QCA and Fuzzy Set Goodness–of-Fit Tests

by Wendy Olsen

- Thanks to John McLoughlin for programming help in Python.
- Funded by **British Academy: Innovation in Global Labour Research Using Deep Linkage and Mixed Methods**

BRITISH ACADEMY

- See also https://www.facebook.com/groups/mixednetwork/
- Integrated Mixed Methods Network
- And www.compasss.org
- And JISCMAIL QUAL-COMPARE (185 members)

CMIST The Cathie Marsh Institute for Social Research

Research Methods Festival July 2018
University of Bath

MANCHESTER 1824 The University of Manchester

Contents of Presentation

References

For Qualitative folks: Hodson, R. (2004). "A meta-analysis of workplace ethnographies - Race, gender, and employee attitudes and behaviors." Journal of Contemporary Ethnography **33**(1): 4-38.

Ragin, C. C. (1987). The comparative method : moving beyond qualitative and quantitative strategies. Berkeley ; Los Angeles ; London, University of California Press.

- For Quantitative Folks: **Ragin, C.C. (2008). Redesigning social inquiry: Set relations in social research. Chicago: Chicago University Press.**
- **Rihoux, B. (2006). Qualitative Comparative Analysis (QCA) and related systematic comparative methods: recent advances and remaining challenges for social science research. International Sociology, 21(5), 679-706.**
- **Rihoux, B., & Ragin, C. C. (2009). Configurational comparative methods. Qualitative Comparative Analysis (QCA) and related techniques (Applied Social Research Methods). Thousand Oaks and London: Sage.**
- Byrne, D., and C. Ragin, eds. (2009), Handbook of Case-Centred Research Methods, London: Sage.
- Cooper, B. & Glaesser, J. (in press 2011) Using case-based approaches to analyse large datasets: a comparison of Ragin's fsQCA and fuzzy cluster analysis, in International Journal of Social Research Methodology.
- Olsen, W.K. (2009), Non-Nested and Nested Cases in a Socio-Economic Village Study, chapter in D. Byrne and C. Ragin, eds. (2009), Handbook of Case-Centred Research Methods, London: Sage.
- Olsen, W.K., and J. Morgan (2005) A critical epistemology of analytical statistics: Addressing the sceptical realist, Journal for the Theory of Social Behaviour, 35:3, September, pages 255-284.

SAMPLE DATA SETS:

1) the website of my course for some past years:

http://Course-data.ccsr.ac.uk/qca

2) the COMPASSS web site (*sic*) www.compasss.org (They have a lot of CSV files there)

Background References to Works Cited

- Eliason S. & Stryker R. 2009. Sociological Methods & Research 38:102-146.
- Freitag, M., & Schlicht, R. (2009). Educational Federalism in Germany: Foundations of Social Inequality in Education. Governance: An International Journal of Policy, Administration, and Institutions, *22*(1), 47–72.
- Ragin, C. C. (2000). Fuzzy-Set Social Science. Chicago; London, University of Chicago Press.
- Snow, D. and D. Cress (2000). "The Outcome of Homeless Mobilization: the Influence of Organization, Disruption, Political Mediation, and Framing." American Journal of Sociology **105**(4): 1063-1104.

1 Defining our terms and conceptual framework

- QCA=Qualitative Comparative Analysis
- QCA and fuzzy set comparative analysis is a set of systematic ways of studying causality.
- We make a simple data table of binary or ordinal variables.
- QCA helps discern necessary causality as well as sufficient causality.
- Any Sample Size, or whole population.
- QCA offers formal methods for analyzing contingency.

A Conjunctural Logic Reflects The Nature Of The World

QCA, ... is conjunctural in its logic, examining the various ways in which specified factors interact and combine with one another to yield particular outcomes. " (Cress and Snow, 2000: 1079)

The QCA analyst uses qualitative methods and assumes fluidity in the social world. "X affects Y" is also contingent on Z.
We have to understand the cases.
Get to grips with social contexts.
Code all this up so it's a systematic mixed methods dataset.
Then analyse the patterns.

How QCA Data Are Organised

- The Truth Table.
  - Crisp-Set Truth Table. All 0s and 1s.
  - Fuzzy sets involve measuring the degree of membership of a case in a set.
  - One column is set aside as the ‘outcome’.
- Use The NVIVO Approach as Well.
  - Combining data, multiple ‘modes’ of research
  - The “casebook” in NVIVO.
  - The concept of multilevel cases – e.g. INTERVIEWs

Appendix: A Fuzzy Set Interim Truth Table (Olsen, 2009)

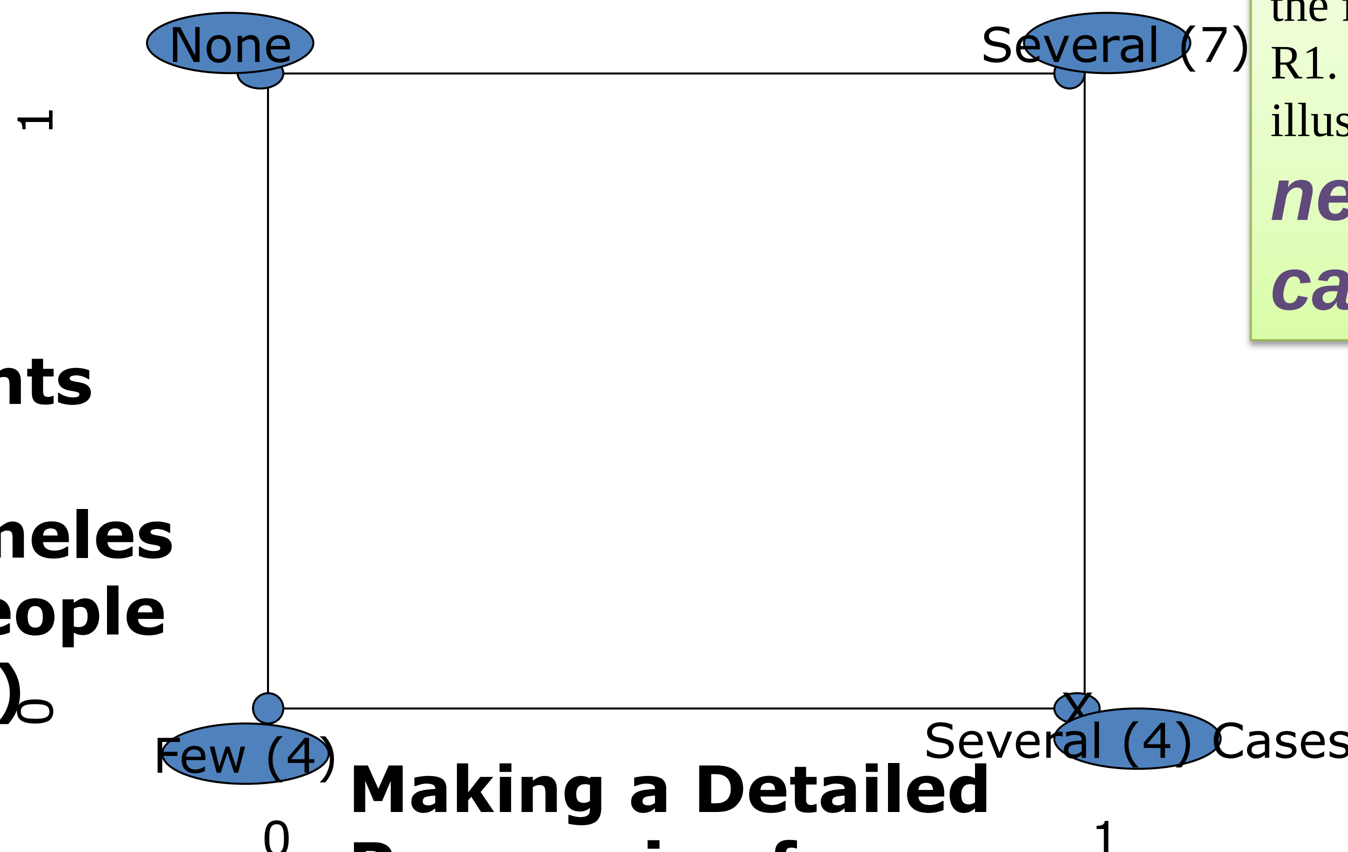
Y	X1	X2	X3	X4	X5	X6	Number Of Cases	Configu ration
Fuzzy	Fuzzy	Fuzzy	Crisp	Crisp	Fuzzy	Crisp		
0	0	0	1	0	1	0	1	**1**
0	0	0	1	1	0	0	4	**2**
0	0	1	0	0	0	1	1	**3**
0	0	1	1	0	0	0	2	**4**
0	1	0	0	0	1	1	3	**5**
0	1	1	0	0	0	0	1	**6**
0	1	1	0	1	1	0	1	**7**
0	1	1	1	1	1	1	1	**8**
1	0	0	0	0	0	1	1	**9**
1	1	0	0	1	1	1	4	**10**
1	1	0	1	0	0	0	1	**11**
1	1	0	1	0	1	1	1	**12**
1	1	0	1	1	0	1	1	**13**
1	1	0	1	1	1	1	1	**14**
1	1	1	0	0	1	0	2	**15**
1	1	1	0	0	1	1	4	**16**
1	1	1	0	1	0	0	1	**17**

2 Empirical measure of Csuff (consistency)

An Example. Cress and Snow ethnographic research in USA

- In 2000 the *American Journal of Sociology* published a QCA article which has become a standard reference work.
- The topic is the mobilisation of resources to help homeless people in USA.
- Their paper uses QCA very creatively by first of all noting (from their literature review) that four outcomes, not one, need to be taken into account. R1 R2 R3 R4 take up four columns of the data table.
- 17 US cities. Among these 8 cities, 15 cases of Social Movement Organisations.
- The data table has 4 outcomes, 15 cases (rows), and about 8 causal factors. (12 columns in total)

Snow and Cress's Findings Used Crisp Sets



Rights for Homeless People (Y1)

Making a Detailed Prognosis of Homelessness and SMO Viability, X1∩X3

'Rights' was one of the four outcomes, R1. This diagram illustrates ***necessary cause.***

Snow and Cress's Findings

- There was no single pathway for a single outcome
- Each ***pathway*** deserved, and got, ethnographic, observational (shadowing, buddying) treatment.

In our 'GITHUB' software package, we offer software to measure the impact of X1 X2 X3 X4 X5 X6 on either Y1 Y2 Y3 or Y4.

See https://github.com/WendyOlsen/fsgof

It's an input-output system, very simple. Just put your data in and you get graphs and consistency values out.

3 Empirical measure of Goodness-of-fit (F)

Based on Eliason S. & Stryker R. 2009. Sociological Methods & Research 38:102-146.

Eliason & Stryker 2009 offered a test of fit to a hypothesis, e.g. that X is sufficient for Y.

See https://github.com/WendyOlsen/fsgof

I have developed this further to enable statistical testing simply using EXCEL spreadsheets.

Two types of causal MODELS

- (A) Necessary causes
- (universal across the sample)
- (B) Sufficient pathways
- These are partial pathways which don’t explain all the ‘INSTANCES’ (Y=1)

Appendix: A Fuzzy Set Interim Truth Table (Olsen, 2009)

Y Fuzzy	X1 Fuzzy	X2 Fuzzy	X3 Crisp	X4 Crisp	X5 Fuzzy	X6 Crisp	Number Of Cases	Configuration
0	0	0	1	0	1	0	1	**1**
0	0	0	1	1	0	0	4	**2**
0	0	1	0	0	0	1	1	**3**
0	0	1	1	0	0	0	2	**4**
0	1	0	0	0	1	1	3	**5**
0	1	1	0	0	0	0	1	**6**
0	1	1	0	1	1	0	1	**7**
0	1	1	1	1	1	1	1	**8**
1	0	0	0	0	0	1	1	**9**
1	1	0	0	1	1	1	4	**10**
1	1	0	1	0	0	0	1	**11**
1	1	0	1	0	1	1	1	**12**
1	1	0	1	1	0	1	1	**13**
1	1	0	1	1	1	1	1	**14**
1	1	1	0	0	1	0	2	**15**
1	1	1	0	0	1	1	4	**16**
1	1	1	0	1	0	0	1	**17**

3.1 Empirical measure of Goodness-of-fit (F)

A Basic measure, C_{suff}

1. See also journal special issue, *<u>Sociological Methodology</u>* *2015 debated this question. My (Olsen) paper in that journal is very helpful and short.*
2. Follow Rihoux and Ragin's protocol.

   2a) find what's Necessary. 2b) then Sufficient. 2c) then Converses.
3. For tests of sufficiency, you are now looking at joint membership in sets, known as $X1 \cap X2 \cap X3 = \mathbf{X}$ etc.
   A. The sufficiency triangle is the upper left area.
   B. MIN(X1, X2, X3) is the same as $X1 \cap X2 \cap X3$.
   C. Eliason and Stryker advise to recalibrate into normal distributions.
4. You are now looking at individual X's first, and then at configurations that embed these. Thus the effects are found to occur in combinations, known as configurations.

Rihoux and Ragin offer this measure of goodness of fit:

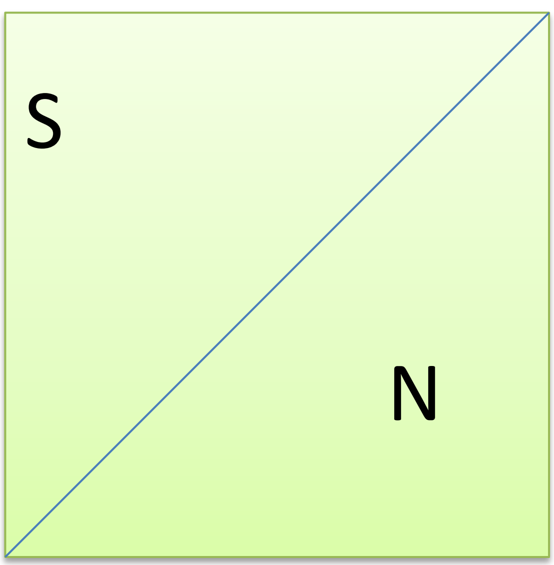
$$\boldsymbol{C_{suff}} = \textbf{Consistency} = \textbf{Sum}(\mathbf{X} \cap \mathbf{Y}) / \textbf{Sum}(\mathbf{X}) \quad \textbf{Eq. 1}$$

You sum over the cases. If $Y<\mathbf{X}$, then the numerator, $\sum \text{Min}(\mathbf{X}, Y)$, is less than the denominator.

For patterns with many cases lying in the Sufficiency Triangle, C_{suff} is =1 or close to 1. The cutoff point recommended by Ragin is 0.8, or 0.75.

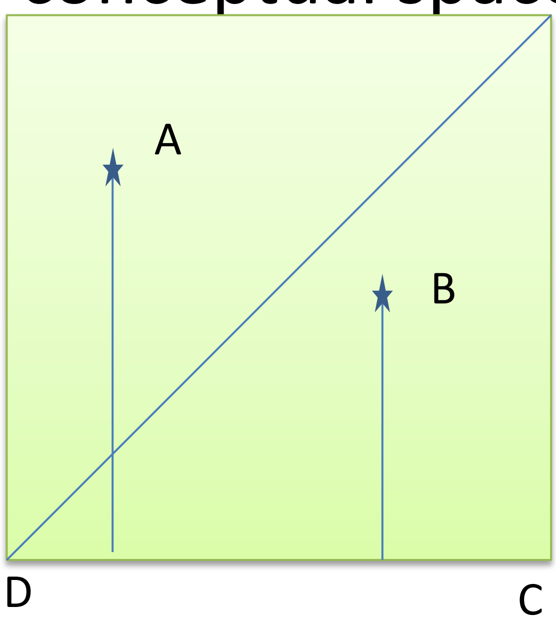
Visualising the Csuff Criterian

- The Consistency measure depends on the slopes of the lines that reach each point in the lower triangle. So it uses the vertical distances to the Diagonal in a crucial way.



A Fuzzy Set Measure of Fit, C_{suff}

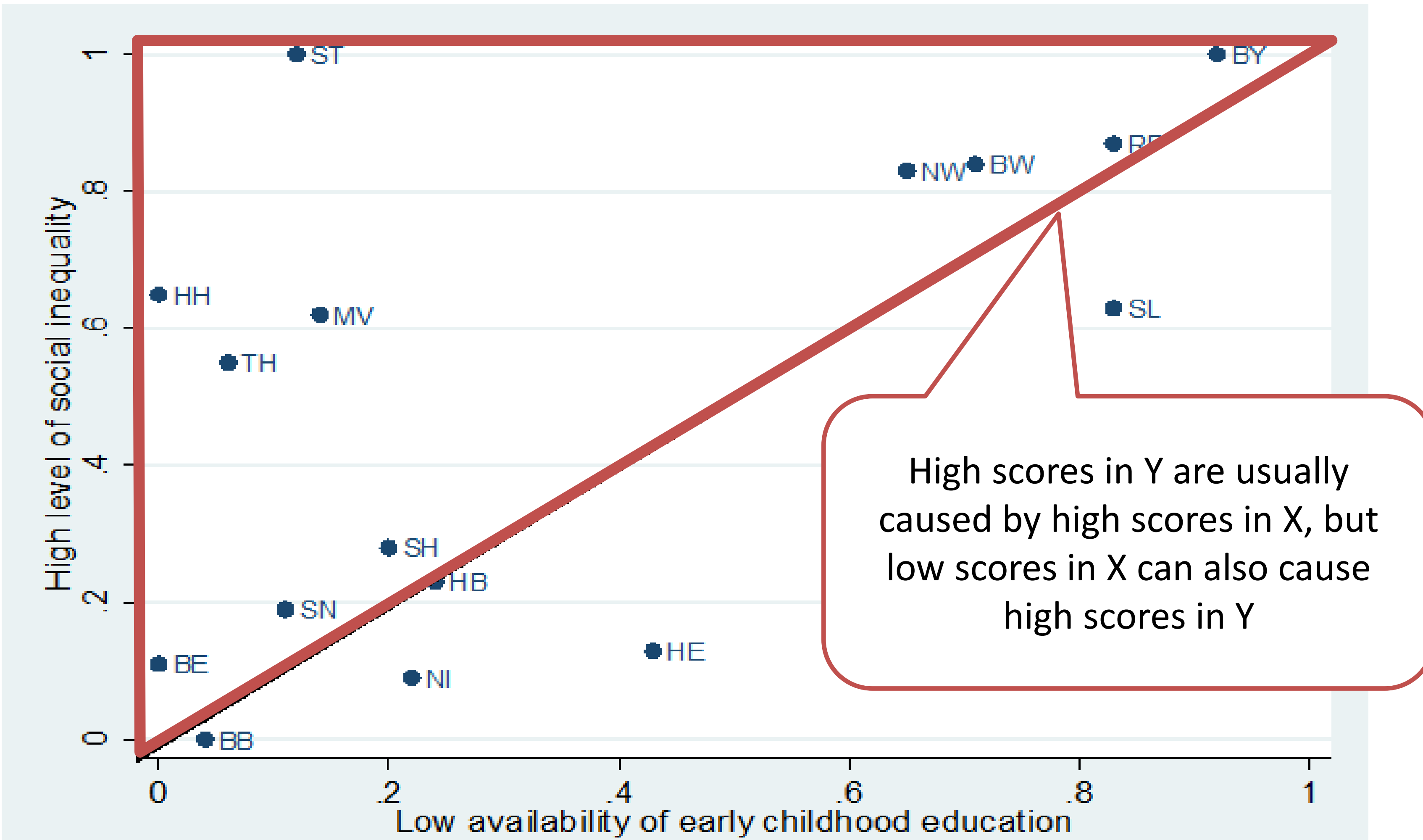
- Point A adds 1 unit to the numerator and denominator of Csuff. At Point B, the Y value is less than X. So it only adds to the denominator.
- Notice the fuzzy set space {0,0} to {1,1}. This conceptual space is not Euclidean.



- A point represents a case.
- From B to the diagonal is a non-zero distance. C_{suff} < 1 because of B.

- Suppose C is a case at (1,0)
- From C to the Diagonal is 1 unit! Huge.
- Suppose D is a case at (0,0)
- From D to the Diagonal is distance 0.
- D counts as 'in' the triangle S.

Sufficiency of low availability of early childhood education for high level of social inequality

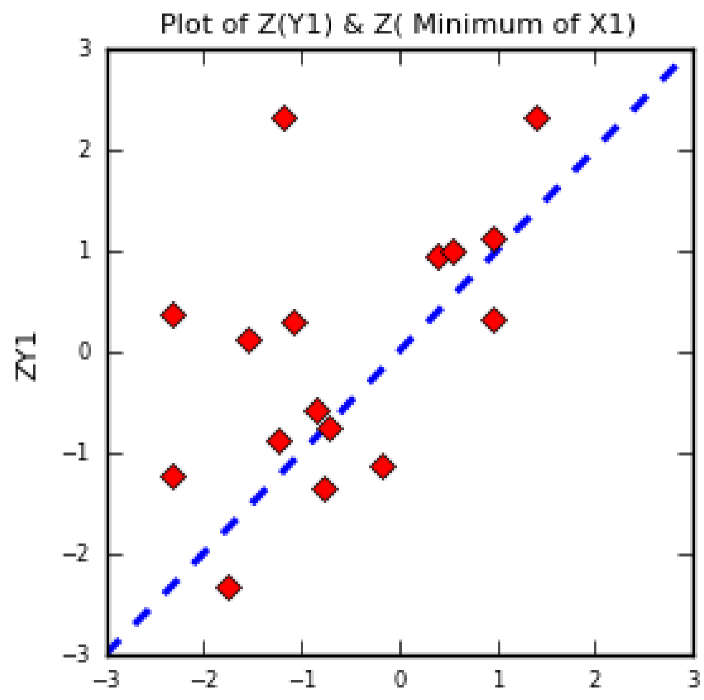


Thanks Patricio Troncoso-Ruiz. He helped prepare these data for re-use. See our Github area, to do this estimate yourself!

A German-Regions Education Illustration

Using our Python Freeware Program

Freitag, M., & Schlicht, R. (2009). Educational Federalism in Germany



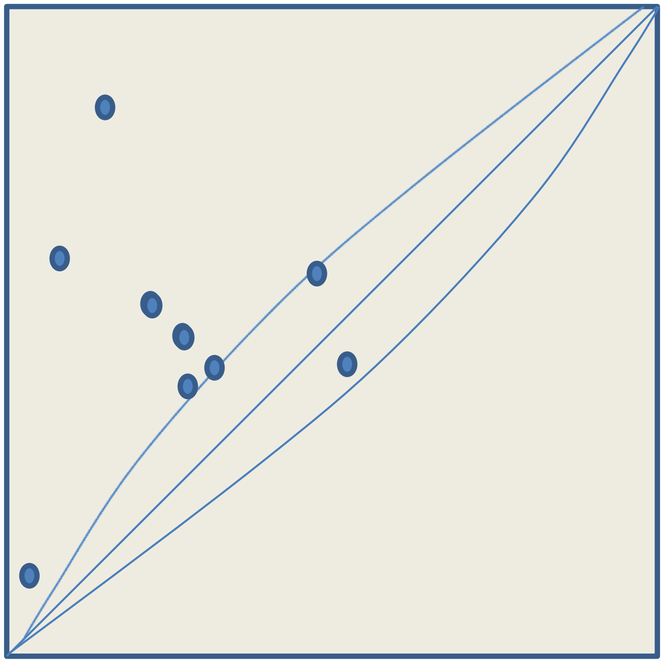
The pattern suggests that X is sufficient for Y with 5 exceptions. The consistency Csuff is .876. This meet's Ragin and Rihoux's criterion.

caseid	Late Education	Social Inequality
SH	0.2	0.28
HH	0	0.65
NI	0.22	0.09
HB	0.24	0.23
NW	0.65	0.83
HE	0.43	0.13
RP	0.83	0.87
BW	0.71	0.84
BY	0.92	1
SL	0.83	0.63
BE	0	0.11
BB	0.04	0
MV	0.14	0.62
SN	0.11	0.19
ST	0.12	1
TH	0.06	0.55

A More Advanced Measure of Fit, D_{suff}

- The fuzzy-set measurements could have measurement error?
  - If so:
  - A frequentist discourse and we use an F test.
  - Using mixed methods we also explore WHY and TO WHAT EXTENT the causal mechanisms work the way they appear to do.
  - The patterns are not the real; ***<u>the real causes are making these patterns appear.</u>***

Another illustration of Eliason & Stryker's concept of measurement error



3.2 Empirical estimate of distance: Stryker's measure: $(1\text{-}D)*(zy\text{-}zx)^2$

- D is 1 if the case lies in the upper lefthand triangle.
- D is 0 otherwise.
- In PYTHON language:

if (ylist[XL] > xlist[XL]): d = 1 else: d = 0

- Sum up the $\mathbf{D_{suff}}$ measure for all the cases in the group below the diagonal.

(If D=1 we multiply the distance by 1-D so that it is cancelled out.)

- For example, if N=30 and 20 are above the diagonal, we are adding up 10 items to give the Dsuff measure. $\mathbf{D_{suff}i}$ is zero where D=1.

*(NOTE: Also, if **X**=0 for certain cases in a configuration, then cases should add nothing! ! !!) (By implication, if **X** is 0 for all cases, then that configuration is not causal on Y.)*

Exploring Sufficiency Testing

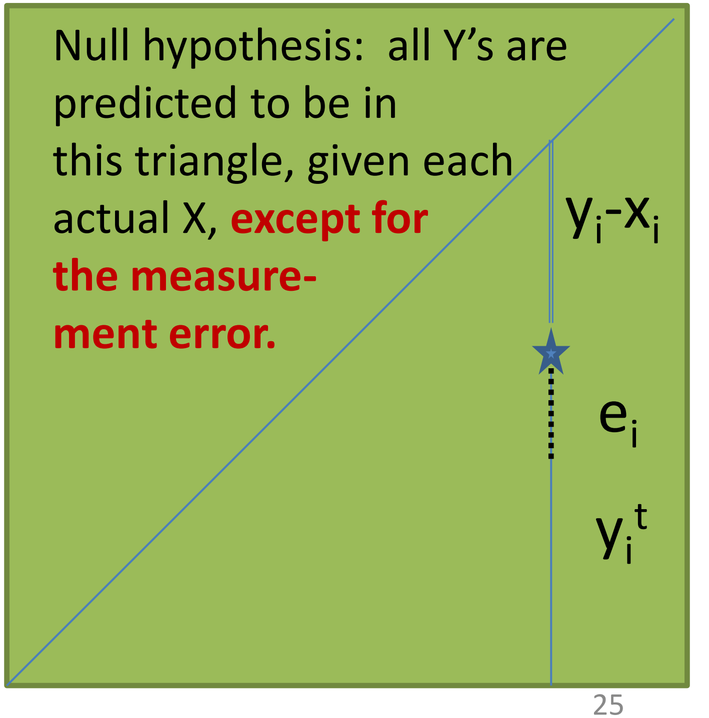
- If the mean of Y and the mean of X give a point low down in the diagram, we tend to get a low Consistency level, depending on the skewness of the two variates.
- If the mean of Y and mean of X give a point high up in the diagram, the Csuff tends toward being large, and the Dsuff tends toward being small.
- When Dsuff is small, there's no need to reject the null hypothesis of **X** is sufficient for Y.
- *A "Csuff large" can be tested using the idea that the credible interval must not include 0.8.*
- B "Dsuff small" can be tested using the F test claim that F is greater than the F cutoff. [OR that the c.i. for Dsuff is small.
  - C We do not have a cutoff criterion for Dsuff. Further research may suggest such a criterion value. The issue of measurement error must be taken into account, as well as the spread of X along the X axis.]

What is the total distance in the numerator of the F?

- It's the sum of the individual distances from the point to the diagonal line, each squared before they're added up.

- The formula uses D_{suff}

$$\Sigma(1-D)(ZY - ZX)^2 \quad \text{Eq. 4}$$



F statistic

A ratio of two r.v.s follows an F distribution if both r.v.s follow chi-squared distribution.

We see this in ANOVA and in the F test of Regression: If F is large, P is near 0 and we reject the null hypothesis, because the numerator exceeds the denominator more than it would by chance.

For our F statistic, **the H_0 is: X is <u>sufficient</u> for Y.**

Rejecting H_0 means we have X is NOT sufficient for Y. "Accepting" H_0 means we have <u>*not falsified*</u> H_0.

This particular F Statistic

- When we take Zx, this now becomes a point in space, so it does add something. The algebraic rules shift from Boolean to Euclidean.

F = msd/emsd on df1, df2 degrees of freedom. Eq. 2
= mean of the sum of Distance from Sufficiency / Expected Mean under Null Hypothesis
= ($\sum$Dsuff / df1) / E(ε_i)

WHERE: msd = $\mathbf{D_{suff}}$/df1 Eq. 2a
And emsd = nullsd Eq. 2b
$\mathbf{D_{suff}}$ = the sum of all $(1 - d) * (zy - z\mathbf{x})^2$ Eq. 4
E (ε_i) = nullsd = df2 * error_value^2 Eq. 5

- The numerator arises as a measure of the observed distances from the hypothesized sufficiency relationship (which is independent of the denominator).
- The denominator is a measure of the expected value of the error in the model. The expectation of the squared errors.
- This error must be independent of X and Y. It is a piecewise linear function. Actually from a scalar 'Error_value' we want to generate the errors for each X but we have not allowed this correlation of X and error in this model. We follow Huang, R. https://r-forge.r-project.org/scm/viewvc.php/pkg/QCA3/R/fsgof.R?view=markup&root=asrr with error_value=0.05

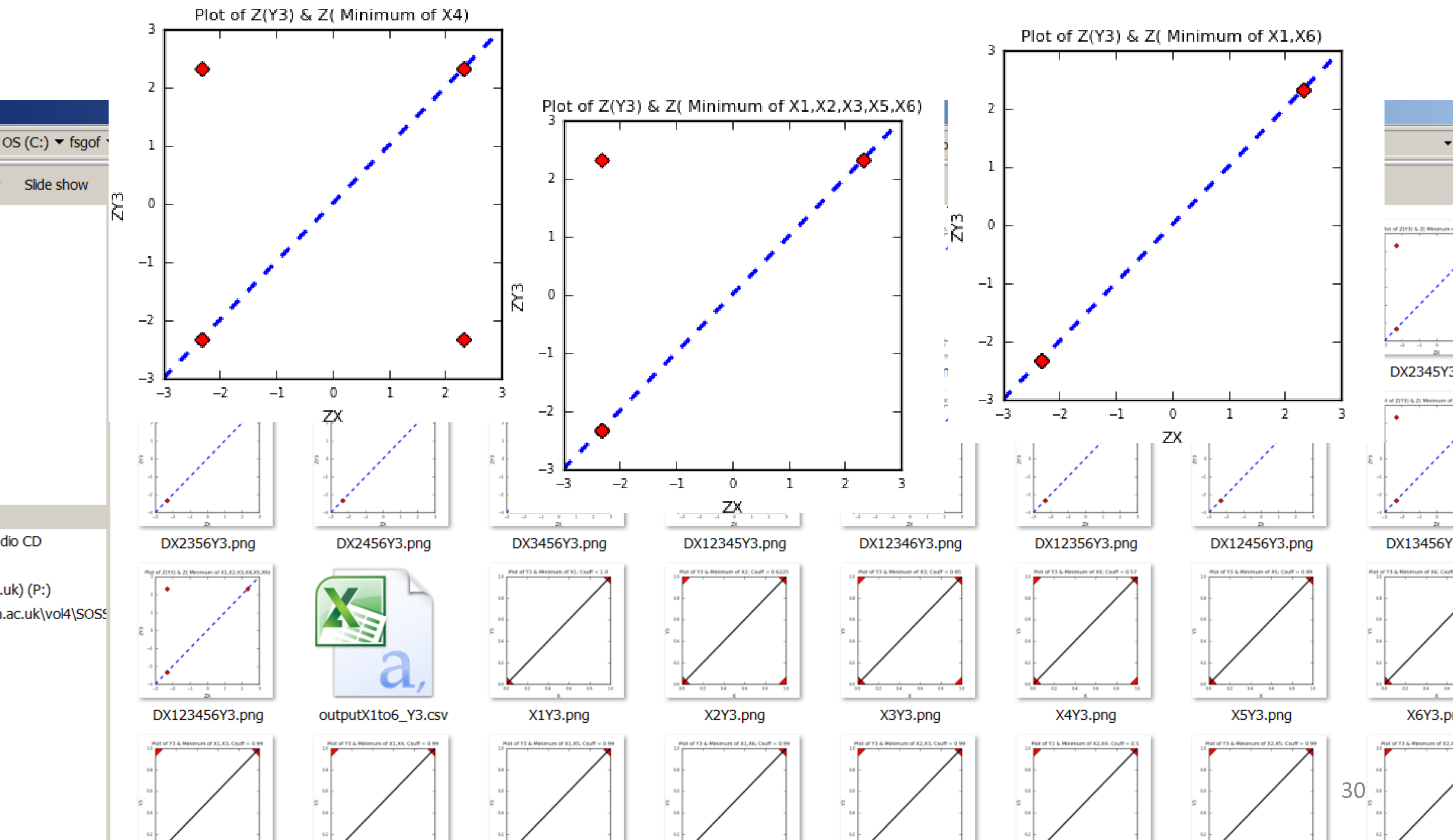
Interpretation of the denominator

- It is an innocuous feature, based on a null assumption.
- If F is large, there's a lack of support for the null hypothesis.
- If F is small, there's no way to reject the SUFF hypothesis. We want F small! ☺
- If F =0 and X is always zero, you can't test causality of X.
- Watch out for remainders.

4 Empirical findings
Real data illustrations

- Aims of this section:
- Show the graphs that our program makes.
- See https://github.com/WendyOlsen/fsgof
- Show that the Dsuff matches the Csuff in measuring the degree of deviation of the pattern from what would be expected if X were sufficient for Y.
- Show how an F test is interpreted for different sample sizes.
- Show how the degree of measurement error affects the test of goodness of fit.

Cress & Snow (2000) Homeless Organisations Data



Indian village people's resistance to the landlord-employer's dictates

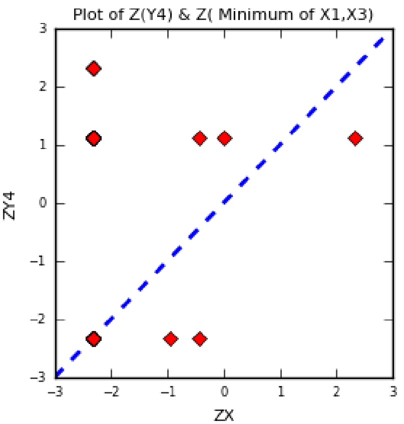
- Y4 is the key outcome reported on in Chapter by Olsen (2009) in Byrne & Ragin, eds. *Handbook. Data sample:*

hhid	worker	farmerll	assets	education	tenancy	wetaccess	havecows	conformn	innovaten	resistfz
1	0	0	0.87	0.17	1	1	1	1	0	0
2	0	0	0.5	0.5	1	0	1	0	3	0.87
3	0	0	0.5	1	0	1	1	3	1	1
4	0	0	0.67	0.33	0	0	0	1	0	0.87
5	0	0	0.33	0.17	1	0.87	0	3	1	0
6	0	0	1	0.67	1	1	1	2	0	0

- *Results (Sorted by Significance = Low)*

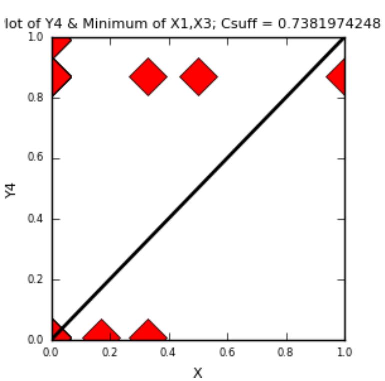
Do Boolean Algebra? (reduce)
Only if the H_0 is **not rejected.**

(or use fsQCA freeware, see http://www.u.arizona.edu/~cragin/fsQCA/software.shtml



Df1 is the number of exceptions.

Config	Y	Csuff	Dsuff	F	PVAL	Df1	Num
X13Y1	1	0.927	1.883	4.828	0.03	1	39
X45Y1	1	0.963	1.883	4.828	0.03	1	39
X134Y1	1	0.88	1.883	4.828	0.03	1	39
X345Y1	1	0.963	1.883	4.828	0.03	1	39
X456Y1	1	0.955	1.883	4.828	0.03	1	39
X3456Y1	1	0.955	1.883	4.828	0.03	1	39
X1Y1	1	0.4	129.885	55.507	0	6	39
X2Y1	1	0.623	64.943	55.507	0	3	39
X3Y1	1	0.769	72.701	23.302	0	8	39
X4Y1	1	0.581	119.836	20.485	0	15	39
X5Y1	1	0.925	21.648	55.507	0	1	39
X6Y1	1	0.798	76.864	49.272	0	4	39
X12Y1	1	0	0	0	0	0	39



Boolean algebra rules

- If AB and Ab are associated with Y, then
- A(B or b) are associated with Y, so
- A → Y is justified as a simplification. (? Check your remainders, and your N and df1!). Boolean reduction.

- If AB and AC are associated with Y, then
- A(B or C) is a similar way to express this association. So A(B or C) can be tested for its overall sufficiency for Y. Commutative, symmetrical? NO… if you again test using Not-Y your results may surprise you.

Config	Y	Csuff	Dsuff	F	PVAL	Df1	Num
X13Y1	1	0.927	1.883	4.828	0.03	1	39
X45Y1	1	0.963	1.883	4.828	0.03	1	39
X134Y1	1	0.88	1.883	4.828	0.03	1	39
X345Y1	1	0.963	1.883	4.828	0.03	1	39
X456Y1	1	0.955	1.883	4.828	0.03	1	39
X3456Y1	1	0.955	1.883	4.828	0.03	1	39
X1Y1	1	0.4	129.885	55.507	0	6	39
							39
							39
							39
							39
							39
							39

- To illustrate ‘reduction’:
- X1X3 + X4X5 + X1X3X4 + X3X4X5 + X4X5X6 + X3X4X5X6 $\rightarrow$ Y implies:
- X1X3 + X4*(X5 or X1X3 or X3X5 or X5X6 or X3X5X6).
- So in summary there are two pathways here.

- The Csuff suggested each of these is sufficient (Olsen, 2009).
- But the F test is falsifying this finding.
- Note also the role of a factor like X6. It, for example, is not necessary overall.
- But X6 is an INUS condition if you use the C_{suff} criterion.

Conclusions

- If not a random sample, simply use Ragin's Consistency measure.
- **If it's a random sample, use both measures – Ragin's Consistency and the F test that Eliason and Stryker (2003, 2009) and I have developed.**
- Download our powerpoint and program and samples from GITHUB. See https://github.com/WendyOlsen/fsgof
- If it's a whole population, you may use both methods.

Appendix 1A: A Fuzzy Set Interim Truth Table (Olsen, 2009)

Y Fuzzy	X1 Fuzzy	X2 Fuzzy	X3 Crisp	X4 Crisp	X5 Fuzzy	X6 Crisp	Number Of Cases	Configu ration
0	0	0	1	0	1	0	1	**1**
0	0	0	1	1	0	0	4	**2**
0	0	1	0	0	0	1	1	**3**
0	0	1	1	0	0	0	2	**4**
0	1	0	0	0	1	1	3	**5**
0	1	1	0	0	0	0	1	**6**
0	1	1	0	1	1	0	1	**7**
0	1	1	1	1	1	1	1	**8**
1	0	0	0	0	0	1	1	**9**
1	1	0	0	1	1	1	4	**10**
1	1	0	1	0	0	0	1	**11**
1	1	0	1	0	1	1	1	**12**
1	1	0	1	1	0	1	1	**13**
1	1	0	1	1	1	1	1	**14**
1	1	1	0	0	1	0	2	**15**
1	1	1	0	0	1	1	4	**16**
1	1	1	0	1	0	0	1	**17**

Appendix 1B: A Fuzzy Set **Raw** Truth Table (Olsen, 2009) (White=X1-X6) (Purple=Y1-Y4)

hhid	worker	farmerll	assets	education	tenancy	wetaccess	havecows	conformn	innovaten	resistfz
1	0	0	0.87	0.17	1	1	1	1	0	0
2	0	0	0.5	0.5	1	0	1	0	3	0.87
3	0	0	0.5	1	0	1	1	3	1	1
4	0	0	0.67	0.33	0	0	0	1	0	0.87
5	0	0	0.33	0.17	1	0.87	0	3	1	0
6	0	0	1	0.67	1	1	1	2	0	0
7	0	0	0.5	0.87	0	0	1	2	1	1
8	0	0	0.87	0.67	0	0.87	1	0	1	0
9	0	1	0.87	1	0	1	0	0	0	0.87
10	0	0	1	1	0	1	1	0	1	0.87
11	0	0	0.87	0.17	1	1	1	2	0	0.87
12	0	1	1	0.17	1	1	1	0	1	0.87
13	0	1	1	0.33	1	1	1	0	1	0
14	0	0	0.17	0	1	0	1	1	0	0.87
15	0	0	0.87	0.67	0	0	0	0	0	0
16	1	0	0.33	0.87	0	0	1	1	2	0
17	0	1	0.87	1	0	1	0	0	0	0.87
18	0	0	0.87	0.33	1	0	1	2	3	1
19	1	0	0	0.33	0	0	0	2	1	0
20	0	0	1	0.33	1	0.87	1	0	1	1
21	0	0	0.5	0	1	0	1	0	2	0.87
22	0	0	0.87	0.87	0	0	0	0	2	0.87
23	1	0	0	0.17	0	0	0	0	0	0
24	1	0	0	0.17	0	0	0	2	0	0.87
25	0	1	0.87	0.87	0	1	0	0	1	0
26	0	1	1	0.87	0	1	1	0	0	0.87
27	1	0	0.33	0.5	0	0	1	3	0	0.87
28	1	0	1	0.33	1	1	1	4	0	0.87
29	0	1	1	0.87	1	1	1	1	0	0.87
30	0	0	0.87	0.17	1	1	1	0	0	0.87

Appendix 2: Ragin gave a Z score with a p value

- (*Fuzzy Set Social Science*, 2000)
- The p value is the risk of being wrong in rejecting a null hypothesis – here, the null is that the X is not sufficient for the Y.
- Each case has a p value.
- Each group of cases has a p value.

- Few scholars have emulated his Z test.
- Stryker and Eliason (2009) comment on a weakness of this test.

Appendix 3: Snippet from Eliason and Stryker 2009

indicator (dummy) variable coded 1 when $y_i > x_i$ and 0 when $y_i \leq x_i$.

For an xy biplot with $N(x_i,\ y_i)$ pairs, the accumulated squared Euclidean distance of the normalized fuzzy-set membership scores from that expected under each argument may now be defined.[14]

Squared distance from a null association:

$$D_{null} = \sum_{i=1}^{N} \left(z_{y(i)} - E\left\{Z_{y(i)} | \text{null XY association}\right\}\right)^2,$$

Squared distance from causal necessity: $D_{nec} = \sum_{i=1}^{N} d_i \left(z_{y(i)} - z_{x(i)}\right)^2$,

Squared distance from causal sufficiency: $D_{suf} = \sum_{i=1}^{N} (1 - d_i)\ (z_{y(i)} - z_{x(i)})^2$,

Squared distance from causal necessity and sufficiency:

$$D_{(nec\&suf)} = \sum_{i=1}^{N} \left(z_{y(i)} - z_{x(i)}\right)^2 = \sum_{i=1}^{N} d_i \left(z_{y(i)} - z_{x(i)}\right)^2 + \sum_{i=1}^{N} (1 - d_i)\left(z_{y(i)} - z_{x(i)}\right)^2 = D_{nec} + D_{suf},$$

where $E\left\{Z_{y(i)} | \text{null XY association}\right\}$ is the expected value of the standardized outcome membership score for case i given a null association between the hypothesized cause and the outcome.[15]

With $Z_{y(i)}$ and $Z_{x(i)}$ normally distributed by definition, a null association implies independence of $Z_{y(i)}$ and $Z_{x(i)}$ and thus $E\left\{Z_{y(i)} | Z_{y(i)} \otimes Z_{x(i)}\right\} = E\left\{Z_{y(i)}\right\} = \bar{Z}_y$, where $Z_{y(i)} \otimes Z_{x(i)}$ indicates independence and $\bar{Z}_y$ gives the sample mean of $Z_{y(i)}$. Thus, substituting $\bar{Z}_y$ for $E\left\{Z_{y(i)} | \text{null XY association}\right\}$ gives the minimum-distance expected value

Appendix 4: Pseudo Code for Programs for Csuff, Dsuff

- A. input the parameters that are scalars
  Input the data as a rectangle without missing values.
- B. Label the permutations (ie X configurations), calculate fuzzy **X** = min(**X**k) for each configuration, count the length of Y and the Number of instances in each X configuration (N in set for **X** where Yi>**X**i)
- C. Calculate Consistency for Sufficiency
  Calculate Distance for Sufficiency
- D. Output plots of the X and Y as fuzzy scores
  Output plots of the rescaled ZY by ZX, and a table of Csuff, Dsuff
- E. Test for sensitivity to the parameters by looping around, changing either the damping factor or the measurement error.

See https://github.com/WendyOlsen/fsgof

Appendix 4: Pseudo Code for Programs With Bootstrap

•Input S the scale of the bootstrap activity.
Start loop.
•Create S=1000 resamples with replacement
These have some repeats of cases.
Each case in each sample is a replica of the original data.
Some cases in the data may not appear, at random in a particular sample.

- A. input the parameters that are scalars
  Input the data as a rectangle without missing values.
- B. Label the permutations (ie X configurations), calculate fuzzy **X** = min(**X**k) for each configuration, count the length of Y and the Number of instances in each X configuration (N in set for **X** where Yi>**X**i)
- C. Calculate Consistency for Sufficiency
  Calculate Distance for Sufficiency
- D. Output plots of the X and Y as fuzzy scores
  Output plots of the rescaled ZY by ZX, and a table of Csuff, Dsuff
- E. Test for sensitivity to the parameters by looping around, changing either the damping factor or the measurement error.

End loop. Average the Csuff over all the S samples.
Average the Dsuff over all the S samples.

•Empirically compare the mean of Csuff with the original Csuff (Bias of consistency measure)
•Empirically compare the mean of Dsuff with the original Dsuff (Bias of distance measure)
•Create a table or graph showing the empirical distribution of the S Csuff's, 95% of which forms a credible interval.
•Create a table or graph showing the empirical distribution of the S Dsuff's, 95% of which forms a credible interval.

References

For Qualitative folks: Hodson, R. (2004). "A meta-analysis of workplace ethnographies - Race, gender, and employee attitudes and behaviors." Journal of Contemporary Ethnography **33**(1): 4-38.

Ragin, C. C. (1987). The comparative method : moving beyond qualitative and quantitative strategies. Berkeley ; Los Angeles ; London, University of California Press.

- For Quantitative Folks: **Ragin, C.C. (2008). Redesigning social inquiry: Set relations in social research. Chicago: Chicago University Press.**
- **Rihoux, B. (2006). Qualitative Comparative Analysis (QCA) and related systematic comparative methods: recent advances and remaining challenges for social science research. International Sociology, 21(5), 679-706.**
- **Rihoux, B., & Ragin, C. C. (2009). Configurational comparative methods. Qualitative Comparative Analysis (QCA) and related techniques (Applied Social Research Methods). Thousand Oaks and London: Sage.**
- Byrne, D., and C. Ragin, eds. (2009), Handbook of Case-Centred Research Methods, London: Sage.
- Cooper, B. & Glaesser, J. (in press 2011) Using case-based approaches to analyse large datasets: a comparison of Ragin's fsQCA and fuzzy cluster analysis, in International Journal of Social Research Methodology.
- Olsen, W.K. (2009), Non-Nested and Nested Cases in a Socio-Economic Village Study, chapter in D. Byrne and C. Ragin, eds. (2009), Handbook of Case-Centred Research Methods, London: Sage.
- Olsen, W.K., and J. Morgan (2005) A critical epistemology of analytical statistics: Addressing the sceptical realist, Journal for the Theory of Social Behaviour, 35:3, September, pages 255-284.

SAMPLE DATA SETS:

1) the website of my course for some past years:

http://Course-data.ccsr.ac.uk/qca

2) the COMPASSS web site (*sic*) www.compasss.org (They have a lot of CSV files there)

Background References to Works Cited

- Eliason S. & Stryker R. 2009. Sociological Methods & Research 38:102-146.
- Freitag, M., & Schlicht, R. (2009). Educational Federalism in Germany: Foundations of Social Inequality in Education. Governance: An International Journal of Policy, Administration, and Institutions, *22*(1), 47–72.
- Ragin, C. C. (2000). Fuzzy-Set Social Science. Chicago; London, University of Chicago Press.
- Snow, D. and D. Cress (2000). "The Outcome of Homeless Mobilization: the Influence of Organization, Disruption, Political Mediation, and Framing." American Journal of Sociology **105**(4): 1063-1104.