The Complex Systems Approach to Behavioural Science

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2019

Inhoudsopgave

Course Guide

This is a companion book for a number of courses listed on this website: https://complexity-methods.github.io :

- Research Master Behavioural Science curriculum: **Dynamics of Complex Systems**
- Radboud University Summerschool: **Complexity Methods for Behavioural Science: A toolbox for studying change.**
- Shorter workshops, for example: 2.5 day course in Helsinki 2020

Image from Grip on Complexity

The Complex Systems Approach

Complexity research transcends the boundaries between the classical scientific disciplines and is a hot topic in physics, mathematics, biology, economy as well as psychology and the life sciences. This course will discuss techniques that allow for the study of human behaviour from the perspective of the Complexity Sciences, specifically, the study of complex physical systems that are alive and display complex adaptive behaviour such as learning, development and creativity. Contrary to what the term "complex" might suggest, complexity research is often about finding simple models/explanations that are able to describe a wide range of qualitatively different behavioural phenomena. "Complex" generally refers to the object of study: Complex systems are composed of many constituent parts that interact with one another across many different temporal and spatial scales to generate behaviour at the level of the system as a whole, in complex systems "everything is interacting with everything".

The idea behind many methods for studying the dynamics of complex systems is to exploit the fact that "everything is interacting" and quantify the degree of periodicity, nonlinearity, context sensitivity or resistance to perturbation (resilience) of system behaviour. Applications in the behavioural sciences are very diverse and concern analyses of continuous time or trial series data such as response times, heart rate variability or EEG to assess proficiency of skills, or health and well-being. Complexity methods can also be used for the analysis of categorical data, such as behaviour observation of dyadic interactions (client-therapist, child-caregiver), daily experience sampling, social and symptom networks. The complex systems approach to behavioural science often overlaps with the idiographical approach of "the science of the individual", that is, the goal is not to generalise properties or regularities to universal or statistical laws that hold at the level of infinitely large populations, but to apply general principles and universal laws that govern the adaptive behaviour of all complex systems to a specific case, in a specific context, at a specific moment in time.

The main focus of the course will be hands-on data-analysis. Practical sessions will follow after a lecture session in which a specific technique will be introduced.

We will cover the following topics:

- Theoretical background of phase transitions (self-organised criticality), synchronisation (coupling dynamics) and resilience (resistance to perturbation) in complex dynamical systems and networks.

- Simple models of linear and nonlinear dynamical behaviour (Linear & logistic growth, Predator-Prey dynamics, Deterministic chaos),

- Analysis of (multi-) scale dependence in time and trial series (Entropy, Relative roughness, Standardized Dispersion Analysis, (multi-fractal) Detrended Fluctuation Analysis).

- Quantification of temporal patterns in time and trial series including dyadic interactions (Phase Space Reconstruction, [Cross-] Recurrence Quantification Analysis).

- Dynamical network analyses for univariate (recurrence networks) and multivariate time series (multiplex recurrence networks).

- Using the method of surrogate data analysis (constrained realisations of time series data) to test hypotheses about the nature of the data generating process.

Learning outcomes

After completing a course you will able to:

- Simulate linear, nonlinear and coupled dynamics using simple models.
- Conduct (multi-fractal) Detrended Fluctuation Analysis and related techniques to quantify global and local scaling relations.
- Conduct Recurrence Quantification Analysis and related techniques to quantify temporal patterns, synchronisation and coupling direction.
- Conduct analyses on (multiplex) Recurrence Networks to quantify structure and dynamics of (multivariate) time series.

Naturally the (depth of) topics discussed will be limited by the duration of the course.

Level of participant

- Master
- PhD
- Post-doc
- Professional

For whom are these courses designed?

The courses are designed for all researchers who are interested in acquiring hands-on experience with applying research methods and analytic techniques to study human behaviour from the perspective of Complexity Science. Prior knowledge is not required, some experience using R is recommended.

Admission requirements

During the course we will mostly be using the R statistical software environment. Basic experience with R is highly recommended (e.g. installing packages, calling functions that run analyses, handling and plotting data). We also offer a module for the Jamovi software with which the most basic analyses can be conducted. Using Jamovi does not require any prior knowledge of R, but you will not be able to use more advanced features of certain analyses.

Please bring your own laptop to the course. We will help you to install the necessary open source software, all of which can run on Windows, MacOS and most likely also on common varieties of Unix/Linux. The specifications for your computer are simply this: You need to be able to connect to a wireless network (wifi) and you should be able to install and run R (https://www.r-project.org). In addition, you might want to be able to use RStudio (https://www.rstudio.com) and Jamovi (https://www.jamovi.org).

If you do not have the resources to bring a laptop that meets the required specifications, please let us know in advance so we can try to find an alternative solution.

Literature

Pre-course literature:

It will be helpful to read the following articles before the first day of the course:

- Molenaar, P. C., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. Current directions in psychological science, 18(2), 112-117.
- Kello, C. T., Brown, G. D., Ferrer-i-Cancho, R., Holden, J. G., Linkenkaer-Hansen, K., Rhodes, T., & Van Orden, G. C. (2010). Scaling laws in cognitive sciences. Trends in cognitive sciences, 14(5), 223-232.
- Thelen, E., & Ulrich, B. D. (1991). Hidden skills: A dynamic systems analysis of treadmill stepping during the first year. *Monographs of the Society for Research in Child Devevelopment, 56(1)*, 1-98; discussion 99-104. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/1922136
- Lewis, M. D. (2000). The promise of dynamic systems approaches for an integrated account of human development. Child development, 71(1), 36-43.

Selected chapters from these books will be made available so you can make a personal copy:

- Friedenberg, J. (2009). Dynamical psychology: Complexity, self-organization and mind. ISCE Publishing.
- Kaplan, D., & Glass, L. (2012). Understanding nonlinear dynamics. Springer Science & Business Media.
- Rose, T. (2016). The end of average: How we succeed in a world that values sameness. Penguin UK.

Links to online materials on specific topics will be provided (*Study Materials*) that may provide additional explanation and information about key concepts. These materials are not obligatory, but highly recommended to study at least once.

Notes about this book and the assignments

The texts in the chapters of this book are somewhat of a work in progress, and are intended as a rough introductory guide to accompany the lectures. Sometimes, you will notice a paragraph or chapter rather resembles a set of lecture notes instead of a self-contained text. Do not hesitate to let us know if you think anything is unclear or too far out of context for you to understand.

An essential part of the course are the assignments that are available online and are linked to from the course pages, for example: https://complexity-methods.github.io/courses/helsinki-workshop-2020/day1_2/

The text inside these blocks provides important information about the course, the assignments, or the exam.

The text inside these blocks provides examples, or, information about a topic you should pay close attentiont to and try to understand.

The text inside these blocks provides a note, a comment, or observation.

The content in these blocks are often questions about a topic, or, suggestions about connections between different topics discussed in the book and the assignments. You should decide for yourself if you need to dig deeper to answer the questions or if you want to discuss the content. One way to find an answer or start a discussion is to open a thread in the discussion forum on Blackboard labelled *ThinkBox*.

The content in these blocks is provided as entertainment :)

Schedule

You can find detailed schedules on the course website: https://complexity-methods.github.io/courses/

Some Notes on Using R

You have probably heard many people say they should invest more time and effort to learn to use the R software environment for statistical computing… *and they were right*. However, what they probably meant to say is: "I tried it, but it's so damned complicated, I gave up"… *and they were right*. That is, they were right to note that this is not a point and click tool designed to accommodate any user. It was built for the niche market of scientists who use statistics, but in that segment it's actually the most useful tool I have encountered so far.

New to `R`?

Now that your struggles with getting a grip on `R` are fully acknowledged in advance, let's try to avoid the 'giving up' from happening. Try to follow these steps to get started:

1. **Get `R` and add some user comfort:** Install the latest `R` software *and* install a user interface like RStudio… *It's all free!* An R interface will make some things easier, e.g., searching and installing packages from repositories. R Studio will also add functionality, like git/svn version control, project management and more, like the tools to create html pages like this one (`knitr` and `Rmarkdown`). Another source of user comfort are the `packages`. `R` comes with some basic packages installed, but you'll soon need to fit generalised linear mixture models, or visualise social networks using graph theory and that means you'll be searching for packages that allow you to do such things. A good place to start *package hunting* are the CRAN task view pages.

2. **Learn by running example `code`:** Copy the commands in the `code` blocks you find on this page, or any other tutorial or help files (e.g., Rob Kabacoff's Quick R). Paste them into an `.R` script file in the script (or, source) editor. In R Studio You can run code by pressing `cmd` + `enter` when the cursor is on a single single line, or you can run multiple lines at once by selecting them first. If you get stuck remember that there are expert `R` users who probably have answered your question already when it was posted on a forum. Search for example through the Stack overflow site for questions tagged with `R`)

3. **Examine what happens… when you tell `R` to make something happen:** `R` stores variables (anything from numeric data to functions) in an `Environment`. There are in fact many different environments, but we'll focus on the main workspace for the current `R` session. If you run the command `x <- 1+1`, a variable `x` will appear in the `Environment` with the value `2` assigned to it. Examining what happens in the `Environment` is not the same as examining the output of a statistical analysis. Output in `R` will appear in the `Console` window. Note that in a basic set-up each new `R` session starts with an empty `Environment`. If you need data in another session, you can save the entire `Environment`, or just some selected variables, to a file (`.RData`).

4. **Learn about the properties of `R` objects:** Think of objects as containers designed for specific content. One way to characterize the different objects in `R` is by how picky they are about the content you can assign it. There are objects that hold `character` and `numeric` type data, a `matrix` for numeric data organised in rows and

columns, a `data.frame` is a matrix that allows different data types in columns, and least picky of all is the `list` object. It can carry any other object, you can have a `list` of which item 1 is an entire `data.frame` and item 2 is just a `character` vector of the letter `R`. The most difficult thing to master is how to efficiently work with these objects, how to assign values and query contents.

5. **Avoid repeating yourself:** The `R` language has some amazing properties that allow execution of many repetitive algorithmic operations using just a few lines of code at speeds up to warp 10. Naturally, you'll need to be at least half Vulcan to master these features properly and I catch myself copying code when I shouldn't on a daily basis. The first thing you will struggle with are the `apply` functions. These functions pass the contents of a `list` object to a function. Suppose we need to calculate the means of column variables in 40 different SPSS `.sav` files stored in the folder `DAT`. With the `foreign` package loaded we can execute the following commands:

```
data <- lapply(dir(/DAT/",pattern=".sav$"),read.spss)
out  <- sapply(data,colMeans)
```

The first command applies read.spss to all files with a `.sav` extension found in the folder `/DAT`. It creates a data frame for each file which are all stored as elements of the list `data`. The second line applies the function `colMeans` to each element of `data` and puts the combined results in a matrix with dataset ID as columns (1-40), dataset variables as rows and the calculated column means as cells. This is just the beginning of the `R` magic, wait 'till you learn how to write functions that can create functions.

Getting started with R tutorials

- Tutorials on using **functions**:
  - Quick-R
  - Software Carpentry
  - Nicer Code
  - Advanced R
- Tutorials on using **conditionals** and **for loops**:
  - Quick-R
  - Software Carpentry
  - R-Bloggers
- Tutorials on the **-ply family** of functions: + R-bloggers + Nicer Code + R for Dummies
- **Plotting**, **plotting** and more **plotting**: + A Compendium of Clean Graphs in R + ggplot2 reference + ggplot2 extensions + patchwork, the ultimate ggplot2 extension + The R-graph gallery + Quick-R + Nicer Code
- Tutorial on **Effect Size Confidence Intervals** and more:
  - In this tutorial on estimating Effect Size Confidence Intervals (ESCI) there are a lot of examples on how to use R.
  - It was written as an addendum for a post on the **Open Science Collaboration Blog**, which contains many interesting entries on diverse subjects (like behavioural priming, theoretical amnesia and anonymous peer review)

Not new to R?

If you have been using R for a while, but do not consider yourself a master yet, I recommend learning to use the **tidyverse** packages and the accompanying web-book **R for data scientists**.

- Welcome to the **tidyverse**: + Install the tidyverse + Learn how to use the tidyverse + Learn how to use the tidyverse to do statistics + Learn how to use the tidyverse to create networks + How to make R purrr

Time series analyses in R

In this book you can find some tips on plotting time series (see section **Working with time series in R**) and we will be using package `casnet` as our main tool for analyses. However, if you really want a deep dive into everything related to time series in R be sure to check the CRAN task view on time series: https://cran.r-project.org/web/views/TimeSeries.html

casnet

To install `casnet` you need to have package `devtools` or `remotes` installed and call the following code from the commands line:

```
library(devtools)
devtools::install_github("FredHasselman/casnet", dependencies = TRUE)

# or equivalently
library(devtools)
remotes::install_github("FredHasselman/casnet", dependencies = TRUE)
```

If all goes well this should install the package and all the packages it depends on. If the vignette build fails, don't worry, you can access them through the casnet website under *Articles*.

We used R!

This text was transformed to HTML, PDF en ePUB using bookdown(**?**) in **RStudio**, the graphical user interface of the statistical language **R** (**?**). bookdown makes use of the R version of markdown called Rmarkdown (**?**), together with knitr (**?**) and pandoc.

We'll use some web applications made in Shiny (**?**)

Other R packages used are: DT (**?**), htmlTable (**?**), plyr (**?**), dplyr (**?**),tidyr (**?**), png (**?**), rio (**?**).

Deel I

Introduction

Chapter 1

A Quick Guide to Scientific Rigour

> "Meanwhile our eager-beaver researcher, undismayed by logic-of-science considerations and relying blissfully on the "exactitude" of modern statistical hypothesis-testing, has produced a long publication list and been promoted to a full professorship. In terms of his contribution to the enduring body of psychological knowledge, he has done hardly anything."
>
> —Paul Meehl (**?**, p. 114)

Before we can begin our introduction to the wonderful world of Complex Adaptive Systems and Complex Networks, we briefly discuss the philosophy of science and perspective on the goal of scientific inquiry that is used throughout this book. This will allow us to highlight some differences between the **Complex Systems Approach (CSA)** we propose for the scientific study of human nature and the perspective (implicitly) used in most disciplines of the social and life sciences, we will call the **Machine Metaphor Approach (MMA)**, **Cognitivism**, or, **Computationalism**.

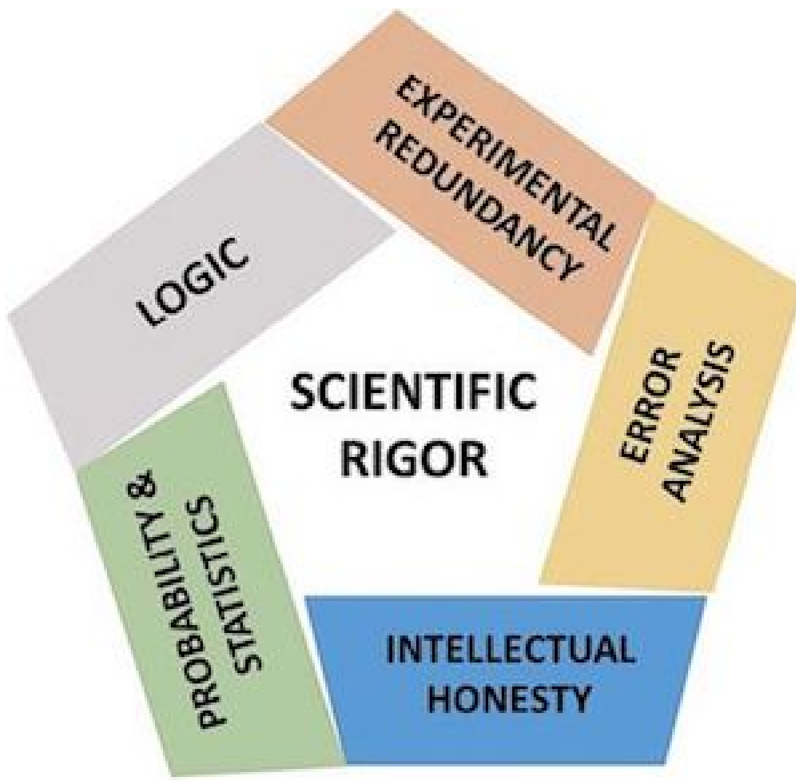
Use of the **scientific method** is what separates scientific, from non-scientific claims about the nature of reality. It consists of all philosophical, theoretical, and empirical tools that can be used to systematically evaluate the veracity of such explanatory claims. The repeated application of the scientific method, to study scientific questions, promises to generate **valid** (accurate) inferences and **reliable** (precise) facts about a certain explanatory domain. It does not guarantee that any kind of absolute 'truth' will be discovered.

The ‘**scientific method song**’ discusses the most important phases of the *empirical cycle*. Be aware that there is also a *theoretical cycle* and a *diagnotsic cycle*.

One factor affecting the perceived veracity of scientific inferences, is the quality of the body of scientific knowledge from which the inferences were deduced, induced or abducted. For example, when a *crisis of confidence* about the trustworthiness of facts in the scientific record generated by some sub disciplines of psychological science was suggested (**?**), the immediate consequence was that the veracity of all claims by psychological science was called into question.

1.1 Rigorous Open Science

Less tangible, but not less important for the perceived veracity of scientific knowledge are concepts such as *intellectual honesty* and *scientific integrity* of the scientists laying explanatory claims on some domain in reality. Merely checking whether the scientific method has been applied does not fully grasp all the prerequisites for generating a solid body of knowledge. We will use the term **rigorous open science** to denote the ideal set of conditions that should be in place to allow us to distinguish scientific claims that are likely to be false, from claims that are likely to be true, given the perceived *verisimilitude* (truth-likeness) of the knowledge accumulated in the scientific record.



Figuur 1.1 – Rigorous Science according to @casadevall2016a.

When a claim is based on **Scientific Rigour** (**?**), we mean it was posited based on the following set of principles:

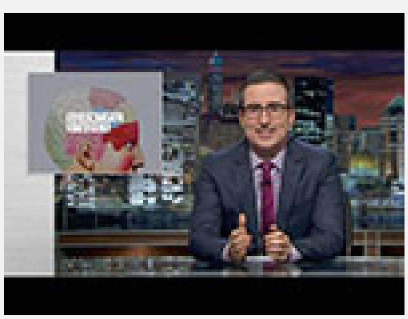
1. **Experimental Redundancy** - The claim has been examined by all methodological and analytical tools that are available and are appropriate given the context. Ri-

gorous Science does not rely on one type of experimental design or one type of statistical analysis.

2. **Recognition of Error** - Without failure there can be no progress, therefore we should carefully study failures and not just report success stories. Any sources of error should be carefully studied and reported to the scientific community.
3. **Sound Probability & Statistics** - Use of the most recent and appropriate statistical theories, models and analytical techniques. Statistical modelling techniques become more realistic over time and often the models that were taught in undergraduate statistics courses have long been replaced and should not be used any more.
4. **Efforts to Avoid Logical Traps** - When generating theories and defining constructs and laws, make sure logical inconsistencies are avoided. When making inferences, avoid the common logical traps such as *The Effect = Structure Fallacy* in null hypothesis significance testing (NHST).
5. **Intellectual Honesty** - Rigorous science is ethical, has integrity and thrives on critical reflection on scientific practice. The right mindset is *"Prove yourself wrong!"*, not *"Prove yourself right!"*

We add to the list that science must be open and transparent. This may seem like an obvious statement to a fresh student of human behaviour, but concepts that make up an essential part of the scientific debate in 2017, such as *open science*, *open data*, *reproducibility*, *Questionable Research Practices (QRPs)*, *Hypothesizing After the Results are Known (HARKing)* and *preregistration*, were practically unknown 5 years ago.

Comedian John Oliver discusses how and why media outlets so often report untrue or incomplete information as science:



Tabel **1.1**

Strong Inference according to @platt1964strong

	Strong inference consists of applying the following steps to every problem in science, formally and explicitly and regularly:
1.	Devising alternative hypotheses
2.	Devising a crucial experiment (or several of them), with alternative possible outcomes, each of which will, as nearly as possible, exclude one or more of the hypotheses
3.	Carrying out the experiment so as to get a clean result
1'	Recycling the procedure, making subhypotheses or sequential hypotheses to refine the possibilities that remain
...	and so on.

Strong Inference

> A difficulty of much psychological theorizing is vagueness in the terms employed. In this work, the above ideas have been studied in mathematical form throughout, the definitions and proofs being given corresponding precision.
>
> —W. R. Ashby in 'The Physical Origin of Adaptation by Trial adn Error' (**?**, p. 13)

The Effect = Structure Fallacy refers to the logical error that occurs a predicted effect is observed (i.e. a statistically significant test result leads to a rejection of the null hypothesis), it is not valid to infer the existence of the assumed cause was evidenced. NHST is based on *the falsification principle*, which means the perceived veracity of a scientific claim will increase only if it has resisted many rigorous attempts to prove it is wrong. If a scientific claim has a large track-record of resisting falsification attempts, we can call it plausible, or high in verisimilitude, but this could all change with one crucial experiment. Contrary to what some scholars suggest, falsifiability is not optional in a rigorous science (**?**).

An excellent recipe for a rigorous application of the scientific method was provided by **?**. Perhaps we should implement it and get us out of the curious situation in which so many different "theories" competing to explain the same pehnomena can be considered to be "true" at the same point in time.

1.2 Theoretical Tunnelvision

> "It is the theory that decides what we may observe"
>
> —Einstein (as quoted by Heisenberg)

Many of the initiatives proposed to improve the social and life sciences focus on improving methodology and statistics. This is understandable, it's where errors are easily made (and discovered) and it allows for relatively simple interventions, e.g. more stringent control on appropriate use of statistics by journals. However, the goal of generating empirical facts is ultimately because we want to find out which scientific claim about the structure of reality best explains why those empirical facts were observed.

The quote attributed to Einstein refers to an important, and grossly underestimated phenomenon one might call the *theoretical tunnelvision*. It is best explained by an example that is commonly encountered in the literature in psychological science and goes something like this:

1. A study tries to find independent causes (predictors) of a certain disease-entity, a pathological state or behavioural mode people can 'get stuck in'.
2. Typically, a statistical model fitted on a large, representative sample of individuals in which many different predictors were measured will yield associations between predictor and disease-entity that are significant but small (on average $r \approx 0.3$, or $\approx 9\%$ explained variance).
3. Often, if other known (non-clinical) covariates are included in a model, or, if the multivariate nature of the phenomenon is taken seriously by including repeated measurements and/or multiple dependent variables, these predictors will no longer explain any unique variance in the outcome measures.

Here's an example of a 'predictor' study (**?**) to find predictors of persistence of Major Depressive Disorder MDD 10 over the course of 10 years in a representative sample of 331 individuals who suffered MDD 10 years earlier:

> "Clinical variables in this analysis were not strongly associated with persistence of MDD over the course of 10 years. Comorbid generalized anxiety disorder, baseline depression severity, and taking a prescription for nerves, anxiety, or depression were significantly associated with persistent depression in the unadjusted logistic regression models, but the associations became non-significant when in the multivariate model. These findings are in contrast to the results from several other studies."

The study concludes by discussing three factors that play a statistically significant role in the persistence of MDD (text between brackets not in original):

- "*having two or more chronic medical conditions [in 1995-1996] contributes to experiencing depression ten years later.* [2.89 more likely] *However, only having one chronic medical condition did not increase the odds of being classified as having MDD in 2004–2006.*"
- "*days of activity limitation in 1995–1996 were significantly associated with a greater risk of depression ten years later,* [2.19 more likely] *independent of the number of chronic medical conditions a person had.*"
- "*Individuals who were in contact with family less than once a week* [in 1995-1996] *were more likely to have MDD in 2004–2006.* [2.07 more likely] *Likewise, people who were married were less likely to have persistent depression compared to those who have never married* [never married 2.42 more likely]"

So? What's wrong?

So what's wrong with these inferences? The study shows some previous assumptions about the relevance of clinical predictors should be reconsidered, and it adds to scientific record some facts about risk factors that might have eluded scientists, clinicians and health professionals. Let's look at the main conclusion of the study, in addition to a plea for more attention for people with two or more chronic medical conditions, **?** end the article with:

> Future research should continue to examine the complex nature of the relationship between chronic medical disorders and comorbid psychiatric conditions. Addressing these conditions and strengthening social support systems could be important strategies for reduce the burden of depression.

Here's what is odd from the perspective of *rigorous science*:

1. If clinical predictors play no role in explaining why some people remain depressed for such long periods of time, why isn't the main conclusion of the study that we must re-appraise the scientific theories laying explanatory claim on the aetiology of MDD? It is from these theories that the diagnostic tools, the medical, and psychological interventions to which these patients have been exposed, were derived.

2. Even though the authors acknowledge –and indeed show– that the propagation of a pathological state like MDD over many years is a very complex multivariate

phenomenon, their suggestion for future research is still based on an implicit assumption about causation that is extremely simple. The idea is that there is a chain of unique (efficient) causes, each contributing independently to the emergence, and persistence in time of the MDD state. The authors basically suggest some component causes have to be added to the aetiology. The metaphor is that of a *machine* of which the sum output of its constituent components is equal to the purpose or function of the machine as a whole. Should a component fail, then it can be repaired or replaced as long as it performs the same function as the defective part, thereby restoring the function of the machine as a whole. This is why the authors suggest that strengthening social support systems could be an intervention to reduce the burden of depression: The absence of a partner or visits by family members were predictors that explained some unique variance in the data on the persistence of MDD. Obviously, restoring this defective social support component should restore or at least facilitate the escape from the MDD state. Meanwhile, they seem to forget that they convincingly argued that MDD is a very complex phenomenon that cannot be dissected into neat, independent component causes.

3. Very much related to the previous point: The authors mention three important factors in the discussion and conclusion section, however, the results section contains another factor that was omitted, it is in fact the second most important predictor of the persistence of MDD:

> "Women had 2.48 the odds of remaining depressed compared to men"

Why did they ignore this predictor in the discussion? This is speculation, but could it be that this factor is not mentioned because it would have to be considered a 'deficient' component and suggesting any kind of 'treatment' intended to 'repair' it is of course beyond the realm of sane things to suggest. Nevertheless, it does seem rather important to figure out why women are 2.5 times more likely than men to still be depressed after 10 years. Perhaps *not* considering gender to be a unique causal component in a chain of *in*dependent predictors might help. Instead, gender could be considered a complex aggregate, or, contextual variable that is associated to the dependent variable through a vast network of *inter*dependent facts, events and states of affair. An obvious factor of importance is that effect-studies of medical interventions are mainly conducted on white, male, 20-30 year old, right-handed, subjects with above average SES. Also, it is likely that on average, the stability of mood over longer periods of time is more variable in women than in men due to fluctuations of hormone levels, but also due to antenatal and postnatal depression (**?**). It does not seem unreasonable to suggest this poses extra challenges for women who want to escape the MDD state.

No such thing as theory-free 'facts'

The analytical tools selected by the researchers (a generalized linear statistical model) restricts the kinds of associations we might observe in the data. In the the present case all associations will –after transformation– be linear compositions of independent components.[1] One never reads this valid equally valid conclusion: "*We conclude that the linear model is inadequate to describe the complexity of this phenomenon.*" The reason is that the implicit assumptions about causality underlying scientific claims never enter the empirical cycle and therefore escape falsification by the repeated application of the scientific method even though those causality assumptions are also based on a scientific theory about the structure of reality that is in principle falsifiable.

[1] Naturally, if one would use mixed models we can account for dependencies in the data, but they will still be limited to linear associations.

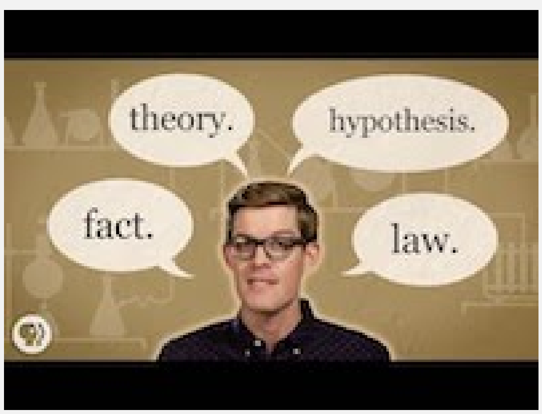
Study Materials

Phenomena, theories, facts and laws

> "All science is either physics or stamp collecting."
>
> —Ernest Rutherford (Physics Nobel Laureate, 1872-1937)

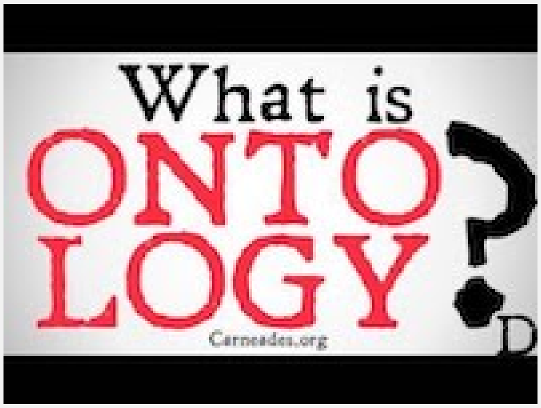
It's important to distinguish between phenomena, hypothesis, theory and law. For example, we will be discussing, nonlinear *phenomena*, catastrophe *theory* and power *law* scaling.

The video is provides a very clear explanation of the differences between these concepts.

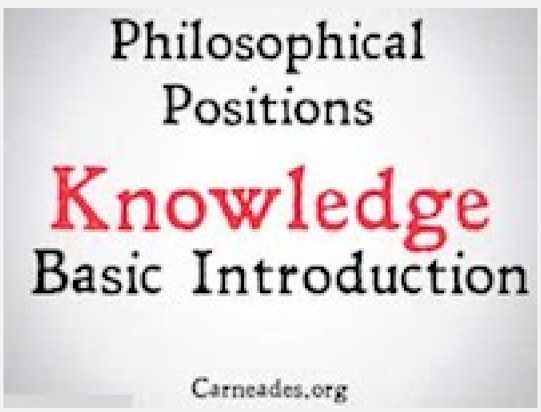


You might also want to refresh your knowledge about some important aspects of scientific theorising about reality: *Ontology* and *Epistomology*

Ontology.



Epistemology



Intellectual Honesty and *Epistemic Responisiblity*:

Epistemic Responsibility


CC
14
conspiracy theories
& EPISTEMIC
RESPONSIBILITY

Chapter 2

Introduction to Complexity Methods

Psychological systems are biological systems which are physical systems that are alive. Therefore, any theory that lays explanatory claim to phenomena of the mind, ultimately must be a theory about how a physical system is able to accumulate non-random order into its internal structure that appears to codetermine its behaviour. Less formally stated, a science that studies the behaviour of physical systems that are alive, that appear to have a memory which makes their behaviour adaptive, future oriented and intelligent, should be grounded in physical and biological principles and laws.

For now, generating such a theory might be a bridge too far (however, see **?**), the least we may demand is that our current theories of human behaviour should *not* contradict highly corroborated theories of physics that describe (constituent components of) simple or complex dynamical systems. This is arguably not the case in current psychological theorising, theories assume internal, highly organised structures (such as mental representations) as causes for behaviour, without explaining where the order came from, or how it is maintained or increased. Well studied and formally defined constructs from other sicentitif disciplines are often imported at a metaphorical level, or are misinterpreted and essentially wrong. For example, *plasticity*, *holism*, *behavioural state/mode/change*, and especially, any concept related to the term *information* (computation, coding/decoding, information processing/storage/retrieval, entropy, etc.). Information is a formally defined quantity that resolves uncertainty about the states or properties of a theoretical object of measurement (e.g. a system, a signal) relative to its degrees of freedom, by assigning it (the uncertainty), a value. If a system represents 1 bit of information (e.g. a coin-toss system), this means it means it can be in 1 of 2 states, or have one of 2 distinct values.

This is clearly not the same as "meaning" with which it is often conflated in theorising about cognition and behaviour. Shannon lucidly explained this in his seminal paper, which was to be the start of a new scientific discipline, information theory:

> "The fundamental problem of communication is that of reproducing at one point either exactly or approximately a message selected at another point. Frequently the messages have *meaning*; that is they refer to or are correlated according to some system with certain physical or *conceptual entities*. These *semantic aspects of communication* are irrelevant to the engineering problem. The significant aspect is that the actual message is one selected from a set of possible messages. The system must be designed to operate for each possible selection, not just the one which will actually be chosen since this is unknown at the time of design."
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> —Shannon (1948, p.379)

2.1 The Complex Systems Approach

The *Complex Systems Approach* to behavioural science departs from the assumption (which is probably not very constroversial) that human behaviour originates from a complex adaptive system.

A *system* is an entity that can be described as a composition of components, according to one or more organizing principles. The organizing prniciples can take many different forms, but essentially they decide three important features of systems that have to do with the relationship between parts and wholes and therefore whether we would call a system complex or not.

In order to find out what kind of system we are dealing with, we can ask three basic questions:

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 of observation, and are there any interactions across the relevant scales of observation that are needed to explain the relevant phenomena?
3. Can interactions with the internal and external environment of a system occur, and if so, do these interactions have any after-effects on the structure and/or behaviour of the system?

If the answer to the first question is "many" and to the second and third "yes" it is very likely we are dealing with a complex dynamical system.

So let's look at some properties of this system that generates human behaviour, it's a system:

- … which has many different constituent parts, and those parts are often also systems with many different constituent parts (the tRNA system, the prefrontal cortex, the respiratory system, the speech system, the endocrine system, the microbiome, etc.).
- … that is *open* and can exchange energy, matter and information with its internal and external environment, as a consequence, dissipating heat (disorder, entropy) back into the environment.
- … which has many different internal states that can have their own specific dynamics, sometimes appearing to be independent of, but oftentimes coupled to, the dynamics of other internal states (emotional states, motivational states, attentional states, physical fitness, general health, biological development, etc.).

- … in which there are many potential levels of organisation and, therefore, potentially many different levels of analysis (cognitive development, cognitive neuroscience, lifespan IQ, socio-cultural differences in IQ, etc.).
- … in which many processes operate on, and, interact across, many different spatial and temporal scales (Studying proficiency at playing chess: social/cultural/pedagogical/genetic contexts, development of social/emotional/motor/cognitive skills, availability/quality of education, motivation, personality, etc.).

So… that's probably a *yes* on complex dynamical system. To be more specific, we can state that most living organisms, including human beings, are **complex adaptive systems with internal state dynamics**.

2.2 Ergodicity and the Measurment Problem

It does not take an expert on *population statistics* to see there is probably a mismatch between the interesting behavioural pehnomena and the analytical toolbox most frequently used to study human behaviour in the social and life sciences. Anyone who took an introductory class in inferential statistics will remember the assumptions of statistical models require observations to be independent of one another, variances to be homogeneous (e.g. Levene's test), and measurement error to be essentially random in nature and normally distributed, not correlated to any other factors that might cause the phenmenon under scrutiny.

Given the nature of the phenomena of interest and the properties of the system under scrutiny, there are two main concerns about the scientific study of human behaviour:

1. The assumption that *the ergodic theorems apply* to the theoretical objects of measurement and data generating processes (**??**): Ensemble averages of variables observed in samples of sufficiently many individuals are expected to be arbitrarily similar to the time averages of variables evolving over a sufficiently long interval of time, from any single initial condition.
2. The assumption that the interpretation of outcomes of psychological measurement is, or should be, equivalent to *classical physical measurement* (**?**): It is considered unproblematic to interpret a measurement outcome as a property of the theoretical object of measurement confounded by some random additive measurement noise or sampling error.

The validity of the assumptions related to ergodicity (i.e. stationarity and homogeneity of central moments) are obviously important for making valid statistical inferences and generalizations. However, even if some of the core assumptions for an ergodic data generating process are formally valid, one cannot rely on parameter estimates to converge on a characteristic expected value within the time scale of observation, or, scale of fluctuation, as is the case when the process samples from a stable distribution with one or more undefined central moments like the Cauchy distribution. This has led some scholars to suggest that "*the very notion of probability may not make sense*" (**?**) when studying complex systems with internal state dynamics.

Recent observations of discrepancies between inferred properties at the ensemble level (inter-individual) and the individual level (intra-individual), have been suggested as a cause of the so-called reproducibility crisis in the social and life sciences (**???**). A study which observed a lack of 'group-to-individual generalizability' in the context of psychopathology described the phenomenon as a threat to human subjects research: "*In clini-*

cal research, diagnostic tests may be systematically biased and our classification systems may be at least partially invalid. In terms of theory development, we may have a misleading impression about the nature of psychological variables and their interactions." (**?**). A study of the neuroanatomical phenotypes of schizophrenia and bi-polar disorder (**?**) concluded: "*This study found that group-level differences disguised biological heterogeneity and interindividual differences among patients with the same diagnosis. This finding suggests that 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.*"

The second concern is about the lack of a clear notion in psychology and the life sciences of how to incorporate the measurement context and the act of measurement into the description of a phenomenon (**?**). Psychological measurement is an interaction between a (prepared) theoretical object of measurement and the elements of the measurement procedure (experimental design, instruments, etc.). The very act of asking someone to project their current internal state of happiness onto an arbitrary ordinal scale will interfere with their "true" state of happiness (if such a thing even exists without the measurement context). There is no "happiness" equivalent for unobtrusive measurement of body temperature using an infrared camera.

Resolutions to these and other problems with psychological measurement have been proposed, for example the various types of conjoint measurement (**??**), or suggestions to adopt concepts from quantum measurement (**??**). However, when measurement and analysis of the temporal evolution of internal states is concerned, problems arise due to the fact that living systems are subject to *ageing* (loss of identity over time) and appear to be able to coordinate their current behavior relative to some record of previously experienced events. In more general terms, the behavior of a complex adaptive system will display after-effects of interactions with its internal or external environment that extend far beyond any timescale that might be understood as a simple stochastic process with autoregressive components. Time series of observables of living systems will often lack the memoryless-ness property (**??**), suggesting anomalous, rather than normal diffusion processes should be considered as a model for the data generating process (**?**).

2.3 Component- vs. Interaction-dominant Dynamics

> In summary, with conventional computing technology we often "torture" the physical substrate so that it implements desired computations (e.g., using continuous electronic processes to implement binary logic), whereas embodied computation "respects the medium," conforming to physical characteristics rather than working against them. The goal in embodied computation is to exploit the physics, not to circumvent it (which is costly)."
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> —Bruce Maclennan (**?**, p.230)

A helpful framework for discussing the differences between a Complex Systems Approach and a Machine Metaphor Approach to the scientific study of human behaviour is to describe the causal ontology used to explain behaviour. Familiar "degrees of causation", or entailment are possible in component dominant dynamics, such as uniquely explained variance, beta weights or effect sizes. In general, a linear arrangement of partial causes always neatly sum up to produce the behaviour of interest. An alternative causal ontology is interaction dominant dynamics in which not the components themselves, but their interactions as a whole are the source of the observed behaviour (Ihlen & Vereijken, 2010; Kello, Beltz, Holden, & Van Orden, 2007; Van Orden, Holden & Turvey, 2003; Van Orden, Holden & Turvey, 2005; Wijnants, Cox, et al., 2012). Here the contribution of components is not additive, but multiplicative and nonlinear (Holden et al., 2009; van Rooij, Nash, Rajaraman, & Holden, 2013). Such interaction dominant dynamics render individual component behaviour (which are still posited to exist), such as poor performance on ability X, impaired representation of that feature Y, as a less interesting object of theoretical and empirical inquiry.

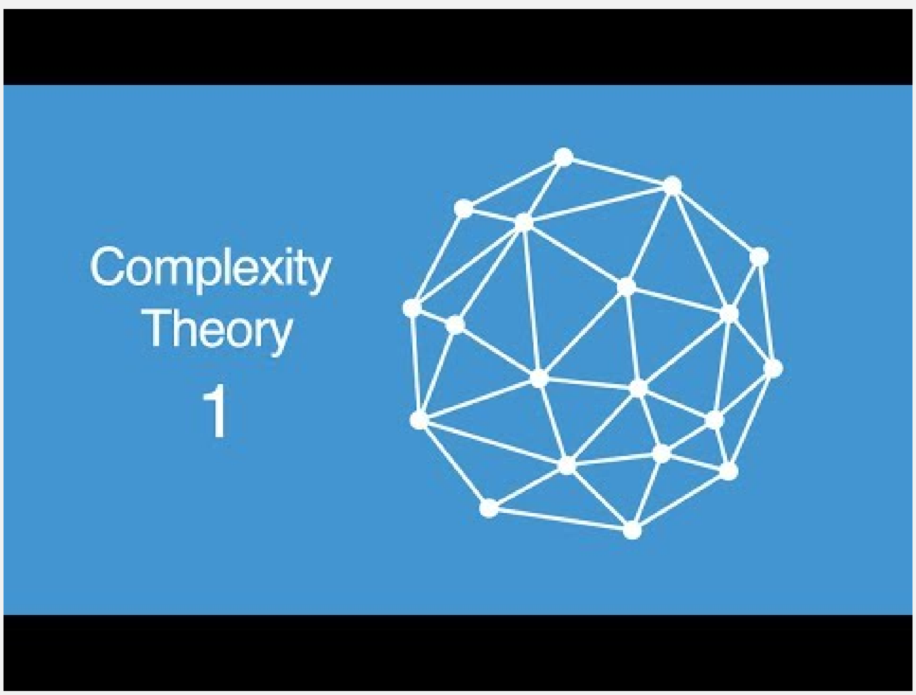
As a consequence, theoretical and empirical inquiry is aimed at identifying and understanding the contexts in which impaired behaviour emerged. Adopting such a perspective entails that all observable behaviour can only be understood relative to the context in which it was observed, that is, the measurement context (cf. Holden, Choi, Amazeen, & Van Orden, 2010; Van Orden, Kello, & Holden, 2010). Figure presents the fundamental differences between the two ontologies in their assumptions about the causes of behaviour and their assumed place of measurement. Figure may reveal why the nature of cognitive components and processes remain elusive in their causal role. They are inferred, not postulated, based on data from different places of measurement. Their causal structure does not incorporate the nested nature of both measurements as well as posited entities. Applying the concept of the complex conditional reveals hierarchical dependencies of one condition on another and such a complex, if it were composed of the correct conditionals, should be considered as a whole. As a consequence, impaired behaviour should be understood as emerging from the whole of constituent components, not from an individual component. The notion of a cause is somewhat more radical than the complex conditionals and is known as impredicative, circular causation (Chemero & Turvey, 2010; Freeman, 1999; Turvey, 2007), or nested causation.

Study Materials and Resources

Systems Innovation videos

The Systems Innovation platform has lots of resources on Complex Systems, Complex Networks and related topics. Their YouTube channel contains a wealth of informative videos.

A working definition of complex systems



Self-organization

The butterfly effect