Qualitative Comparative Analysis: A Cross-Disciplinary Methodology for Studying Similarities and Differences

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Overview

Day 1: The Logic of QCA

- Introductions and discussion of research projects

Day 2: Three Analytic Components of QCA

- Calibration, Necessity Analysis, Sufficiency Analysis

Day 3: Putting QCA into Practice

- Software for conducting QCA

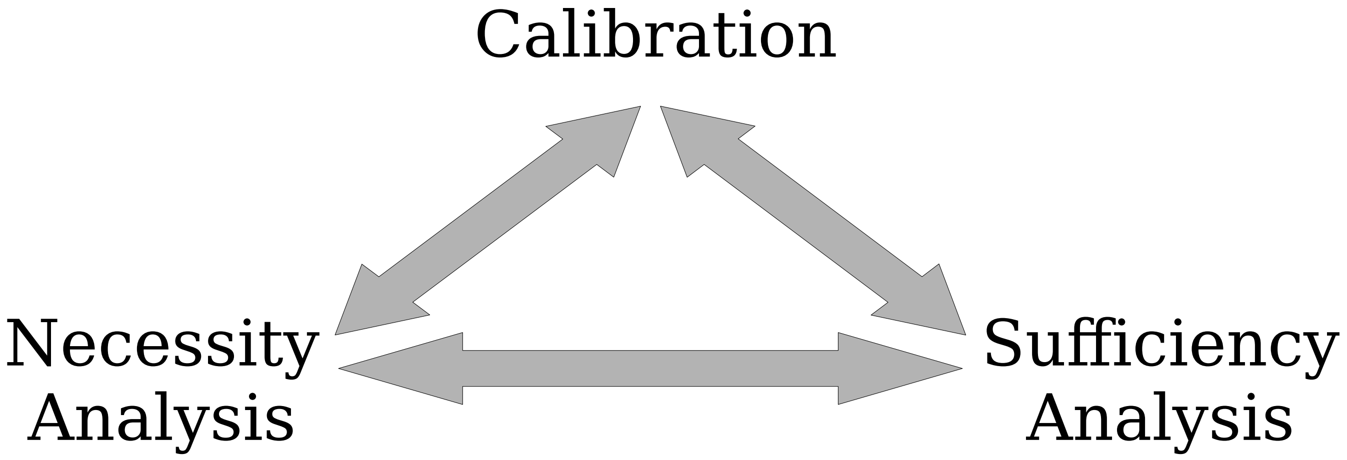
Day 4: Advances in QCA

- Time in QCA, Generalized Analytic Induction

Day 5: Pulling it all Together

- Building robust models, Visualizing and presenting QCA
- Discussion of research projects

Three Analytic Components of QCA



Calibration

(with Roel Rutten, Tilburg University)

“

Uncalibrated measures, however, are clearly inferior to calibrated measures. With an uncalibrated measure of temperature, for example, it is possible to know that one object has a higher temperature than another or even that it has a higher temperature than average for a given set of objects but still not know whether it is hot or cold.

— Ragin (2008) *Redesigning Social Inquiry*

”

Calibration: What is calibration?

- The process of constructing fuzzy-sets
- May be crisp {0,1} or fuzzy $\{0.0 \leq x \leq 1.0\}$
- Is about defining set memberships
  - degree of membership in the set of rich people (vs annual income)
  - degree of membership in the set of developed countries (vs GDP/capita)
- Importance of negation and asymmetry
  - degree of membership in the set of *not* rich people
  - degree of membership in the set of *not* developed countries

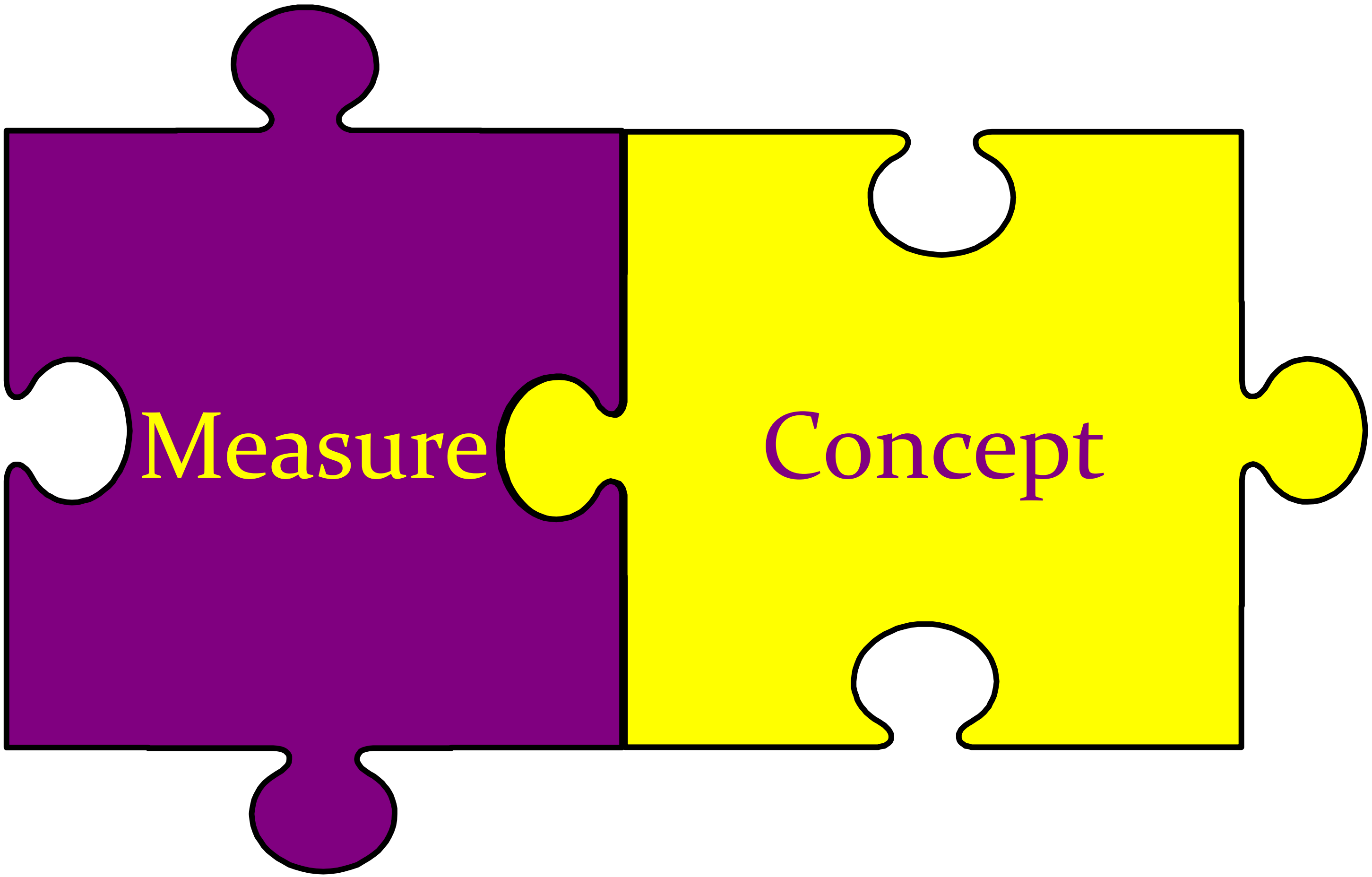
Calibration: What is a condition?

- QCA speaks of “conditions” rather than “variables.” Why?
- ***Variables*** are nouns that measure magnitudes: Income measures how much a person earns.
- ***Adjective phrases*** describe a specific quality such as the “condition” of being rich. An adjective phrase describes a set: the set of rich people.
- QCA analyzes sets and set relationships.
- Therefore: QCA analyzes adjective phrases; i.e., “conditions.”

Calibration: What is a condition?

- An adjective phrase qualifies a noun: "*educated* individual," "*profitable* company," "*democratic* country"
- Nouns may be complex:
  - "Sci-fi film" vs "Hard sci-fi film" vs "Popular hard sci-fi film"
- A condition measures the degree to which the object (noun) exhibits the quality (adjective)
- Calibration is challenging b/c you must operationalize: (a) the object, (b) the quality, and (c) the expression of the quality by the object.

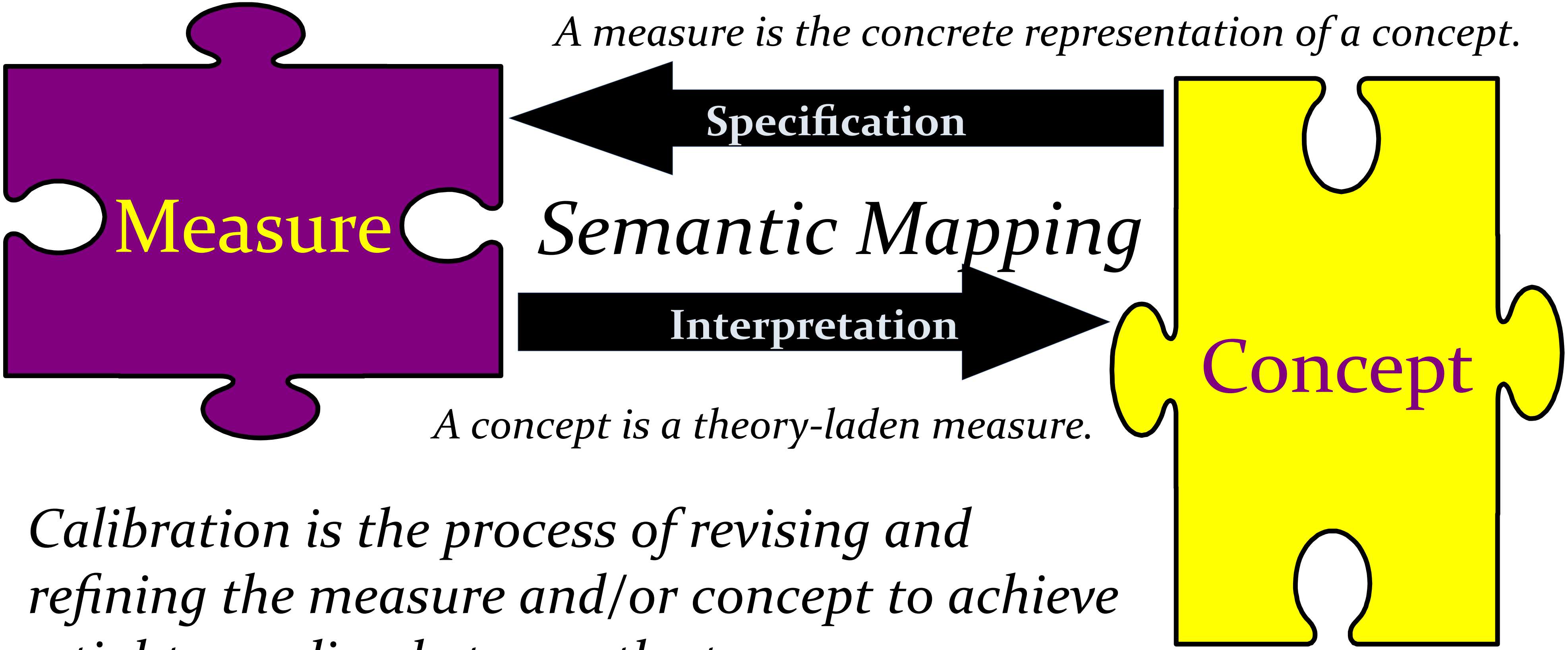
Calibration: What is a condition?



Calibration: What is a condition?

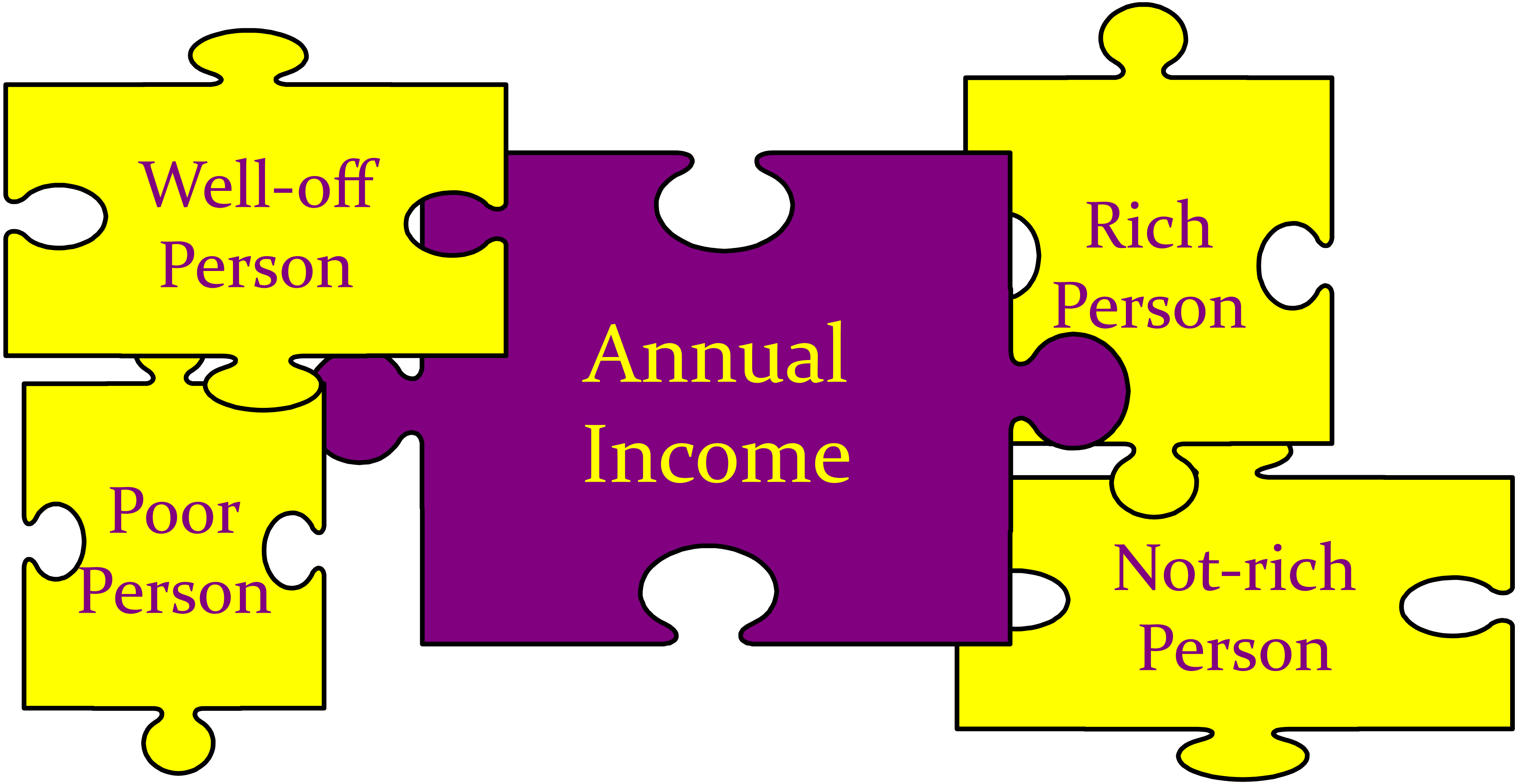
	Quality (Adjective)	**Object (Noun)**
Condition:	“Democratic	Country”
Ontological questions identify *the concept*:	What does it mean for a country to be democratic?	What is a country?
Epistemological questions identify *the measure*:	How do we assess the degree to which a country is democratic?	How do we distinguish countries from non-countries?

Calibration: Achieving fit via iteration

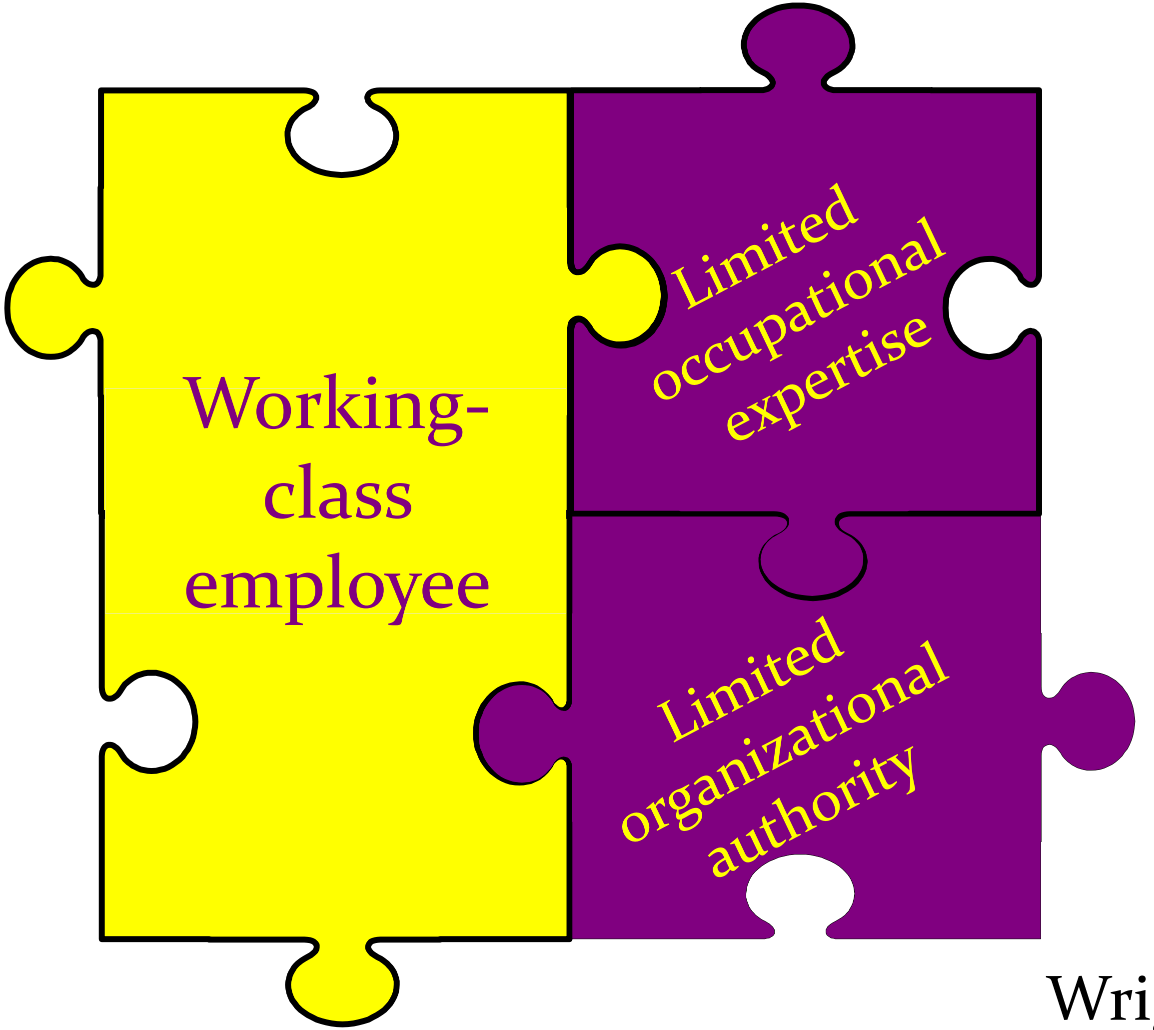


Calibration is the process of revising and refining the measure and/or concept to achieve a tight coupling between the two.

Calibration: Single measure, multiple concepts



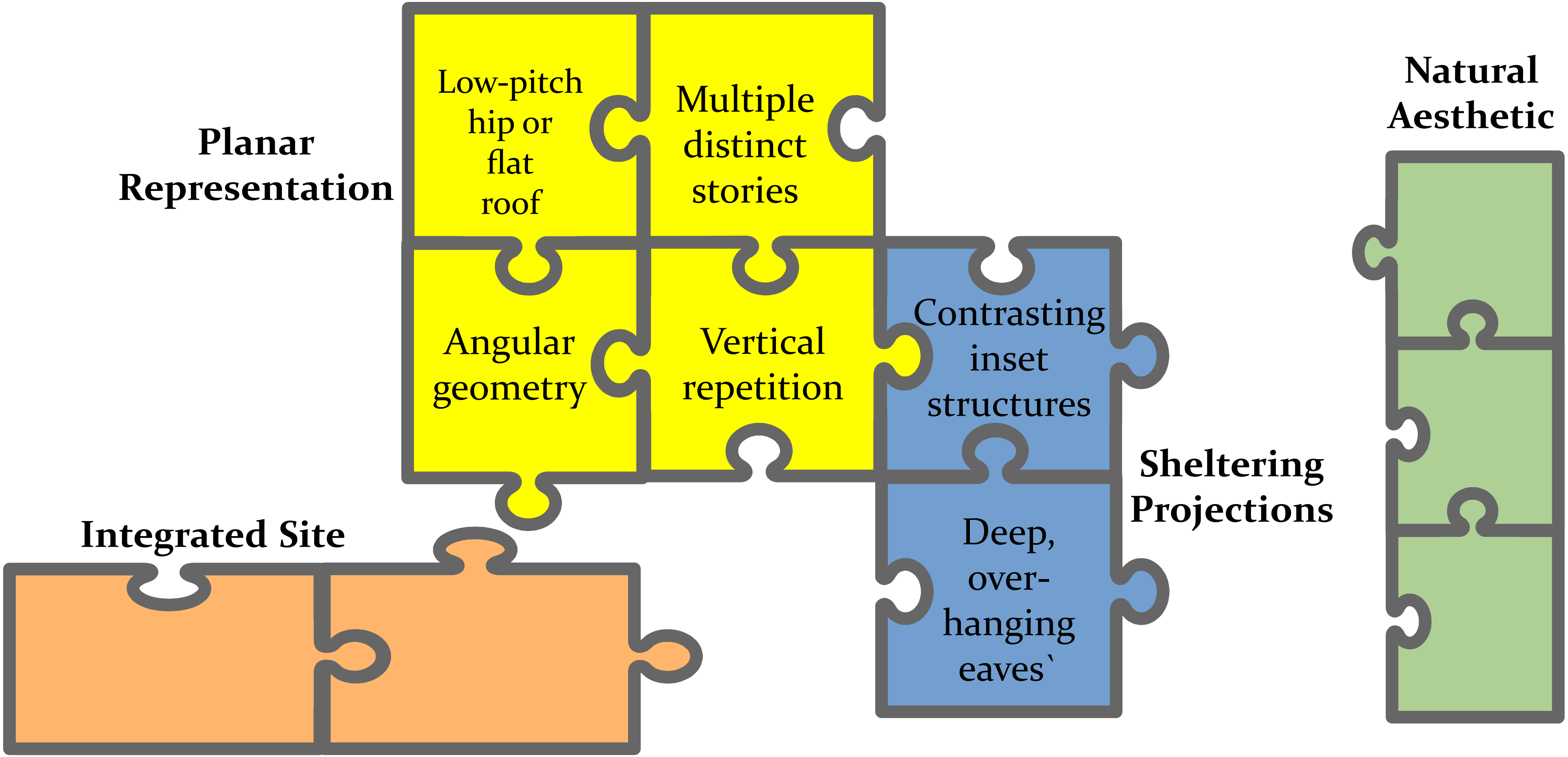
Calibration: Single concept composed of multiple measures



Wright (1985, 1997)

Calibration: Macroconditions are composed of multiple conditions

The Prairie Style Home



Calibration: Mapping Concepts to Measures

Three semantic thresholds common to all conditions:

- 1.0 = full membership (ideal-typical case)
- 0.0 = full non-membership (negative case)
- 0.5 = crossover point (ambiguous case)

    > 0.5 = typical case possesses enough characteristics to be recognizable as an instance of the case

    < 0.5 = atypical case possesses some characteristics but is not recognized as an instance of the case

    Note: Crossover point is always implicit except when using the direct method of calibration.

Including additional semantic thresholds is common (0.0, 0.25, 0.75, 1.0).

- Be aware of the danger of over-precision. Can you really distinguish 0.25 from 0.3?
- Consider irrelevant variation, both beyond *and within* the lower and upper bounds.

Successful calibration answers two questions:

1. What does each semantic threshold mean ontologically?
2. What are the epistemological rules that produces each membership score?

Calibration: Types of Fuzzy Sets—Crisp, Discrete and Continuous

	Crisp set	Three-value fuzzy set	Four-value fuzzy set	Six-value fuzzy set	Continuous fuzzy set
	------ Ideal-typical case = Fully in = 1.0 ------				
Typical cases (instances of the set)		More in than out = 0.7	More in than out = 0.7	Mostly but not fully in = 0.8 More or less in = 0.6	Degree of membership is more “in” than “out” 0.5 < X < 1
	----- Ambiguous case = Crossover Point = 0.5 -----				
Atypical cases (non-instances of the set)			More out than in = 0.3	More or less out = 0.4 Mostly but not fully out = 0.2	Degree of membership is more “out” than “in” 0.0 < X < 0.5
	-------- Negative case = Fully out = 0.0 --------				

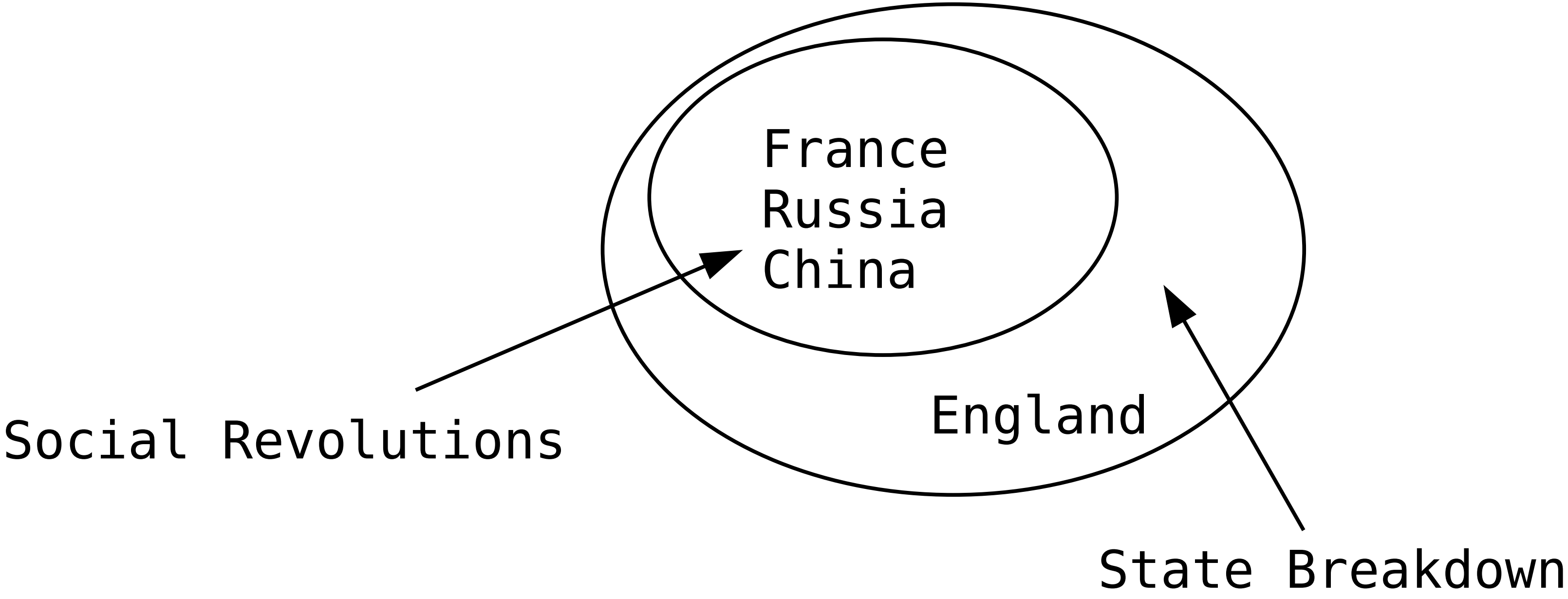
Analysis of Necessary and Sufficient Conditions

- Necessity analysis is underdeveloped in the literature; QCA development—and applications—have focused on sufficiency
- Sufficiency analysis assumes causal complexity and emphasizes multiple conjunctural causation
  - Intersectionality: combinations of conditions explain empirical phenomena
  - Equifinality: different combinations of conditions can produce the same outcome
- Primary measures of model fit:
  - Consistency measures the strength of a superset/subset relationship (a perfect subset relationship=1.0)
  - Coverage measures the empirical importance of a particular solution (explaining all instances of the outcome=1.0)

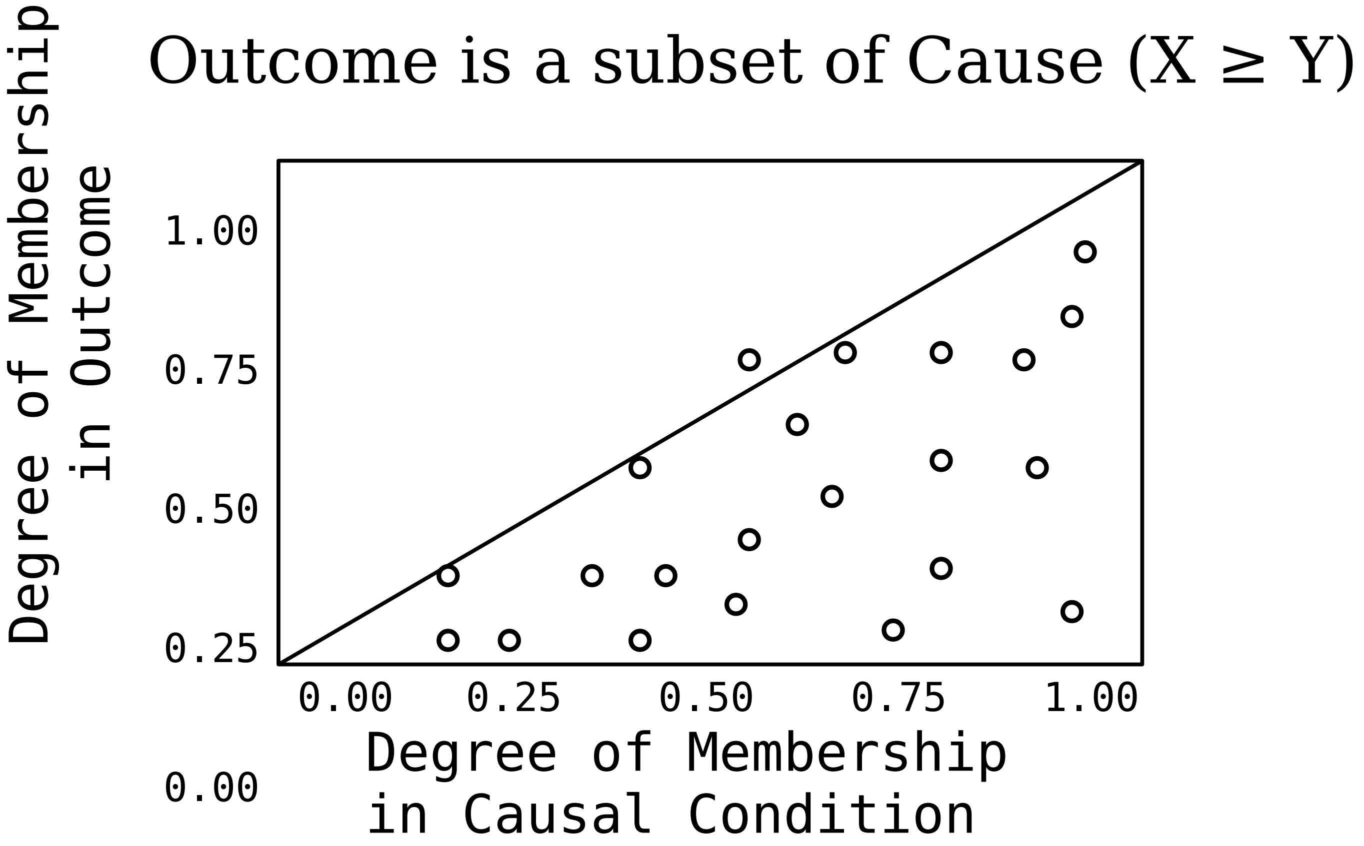
Analyzing Necessary Conditions

Necessary Conditions:
Cause must (almost always) be present for outcome to occur

Outcome is a subset of Cause

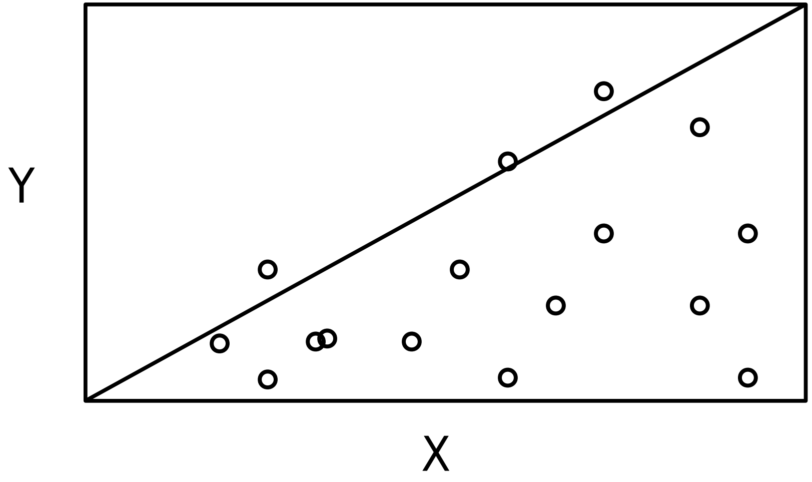


Fuzzy Subset Relationship Consistent with Necessity

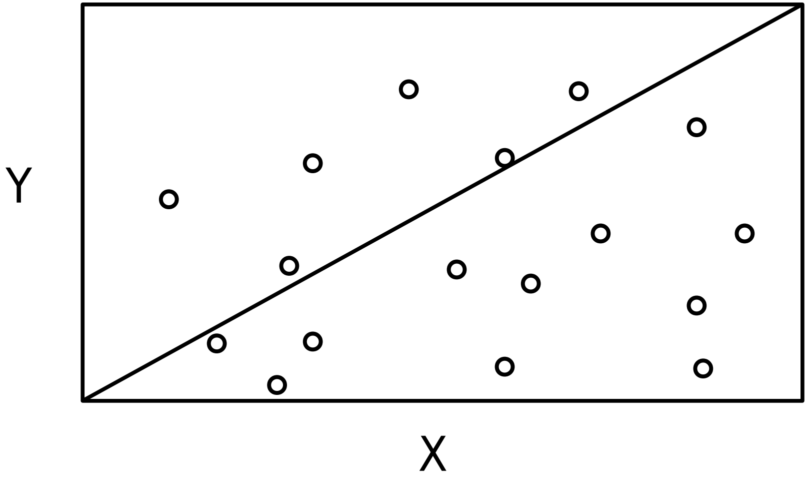


Assessing Necessary Conditions

Consistency measures the degree to which the subset relationship is “consistent” with necessity

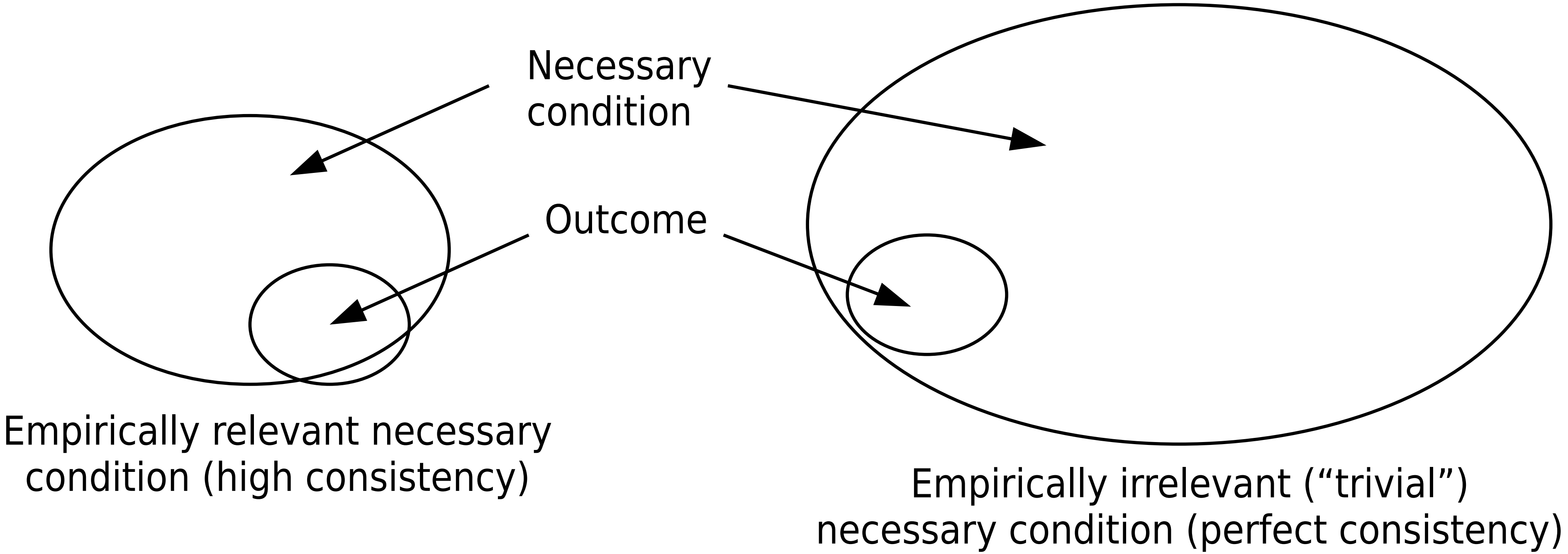


Subset relationship consistent with necessity



Subset relationship with substantial inconsistency

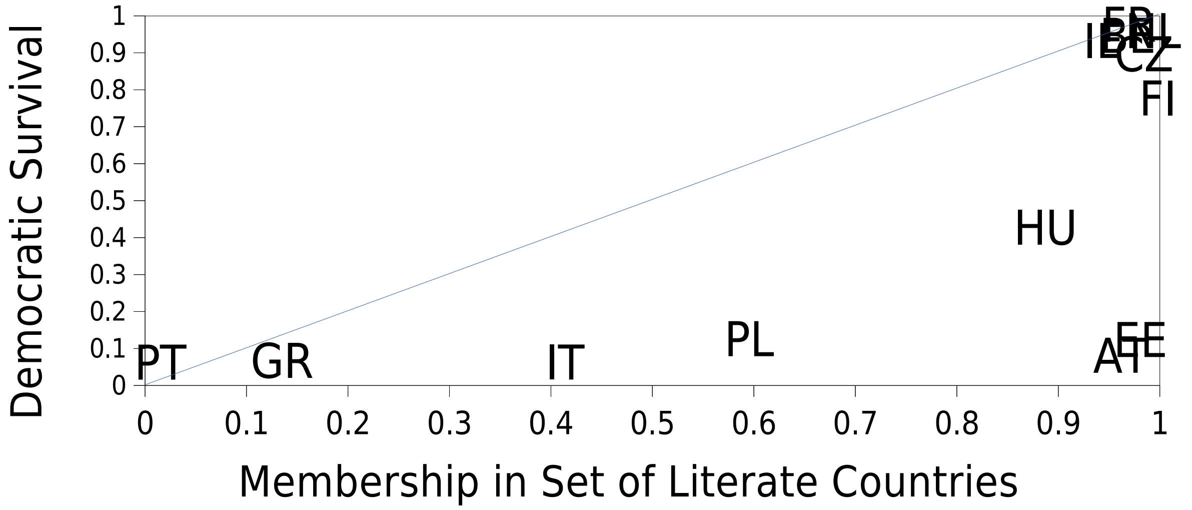
Assessing Necessary Conditions



- ***Coverage*** measures how “relevant” (empirically prominent) a necessary condition is
- Must establish consistency ***before*** assessing coverage
- Application of ***theory*** is crucial: What is the justification for claiming necessity?

Testing for Necessary Conditions

Obs	Dev	Urb	Lit	Sur
AT	.81	.12	.99	.05
BE	.99	.89	.98	.95
CZ	.58	.98	.98	.89
EE	.16	.07	.98	.12
FI	.58	.03	.99	.77
FR	.98	.03	.99	.95
DE	.89	.79	.99	.05
GR	.04	.09	.13	.06
HU	.07	.16	.88	.42
IE	.72	.05	.98	.92
IT	.34	.10	.41	.05
NL	.98	1.00	.99	.95
PL	.02	.17	.59	.12
PT	.01	.02	.01	.05



Term	Consis	Cov
LIT	0.99	0.58
Solution	0.99	0.58

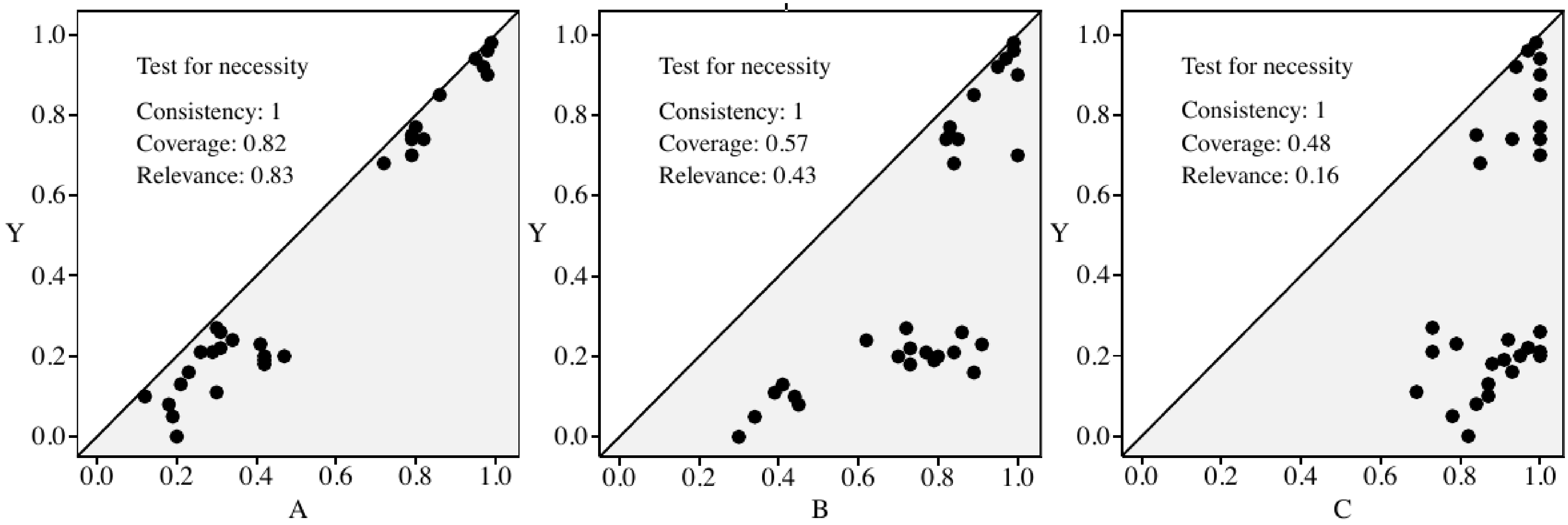
Necessary Conditions: Consistency, Coverage and Trivialness

	Conditions			Outcome
Obs	A	B	C	Y
1	0.9	1.0	1.0	0.9
2	0.8	1.0	1.0	0.7
3	0.3	0.7	1.0	0.2
4	0.4	0.8	0.9	0.2
5	0.1	0.2	0.8	0.0

	Test for Necessity		
	Consis	Cov	RoN
A	1.0	0.80	0.83
B	1.0	0.54	0.43
C	1.0	0.43	0.10

(from Mello 2021)

Necessary Conditions: Consistency, Coverage and Trivialness

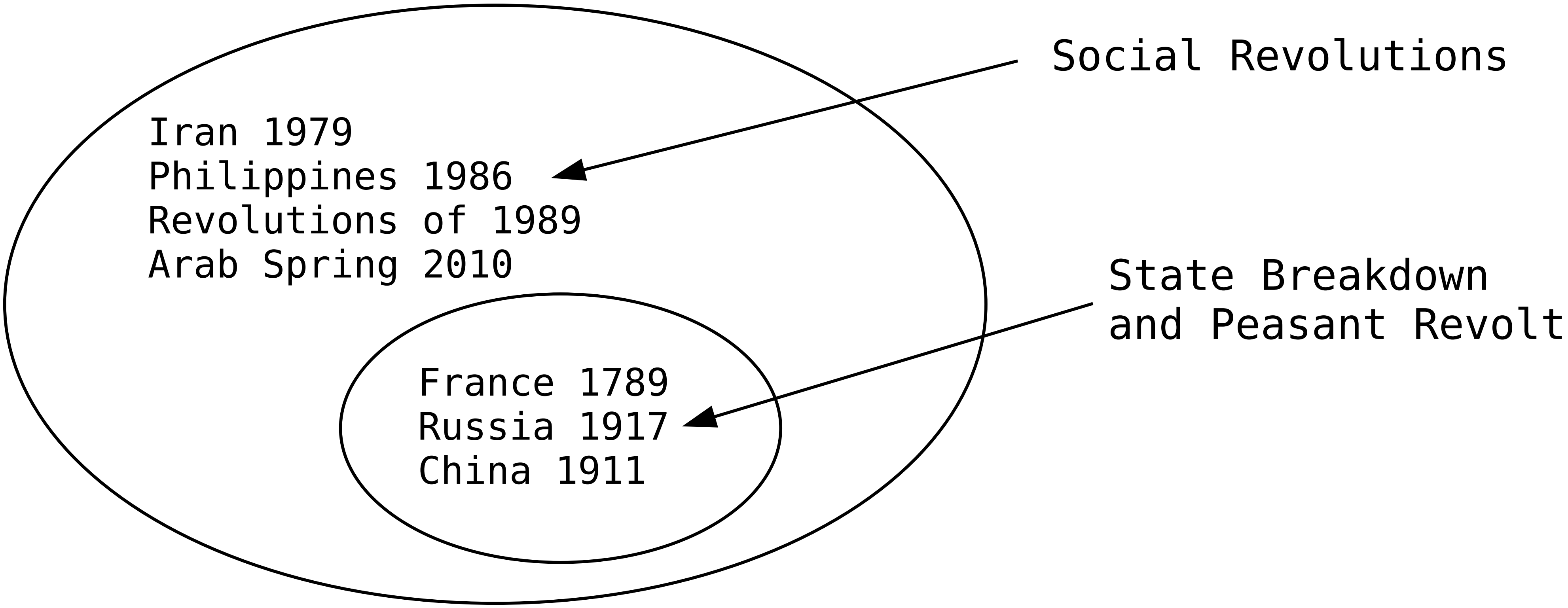


(from Mello 2021)

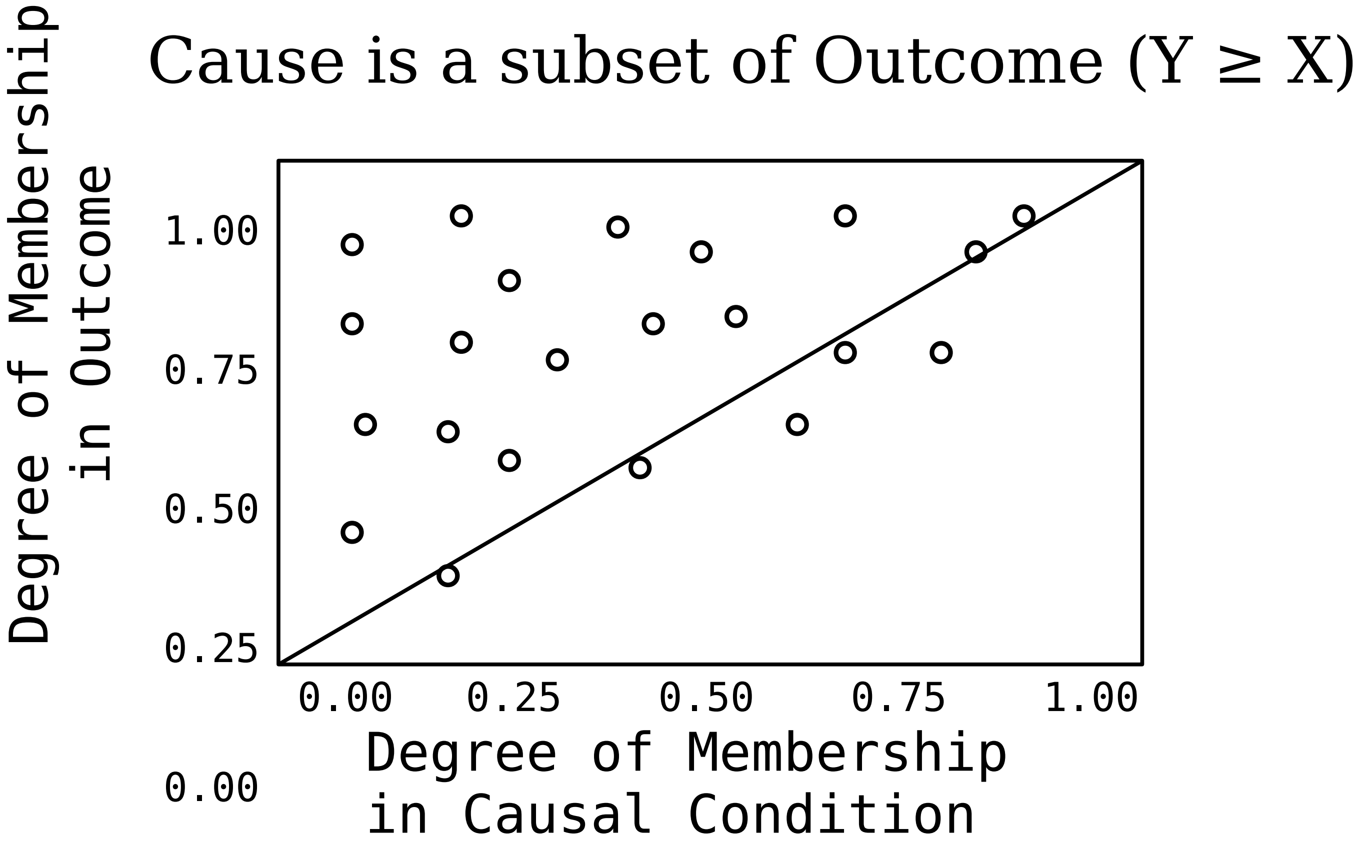
Analyzing Sufficient Conditions

Assessing Sufficient Conditions:
When cause is present, outcome will (almost always) occur

Cause is a subset of the Outcome

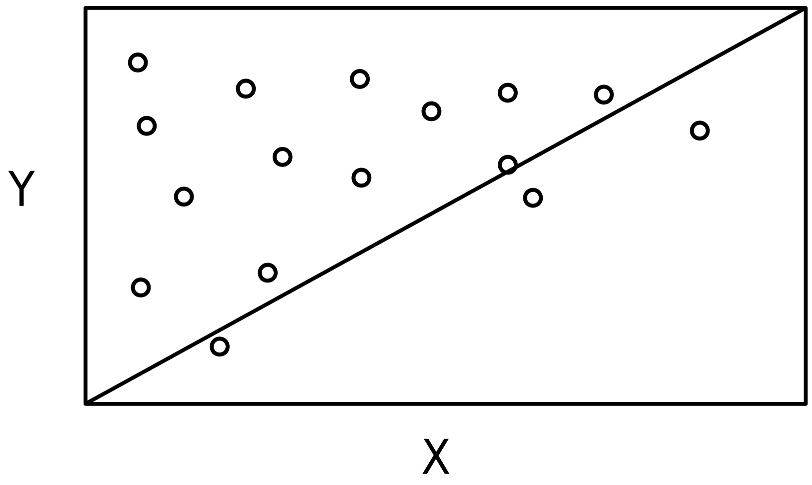


Fuzzy Subset Relationship Consistent with Sufficiency

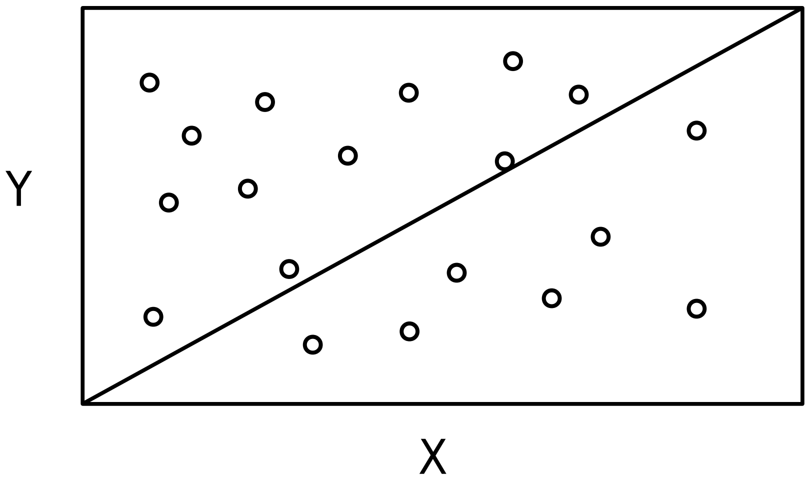


Assessing Sufficient Conditions

Consistency measures degree to which subset relationship is “consistent” with sufficiency

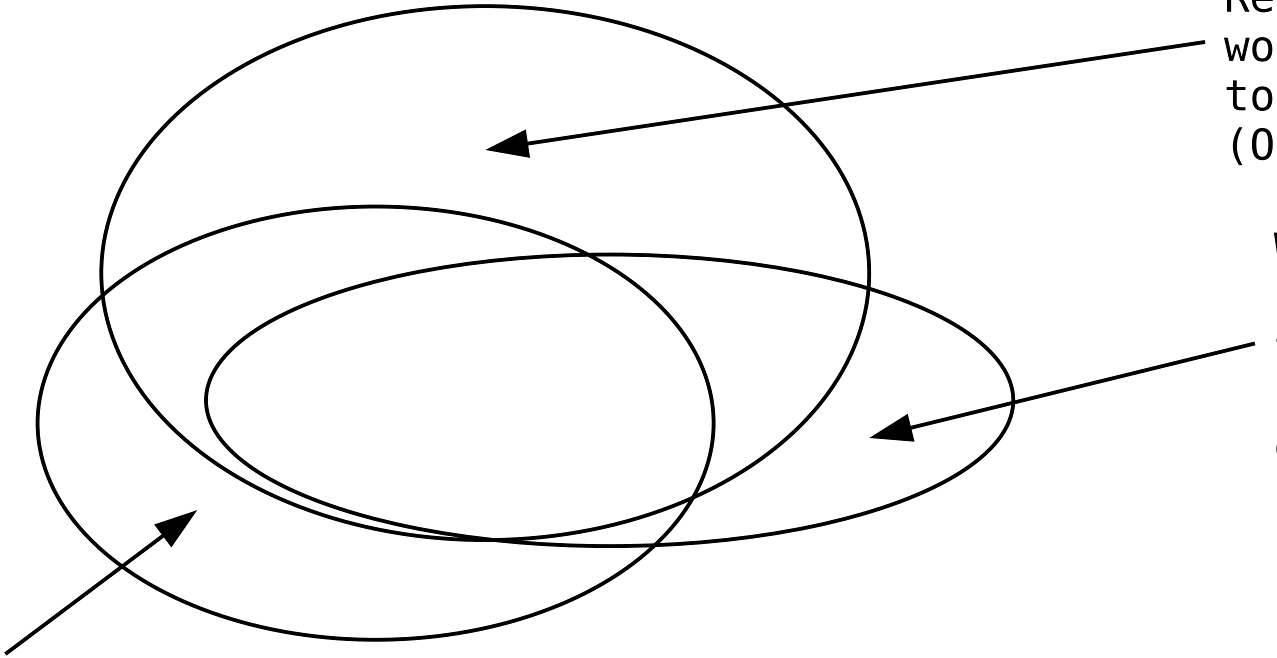


Subset relationship consistent with sufficiency

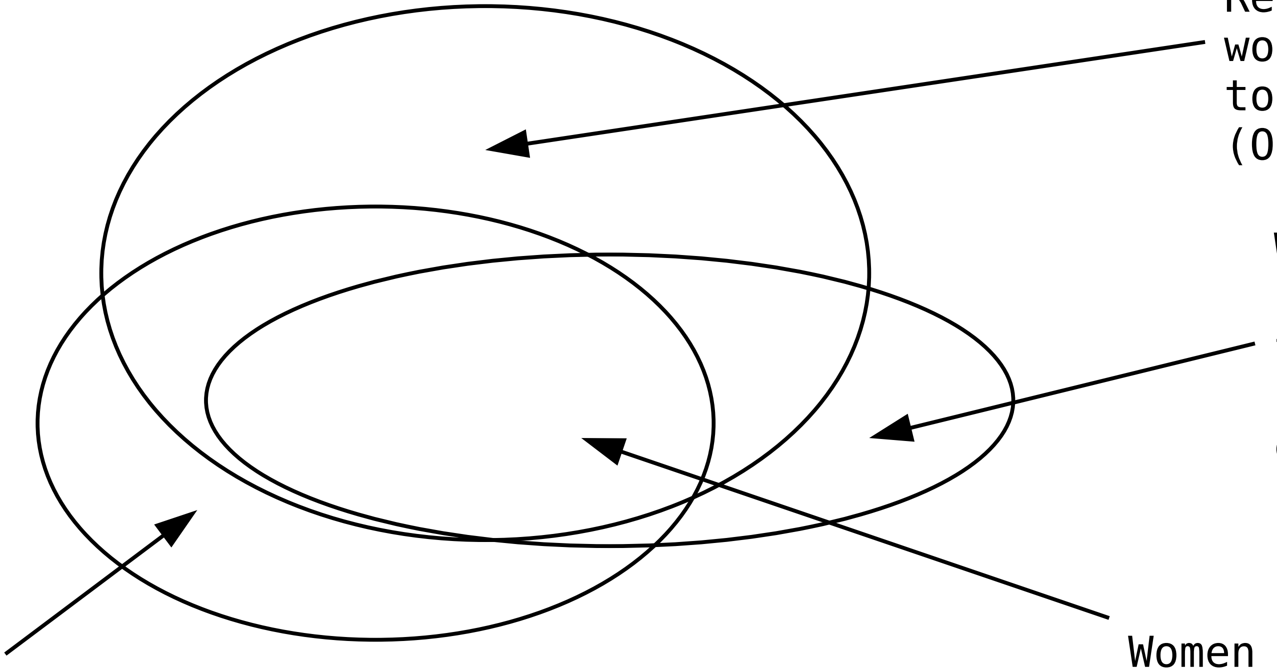


Subset relationship with substantial inconsistency

Assessing Sufficient Conditions:
When cause is present, outcome will (almost always) occur



Assessing Sufficient Conditions: When cause is present, outcome will (almost always) occur



Truth Table Construction
Truth table algorithm sorts observations into types

Obs	**Dev**	**Urb**	**Lit**	**Brk**
AT	.81	.12	.99	.95
BE	.99	.89	.98	.05
CZ	.58	.98	.98	.11
EE	.16	.07	.98	.88
FI	.58	.03	.99	.23
FR	.98	.03	.99	.05
DE	.89	.79	.99	.95
GR	.04	.09	.13	.94
HU	.07	.16	.88	.58
IE	.72	.05	.98	.08
IT	.34	.10	.41	.95
NL	.98	1.00	.99	.05
PL	.02	.17	.59	.88
PT	.01	.02	.01	.95

	Dev	**Urb**	**Lit**	**Consis**	**Y**	**Consis Obs**	**Inconsis Obs**
1	T	T	T	0.41	F	DE	BE, CZ, NL
2	T	T	F	—	—		
3	T	F	T	0.51	F	AT	FI, FR, IE
4	T	F	F	—	—		
5	F	T	T	—	—		
6	F	T	F	—	—		
7	F	F	T	0.83	T	EE, PL	HU
8	F	F	F	0.99	T	GR, IT, PT	

Truth Table Construction
Truth table assesses consistency between types and outcome

Democracy usually did not break down in countries that were:
(a) developed, urbanized, and literate *(row 1)*, or
(b) developed, not urbanized, and literate *(row 3)*.

Democracy usually did break down in countries that were:
(c) not developed, not urbanized, and literate *(row 7)*, or
(d) not developed, not urbanized, and not literate *(row 8)*

	Dev	Urb	Lit	Consis	Y	Consis Obs	Inconsis Obs
1	T	T	T	0.41	F	DE	BE, CZ, NL
2	T	T	F	—	—		
3	T	F	T	0.51	F	AT	FI, FR, IE
4	T	F	F	—	—		
5	F	T	T	—	—		
6	F	T	F	—	—		
7	F	F	T	0.83	T	EE, PL	HU
8	F	F	F	0.99	T	GR, IT, PT	

Reading Truth Tables
Remainders are logically-possible configurations w/o empirical instances

Remainders

	Dev	Urb	Lit	Consis	Y	Consis Obs	Inconsis Obs
1	T	T	T	0.41	F	DE	BE, CZ, NL
2	T	T	F	—	—		
3	T	F	T	0.51	F	AT	FI, FR, IE
4	T	F	F	—	—		
5	F	T	T	—	—		
6	F	T	F	—	—		
7	F	F	T	0.83	T	EE, PL	HU
8	F	F	F	0.99	T	GR, IT, PT	

Invariance in Truth Tables

	Dev	Urb	Consis	Y	Consis Obs	Inconsis Obs
1	T	T	0.41	F	DE	BE, CZ, NL
2	T	F	0.51	F	AT	FI, FR, IE
3	F	T	—	—		
4	F	F	0.89	T	EE, GR, IT, PL, PT	HU

	Dev	Urb	Lit	Consis	Y	Consis Obs	Inconsis Obs
1a	T	T	T	0.41	F	DE	BE, CZ, NL
1b	T	T	F	—	—		
2a	T	F	T	0.51	F	AT	FI, FR, IE
2b	T	F	F	—	—		
3a	F	T	T	—	—		
3b	F	T	F	—	—		
4a	F	F	T	0.83	T	EE, PL	HU
4b	F	F	F	0.99	T	GR, IT, PT	

Reducing Truth Tables to Boolean Expressions

To Primitive Expressions:

Term	**Consis**	**Raw Cov**	**Uniq Cov**	**Observations**
dev*urb*LIT +	0.83	0.42	0.27	EE, PL, [HU]
dev*urb*lit	0.99	0.40	0.24	GR, IT, PT
Solution	0.88	0.66		

Reducing Truth Tables to Boolean Expressions

To Primitive Expressions:

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb*LIT +	0.83	0.42	0.27	EE, PL, [HU]
dev*urb*lit	0.99	0.40	0.24	GR, IT, PT
Solution	0.88	0.66		

To Prime Implicants:

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb	0.89	0.71	0.71	EE, PL, GR, IT, PT, [HU]
Solution	0.89	0.71		

Reducing Truth Tables to Boolean Expressions

To Primitive Expressions:

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb*LIT +	0.83	0.42	0.27	EE, PL, [HU]
dev*urb*lit	0.99	0.40	0.24	GR, IT, PT
Solution	0.88	0.66		

To Prime Implicants:

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb	0.89	0.71	0.71	EE, PL, GR, IT, PT, [HU]
Solution	0.89	0.71		

Reduce Prime Implicants (Complex Solution):

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb	0.89	0.71	0.71	EE, PL, GR, IT, PT, [HU]
Solution	0.89	0.71		

Reducing Truth Tables to Boolean Expressions

To Primitive Expressions:

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb*LIT +	0.83	0.42	0.27	EE, PL, [HU]
dev*urb*lit	0.99	0.40	0.24	GR, IT, PT
Solution	0.88	0.66		

To Prime Implicants:

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb	0.89	0.71	0.71	EE, PL, GR, IT, PT, [HU]
Solution	0.89	0.71		

Reduce Prime Implicants (Complex Solution):

Term	Consis	Raw Cov	Uniq Cov	Observations
dev*urb	0.89	0.71	0.71	EE, PL, GR, IT, PT, [HU]
Solution	0.89	0.71		

Reduce Prime Implicants Using Remainders (Parsimonious Solution):

Term	Consis	Raw Cov	Uniq Cov	Observations
dev	0.82	0.73	0.73	EE, PL, GR, IT, PT, [HU]
Solution	0.82	0.73		

A Range of Solutions are Possible

More Complex

(a)	Acsir	*or*	ACSir	*or*	ASIR
(b)	Air	*or*	ACSi	*or*	ASIR
(c)	Air		*or*		ASIR
(d)	Ai		*or*		ASR
(e)	i		*or*		SR

More Parsimonious

Intermediate solutions constructed manually, or via directional expectations using software

Outcome: *Successful shaming of targeted regimes*

Explanatory conditions: (A)dvice, (C)ommittment, (S)hadow of the future, (I)nconvenience, (R)everberation

Factoring Results

Initial Solution:

ELECTIONS * POLICE +
urban * POLICE +
CONFLICT * ELECTIONS * URBAN +
CONFLICT * elections * urban +
conflict * ELECTIONS * urban

Factored Solution:

POLICE (ELECTIONS + urban) +
URBAN (CONFLICT * ELECTIONS) +
urban ((CONFLICT * elections) + (conflict * ELECTIONS)