

Complexity Social Science

Barbara Befani & Corinna Elsenbroich







Everything should be made as simple as possible, but not simpler

> – Albert Einstein (simplest attribution)

What is Social Science?

social science

noun: social science

the scientific study of human society and social relationships.

 a subject within the field of social science, such as economics or politics. plural noun: social sciences

Social Science



Surveys

Interviews

Participant observations

Document analysis





What is complexity?	Relationship Status: Interested in: Looking for: Political Views:	Add another family member Add another family member Single In a Relationship Engaged Married It's Complicated In an Open Relationship Widowed Networking
Complexity /kəm'plɛksəti/ • noun the state or quality of being intricate or complicated. "an issue of great complexity" synonyms: complication, problem, difficulty, twist, turn, convo • a factor involved in a complicated process or situation. plural noun: complexities "the complexities of family life"	Substantian State Stat	

Activity 1



- Why might social science need complexity science?
- Write down 5 reasons

What is complexity?

complexity /kəmˈplɛksəti/ •

noun

 a property of a system (of systems) resulting from the parts and the relationships between system parts.
 Complexity leads to the impossibility to partition the system to analyse parts in isolation.



Heterogeneity

Heterogeneity Relationships

Heterogeneity Relationships Social Influence

Heterogeneity Relationships Social Influence Dynamics

Heterogeneity Relationships Social Influence Dynamics Emergence

Heterogeneity Relationships Social Influence Dynamics Emergence Imergence Create emergency lane immediately in case of traffic jam.

As soon as one thinks "social system" one

enters complexit

Complexity . . .

... it's (not just) complicated!

7. Adaptation	8. Path and path dependency	9. Tipping points 9. Tipping points $ \begin{array}{ccccccccccccccccccccccccccccccccccc$

- Feedback
- Non-linearity
- Emergence
- Change over time
- Adaptation
- Path dependency
- Tipping points

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Run on a Bank (think Mary Poppins) Mobile Phone Uptake Traffic Jam Anything, really. 051 118889 000 (++

Change over Time

Run on a Bank (think Mary Poppins)

Traffic Jam

Anything, really.

Congestion Charge

Mobile Phone Uptake

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The law of causality, I believe, like much that passes muster among philosophers, is a relic of a bygone age, surviving, like the monarchy, only because it is erroneously supposed to do no harm.

– Bertrand Russell

Causality in Complex Systems

- X is a necessary and/or sufficient condition of Y
- If X had not occurred, Y would not have occurred.
- The conditional probability of Y given X is different from the absolute probability of Y (P(YIX) <> P(Y)).
- X appears with a non-zero coefficient in a regression equation predicting the value of Y.
- There is a causal mechanism leading from the occurrence of X to the occurrence of Y.

X is a necessary and or sufficient condition of Y

Ceteris Paribus – all things being equal – but in a complex system there is no way to isolate for ceteris paribus.

If X had not occurred, Y would not have occurred.

Multiple Causes - you don't even have to go complex to recognise multiple causes.

The conditional probability of Y given X is different from the absolute probability of Y (P(Y|X) <> P(Y)).

Spurious altribution.

X appears with a non-zero coefficient in a regression equation predicting the value of Y

Correlation is not causation.

There is a causal mechanism leading from the occurrence of X to the occurrence of Y.

Telling the causal story - but how do we make sure it is the right one?

Complexity Sensitive Social Science Methods

- Qualitative Comparative Analysis (QCA)
- Process Tracing
- Dependency Models/Bayesian Networks
- Agent-Based Modelling

QCA

- Grounded on multiple-conjunctural causality
 - A.k.a. configurational, chemical causation
- Configurations of factors are causally related to outcomes, not single causes
- Even when you can disentangle the effect of a single cause, you can't take it away from its context (the other causes it's combined with)
 - Hence "conjunctural"
- Causal asymmetry: causes can be only necessary, only sufficient, both or neither
 - INUS and SUIN causes

Causal asymmetry, causal diversity

- If you light a match, you need the surface to be dry
 - Fire powder AND dry surface AND the movement = FIRE
- While the above is sufficient, it's not necessary: there are other ways to get fire (hence multiple)
 - Lighter: metal mechanism using flammable liquid (butane)
- INUS: some causes are necessary in a specific context but not in others
 - The movement when you have a match AND the right dry surface
 - Lighters only work with specific liquids
- SUIN: equivalent requirements. Different factors are good enough but one of these is required
 - A dry surface is required, but different types of dry surface do the job

Data organisation and Calibration

CaseID	GOVCON	DIVEQ	GBVLAW	RES	CAM	CAP	NEWPOL	PJCAP
PL140001	1	0	1	1	0	1	1	1
PL140002	1	0	1	0	0	0	0	0
PL140007	1	0	1	0	0	0	0	1
PL140003	1	0	1	0	0	1	0	0
PL140015	1	0	1	1	0	1	1	0
PL140019	1	0	1	0	0	0	0	0
PL140004	1	0	1	0	0	0	0	0
RO20001	0	1	0	1	1	0	1	1
RO20006	0	1	0	0	1	0	0	0
RO20007	0	1	0	0	0	1	0	1
RO200015	0	1	0	0	1	1	0	1
RO20002	0	1	0	0	1	0	0	1
RO20003	0	1	0	0	0	0	0	0
R020010	0	1	0	0	1	0	0	0
BG120013	0	1	1	1	1	1	1	1
BG120022	0	1	1	0	0	1	0	1
BG120020	0	1	1	1	1	1	0	1
BG120016	0	1	1	0	1	1	0	1
BG120005	0	1	1	0	0	1	0	1
BG120018	0	1	1	1	1	1	0	1
SK090020	1	0	0	0	1	1	0	0
SK090013	1	0	0	0	1	1	0	0
SK090009	1	0	0	1	1	1	1	1
SK090008	1	0	0	0	1	1	0	0
SK090010	1	0	0	0	1	1	0	0
SK090004	1	0	0	0	1	1	0	0
SK090025	1	0	0	0	1	1	0	1
SK090014	1	0	0	0	1	1	0	0
EE110005	0	1	1	1	1	1	1	1
EE110006	0	1	1	1	1	1	1	1
EE110002	0	1	1	1	0	0	1	0
EE110001	0	1	1	1	1	1	1	1

Progressive, smart reduction of complexity

Combination

ID	GBVLAW	RES	CAM	CAP	NEWPOL
1	0	0	1	1	0
2	1	1	1	1	С
3	1	0	0	0	0
4	1	0	0	1	0
5	0	0	1	0	0
6	1	1	0	1	1
7	1	1	0	0	1
8	1	0	1	1	0
9	0	1	1	1	1
10	0	1	1	0	1
11	0	0	0	1	0
12	0	0	0	0	0
13	1	1	1	0	?
14	1	0	1	0	?
15	0	1	0	1	?
16	0	1	0	0	?

Minimal combinations

CaseID	GBVLAW	RES	CAM	CAP	NEWPOL
1	-	0	1	1	0
2	1	0	0	-	0
3	0	0	-	0	0
4	1	1	0	-	1
5	0	1	1	-	1
6	0	0	0	-	0

CaseID	GBVLAW	RES	CAM	САР	NEWPOL
1	-	0	-	1	0
2	-	0	0	-	0
3	0	0	-	-	0
4	1	1	0	-	1
5	0	1	1	-	1

The INUS Analysis

CaseID	GBVLAW	RES	CAM	CAP	NEWPOL	
1		0	0	1	1	0
2		1	1	1	1	С
3		1	0	0	0	0
4		1	0	0	1	0
5		0	0	1	0	0
6		1	1	0	1	1
7		1	1	0	0	1
8		1	0	1	1	0
9		0	1	1	1	1
10		0	1	1	0	1
11		0	0	0	1	0
12		0	0	0	0	0
13		1	1	1	0	?
14		1	0	1	0	?
15		0	1	0	1	?
16		0	1	0	0	?

A progressive, smart reduction of complexity

Country	PAF	GWG	AID	EDU	OUT	Country	PAF	GWG	AID	EDU	OUT
Ethiopia	1	1	1	1	1	Ethiopia, Mozambique, Tanzania	1	1	1	1	1
Mozambique	1	1	1	1	1	Burkina Faso, Mali	1	1	1	0	1
Tanzania	1	1	1	1	1	Ghana, Senegal	1	1	0	1	1
Burkina Faso	1	1	1	0	1	Malawi	0	1	1	1	1
Mali	1	1	1	0	1	Niger	1	0	1	0	1
Ghana	1	1	0	1	1	Zambia	1	0	1	1	0
Senegal	1	1	0	1	1	Gambia	0	0	1	1	0
Malawi	0	1	1	1	1	Kenva, Lesotho	0	0	0	1	0
Niger	1	0	1	0	1	Botswana	0	0	0	0	0
Zambia	1	0	1	1	0						
Gambia	0	0	1	1	0						
Kenya	0	0	0	1	0						
Lesotho	0	0	0	1	0						
Botswana	0	0	0	0	0						

OUT = AID*EDU*GWG(5) + AID*edu*PAF(3) + EDU*PAF*GWG(2)

out = AID*EDU*gwg (2) + EDU*gwg*paf (2) + aid*paf*gwg (2)

PAF (Int #1)	GWG (Int #2)	AID	EDU	OUT	# cases covered
	Ð	Ð	Ð	/	5
Ð		Ð	Θ	/	3
Ð	Ð		Ð		2
	e	Ð	Ð	X	2
Θ	e		Ð	X	2
e	e	e		X	2

Generative/Mechanism-Based Causality

- Correlations and associations are not good enough
- Open the "black box" and investigate the "inner workings" that "generate" the effect
- High degree of precision is required
- "Magnifying lens"
- Ideally we want to observe the effect while it is being "caused"
- If not possible, we seek evidence that a specific process took place...

Process Tracing (with Bayesian Updating)

- Grounded on Generative Causality
 - A.k.a. mechanism-based: how and why the outcome occurred, what generated the outcome
 - The mechanism representation can take several forms
 - The whole system, some of the cogs / wheels, a process
- In PT it is often represented as a **process**
 - But that's just because it's easier to apply the method!
- Clear distinction between theory, data, and our levels of confidence
- Rigorous / replicable way of dealing with uncertainty
- Our confidence can be estimated with the **Bayes** formula

Basic elements of Process Tracing with BU

- Theory / mechanism / explanation / statement = ontological object
 - Could be true, could be false. It's usually a statement about how things work
- Our confidence that the theory / statement, etc. is TRUE (or false)
- Two levels of confidence: one before observing empirical data, and one after
 - Prior, Posterior (in Bayes formula the Posterior is a function of the Prior et al.)
- Empirical data / observations
- Organises data into categories, on the basis of two characteristics:
- **Probative value** (strength, weight of evidence);
- Whether data confirms / strengthens or disconfirms / weakens theory

Quali-quanti confidence translator

Practically certain that () is true	0.99+
Reasonably certain that () is true	0.95 – 0.99
Highly confident that () is true	0.85 – 0.95
Cautiously confident that () is true	0.70 – 0.85
More confident than not confident that () is true	0.50 - 0.70
Neither confident nor not confident that () is true (or	0.5
false) – no idea	
More confident than not confident that () is false	0.30 – 0.50
Cautiously confident that () is false	0.15 – 0.30
Highly confident that () is false	0.05 – 0.15
Reasonably certain that () is false	0.01 - 0.05
Practically certain that () is false	Less than 0.01

Process Tracing tests

Three strong tests (with high probative value)

- Smoking Gun
- Hoop Test
- Doubly Decisive
- One weak test (with low probative value)
 - Straw-in-the-Wind
- The Smoking Gun: if observed, it CONFIRMS the theory but, if not observed, does NOT WEAKEN it
- The Hoop Test: if not observed, it WEAKENS the theory but if observed, does NOT CONFIRM it
- The Doubly Decisive: if observed, it confirms; if not observed, it weakens.

Likelihood Ratio = Sensitivity / Type I Error



Type I Error = $(1 - \text{Specificity}) = P(E|^T) = 1 - P(^E|^T)$

Likelihood Ratio = Sensitivity / Type I Error



Relation with the Confusion Matrix

		Reality (ontolog	gical reality)	C.	
		The Contribution Claim (CC) is TRUE	The Contribution Claim (CC) is FALSE		
Evidence (observable reality)	Evidence (E) showing the Contribution Claim (CC) is TRUE Evidence (E) showing the Contribution Claim (CC) is FALSE	True Positive (A)	False Positive (B)	Positive Predictive Value = A / (A + B)	False Discovery Rate = B / A + B)
		False Negative (C)	True Negative (D)	False omission rate = C / (C + D)	Negative Predictive Value = D / (C + D)
		True positives rate = Sensitivity = 1 – Type II error – A / (A + C)	False positives rate = 1 - Specificity = Type I error - B / (B + D)	Likelihood ratio = TPR / FPR = Sensitivity / Type I error	
		False negatives rate = Type II error = 1 – Sensitivity – C / (A + C)	True negatives rate = Specificity = 1 - Type I error - D / (B + D)		



Everyone always says there's nothing worse than the jigsaw with a single piece missing, but a jigsaw that is *really* useless is one that doesn't come in a box. One that hasn't got a picture.

– Inspector Tanner

Getting the Picture

Understanding a system will help to make better policy, even without the possibility of prediction.











Special kind of dependency model



acyclic graph

Agent based Modelling

In the beginning there was nothing . . .



... but then grew the ...



Environment

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... which was populated by ...

Agents

Environment



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... that interacted, exchanging information

Agents

Interactions

Environment



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... and moved about autonomously

Agents Autonomy Interactions

Environment



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... following rules of behaviour*

Agents Autonomy Interactions Behaviour Environment

* follow my friends



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Simulating the Housing Market





Individual behaviour leading to macro-level patterns

- We have agents with plausible individual (micro) behaviour
- Buyers
- Sellers
- Estate Agents





The credit crunch





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A bounce



LTV changed from 100% to 60%



"Uncertainty is an uncomfortable position. But certainty is an absurd one."

- Voltaire

Summing Up



Society is a complex system

If we want to understand society we need to understand causality - in the context of all the other complex features.

There are some (cool) methods that grapple with that problem.





"If you judge, investigate."

-Seneca