Complexity Science:

It's about time!

Fred Hasselman
Radboud University
School of Pedagogical and Educational Sciences
Behavioural Science Institute

Email: f.hasselman@pwo.ru.nl
Twitter: @FredHasselman
https://www.ru.nl/bsi/research/group-pages/complex-systems-group/

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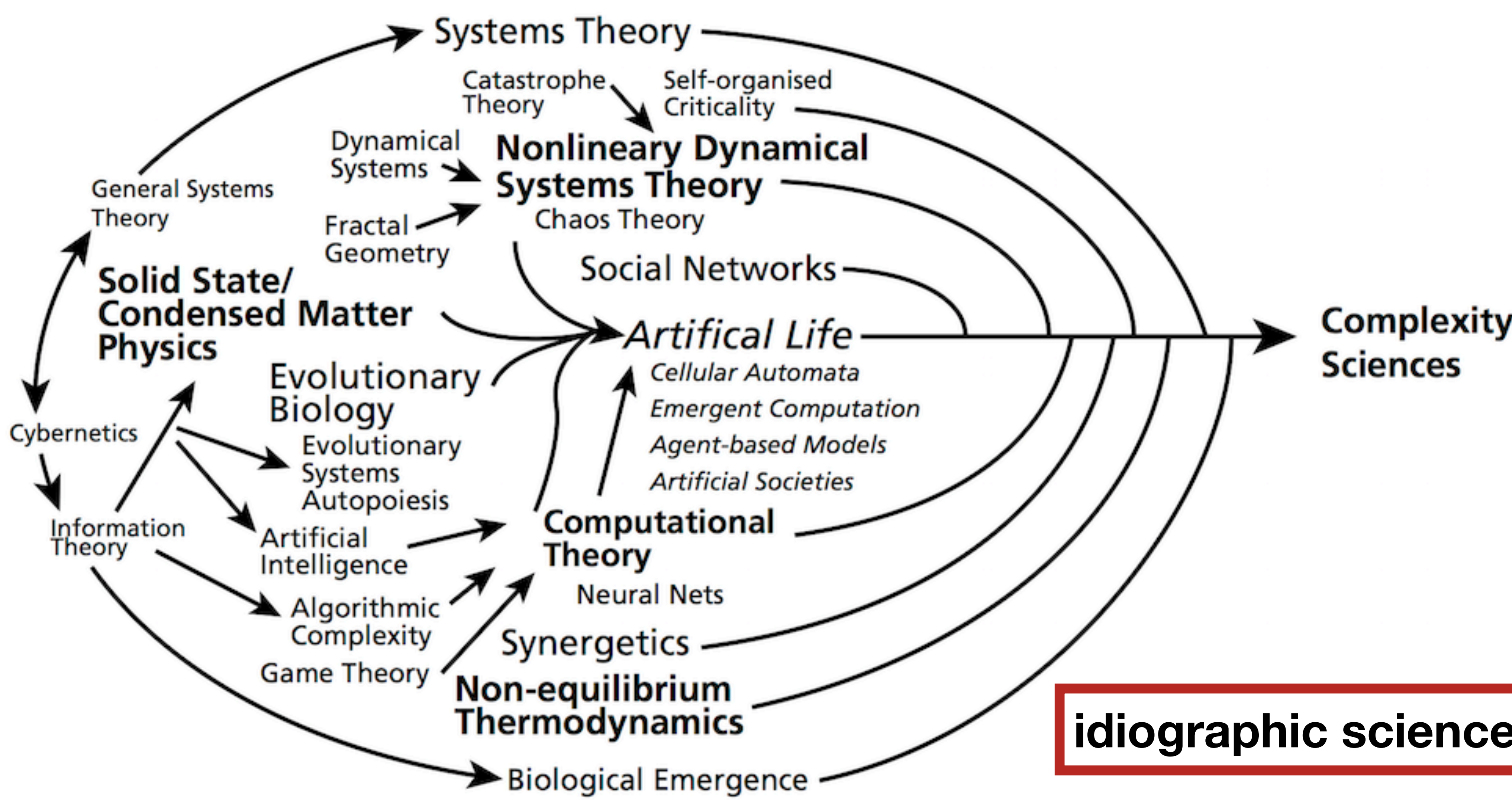
What is Complexity Science?
[and why should scientist studying human nature embrace it?]

The scientific study of complex dynamical systems and networks



The many foundations of complexity science.

idiographic science!

Our goal is to develop methods for personalised diagnosis and intervention that can actually be used in practice

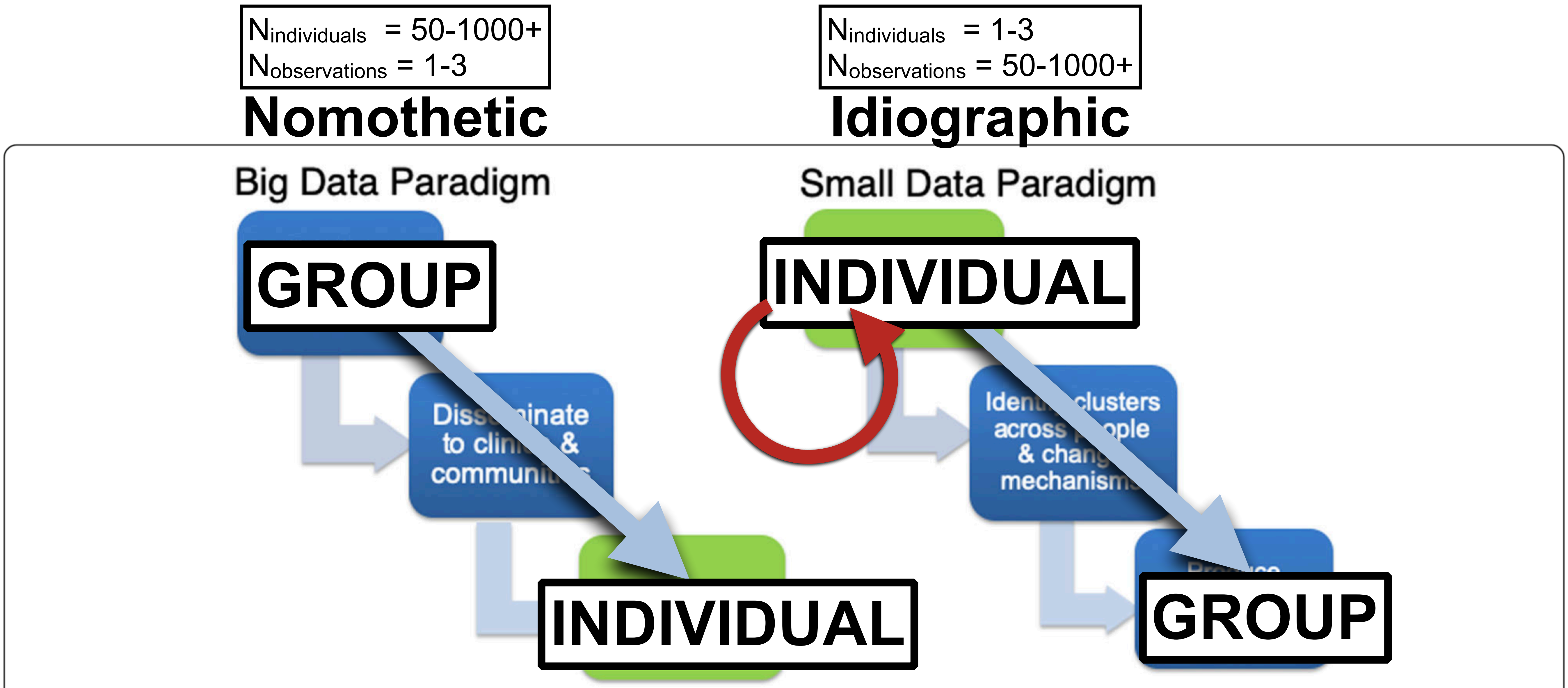


Fig. 1 Small versus big data paradigm pathways to help individuals and transportable knowledge

Hekler, E. B., Klasnja, P., Chevance, G., Golaszewski, N. M., Lewis, D., & Sim, I. (2019). Why we need a small data paradigm. *BMC Med, 17*(1), 133. doi:10.1186/s12916-019-1366-x

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Critical Fluctuations as an Early-Warning Signal for Sudden Gains and Losses in Patients Receiving Psychotherapy for Mood Disorders

Merlijn Olthof, Fred Hasselman, Guido Strunk, Marieke van Rooij, Benjamin Aas, Marieke A. Helmich, Günter Schiepek, Anna Lichtwarck-Aschoff

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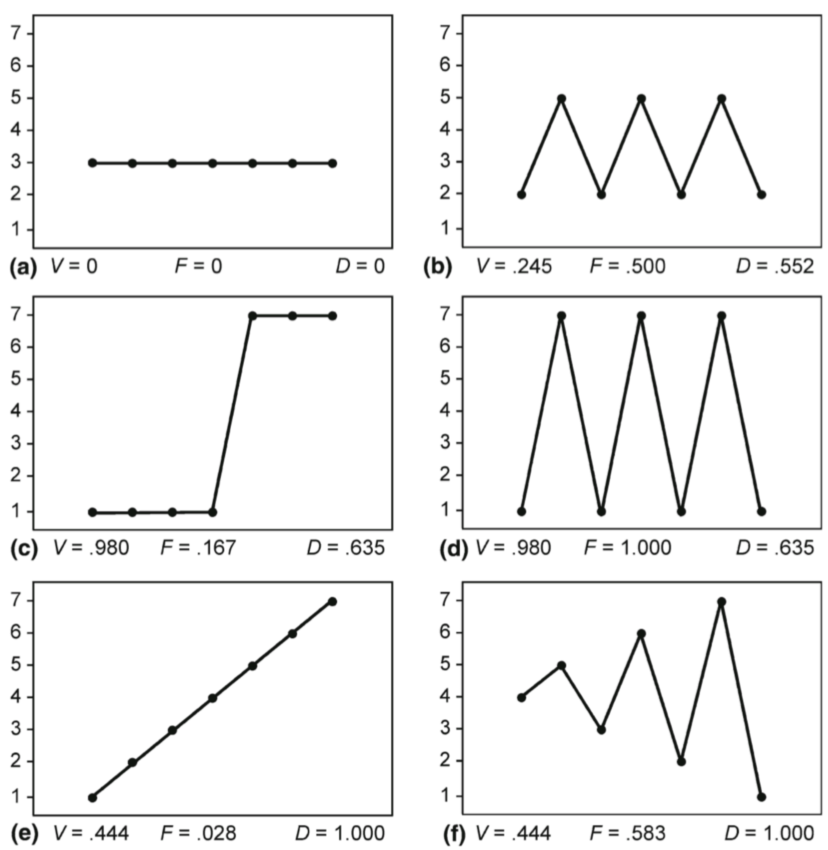
Article information

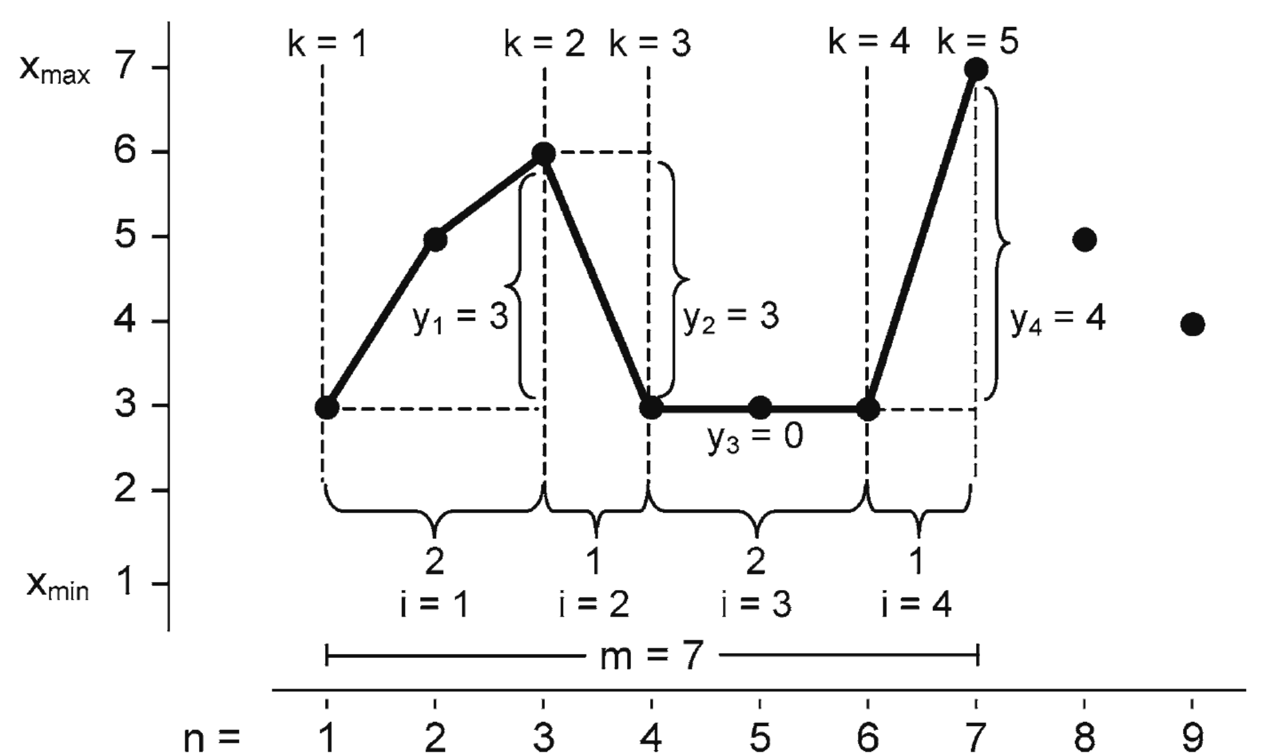
Altmetric 12

Biol Cybern (2010) 102:197–207 201

Fig. 2 Variance score (V), degree of fluctuation (F), and degree of distribution (D) of 6 dummy sequences. The ordinate corresponds to a 7-point Likert scale. The variance score V is the ratio between the variance and the greatest possible variance in this case (s^2 = 10.29), and thus normalized between [0, 1], as are F and D. **a** In the case of a horizontal line all three scores have the same result: 0. **b** Periodic alternation: F and D are more sensitive than V. **c** The system jumps from one stable state to the other, but without fluctuations. Therefore, F remains small. **d** The sequence realizes the same values as in **c**, but now by manifesting strong fluctuations. F is sensitive to this, V and D do not differ from **c**. **e** and **f** have the same variance, whereas the differences in the shape of the time series are evident. The fluctuation is more accentuated in **f** than in **e**

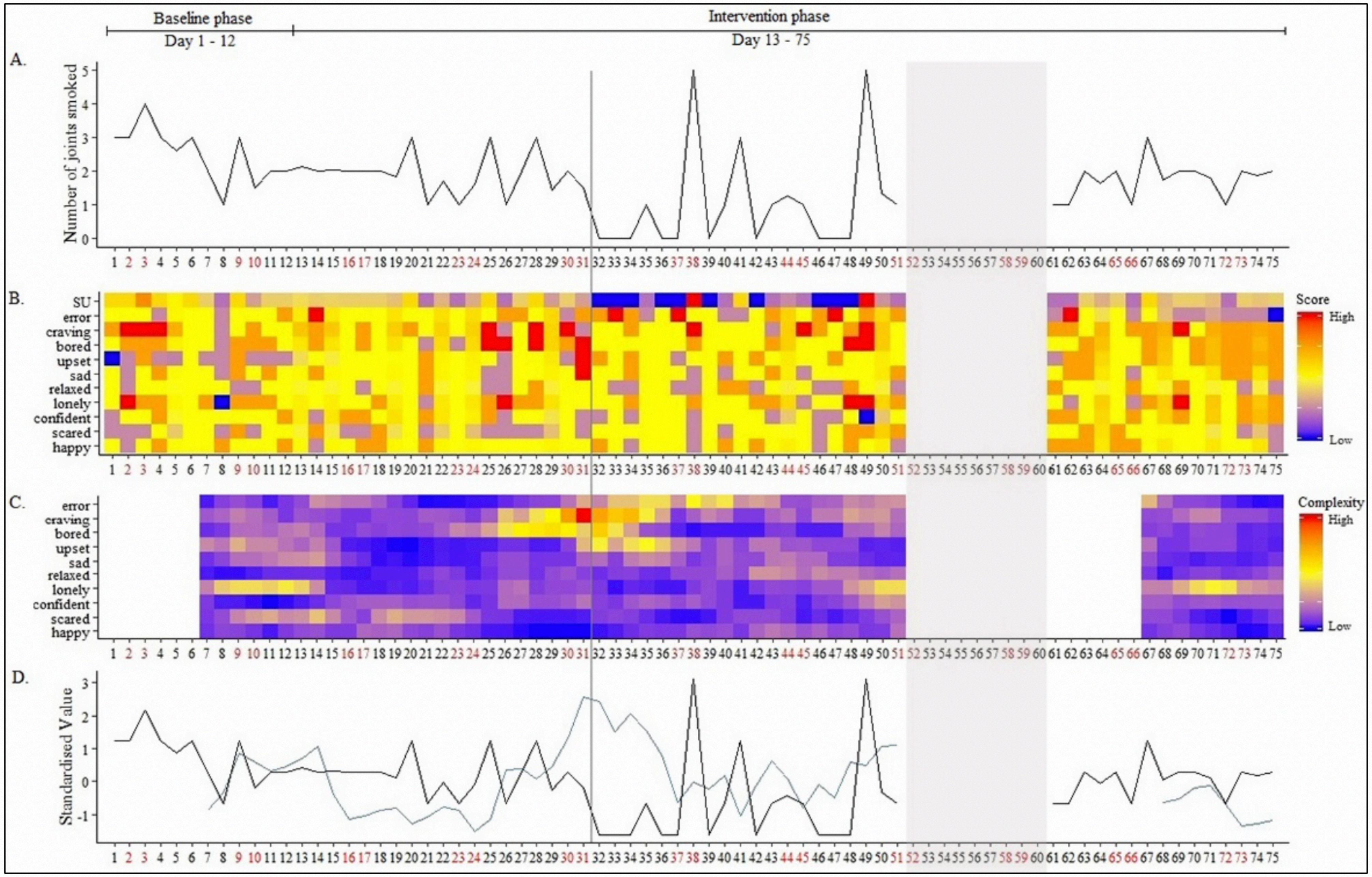


Biol Cybern (2010) 102:197–207



Our goal is to develop methods for personalised diagnosis and intervention that can actually be used in practice

SUBSTANCE USE IN INTELLECTUAL DISABILITY 30



Our goal is to develop methods for personalised diagnosis and intervention that can actually be used in practice

I Stress and Coping (state-cluster "child", EP, corresponds to factor I of the individual questionnaire)

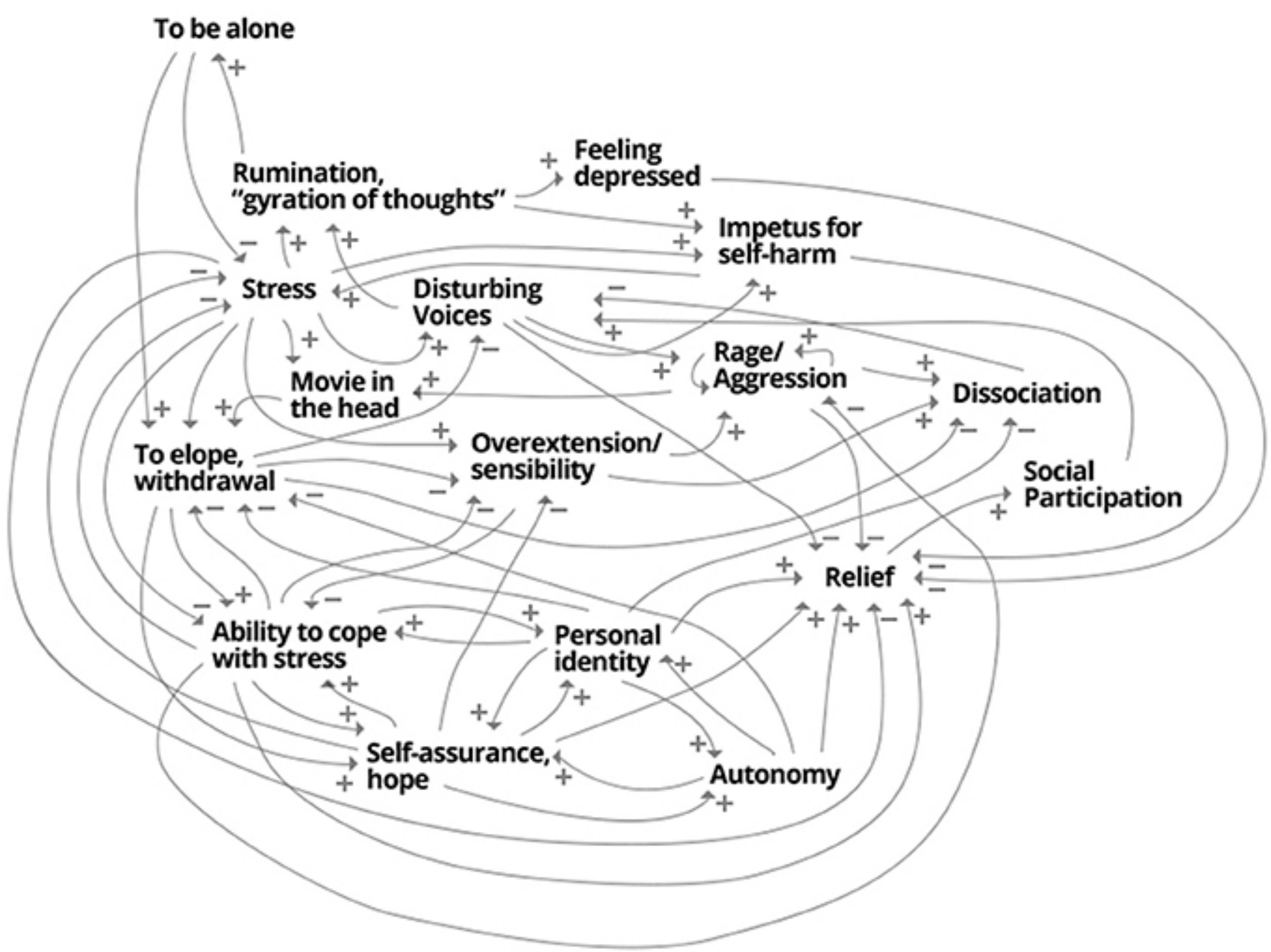
1. Today, I experienced stress …
2. Today, I had to activate my "head-cinema" ("movie in the head") …
3. Today, I zoomed out - dissociated …
4. Today, it was important to me to be alone …
5. Today, the depression carried me away …
6. The impulse to hurt myself was today …
7. Today, I ruminated …
8. The intrusive voices were today …
9. My level of aggression was today …
10. My level of anger was today …
11. Today, I felt overwhelmed …
12. My need for distancing myself from others was today …

II Positive goals and development of identity (state-cluster "adult", ANP, corresponds to factor II of the individual questionnaire)

13. Today, I felt resilient and able to cope with stress …
14. My feelings of inner security were today …
15. My feelings of independence were today …
16. The sense of my own inner identity was today …
17. Today I had a sense of relief …
18. Today, I took part in social life …

*Match the 18 variables of her ISM, as shown in **Figure 1**, separated into two factors. The client answered these items daily via the online monitoring system SNS. Each question is scored by a visual analog slider (VAS), ranging from 0 to 100 and extrema of "not at all" to "very much" (where applicable).*

Idiographic system modeling



Schiepek, G. K., Stöger-Schmidinger, B., Aichhorn, W., Schöller, H., & Aas, B. (2016). Systemic case formulation, individualized process monitoring, and state dynamics in a case of dissociative identity disorder. *Frontiers in Psychology*, *7*, 1545. https://www.frontiersin.org/articles/10.3389/fpsyg.2016.01545/full

What is Complexity Science?
[and why should scientist studying human nature embrace it?]

- **Fundamental problems for main-stream Social & Life Sciences:**
  - ➡ Mismatch between research methods and object of measurement
  - ➡ Not interdisciplinary (theoretical, empirical, formal, …)

- **Complex behaviour from (physical) principles & laws (bottom-up):**
  - ➡ Ecological Psychology / Ecological Physics / Natural Computation

- **Complex behaviour from (physical) principles & laws (top-down):**
  - ➡ Complex Systems Approach to Behavioural Science
  - ➡ Personalised diagnosis and intervention

What is Complexity Science?

[and why should scientist studying human nature embrace it?]

First
some
basic
(abstract)
concepts

What is a

complex, adaptive, self-organizing, multi-stable, far-from-equilibrium, dissipative, etc.

system?

A system is an entity that can be described as a composition of components, according to one or more organising principles.

The organising principles can take many different forms, but essentially they decide the three important features of systems that have to do with the relationship between **parts** and **wholes**:

1. What are the **relevant scales of observation** of the system?

2. What are the **relevant phenomena** that may be observed at the different scales?

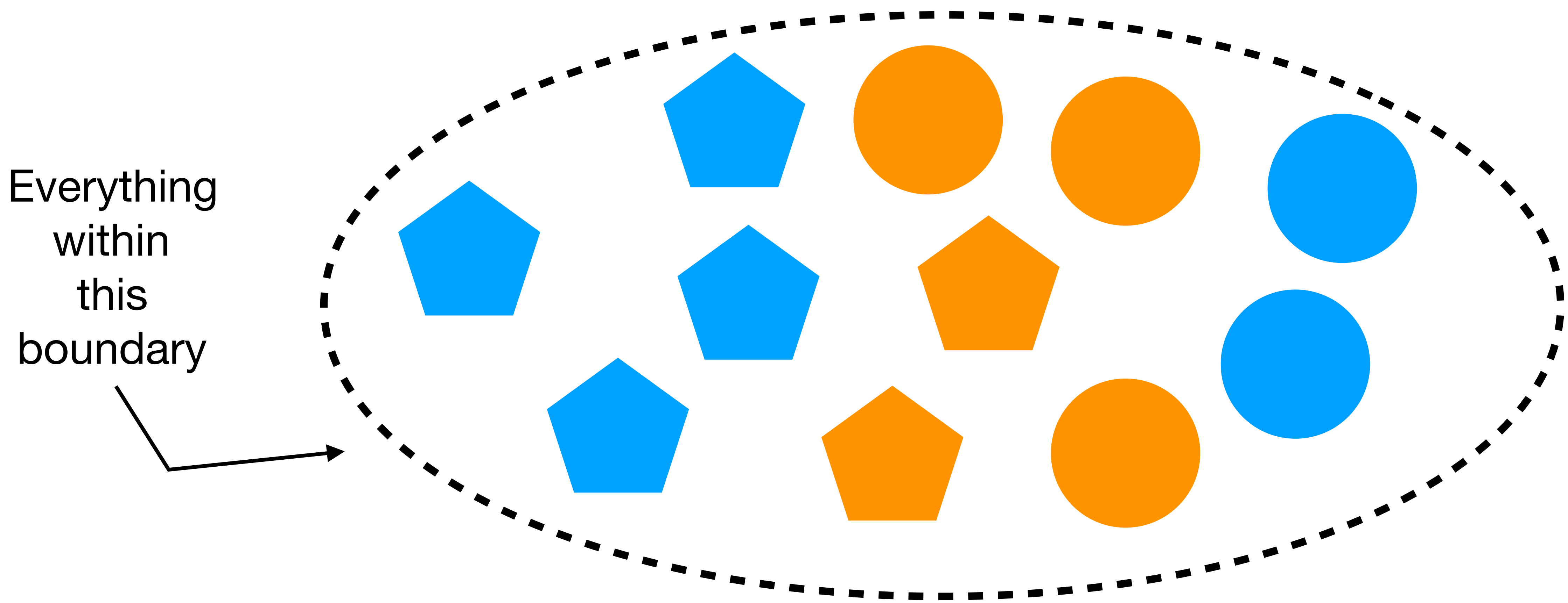
3. Can **interactions** with the internal and external environment occur, and if so, do interactions have any effects on the structure and/or behaviour of the system?

What is a

complex, adaptive, self-organizing, multi-stable, far-from-equilibrium, dissipative, etc.

system?

A system is an entity that can be described as a composition of components, according to one or more organising principles.



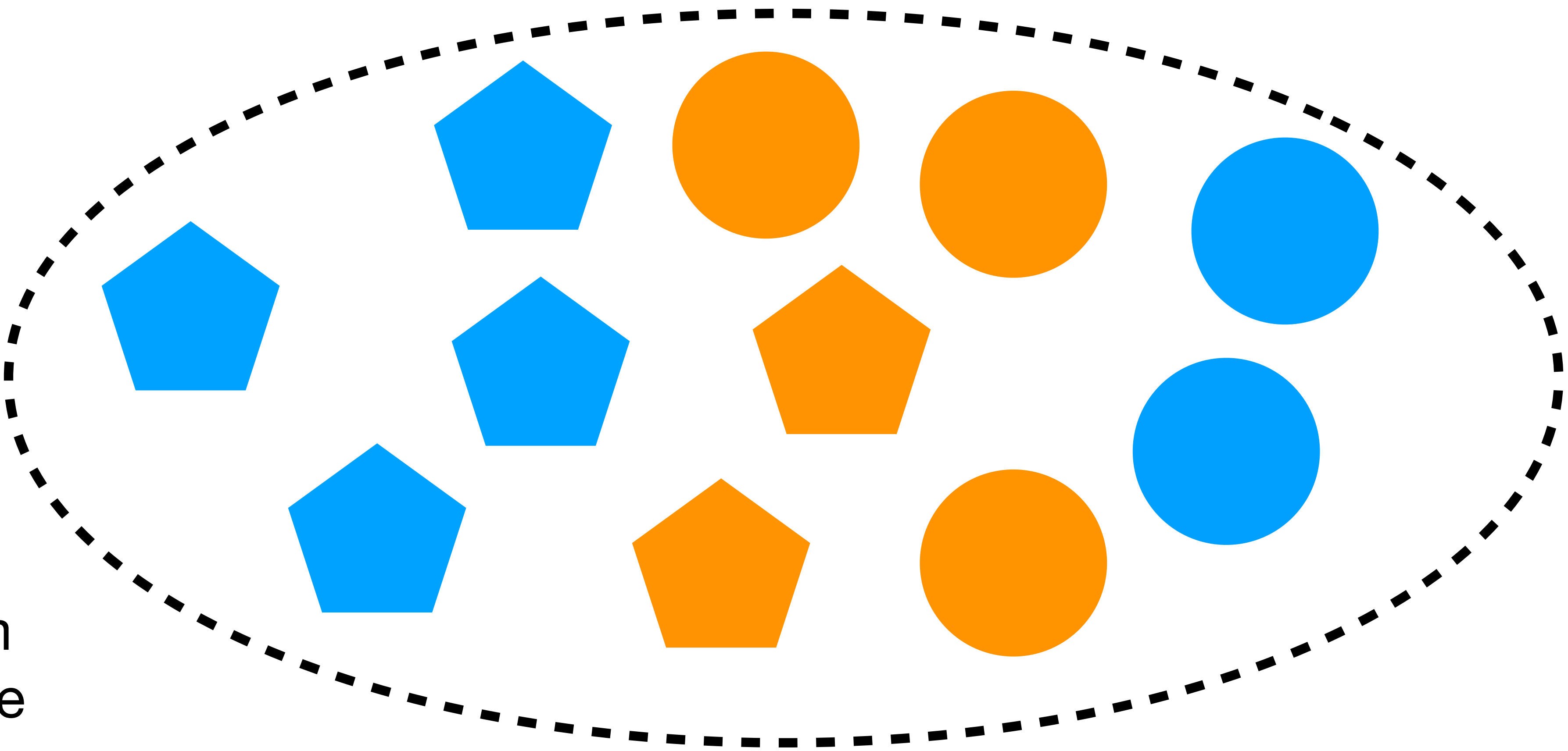
What is a

complex, adaptive, self-organizing, multi-stable, far-from-equilibrium, dissipative, etc.

system?

Degrees of freedom:

The constituent parts of a system whose state configuration at some micro scale, is associated with the behaviour of the system *as a **whole**,* the global, or, macro state.



Degrees of freedom available to generate behaviour as a whole

What is a

complex, adaptive, self-organizing, multi-stable, far-from-equilibrium, dissipative, etc.

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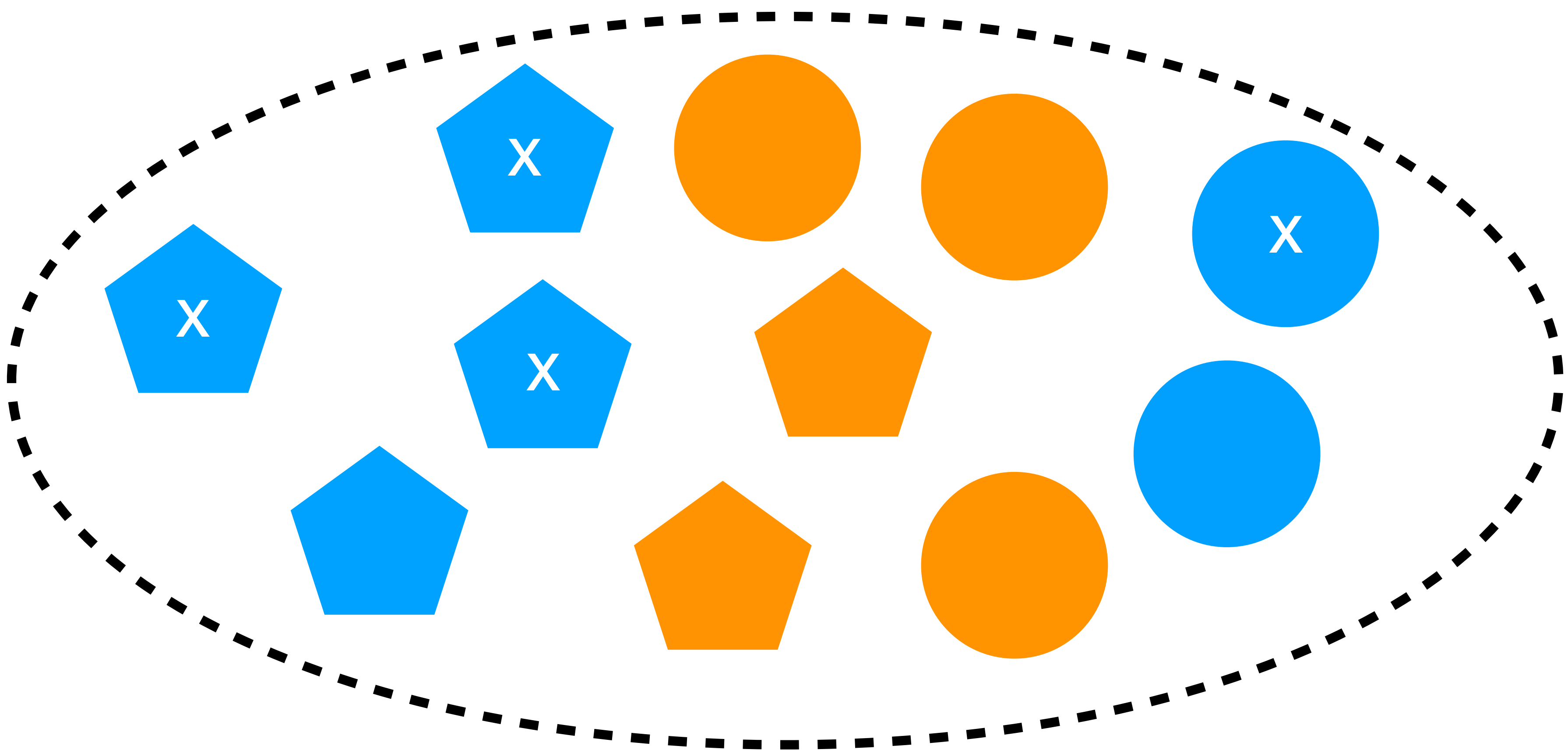
Global state:
Blue

Degrees of freedom can be fixed or free



X = DoF recruited to generate the global state

What is a

complex, adaptive, self-organizing, multi-stable, far-from-equilibrium, dissipative, etc.

system?

“What is order? Order was usually considered as a wonderful building, a loss of uncertainty. Typically it means that if a system is so constructed that **if you know** the location or **the property of one element, you can make conclusions about the other elements. So order is essentially the arrival of redundancy in a system, a reduction of possibilities.**”

- von Foerster (2001)

Global state:
Blue

Degrees of freedom
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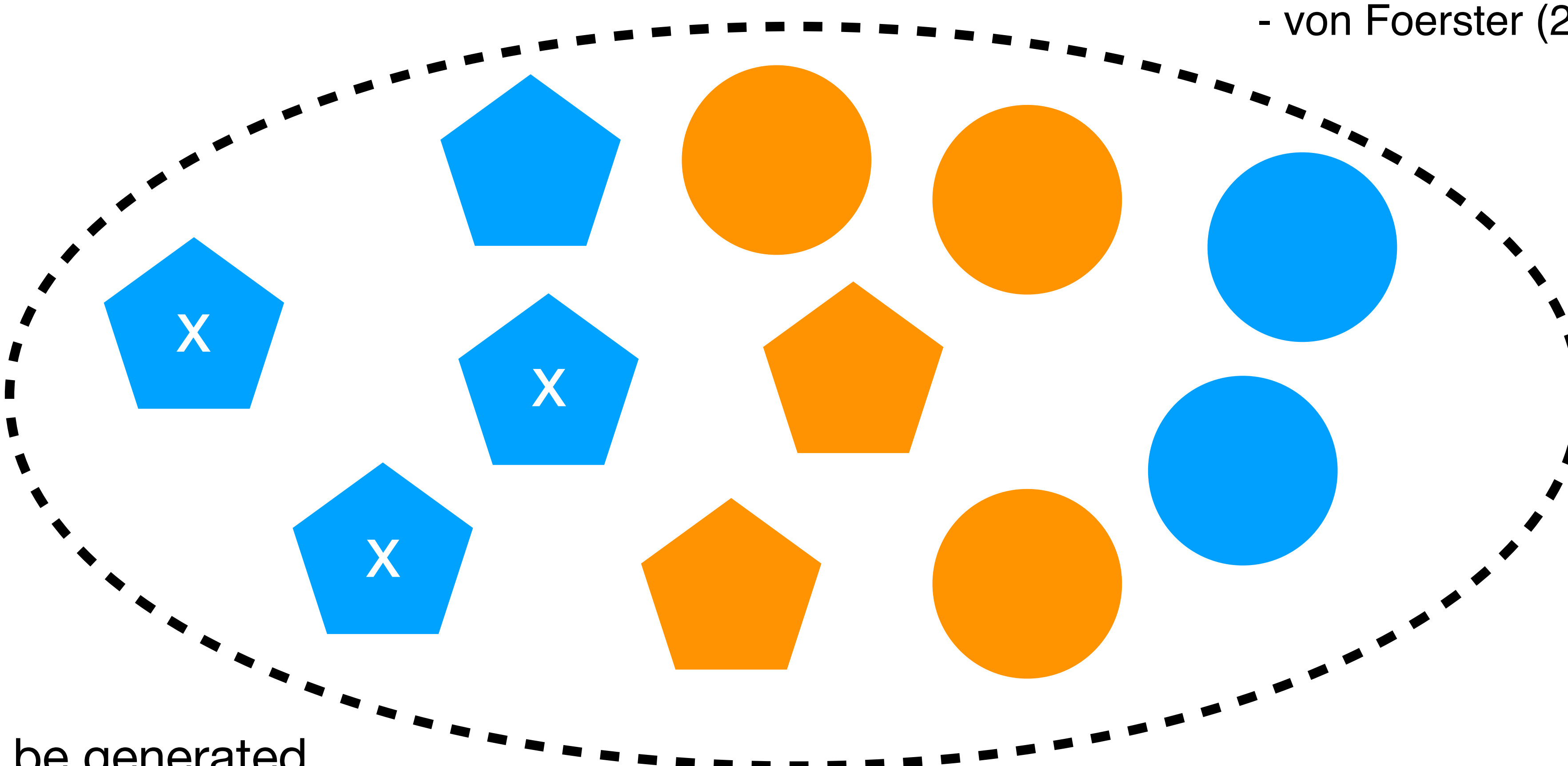

In systems with many DoF
The same global state can be generated
by many different configurations at the micro-scale:
Uncertainty, disorder, entropy

X = DoF recruited to generate the global state

What is a

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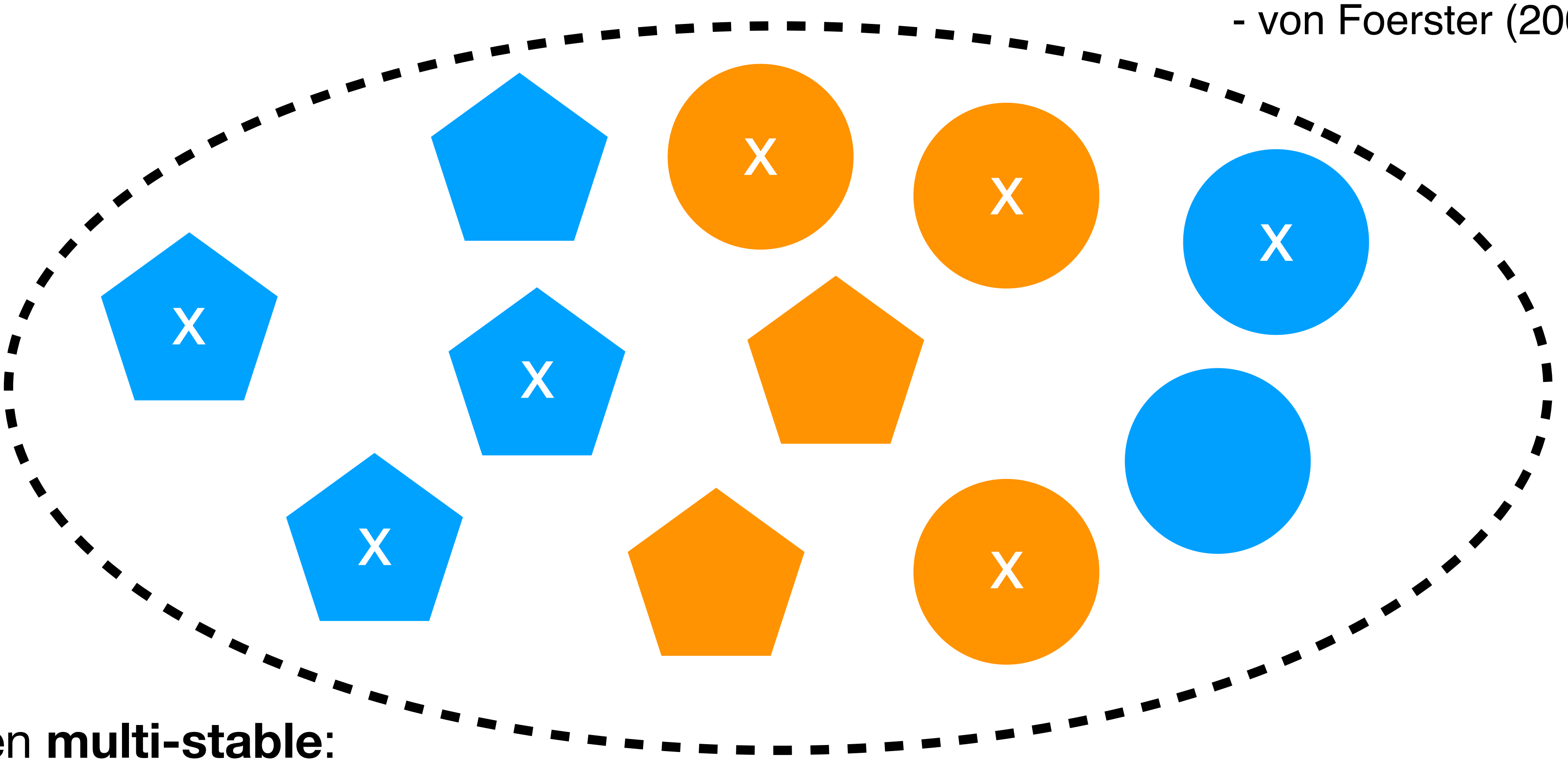
"What is order? Order was usually considered as a wonderful building, a loss of uncertainty. Typically it means that if a system is so constructed that **if you know** the location or **the property of one element, you can make conclusions about the other elements. So order is essentially the arrival of redundancy in a system, a reduction of possibilities.**"

- von Foerster (2001)

Global states:
Blue | **Round**

Degrees of freedom can be fixed or free



Complex systems are often **multi-stable**:
Different macro states can co-exist, or,
a system can quickly switch between states

X = DoF recruited to generate the global state

What is a

complex, adaptive, self-organizing, multi-stable, far-from-equilibrium, dissipative, etc.

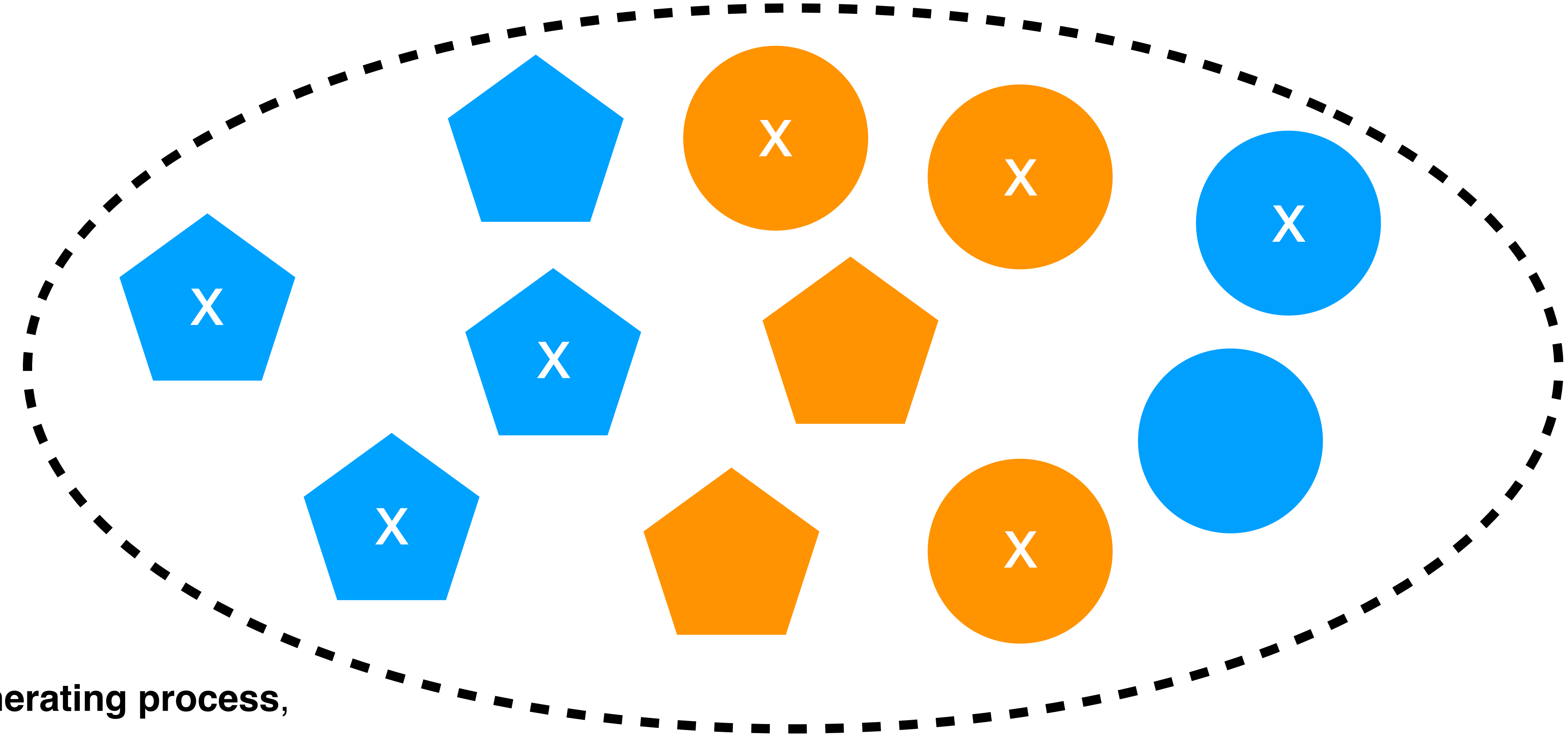
system?

The process of fixing and freeing-up degrees of freedom in is called **self-organisation**:

- In general, the **stability** or **resilience** of a macro state is associated with a reduction, or, constraining of the available DoF
- **Self-Organised Criticality** (SOC) refers a particular state/property that allows easy transition between several different modes of behaviour / dynamic regimes / orders of the system (Complex Adaptive Systems)

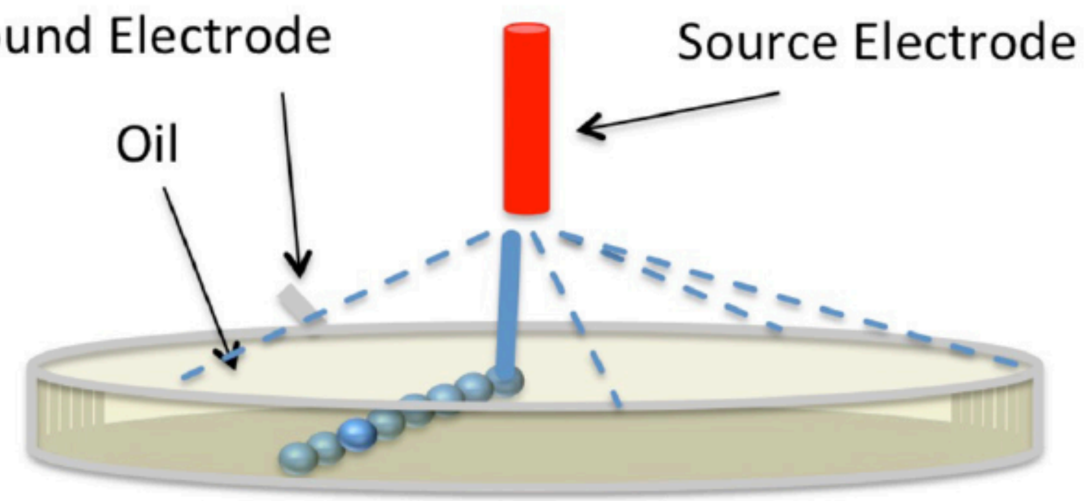
Global states:
Blue | **Round**

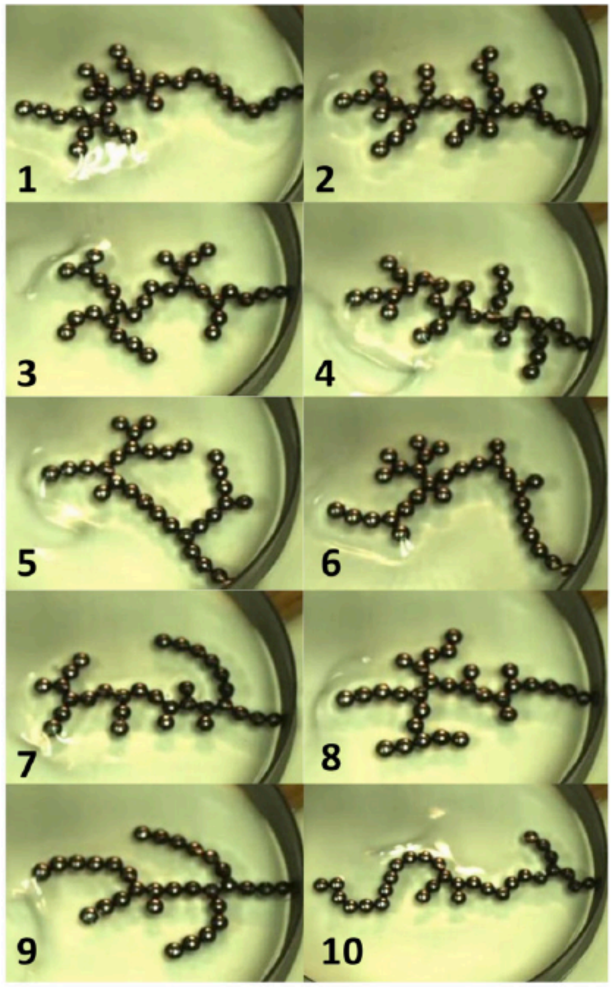
Degrees of freedom can be fixed or free

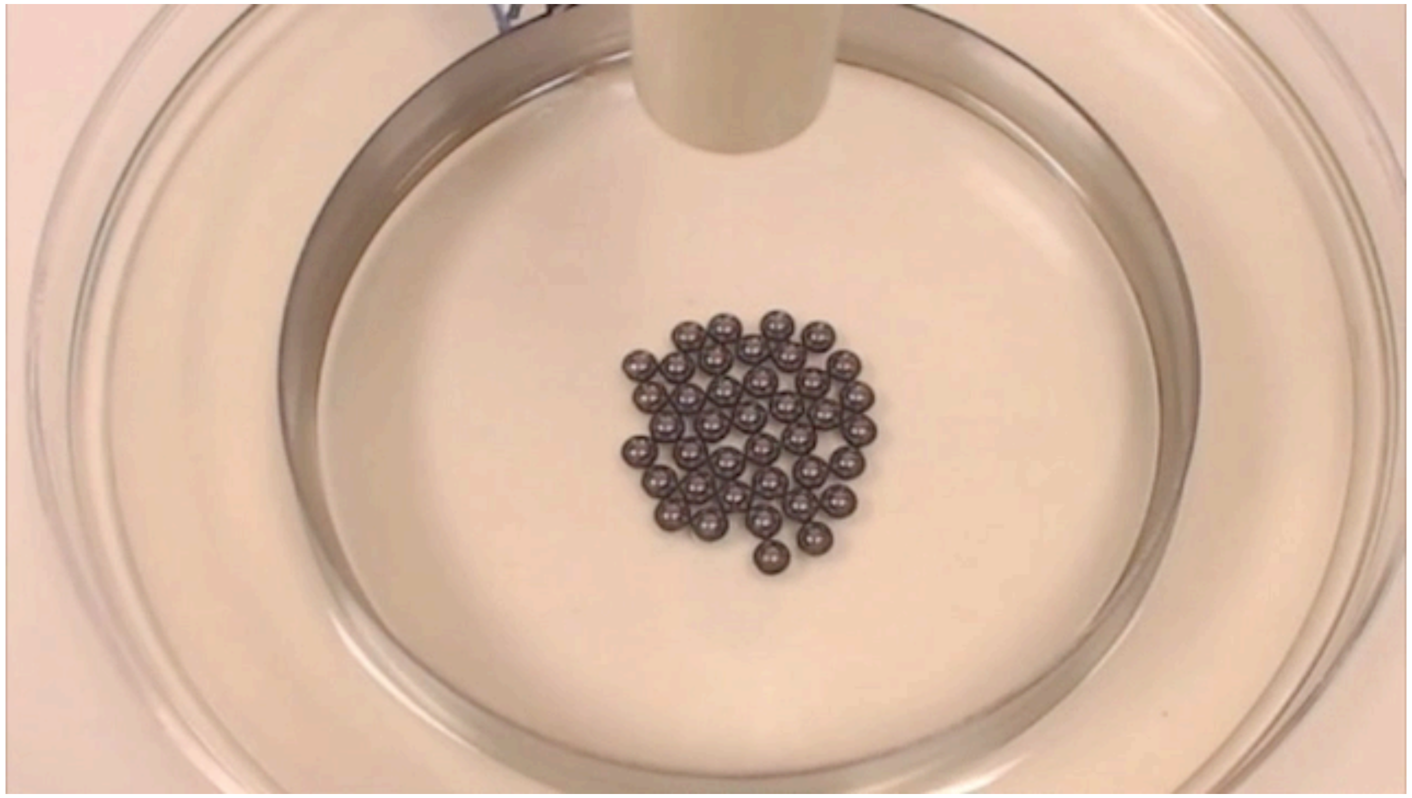


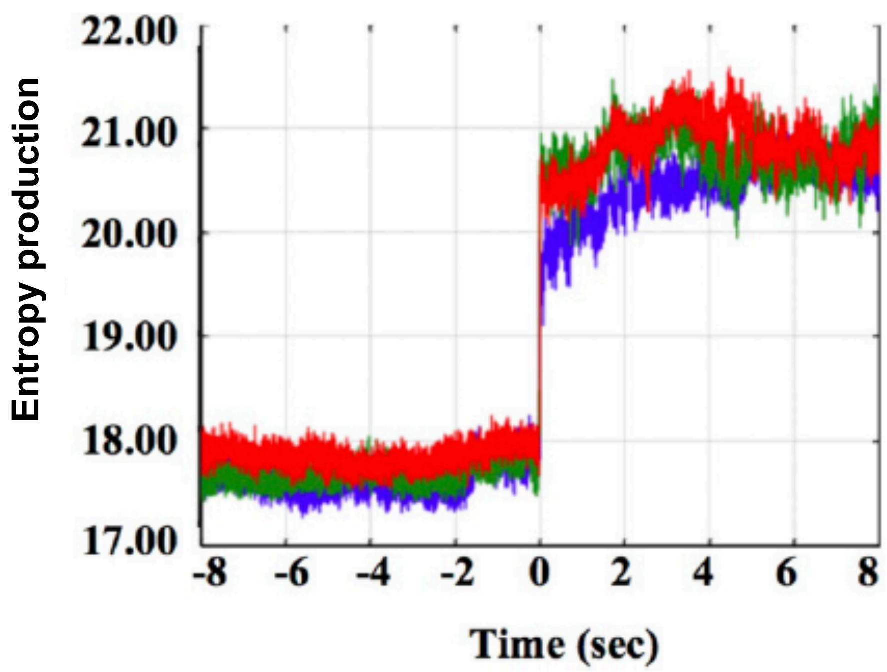
Self-organisation is an **order-generating process**,
it requires the transformation of free-energy into heat-energy / entropy
Fixing a DoF (generating order) requires the same amount of energy as Freeing up a DoF (= dissipative systems)

Self-Organisation in Dissipative Systems





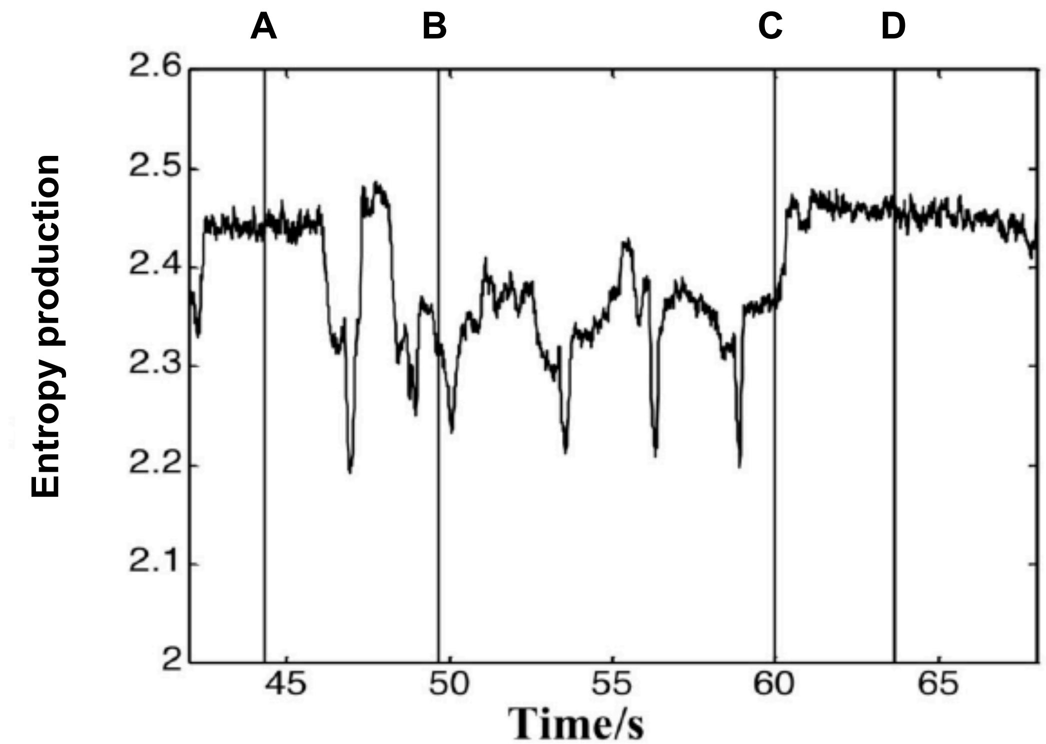


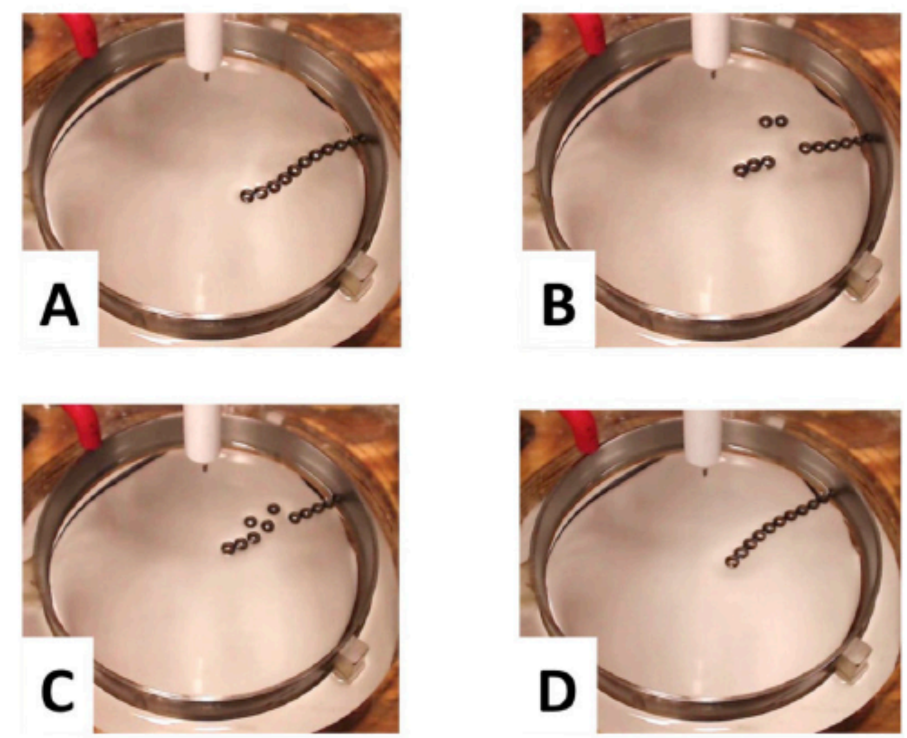


self-organisation:
Tree formation

Kondepudi D, Kay B, Dixon J. (2017). Dissipative structures, machines, and organisms: A perspective. *Chaos, 27(10),* 104607.

Self-Organisation in Dissipative Systems





self-repair:
Resilience to perturbation

Kondepudi D, Kay B, Dixon J. (2017). Dissipative structures, machines, and organisms: A perspective. *Chaos, 27(10),* 104607.

Self-Organisation in Dissipative Systems

END DIRECTED EVOLUTION TO STATES OF HIGHER ENTROPY PRODUCTION

TABLE I. Fundamental differences between machines and organisms.

Designed structures (machines/computers)	Dissipative structures (non-equilibrium systems and organisms)
— Structure designed and assembled through processes external to the system	— Structure arises spontaneously through entropy generating dissipative processes
— Dissipative processes limit the efficiency of the system; ideal machines have zero dissipation	— Dissipative processes are essential to the system; without them the structure ceases to exist
— Based on the reversible laws of mechanics	— Based on irreversible processes and the law of thermodynamics
— Parts exist for the whole but the whole does not support the parts	— Parts exist for the whole and whole supports the parts
— Not self-healing	— Generally self-healing
— Structure designed to perform a certain function	— Context dependent function arises because of end-directed evolution

More properties:
Memory
Classical conditioning (aversion / preference)

Memristors
[memristor.org]
"memory resistors", are a type of passive circuit elements that maintain a relationship between the time integrals of current and voltage across a two terminal element. Thus, a memristors' resistance varies according to a devices memristance function, allowing, via tiny read charges, access to a "history" of applied voltage

Sah, M. P., Kim, H., & Chua, L. O. (2014). Brains are made of memristors. *IEEE circuits and systems magazine*, *14*(1), 12-36.

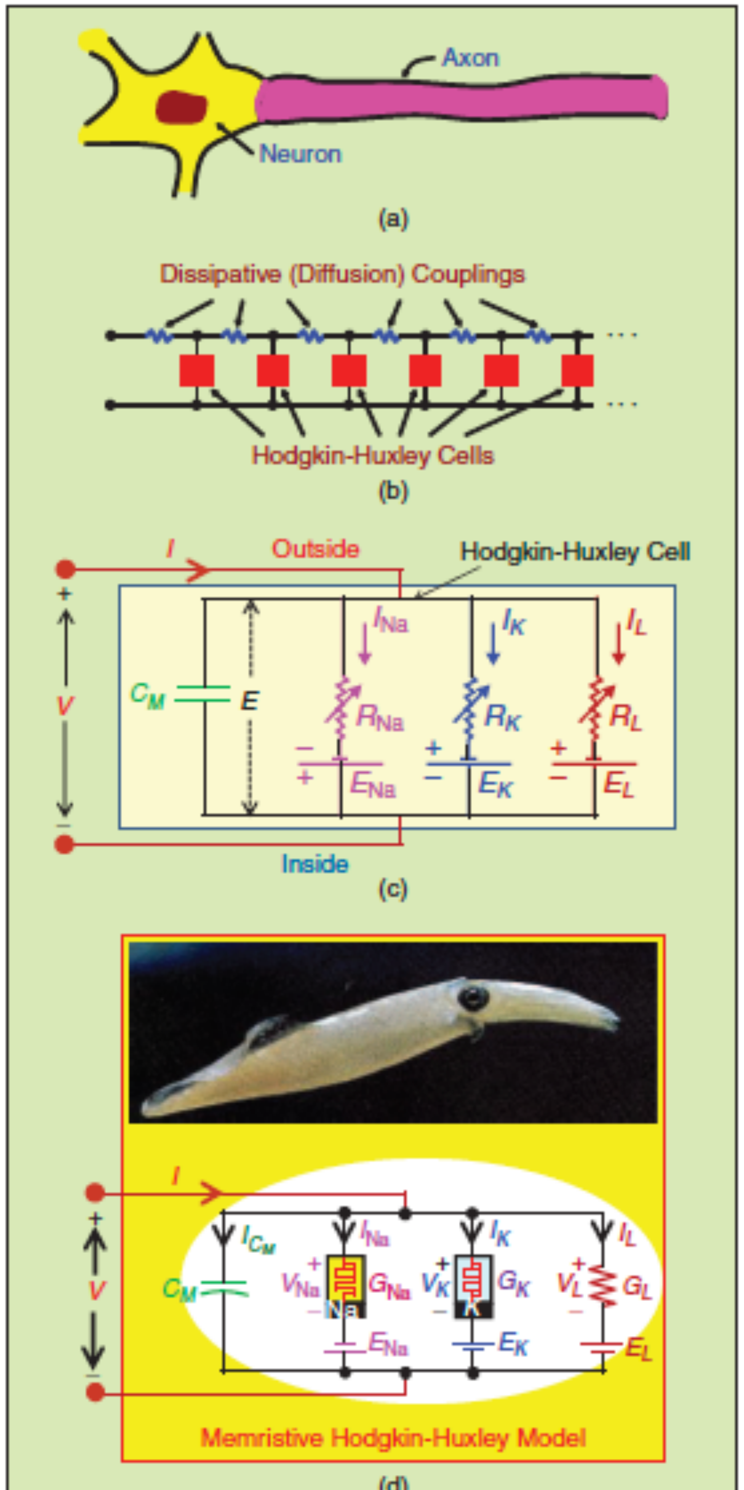


Figure 1. (a) Schematic of a neuron and its axon. (b) One-dimensional axon model made of resistively coupled Hodgkin-Huxley cells. (c) Hodgkin-Huxley circuit model made of a capacitor C_M, a resistor R_L, three batteries E_{Na}, E_K, and E_L, a *time-varying* potassium resistor R_K, and a *time-varying* sodium resistor R_{Na}. (d) Memristive Hodgkin-Huxley axon circuit model.

utation in Dissipative Systems

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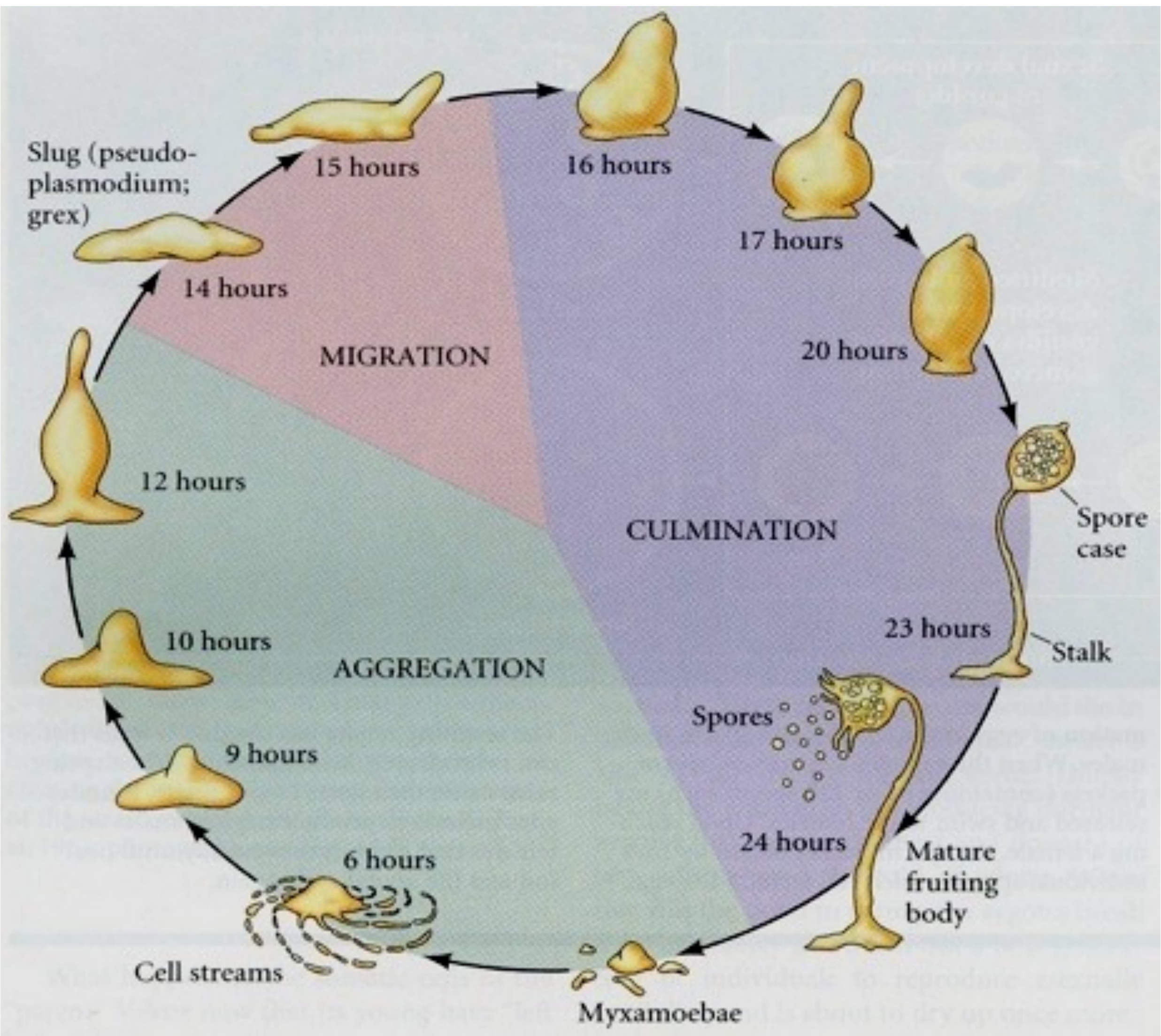
Emergence and Self-Organization: The life-cycle of *Dictyostelium*

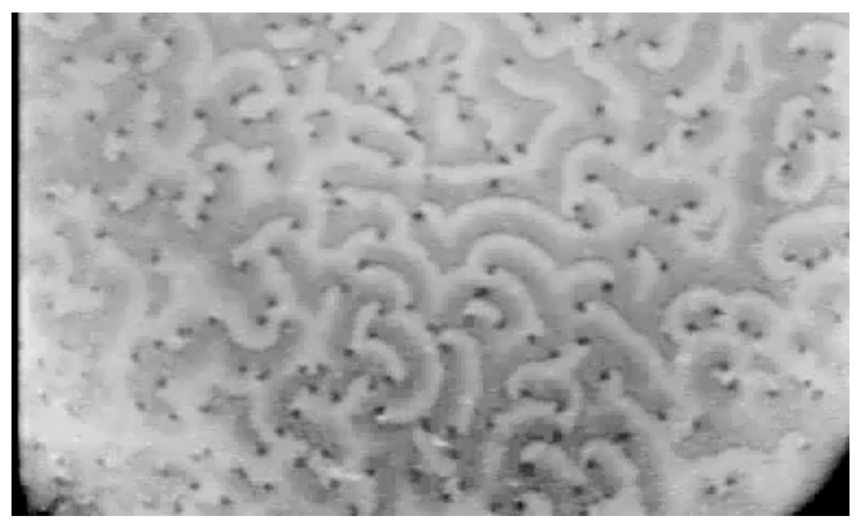


1. Free living myxamoebae feed on bacteria and divide by fission.
2. When food is exhausted they aggregate to form a mound, then a multicellular slug.
3. Slug migrates towards heat and light.
4. Differentiation then ensues forming a fruiting body, containing spores.
5. It all takes just 24 hrs.
6. Released spores form new amoebae.

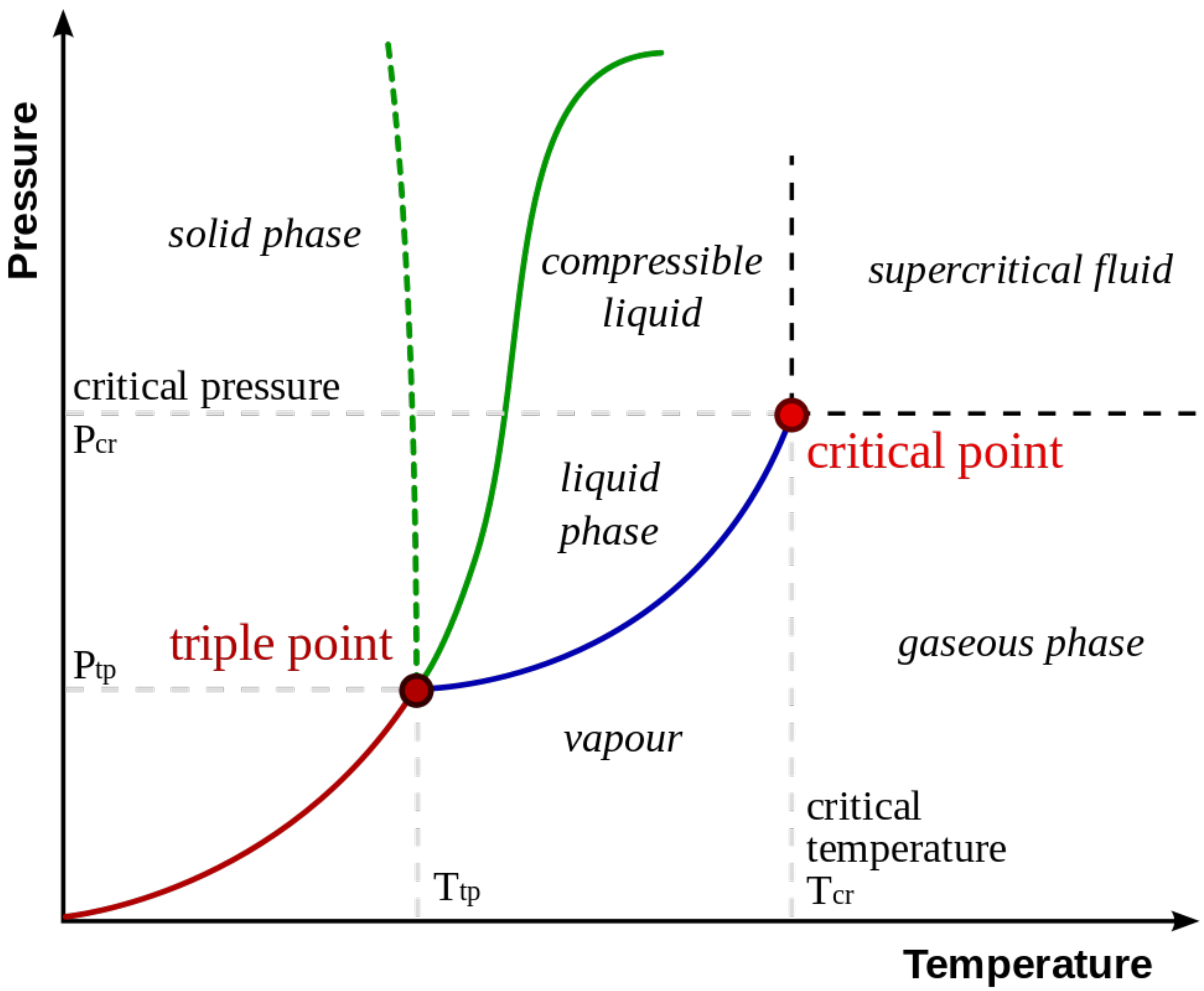
Order parameter: Labelling states of a complex system

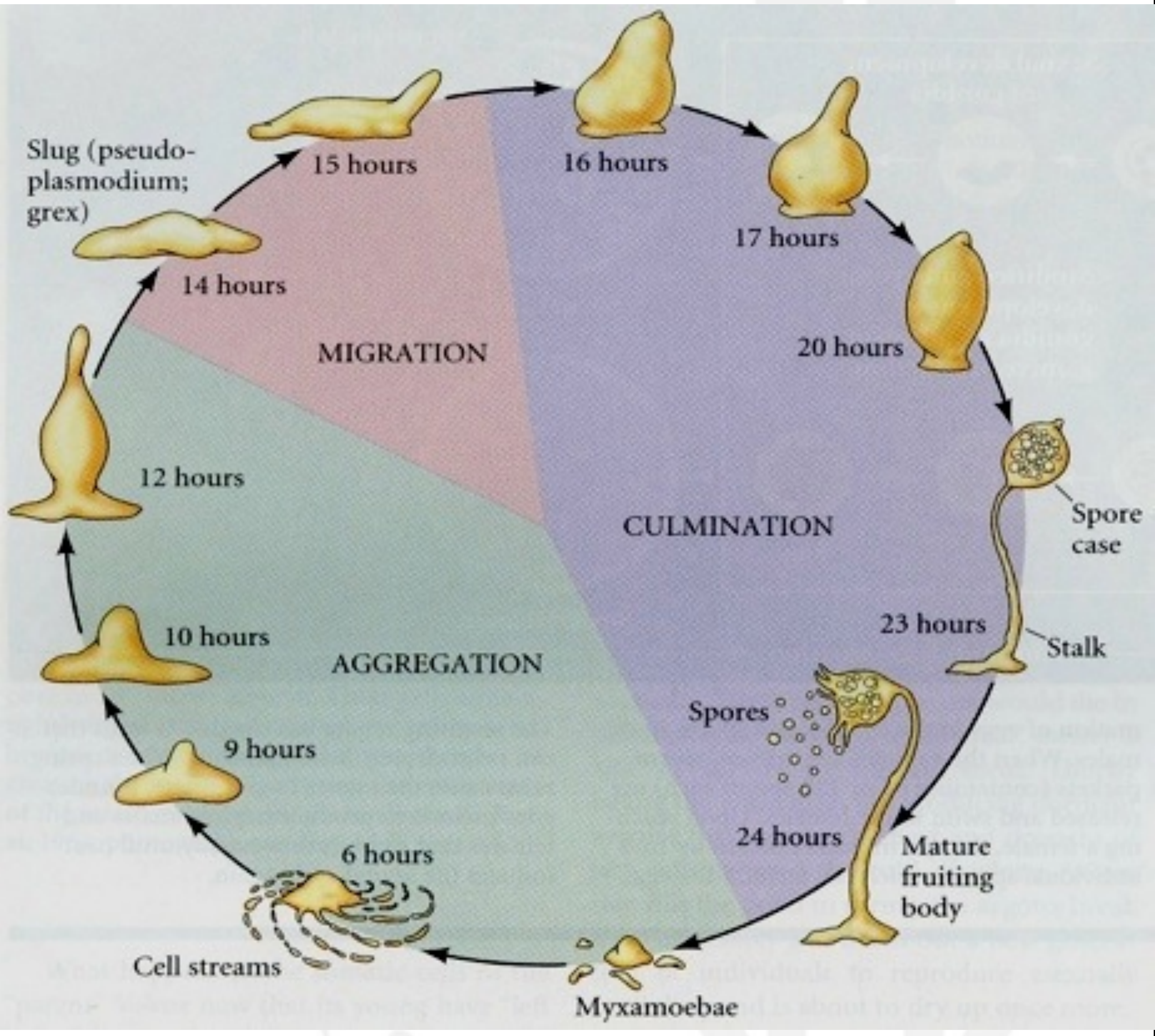
Forms are emergent, self-organised:

Arise from interactions between components → reduction of degrees of freedom



Phase Diagram & Order parameter





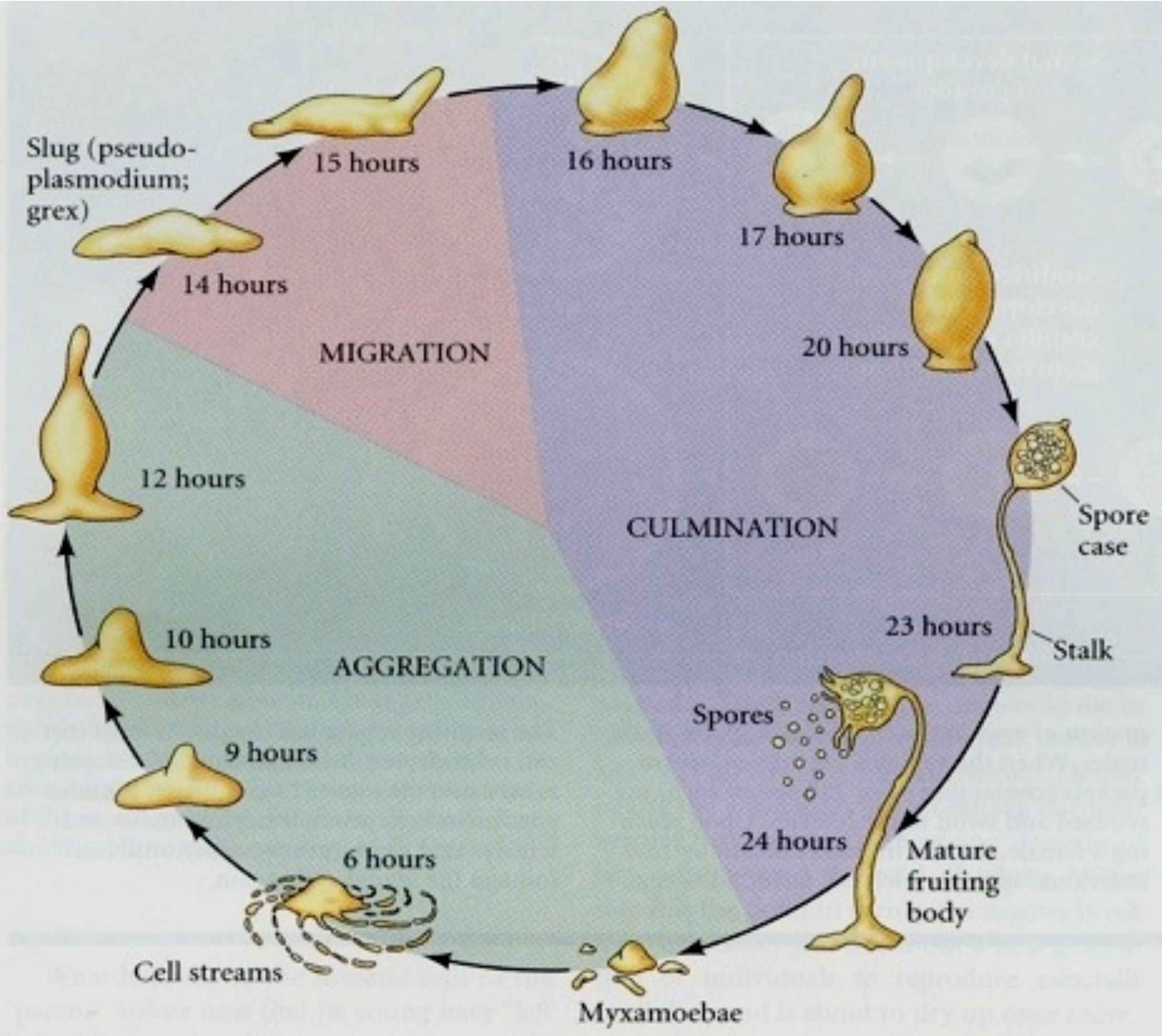
The order parameter is often a qualitative description of a macro state / global organisation of the system, conditional on the control parameters:

H_2O: Ice (Solid), Water (Liquid), Steam (Vapour)

Disctyostelium: Aggregation (Mound), Migration (Slug), Culmination (Fruiting Body)

Dynamic Metaphor vs. Dynamic Measure

Metaphor: Sate Space / Order Parameter
Measures: Attractor strength / Stability



Order parameter: the qualitatively different states

Control parameter: available food (actually concentration of a chemical that is released if they are starving)

Experiments:
Find out if the process is reversible... add food

perturb the system during the various phases...

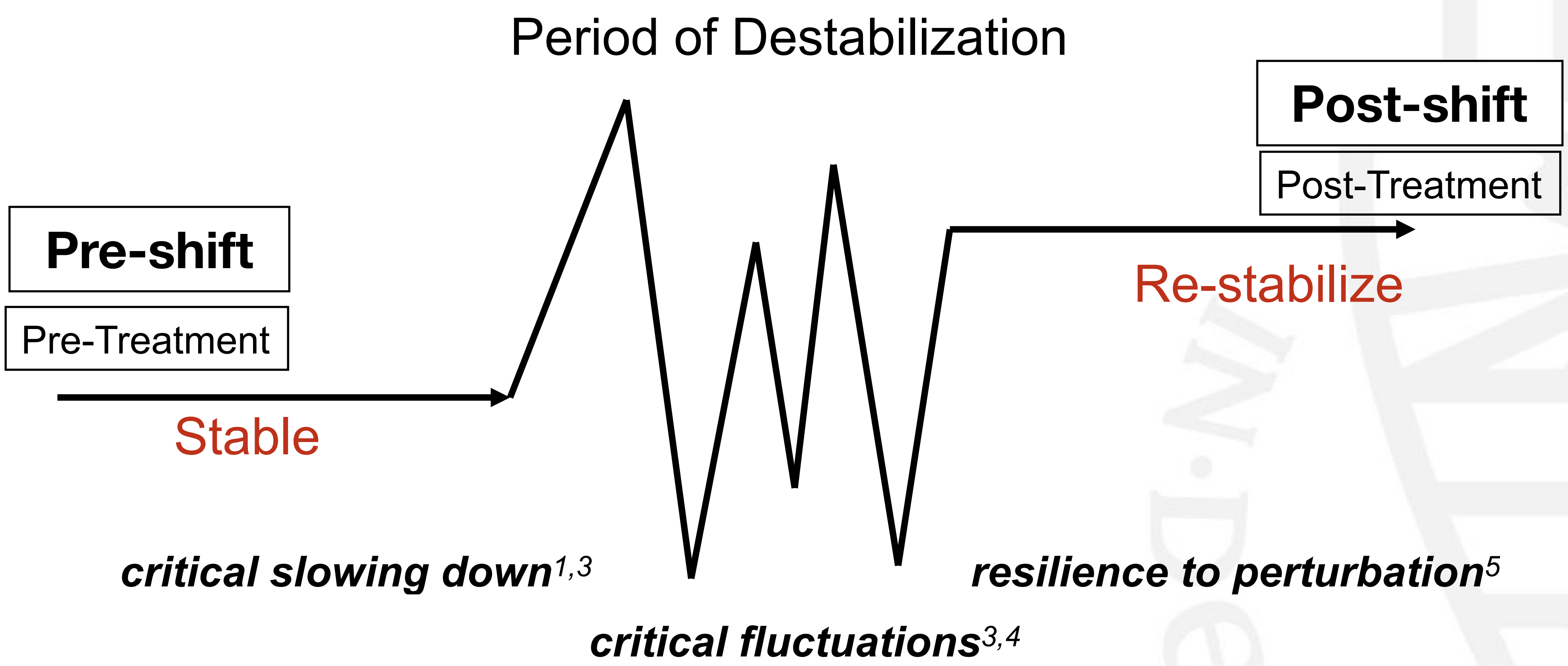
the degrees of freedom of the individual components are increasingly constrained by the interaction:

free living amoebae... slug... immovable sporing pod

nb State space and Phase Space (or: Diagram) are different concepts, but often used interchangeably to describe a State Space… see slide 18

Self-Organisation in Dissipative Systems

>> Application



- increase in recovery and switching time after perturbation
- increase in variance, autocorrelation, long-range dependence
- increase in occurrence and diversity of unstable states
- **increase in the entropy** of the distribution of state occurrences

[1]Scholz JP, Kelso JAS, Schöner G. (1987). Nonequilibrium phase transitions in coordinated biological motion: critical slowing down and switching time. *Physics Letters A 123,* 390–394.

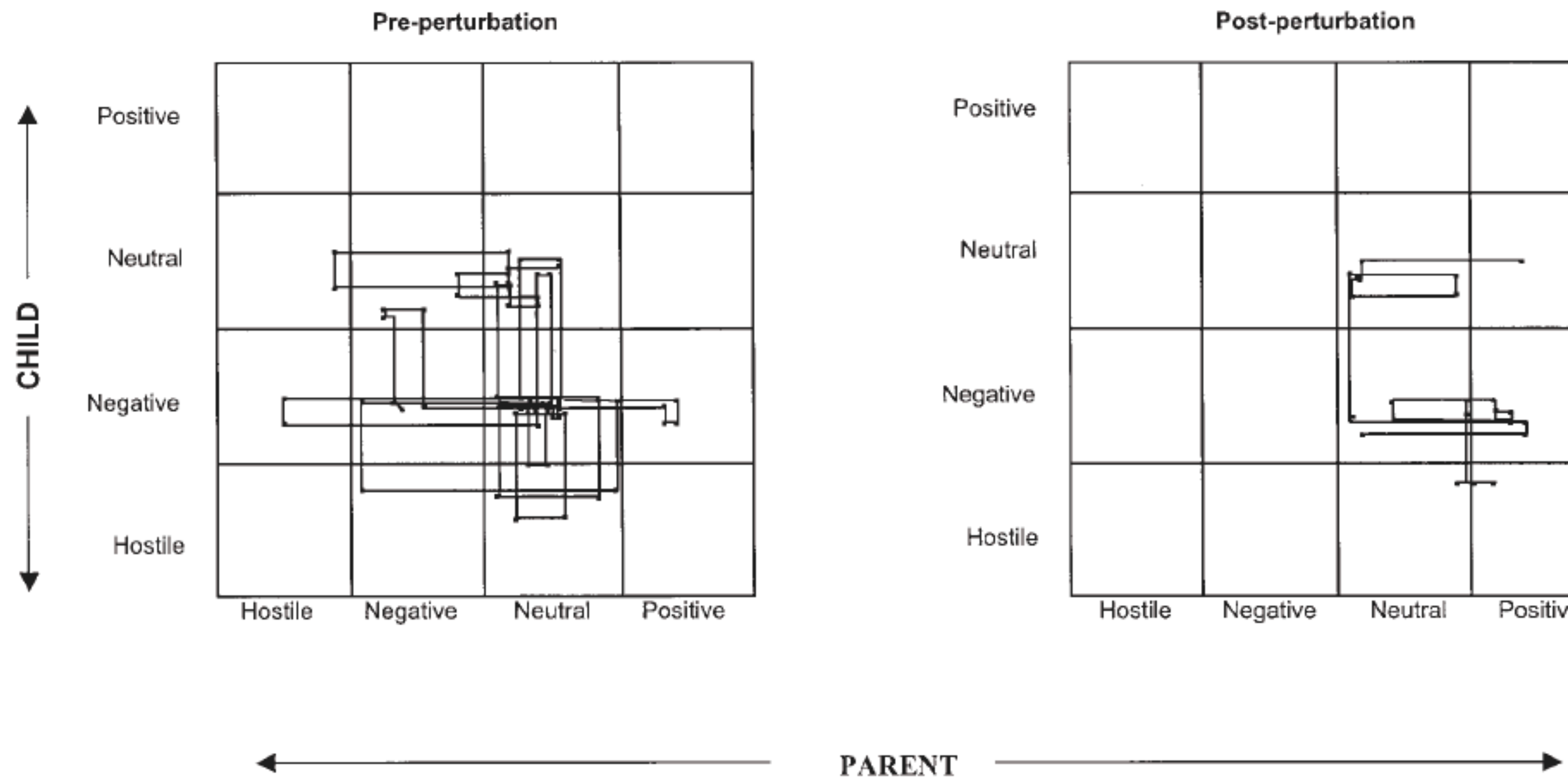
[2]Scheffer M, Bascompte J, Brock W A, Brovkin V, Carpenter SR, Dakos V, Held H, van Nes EH, Rietkerk M, Sugihara G. (2009). Early-warning signals for critical transitions. *Nature 461,* 53–9.

[3]Stephen DG, Dixon JA, Isenhower RW. (2009). Dynamics of representational change: Entropy, Action and Cognition. *JEP: Human Perception and Performance 35,* 1811–1832.

[4]Schiepek G, Strunk G. (2010). The identification of critical fluctuations and phase transitions in short term and coarse-grained time series … *Biological cybernetics 102,*197–207.

Self-Organisation in Dissipative Systems

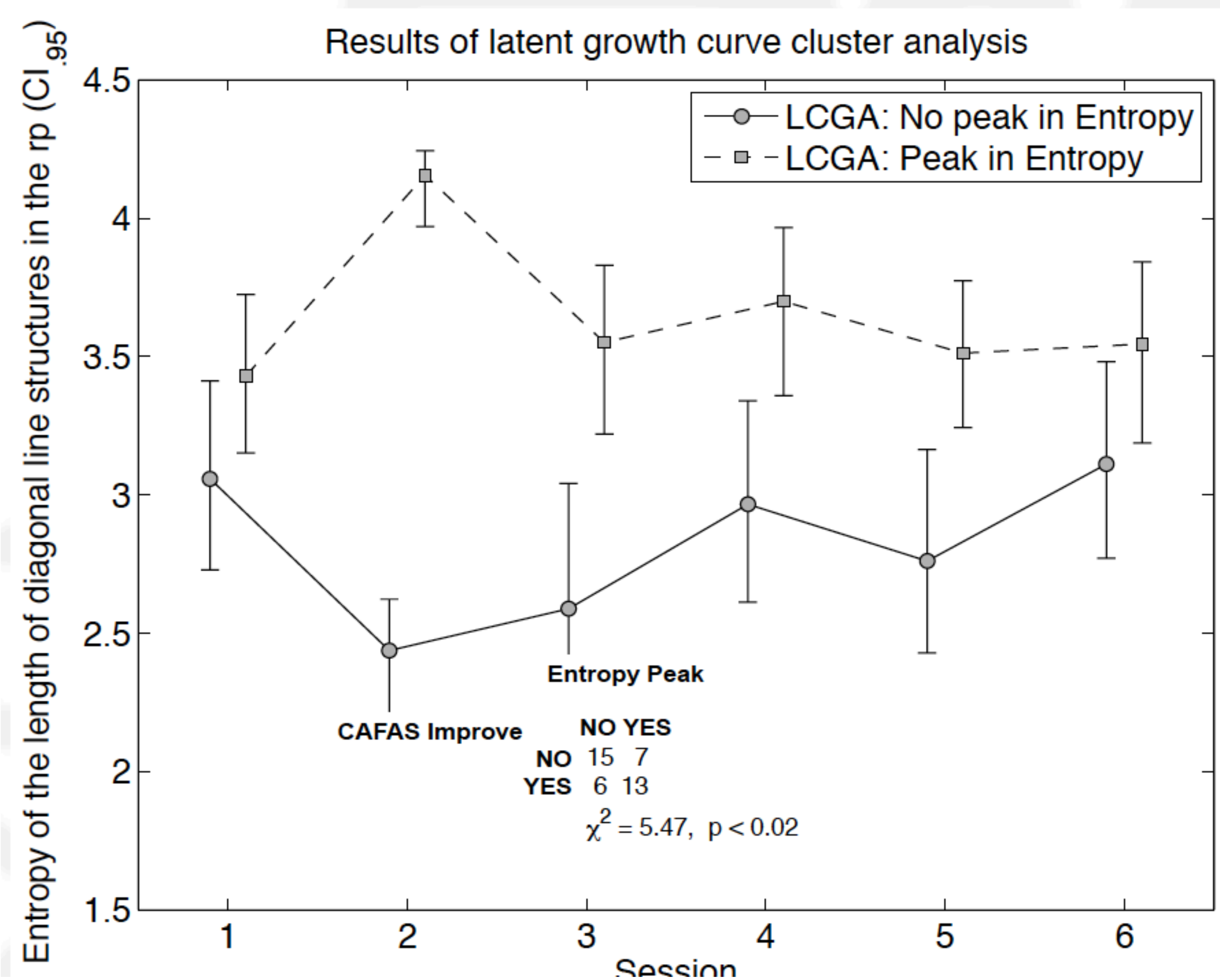
>> Application



Lichtwarck-Aschoff A, Hasselman F, Cox R, Pepler D, Granic I. (2012). A characteristic destabilization profile in parent-child interactions associated with treatment efficacy for aggressive children. *Nonlinear Dynamics-Psychology and Life Sciences 16*, 353.

Self-Organisation in Dissipative Systems

>> Application



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Self-Organisation in Dissipative Systems

>> Application

Critical Fluctuations as an Early-Warning Signal for Sudden Gains and Losses in Patients receiving Psychotherapy for Mood Disorders

Merlijn Olthof, Fred Hasselman, Guido Strunk, Marieke van Rooij, Benjamin Aas, Marieke A. Helmich, Günter Schiepek & Anna Lichtwarck-Aschoff.

Clinical Psychological Science:

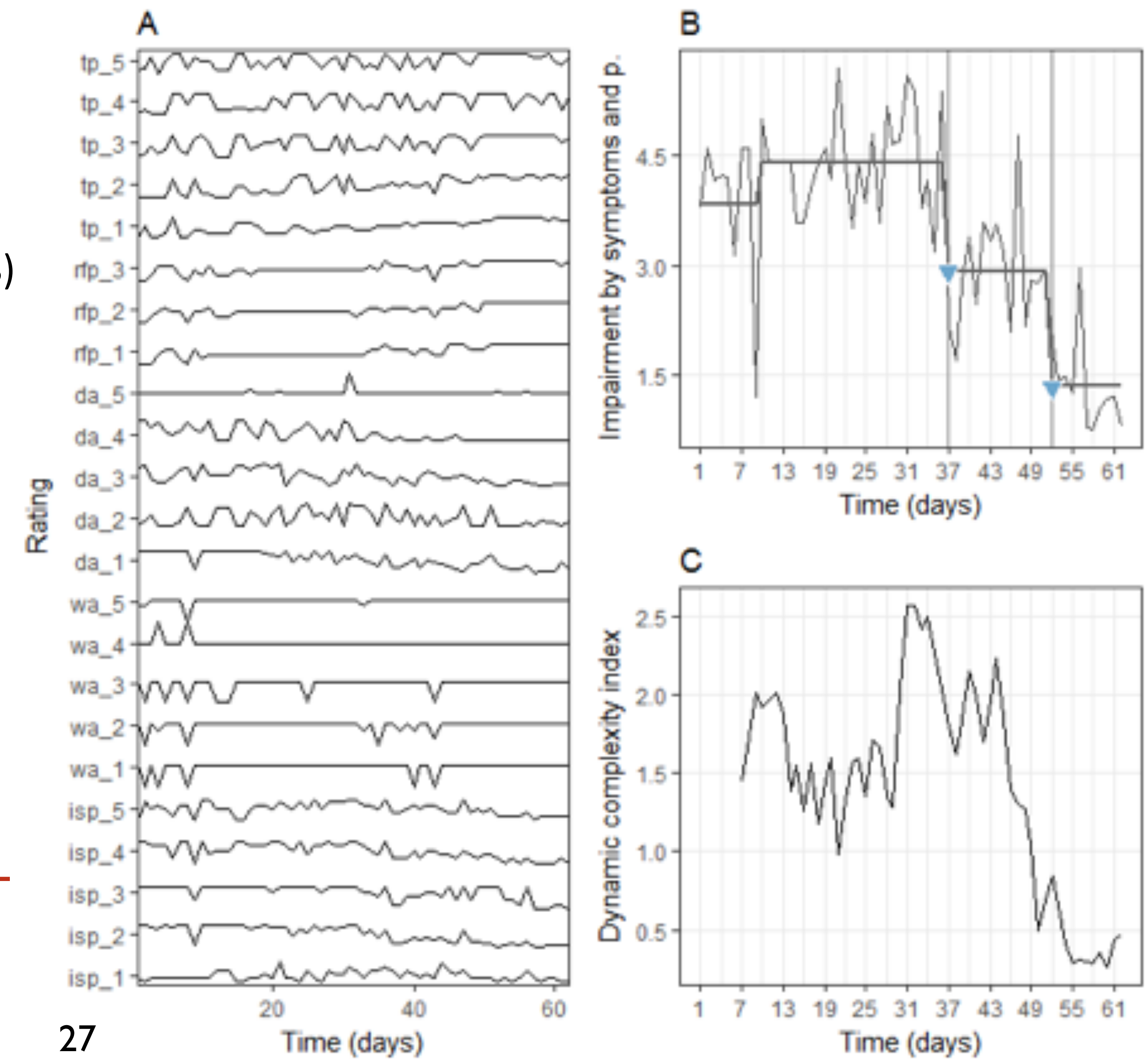
N = 329

Median time series duration: 59 days (range: 31-318)

LDC positively predicted sudden gains and losses

OR = 1.55

This means that an increase in LDC of 1 s tandard deviation relates to a 55% increased probability for the occurrence of a sudden gain or loss within 4 days after the peak .



Ecological Momentary Assessment

- Lots of multivariate time series data are collected and scrutinised (Experience Sampling Method, EMA)

- Analysed as if data have the memorylessness property and originate from an ergodic, non-ageing system, with fixed boundaries, without internal state dynamics

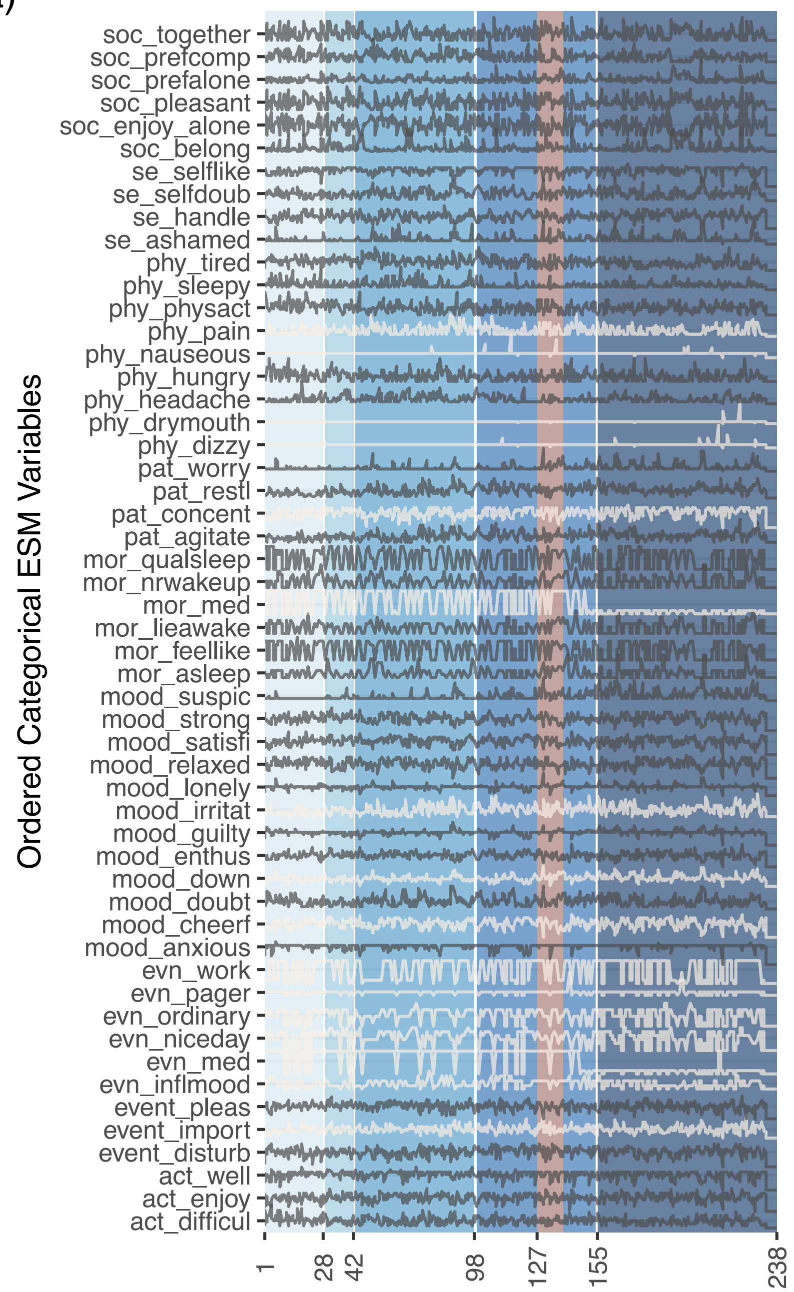
- E.g. symptom networks (Gaussian Graphic Model); Time Varying-Auto Regressive models, etc.

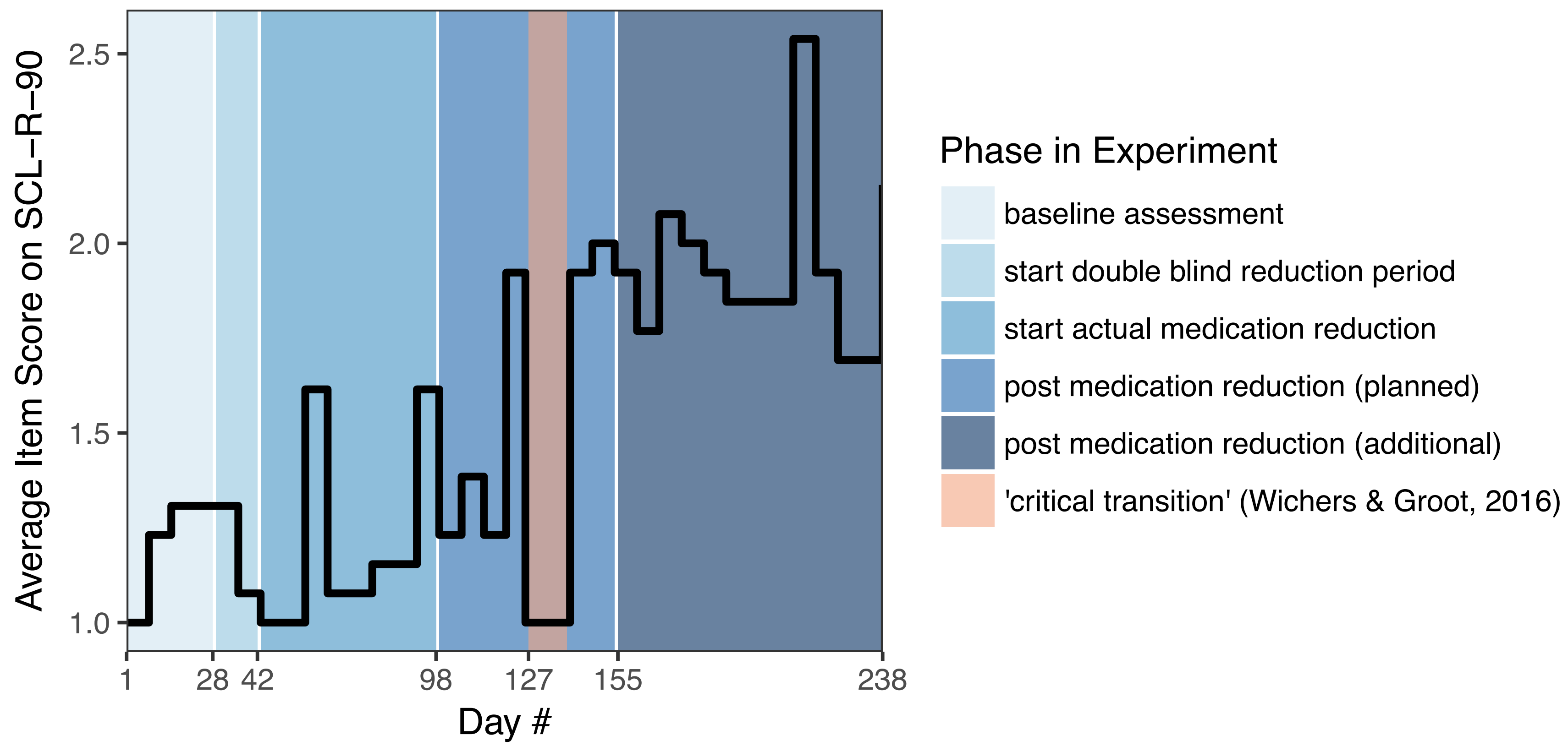
- Unnecessary data reduction: Averaging, Factor Analysis, only look lag 1, etc.

- **First analyse then aggregate!**

“Critical Slowing Down as a Personalized Early Warning Signal for Depression”

(a)





Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. Psychotherapy and psychosomatics, 85(2), 114-116. DOI: 10.1159/000441458

Kossakowski, J., Groot, P., Haslbeck, J., Borsboom, D., and Wichers, M. (2017). Data from ‘critical slowing down as a personalized early warning signal for depression’. Journal of Open Psychology Data, 5(1).

What kind of system is a living system?

Major Depression as a Complex Dynamic System

Angélique O. J. Cramer, Claudia D. van Borkulo, Erik J. Giltay, Han L. J. van der Maas, Kenneth S. Kendler, Marten Scheffer, Denny Borsboom

Published: December 8, 2016 • https://doi.org/10.1371/journal.pone.0167490

Personalized Models of Psychopathology

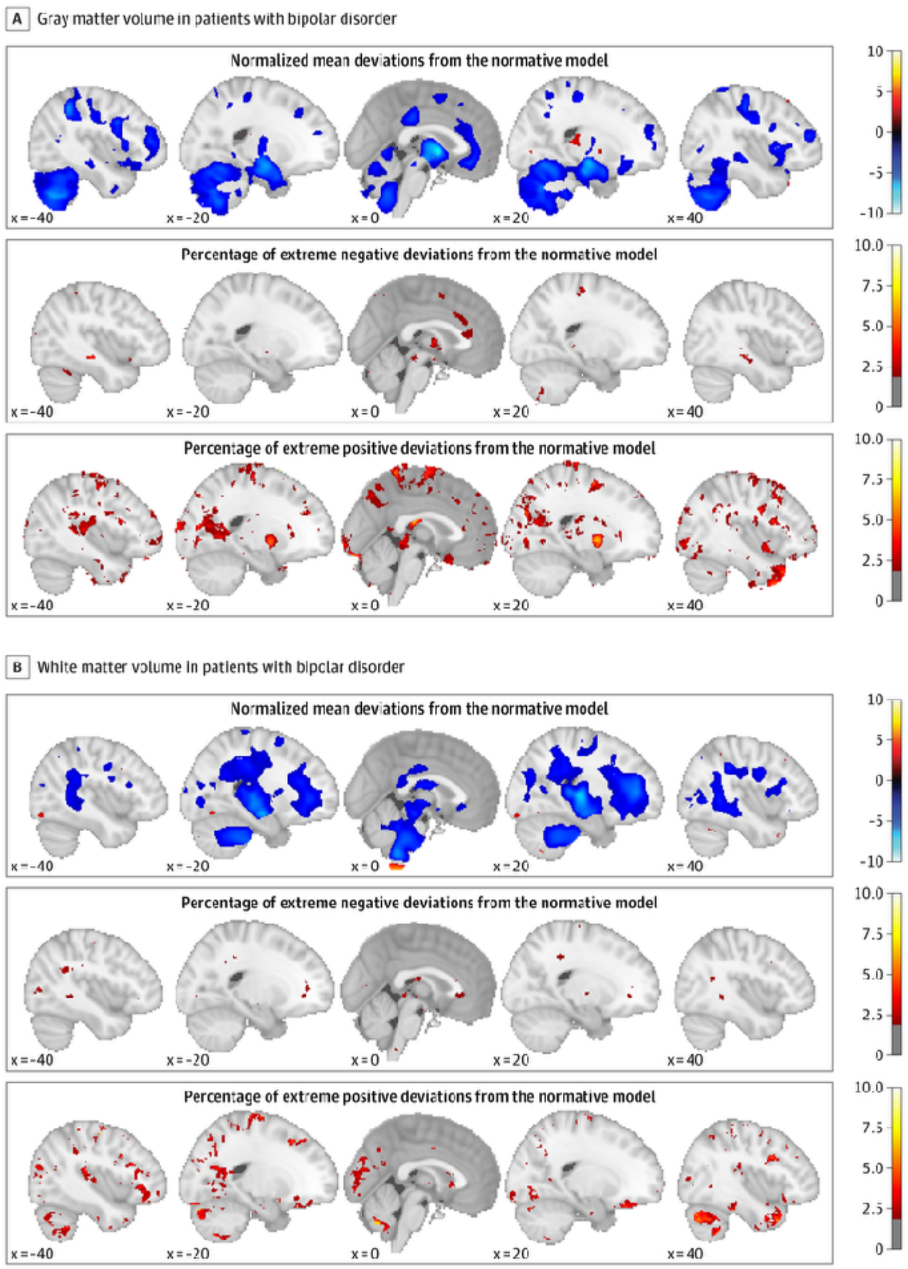
Aidan G.C. Wright, Ph.D., Department of Psychology, University of Pittsburgh, aidan@pitt.edu, ORCID: 0000-0002-2369-0601

William C. Woods, M.S., Department of Psychology, University of Pittsburgh, wcw8@pitt.edu, ORCID: 0000-0002-8385-9106

This manuscript has been accepted for publication for the 2020 volume of the Annual Review of Clinical Psychology. It has not been copyedited, and therefore is not the version of record.

"The personalized approach to psychopathology conceptualizes mental disorder as ***a complex system of contextualized dynamic processes that is nontrivially specific to each individual***, and seeks to develop formal idiographic statistical models to represent these individual processes."

What kind of system?



“The idea of **the average patient is a noninformative construct in psychiatry** that falls apart when mapping abnormalities at the level of the individual patient”

Wolfers, T., Doan, N. T., Kaufmann, T., Alnaes, D., Moberget, T., Agartz, I., . . . Marquand, A. F. (2018). Mapping the Heterogeneous Phenotype of Schizophrenia and Bipolar Disorder Using Normative Models. *JAMA Psychiatry, 75*(11), 1146-1155. doi:10.1001/jamapsychiatry.2018.2467

What kind of system?

Lack of group-to-individual generalizability is a threat to human subjects research

Aaron J. Fisher[a,1], John D. Medaglia[b,c], and Bertus F. Jeronimus[d]

[a]Department of Psychology, University of California, Berkeley, CA 94720; [b]Department of Psychology, Drexel University, Philadelphia, PA 19104; [c]Department of Neurology, University of Pennsylvania, Philadelphia, PA 19104; and [d]Department of Developmental Psychology, Faculty of Behavioural and Social Sciences, Groningen University, 9712 TS Groningen, The Netherlands

Edited by David L. Donoho, Stanford University, Stanford, CA, and approved May 25, 2018 (received for review July 4, 2017)

Only for ergodic processes will inferences based on group-level data generalize to individual experience or behavior. Because human social and psychological processes typically have an individually variable and time-varying nature, they are unlikely to be ergodic. In this paper, six studies with a repeated-measure design were used for symmetric comparisons of interindividual and intraindividual variation. Our results delineate the potential scope and impact of nonergodic data in human subjects research. Analyses across six samples (with 87–94 participants and an equal number of assessments per participant) showed some degree of agreement in central tendency estimates (mean) between groups and individuals across constructs and data collection paradigms. However, the variance around the expected value was two to four times larger within individuals than within groups. This suggests that literatures in social and medical sciences may overestimate the accuracy of aggregated statistical estimates. This observation could have serious consequences for how we understand the consistency between group and individual correlations, and the generalizability of conclusions between domains. Researchers should explicitly test for equivalence of processes at the individual and group level across the social and medical sciences.

research methodology | replicability | idiographic science | generalizability | ecological fallacy

Inferences made in social and medical research typically result from statistical tests conducted on aggregated data. The implicit assumption is that group-derived estimates can be applied

consistency between individual and group variability before generalizing results across levels of analysis. We will refer to this latter condition as the "group-to-individual generalizability" of a given statistical estimate. However, whether couched in prosaic terms, or within formal mathematical theorems, researchers have not systematically examined such generalizability in extant literatures, despite a number of calls to do so throughout the years (cf. refs. 6–11). Hitherto, the highest-impact publications in medical and social sciences have been largely based on data aggregated across large samples, with best-practice guidelines almost exclusively based on statistical inferences from group designs. The worst-case scenario—a global, uniform absence of group-to-individual generalizability due to nonergodicity in the social and medical sciences—would undermine the validity of our scientific canon in these domains. However, even moderate incongruities between group and individual estimates could result in imprecise or potentially invalid conclusions. We argue that this possibility should be formally tested, wherever possible, to be ruled out.

Ergodicity, the Ecological Fallacy, and Simpson's Paradox

The ergodic theorem is a general and formal mathematical expression that deals with the generalizability of statistical phenomena across levels and units of analysis. [While a more thorough explication of the ergodic theorem is outside of the scope of the present paper, readers are referred to Molenaar (1) for a comprehensive mathematical treatment of ergodicity in human subjects research.] Ergodic theory postulates that the

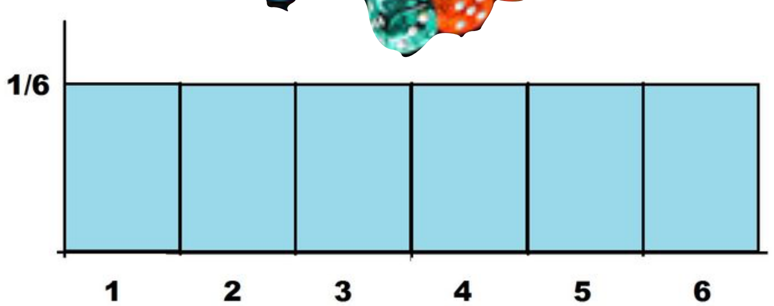
"Inattention to nonergodicity and a lack of group-to-individual generalizability **threaten the veracity of countless studies, conclusions, and best-practice recommendations.**"

Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proc Natl Acad Sci U S A, 115*(27), E6106-E6115. doi:10.1073/pnas.1711978115

What kind of system?

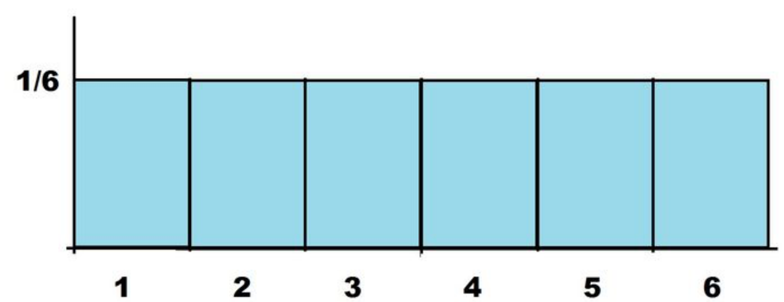
Ergodic process/measure/system

1 time 100 dice
“space-average”



=

100 times 1 die
“time average”



Einstein (1905) on Brownian motion:

(i) the **independence** of individual particles,

(ii) the existence of a **sufficiently small time scale** beyond which *individual displacements are statistically independent*, and

(iii) the property that the particle displacements during this time scale correspond to **a typical mean free path** *distributed symmetrically in positive or negative directions*.

What kind of system?

1. Non-*ergodic*
(non-stationarity of level & trend of central moments, non-homogeneous fluctuations/variance)

2. No *memorylessness* property
(after-effects of interactions with internal and external environment: long-range dependence, anomalous diffusion)

3. Subject to *ageing* and ‘*ecometamorphism’*
(loss of identity over time which leads to increased individuality; loss of specificity/coherence of form/boundary/individuality)

>> Complex Adaptive System with Internal State Dynamics
(*internal state dynamics = internal degrees of freedom*: Many interacting constituent parts which can also be complex adaptive systems with their own dynamics, unique interaction biography, idiographic approach. A coupled system can also have an “internal” state = *not* a physical boundary)

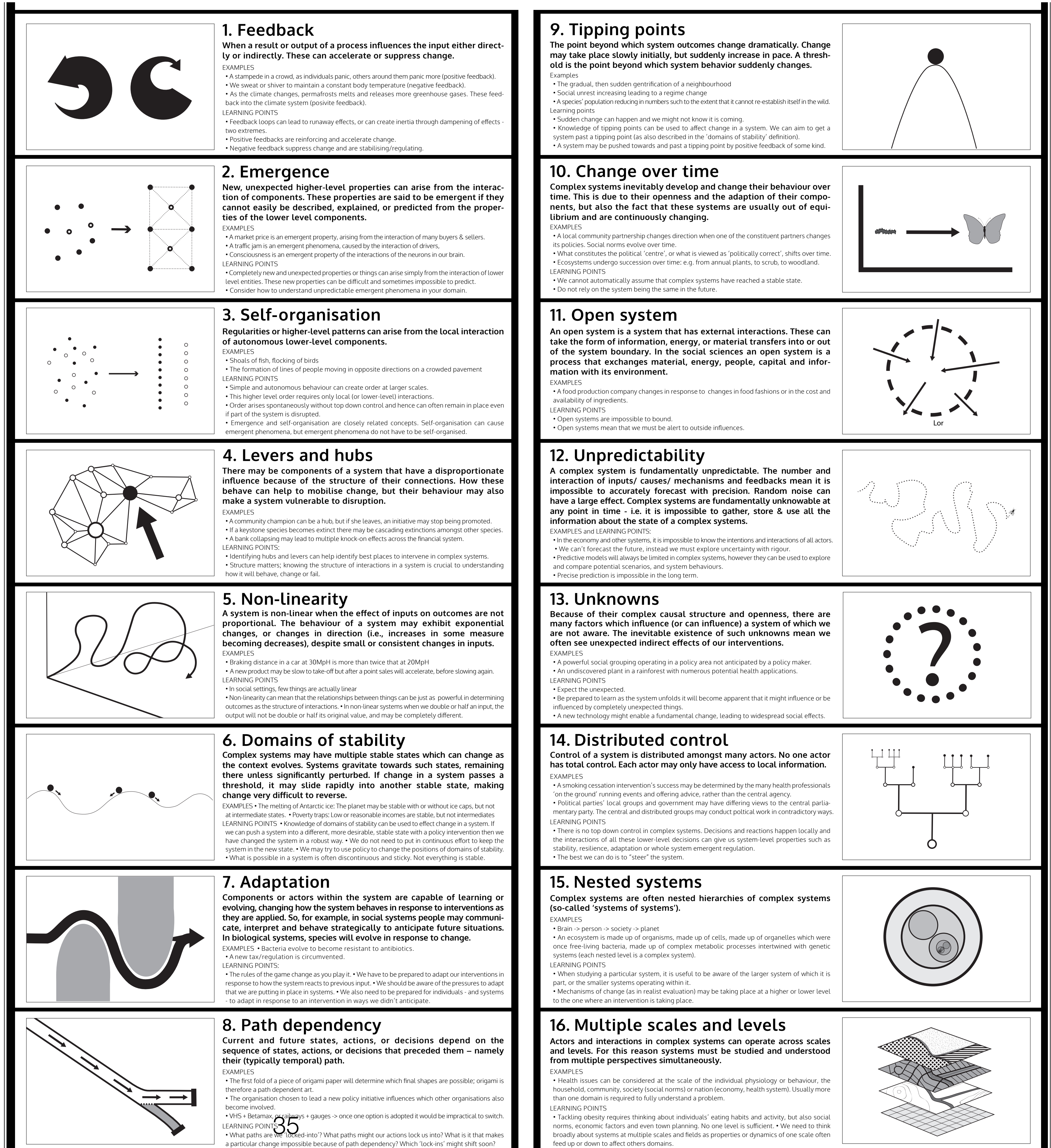
What kind of system?

I call the methods we use: "mostly model-free" "descriptive techniques"

detect / quantify
many characteristic
phenomena observed
in
complex adaptive systems

- Multi-scale fluctuations
- Non-linear dynamics
- Prediction horizons
- Regime changes
- Divergence

There is always a model of course!



1. Feedback

When a result or output of a process influences the input either directly or indirectly. These can accelerate or suppress change.

EXAMPLES
- A stampede in a crowd, as individuals panic, others around them panic more (positive feedback).
- We sweat or shiver to maintain a constant body temperature (negative feedback).
- As the climate changes, permafrosts melts and releases more greenhouse gases. These feedback into the climate system (posivite feedback).

LEARNING POINTS
- Feedback loops can lead to runaway effects, or can create inertia through dampening of effects - two extremes.
- Positive feedbacks are reinforcing and accelerate change.
- Negative feedback suppress change and are stabilising/regulating.

2. Emergence

New, unexpected higher-level properties can arise from the interaction of components. These properties are said to be emergent if they cannot easily be described, explained, or predicted from the properties of the lower level components.

EXAMPLES
- A market price is an emergent property, arising from the interaction of many buyers & sellers.
- A traffic jam is an emergent phenomena, caused by the interaction of drivers,
- Consciousness is an emergent property of the interactions of the neurons in our brain.

LEARNING POINTS
- Completely new and unexpected properties or things can arise simply from the interaction of lower level entities. These new properties can be difficult and sometimes impossible to predict.
- Consider how to understand unpredictable emergent phenomena in your domain.

3. Self-organisation

Regularities or higher-level patterns can arise from the local interaction of autonomous lower-level components.

EXAMPLES
- Shoals of fish, flocking of birds
- The formation of lines of people moving in opposite directions on a crowded pavement

LEARNING POINTS
- Simple and autonomous behaviour can create order at larger scales.
- This higher level order requires only local (or lower-level) interactions.
- Order arises spontaneously without top down control and hence can often remain in place even if part of the system is disrupted.
- Emergence and self-organisation are closely related concepts. Self-organisation can cause emergent phenomena, but emergent phenomena do not have to be self-organised.

4. Levers and hubs

There may be components of a system that have a disproportionate influence because of the structure of their connections. How these behave can help to mobilise change, but their behaviour may also make a system vulnerable to disruption.

EXAMPLES
- A community champion can be a hub, but if she leaves, an initiative may stop being promoted.
- If a keystone species becomes extinct there may be cascading extinctions amongst other species.
- A bank collapsing may lead to multiple knock-on effects across the financial system.

LEARNING POINTS:
- Identifying hubs and levers can help identify best places to intervene in complex systems.
- Structure matters; knowing the structure of interactions in a system is crucial to understanding how it will behave, change or fail.

5. Non-linearity

A system is non-linear when the effect of inputs on outcomes are not proportional. The behaviour of a system may exhibit exponential changes, or changes in direction (i.e., increases in some measure becoming decreases), despite small or consistent changes in inputs.

EXAMPLES
- Braking distance in a car at 30MpH is more than twice that at 20MpH
- A new product may be slow to take-off but after a point sales will accelerate, before slowing again.

LEARNING POINTS
- In social settings, few things are actually linear
- Non-linearity can mean that the relationships between things can be just as powerful in determining outcomes as the structure of interactions. • In non-linear systems when we double or half an input, the output will not be double or half its original value, and may be completely different.

6. Domains of stability

Complex systems may have multiple stable states which can change as the context evolves. Systems gravitate towards such states, remaining there unless significantly perturbed. If change in a system passes a threshold, it may slide rapidly into another stable state, making change very difficult to reverse.

EXAMPLES • The melting of Antarctic ice: The planet may be stable with or without ice caps, but not at intermediate states. • Poverty traps: Low or reasonable incomes are stable, but not intermediates

LEARNING POINTS • Knowledge of domains of stability can be used to effect change in a system. If we can push a system into a different, more desirable, stable state with a policy intervention then we have changed the system in a robust way. • We do not need to put in continuous effort to keep the system in the new state. • We may try to use policy to change the positions of domains of stability. • What is possible in a system is often discontinuous and sticky. Not everything is stable.

7. Adaptation

Components or actors within the system are capable of learning or evolving, changing how the system behaves in response to interventions as they are applied. So, for example, in social systems people may communicate, interpret and behave strategically to anticipate future situations. In biological systems, species will evolve in response to change.

EXAMPLES • Bacteria evolve to become resistant to antibiotics.
- A new tax/regulation is circumvented.

LEARNING POINTS:
- The rules of the game change as you play it. • We have to be prepared to adapt our interventions in response to how the system reacts to previous input. • We should be aware of the pressures to adapt that we are putting in place in systems. • We also need to be prepared for individuals - and systems - to adapt in response to an intervention in ways we didn't anticipate.

8. Path dependency

Current and future states, actions, or decisions depend on the sequence of states, actions, or decisions that preceded them – namely their (typically temporal) path.

EXAMPLES
- The first fold of a piece of origami paper will determine which final shapes are possible; origami is therefore a path dependent art.
- The organisation chosen to lead a new policy initiative influences which other organisations also become involved.
- VHS + Betamax, or railways + gauges -> once one option is adopted it would be impractical to switch.

LEARNING POINTS
- What paths are we 'locked-into'? What paths might our actions lock us into? What is it that makes a particular change impossible because of path dependency? Which 'lock-ins' might shift soon?

9. Tipping points

The point beyond which system outcomes change dramatically. Change may take place slowly initially, but suddenly increase in pace. A threshold is the point beyond which system behavior suddenly changes.

Examples
- The gradual, then sudden gentrification of a neighbourhood
- Social unrest increasing leading to a regime change
- A species' population reducing in numbers such to the extent that it cannot re-establish itself in the wild.

Learning points
- Sudden change can happen and we might not know it is coming.
- Knowledge of tipping points can be used to affect change in a system. We can aim to get a system past a tipping point (as also described in the 'domains of stability' definition).
- A system may be pushed towards and past a tipping point by positive feedback of some kind.

10. Change over time

Complex systems inevitably develop and change their behaviour over time. This is due to their openness and the adaption of their components, but also the fact that these systems are usually out of equilibrium and are continuously changing.

EXAMPLES
- A local community partnership changes direction when one of the constituent partners changes its policies. Social norms evolve over time.
- What constitutes the political 'centre', or what is viewed as 'politically correct', shifts over time.
- Ecosystems undergo succession over time: e.g. from annual plants, to scrub, to woodland.

LEARNING POINTS
- We cannot automatically assume that complex systems have reached a stable state.
- Do not rely on the system being the same in the future.

11. Open system

An open system is a system that has external interactions. These can take the form of information, energy, or material transfers into or out of the system boundary. In the social sciences an open system is a process that exchanges material, energy, people, capital and information with its environment.

EXAMPLES
- A food production company changes in response to changes in food fashions or in the cost and availability of ingredients.

LEARNING POINTS
- Open systems are impossible to bound.
- Open systems mean that we must be alert to outside influences.

12. Unpredictability

A complex system is fundamentally unpredictable. The number and interaction of inputs/ causes/ mechanisms and feedbacks mean it is impossible to accurately forecast with precision. Random noise can have a large effect. Complex systems are fundamentally unknowable at any point in time - i.e. it is impossible to gather, store & use all the information about the state of a complex systems.

EXAMPLES and LEARNING POINTS:
- In the economy and other systems, it is impossible to know the intentions and interactions of all actors.
- We can't forecast the future, instead we must explore uncertainty with rigour.
- Predictive models will always be limited in complex systems, however they can be used to explore and compare potential scenarios, and system behaviours.
- Precise prediction is impossible in the long term.

13. Unknowns

Because of their complex causal structure and openness, there are many factors which influence (or can influence) a system of which we are not aware. The inevitable existence of such unknowns mean we often see unexpected indirect effects of our interventions.

EXAMPLES
- A powerful social grouping operating in a policy area not anticipated by a policy maker.
- An undiscovered plant in a rainforest with numerous potential health applications.

LEARNING POINTS
- Expect the unexpected.
- Be prepared to learn as the system unfolds it will become apparent that it might influence or be influenced by completely unexpected things.
- A new technology might enable a fundamental change, leading to widespread social effects.

14. Distributed control

Control of a system is distributed amongst many actors. No one actor has total control. Each actor may only have access to local information.

EXAMPLES
- A smoking cessation intervention's success may be determined by the many health professionals 'on the ground' running events and offering advice, rather than the central agency.
- Political parties' local groups and government may have differing views to the central parliamentary party. The central and distributed groups may conduct poltical work in contradictory ways.

LEARNING POINTS
- There is no top down control in complex systems. Decisions and reactions happen locally and the interactions of all these lower-level decisions can give us system-level properties such as stability, resilience, adaptation or whole system emergent regulation.
- The best we can do is to "steer" the system.

15. Nested systems

Complex systems are often nested hierarchies of complex systems (so-called 'systems of systems').

EXAMPLES
- Brain -> person -> society -> planet
- An ecosystem is made up of organisms, made up of cells, made up of organelles which were once free-living bacteria, made up of complex metabolic processes intertwined with genetic systems (each nested level is a complex system).

LEARNING POINTS
- When studying a particular system, it is useful to be aware of the larger system of which it is part, or the smaller systems operating within it.
- Mechanisms of change (as in realist evaluation) may be taking place at a higher or lower level to the one where an intervention is taking place.

16. Multiple scales and levels

Actors and interactions in complex systems can operate across scales and levels. For this reason systems must be studied and understood from multiple perspectives simultaneously.

EXAMPLES
- Health issues can be considered at the scale of the individual physiology or behaviour, the household, community, society (social norms) or nation (economy, health system). Usually more than one domain is required to fully understand a problem.

LEARNING POINTS
- Tackling obesity requires thinking about individuals' eating habits and activity, but also social norms, economic factors and even town planning. No one level is sufficient. • We need to think broadly about systems at multiple scales and fields as properties or dynamics of one scale often feed up or down to affect others domains.

Over restaurant

×

Beoordelingen Info

Hans

Zaterdag, 23 November 2019

Eten ★★☆☆☆

Bezorging ★★★★☆

De friet was heel hard. Veel friet weg gegooid.

Anoniem

Dinsdag, 19 November 2019

Eten ★★★☆☆

Bezorging ★☆☆☆☆

Eten was lauw en 45 minuten te laat

Anoniem

Dinsdag, 19 November 2019

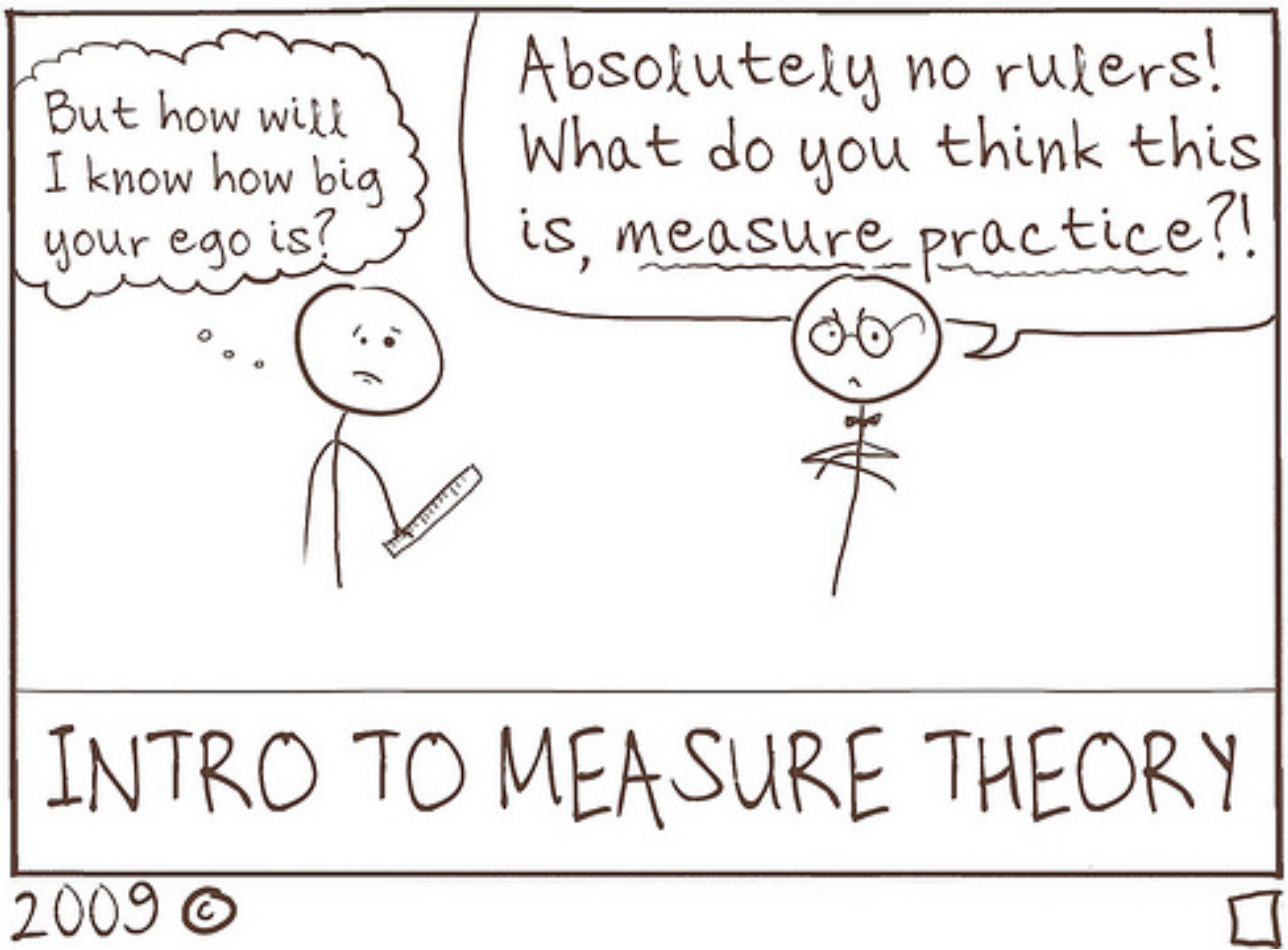
Eten ★☆☆☆☆

Bezorging ★☆☆☆☆

Veel te laat bezorgd, niet erg smakelijk, en die nacht en volgende dag, de hele familie uitgeschakeld door voedselvergiftiging!

** Deze bestelling werd geplaatst op een zondag. Bezorgtijden zijn dan meestal wat langer wegens drukte.*

some measure(ment) problems with EMA / ESM data



http://brownsharpie.courtneygibbons.org/comic/measure-theory-2/

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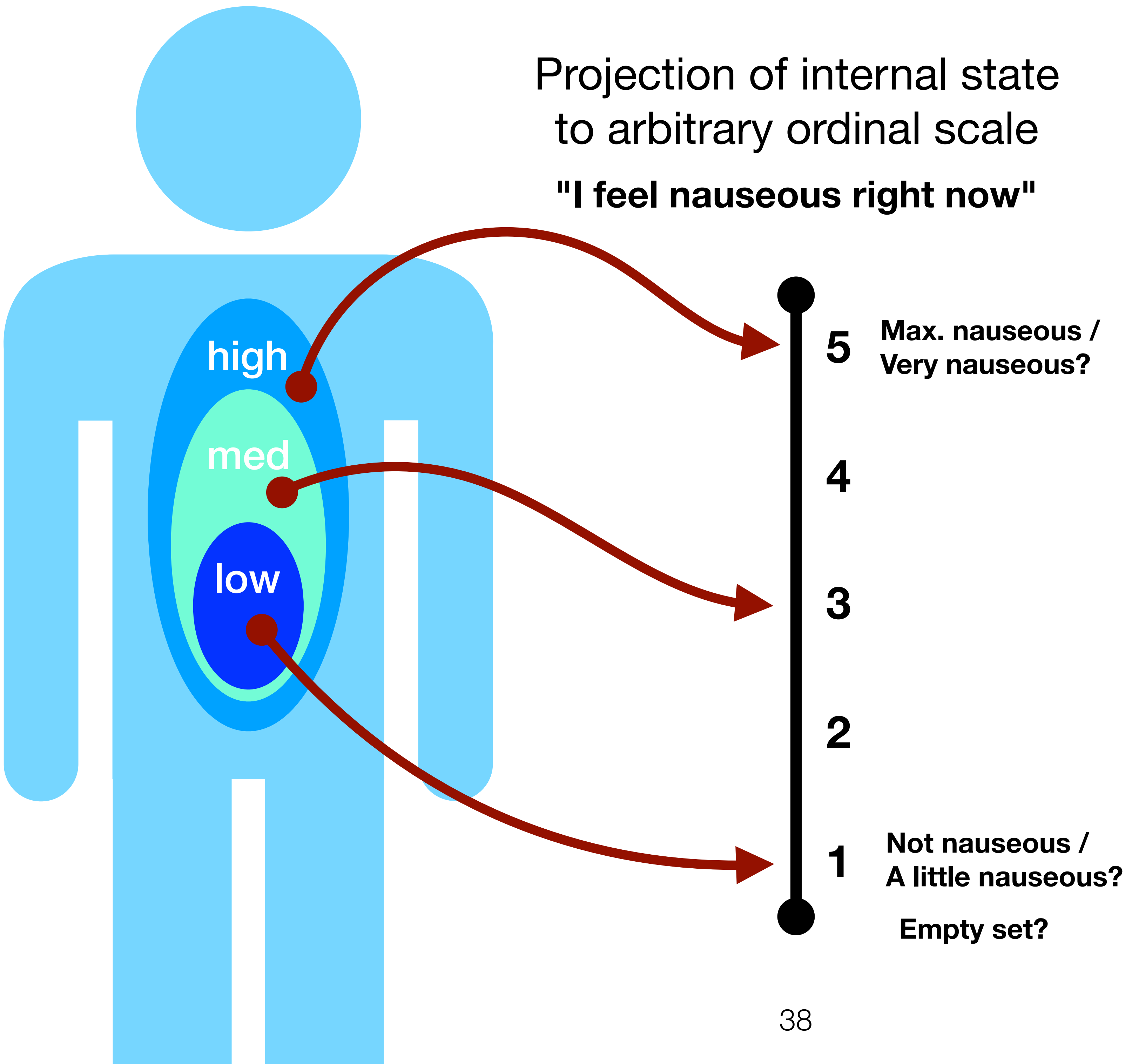

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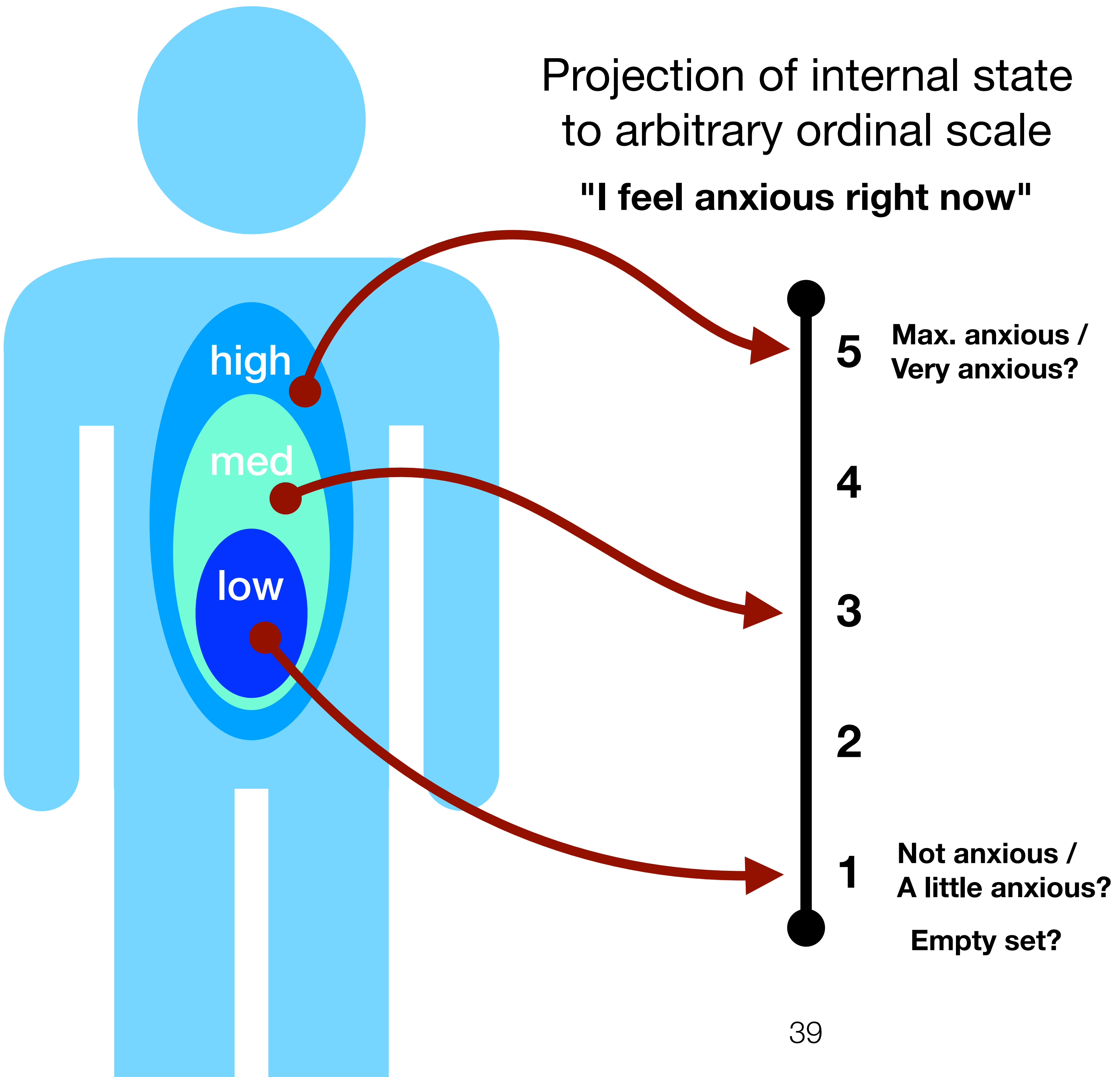

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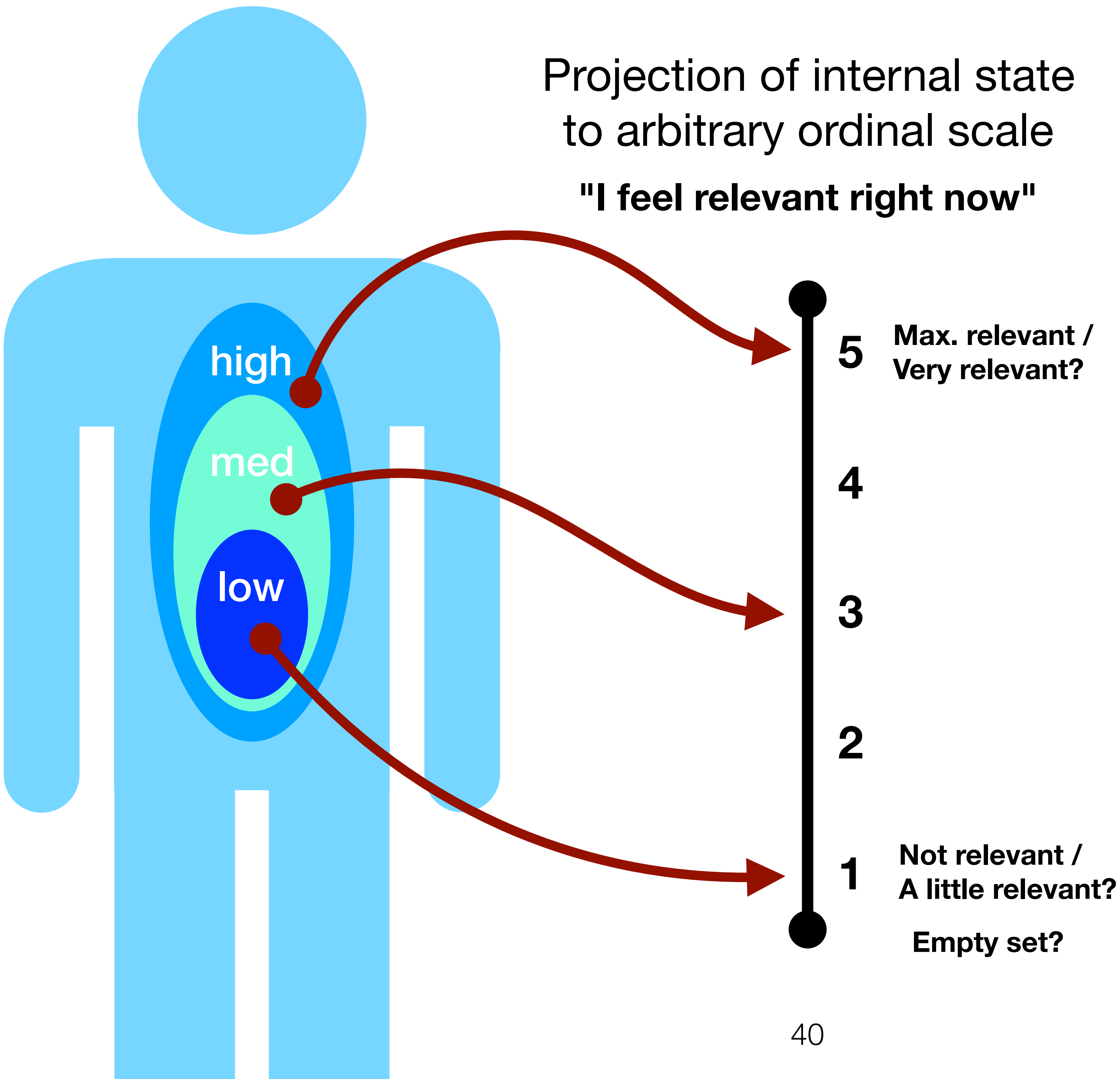
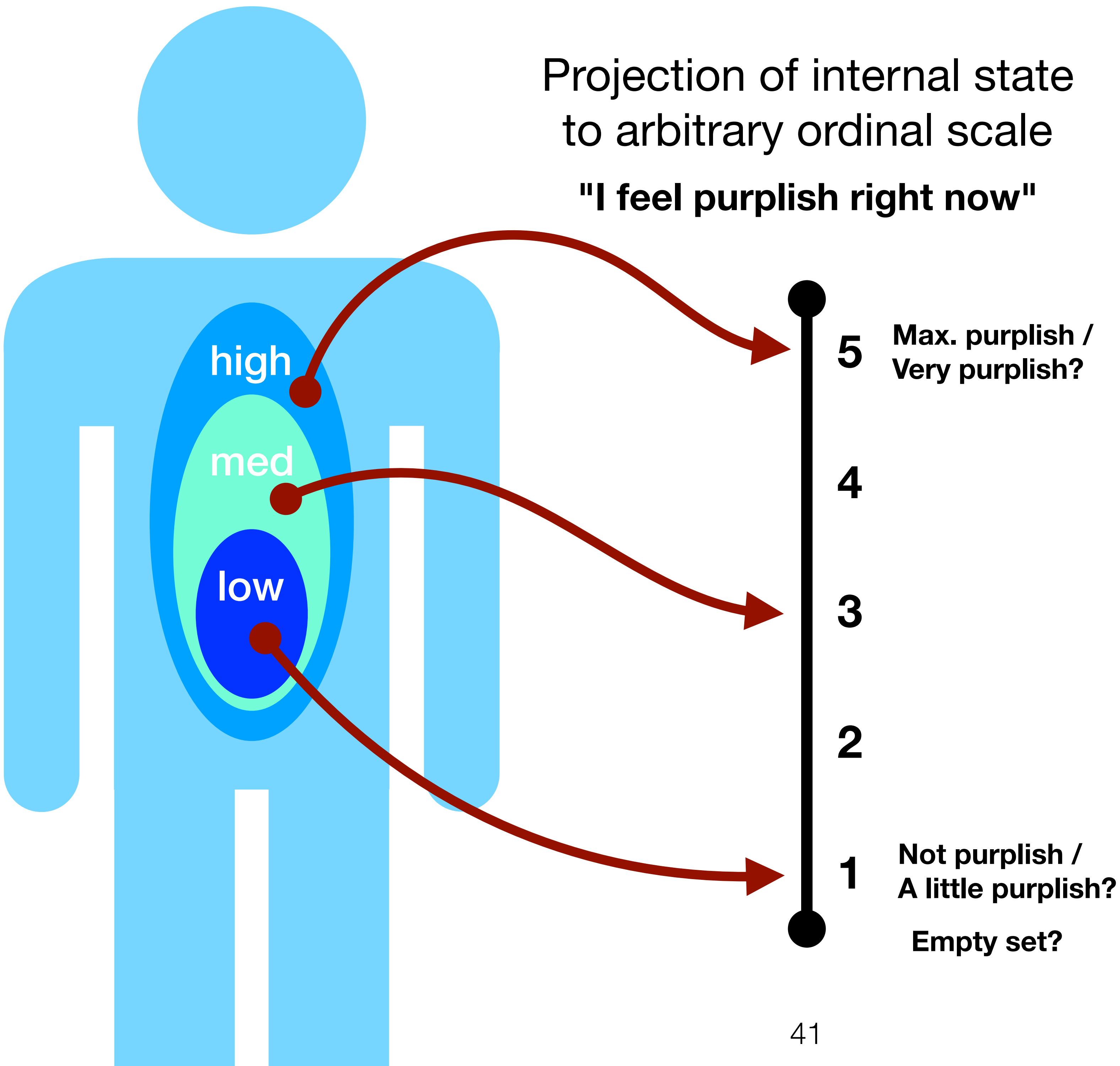


some measure(ment) problems with EMA / ESM data

Projection of internal state to arbitrary ordinal scale

"I feel purplish right now"



Projection function will change 'intra-individual':

- Interactions (experienced events)
- Remembering / Forgetting
- Across different observables
- Projected onto linear transform of ordinal scale
- ...

Projection function will be different 'inter-individual':

- Because different people have different interaction biographies
- ...

Measurement = Interaction?

Lack of a clear notion of how to incorporate the measurement context and the act of measurement of psychological variables into the description of a phenomenon.

some measure(ment) problems with EMA / ESM data

Projection of external state
through internal state
to arbitrary ordinal scale

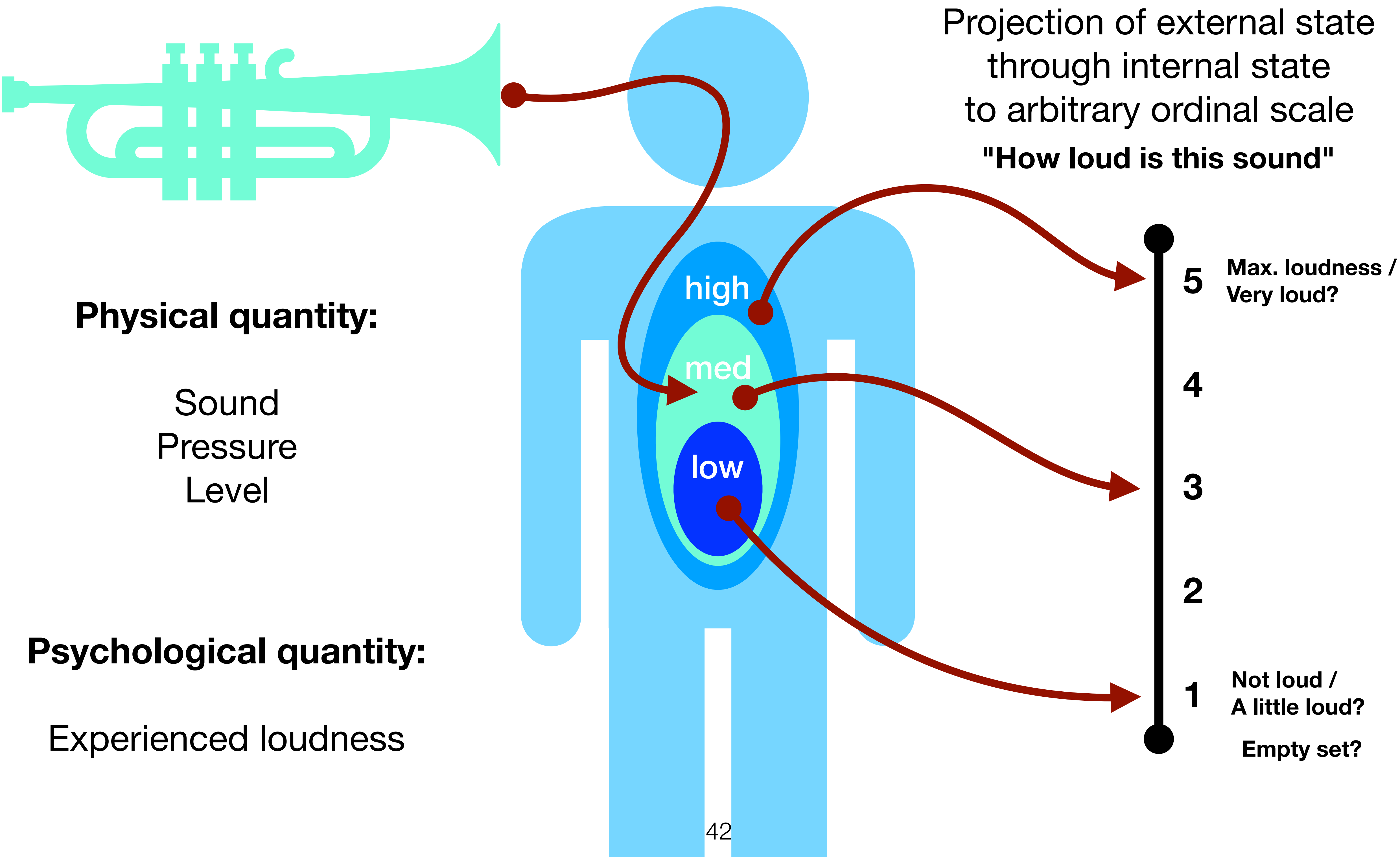
"How loud is this sound"

Physical quantity:

Sound
Pressure
Level

Psychological quantity:

Experienced loudness



some measure(ment) problems with EMA / ESM data

Chapter 1

MEASUREMENT, SCALING, AND PSYCHOPHYSICS

R. Duncan Luce, *Harvard University*

Carol L. Krumhansl, *Cornell University*

Possible Relations to Measurement Theory

Clearly, psychophysicists doing global experiments, whether they use partition or magnitude methods, are in a sense measuring something. We may therefore ask: do their data satisfy any of the axiomatic theories of measurement and, if so, does the structure of the scales that result mesh with the highly structured family of scales from physics?

Luce, R. D., & Krumhansl, C. L. (1988). Measurement, scaling, and psychophysics. *Stevens' handbook of experimental psychology*, *1*, 3-74.

scales of physics. One cannot but be concerned by the demonstration (King & Lockhead, 1981) that the exponents can easily be shifted by as much as a factor of 3 and by the earlier data that the exponents are affected by a variety of experimental manipulations (Poulton, 1968). Clearly, much more work, using the data from individual subjects, is needed before we will be able to develop any clear picture of the structure of psychophysical scales.

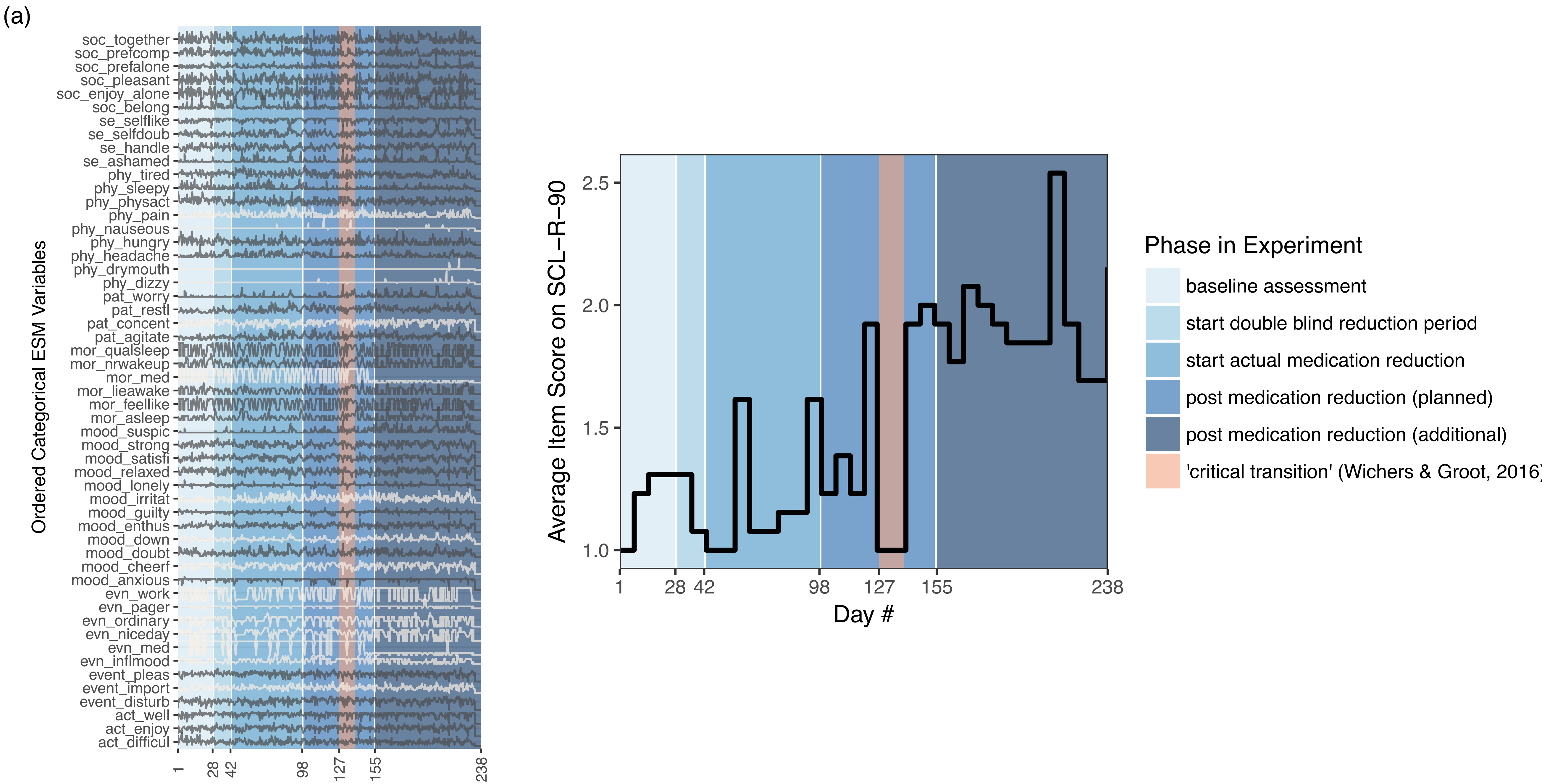
ACKNOWLEDGMENTS

We have had useful comments on drafts from N.H. Anderson, P. Arabie, J.C. Baird, and two anonymous readers. Although we have modified the text as a result of these comments, we are of course solely responsible for what is said.

REFERENCES

Aczél, J. (1966). *Lectures on functional equations and their applications*. New York: Academic Press.

“Critical Slowing Down as a Personalized Early Warning Signal for Depression”



Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. Psychotherapy and psychosomatics, 85(2), 114-116. DOI: 10.1159/000441458

Kossakowski, J., Groot, P., Haslbeck, J., Borsboom, D., and Wichers, M. (2017). Data from ‘critical slowing down as a personalized early warning signal for depression’. Journal of Open Psychology Data, 5(1).

Rank Version of von Neumann's Ratio Test for Randomness

Kwiatkowski–Phillips–Schmidt–Shin (KPSS)

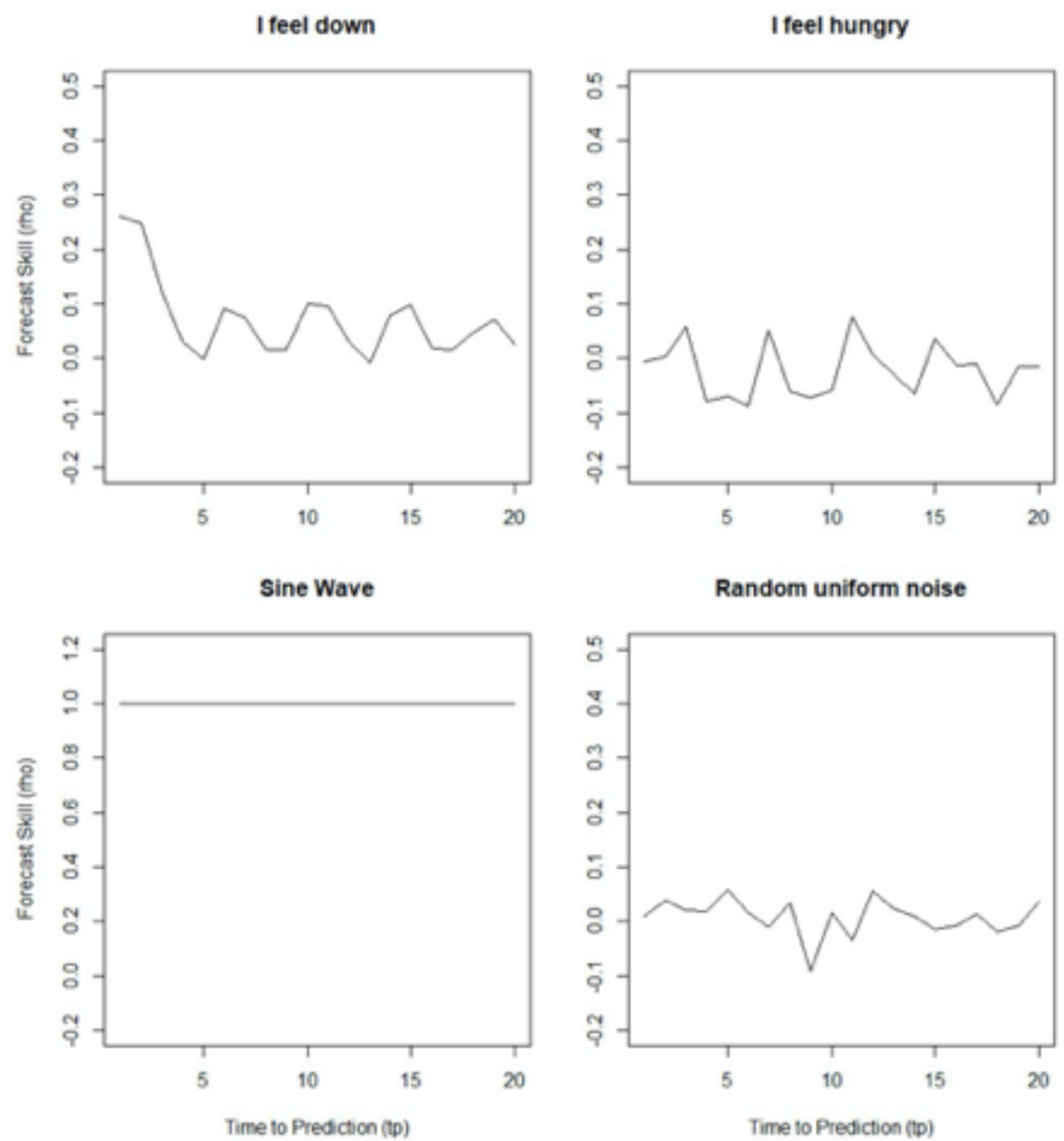
	Bartels rank test H0 = Random H1 = Non-random		**KPSS test H0 = Level Stationary H1 = Unit root**		**KPSS test H0 = Trend Stationary H1 = Unit root**		**Significant partial autocorrelations**	
Item	*All data*	*Subset*	*All data*	*Subset*	*All data*	*Subset*	*Lag 2-99*	*Lag 100-1000*
I feel relaxed	<.001*	<.001*	0.092	0.046	0.036	0.021	2	6
I feel down	<.001*	<.001*	<.010*	0.100	0.100	0.100	8	8
I feel irritated	<.001*	<.001*	<.010*	0.052	<.010*	0.100	5	7
I feel satisfied	<.001*	<.001*	0.100	0.019	0.100	0.098	2	4
I feel lonely	<.001*	<.001*	<.010*	0.100	0.100	0.100	5	9
I feel anxious	<.001*	<.001*	<.010*	0.100	0.100	0.100	8	11
I feel enthusiastic	<.001*	<.001*	0.100	0.100	0.100	0.100	4	6
I feel suspicious	<.001*	<.001*	<.010*	0.061	0.041	0.027	9	9
I feel cheerful	<.001*	<.001*	0.100	0.059	0.100	0.046	4	6
I feel guilty	<.001*	<.001*	<.010*	<.010*	0.094	0.100	7	7
I feel indecisive	<.001*	<.001*	0.100	<.010*	0.050	0.100	7	7
I feel strong	<.001*	<.001*	0.100	0.021	0.100	0.100	6	6
I feel restless	<.001*	<.001*	<.010*	0.070	<.010*	0.075	11	4
I feel agitated	<.001*	<.001*	<.010*	0.100	<.010*	0.100	6	5
I worry	<.001*	<.001*	<.010*	0.100	0.100	0.100	10	11
I can concentrate well	<.001*	<.001*	<.010*	<.010*	0.100	0.100	4	8
I like myself	<.001*	<.001*	0.100	<.010*	0.082	0.100	5	5
I am ashamed of myself	<.001*	<.001*	<.010*	0.100	0.100	0.100	8	6
I doubt myself	<.001*	<.001*	0.048	0.100	0.093	0.100	7	5
I can handle anything	<.001*	<.001*	0.055	0.047	0.100	0.100	4	8
I am hungry	0.068	0.068	<.010*	0.020	<.010*	0.049	6	2
I am tired	<.001*	<.001*	<.010*	0.100	0.079	0.978	11	5
I am in pain	<.001*	<.001*	0.100	0.024	<.010*	0.100	4	2
I feel dizzy	0.854		<.010*		0.050		6	7
I have a dry mouth	0.958		0.029		0.042		1	8
I feel nauseous	0.854		0.100		0.100		4	9
I have a headache	<.001*	0.8544	0.018	0.020	<.010*	0.100	7	4
I am sleepy	<.001*	0.958	<.010*	0.011	<.010*	0.100	7	4
From the last beep onwards I was physically active	<.001*	0.854	<.010*	0.100	<.010*	0.100	3	3
Sum of significant tests (%)	25 (86%)	22 (85%)	16 (55%)	4 (15%)	8 (28%)	0 (0%)		

Note.

N = 1476 for all data. N = 292 for the subset **[= START ACTUAL REDUCTION]**.

* indicates statistically significant test statistics. For Bartels rank test, results were considered significant for *p*<.002. The KPSS test only provides *p*-values in between .01 and .10. For the KPSS test, *p*<.010 was considered significant. Three items showed no variance during the baseline period included in the subset and were therefore omitted from analysis of the subset.

State Space Reconstruction (False Nearest Neighbour Analysis): Forecast skill / Prediction horizon

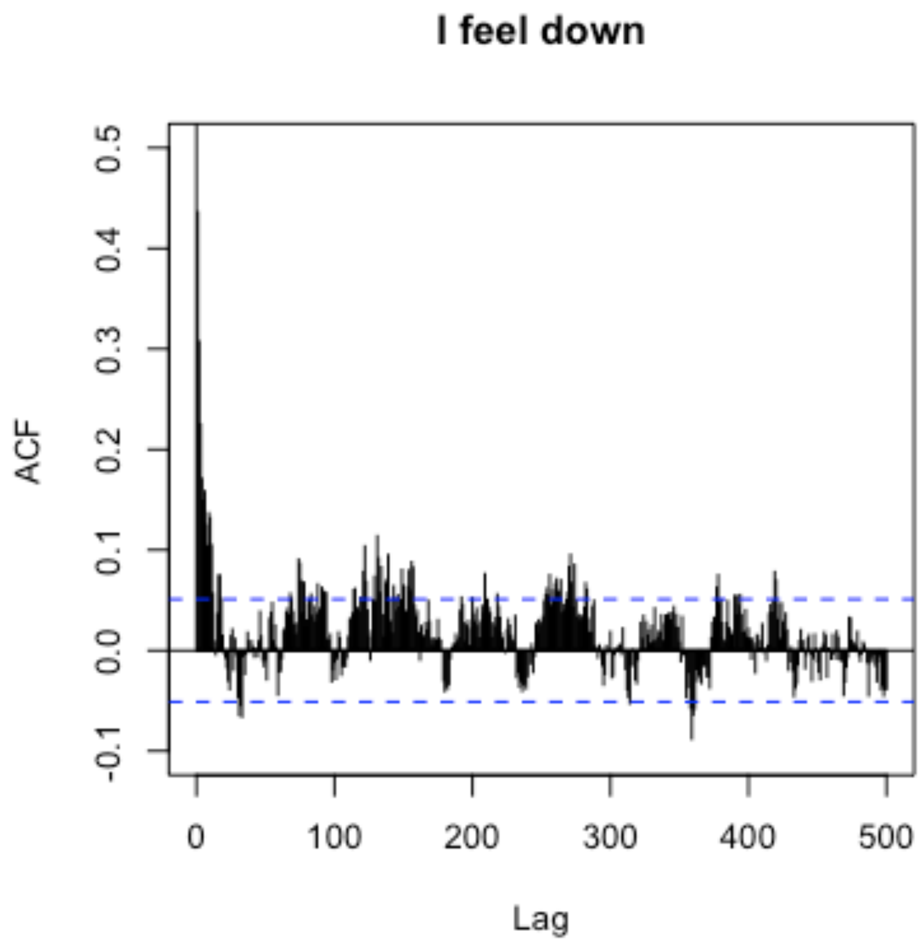


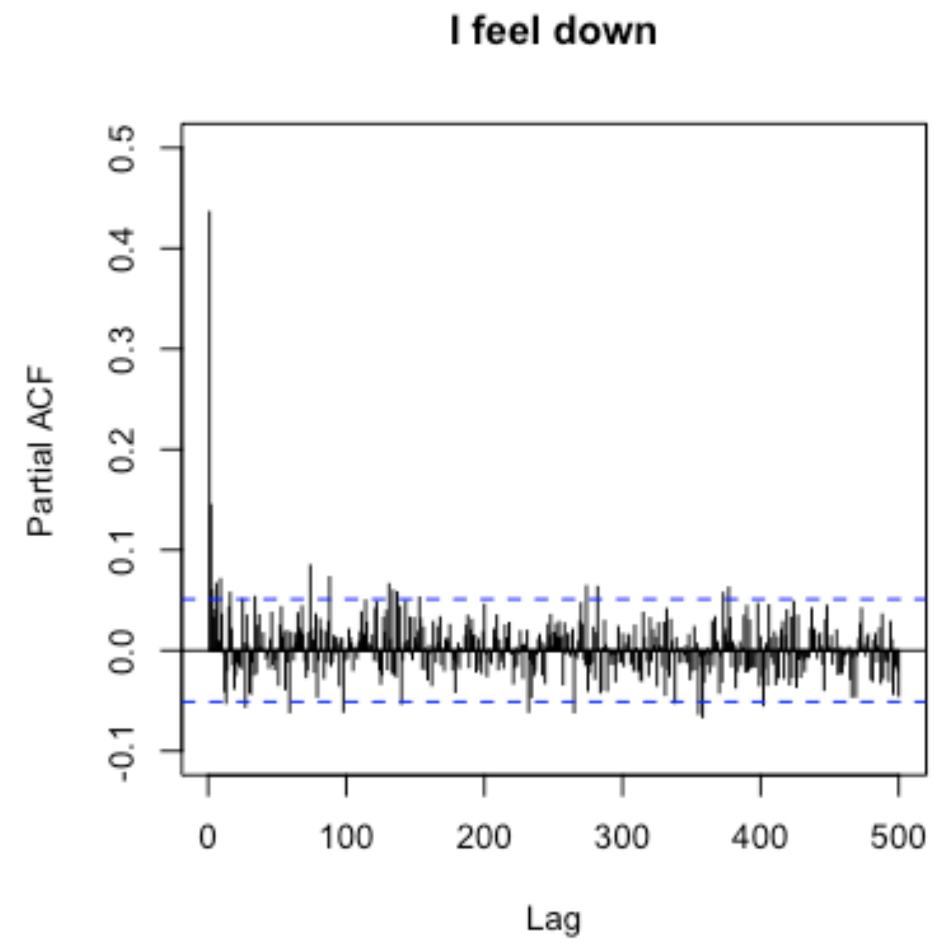
"I feel down"
has a forecast skill
with ± lag 5
(prediction horizon)

"I feel hungry"
has no forecast skill

Sine wave
has a perfect forecast skill

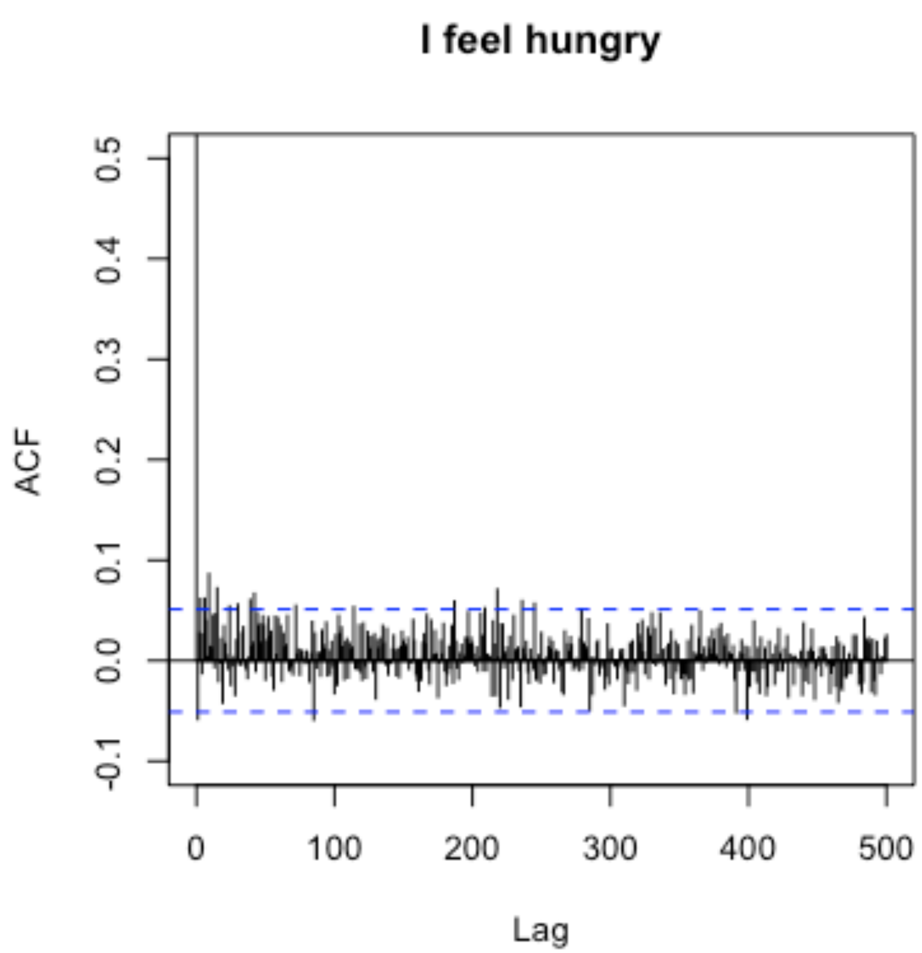
Random noise
has no forecast skill

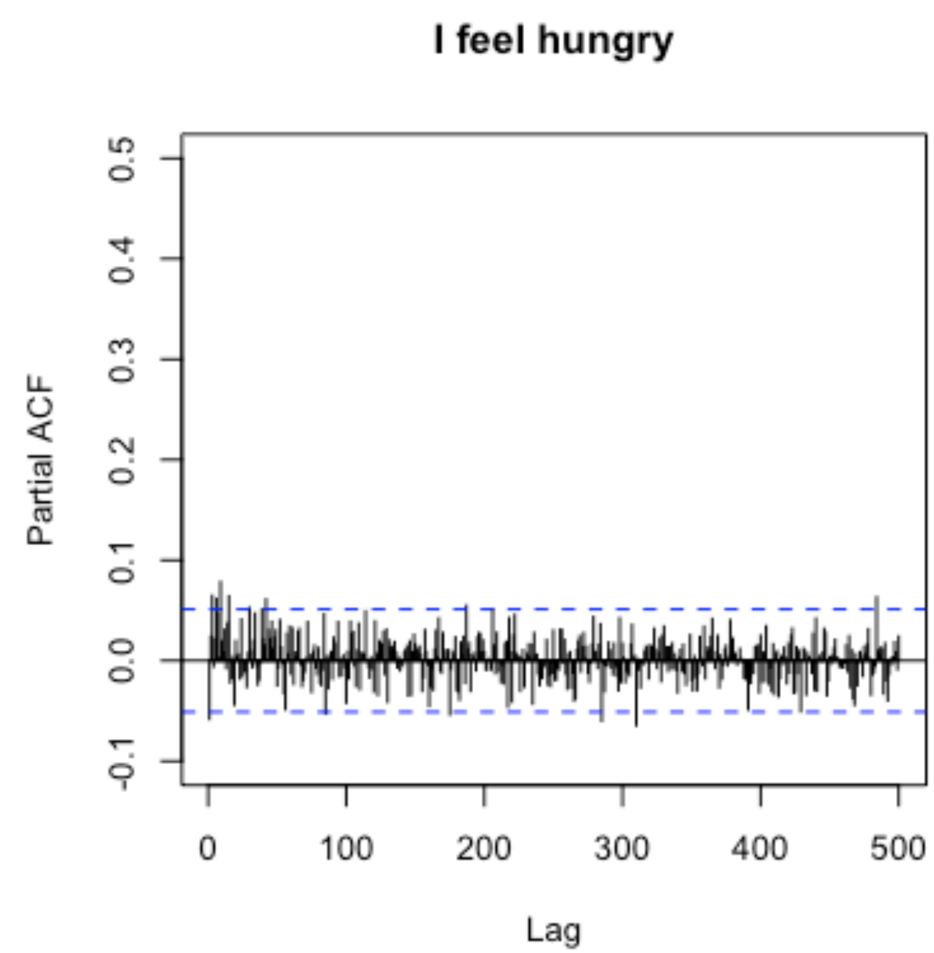




Questions abt. *mental internal states* like ***mood*** resemble non-ergodic processes:

- long memory
- non-stationary
- non-homogeneous
- non-stationary ACF





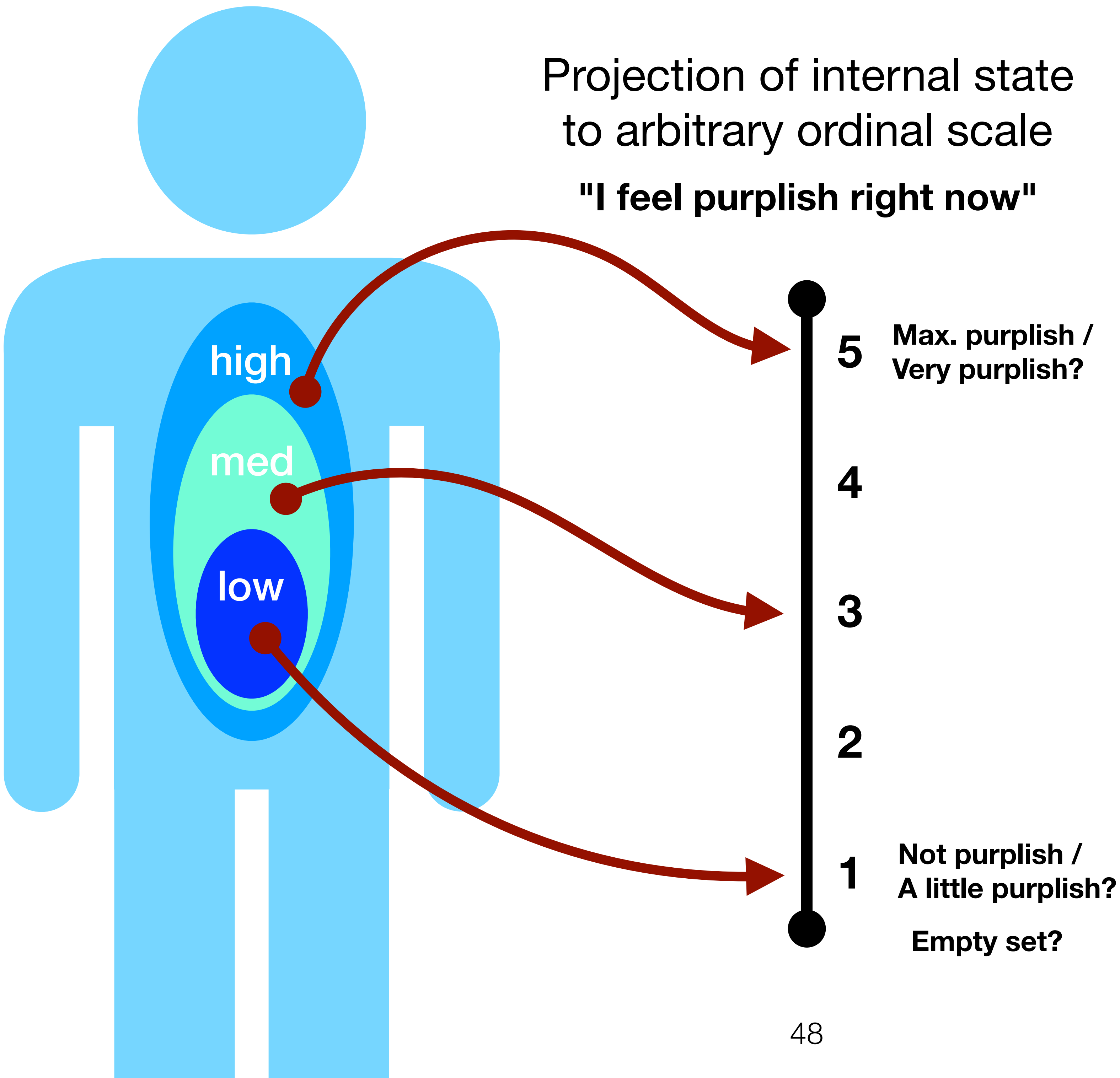
Questions abt. *physical internal states* like ***hunger*** resemble ergodic processes:

- no long memory
- stationary
- homogeneous
- stationary ACF

some measure(ment) problems with EMA / ESM data

Projection of internal state to arbitrary ordinal scale

"I feel purplish right now"



Physiological internal states are less perturbed by the act of measurement:

Current level of hunger does not really depend on the answer from yesterday or last week, it may be affected by events/disease

Measurement = Interaction?
Lack of a clear notion of how to incorporate the measurement context and the act of measurement of psychological variables into the description of a phenomenon.

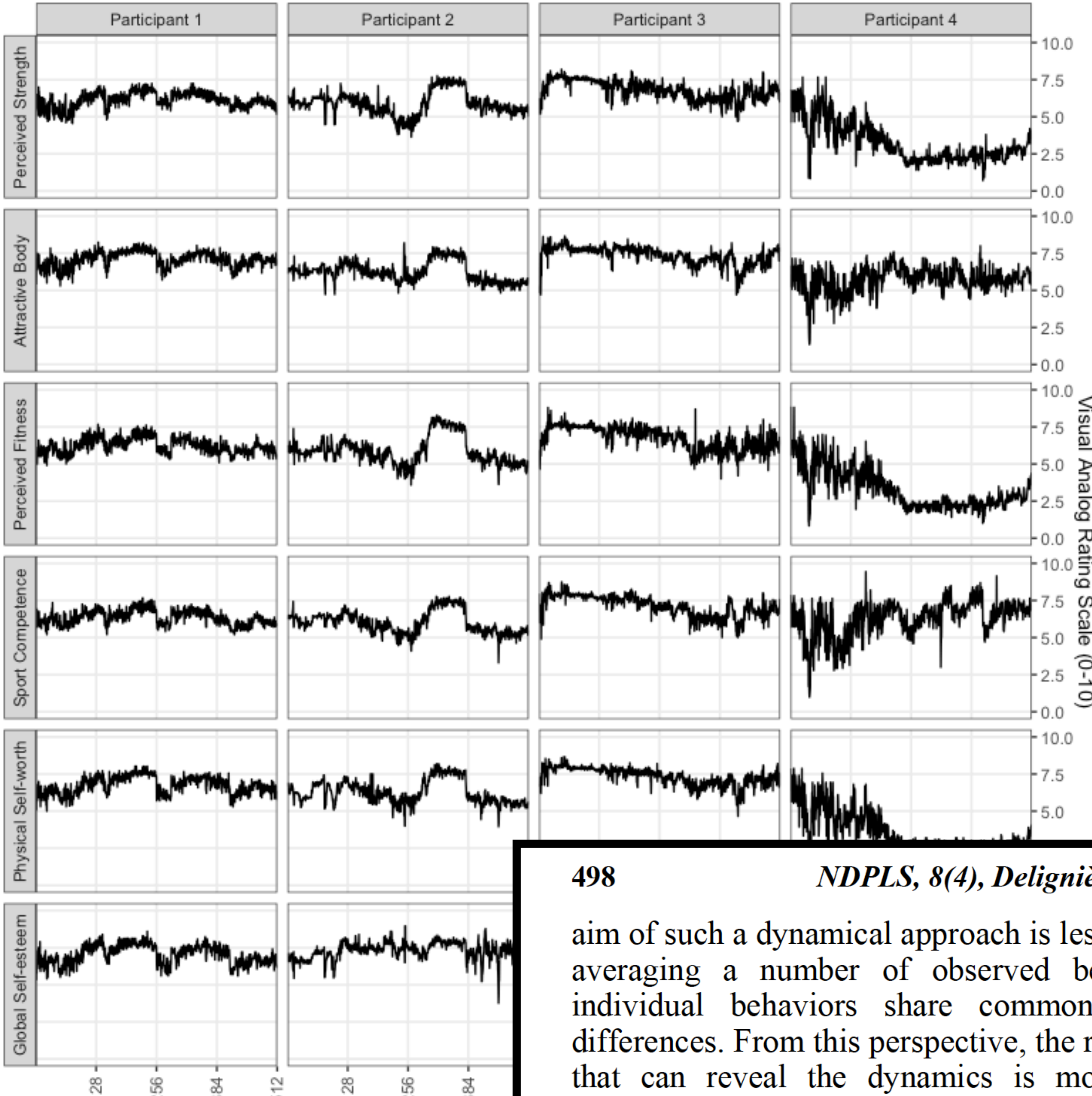
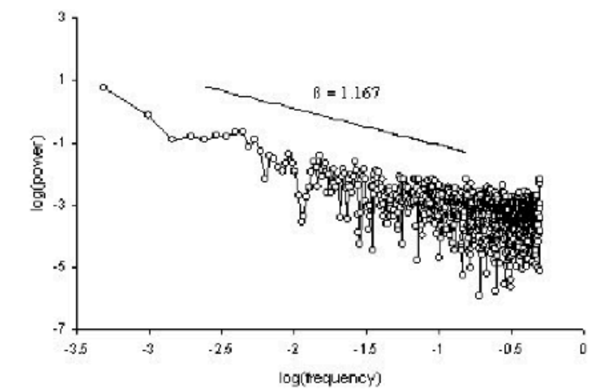


Table 2. Individual Moving Average Coefficients (θ) Obtained through ARIMA Modeling.

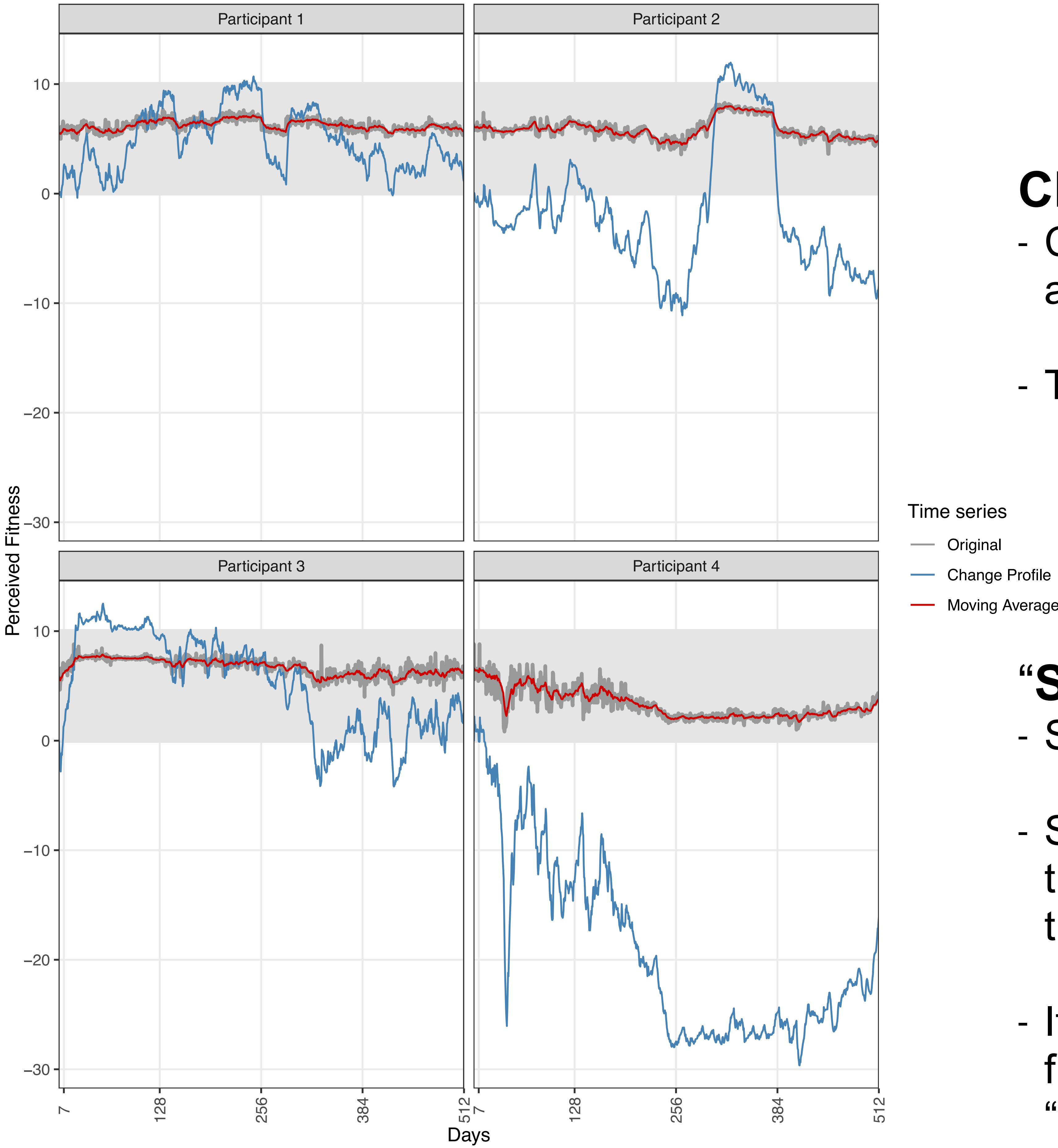
Participant	GSE	PSW	PC	SC	APP	PS
1	0.58	0.65	0.70	0.66	0.63	0.69
2	0.35	0.46	0.48	0.50	0.45	0.46
3	0.58	0.65	0.75	0.63	0.56	0.68
4	0.66	0.56	0.60	0.59	0.64	0.53

Table 3. Individual ß Exponents Obtained with Spectral Analysis.

Participant	GSE	PSW	PC	SC	APP	PS
1	1.17	1.15	0.95	1.00	1.15	0.95
2	1.13	1.39	1.36	1.24	1.27	1.23
3	1.09	1.05	0.96	1.34	1.12	1.11
4	0.96	1.14	1.02	1.18	0.95	1.05



aim of such a dynamical approach is less to derive an epistemic model by averaging a number of observed behaviors than to evidence that individual behaviors share common dynamics, despite superficial differences. From this perspective, the richness of the individual data sets that can reveal the dynamics is more crucial than the number of participants involved in the experiment. Researchers in many fields, for



Change Profiles:

- Center on a moving average in a sliding window
- Take the cumulative sum

"Solves" some concerns:

- Scale is irrelevant/relative
- Small fluctuations are added in the cum. sum but, don't impact the shape of the overall profile
- If present, persistent levels & fluctuation patterns can be "exaggerated" (see y-scale)

What are the interesting phenomena?
What kind of formalism / theory do we need to understand human behaviour?

Epke wanted to win by a combination never before performed on a tournament:

casina - kolman

… but made an “error” in the *casina* movement…

so he <u>decided</u> to follow up with another combination that had never been performed:

casina - kovacks

and won the world-cup anyway!

Epke Zonderland @ world-cup Paris 2011

If this is “just”motor control:

Why didn’t he just continue on auto-pilot?
Why add an untrained manoeuvre?

What are the interesting phenomena?
What kind of formalism / theory do we need to understand human behaviour?

Participants can inspect the randomly scrambled cube for max. 15 seconds.

There are about 43,252,003,274,489,856,000 possible permutations of the cube.

Particpants place the cube on the Stackmat and their hands on the timer area of the Stackmat.

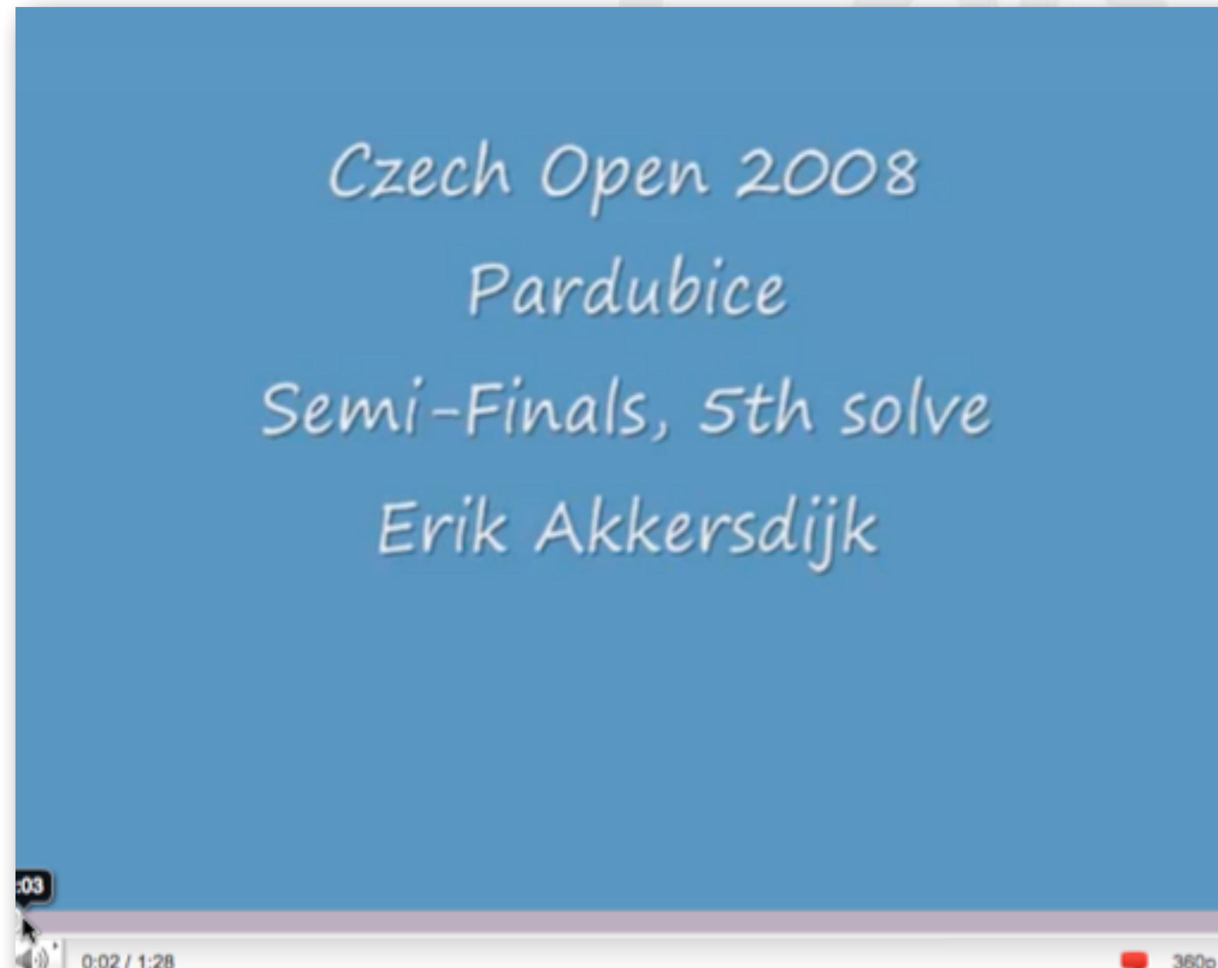
Once their hands leave the timer area, the timer starts.

In the video Erik Akkersdijk, a 19-year old boy from Deventer, the Netherlands, solves the cube in a world record: 7.08 seconds!!

It is currently the European record, the current world record is: 6.24 seconds by 16-year old Feliks Zemdegs of Australia.

The average solving time at speedcubing championships is ±10 seconds

Erik Akkersdijk @ Czec open speedcubing world championships 2008



Is this “just” cognition?

Two Metaphors to explain Human Behaviour

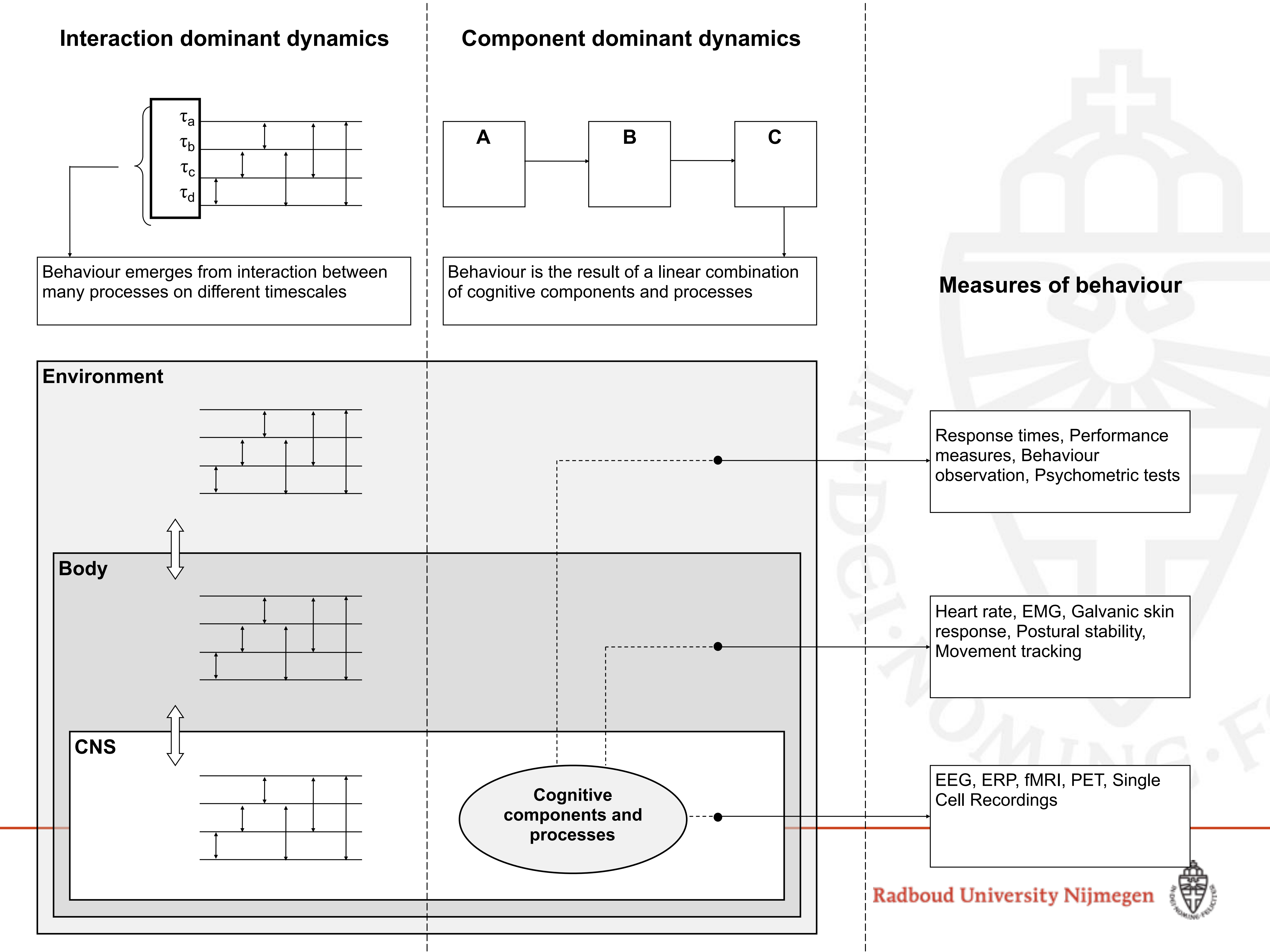
Machine Metaphor

- Parts exist for each other, but not by means of each other
- Parts act together to meet the things purpose, but their actions have nothing to do with the thing's construction
- **Open to efficient cause (predicative logic)**
- Human behaviour: **Computation; Information processing**

- **Organism Metaphor**
- Parts are both causes and effects of the thing, both means and end
- Parts act together but also construct and maintain themselves as a whole
- **Closed to efficient cause (impredicative logic)**
- Human Behaviour: **Concinnity; Embodied and Embedded**

Concinnity: Harmony in the arrangement or interarrangement of parts with respect to a whole.

Adapted from Turvey (2007)


Interaction dominant dynamics
Component dominant dynamics
τ_a
τ_b
τ_c
τ_d
A
B
C
Behaviour emerges from interaction between many processes on different timescales
Behaviour is the result of a linear combination of cognitive components and processes
Measures of behaviour
Environment
Body
CNS
Cognitive components and processes
Response times, Performance measures, Behaviour observation, Psychometric tests
Heart rate, EMG, Galvanic skin response, Postural stability, Movement tracking
EEG, ERP, fMRI, PET, Single Cell Recordings
Radboud University Nijmegen

Two types of Causality:

Snooker

Monocausality - *"Newtons Curse"*

The behaviour of one ball can be causally traced to other balls and the cue (influences on the trajectory are linear and additive):

Behaviour is seen as a a linear arrangement of additive causal components.

Ant Hills

Multicausality

An ant hill emerges out of the local interactions of ants, with each other and their environment… there is no one ant guiding this process:

There is no single cause, all components, processes, events and their interactions are relevant

Two types of Causality:

Snooker

"Newtons Curse"

"… conceptualising causal primacy in terms of a reduction of wholes to parts, where the wholes are causally impotent epiphenomena, i.e. merely aggregates of microphysical constituents." (pp. 38).

van Leeuwen, M. (2009). *Thinking Outside the Box: A Theory of Embodied and Embedded Concepts.* Universal Press, Veenendaal, The Netherlands.

Monocausality - *"Newtonian world view"*

The behaviour of one ball can be causally traced to other balls and the cue (influences on the trajectory are linear and additive):

Behaviour is seen as a a linear arrangement of additive causal components.

Ant Hills

"Holistic world view"

"The whole is more than the sum of its parts"
- Proverb

"We are an endless moving stream in an endless moving stream. "
- Jisho Warner

Multicausality - *"Holistic world view"*

An ant hill emerges out of the local interactions of ants, with each other and their environment… there is no one ant guiding this process:

There is no single cause, all components, processes, events and their interactions are relevant

Two types of mathematical formalism:

Random events / processes
Linear
Efficient causes

component dominant dynamics

The Law of Large Numbers (Bernouiili, 1713) +
The Central Limit Theorem (de Moivre, 1733) +
The Gauss-Markov Theorem (Gauss, 1809) +
Statistics by Intercomparison *(Galton, 1875)* =
Social Physics *(Quetelet, 1840)*

Collectively known as:
The Classical Ergodic Theorems

Molenaar, P.C.M. (2008). On the implications of the classical ergodic theorems: Analysis of developmental processes has to focus on intra individual variation. *Developmental Psychobiology, 50*, 60-69

Random events / processes
Deterministic events / processes
Linear / Nonlinear
Efficient causes / Circular causality

interaction dominant dynamics

Deterministic chaos (Lorenz, 1972)
(complexity, nonlinear dynamics, predictability)

Takens' Theorem (1981)
(phase space reconstruction)

Systems far from thermodynamic equilibrium
(Prigogine, & Stengers, 1984)

SOC / $\frac{1}{f^{\alpha}}$ noise (Bak, 1987)
(self-organized criticality, interdependent measurements)

Fractal geometry (Mandelbrot, 1988)
(self-similarity, scale free behaviour, infinite variance)

Aczel's Anti-Foundation Axiom (1988)
(hyperset theory, circular causality, complexity analysis)

Two types of mathematical formalism for two types of systems

component dominant dynamics

Jakob Bernouiili (1654-1704): [The application of the Law of large numbers in chance theory] *to predict the weather next month or year, predicting the winner of a game which depends partly on psychological and or physical factors or to the investigation of matters which depend on hidden causes, which can interact in a multitude of ways is* ***completely futile!****"* Vervaet (2004)

*A system is **ergodic** iff:*

The average dynamical behaviour of an ensemble of components is reducible to the dynamical behaviour of the components in the ensemble

(dynamical behaviour: change of behaviour over time)

f.i. The developmental trajectory of a cognitive variable of one individual measured from age 1-80 should be the same as measured in 80 different individuals, aged 1-80.

interaction dominant dynamics

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