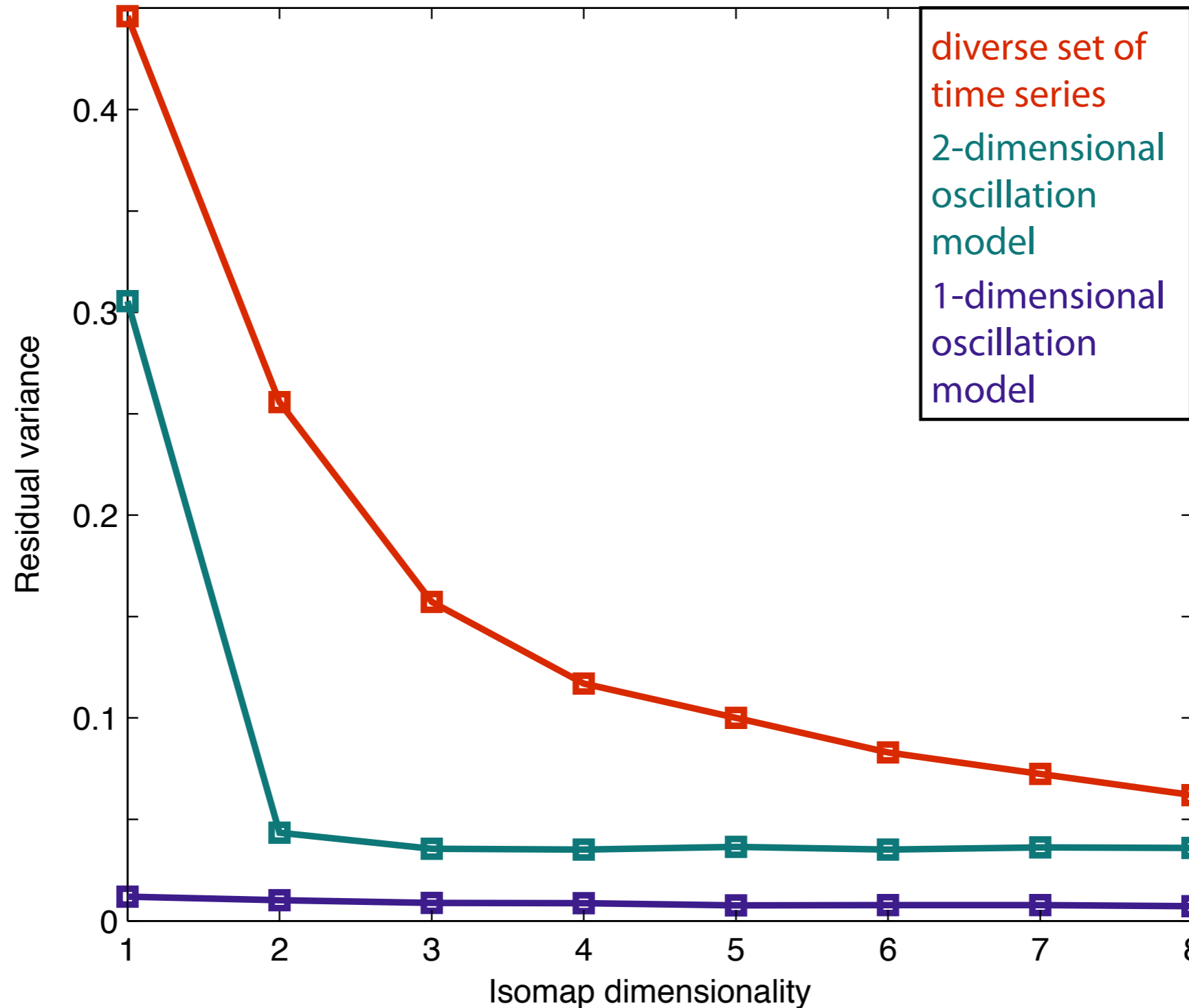
One parameter



Two parameters



Isomap can quantify this



Conclusions



- Empirical organization of the methods we use in science
- Empirical organization of the time series and models we study in science
- Automatic classification and regression with the ability to give insights into underlying dynamics