Automating biomedical time-series analysis using massive feature extraction

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Time-series analysis

*it's an **art***

measure data

analyse data

How? *Non-systematic*

"Do what I did during my PhD"

"Use standard analysis methods from my field"

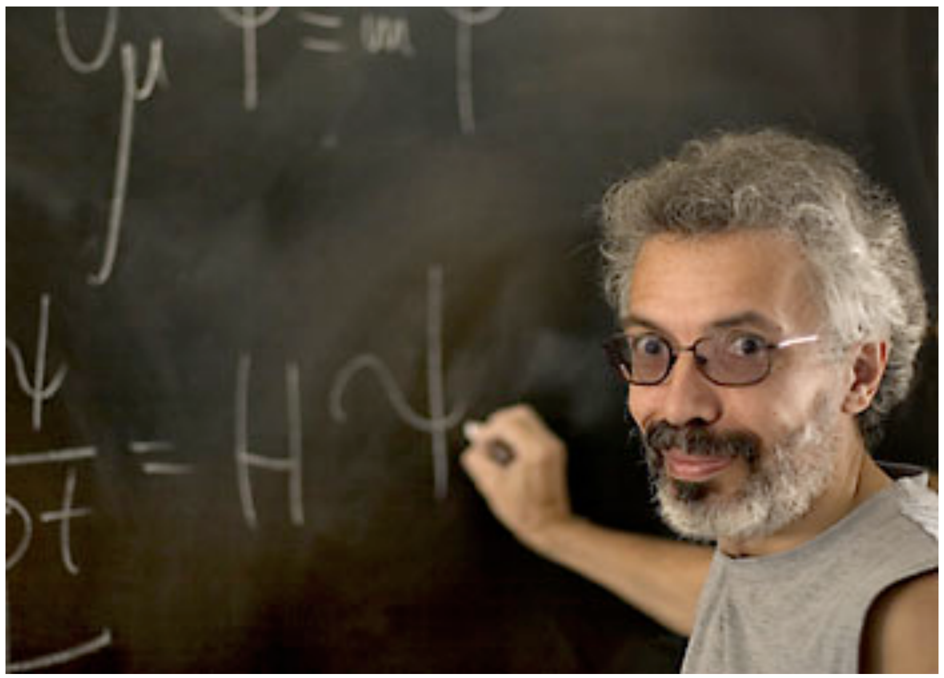
"Apply a hot new method I read about this week"

- Is your proposed method best, or can another (perhaps simpler) method outperform it?
- Are 'new' methods really new, or do they reproduce the performance of existing methods (e.g., from another field, or developed in the past)? *Is any progress being made?*
- Comparison required, but not done in practice (an average of 0.91 other methods, and 1.85 different datasets*).

*Keogh, E. and Kasetty, S., Data Min. Knowl. Disc. **7**, 349 (2003)

Time-series modeling

Case 1: "the dream"



"I knew it! My years of mathematical training are so useful!"

- Domain knowledge
- Some key interactions
- Periodicities
- Noise model
- Analyze and understand mechanistic / statistical underpinnings of time series

Case 2: "the common reality"

"Shit."

- Minimal/no domain knowledge
- Complex interactions
- Just data

With little hope of making progress with any mechanistic approach to time-series modeling, how can we learn about structure in our data?

Competing interdisciplinary approaches

vast and growing volumes of data and methods

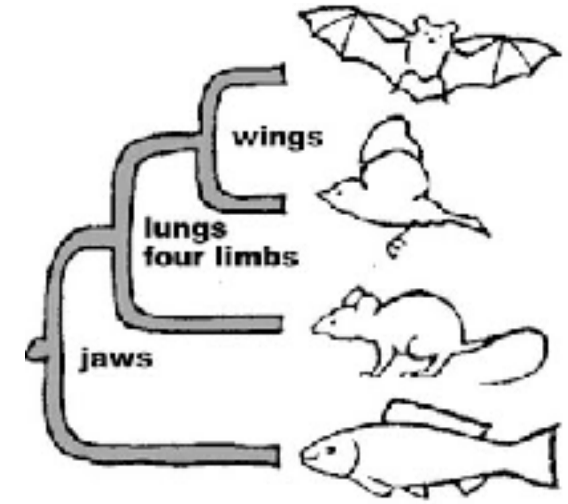
leads to variety of inconsistent opinions

"I know someone smart who uses wavelets"

"Everyone knows you can't apply AR time-series models to nonstationary biomedical data!"

"ARIMA models are a waste of time"

Solution?



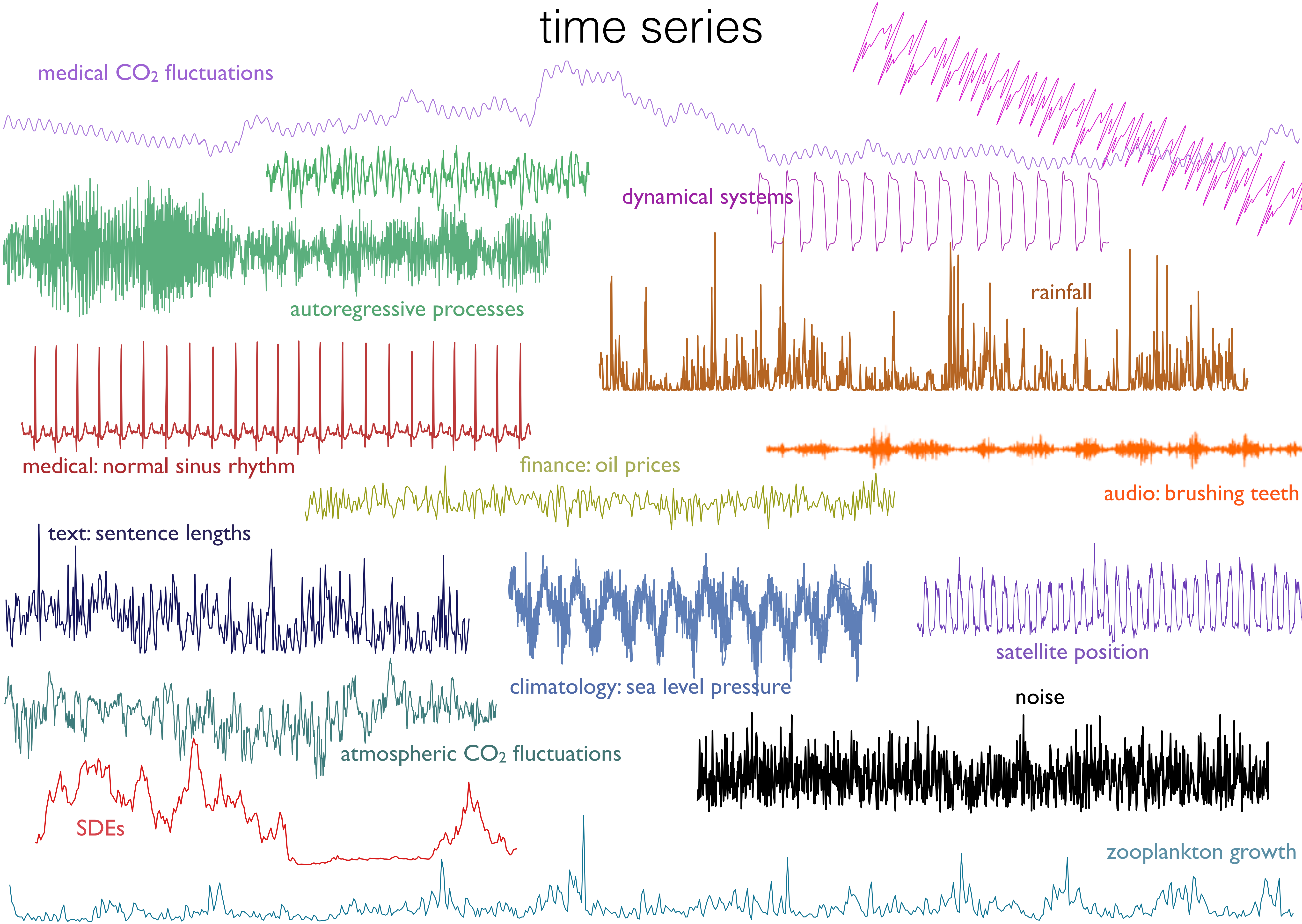
Collect many scientific time series

Collect many scientific time-series analysis methods

Use performance of methods on data to
organize our methods

Use properties of data as measure by the methods to
organize our data

Many of our measurements of the world are in the form of time series



>7700 time-series features

Static distribution

Quantiles
Trimmed means
Fits to standard distributions
Outliers
Moments
Entropy
Rank-orderings
Standard deviation

Correlation

Linear autocorrelation
Decay properties
Additive noise titration
Nonlinear autocorrelations
Time reversal asymmetry
Generalized self-correlation
Recurrence structure
Autocorrelation robustness
Scaling and fluctuation analysis
Permutation robustness
Local extrema
Seasonality tests
Zero crossing rates

(Phys) Nonlinear

2D embedding structure
TSTOOL
TISEAN
Fractal dimension
Correlation dimension
Taken's estimator
Poincaré sections
Surrogate data
Nonlinear prediction error
Lyapunov exponent estimate
False nearest neighbors

Information Theory

Sample Entropy
Automutual information
Entropy rate
Approximate Entropy
Tsallis entropies

Stationarity

StatAv
Sliding window measures
Bootstraps
Step detection
Distribution comparisons

Model fits

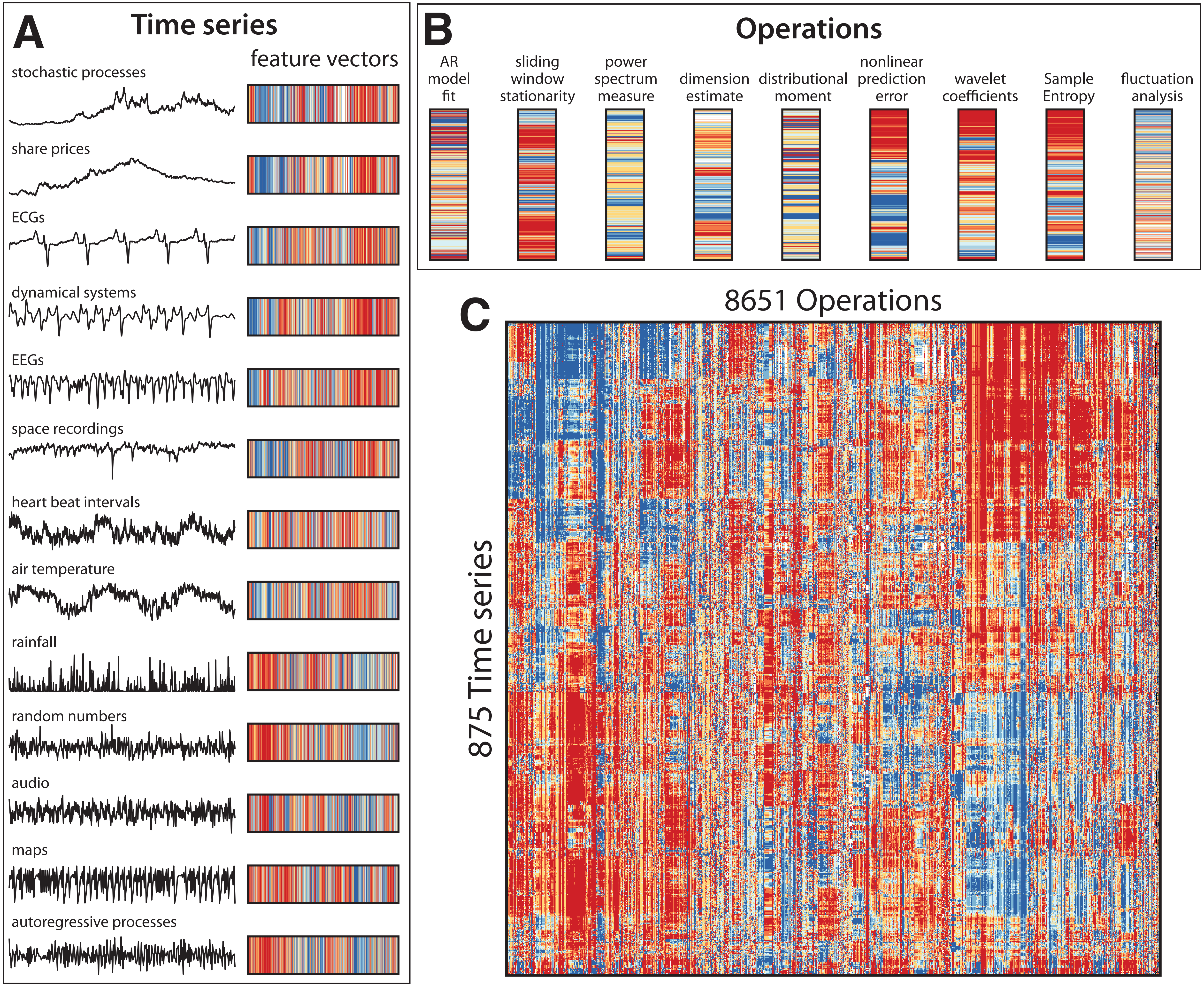
Local prediction
GARCH models
Fourier fits
AR models
Exponential smoothing
State space models
Hidden Markov models
Biased walker simulations
Piecewise splines
ARMA models
Gaussian Processes

Others

Transition matrices
Local motifs
Dynamical system coupling
Visibility graph
Stick angle distribution
Extreme events
Singular spectrum analysis
Domain-specific techniques

Basis Functions

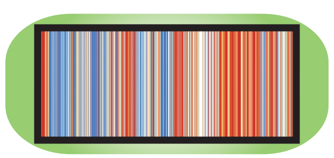
Wavelet transform
Peaks of power spectrum
Spectral measures
Power in frequency bands



A
Time series
feature vectors
stochastic processes
share prices
ECGs
dynamical systems
EEGs
space recordings
heart beat intervals
air temperature
rainfall
random numbers
audio
maps
autoregressive processes
B
Operations
AR model fit
sliding window stationarity
power spectrum measure
dimension estimate
distributional moment
nonlinear prediction error
wavelet coefficients
Sample Entropy
fluctuation analysis
C
8651 Operations
875 Time series

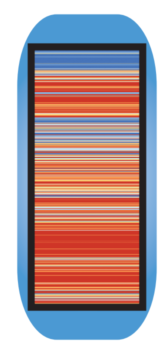
Empirical fingerprints

A flexible, powerful, and data-driven means of comparing time series, and analysis methods.



= time series of type 'green'

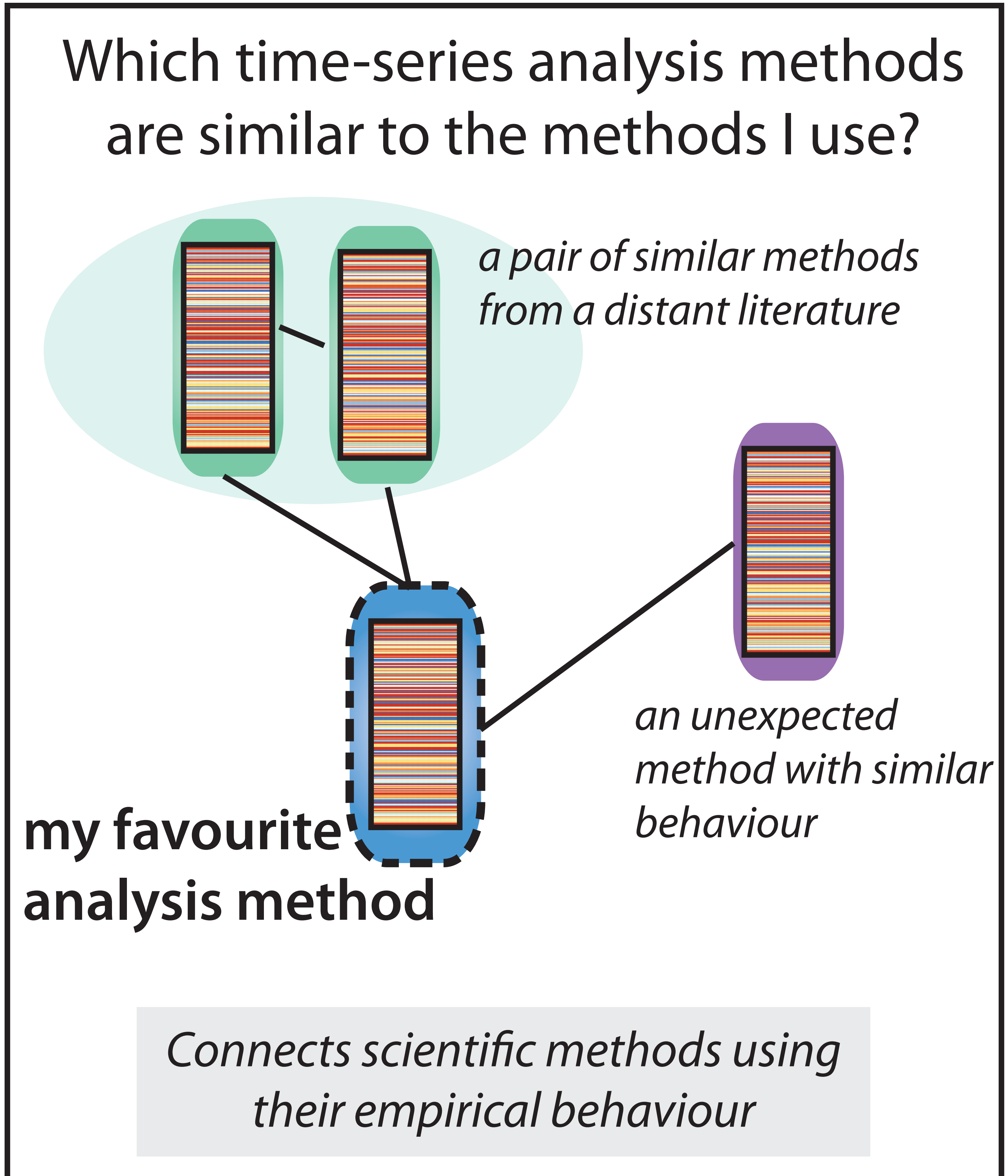
captures properties measured by diverse scientific methods



= operation of type 'blue'

captures behaviour across a range of empirical time series

Organizing our methods



long-range scaling

power spectral density

linear time-series models

stationarity

distribution

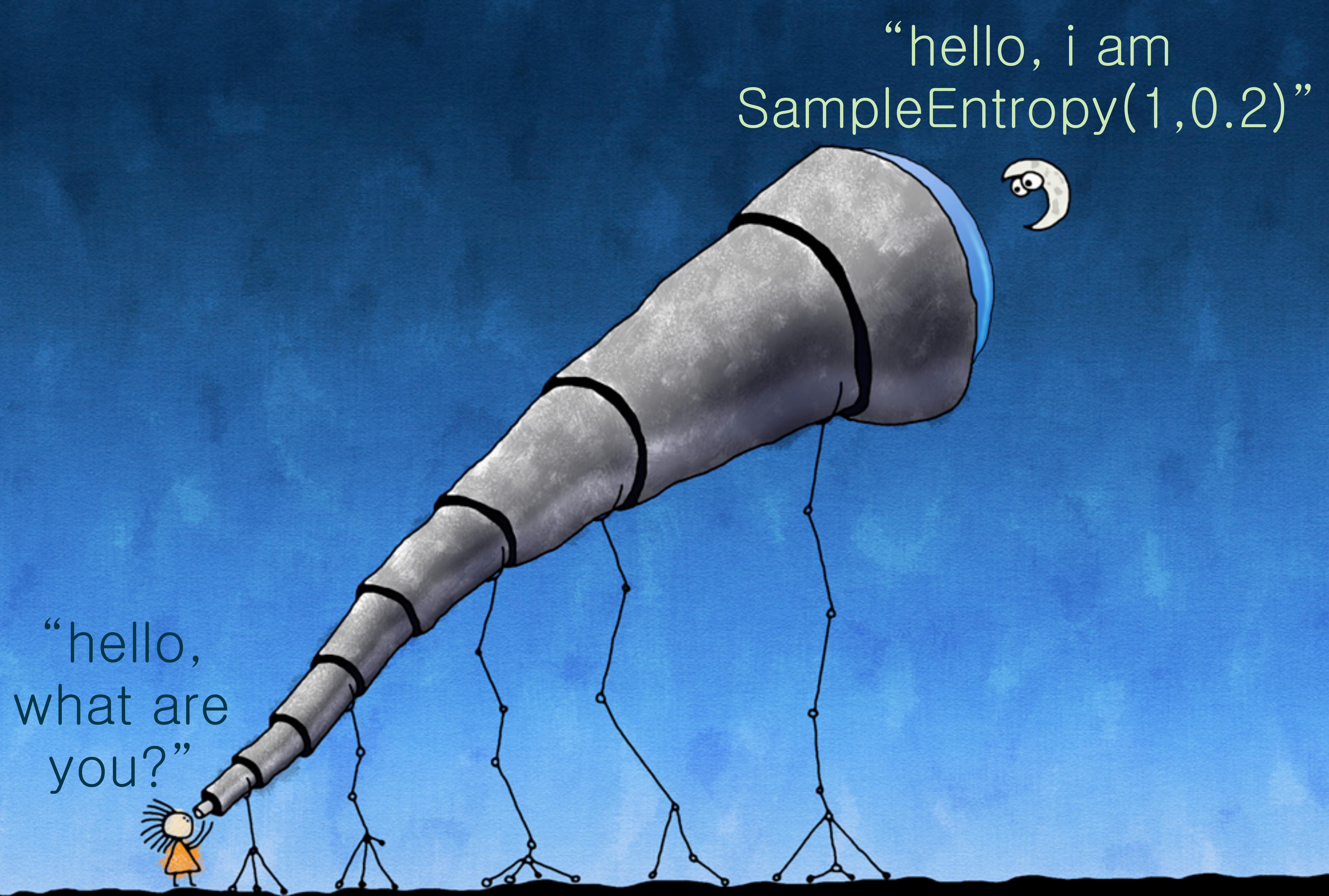
entropy

correlation dimension

complexity

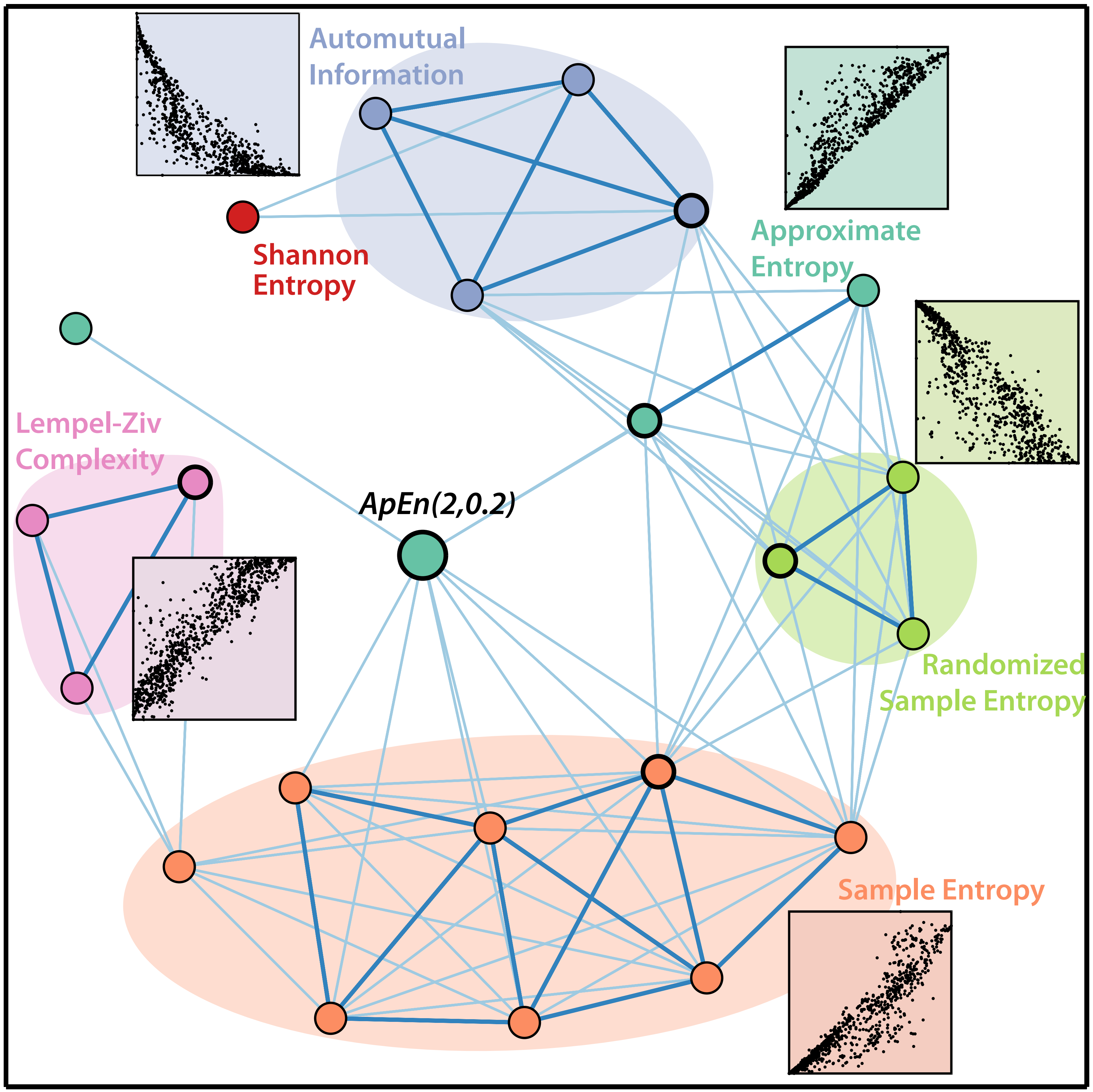
information theory

BIG PICTURE



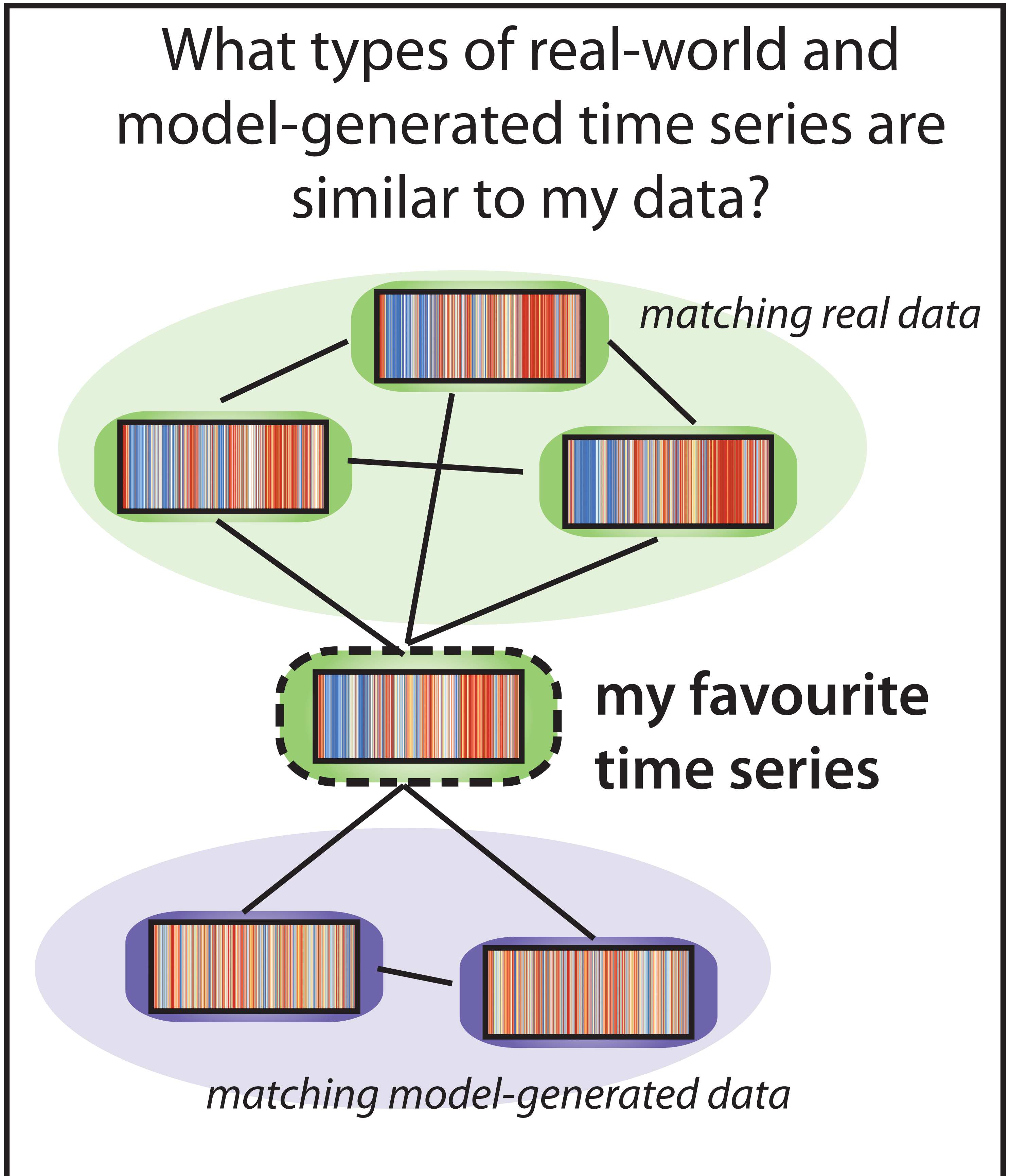
ZOOMING IN

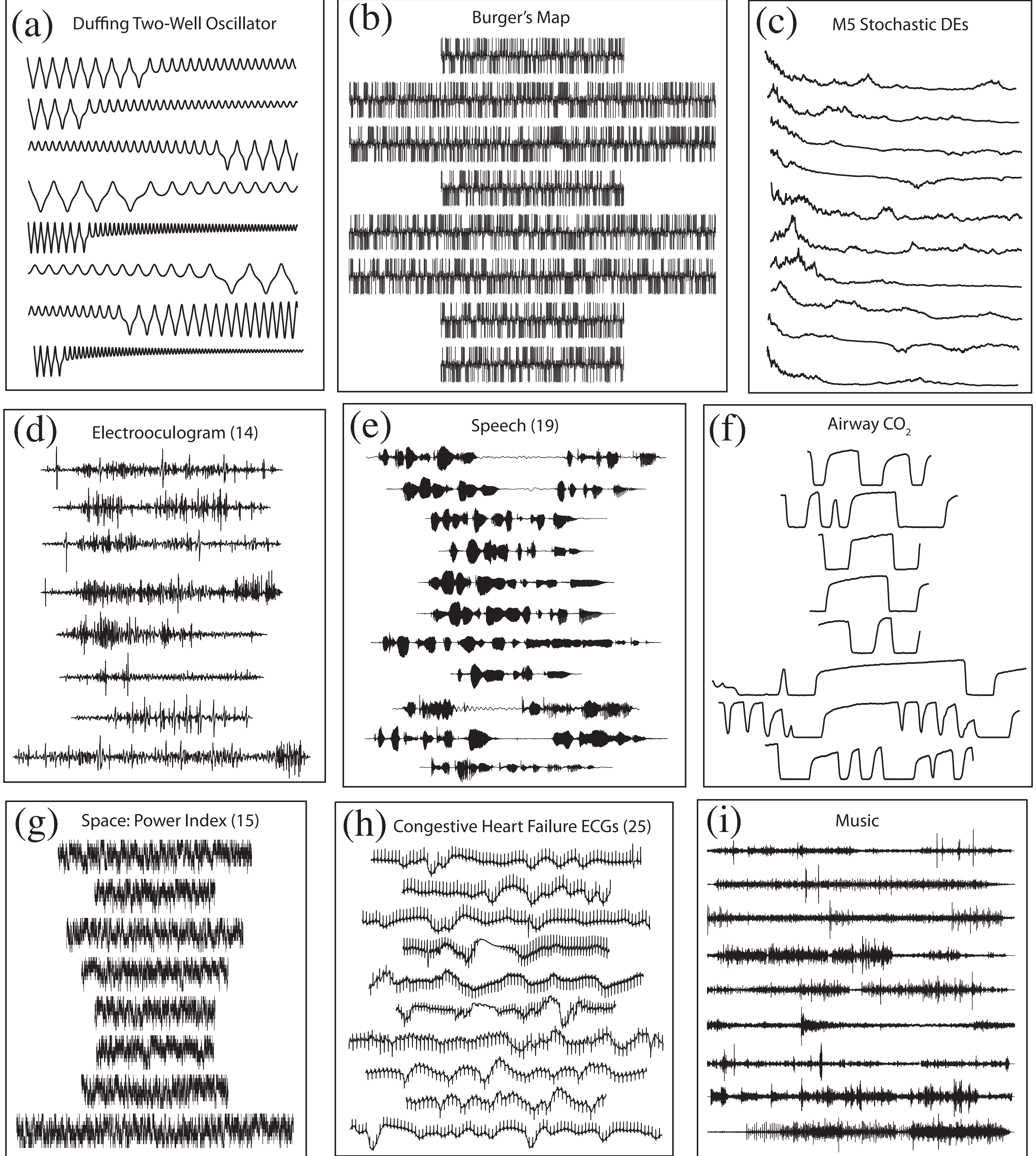
Local neighborhoods



Automatically find interdisciplinary connections between our methods for time-series analysis

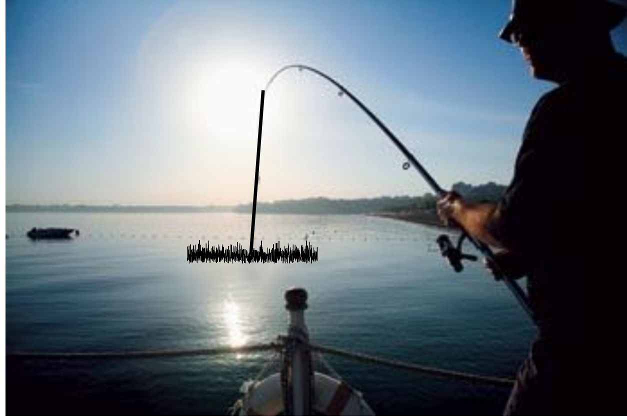
Organizing our data

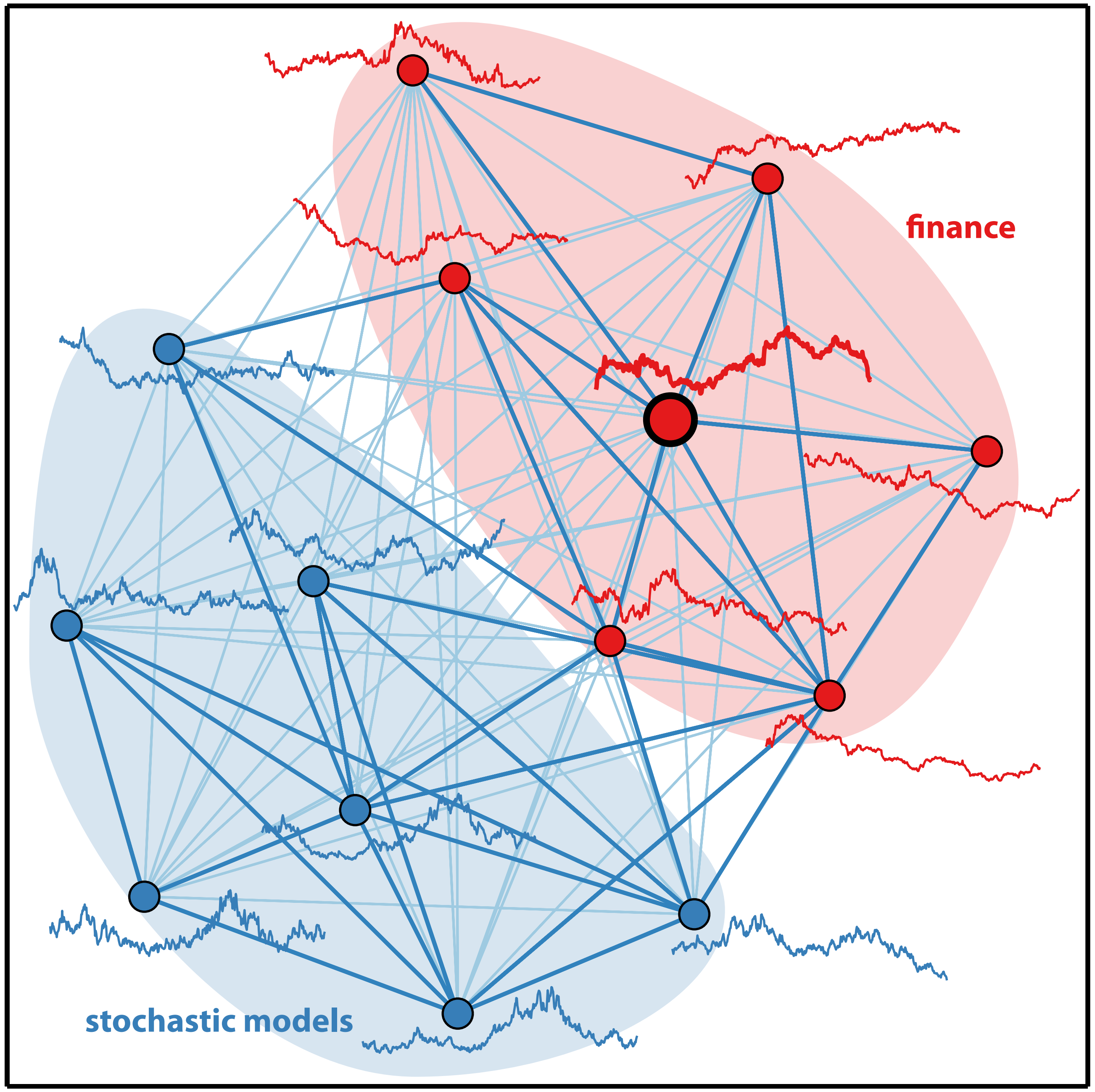


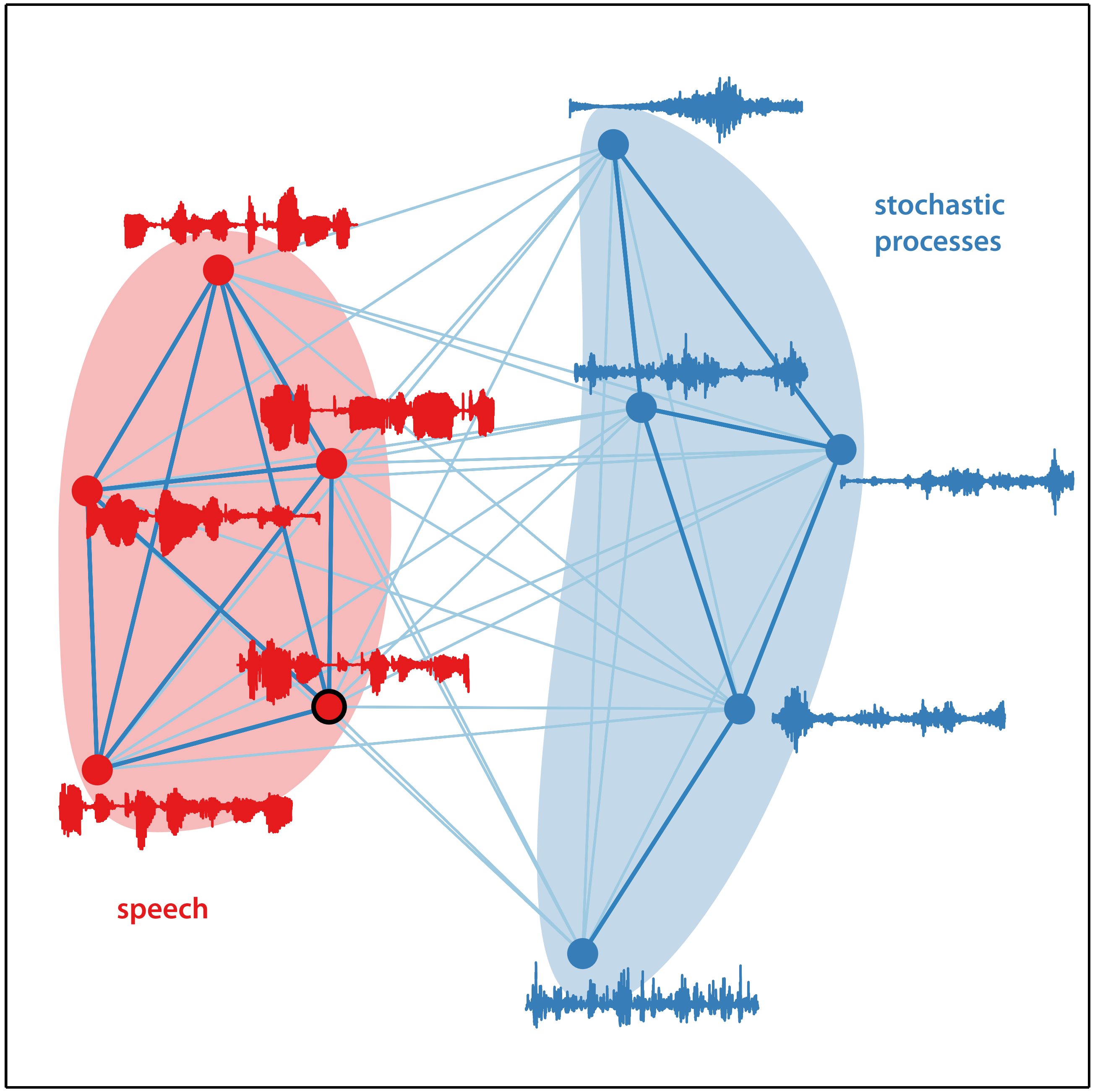


Clusters of time series group systems with common dynamical properties

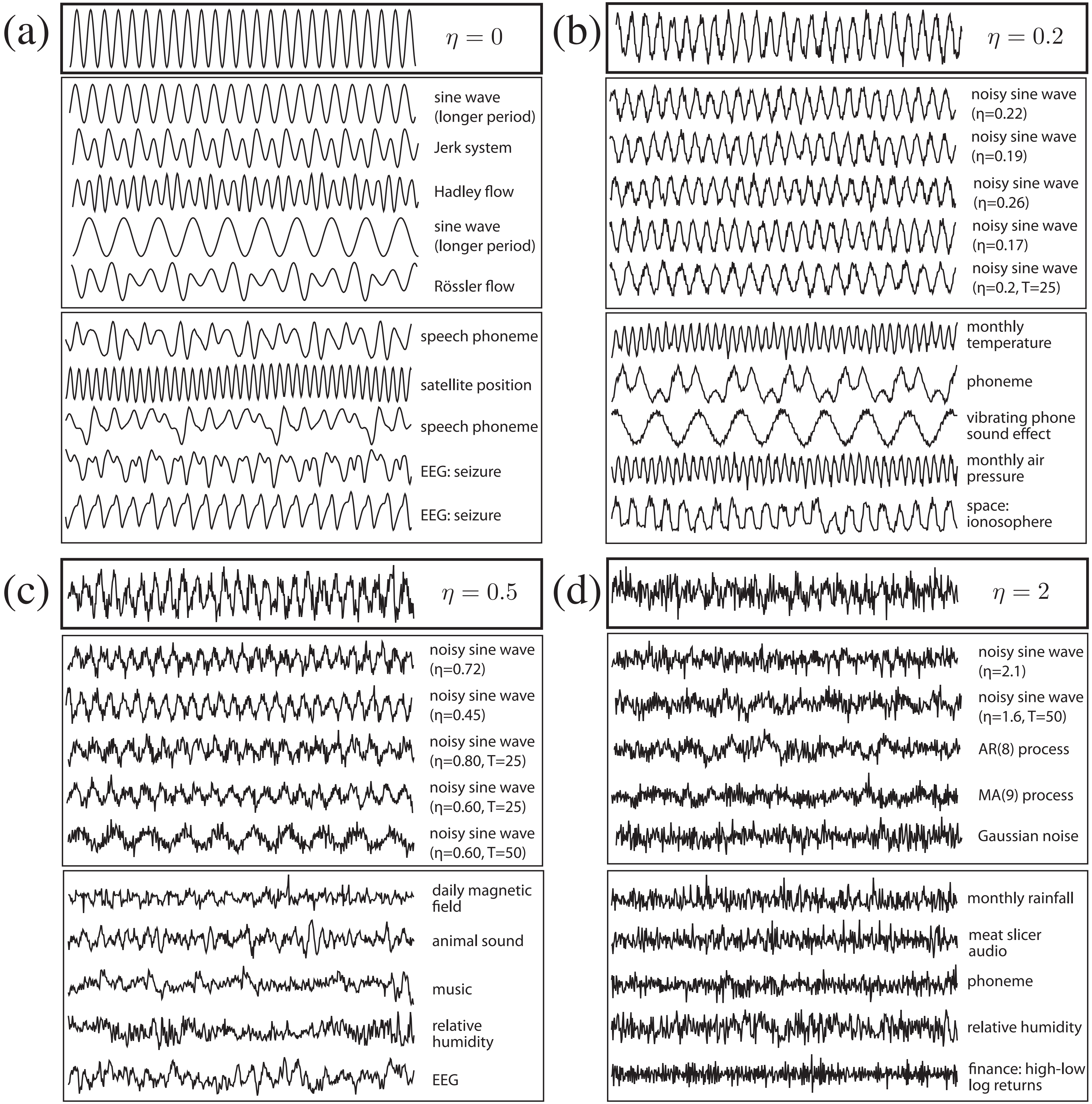
Fishing for data

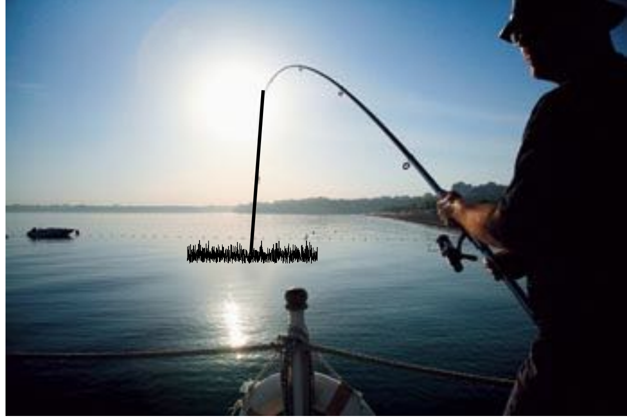






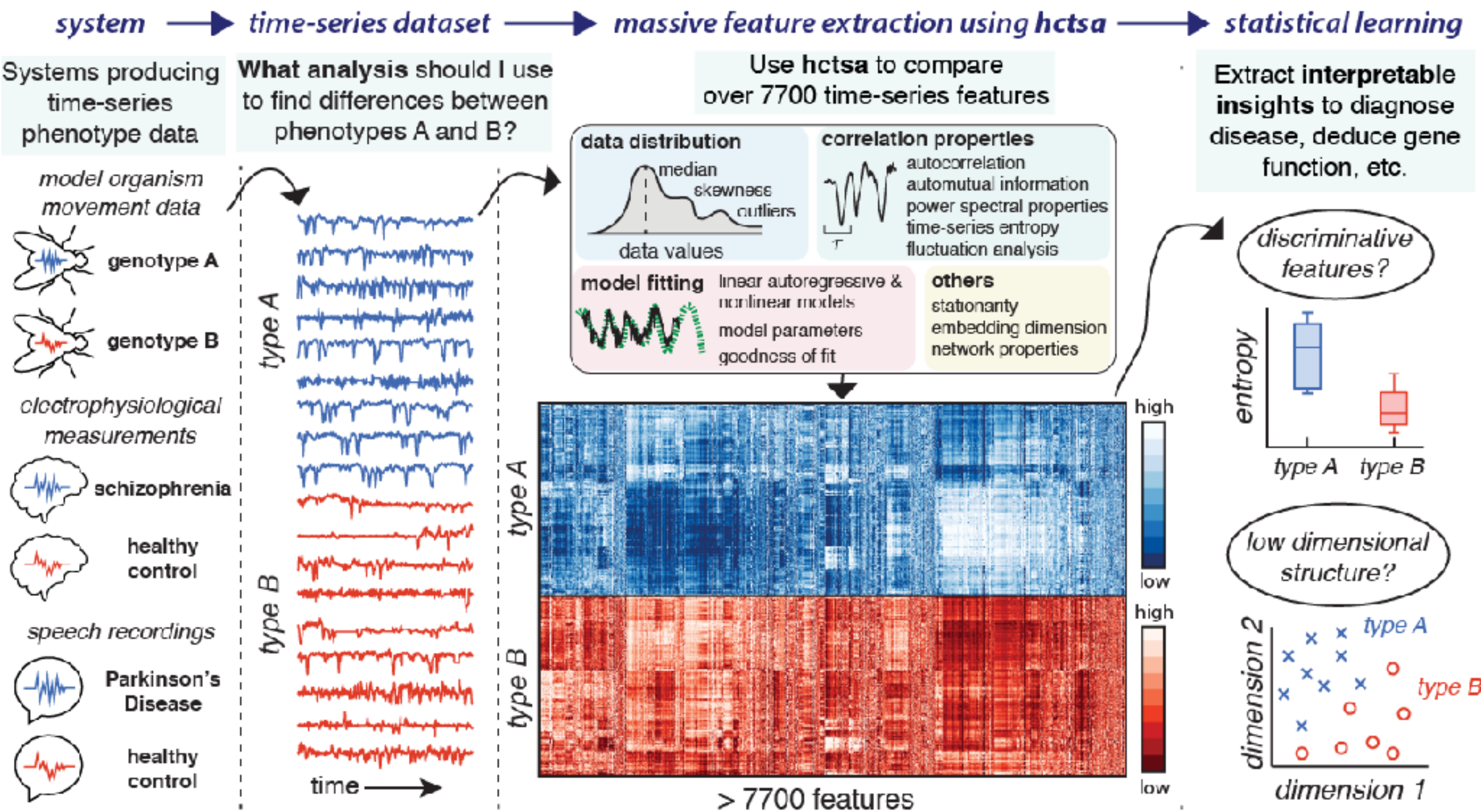
suggest models, or similar real-world processes to our data





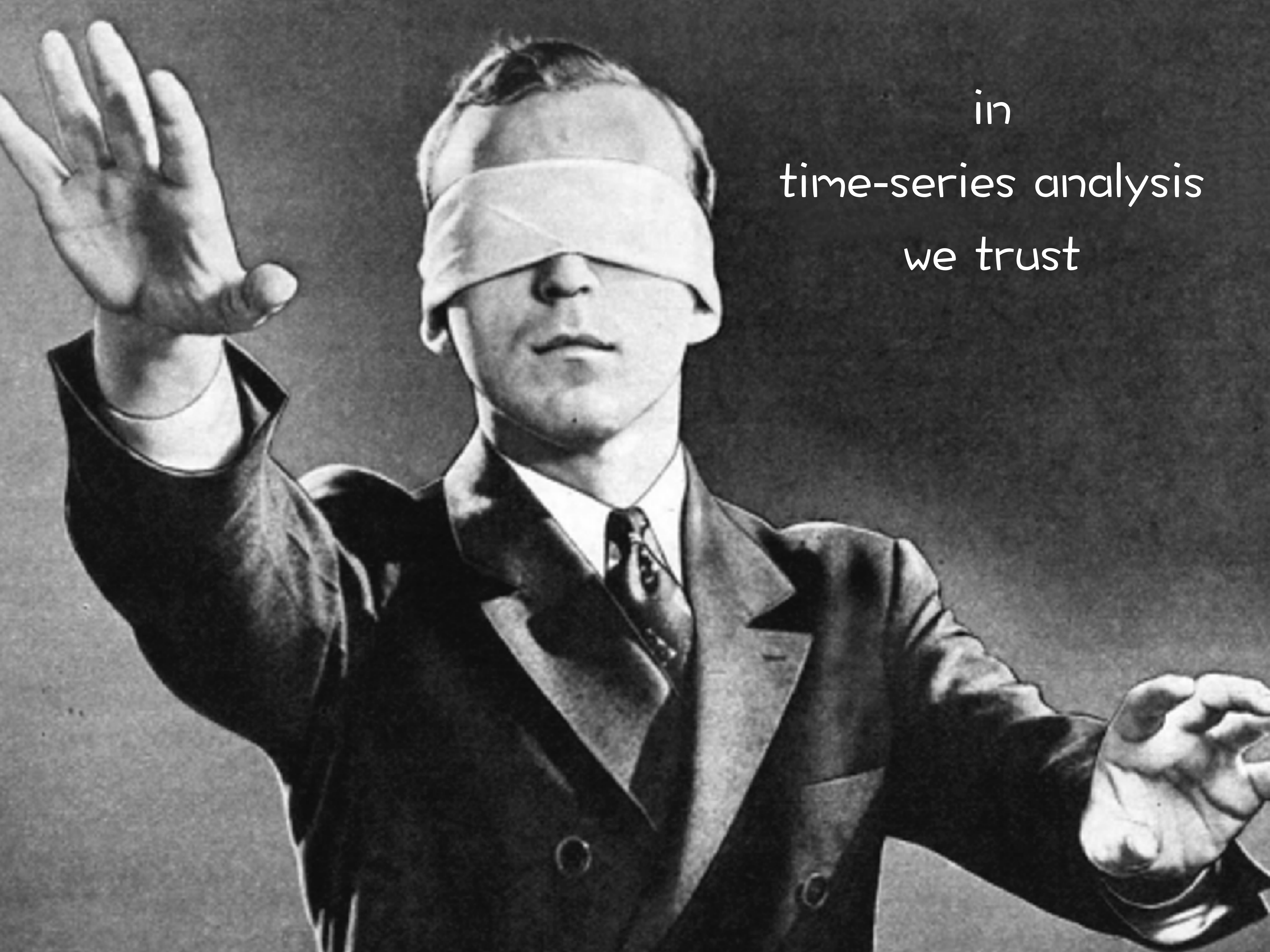
Brings our data and models closer together

Highly comparative time-series analysis for classification



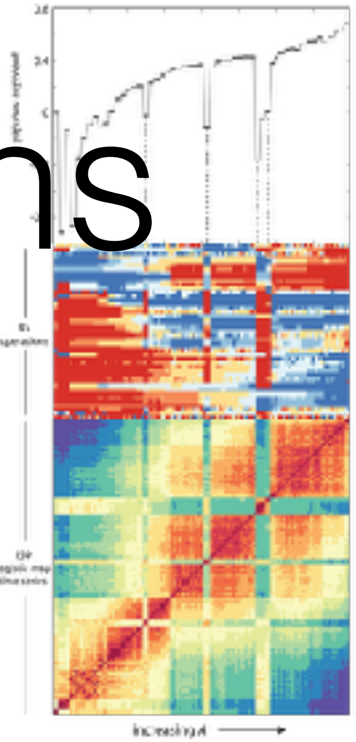
A very general problem: what method should I use?

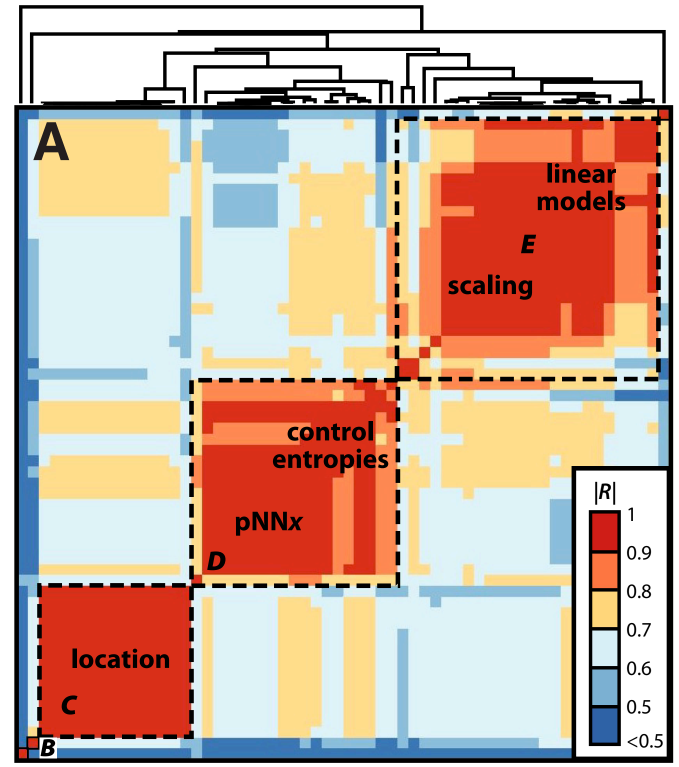
Time-series analysis 101: *always* look at your data

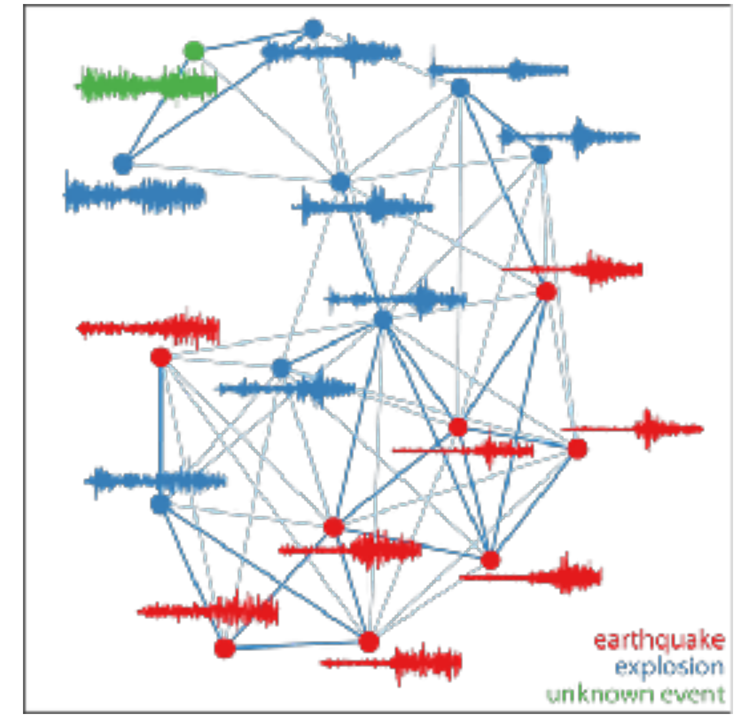

in
time-series analysis
we trust

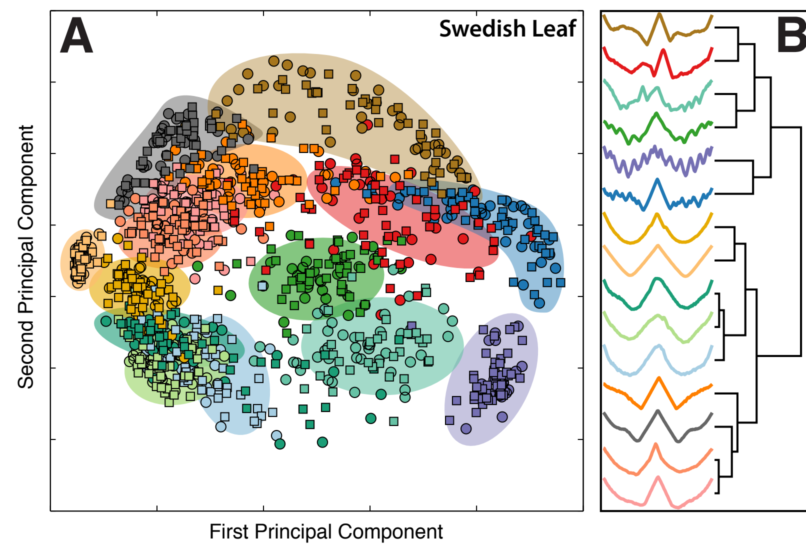
Applications

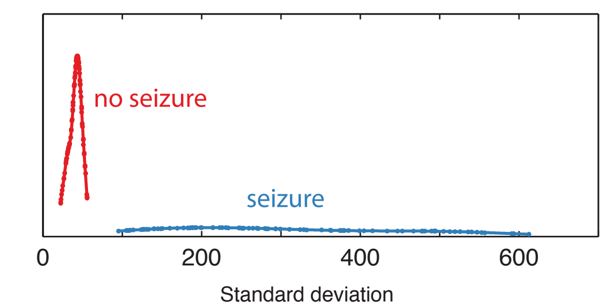
- Seismic data
- Simulated chaos
- Fetal heart rate
- Heart rate intervals
- Parkinsonian speech
- Epileptic EEGs
- Emotional speech

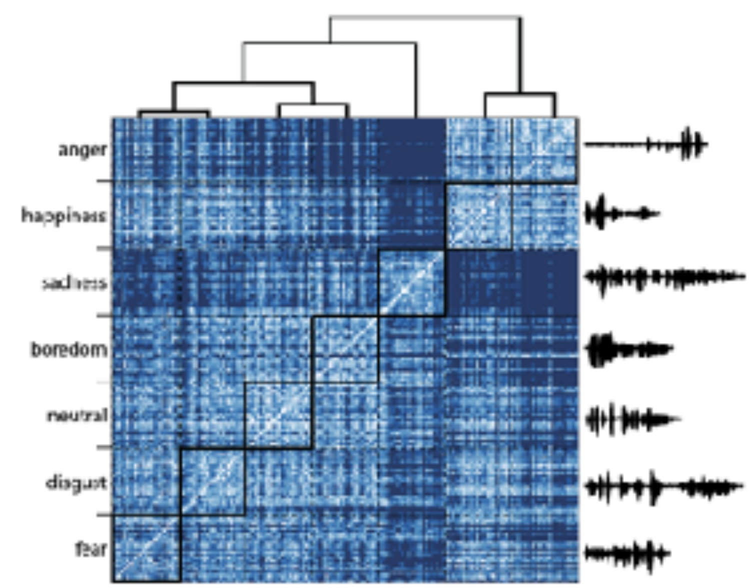


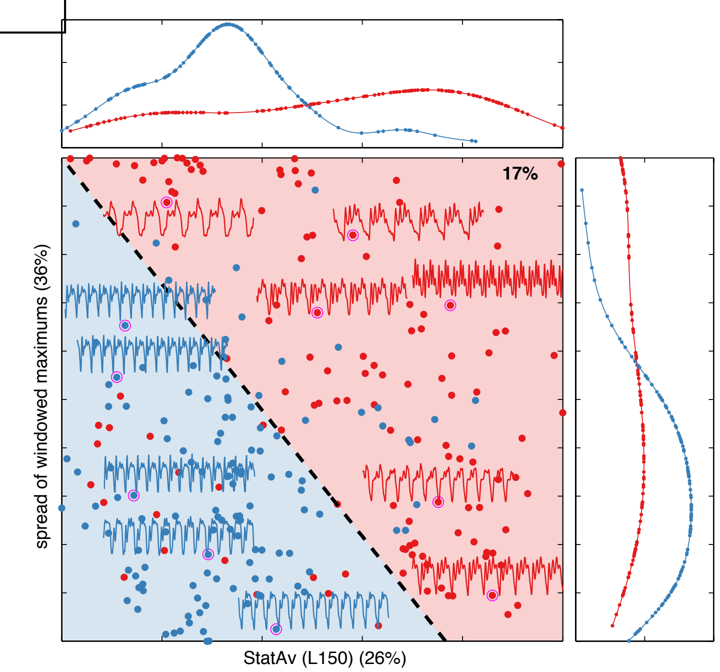










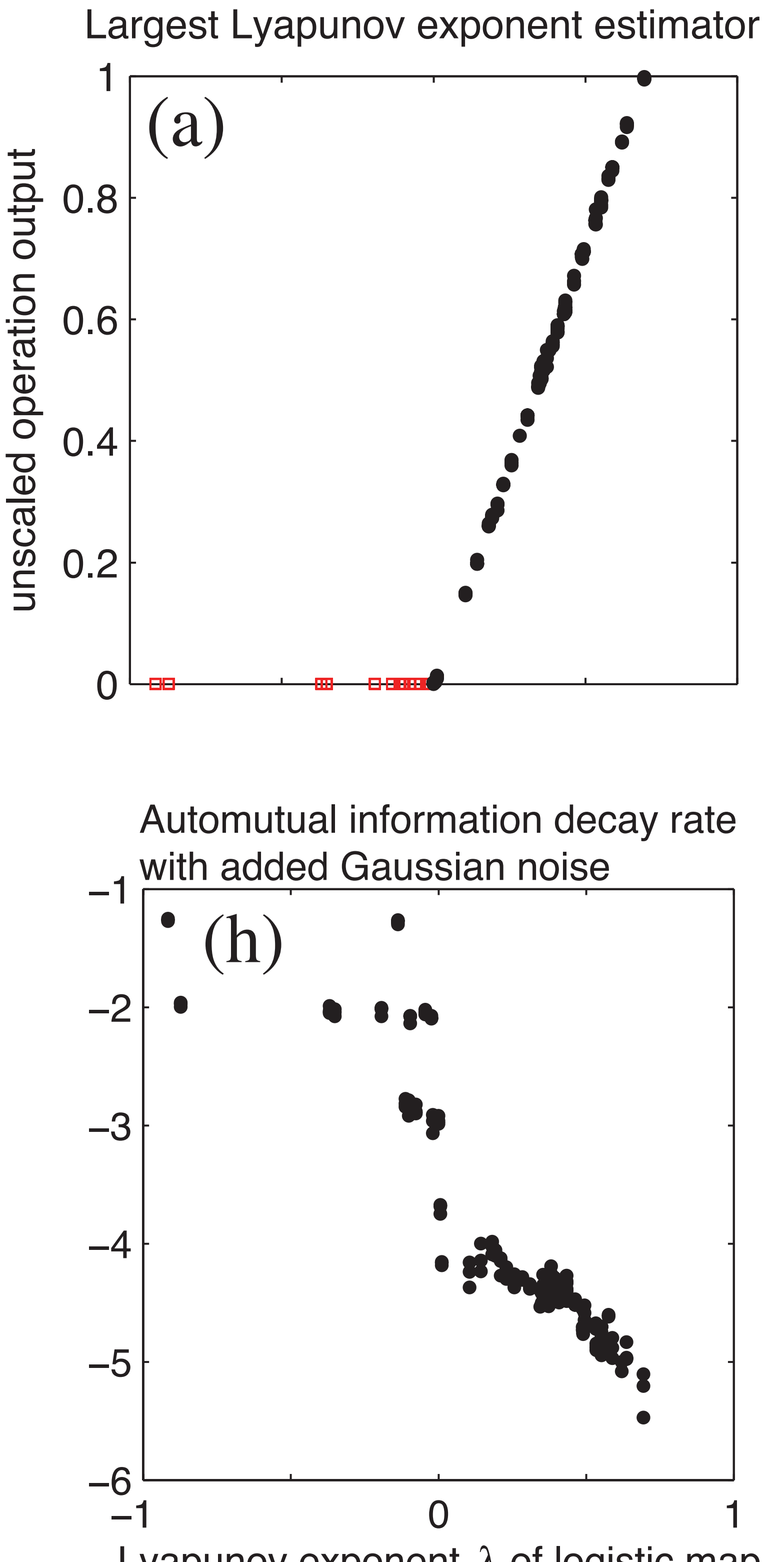


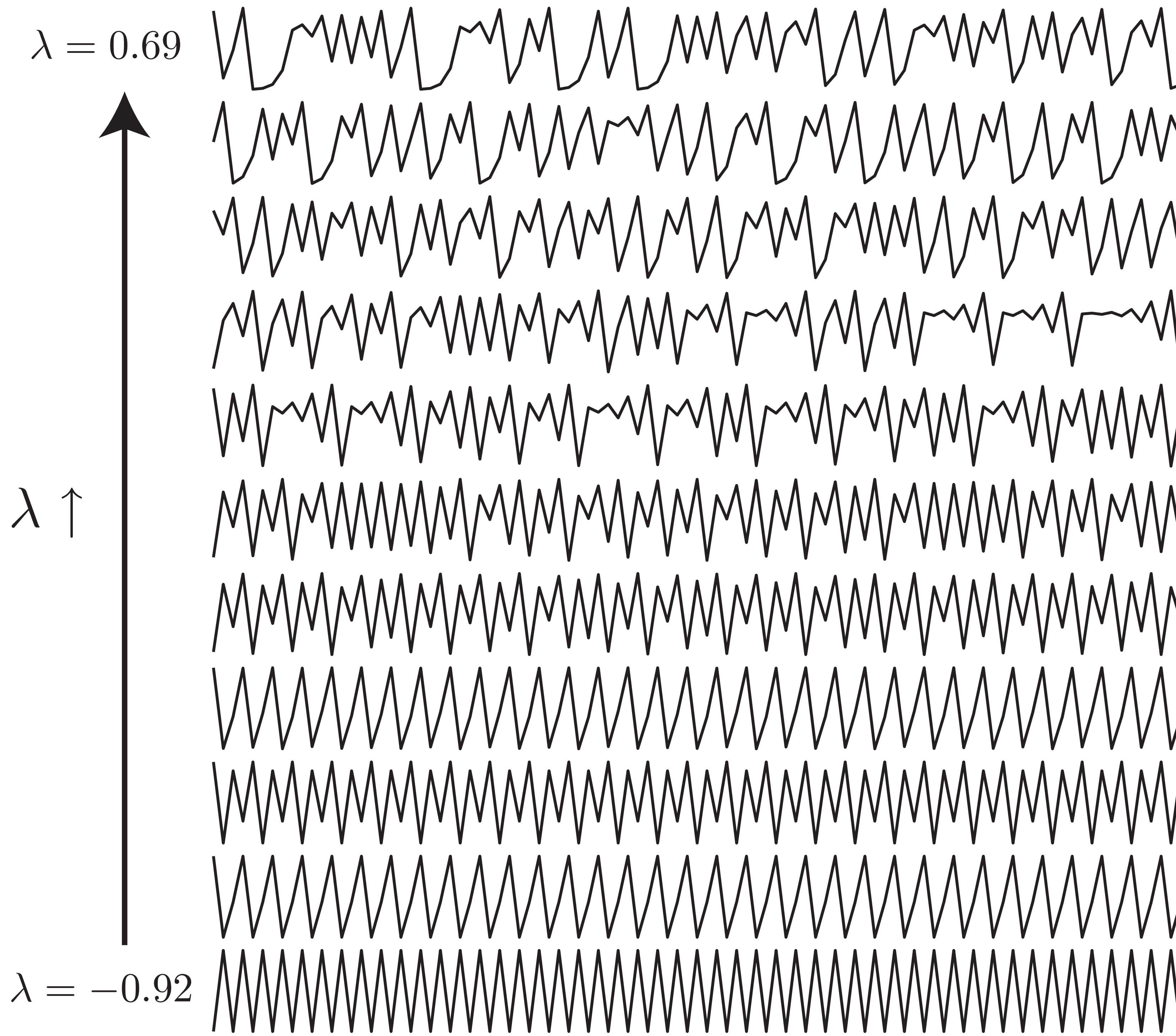
BD Fulcher, NS Jones. *IEEE KDE* (2014), *DOI: 10.1109/TKDE.2014.2316504*

BD Fulcher, MA Little, and NS Jones. *J. R. Soc. Interface*, **10**:83 (2013), *DOI: 10.1098/rsif.2013.0048*

BD Fulcher, AE Georgieva, C Redman, NS Jones, Annual International Conference of the IEEE, EMBC, 3135 (2012), DOI: 10.1109/EMBC.2012.6346629

Logistic Map

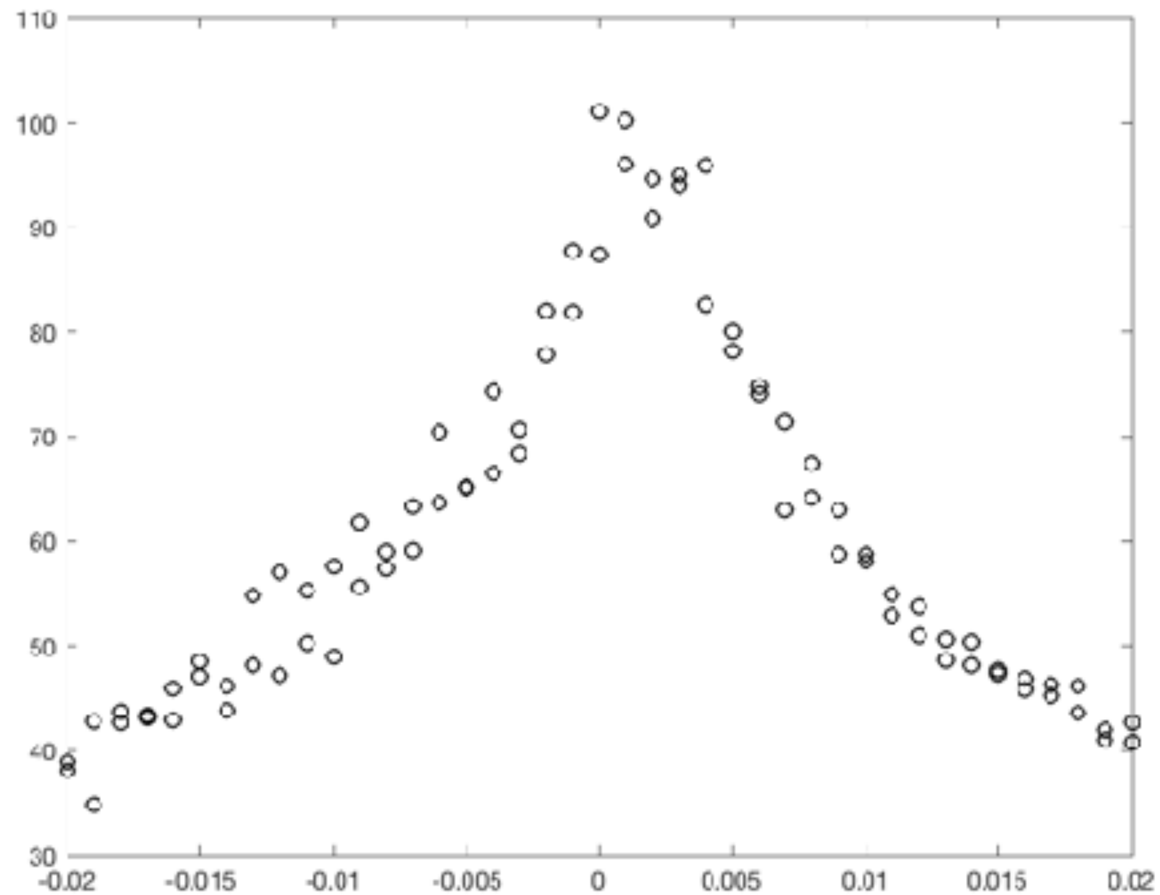


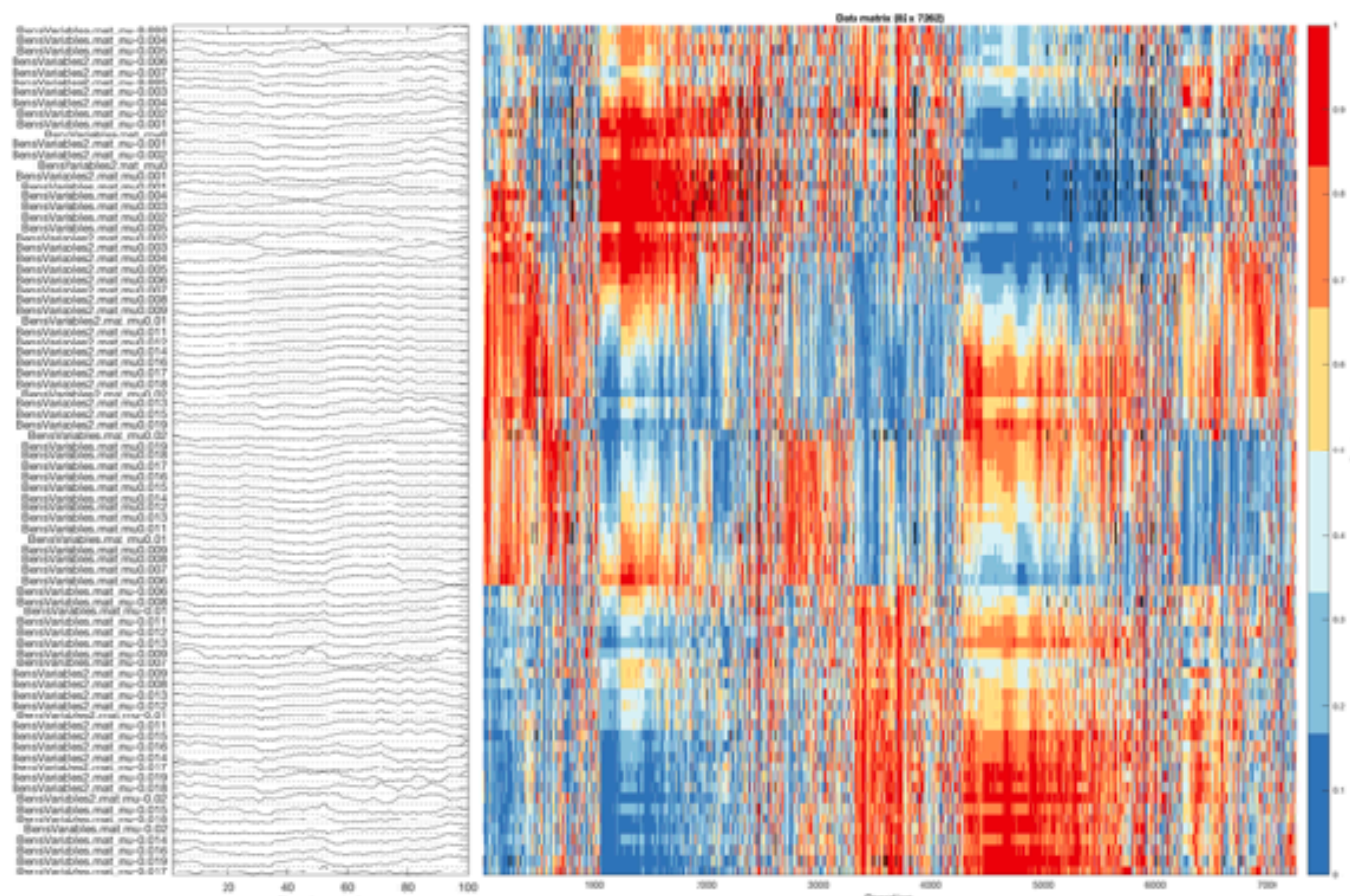


logistic maps: $x_{n+1} = Ax_n(1 - x_n)$

[15] (ind=461) CO_CompareMinAMI_std2_2_80_mean (-0.97) [correlation,AMI]
[16] (ind=2571) EN_mse_1-10_2_015_sampen_s3 (0.97) [entropy,sampen,mse]
[17] (ind=3087) ST_LocalExtrema_l50_stdext (0.97) [distribution,stationarity]
[18] (ind=837) EN_rpde_3_1_meanNonZero (-0.97) [entropy]
[19] (ind=836) EN_rpde_3_1_propNonZero (0.97) [entropy]
[20] (ind=2572) EN_mse_1-10_2_015_sampen_s4 (0.97) [entropy,sampen,mse]
[21] (ind=2009) SY_SpreadRandomLocal_100_100_meanstd (0.97) [stationarity]
[22] (ind=6538) PP_ModelFit_ar_2_rmserrrat_p2_20 (-0.97) [preprocessing,trend]
[23] (ind=6535) PP_ModelFit_ar_2_rmserrrat_p1_40 (-0.97) [preprocessing,trend]
[24] (ind=3089) ST_LocalExtrema_l50_meanabsext (0.97) [distribution,stationarity]
[25] (ind=122) AC_37 (-0.97) [correlation]
[26] (ind=299) IN_AutoMutualInfoStats_40_gaussian_ami40 (-0.97) [information,correlation,AMI]
[27] (ind=296) IN_AutoMutualInfoStats_40_gaussian_ami37 (-0.97) [information,correlation,AMI]
[28] (ind=123) AC_38 (-0.97) [correlation]
[29] (ind=297) IN_AutoMutualInfoStats_40_gaussian_ami38 (-0.97) [information,correlation,AMI]
[30] (ind=121) AC_36 (-0.97) [correlation]
[31] (ind=124) AC_39 (-0.97) [correlation]
[32] (ind=295) IN_AutoMutualInfoStats_40_gaussian_ami36 (-0.97) [information,correlation,AMI]
[33] (ind=7186) CP_ML_StepDetect_l1pwc_10_E (0.97) [stepdetection]
[34] (ind=125) AC_40 (-0.97) [correlation]
[35] (ind=298) IN_AutoMutualInfoStats_40_gaussian_ami39 (-0.97) [information,correlation,AMI]
[36] (ind=294) IN_AutoMutualInfoStats_40_gaussian_ami35 (-0.97) [information,correlation,AMI]
[37] (ind=120) AC_35 (-0.97) [correlation]
[38] (ind=5111) TSTL_localdensity_5_40_1_3_medianden (0.97) [nonlinear,tstool]
[39] (ind=119) AC_34 (-0.97) [correlation]
[40] (ind=2504) PH_Walker_runningvar_15_50_w_std (0.97) [trend]
[41] (ind=219) CO_HistogramAMI_std2_2_5 (-0.97) [information,correlation,AMI]
[42] (ind=293) IN_AutoMutualInfoStats_40_gaussian_ami34 (-0.97) [information,correlation,AMI]
[43] (ind=292) IN_AutoMutualInfoStats_40_gaussian_ami33 (-0.97) [information,correlation,AMI]
[44] (ind=2582) EN_mse_1-10_2_015_meanSampEn (0.97) [entropy,sampen,mse]
[45] (ind=118) AC_33 (-0.97) [correlation]
[46] (ind=291) IN_AutoMutualInfoStats_40_gaussian_ami32 (-0.97) [information,correlation,AMI]
[47] (ind=5107) TSTL_localdensity_5_40_1_3_iqrden (0.97) [nonlinear,tstool]
[48] (ind=117) AC_32 (-0.97) [correlation]
[49] (ind=1993) SY_SpreadRandomLocal_50_100_meanstd (0.97) [stationarity]
[50] (ind=116) AC_31 (-0.96) [correlation]
[51] (ind=2570) EN_mse_1-10_2_015_sampen_s2 (0.96) [entropy,sampen,mse]
[52] (ind=290) IN_AutoMutualInfoStats_40_gaussian_ami31 (-0.96) [information,correlation,AMI]
[53] (ind=114) AC_29 (-0.96) [correlation]
[54] (ind=289) IN_AutoMutualInfoStats_40_gaussian_ami30 (-0.96) [information,correlation,AMI]
[55] (ind=286) IN_AutoMutualInfoStats_40_gaussian_ami27 (-0.96) [information,correlation,AMI]
[56] (ind=288) IN_AutoMutualInfoStats_40_gaussian_ami29 (-0.96) [information,correlation,AMI]
[57] (ind=6539) PP_ModelFit_ar_2_rmserrrat_p2_40 (-0.96) [preprocessing,trend]
[58] (ind=115) AC_30 (-0.96) [correlation]
[59] (ind=112) AC_27 (-0.96) [correlation]
[60] (ind=285) IN_AutoMutualInfoStats_40_gaussian_ami26 (-0.96) [information,correlation,AMI]
[61] (ind=113) AC_28 (-0.96) [correlation]
[62] (ind=287) IN_AutoMutualInfoStats_40_gaussian_ami28 (-0.96) [information,correlation,AMI]
[63] (ind=111) AC_26 (-0.96) [correlation]
[64] (ind=6259) WL_coeffs_db3_5_med_coeff (0.96) [wavelet]
[65] (ind=3201) EX_MovingThreshold_01_002_meanqover (0.96) [outliers]
[66] (ind=5307) NL_TSTL_LargestLyap_n1_01_001_3_1_4_expfit_r2 (0.96) [nonlinear,tstool]
[67] (ind=284) IN_AutoMutualInfoStats_40_gaussian_ami25 (-0.96) [information,correlation,AMI]
[68] (ind=110) AC_25 (-0.96) [correlation]
[69] (ind=7189) CP_ML_StepDetect_l1pwc_10_rmsoff (-0.96) [stepdetection]
[70] (ind=109) AC_24 (-0.96) [correlation]
[71] (ind=2757) EN_Randomize_permute_sampen2_015diff (0.96) [entropy,slow]
[72] (ind=218) CO_HistogramAMI_std2_2_4 (-0.96) [information,correlation,AMI]
[73] (ind=108) AC_23 (-0.96) [correlation]
[74] (ind=283) IN_AutoMutualInfoStats_40_gaussian_ami24 (-0.96) [information,correlation,AMI]
[75] (ind=6257) WL_coeffs_db3_5_mean_coeff (0.96) [wavelet]
[76] (ind=2573) EN_mse_1-10_2_015_sampen_s5 (0.96) [entropy,sampen,mse]
[77] (ind=834) EN_rpde_3_1_H (0.96) [entropy]
[78] (ind=835) EN_rpde_3_1_H_norm (0.96) [entropy]
[79] (ind=282) IN_AutoMutualInfoStats_40_gaussian_ami23 (-0.96) [information,correlation,AMI]
[80] (ind=6318) WL_dwtcoeff_sym2_5_stdd_l5 (0.96) [wavelet,dwt]
[81] (ind=3223) EX_MovingThreshold_1_002_meanqover (0.96) [outliers]
[82] (ind=2517) PH_Walker_runningvar_15_50_sw_ansarib_pval (0.96) [trend]
[83] (ind=107) AC_22 (-0.96) [correlation]
[84] (ind=281) IN_AutoMutualInfoStats_40_gaussian_ami22 (-0.96) [information,correlation,AMI]
[85] (ind=5299) NL_TSTL_LargestLyap_n1_01_001_3_1_4_vse_minbad (0.96) [nonlinear,tstool]
[86] (ind=280) IN_AutoMutualInfoStats_40_gaussian_ami21 (-0.96) [information,correlation,AMI]
[87] (ind=106) AC_21 (-0.96) [correlation]
[88] (ind=4144) SP_Summaries_welch_rect_wmax_75 (0.96) [spectral]
[89] (ind=2040) SY_DriftingMean20_max (-0.96) [stationarity]
[90] (ind=831) SY_LocalGlobal_AC1_unicg500 (0.96) [stationarity]
[91] (ind=4678) NL_TSTL_acp_mi_1__10_ac1_acpf_2 (-0.96) [nonlinear,correlation]
[92] (ind=4489) SY_TISEAN_nstat_z_4_1_3_min (0.96) [nonlinear,tisean,model,stationarity]
[93] (ind=4305) SP_Summaries_fft_logdev_linfitsemilog_all_a1 (0.96) [spectral]
[94] (ind=105) AC_20 (-0.96) [correlation]
[95] (ind=278) IN_AutoMutualInfoStats_40_gaussian_ami19 (-0.96) [information,correlation,AMI]
[96] (ind=279) IN_AutoMutualInfoStats_40_gaussian_ami20 (-0.96) [information,correlation,AMI]
[97] (ind=5308) NL_TSTL_LargestLyap_n1_01_001_3_1_4_expfit_rmse (-0.96) [nonlinear,tstool]
[98] (ind=104) AC_19 (-0.96) [correlation]

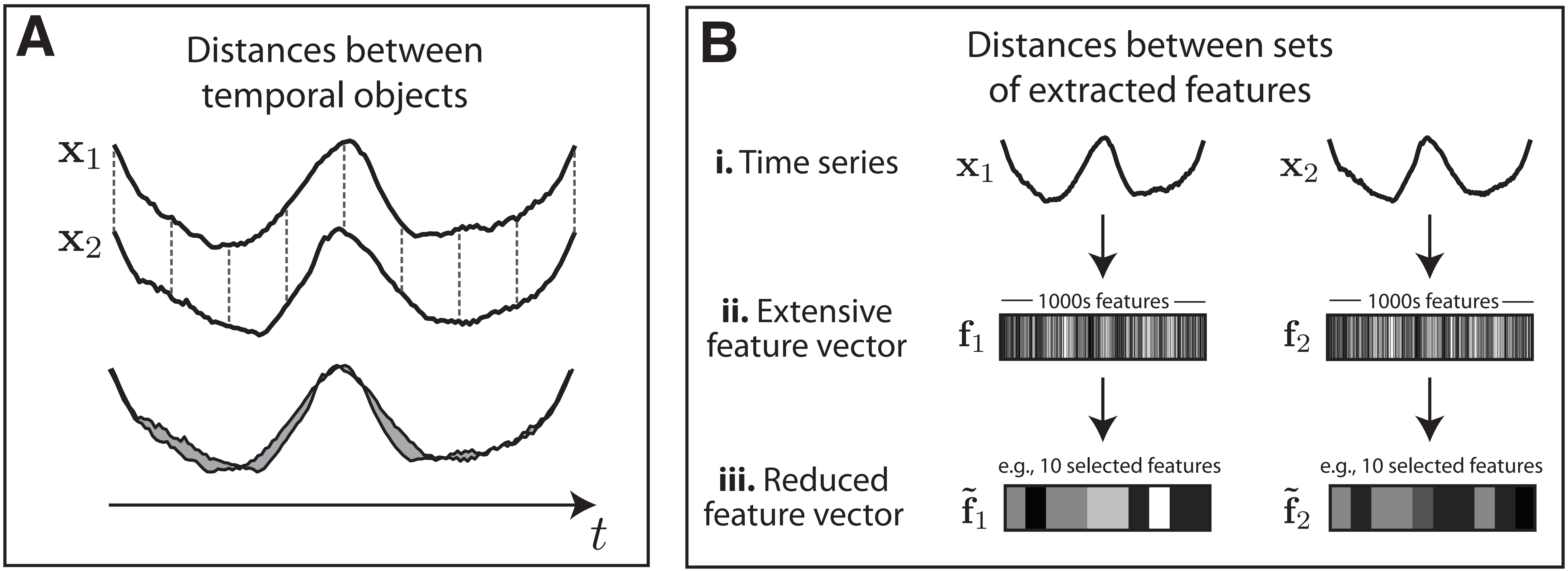
Criticality



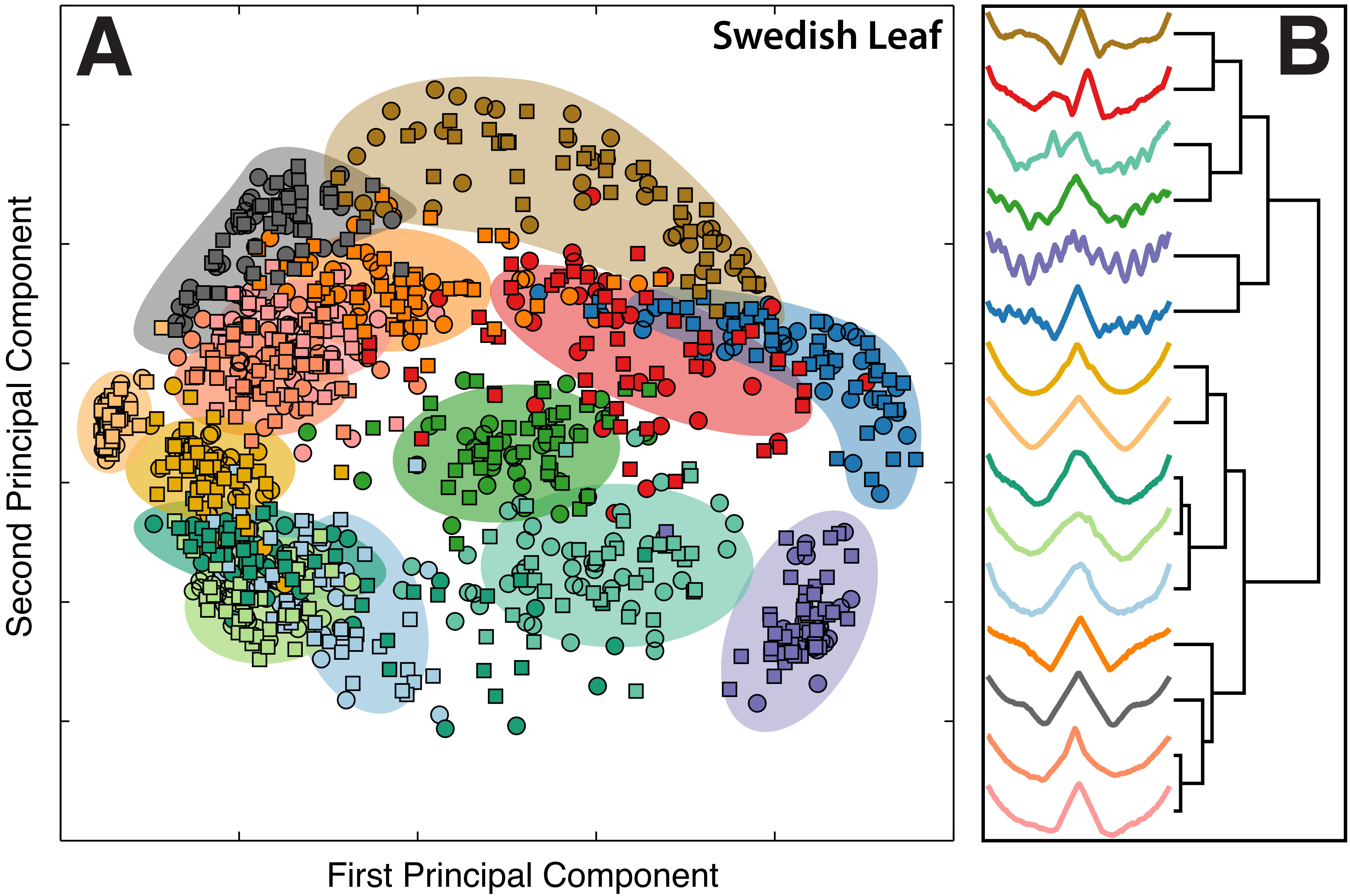


Time series matching

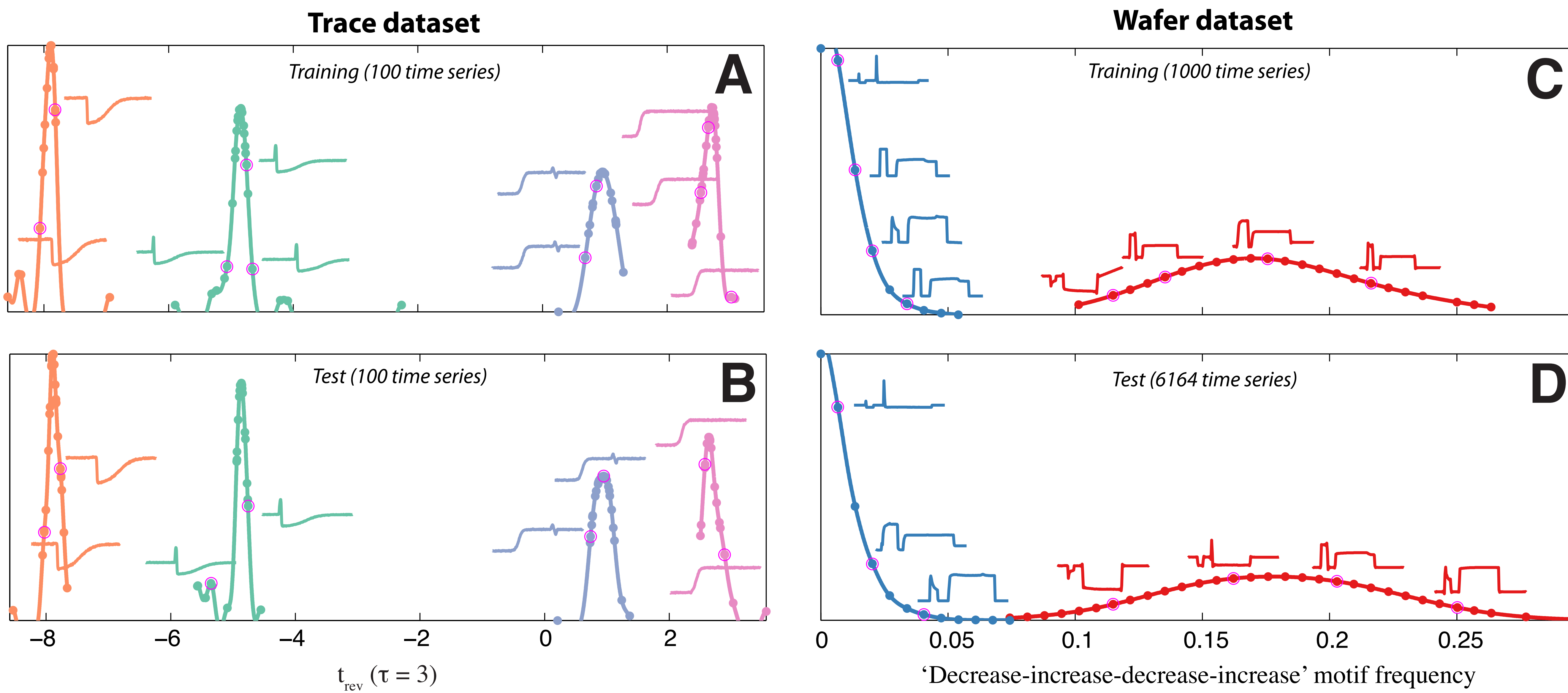
Cluster and classify short time-series 'patterns'



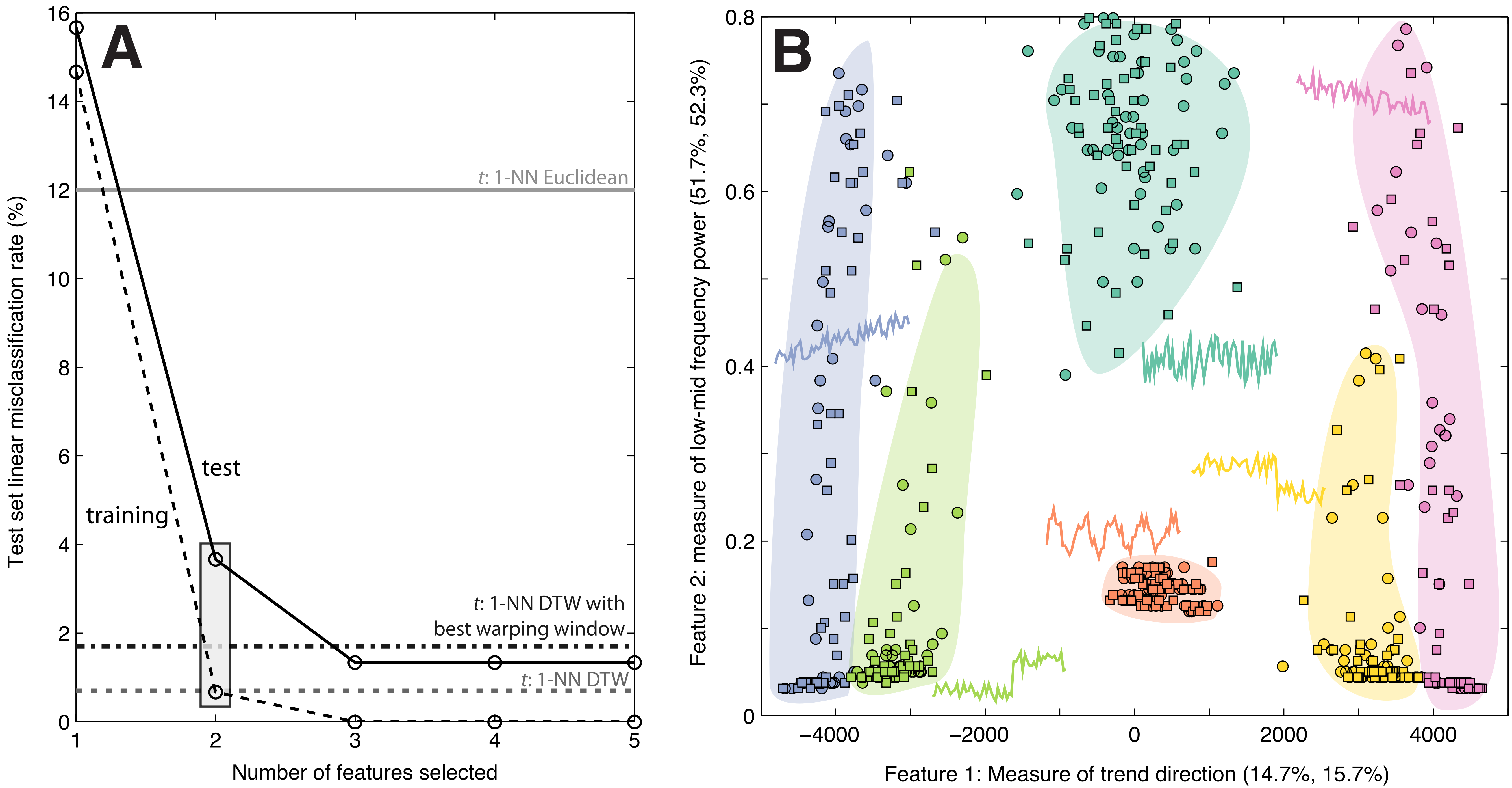
B. D. Fulcher & N. S. Jones, Highly comparative feature-based time-series classification. *IEEE Trans. Knowl. Data Eng.* **26**, 3026–3037 (2014)



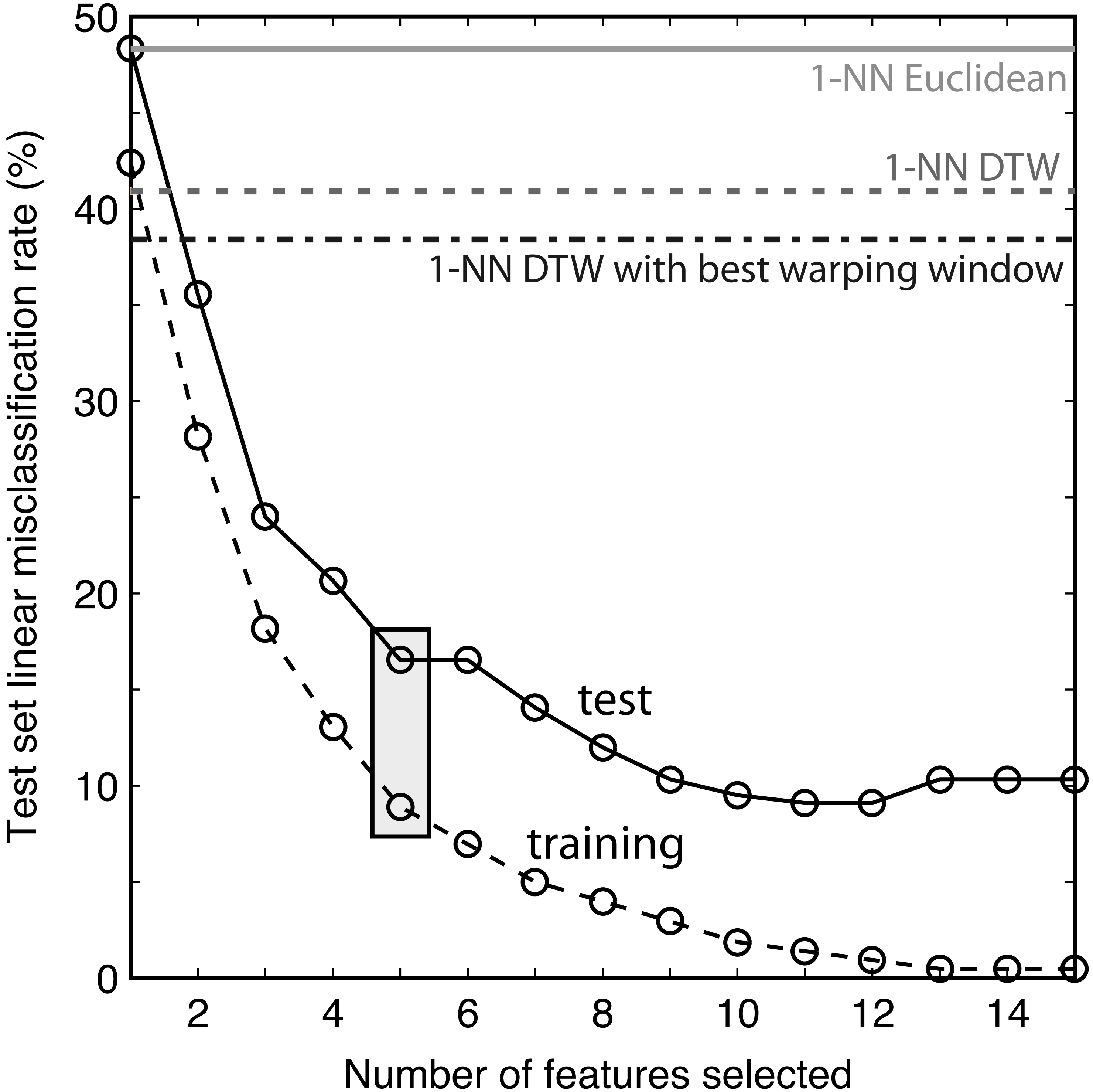
A
Swedish Leaf
B
Second Principal Component
First Principal Component



Trace dataset
Wafer dataset
Training (100 time series)
A
Test (100 time series)
B
Training (1000 time series)
C
Test (6164 time series)
D
−8
−6
−4
−2
0
2
t_{rev} ($\tau = 3$)
0
0.05
0.1
0.15
0.2
0.25
'Decrease-increase-decrease-increase' motif frequency



A
16
14
12
10
8
6
4
2
0
1
2
3
4
5
Test set linear misclassification rate (%)
Number of features selected
t: 1-NN Euclidean
test
training
t: 1-NN DTW with
best warping window
t: 1-NN DTW
B
0.8
0.6
0.4
0.2
0
−4000
−2000
0
2000
4000
Feature 2: measure of low-mid frequency power (51.7%, 52.3%)
Feature 1: Measure of trend direction (14.7%, 15.7%)



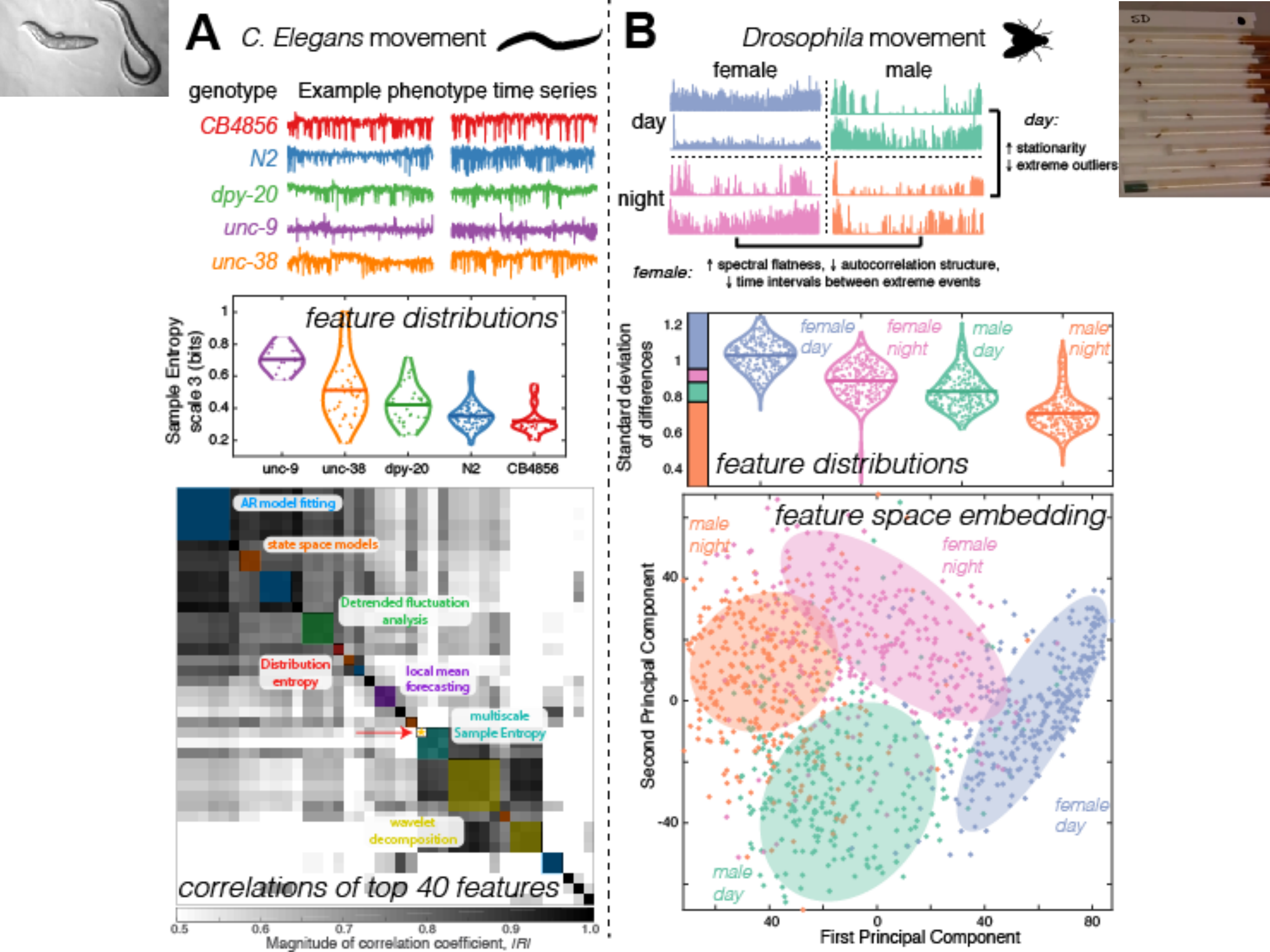
automatic

massive dimensionality reduction

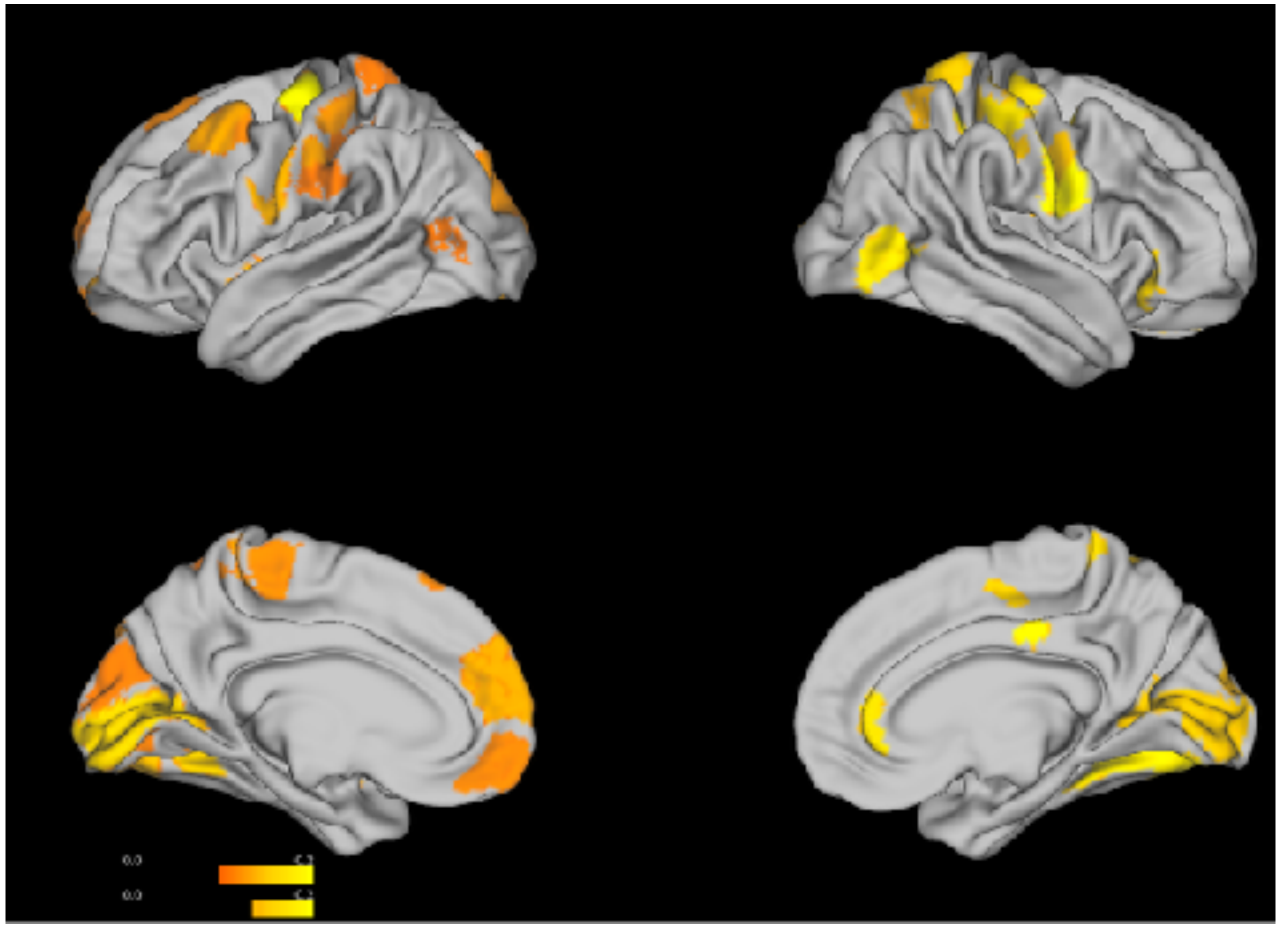
fast classification of new examples

diverse, interpretable features

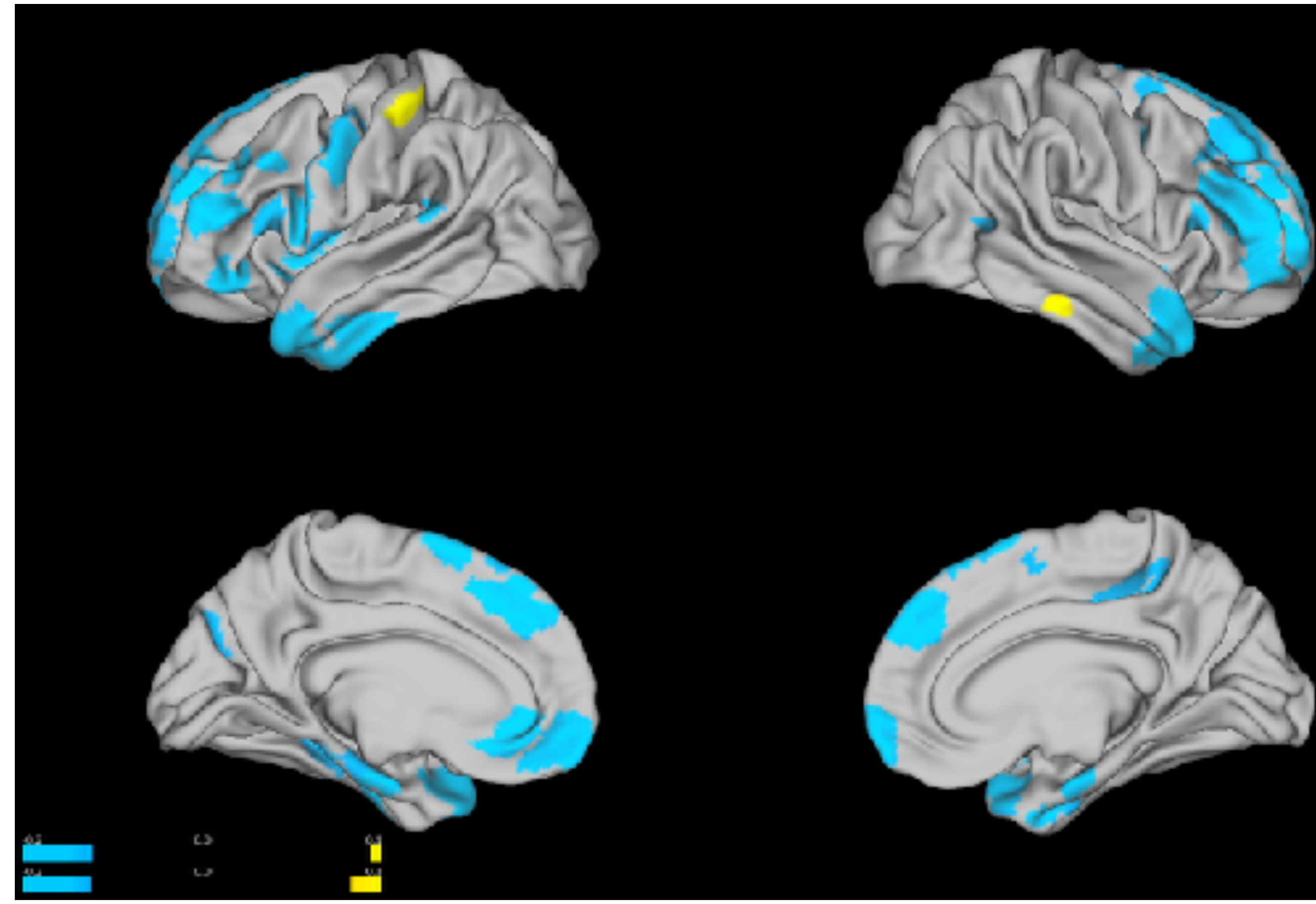
B. D. Fulcher & N. S. Jones, Highly comparative feature-based time-series classification. *IEEE Trans. Knowl. Data Eng.* **26**, 3026–3037 (2014)


A
C. Elegans movement
genotype
Example phenotype time series
CB4856
N2
dpy-20
unc-9
unc-38
feature distributions
Sample Entropy scale 3 (bits)
1
0.8
0.6
0.4
0.2
unc-9
unc-38
dpy-20
N2
CB4856
AR model fitting
state space models
Detrended fluctuation analysis
Distribution entropy
local mean forecasting
multiscale Sample Entropy
wavelet decomposition
correlations of top 40 features
0.5
0.6
0.7
0.8
0.9
1.0
Magnitude of correlation coefficient, |R|
B
Drosophila movement
female
male
day
night
day:
↑ stationarity
↓ extreme outliers
female:
↑ spectral flatness, ↓ autocorrelation structure,
↓ time intervals between extreme events
Standard deviation of differences
1.2
1
0.8
0.6
0.4
female day
female night
male day
male night
feature distributions
feature space embedding
male night
female night
male day
female day
Second Principal Component
40
0
-40
First Principal Component
40
0
40
80
SD

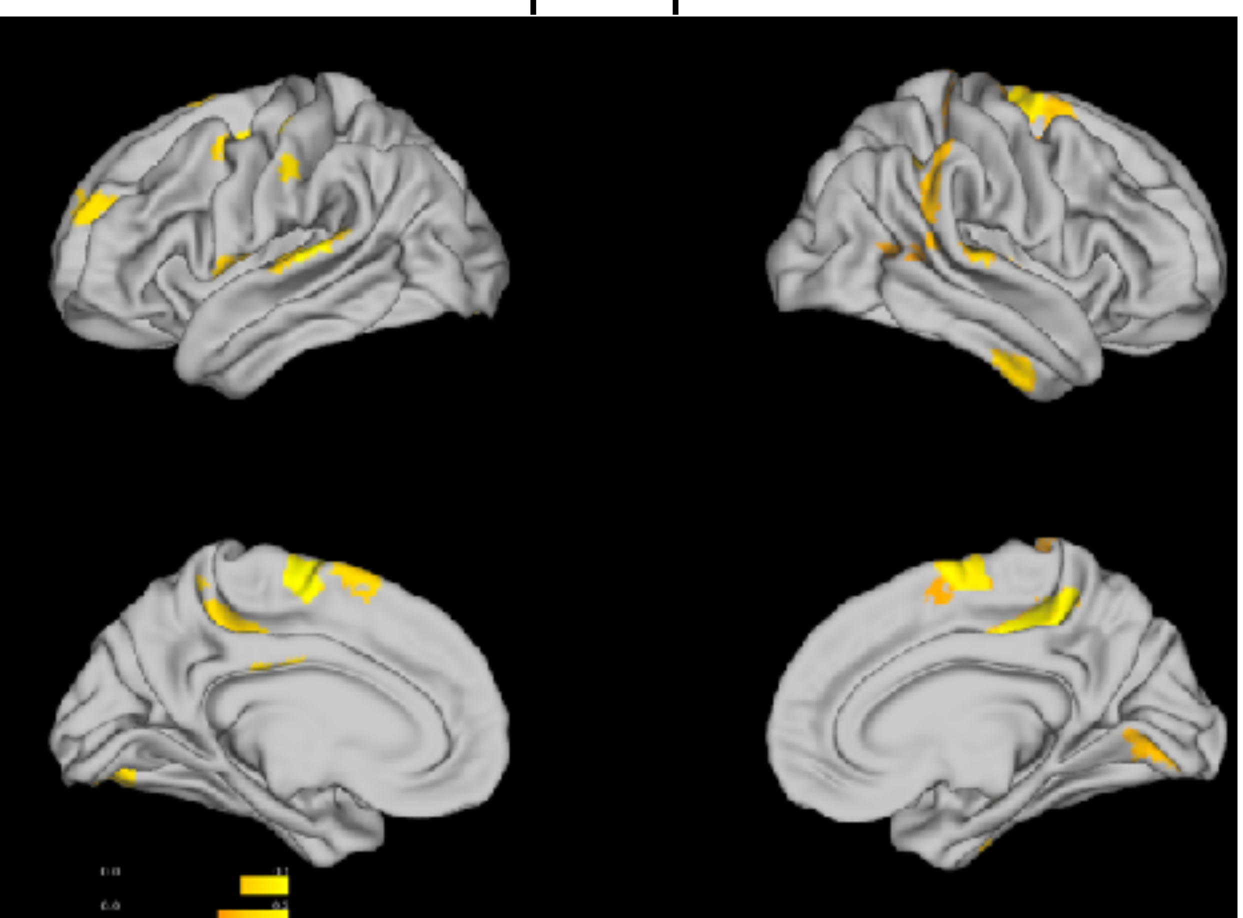
local autocorrelation



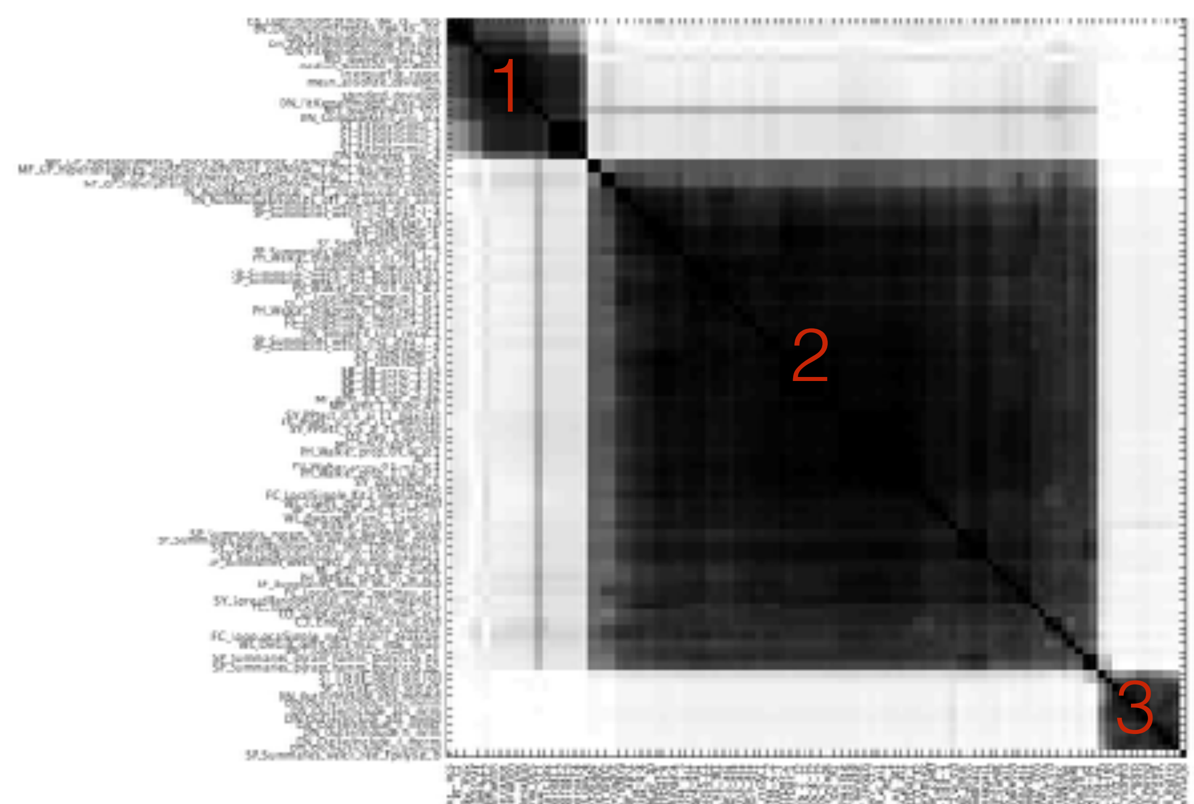
standard deviation

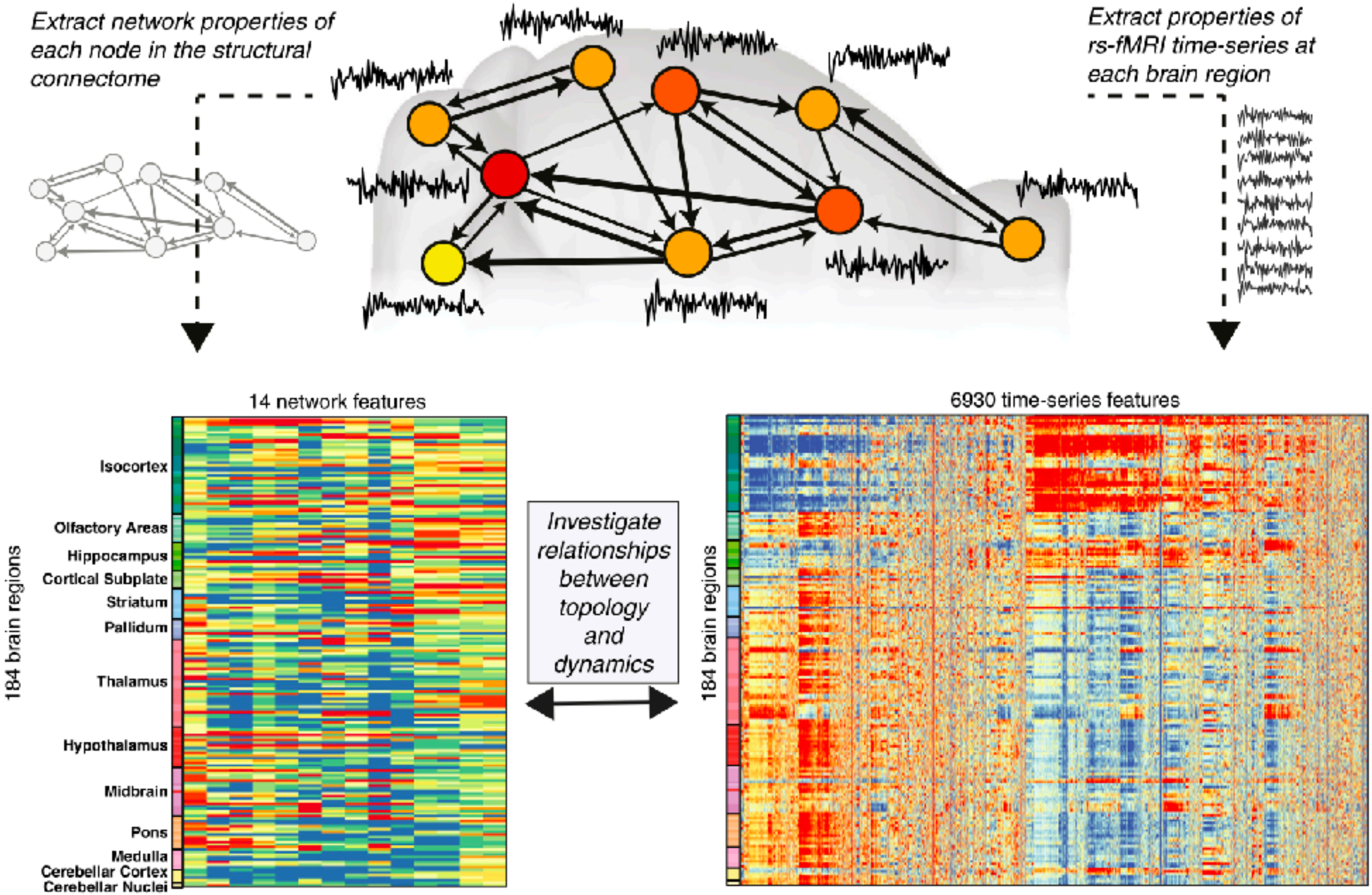


outlier properties

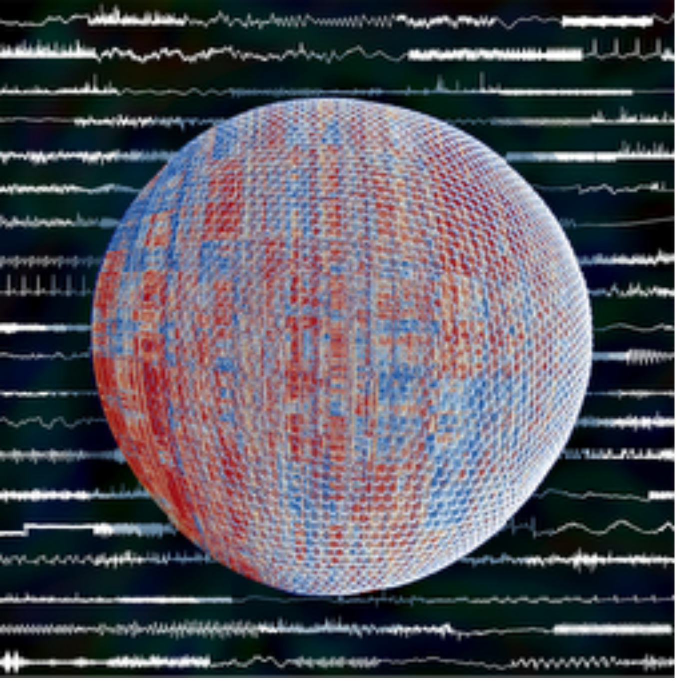


Useful properties come in three main types, with different spatial maps

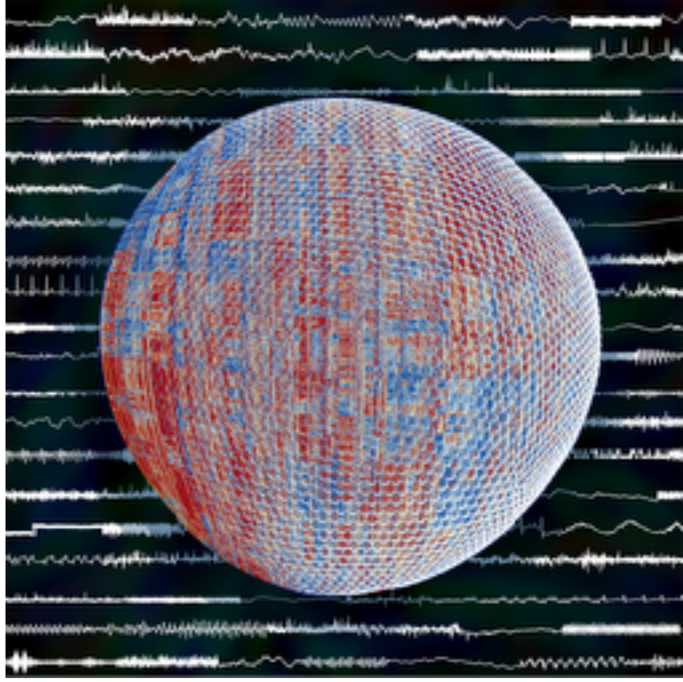




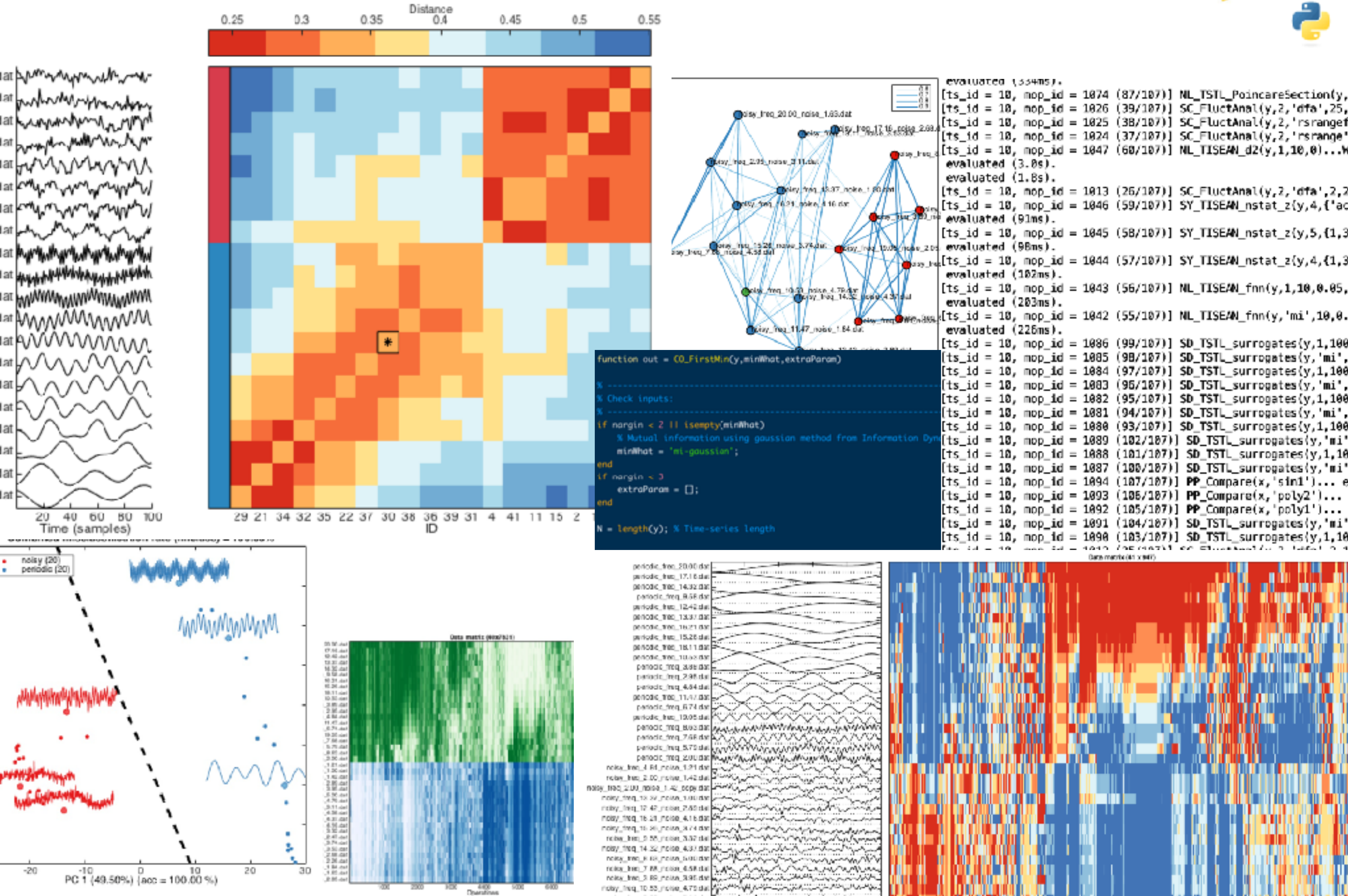
Extract network properties of each node in the structural connectome
Extract properties of rs-fMRI time-series at each brain region
14 network features
6930 time-series features
184 brain regions
Isocortex
Olfactory Areas
Hippocampus
Cortical Subplate
Striatum
Pallidum
Thalamus
Hypothalamus
Midbrain
Pons
Medulla
Cerebellar Cortex
Cerebellar Nuclei
Investigate relationships between topology and dynamics
184 brain regions



Summary



hctsa allows you to leverage a large interdisciplinary literature on time-series analysis automatically https://github.com/benfulcher/hctsa



benfulcher / hctsa

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Highly comparative time-series analysis code repository http://www.comp-engine.org/timeseries/ Edit

time-series | time-series-analysis | matlab | feature-extraction | Manage topics

747 commits | 8 branches | 8 releases | 6 contributors

Branch: master | New pull request | Create new file | Upload files | Find file | Clone or download

benfulcher Careless markdown error fixed — Latest commit e7a3312 11 days ago

Calculation	Inconsequential aesthetic changes	11 days ago
Database	Inconsequential aesthetic changes	11 days ago
Operations	Inconsequential aesthetic changes	11 days ago
PeripheryFunctions	Inconsequential aesthetic changes	11 days ago
PlottingAnalysis	Updated reference to published version of Cell Systems paper	19 days ago
TimeSeries	Bunch of minor updates, from clearing up aesthetic issues, improving ...	3 years ago
Toolboxes	Updated reference to published version of Cell Systems paper	19 days ago
.gitignore	Added some windows-specific mex files	a year ago
LICENSE.txt	Add actual text license file for CC-NC-SA license	3 months ago
README.md	Careless markdown error fixed	11 days ago
install.m	Updated reference to published version of Cell Systems paper	19 days ago
startup.m	Updated reference to published version of Cell Systems paper	19 days ago

README.md

hctsa, highly comparative time-series analysis

hctsa is a software package for running highly comparative time-series analysis using Matlab (full support for versions R2014b or later; for use in python cf. pyopy).

Highly Comparative Time-Series Analysis: Manual

Details of how to use the hctsa package for performing highly comparative time-series analysis using Matlab. — benfulcher

About this book

This manual outlines the steps required to set up and implement highly comparative time-series analysis using the hctsa package, as described in our papers:

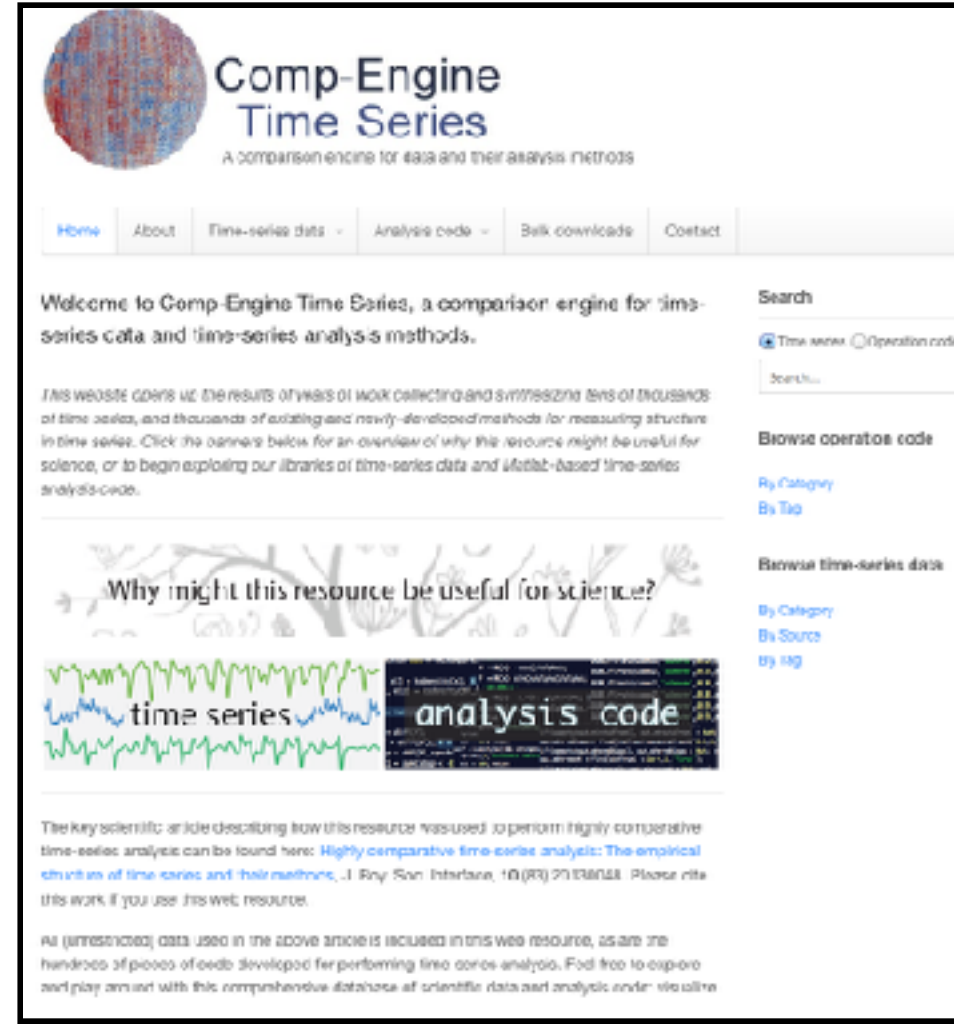
- B. D. Fulcher, M. A. Little and N. S. Jones. **Highly comparative time-series analysis: The empirical structure of time series and their methods**, J. Roy. Soc. Interface, **10**, 20130048 (2013)
- B. D. Fulcher and N. S. Jones. Highly comparative feature-based time-series classification, IEEE Transactions on Knowledge and Data Engineering, **26**, 3026 (2014).
- B. D. Fulcher, A. E. Georgieva, C. W. G. Redman and N. S. Jones. Highly comparative fetal heart rate analysis, 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 3135 (2012).

Updated 4 months ago

Comp-Engine Time Series

A comparison engine for data and its analysis methods

www.comp-engine.org/timeseries



- Web resource for interdisciplinary scientific collaboration on time-series analysis
- Explore relationships between ~30,000 time series and thousands of features

Comp-Engine Time Series

A comparison engine for data and its analysis methods

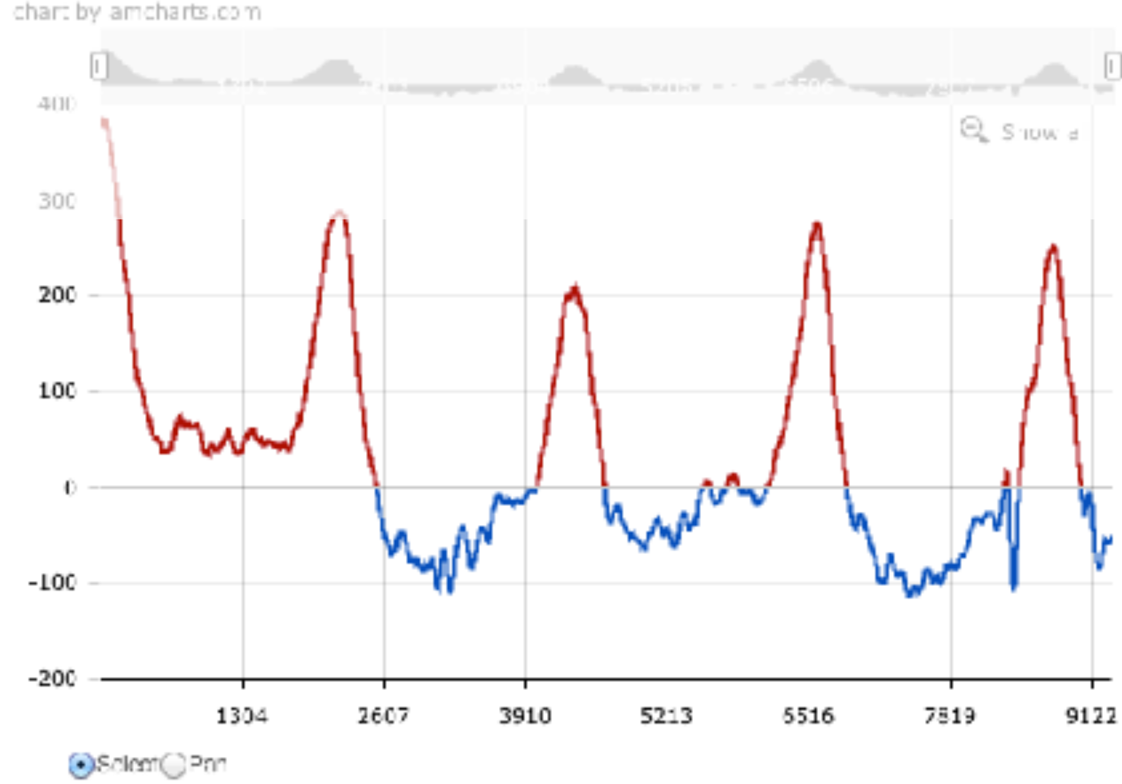
Time Data Source Archives: Physionet: MGHDB (1089 items)

The Massachusetts General Hospital/Marquette Foundation (MGH/MF) Waveform Database is a com
collection of electronic recordings of hemodynamic and electrocardiographic waveforms of patients
units. It is the result of a collaboration between physicians, biomedical engineers and nurses at the M
General Hospital. The database consists of recordings from 250 patients and represents a broad sp
physiologic and pathophysiologic states.
Individual recordings vary in length from 12 to 86 minutes, and in most cases are about an hour lon
The typical recording includes three ECG leads, arterial pressure, pulmonary arterial pressure, centra

MD_mghdb_mgh79_RespImp_SNIP_9145-18444

Share:

Data file: MD_mghdb_mgh79_RespImp_SNIP_9145-18444.dat
Length: 9300



Tags:

medical, mghdb, physionet, respiratory impedance, snip

Categories:

Real-world

Time series measured from real-world systems

Medical

Source:

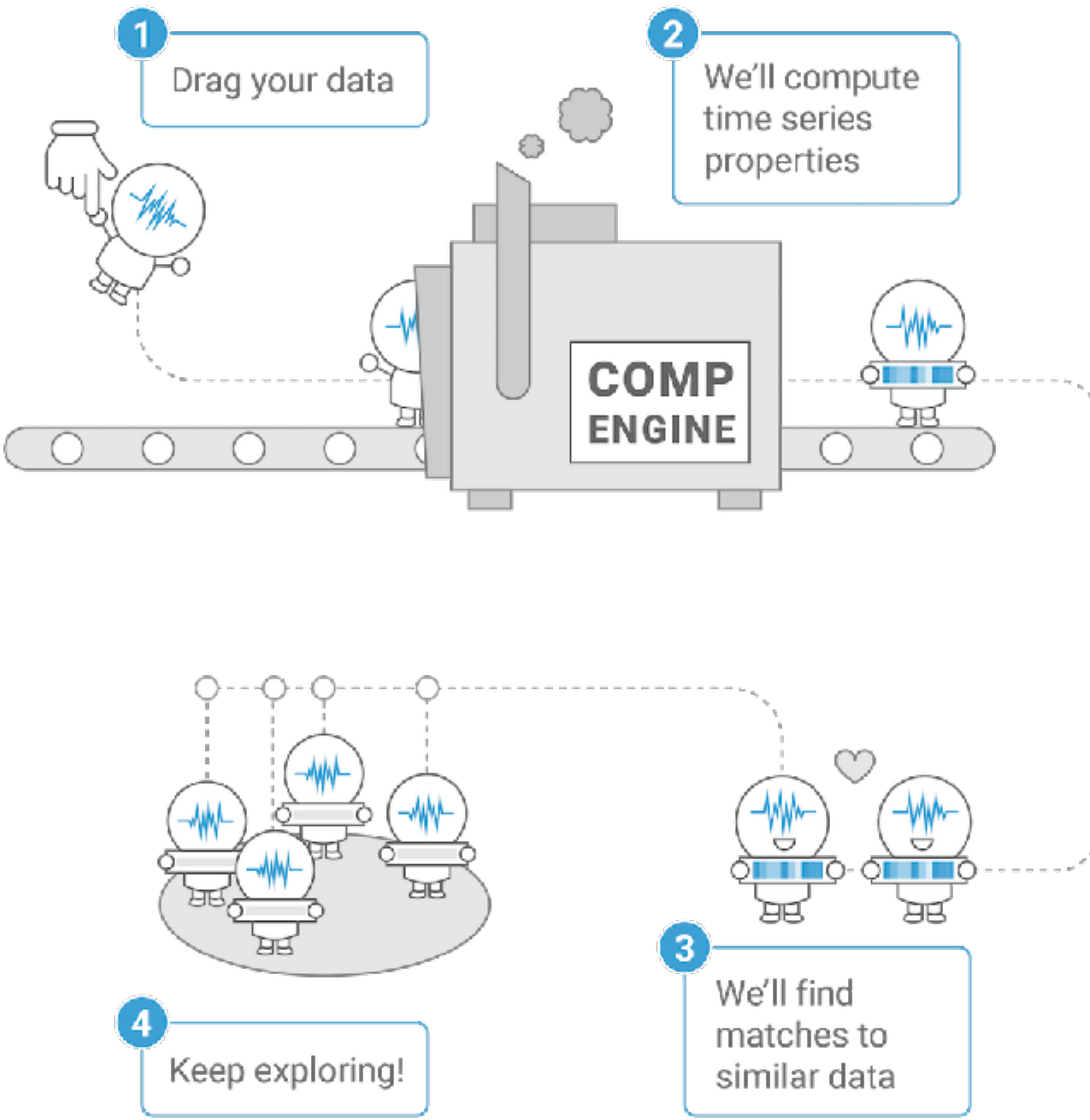
Data by Category

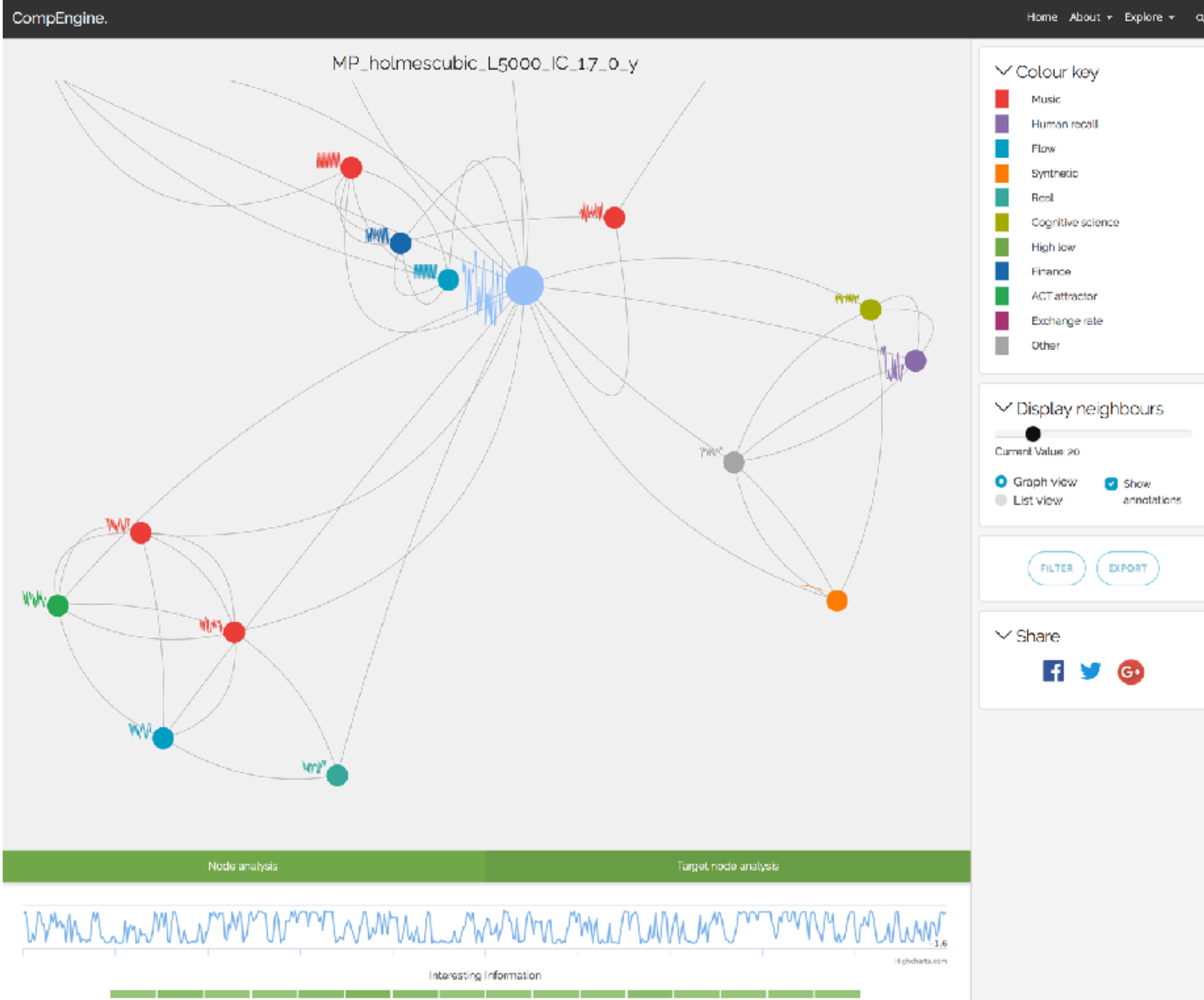
Air pressure Air temperature Animal sounds Astrophysics Audio Autoregressive with noise Beta noise Birdsong Correlated Noise Damped driven pendulum Driven pendulum with dissipation ECG Finance Flow Frietas Stochastic Sine Map Gait High low Like VIX(P) Logistic map Map Medical Meteorology Model M1a Model M5a Model M10a Moving average process Music Nonstationary autoregressive Opening prices Postural sway Powerlaw noise Precipitation rate Real-world Relative humidity Rossler attractor RR SDE models Sound effects Sprott 3D Flows Stochastic processes Synthetic Text Traded volume Uncategorised White noise

Data by Source

Air Temperature, NCEP/NCAR, CRU Ben Fulcher Simulated Ben generated powernoise Ben iTunes Ben making mpnoise Ben MA simulations Ben music downsampled Ben Random coefficient AR simulations Ben simulate like MIX(P) Beta noise Matlab Climatic Research Unit, University of East Anglia Driven pendulum Ben Financial log returns Ben Frietas Stochastic Sine Map Ben Google trends Logistic Map A sweep Ben Macaulay Library NCEP/NCAR, CRU Physionet Physionet: CHFDB Physionet: MGHDB Physionet: NESFDB Physionet: NSRDB Physionet RR CHF NSR Precipitation rate, NCEP/NCAR, CRU Project Gutenberg Relative humidity, NCEP/NCAR, CRU SDE Toolbox M1a SDE Toolbox M5a SDE Toolbox M10a SDE Toolbox Simulated Sea level pressure, NCEP/NCAR, CRU Sound Jay SPIDR SPIDR Geomagnetic annual means – Ionosphere Sprott Conservative Flows Sprott Conservative Maps Ben Sprott Damped driven pendulum Ben Sprott Dissipative Maps Ben Sprott Noninvertible Maps Ben Text processing Ben Time-Series Data Library Timmer nonstationary autoregressive processes Yahoo Finance Yahoo Finance Shares

New interactive compEngine website is coming early 2018!




CompEngine.
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MP_holmescubic_L5000_IC_17_0_y
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Music
Human recall
Flow
Synthetic
Real
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High low
Finance
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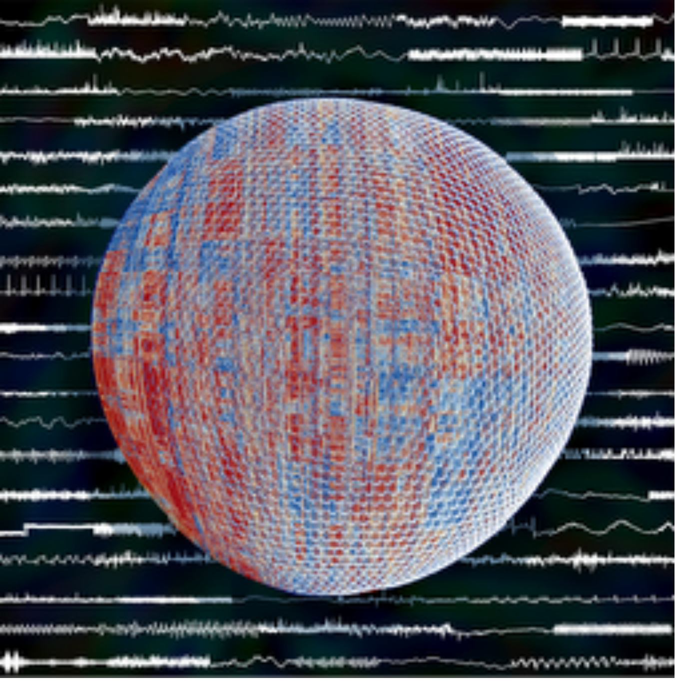
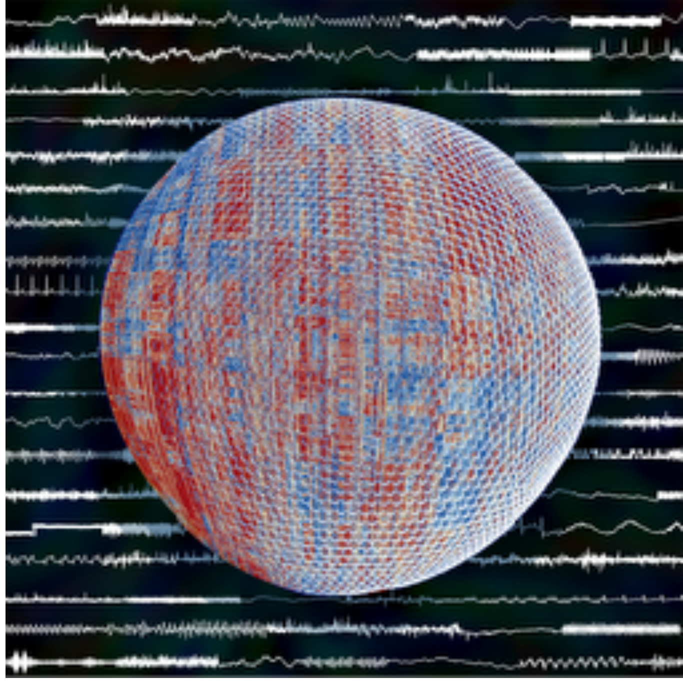
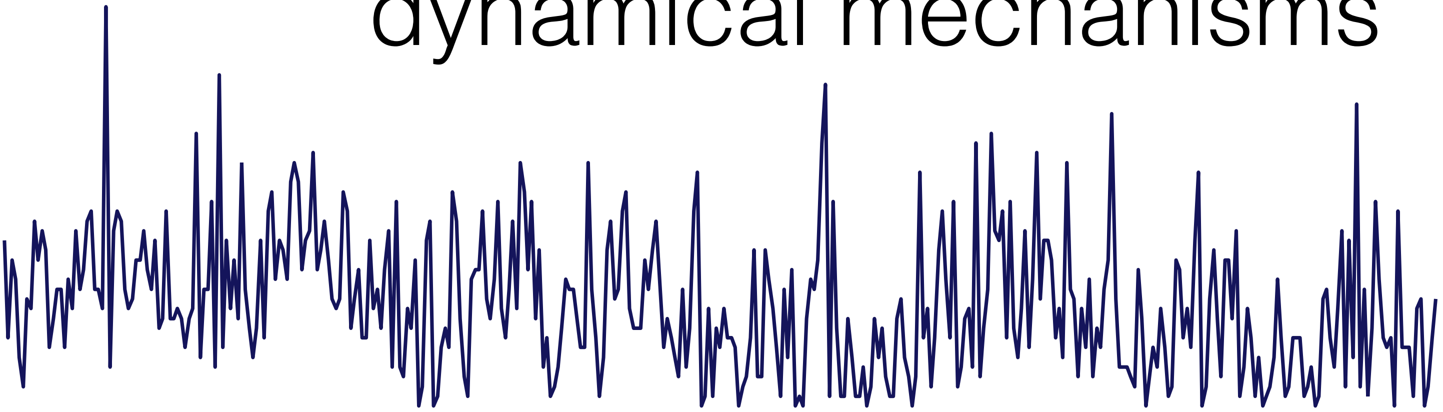
Share
Node analysis
Target node analysis
Interesting Information

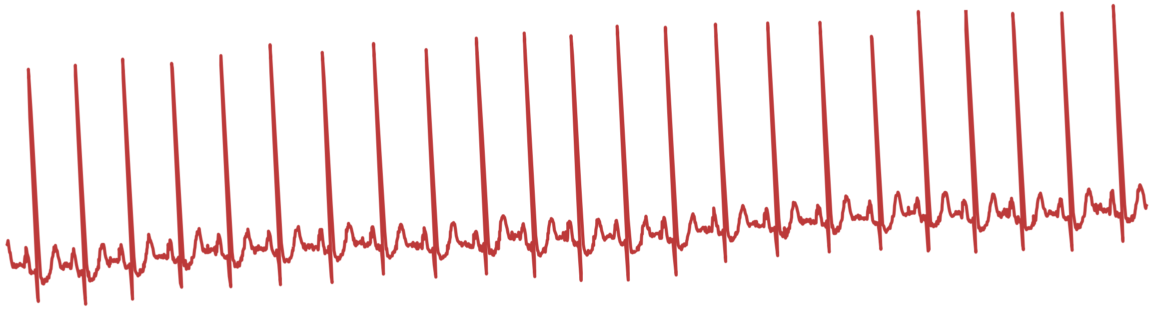


Conclusions



- An automated approach to time-series analysis that compares thousands of interdisciplinary methods
- Can be viewed as a starting point to guide more focused time-series analysis
- Results provide insights into underlying dynamical mechanisms





ACKNOWLEDGEMENTS

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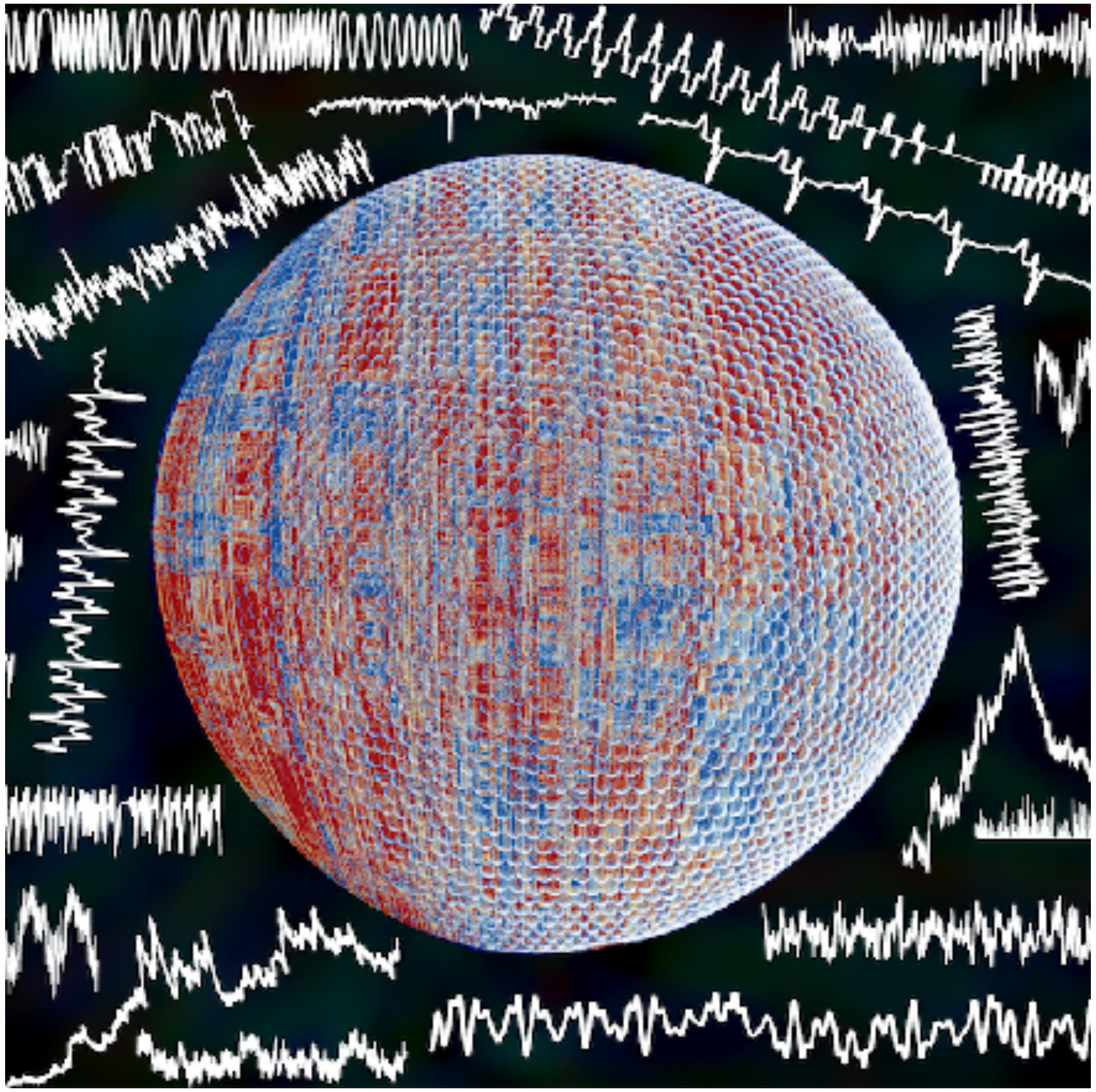
www.comp-engine.org/timeseries



Nick Jones

Imperial College London

Key references:

- Fulcher, B. D. (2017) Feature-based time-series analysis, *arXiv* 1709.08055.
- Fulcher, B. D., & Jones, N. S. (2017). *hctsa*: A Computational Framework for Automated Time-Series Phenotyping Using Massive Feature Extraction. *Cell Systems*, **5**, 527–531.
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- Fulcher, B. D., Georgieva, A. E., Redman, C. W. G. & Jones, N. S. (2012) Highly comparative fetal heart rate analysis. *2012 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* 3135.