Approaching a Robustness Assessment for QCA

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Introduction

One benchmark of many analyses – distinguish from random chance

Introduction

Determine thresholds for analysis – possibly on a case-by-case basis – that reduce the chance that csQCA results are by random chance.

Advantages to QCA

Qualitative elements

- complexity of cases
- holistic analysis of cases

Advantages to QCA

Qualitative elements

- complexity of cases
- holistic analysis of cases

Quantitative elements

- production of generalizations
- replicable

Advantages to QCA

Assumptive alternative to mean-based approaches!!

Criticisms

Criticisms

Seawright (2004,2005)

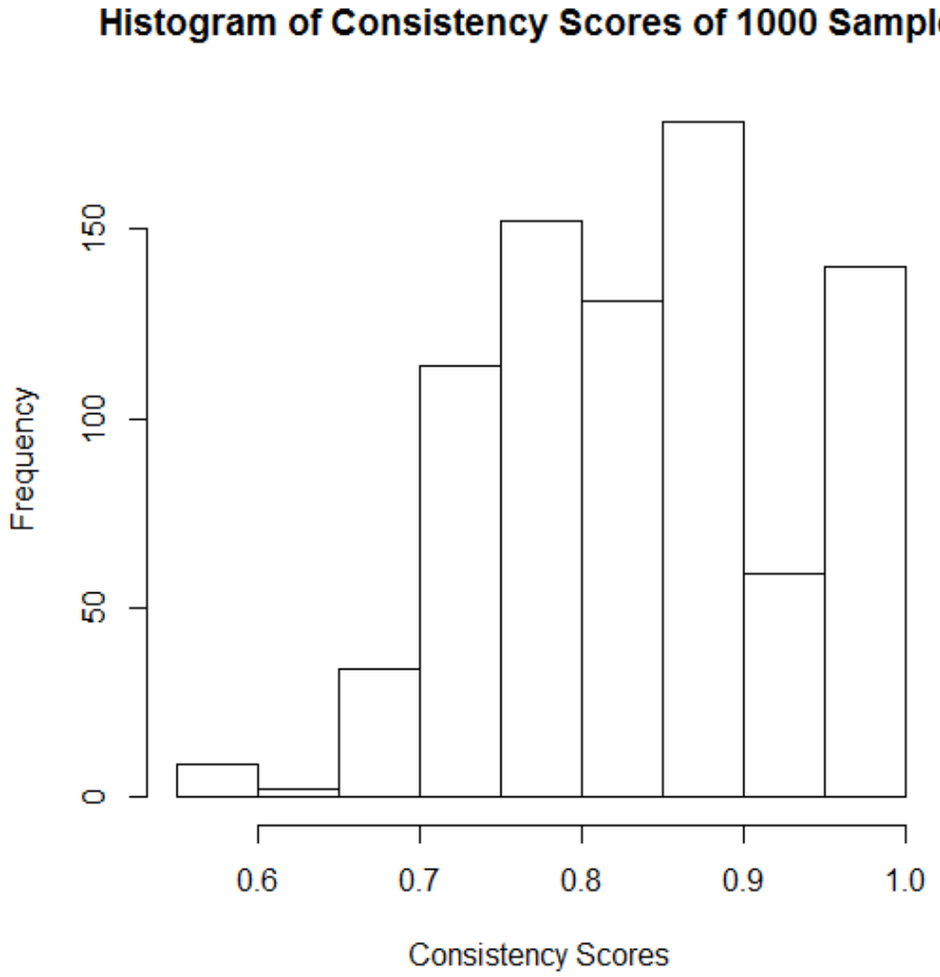
Assumptions:

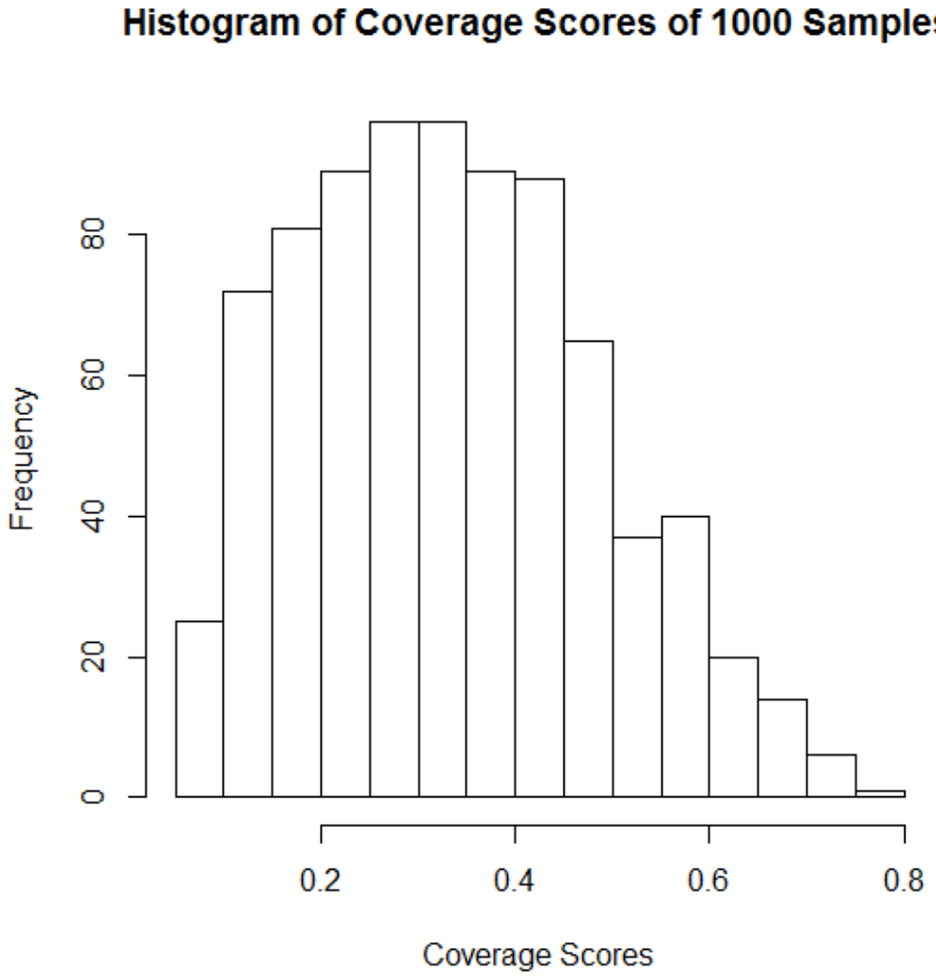
1) assumptions about correct form of the relationship
2) missing variables
3) inferring causation from association

Criticisms

Lieberson (2004)

Doubts the analysis can distinguish from random data


Histogram of Consistency Scores of 1000 Samples
Frequency
0
50
100
150
0.6
0.7
0.8
0.9
1.0
Consistency Scores


Histogram of Coverage Scores of 1000 Samples
Frequency
0
20
40
60
80
0.2
0.4
0.6
0.8
Coverage Scores

Can it?

Researcher Choice

Hicks (1994)

Theory-building prior to analysis

Thorough model specification and resolving of conflicting cases

“consider results relatively provisional insofar as an inductive-statistical rearticulation of the formulation... is practical”

Researcher Choice

Skaaning (2011)

Robustness checks

Sensitivity of models comparing consistency thresholds, calibration, case frequency

Researcher Knowledge

In general, requires intimacy with the cases

- Concrete choices:
  - Case selection
  - Perceptions of patterns
  - causal condition specification
  - Choice of parameters
  - Consistency, configurational n, etc

Researcher knowledge is thus an important factor in ensuring the viability of QCA.

Evaluation Work

- Much of it has relied on observed data
  - or, simulated worlds with a correct model
- What about observing the probability of a “random” configuration?

This Study

Reduce the probability of observing a pattern where this is none

Discuss possible ways to ensure skeptics that the configuration returned from a csQCA is not “random”

Junctures of Choice

Relevant cases.

Causal conditions.

Calibrations.

Consistency threshold.

N threshold for configurations.

Complex, parsimonious, and intermediate solutions

- Direction of relationships

Random Worlds

Random data don't allow analysis of...

- Inclusion of Relevant Cases
- Selection of Causal Conditions
- Calibrations
- Direction of Relationships

Random Worlds

However, we CAN analyze...

- Configurational N
- Consistency score thresholds
- Sample size
- Parsimonious versus complex solutions

Data

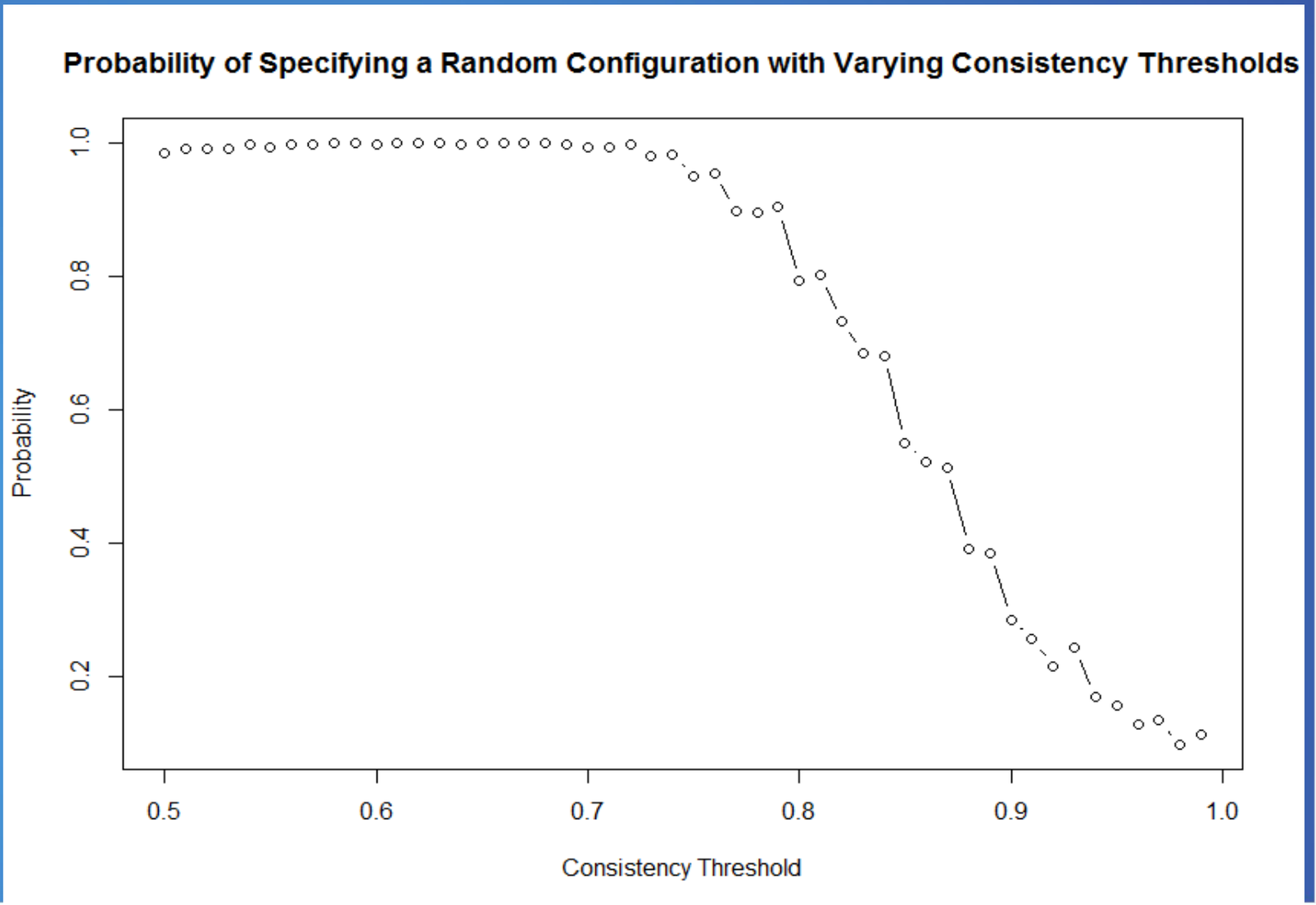
csQCA with four causal conditions and one outcome

All are randomly assigned 0s or 1s (flip-a-coin)

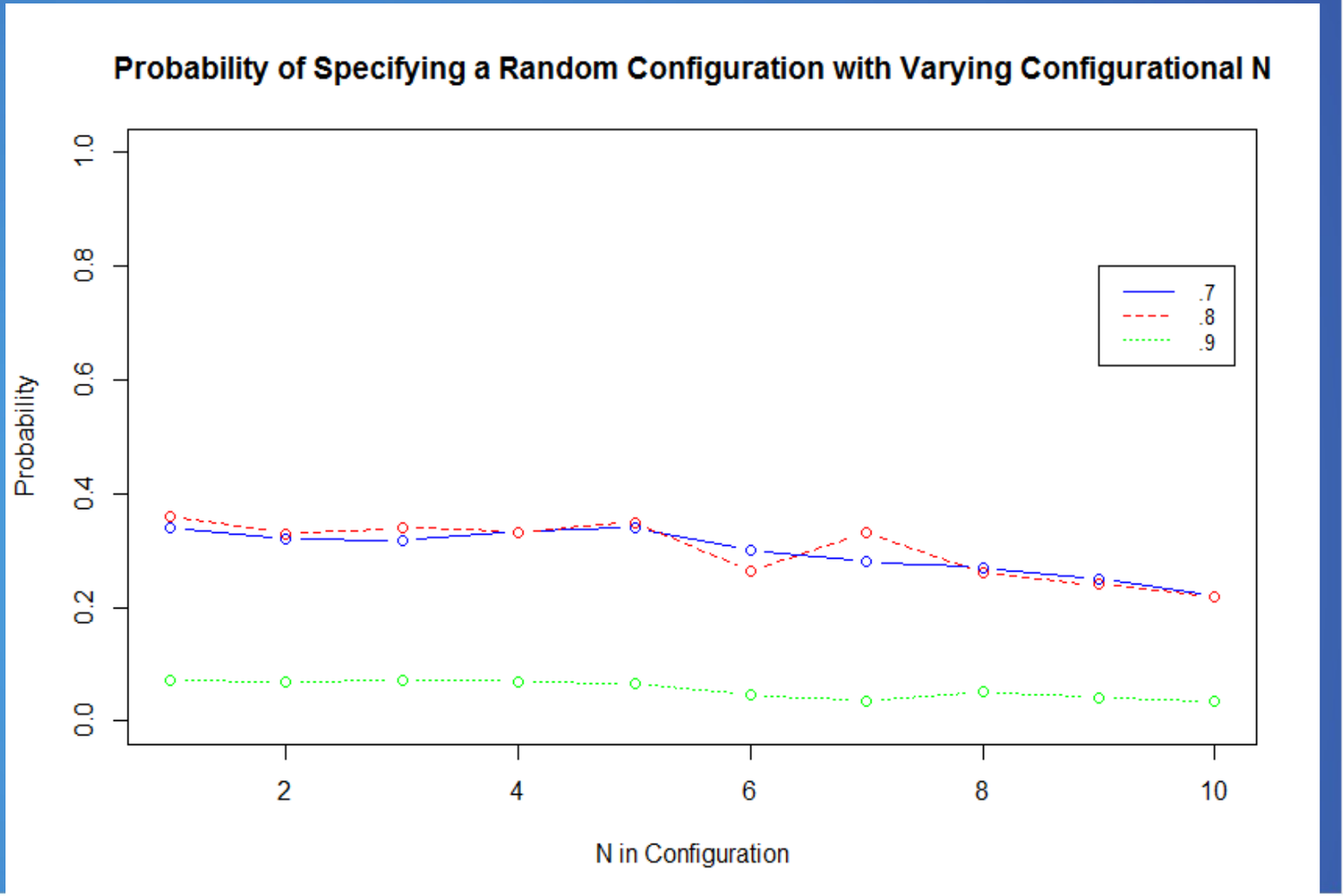
Initial 1000 simulations: sample size 200, consistency threshold .7, configurational n 2, parsimonious solution

(altered later)

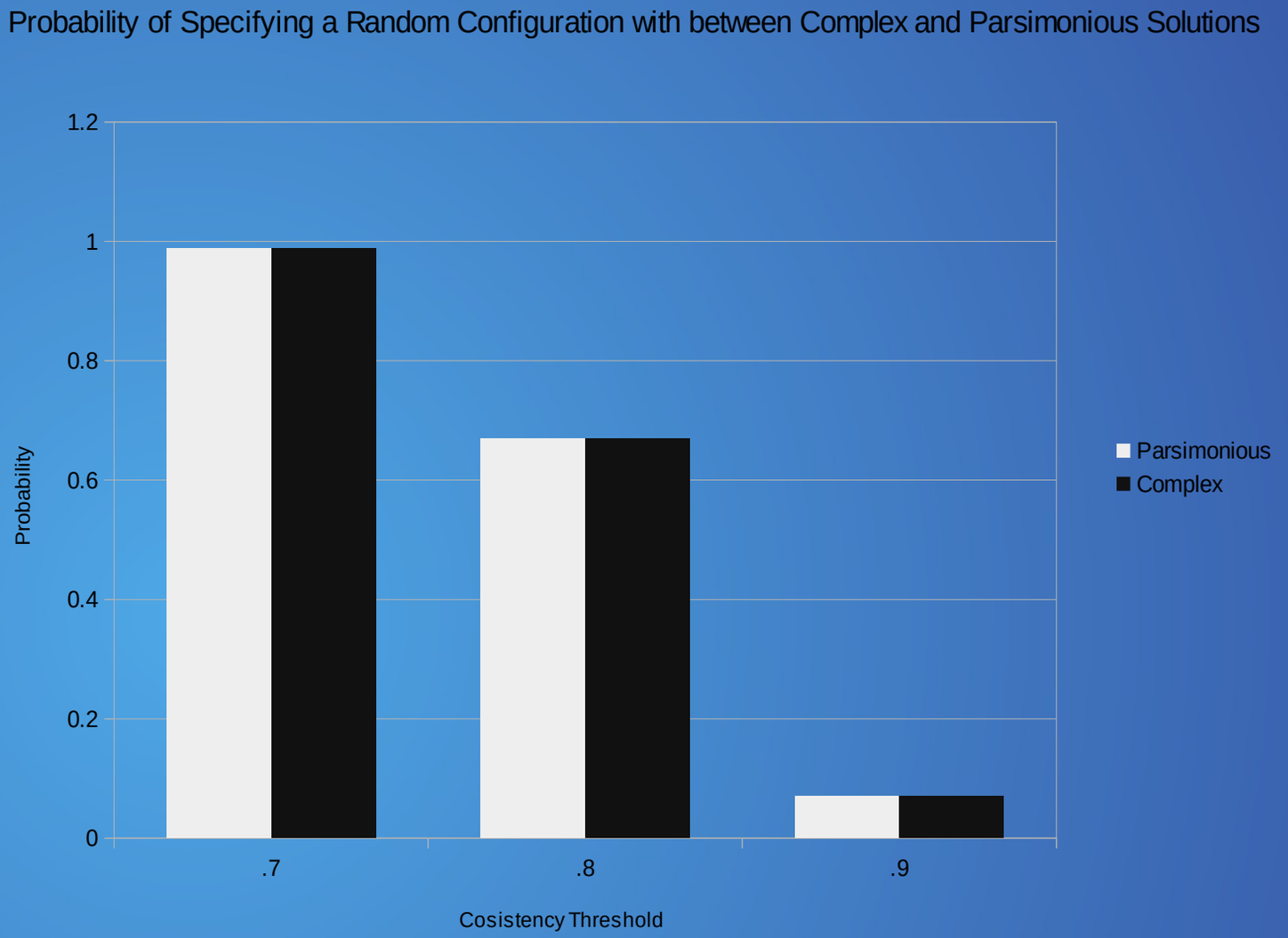
Consistency Thresholds



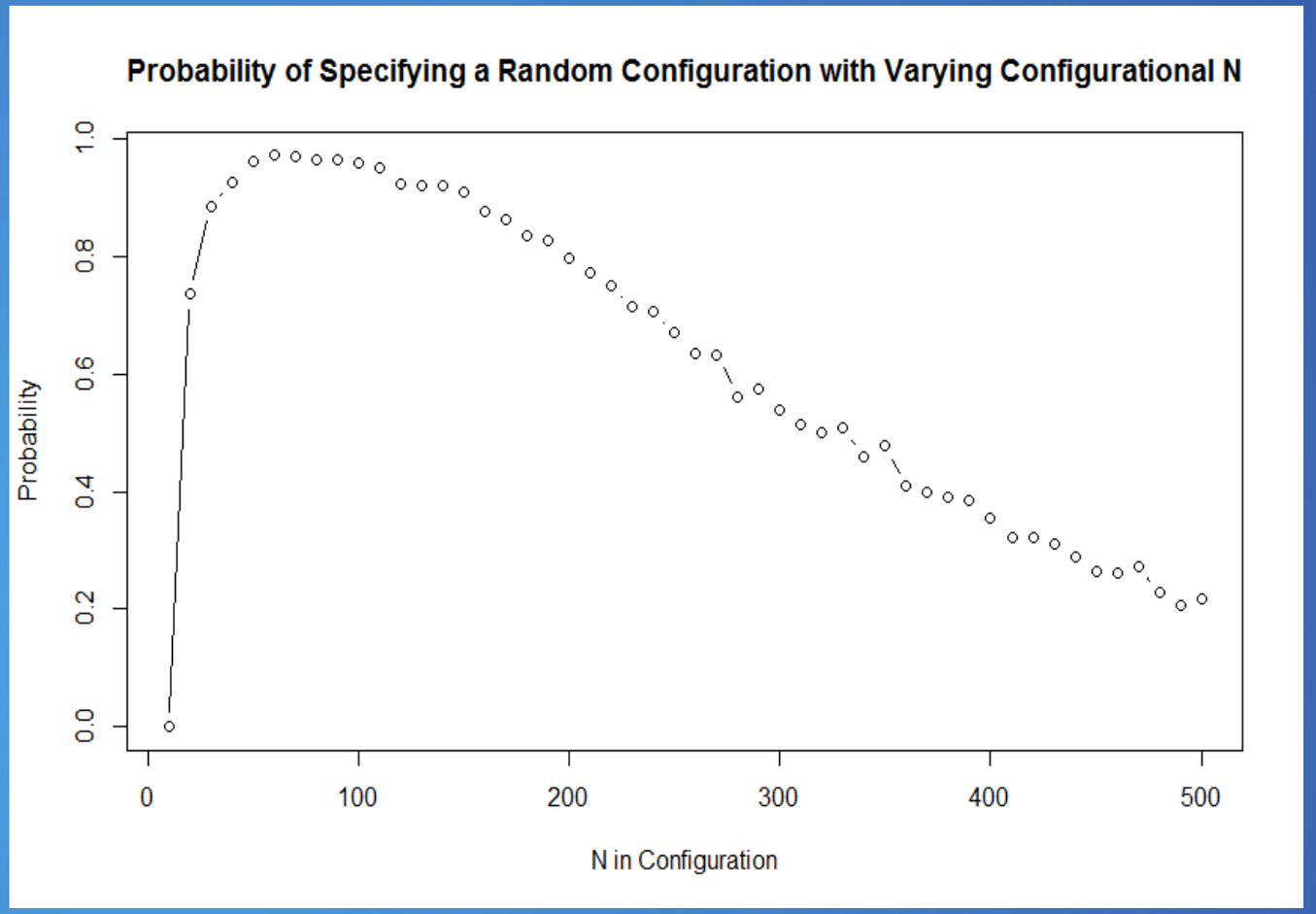
Configuration N Threshold



Parsimonious versus Complex



Sample Size


Probability of Specifying a Random Configuration with Varying Configurational N
Probability
0.0
0.2
0.4
0.6
0.8
1.0
0
100
200
300
400
500
N in Configuration

Part 2

Configural Analysis

fsQCA

Outcome: (not) predicting a spurious configuration

Causal conditions:

- consistency threshold
- n configurations
- sample size
- complex and parsimonious solutions

Researcher Choice

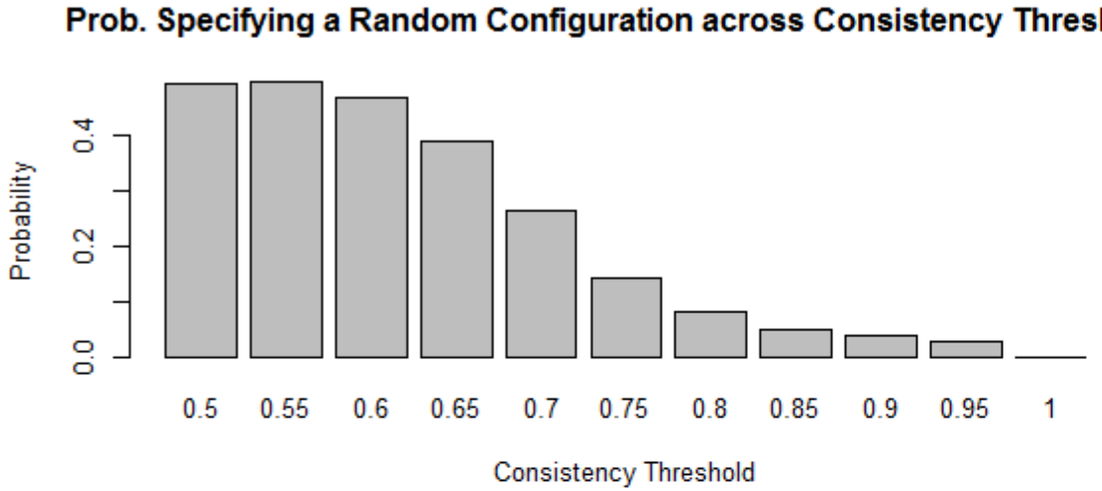
Consistency threshold:

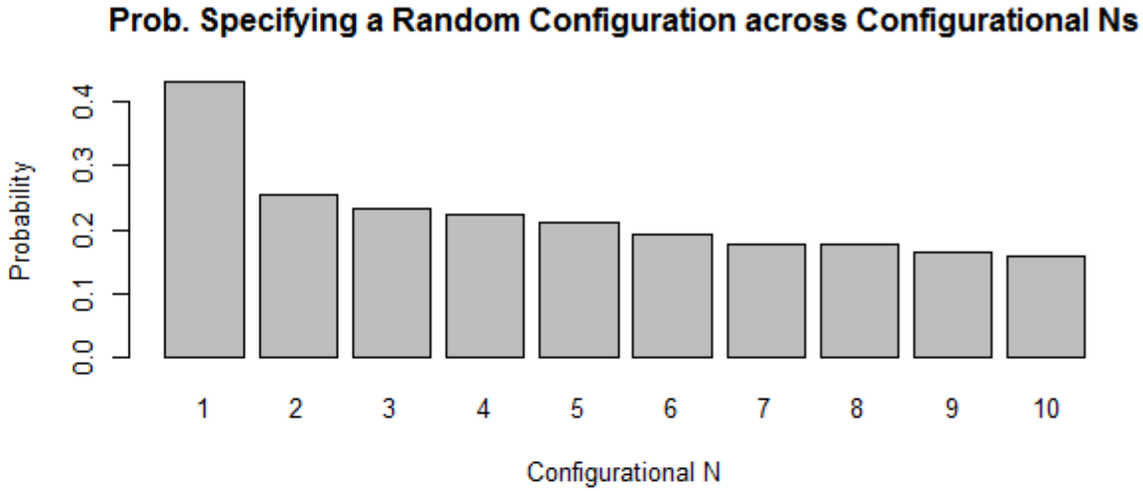
.95

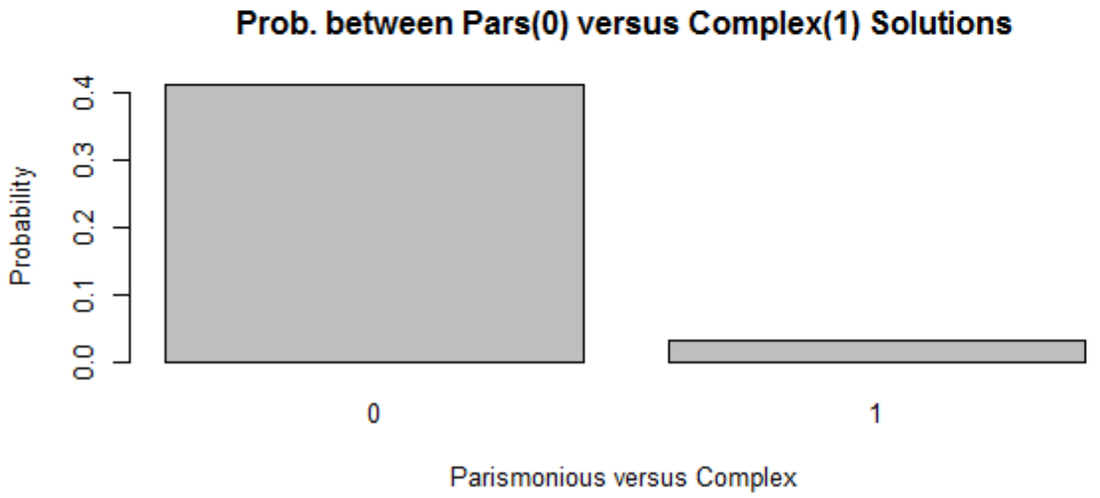
Configurational n threshold:

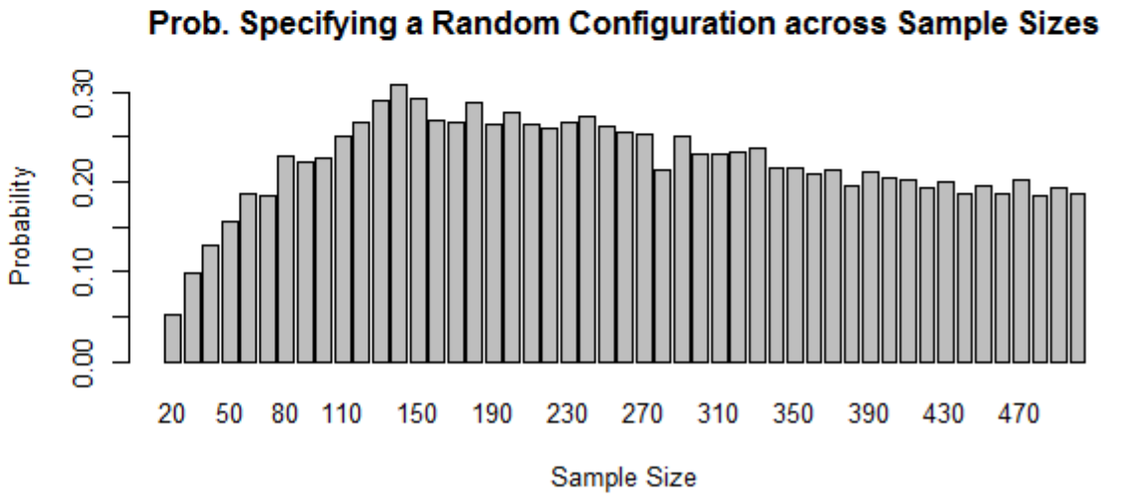
5 (number of simulations ran)

Ran both parsimonious and complex solutions


Prob. Specifying a Random Configuration across Consistency Thresholds
Probability
0.0
0.2
0.4
0.5
0.55
0.6
0.65
0.7
0.75
0.8
0.85
0.9
0.95
1
Consistency Threshold


Prob. Specifying a Random Configuration across Configurational Ns
Probability
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6
7
8
9
10
Configurational N


Prob. between Pars(0) versus Complex(1) Solutions
Probability
0.0
0.1
0.2
0.3
0.4
0
1
Parismonious versus Complex


Prob. Specifying a Random Configuration across Sample Sizes
Probability
0.00
0.10
0.20
0.30
20
50
80
110
150
190
230
270
310
350
390
430
470
Sample Size

TruthTable

	CTH	CNTH	COM	NTH	OUT	n	incl
1	0	0	0	0	0	216	0.515
2	0	0	0	1	0	3240	0.354
3	0	0	1	0	1	216	1
4	0	0	1	1	0	3240	0.893
5	0	1	0	0	0	270	0.866
6	0	1	0	1	0	4050	0.434
7	0	1	1	0	1	270	1
8	0	1	1	1	1	4050	1
9	1	0	0	0	0	180	0.709
10	1	0	0	1	0	2700	0.885
11	1	0	1	0	1	180	1
12	1	0	1	1	1	2700	0.995
13	1	1	0	0	0	225	0.945
14	1	1	0	1	0	3375	0.946
15	1	1	1	0	1	225	1
16	1	1	1	1	1	3375	1

Solution

S1: CNTH*COM + COM*nth + CTH*COM => out

		incl	cov.r	cov.u
1	CNTH*COM	1.000	0.338	0.174
2	COM*nth	1.000	0.052	0.011
3	CTH*COM	0.998	0.248	0.093
	S1	0.999	0.450	

Approaching Diagnostic Assessment

We can find configurations of thresholds that make it highly unlikely that random configurations are returned

> “I am 95% confident this configuration is not due to random chance!”

Future Approaches

fsQCA

sparsity

Conclusions

In these conditions, csQCA typically rejects random patterns at reasonable thresholds of analysis

(fsQCA is likely even more robust)

Conclusions

It is possible to distinguish any returned configuration with random chance configurations, specific to the data set analyzed.