Appendix to Carsten Q. Schneider (2023): Set-Theoretic Multi-Method Research: A Guide to Combining QCA and Case Studies, Cambridge University Press

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This document contains all the analyses presented in the book. Beyond this, additional, auxiliary analyses are provided, mostly to further analyze the properties of the data (skeweness, simplifying assumptions etc.) and to visualize the QCA solution formulas.

All replication files (datasets in csv format and an RMarkdown file that produces this document) can be found in the Harvard Dataverse at https://doi.org/10.7910/DVN/URMOVC

System setting and parameters under which the analyses were performed:

- MacOS: Sonoma 14.0
- R: 4.2.2 "Innocent and Trusting"
- RStudio: 2023.06.0+421

1 Chapter 1: C. Q. Schneider and Makszin (2014)

The data come from Carsten Q. Schneider and Kristin Makszin 2014 article "Forms of welfare capitalism and education-based participatory inequality." [https://doi.org/10.1093/ser/mwu010] The paper analyses whether the degree of political inequality between social groups is shaped by features of the welfare capitalist system. This example is used in chapters 1 and 5.

Outcome:

- `LPI` = Low participatory inequality

Conditions:

- `WC` = High wage coordination
- `UN` = High union density
- `EP` = High employment protection
- `LM` = High labor market expenditure

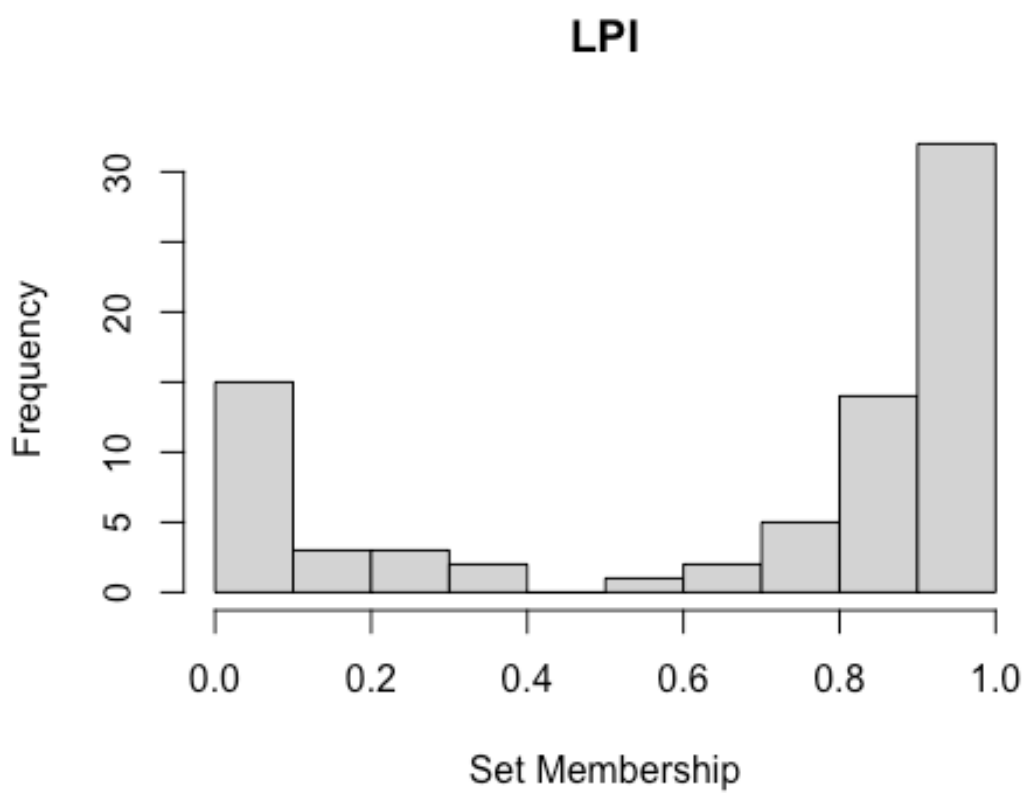
1.1 Loading and checking the data for skeweness and ambiguous cases

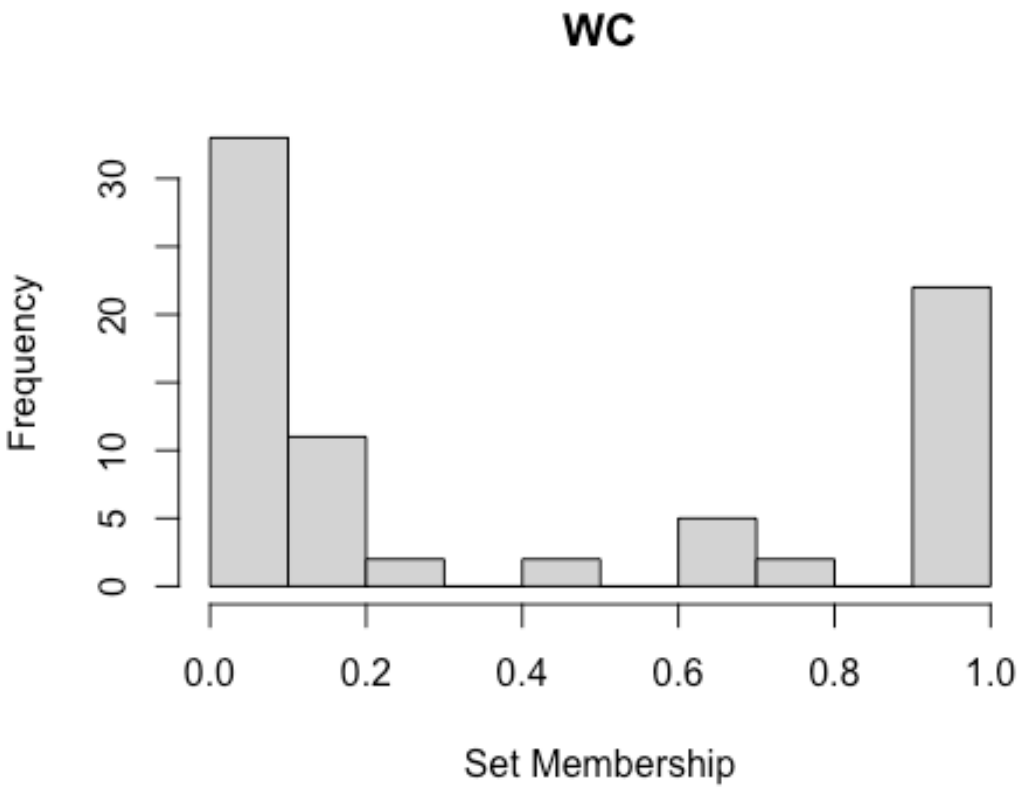
To begin with, we load the data and check for skeweness and the presence of ambiguous cases (that is, cases with 0.5 fuzzy set membership score in a condition or the outcome set).

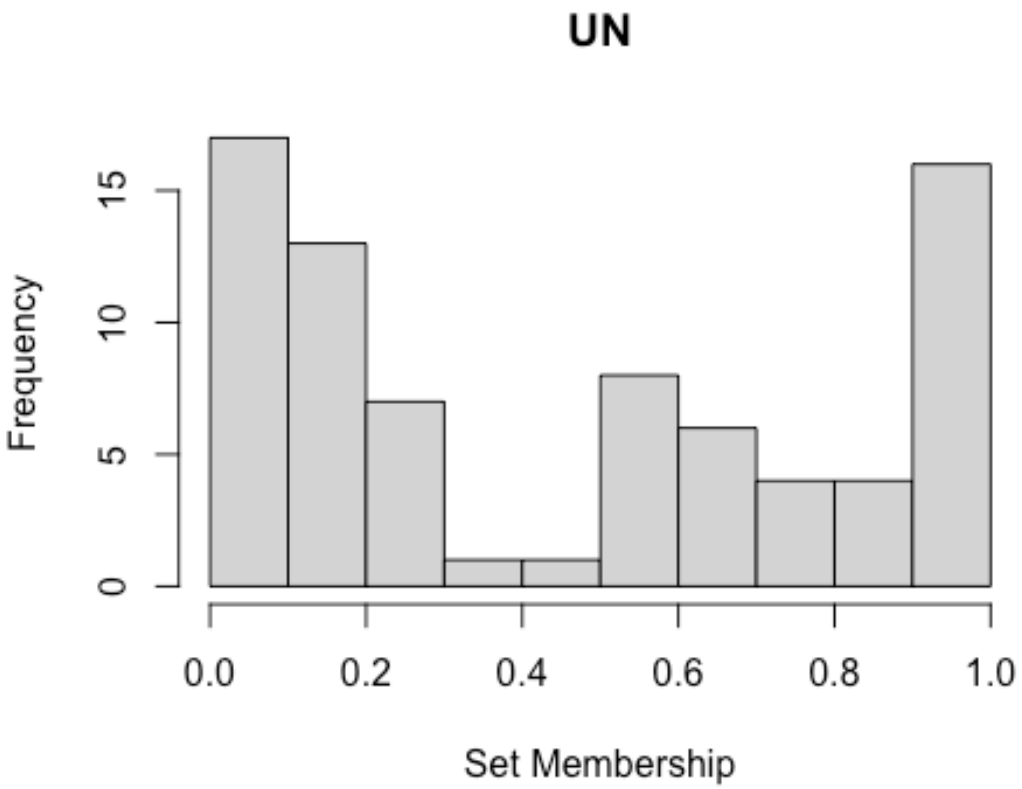
```
MACRO.d <- read.csv('SchneiderMakszin2014.csv', row.names = 1)

head(MACRO.d)
```

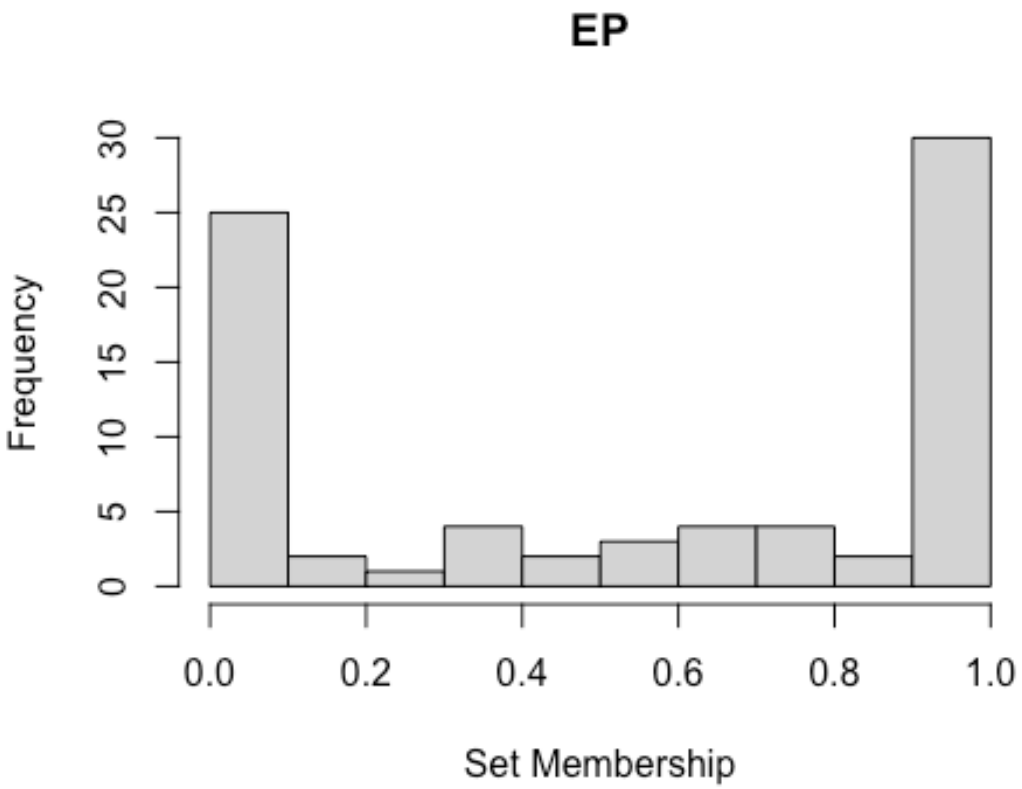
```
            LPI          WC        UN          EP        LM
AT00 0.00253846 0.908674751 0.7000518 0.724116810 0.5498694
AT05 0.00004670 0.908674751 0.1574641 0.545822265 0.5948249
BG95 0.90867475 0.091325249 0.9762687 0.975303710 0.4724572
BG00 0.83529226 0.010000000 0.6056057 0.908674751 0.1248358
BG05 0.50765793 0.010000000 0.2492102 0.500000000 0.0222146
CA95 0.72104641 0.000471777 0.6249398 0.003192034 0.8029896
```

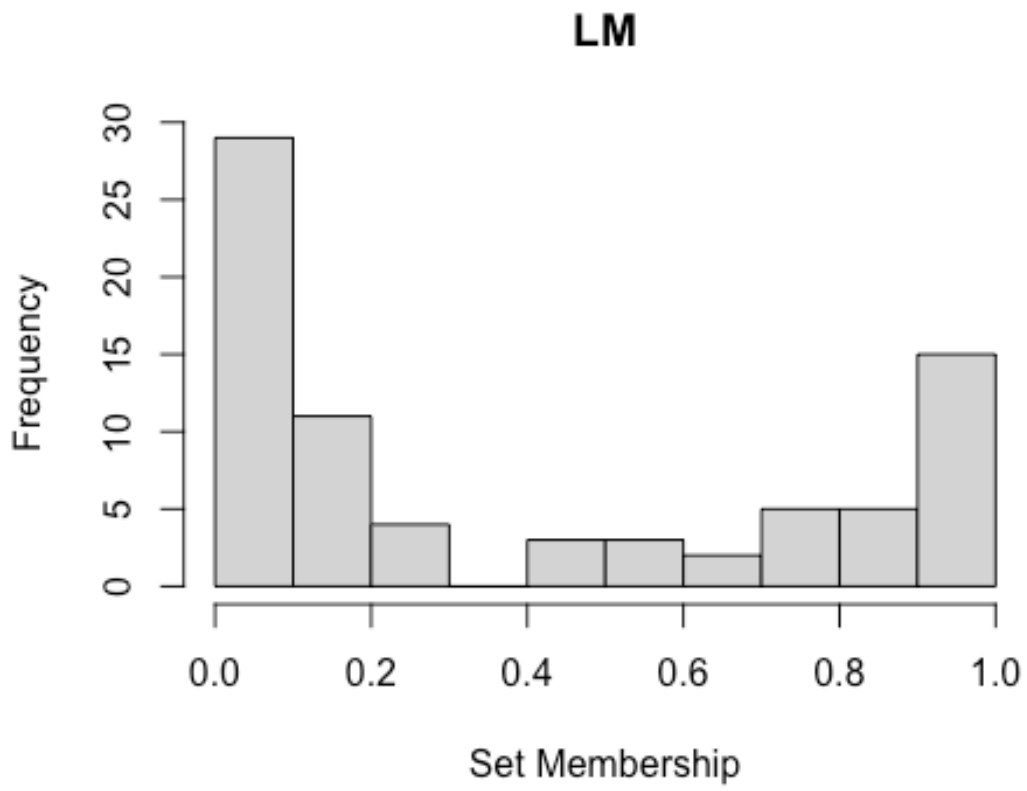
```
# conditions
conds <- c("WC", "UN", "EP", "LM")


# data diagnostics
skew.check(data = MACRO.d,
           hist = TRUE)
```


LPI
Frequency
0
5
10
20
30
0.0
0.2
0.4
0.6
0.8
1.0
Set Membership


WC
Frequency
0
5
10
20
30
0.0
0.2
0.4
0.6
0.8
1.0
Set Membership


UN
Frequency
0
5
10
15
0.0
0.2
0.4
0.6
0.8
1.0
Set Membership


EP
Frequency
0
5
10
15
20
25
30
0.0
0.2
0.4
0.6
0.8
1.0
Set Membership




```
[1] "Set LPI - Cases > 0.5 / Total number of cases: 54 / 77 = 70.13 %"
[2] "Set WC - Cases > 0.5 / Total number of cases: 29 / 77 = 37.66 %"
[3] "Set UN - Cases > 0.5 / Total number of cases: 38 / 77 = 49.35 %"
[4] "Set EP - Cases > 0.5 / Total number of cases: 43 / 77 = 55.84 %"
[5] "Set LM - Cases > 0.5 / Total number of cases: 30 / 77 = 38.96 %"
```

```
# ambiguous cases
ambig.cases(MACRO.d)
```

```
     row col
BG05   5   4
```

```
# BG05  in high employment protection
```

No single set is too skewed. Bulgaria in 2005 holds a membership of 0.5 in condition high employment protection.

1.2 Analysis of sufficiency, outcome *LPI*

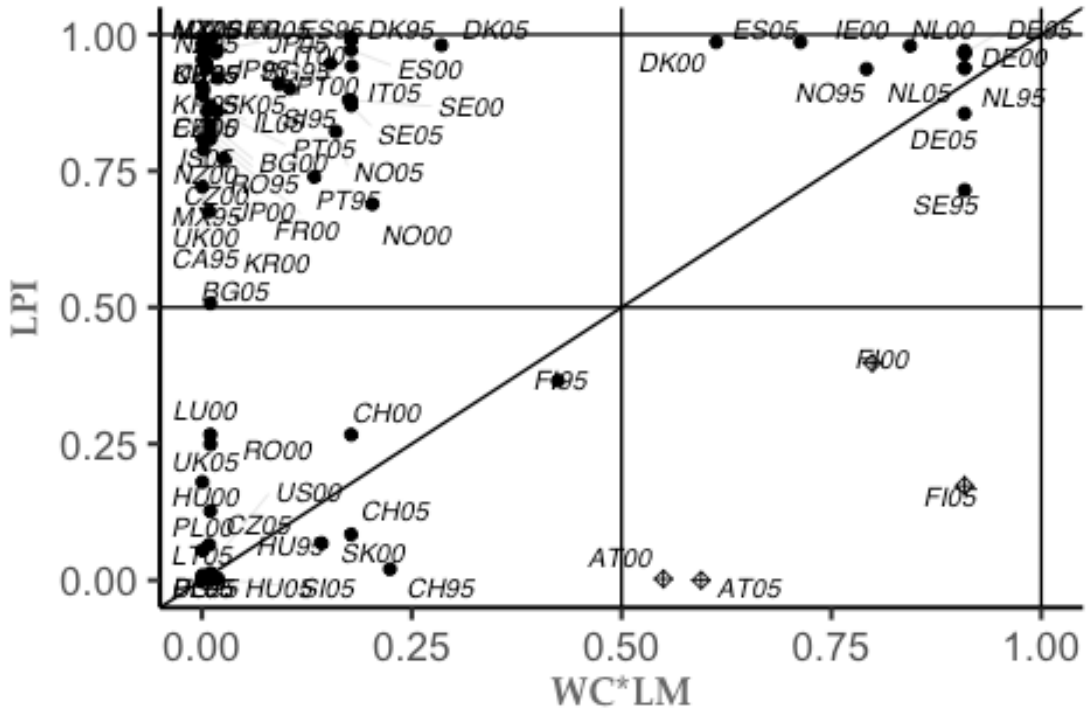
In a first step, we produce a truth table.

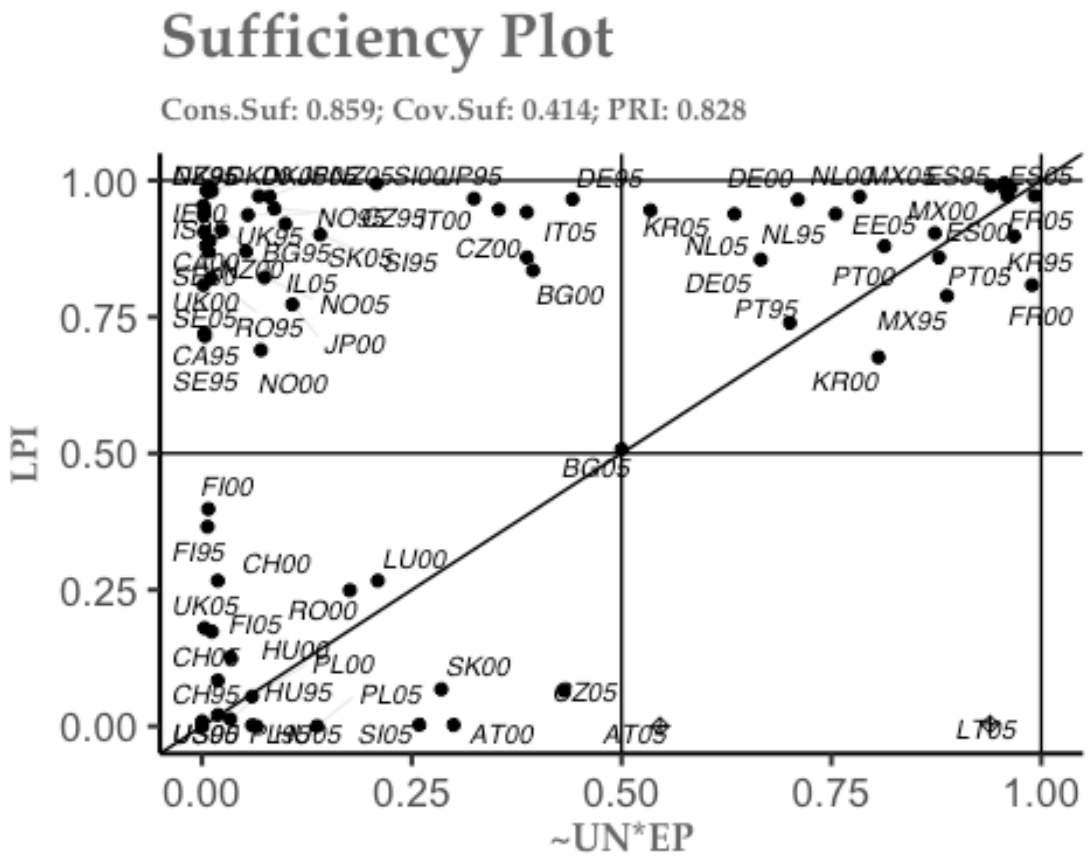
```
# truth table
tt_y <- truthTable(data = MACRO.d,
                   outcome = 'LPI',
```

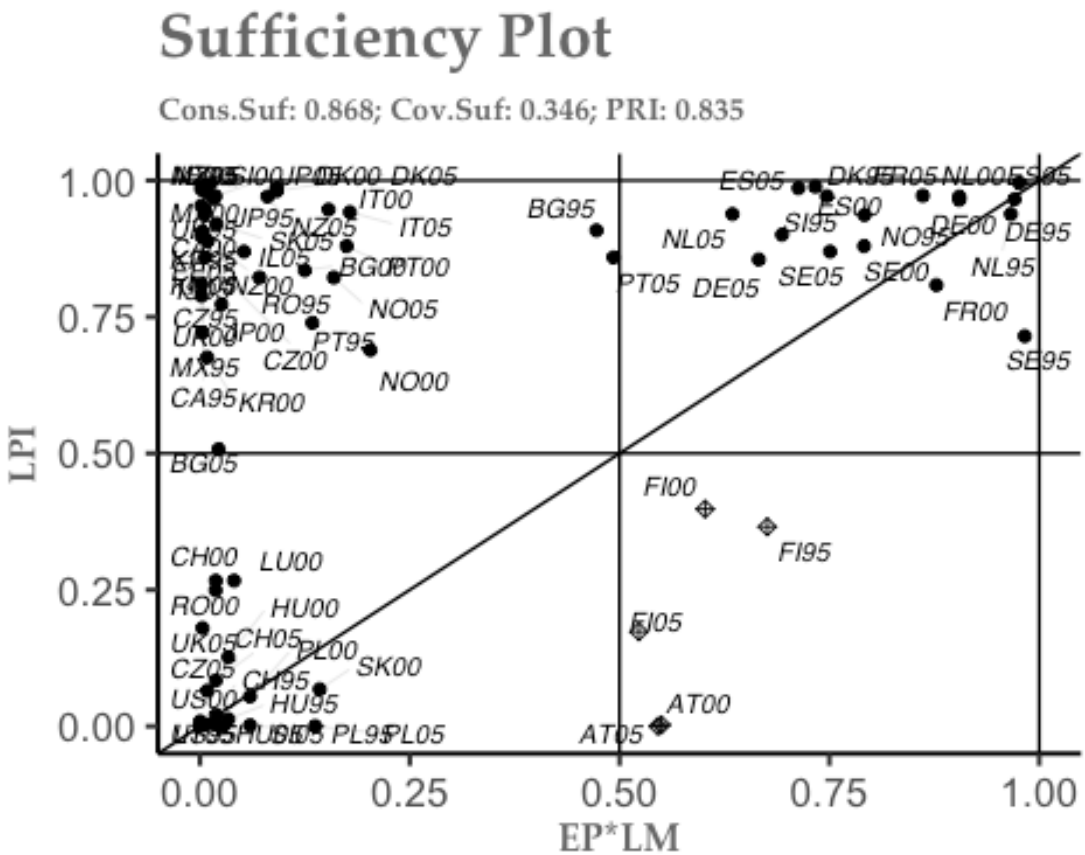
```
                   conditions = conds,
                   incl.cut = 0.8,
                   sort.by = c('OUT', 'incl'),
                   complete = TRUE,
                   show.cases = TRUE)
tt_y


  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

     WC UN EP LM   OUT    n   incl  PRI
 4   0  0  1  1     1     4   0.911 0.871
 8   0  1  1  1     1     5   0.900 0.833
12   1  0  1  1     1     7   0.873 0.839
 3   0  0  1  0     1     9   0.825 0.744
14   1  1  0  1     1     2   0.825 0.698
11   1  0  1  0     1     2   0.818 0.730
16   1  1  1  1     1     6   0.800 0.663
15   1  1  1  0     0     5   0.781 0.683
13   1  1  0  0     0     4   0.769 0.666
 6   0  1  0  1     0     5   0.759 0.618
 7   0  1  1  0     0     5   0.754 0.576
 5   0  1  0  0     0     6   0.726 0.578
 2   0  0  0  1     0     1   0.686 0.476
 9   1  0  0  0     0     3   0.642 0.486
 1   0  0  0  0     0     12  0.537 0.399
10   1  0  0  1     ?     0     -     -
     cases
 4   FR00,FR05,ES95,ES00
 8   DK95,FI95,SI95,SE00,SE05
12   AT05,DE00,DE05,NL95,NL00,NL05,ES05
 3   EE05,KR05,LT05,MX95,MX00,MX05,PT95,PT00,PT05
14   DK00,IE00
11   KR95,KR00
16   AT00,FI00,FI05,DE95,NO95,SE95
15   IT00,NO00,NO05,SI00,SI05
13   CZ95,IS05,IT05,SK00
 6   CA95,DK05,HU95,NZ95,PL95
 7   BG95,BG00,LU00,RO95,RO00
 5   CA00,CZ00,HU00,IL05,UK95,UK00
 2   NZ00
 9   JP95,JP00,CH95
 1   CZ05,HU05,JP05,NZ05,PL00,PL05,SK05,CH00,CH05,UK05,US95,US00
10

# only one logical remainder
```

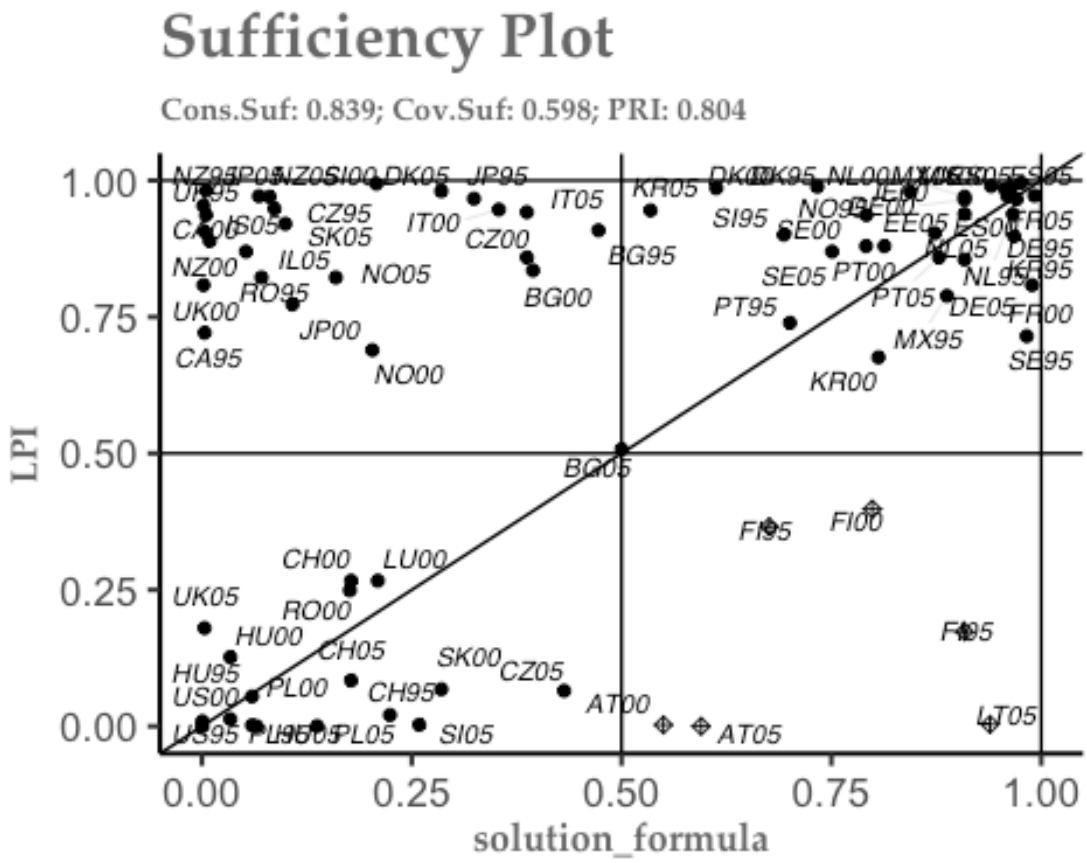
We logically minimize the truth table to obtain the most parsimonious solution, reveal the simplifying assumptions, and display the XY plots of the solution.

```
# most parsimonious solution
sol_yp <- minimize(input = tt_y,
                   include = '?',
                   details = TRUE)
sol_yp


M1: WC*LM + ~UN*EP + EP*LM -> LPI

           inclS   PRI   covS   covU
-------------------------------------
1   WC*LM  0.813  0.760  0.257  0.044
2  ~UN*EP  0.859  0.828  0.414  0.208
3   EP*LM  0.868  0.835  0.346  0.056
-------------------------------------
       M1  0.839  0.804  0.598

           cases
----------------
1   WC*LM  AT05,DE00,DE05,NL95,NL00,NL05,ES05; DK00,IE00;
AT00,FI00,FI05,DE95,NO95,SE95
2  ~UN*EP  EE05,KR05,LT05,MX95,MX00,MX05,PT95,PT00,PT05; FR00,FR05,ES95,ES00;
KR95,KR00;
           AT05,DE00,DE05,NL95,NL00,NL05,ES05
3   EP*LM  FR00,FR05,ES95,ES00; DK95,FI95,SI95,SE00,SE05;
AT05,DE00,DE05,NL95,NL00,NL05,ES05;
           AT00,FI00,FI05,DE95,NO95,SE95
----------------

# simplifying assumptions
sol_yp$SA

$M1
   WC UN EP LM
10  1  0  0  1

# XY plots
pimplot(data = MACRO.d,
        outcome = 'LPI',
        results = sol_yp,
        all_labels = TRUE,
        jitter = TRUE)
```


Sufficiency Plot
Cons.Suf: 0.813; Cov.Suf: 0.257; PRI: 0.760
LPI
WC*LM
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
DK95
DK05
ES00
IT05
SE00
SE05
PT05
NO05
PT95
NO00
FR00
KR00
BG05
LU00
CH00
RO00
UK05
US00
CH05
HU95
SK00
CH95
HU05
SI05
DK00
ES05
IE00
NL00
DE00
NO95
NL05
NL95
DE05
SE95
FI95
FI00
FI05
AT00
AT05

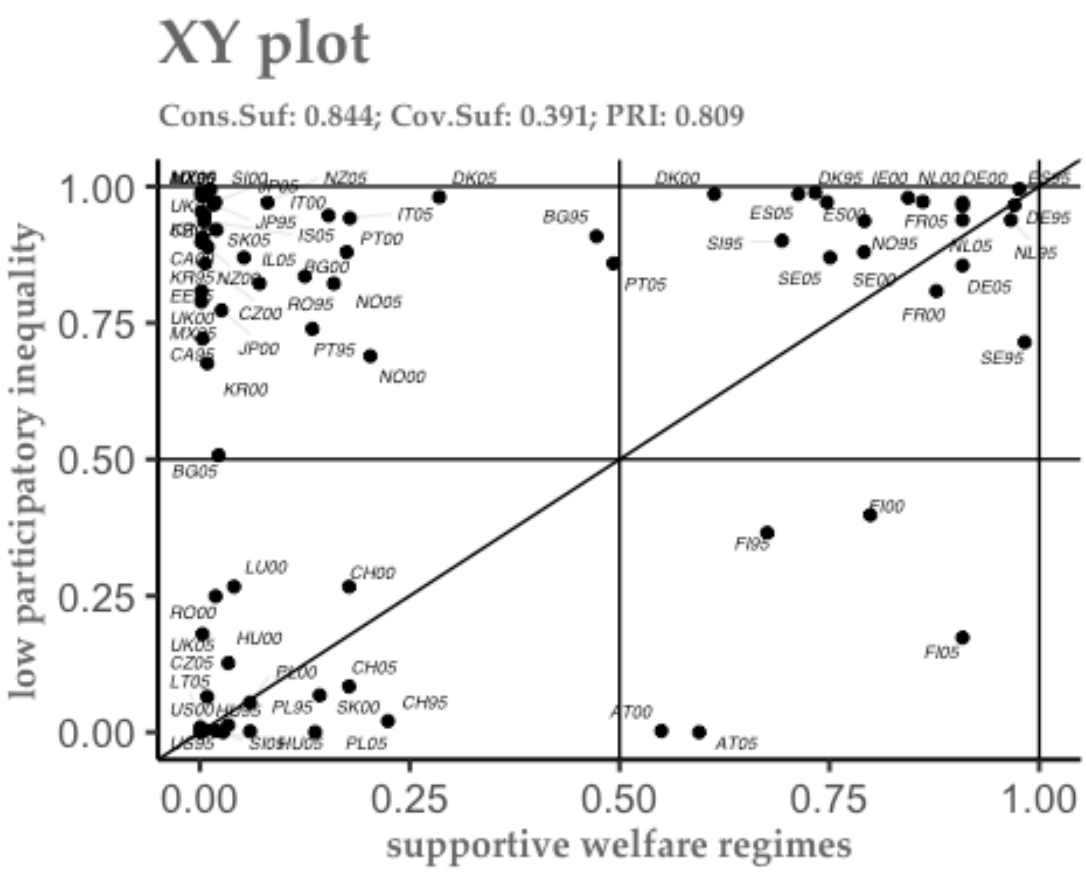

Sufficiency Plot
Cons.Suf: 0.859; Cov.Suf: 0.414; PRI: 0.828
LPI
~UN*EP
0.00
0.25
0.50
0.75
1.00
DE95
DE00
NL00
MX05
ES95
ES05
IT00
IT05
KR05
NL05
NL95
EE05
MX00
ES00
FR05
CZ00
BG95
SK05
SI95
IL05
NO05
BG00
DE05
PT00
PT05
KR95
UK00
SE05
RO95
JP00
PT95
MX95
FR00
CA95
SE95
NO00
KR00
BG05
FI00
FI95
CH00
LU00
UK05
FI05
RO00
HU00
PL00
SK00
CH95
HU95
PL05
CZ05
SI05
AT00
AT05
LT05


Sufficiency Plot
Cons.Suf: 0.868; Cov.Suf: 0.346; PRI: 0.835
LPI
EP*LM
0.00
0.25
0.50
0.75
1.00
DK05
IT00
IT05
BG95
ES05
NL05
SI95
ES00
NO95
DE00
DE95
NL95
PT05
DE05
SE05
SE00
FR00
SE95
NO05
PT95
CZ00
NO00
MX95
CA95
KR00
BG05
FI00
FI95
CH00
LU00
RO00
HU00
FI05
CH05
PL00
SK00
CZ05
CH95
HU95
AT00
AT05
PL05



We establish each case's membership in *supportive welfare regimes* by intersecting their membership scores in the conjunctions $LM * WC$ and $LM * EP$. We then display the result in an XY plot. It corresponds to the one shown as figure 1.2 in the book.

```
# create XY plot for supportive welfare regime LM(WC+EP)
MACRO.d$SUP1 <- with(MACRO.d, fuzzyor(WC, EP))

MACRO.d$SUPPORT <- with(MACRO.d, fuzzyand(LM, SUP1))

xy.plot(data = MACRO.d,
        x = 'SUPPORT',
        y = 'LPI',
        xlab = 'supportive welfare regimes',
        ylab = 'low participatory inequality',
        fontsize = 2,
        jitter = TRUE)
```


XY plot
Cons.Suf: 0.844; Cov.Suf: 0.391; PRI: 0.809
low participatory inequality
supportive welfare regimes
0.00
0.25
0.50
0.75
1.00

2 Chapter 2: Vis (2009)

In chapter 2, I use the example by Vis (2009). The solution formula consists of a single set. We can therefore postpone all those challenges for SMMR that arise from disjunctions (equifinality) and conjunctions (conjunctural causation).

Outcome

- U = Unpopular welfare state reforms

Conditions

- P = Weak political position
- S = Weak socio-economic position
- R = Right-leaning government

I start by producing the solution formula and then turn first to single-case and then to comparative-case SMMR designs.

2.1 Producing the solution formula

We begin by loading the data

```
VIS_fs <- read.csv("Vis_09_fs.csv", row.names = 1)
VIS_fs
```

```
                P    S    R    U
Lubbers1     0.33 0.83 1.00 0.83
Lubbers2     0.17 0.33 1.00 0.33
Lubbers3     0.33 0.67 0.60 0.67
Kok1         0.17 0.40 0.40 0.67
Kok2         0.33 0.33 0.40 0.17
Balkenende2  0.67 0.67 1.00 0.83
Kohl1        0.17 0.33 1.00 0.33
Kohl2        0.33 0.17 1.00 0.17
Kohl3        0.17 0.33 1.00 0.33
Kohl4        0.67 0.67 1.00 0.67
Schroeder1   0.33 0.40 0.00 0.17
Schroeder2   0.83 0.83 0.00 0.83
Schlueter1   0.33 0.33 1.00 0.33
Schlueter2   0.33 0.60 1.00 0.67
Schlueter4   0.33 0.67 1.00 0.17
Schlueter5   0.60 0.67 1.00 0.33
NRasmussen1  0.17 0.17 0.40 0.17
NRasmussen2_3 0.60 0.60 0.25 0.83
NRasmussen4  0.33 0.33 0.25 0.67
Thatcher1    0.17 0.83 1.00 0.83
Thatcher2    0.33 0.33 1.00 0.67
Thatcher3    0.33 0.67 1.00 0.67
```

```
Major1        0.33 0.60 1.00 0.67
Blair1        0.17 0.33 0.00 0.40
Blair2        0.33 0.33 0.00 0.33
```

```
tt_fy <- truthTable(data = VIS_fs,
                    outcome = "U",
                    conditions = "P, S, R",
                    incl.cut = 0.8,
                    sort.by = "incl",
                    complete = TRUE)
tt_fy
```

```
  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

    P  S  R    OUT    n  incl  PRI
4   0  1  1     1     7  0.918 0.782
7   1  1  0     1     2  0.911 0.773
8   1  1  1     1     3  0.911 0.647
2   0  0  1     0     6  0.719 0.242
1   0  0  0     0     7  0.642 0.307
3   0  1  0     ?     0    -     -
5   1  0  0     ?     0    -     -
6   1  0  1     ?     0    -     -
```

Based on this truth table, we obtain the following most parsimonious solution formula.

```
sol_fyp <- minimize(tt_fy,
                    include = "?",
                    details = TRUE)
sol_fyp
```

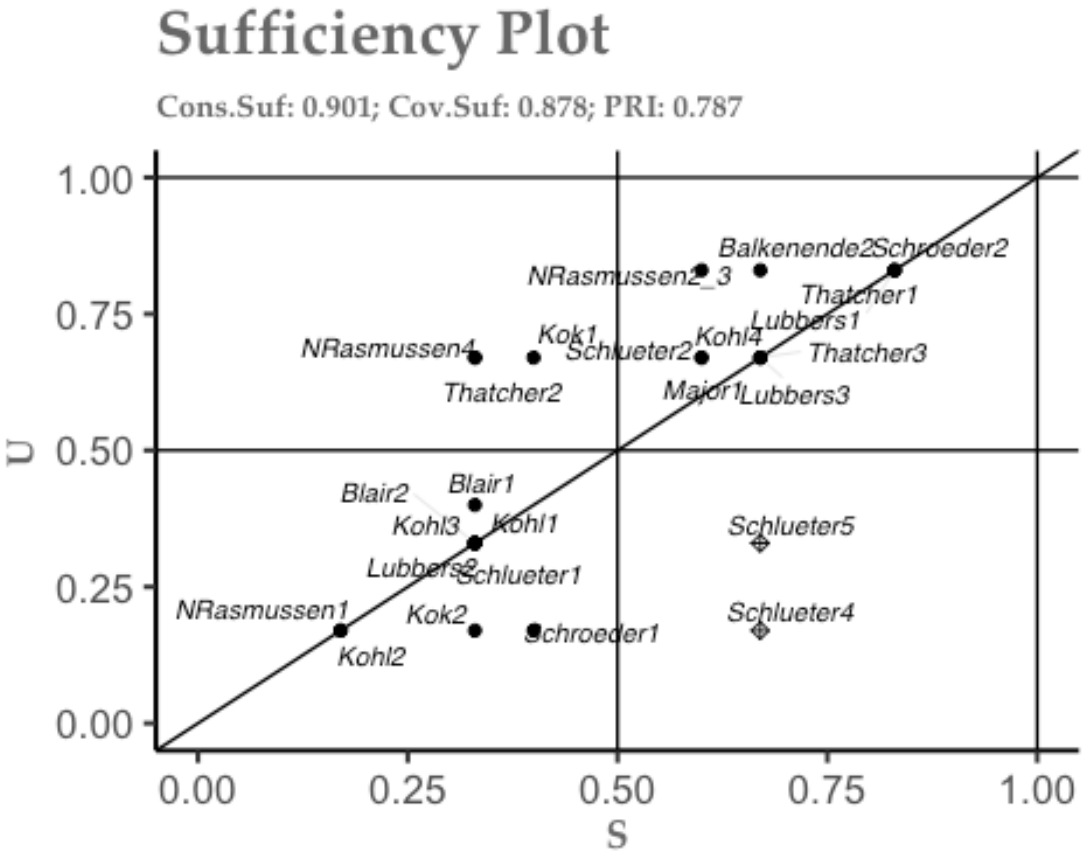
```
M1: S -> U

       inclS   PRI   covS   covU
---------------------------------
1   S  0.901  0.787  0.878    -
---------------------------------
   M1  0.901  0.787  0.878
```

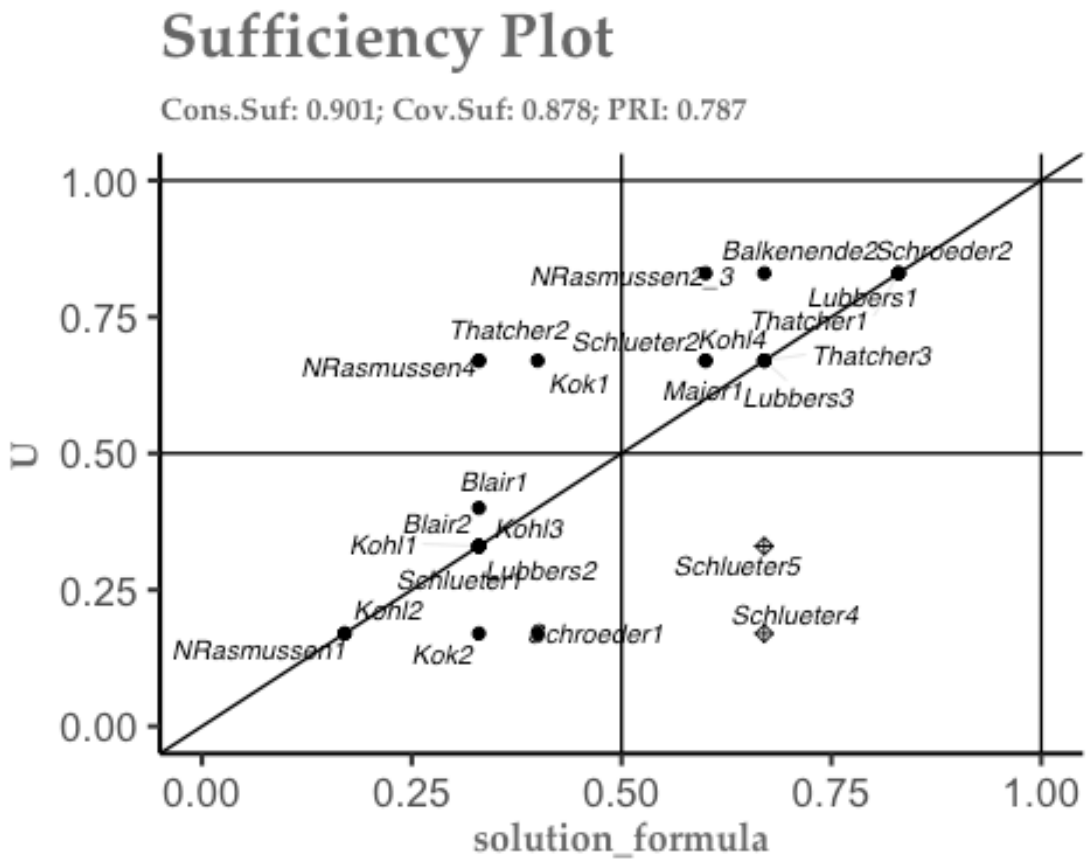
The single condition 'socio-economic trouble' *S* is found to be sufficient for outcome 'unpopular reforms *U*.

The solution can be visualized with an XY plot.

```
pimplot(data = VIS_fs,
        outcome = "U",
```

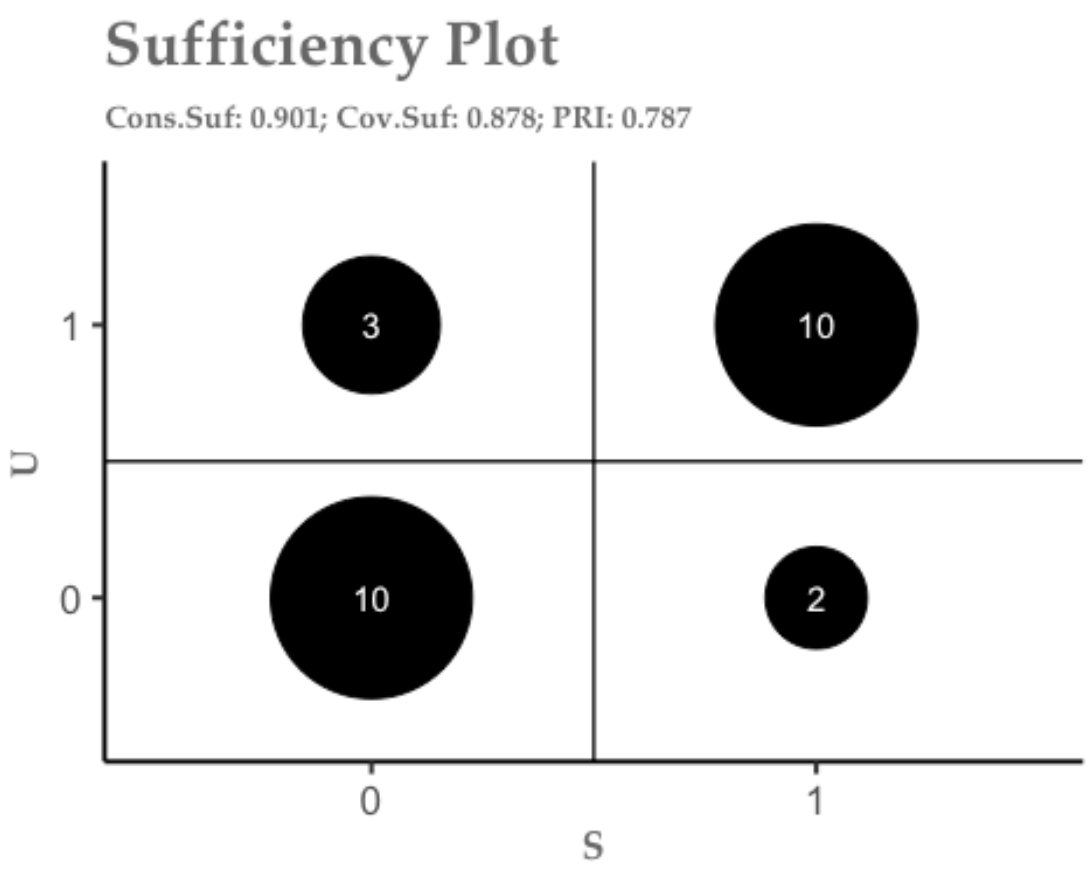
```
        results = sol_fyp,
        jitter = TRUE,
        all_labels = TRUE)
```

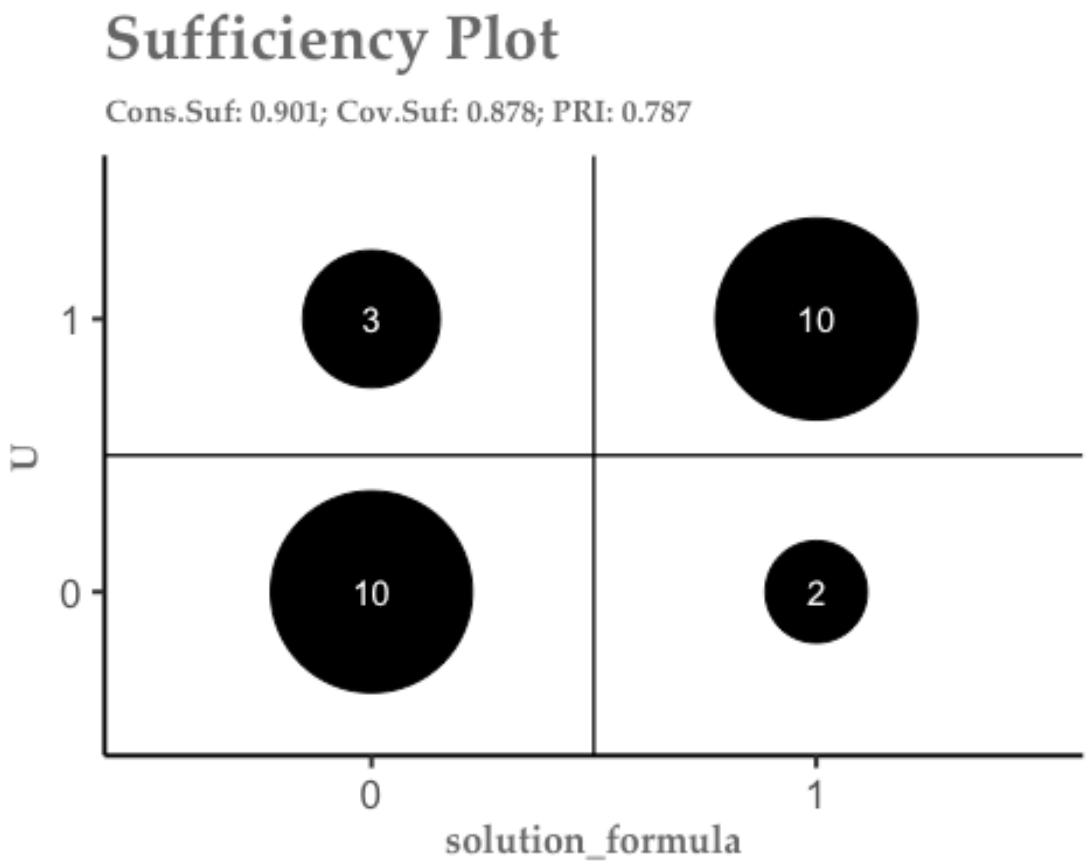

Sufficiency Plot
Cons.Suf: 0.901; Cov.Suf: 0.878; PRI: 0.787
1.00
0.75
0.50
0.25
0.00
U
0.00
0.25
0.50
0.75
1.00
S
Balkenende2
Schroeder2
NRasmussen2_3
Thatcher1
Lubbers1
Kok1
Kohl4
NRasmussen4
Schlueter2
Thatcher3
Thatcher2
Major1
Lubbers3
Blair2
Blair1
Kohl3
Kohl1
Schlueter5
Lubbers2
Schlueter1
NRasmussen1
Kok2
Schlueter4
Schroeder1
Kohl2



If the data was crisp, we could also use the `pimplot()` command and add the argument `crisp = TRUE`.

```
pimplot(data = VIS_fs,
        outcome = "U",
        results = sol_fyp,
        jitter = TRUE,
        all_labels = TRUE,
        crisp = TRUE)
```


Sufficiency Plot
Cons.Suf: 0.901; Cov.Suf: 0.878; PRI: 0.787
3
10
10
2
1
0
U
0
1
S



2.2 Single-case SMMR designs

There are two model-refining single-case designs: the study of a deviant coverage case for identifying a missing disjunct, on the one hand, and the study of a deviant consistency case for identifying a missing conjunct.

```
dcov <- smmr(results = sol_fyp,
             outcome = "U",
             match = FALSE,
             cases = 4)
dcov

Deviant Coverage Cases :
----------
         Case  Sol TT_P TT_S TT_R TT_row Outcome TT<=Y Best MostDCOV
2 NRasmussen4 0.33    0    0    0   0.67    0.67  TRUE 0.33     TRUE
1        Kok1 0.40    0    0    0   0.60    0.67  TRUE 0.40    FALSE
3   Thatcher2 0.33    0    0    1   0.67    0.67  TRUE 0.33     TRUE

dcons <- smmr(results = sol_fyp,
              outcome = "U",
              match = FALSE,
```

```
              cases = 3)
dcons

Deviant Consistency Cases :
----------
       Cases Term TermMemb Outcome Best MostDCONS
1 Schlueter4    S     0.67    0.17 0.83      TRUE
2 Schlueter5    S     0.67    0.33 0.99     FALSE
```

For causal inference SMMR designs, one option exists: the study of a typical case.

```
typ_term <- smmr(results = sol_fyp,
                 outcome = "U",
                 match = FALSE,
                 cases = 1)
typ_term

Typical Cases :
----------
            Case Term TermMemb Outcome UniqCov Best MostTyp
1       Lubbers1    S     0.83    0.83    TRUE 0.17    TRUE
5     Schroeder2    S     0.83    0.83    TRUE 0.17    TRUE
8      Thatcher1    S     0.83    0.83    TRUE 0.17    TRUE
2       Lubbers3    S     0.67    0.67    TRUE 0.33   FALSE
4          Kohl4    S     0.67    0.67    TRUE 0.33   FALSE
9      Thatcher3    S     0.67    0.67    TRUE 0.33   FALSE
6     Schlueter2    S     0.60    0.67    TRUE 0.54   FALSE
10        Major1    S     0.60    0.67    TRUE 0.54   FALSE
3    Balkenende2    S     0.67    0.83    TRUE 0.65   FALSE
7  NRasmussen2_3    S     0.60    0.83    TRUE 0.86   FALSE
```

2.3 Comparative-case SMMR designs

There are two comparative-case descriptive inference SMMR designs. The first matches deviant coverage cases with iir cases with the goal of identifying missing disjuncts.

```
dcoviir <- smmr(results = sol_fyp,
                outcome = "U",
                match = TRUE,
                cases = 4)
dcoviir

Matching Deviant Coverage-IIR Cases :
----------
          DCOV         IIR TT_P TT_S TT_R TT_DCV<=Y Best
1         Kok1  Schroeder1    0    0    0      TRUE 1.30
2         Kok1        Kok2    0    0    0      TRUE 1.30
3         Kok1 NRasmussen1    0    0    0      TRUE 1.30
4  NRasmussen4        Kok2    0    0    0      TRUE 1.30
5  NRasmussen4 NRasmussen1    0    0    0      TRUE 1.30
6    Thatcher2       Kohl2    0    0    1      TRUE 1.16
```

```
7    Thatcher2    Lubbers2    0    0    1      TRUE 1.32
8    Thatcher2       Kohl3    0    0    1      TRUE 1.32
9    Thatcher2       Kohl1    0    0    1      TRUE 1.32
10   Thatcher2  Schlueter1    0    0    1      TRUE 1.32
```

The second design matches typical cases with deviant consistency cases with the goal of identifying missing conjuncts.

```
typdcons <- smmr(results = sol_fyp,
                 outcome = "U",
                 match = TRUE,
                 cases = 3)
typdcons

Term S :
----------
            TYP      DCONS Best MostTypTerm MostDCONS
1      Lubbers1 Schlueter4 1.00        TRUE      TRUE
3    Schroeder2 Schlueter4 1.00        TRUE      TRUE
4     Thatcher1 Schlueter4 1.00        TRUE      TRUE
2   Balkenende2 Schlueter4 1.00       FALSE      TRUE
5 NRasmussen2_3 Schlueter4 1.14       FALSE      TRUE
```

For causal inference, there are two comparative-case SMMR designs. The first matches typical cases with iir cases.

```
typiir_term <- smmr(results = sol_fyp,
                    outcome = "U",
                    match = TRUE,
                    cases = 6,
                    max_pairs = 10)
typiir_term

Term S :
----------
          TYP         IIR UniqCov ConsIIR GlobUncov Best MostTyp
1    Lubbers1       Kohl2    TRUE    TRUE      TRUE 0.68    TRUE
2  Schroeder2       Kohl2    TRUE    TRUE      TRUE 0.68    TRUE
3   Thatcher1       Kohl2    TRUE    TRUE      TRUE 0.68    TRUE
4    Lubbers1 NRasmussen1    TRUE    TRUE      TRUE 0.68    TRUE
5  Schroeder2 NRasmussen1    TRUE    TRUE      TRUE 0.68    TRUE
6   Thatcher1 NRasmussen1    TRUE    TRUE      TRUE 0.68    TRUE
16   Lubbers1       Kohl3    TRUE    TRUE      TRUE 1.00    TRUE
17 Schroeder2       Kohl3    TRUE    TRUE      TRUE 1.00    TRUE
18  Thatcher1       Kohl3    TRUE    TRUE      TRUE 1.00    TRUE
19   Lubbers1  Schlueter1    TRUE    TRUE      TRUE 1.00    TRUE
```

The second matches the most typical with the just-so typical case.

```
typtyp_term <- smmr(results = sol_fyp,
                    outcome = "U",
```

```
                    match = TRUE,
                    cases = 5,
                    max_pairs = 10)
typtyp_term

Term S :
----------
         TYP1      TYP2 UniqCov Best MostTyp
3  Schroeder2     Kohl4    both 0.68    typ1
17 Schroeder2  Lubbers3    both 0.68    typ1
21  Thatcher1     Kohl4    both 0.68    typ1
25   Lubbers1 Thatcher3    both 0.68    typ1
26  Thatcher1 Thatcher3    both 0.68    typ1
46   Lubbers1     Kohl4    both 0.68    typ1
65 Schroeder2 Thatcher3    both 0.68    typ1
75   Lubbers1  Lubbers3    both 0.68    typ1
81  Thatcher1  Lubbers3    both 0.68    typ1
10  Thatcher1    Major1    both 0.75    typ1
```

3 Chapter 3: Stevens (2016)

In chapter 3, the study by Stevens (2016) on corruption perception is used to illustrate how SMMR works in the presence of disjunctions (without conjunctions).

Outcome

- HC = High perceived corruption

Conditions

- LD = Low democracy
- HR = High rational secular orientation
- HS = High self expression orientation
- LH = Low human development
- HI = High income inequality

To bring to the fore the challenges and the solutions provided, I do alter the data by Stevens (2016) in several regards and as outlined in the following code.

```
# Get original data and manipulate to produce altered data set ####
STEVENS <- read.csv(file = 'Stevens_16_fs.csv',
                    sep = ';',
                    dec = ',',
                    row.names = 1)


STEVENS$D <- 1-STEVENS$D  # invert scale so that the presence of condition
appears in sol
STEVENS$H <- 1-STEVENS$H  # invert scale so that the presence of condition
appears in sol

# turn set labels from one-letter to two letter
names(STEVENS) <- c("LD", "HR", "HS", "LH", "HI", "HC")

# recalibrate specific cases to have more deviant cases consistency
STEVENS['Jordan',1] <- 0.7
STEVENS['Georgia',1] <- 0.6
STEVENS['Kazakhstan',1] <- 0.95
STEVENS['Ethiopia',1] <- 0.83
STEVENS['Belarus',1] <- 0.9
STEVENS['Vietnam',1] <- 0.85
STEVENS['Pakistan',4] <- 0.9
STEVENS['Tanzania',4] <- 0.89
STEVENS['Morocco',4] <- 0.62
STEVENS['Rwanda',4] <- 0.903
```

```
write.csv(STEVENS, file = 'Stevens_16_fs_altered.csv')
```

With the altered data set, I first produce the truth table and the most parsimonious solution, which is also visualized via XY plots.

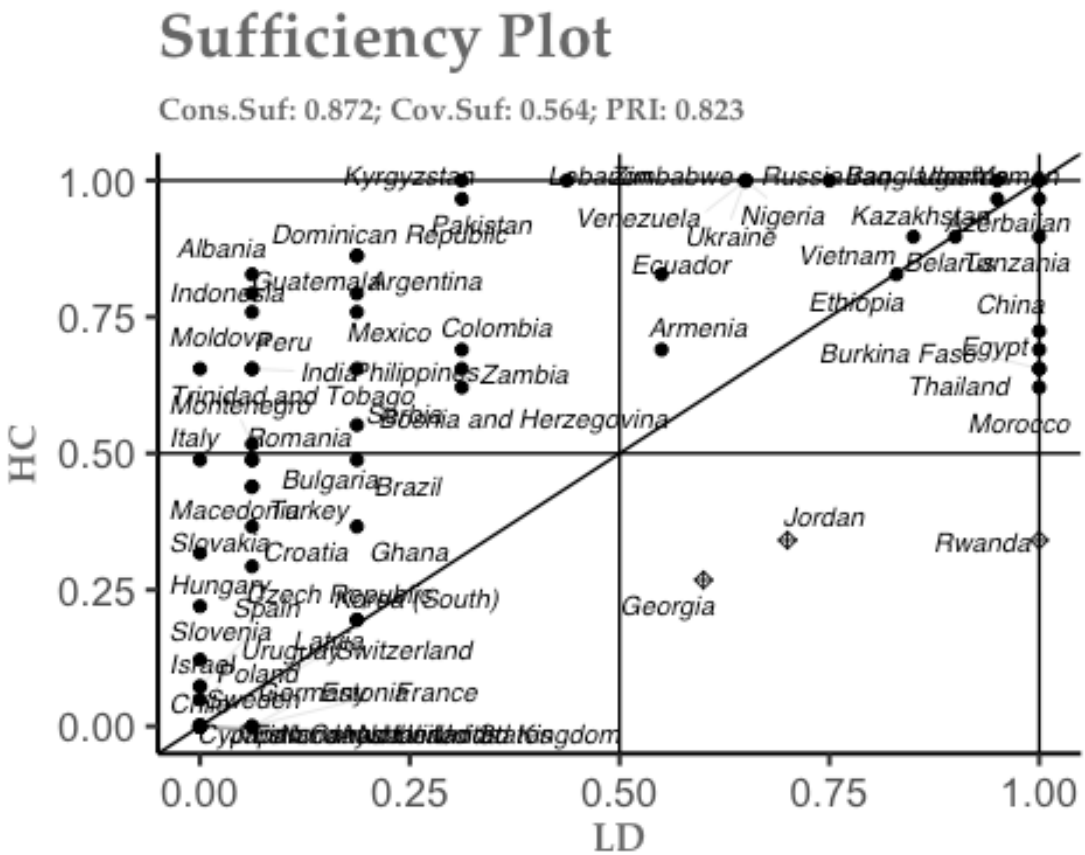
```
STEV <- read.csv('Stevens_16_fs_altered.csv', row.names = 1)

# object containing the condition labels
conds <- c("LD", "HR", "HS", "LH", "HI")

# truth table
TT_y <- truthTable(data = STEV,
           outcome = 'HC',
           conditions = conds,
           incl.cut = 0.85,
           show.cases = TRUE,
           n.cut = 2,
           sort.by = c('OUT', 'incl'),
           complete = TRUE)
TT_y


  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

     LD HR HS LH HI   OUT    n   incl  PRI
22   1  0  1  0  1     1     3   1.000 1.000
23   1  0  1  1  0     1     2   1.000 1.000
19   1  0  0  1  0     1     4   0.995 0.992
 3   0  0  0  1  0     1     2   0.994 0.983
25   1  1  0  0  0     1     3   0.990 0.981
 8   0  0  1  1  1     1     3   0.990 0.974
26   1  1  0  0  1     1     2   0.986 0.963
17   1  0  0  0  0     1     3   0.950 0.892
 4   0  0  0  1  1     1     3   0.946 0.874
20   1  0  0  1  1     1     7   0.938 0.889
 9   0  1  0  0  0     0     9   0.735 0.432
 6   0  0  1  0  1     0     6   0.730 0.498
 5   0  0  1  0  0     0     3   0.603 0.199
14   0  1  1  0  1     0     2   0.515 0.113
13   0  1  1  0  0     0     20  0.240 0.013
11   0  1  0  1  0     ?     1   1.000 1.000
 7   0  0  1  1  0     ?     1   0.983 0.918
18   1  0  0  0  1     ?     1   0.919 0.765
 1   0  0  0  0  0     ?     1   0.882 0.643
10   0  1  0  0  1     ?     1   0.837 0.596
 2   0  0  0  0  1     ?     0     -     -
```

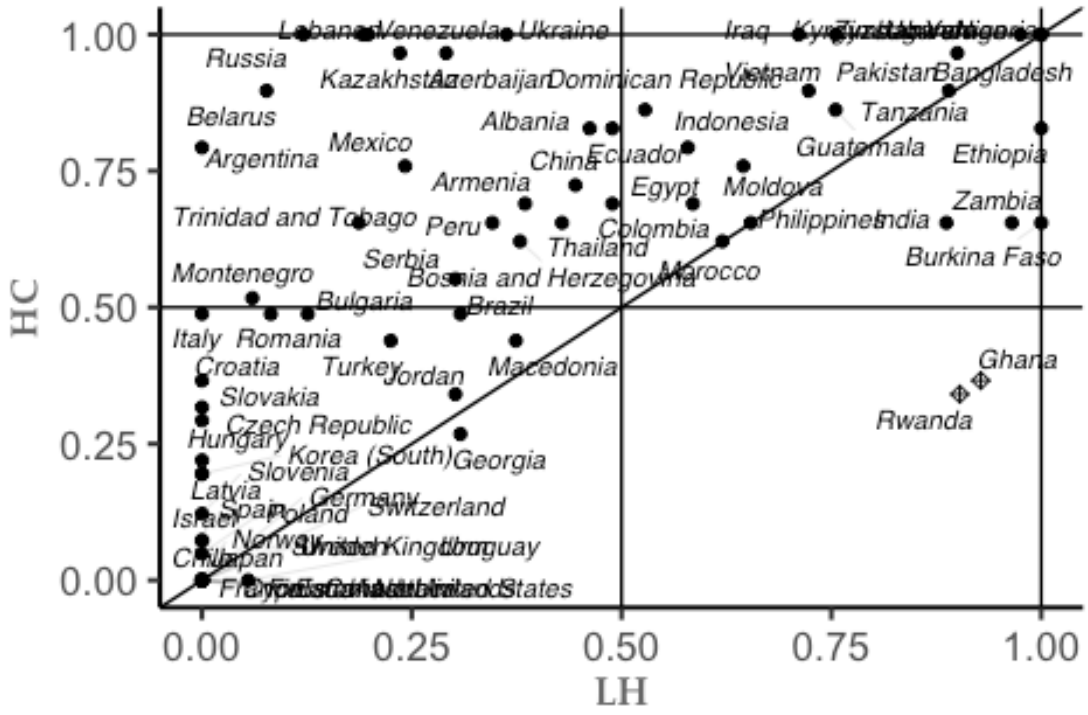
```
12   0  1  0  1  1     ?     0     -     -
15   0  1  1  1  0     ?     0     -     -
16   0  1  1  1  1     ?     0     -     -
21   1  0  1  0  0     ?     0     -     -
24   1  0  1  1  1     ?     0     -     -
27   1  1  0  1  0     ?     0     -     -
28   1  1  0  1  1     ?     0     -     -
29   1  1  1  0  0     ?     0     -     -
30   1  1  1  0  1     ?     0     -     -
31   1  1  1  1  0     ?     0     -     -
32   1  1  1  1  1     ?     0     -     -
     cases
22   Ecuador,Thailand,Venezuela
23   Ethiopia,Vietnam
19   Egypt,Iraq,Tanzania,Yemen
 3   Indonesia,Pakistan
25   Armenia,Belarus,Ukraine
 8   Dominican Republic,Guatemala,Philippines
26   China,Russia
17   Azerbaijan,Jordan,Kazakhstan
 4   Ghana,Kyrgyzstan,Zambia
20   Bangladesh,Burkina Faso,Morocco,Nigeria,Rwanda,Uganda,Zimbabwe
 9   Albania,Bosnia and Herzegovina,Bulgaria,Estonia,Korea
(South),Latvia,Macedonia,Montenegro,Romania
 6   Argentina,Brazil,Chile,Colombia,Mexico,Peru
 5   Cyprus,Poland,Trinidad and Tobago
14   United States,Uruguay
13   Australia,Canada,Croatia,Czech
Republic,Finland,France,Germany,Hungary,Israel,Italy,Japan,Netherlands,Norway
,Serbia,Slovakia,Slovenia,Spain,Sweden,Switzerland,United Kingdom
11   Moldova
 7   India
18   Georgia
 1   Turkey
10   Lebanon
 2
12
15
16
21
24
27
28
29
30
31
32

# a clear cutoff, both in terms of consistency and PRI
```

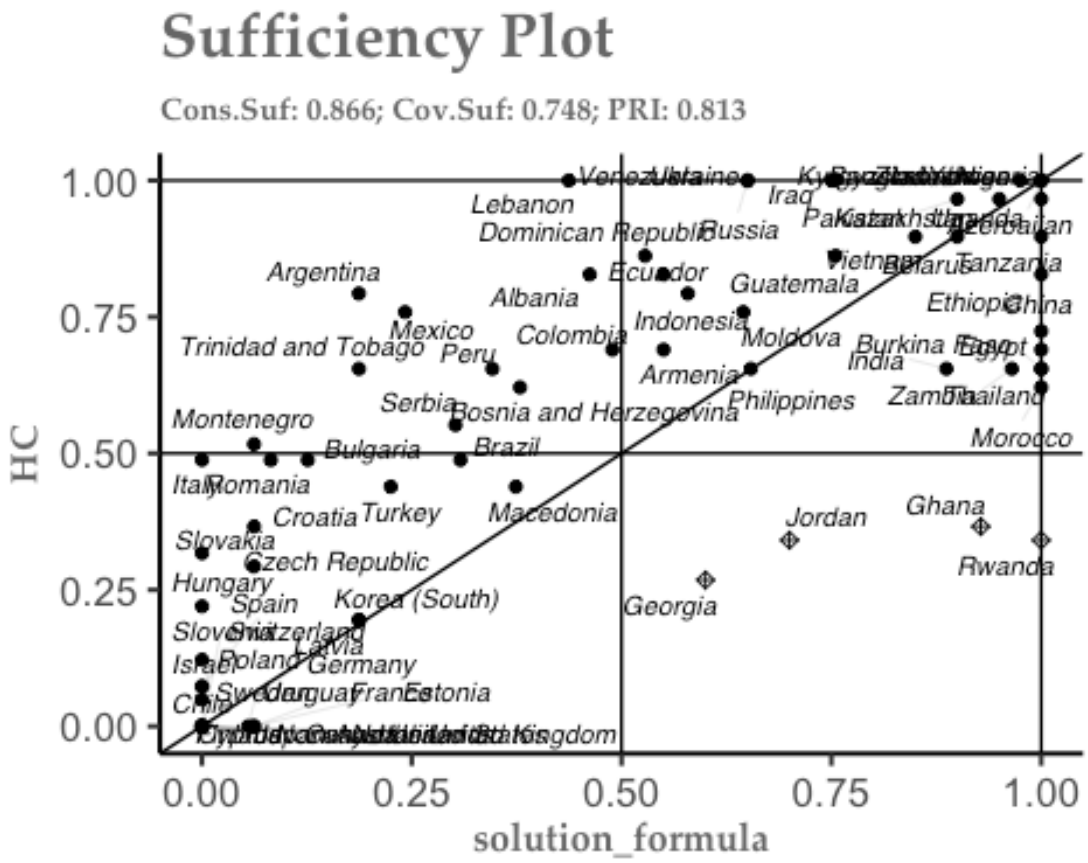
```r
# most parsimonious solution
sol_yp <- minimize(TT_y,
                   details = TRUE,
                   include = '?')
sol_yp
```

```
M1: LD + LH -> HC

       inclS   PRI   covS   covU
---------------------------------
1  LD  0.872  0.823  0.564  0.138
2  LH  0.914  0.871  0.610  0.184
---------------------------------
   M1  0.866  0.813  0.748

       cases
------------
1  LD  Azerbaijan,Jordan,Kazakhstan; Egypt,Iraq,Tanzania,Yemen;
Bangladesh,Burkina Faso,Morocco,Nigeria,Rwanda,Uganda,Zimbabwe;
       Ecuador,Thailand,Venezuela; Ethiopia,Vietnam; Armenia,Belarus,Ukraine;
China,Russia
2  LH  Indonesia,Pakistan; Ghana,Kyrgyzstan,Zambia; Dominican
Republic,Guatemala,Philippines;
       Egypt,Iraq,Tanzania,Yemen; Bangladesh,Burkina
Faso,Morocco,Nigeria,Rwanda,Uganda,Zimbabwe;
       Ethiopia,Vietnam
------------
```

```r
# xy plot
pimplot(data = STEV,
        outcome = 'HC',
        results = sol_yp,
        jitter = TRUE,
        all_labels = TRUE)
```


Sufficiency Plot
Cons.Suf: 0.872; Cov.Suf: 0.564; PRI: 0.823
HC
LD
0.00
0.25
0.50
0.75
1.00
Kyrgyzstan
Pakistan
Venezuela
Nigeria
Kazakhstan
Azerbaijan
Ukraine
Albania
Dominican Republic
Ecuador
Vietnam
Tanzania
Guatemala
Argentina
Indonesia
Ethiopia
China
Moldova
Peru
Mexico
Colombia
Armenia
Burkina Faso
Egypt
India
Philippines
Zambia
Thailand
Trinidad and Tobago
Montenegro
Bosnia and Herzegovina
Morocco
Italy
Romania
Bulgaria
Brazil
Macedonia
Turkey
Jordan
Slovakia
Croatia
Ghana
Rwanda
Hungary
Spain
Georgia
Slovenia
Switzerland
Poland
Sweden
France
Kingdom


Sufficiency Plot
Cons.Suf: 0.914; Cov.Suf: 0.610; PRI: 0.871
HC
LH
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
Lebanon
Venezuela
Ukraine
Iraq
Russia
Kazakhstan
Azerbaijan
Dominican Republic
Vietnam
Pakistan
Bangladesh
Belarus
Albania
Indonesia
Tanzania
Mexico
Ecuador
Guatemala
Ethiopia
Argentina
China
Armenia
Egypt
Moldova
Zambia
Trinidad and Tobago
Peru
Colombia
Philippines
India
Thailand
Serbia
Burkina Faso
Montenegro
Bosnia and Herzegovina
Morocco
Bulgaria
Brazil
Italy
Romania
Croatia
Turkey
Jordan
Macedonia
Ghana
Slovakia
Rwanda
Czech Republic
Hungary
Korea (South)
Georgia
Slovenia
Latvia
Germany
Spain
Switzerland
Israel
Poland
Norway
United Kingdom
Uruguay
Chile
Japan
France
United States



3.1 Descriptive inference SMMR

I start with descriptive inference SMMR designs. To identify missing disjuncts, two designs are available: the study of a single deviant coverage case or the comparison of this case type with an iir case.

```
# deviant coverage case
dcov <- smmr(results = sol_yp,
             outcome = "HC",
             match = FALSE,
             cases = 4)
dcov

Deviant Coverage Cases :
----------
                      Case   Sol TT_LD TT_HR TT_HS TT_LH TT_HI TT_row Outcome
10    Trinidad and Tobago 0.187     0     0     1     0     0  0.530   0.655
6                  Mexico 0.242     0     0     1     0     1  0.748   0.759
8                    Peru 0.346     0     0     1     0     1  0.586   0.655
4                Colombia 0.489     0     0     1     0     1  0.511   0.690
2               Argentina 0.187     0     0     1     0     1  0.502   0.793
3  Bosnia and Herzegovina 0.379     0     1     0     0     0  0.621   0.621
1                 Albania 0.462     0     1     0     0     0  0.538   0.828
```

```
7              Montenegro 0.062     0     1     0     0     0  0.838   0.517
5                 Lebanon 0.437     0     1     0     0     1  0.563   1.000
9                  Serbia 0.302     0     1     1     0     0  0.524   0.552
   TT<=Y  Best MostDCOV
10  TRUE 0.470     TRUE
6   TRUE 0.252     TRUE
8   TRUE 0.414    FALSE
4   TRUE 0.489    FALSE
2   TRUE 0.498    FALSE
3   TRUE 0.379    FALSE
1   TRUE 0.462    FALSE
7  FALSE 0.162     TRUE
5   TRUE 0.437     TRUE
9   TRUE 0.476     TRUE
```

```r
# deviant coverage - iir case
dcoviir <- smmr(results = sol_yp,
                outcome = "HC",
                match = TRUE,
                cases = 4)
dcoviir
```

```
Matching Deviant Coverage-IIR Cases :
----------
                     DCOV           IIR TT_LD TT_HR TT_HS TT_LH TT_HI
TT_DCV<=Y
1     Trinidad and Tobago        Cyprus     0     0     1     0     0
TRUE
2     Trinidad and Tobago        Poland     0     0     1     0     0
TRUE
3                  Mexico         Chile     0     0     1     0     1
TRUE
4                    Peru         Chile     0     0     1     0     1
TRUE
5               Argentina         Chile     0     0     1     0     1
TRUE
6                Colombia         Chile     0     0     1     0     1
TRUE
7                  Mexico        Brazil     0     0     1     0     1
TRUE
8                 Albania       Estonia     0     1     0     0     0
TRUE
9  Bosnia and Herzegovina       Estonia     0     1     0     0     0
TRUE
10                Albania Korea (South)     0     1     0     0     0
TRUE
11                Albania        Latvia     0     1     0     0     0
TRUE
12 Bosnia and Herzegovina Korea (South)     0     1     0     0     0
TRUE
```

```
13                Serbia     Australia     0     1     1     0     0
TRUE
14                Serbia        Sweden     0     1     1     0     0
TRUE
15                Serbia       Finland     0     1     1     0     0
TRUE
16                Serbia        France     0     1     1     0     0
TRUE
17                Serbia        Canada     0     1     1     0     0
TRUE
    Best
1  1.285
2  1.334
3  0.889
4  1.173
5  1.203
6  1.288
7  1.345
8  1.096
9  1.209
10 1.291
11 1.291
12 1.332
13 1.400
14 1.400
15 1.400
16 1.400
17 1.400
```

To identify omitted conjuncts, also two options exist: the within-case analysis of a single deviant consistency case or a comparison of this case type with a typical case.

```
dcons <- smmr(results = sol_yp,
              outcome = "HC",
              match = FALSE,
              cases = 3)
dcons

Deviant Consistency Cases :
----------
     Cases Term TermMemb Outcome  Best MostDCONS
3   Rwanda   LD    1.000   0.341 0.341      TRUE
2   Jordan   LD    0.700   0.341 0.941     FALSE
1  Georgia   LD    0.600   0.268 1.068     FALSE
11   Ghana   LH    0.928   0.366 0.510      TRUE
21  Rwanda   LH    0.903   0.341 0.535     FALSE

typdcons <- smmr(results = sol_yp,
                 outcome = "HC",
                 match = TRUE,
                 cases = 3,
```

```
                 max_pairs = 10)
typdcons
```

```
Term LD :
----------
          TYP  DCONS  Best MostTypTerm MostDCONS
1      Uganda Rwanda 0.341        TRUE      TRUE
2       Yemen Rwanda 0.341        TRUE      TRUE
3  Bangladesh Rwanda 0.441       FALSE      TRUE
4  Kazakhstan Rwanda 0.475       FALSE      TRUE
5     Vietnam Rwanda 0.744       FALSE      TRUE
6        Iraq Rwanda 0.841       FALSE      TRUE
9      Uganda Jordan 0.941        TRUE     FALSE
10      Yemen Jordan 0.941        TRUE     FALSE
7  Bangladesh Jordan 0.941       FALSE     FALSE
8        Iraq Jordan 0.941       FALSE     FALSE

Term LH :
----------
          TYP  DCONS  Best MostTypTerm MostDCONS
2     Nigeria  Ghana 0.510        TRUE      TRUE
3      Uganda  Ghana 0.510        TRUE      TRUE
4       Yemen  Ghana 0.510        TRUE      TRUE
5    Zimbabwe  Ghana 0.510        TRUE      TRUE
1  Bangladesh  Ghana 0.510       FALSE      TRUE
7     Nigeria Rwanda 0.535        TRUE     FALSE
8      Uganda Rwanda 0.535        TRUE     FALSE
9       Yemen Rwanda 0.535        TRUE     FALSE
10   Zimbabwe Rwanda 0.535        TRUE     FALSE
6  Bangladesh Rwanda 0.535       FALSE     FALSE
```

3.2 Causal inference SMMR

There are three causal inference SMMR designs: within-case analysis of a single typical case, the comparison with an iir case, and the comparison between two typical cases.

```
typ_term <- smmr(results = sol_yp,
                 outcome = "HC",
                 match = FALSE,
                 cases = 1)
typ_term
```

```
Typical Cases :
----------
                  Case Term TermMemb Outcome UniqCov  Best MostTyp
5           Kazakhstan   LD    0.950   0.966    TRUE 0.082   FALSE
1              Armenia   LD    0.550   0.690    TRUE 0.730   FALSE
3              Ecuador   LD    0.550   0.828    TRUE 1.006   FALSE
7               Russia   LD    0.650   1.000    TRUE 1.050   FALSE
9              Ukraine   LD    0.650   1.000    TRUE 1.050   FALSE
```

```
10           Venezuela   LD    0.650   1.000    TRUE 1.050   FALSE
8               Uganda   LD    1.000   1.000   FALSE 0.000    TRUE
12               Yemen   LD    1.000   1.000   FALSE 0.000    TRUE
2           Bangladesh   LD    0.950   1.000   FALSE 0.150   FALSE
11             Vietnam   LD    0.850   0.897   FALSE 0.244   FALSE
4                 Iraq   LD    0.750   1.000   FALSE 0.750   FALSE
6               Nigeria   LD    0.650   1.000   FALSE 1.050   FALSE
13             Zimbabwe   LD    0.650   1.000   FALSE 1.050   FALSE
131            Tanzania   LH    0.890   0.897    TRUE 0.124   FALSE
111            Pakistan   LH    0.900   0.966    TRUE 0.232   FALSE
121        Philippines   LH    0.654   0.655    TRUE 0.348   FALSE
91              Morocco   LH    0.620   0.621    TRUE 0.382   FALSE
41            Guatemala   LH    0.755   0.862    TRUE 0.459   FALSE
81              Moldova   LH    0.645   0.759    TRUE 0.583   FALSE
31                Egypt   LH    0.585   0.690    TRUE 0.625   FALSE
71           Kyrgyzstan   LH    0.755   1.000    TRUE 0.735   FALSE
51            Indonesia   LH    0.579   0.793    TRUE 0.849   FALSE
21  Dominican Republic   LH    0.528   0.862    TRUE 1.140   FALSE
101             Nigeria   LH    1.000   1.000   FALSE 0.000    TRUE
14               Uganda   LH    1.000   1.000   FALSE 0.000    TRUE
16                Yemen   LH    1.000   1.000   FALSE 0.000    TRUE
17             Zimbabwe   LH    1.000   1.000   FALSE 0.000    TRUE
110         Bangladesh   LH    0.975   1.000   FALSE 0.075   FALSE
15             Vietnam   LH    0.723   0.897   FALSE 0.625   FALSE
61                Iraq   LH    0.711   1.000   FALSE 0.867   FALSE
```

```
typiir_term <- smmr(results = sol_yp,
                    outcome = "HC",
                    match = TRUE,
                    cases = 6,
                    max_pairs = 10)
typiir_term
```

```
Term LD :
----------
           TYP            IIR UniqCov ConsIIR GlobUncov  Best MostTyp
29  Kazakhstan      Australia    TRUE    TRUE       TRUE 0.116   FALSE
30  Kazakhstan         Canada    TRUE    TRUE       TRUE 0.116   FALSE
33  Kazakhstan        Finland    TRUE    TRUE       TRUE 0.116   FALSE
34  Kazakhstan        Germany    TRUE    TRUE       TRUE 0.116   FALSE
35  Kazakhstan          Japan    TRUE    TRUE       TRUE 0.116   FALSE
37  Kazakhstan         Norway    TRUE    TRUE       TRUE 0.116   FALSE
71  Kazakhstan         Israel    TRUE    TRUE       TRUE 0.335   FALSE
72  Kazakhstan          Spain    TRUE    TRUE       TRUE 0.335   FALSE
99  Kazakhstan  Korea (South)    TRUE    TRUE       TRUE 0.514   FALSE
134 Kazakhstan Czech Republic    TRUE    TRUE       TRUE 0.933   FALSE

Term LH :
----------
         TYP         IIR UniqCov ConsIIR GlobUncov  Best MostTyp
```

```
93  Tanzania   Australia    TRUE    TRUE      TRUE 0.227   FALSE
94  Tanzania      Canada    TRUE    TRUE      TRUE 0.227   FALSE
97  Tanzania     Estonia    TRUE    TRUE      TRUE 0.227   FALSE
98  Tanzania     Finland    TRUE    TRUE      TRUE 0.227   FALSE
100 Tanzania     Germany    TRUE    TRUE      TRUE 0.227   FALSE
101 Tanzania       Japan    TRUE    TRUE      TRUE 0.227   FALSE
102 Tanzania Netherlands    TRUE    TRUE      TRUE 0.227   FALSE
105 Tanzania Switzerland    TRUE    TRUE      TRUE 0.227   FALSE
109 Pakistan   Australia    TRUE    TRUE      TRUE 0.266   FALSE
110 Pakistan      Canada    TRUE    TRUE      TRUE 0.266   FALSE
```

```
typtyp_term <- smmr(results = sol_yp,
                    outcome = "HC",
                    match = TRUE,
                    cases = 5,
                    max_pairs = 10)
typtyp_term
```

```
Term LD :
----------
          TYP1      TYP2 UniqCov  Best MostTyp
4   Kazakhstan   Armenia    both 0.636    none
2   Kazakhstan   Ecuador    both 1.050    none
92  Kazakhstan   Ukraine    both 1.466    none
97  Kazakhstan Venezuela    both 1.466    none
128 Kazakhstan    Russia    both 1.466    none
64     Armenia   Ecuador    both 1.974    none
90     Armenia    Russia    both 2.390    none
95     Armenia Venezuela    both 2.390    none
132    Armenia   Ukraine    both 2.390    none
21   Venezuela   Ukraine    both 2.400    none

Term LH :
----------
           TYP1        TYP2 UniqCov  Best MostTyp
255    Tanzania     Morocco    both 0.470    none
130    Pakistan     Morocco    both 0.509    none
155    Tanzania Philippines    both 0.538    none
117    Pakistan Philippines    both 0.577    none
138    Tanzania       Egypt    both 0.712    none
223    Pakistan       Egypt    both 0.751    none
240    Tanzania     Moldova    both 0.859    none
289    Pakistan     Moldova    both 0.898    none
164 Philippines     Morocco    both 0.936    none
14     Tanzania   Indonesia    both 1.027    none
```

4 Chapter 4: Haesebrouck and Van Immerseel (2020)

In chapter 4, I discuss the challenges for SMMR that arise from the presence of conjunctions (without disjunctions). For this, I use the example by Haesebrouck and Van Immerseel (2020) on decisions to deploy military abroad.

Outcome

- ~PC = No political contestation

Conditions

- PD = Not potentially divisive operation (PD)
- HR = High risk operation
- PI = Parliament involved
- PF = Parliament fractionalized
- RO = Right opposition
- GS = Government strong
- GP = Government polarized

Just as in the previous chapter, also in this example, I alter the data slightly such that the challenges to SMMR triggered by conjunctions are brought to the fore. The following code provides the details of the changes to the data.

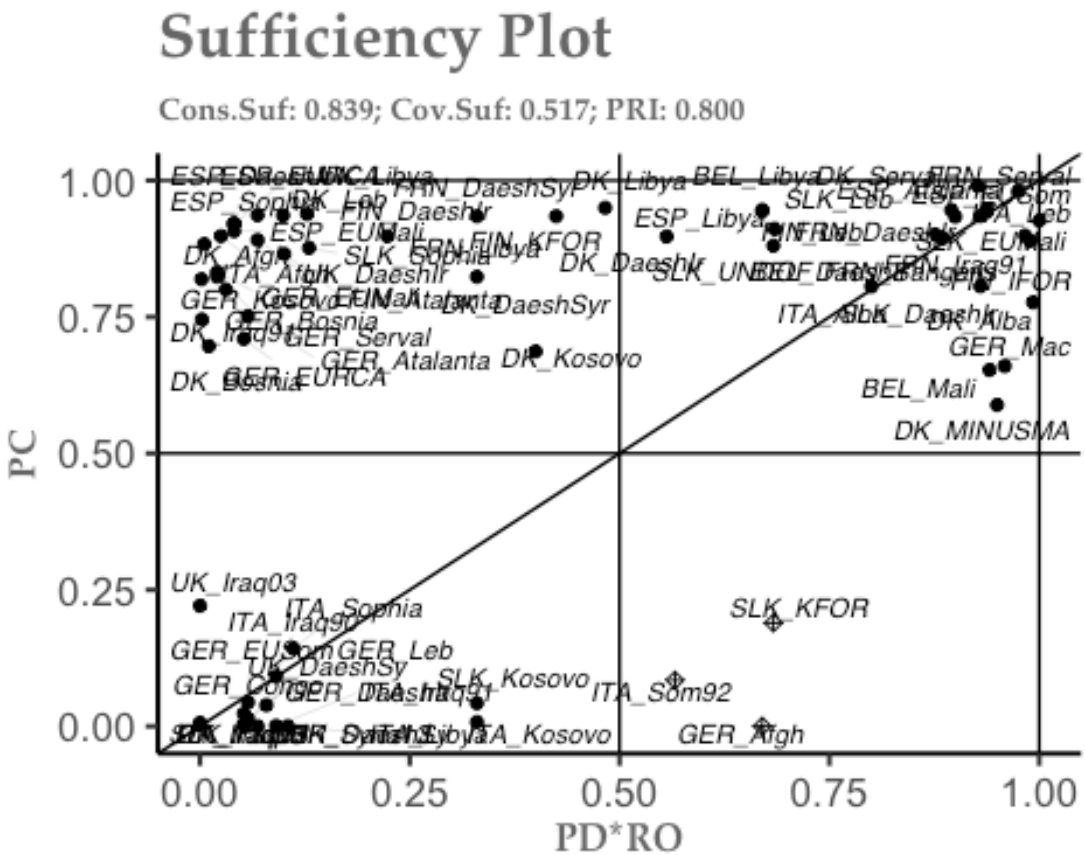
```
# Adjusting data for didactical purposes
HAES.d <- read.csv('data_fs.csv', row.names = 1)

HAES.d['ITA_Alba', 5] <- 0.8
HAES.d['FRN_Sangaris', 5] <- 0.885
HAES.d['FRN_DaeshIr', 5] <- 0.9
HAES.d['SLK_EUMali', 5] <- 0.93
HAES.d['SLK_Sophia', 1] <- 0.87
HAES.d['DK_Kosovo', 1] <- 0.6

HAES.d['BEL_DaeshIr', 4] <- 0.1
HAES.d['DK_Serval', 4] <- 0.01
HAES.d['FRN_Serval', 4] <- 0.02

HAES.d$PD <- 1 - HAES.d$PD

write.csv(HAES.d, "HaesebrouckImmerseel_20_data_fs_altered.csv")

HAES.data <- read.csv('HaesebrouckImmerseel_20_data_fs_altered.csv',
row.names = 1)
```

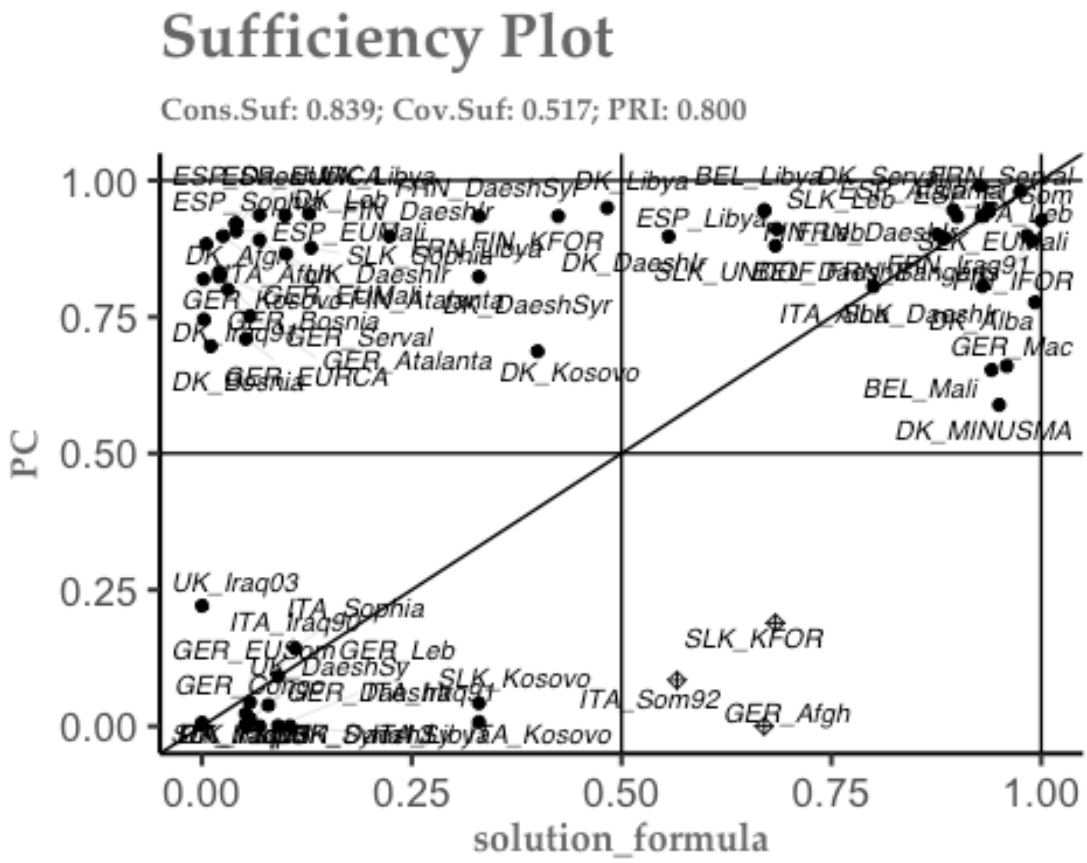
I produce the truth table, the most parsimonious solution, and the XY plots for this solution

```
# truth table
TT_yn <- truthTable(data = HAES.data, outcome = "~PC",
                    conditions = c("PD", "HR", "PI","PF", "RO", "GP"),
                    incl.cut = 0.75,
                    show.cases = TRUE,
                    complete = FALSE,
                    sort.by = c("OUT", "incl"))

TT_yn


  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

     PD HR PI PF RO GP   OUT    n  incl  PRI
51    1  1  0  0  1  0     1     3  0.925 0.903
39    1  0  0  1  1  0     1     2  0.923 0.878
48    1  0  1  1  1  1     1     4  0.902 0.841
43    1  0  1  0  1  0     1     3  0.901 0.833
47    1  0  1  1  1  0     1     5  0.859 0.782
40    1  0  0  1  1  1     1     1  0.853 0.717
64    1  1  1  1  1  1     1     2  0.825 0.706
55    1  1  0  1  1  0     1     2  0.794 0.715
59    1  1  1  0  1  0     1     1  0.770 0.575
63    1  1  1  1  1  0     1     3  0.754 0.602
45    1  0  1  1  0  0     0     4  0.740 0.619
61    1  1  1  1  0  0     0     3  0.701 0.546
41    1  0  1  0  0  0     0     3  0.692 0.518
46    1  0  1  1  0  1     0     5  0.688 0.508
57    1  1  1  0  0  0     0     3  0.684 0.537
16    0  0  1  1  1  1     0     1  0.674 0.581
49    1  1  0  0  0  0     0     2  0.665 0.568
19    0  1  0  0  1  0     0     2  0.646 0.514
62    1  1  1  1  0  1     0     1  0.625 0.340
31    0  1  1  1  1  0     0     2  0.609 0.474
15    0  0  1  1  1  0     0     1  0.539 0.435
42    1  0  1  0  0  1     0     3  0.515 0.171
53    1  1  0  1  0  0     0     3  0.509 0.312
25    0  1  1  0  0  0     0     2  0.454 0.269
29    0  1  1  1  0  0     0     1  0.427 0.285
17    0  1  0  0  0  0     0     1  0.426 0.272
37    1  0  0  1  0  0     0     2  0.424 0.189
23    0  1  0  1  1  0     0     1  0.420 0.241
26    0  1  1  0  0  1     0     1  0.396 0.089
21    0  1  0  1  0  0     0     1  0.328 0.184
14    0  0  1  1  0  1     0     1  0.266 0.101
```

```
     cases
51   FRN_DaeshIr,FRN_Sangaris,FRN_Serval
39   ITA_Alba,ITA_Leb
48   DK_Serval,FIN_IFOR,SLK_DaeshIr,SLK_Leb
43   ESP_Atalanta,ESP_EUSom,SLK_EUMali
47   DK_Alba,FIN_Leb,GER_Mac,SLK_KFOR,SLK_UNDOF
40   BEL_Mali
64   BEL_DaeshIr,BEL_Libya
55   FRN_Iraq91,ITA_Som92
59   ESP_Libya
63   DK_DaeshIr,DK_MINUSMA,GER_Afgh
45   DK_Leb,FIN_Atalanta,GER_EUMali,GER_Serval
61   DK_Afgh,DK_Bosnia,DK_Libya
41   ESP_DaeshIr,ESP_EUMali,ESP_Sophia
46   DK_Iraq91,FIN_DaeshIr,FIN_KFOR,GER_Atalanta,GER_Leb
57   ESP_EURCA,GER_Bosnia,UK_DaeshIr
16   SLK_Sophia
49   FRN_Libya,UK_Libya
19   FRN_DaeshSyr,UK_Iraq03
62   GER_Congo
31   DK_DaeshSyr,DK_Kosovo
15   SLK_Kosovo
42   GER_DaeshIr,GER_EURCA,GER_EUSom
53   ITA_Afgh,ITA_Iraq91,ITA_Libya
25   GER_Kosovo,UK_DaeshSy
29   DK_Iraq03
17   UK_Syria13
37   ITA_Iraq90,ITA_Sophia
23   ITA_Kosovo
26   GER_DaeshSy
21   ITA_Iraq03
14   SLK_Iraq03

# most parsimonious solution
sol_nyp <- minimize(TT_yn,
                    include = "?",
                    details = TRUE)
sol_nyp


M1: PD*RO -> ~PC

          inclS   PRI   covS   covU
-----------------------------------
1  PD*RO  0.839  0.800  0.517    -
-----------------------------------
      M1  0.839  0.800  0.517

          cases
---------------
```

```
1  PD*RO  ITA_Alba,ITA_Leb; BEL_Mali; ESP_Atalanta,ESP_EUSom,SLK_EUMali;
DK_Alba,FIN_Leb,GER_Mac,SLK_KFOR,SLK_UNDOF;
          DK_Serval,FIN_IFOR,SLK_DaeshIr,SLK_Leb;
FRN_DaeshIr,FRN_Sangaris,FRN_Serval;
          FRN_Iraq91,ITA_Som92; ESP_Libya; DK_DaeshIr,DK_MINUSMA,GER_Afgh;
BEL_DaeshIr,BEL_Libya
---------------

# XY plots
pimplot(data = HAES.data,
        outcome = "PC",
        results = sol_nyp,
        jitter = TRUE,
        all_labels = TRUE)
```


Sufficiency Plot
Cons.Suf: 0.839; Cov.Suf: 0.517; PRI: 0.800
PC
PD*RO
0.00
0.25
0.50
0.75
1.00
UK_Iraq03
ITA_Sophia
SLK_KFOR
GER_Leb
SLK_Kosovo
ITA_Som92
GER_Afgh
BEL_Mali
DK_MINUSMA
GER_Mac
DK_Kosovo
GER_Atalanta
GER_Serval
DK_DaeshSyr
ESP_Libya
DK_Libya
FIN_KFOR
SLK_EUMali
FIN_IFOR
DK_Alba
ITA_Kosovo



4.1 Descriptive inference SMMR

The two SMMR designs for identifying missing disjuncts are implemented as follows.

```
# deviant coverage
dcov <- smmr(results = sol_nyp,
             outcome = "~PC",
             match = FALSE,
             cases = 4)
dcov

Deviant Coverage Cases :
----------
           Case   Sol TT_PD TT_HR TT_PI TT_PF TT_RO TT_GP TT_row Outcome
TT<=Y
24   SLK_Sophia 0.130     0     0     1     1     1     1  0.570   0.876
TRUE
15 FRN_DaeshSyr 0.330     0     1     0     0     1     0  0.670   0.935
TRUE
21   GER_Kosovo 0.002     0     1     1     0     0     0  0.569   0.819
TRUE
3   DK_DaeshSyr 0.330     0     1     1     1     1     0  0.670   0.824
TRUE
```

```
5     DK_Kosovo 0.400     0     1     1     1     1     0  0.600   0.687
TRUE
11   ESP_Sophia 0.041     1     0     1     0     0     0  0.707   0.921
TRUE
8   ESP_DaeshIr 0.041     1     0     1     0     0     0  0.670   0.921
TRUE
9    ESP_EUMali 0.041     1     0     1     0     0     0  0.670   0.907
TRUE
20    GER_EURCA 0.052     1     0     1     0     0     1  0.641   0.710
TRUE
6        DK_Leb 0.099     1     0     1     1     0     0  0.830   0.936
TRUE
22   GER_Serval 0.020     1     0     1     1     0     0  0.806   0.824
TRUE
19   GER_EUMali 0.020     1     0     1     1     0     0  0.670   0.832
TRUE
12 FIN_Atalanta 0.100     1     0     1     1     0     0  0.887   0.866
FALSE
4     DK_Iraq91 0.002     1     0     1     1     0     1  0.683   0.746
TRUE
13  FIN_DaeshIr 0.128     1     0     1     1     0     1  0.670   0.938
TRUE
17 GER_Atalanta 0.057     1     0     1     1     0     1  0.656   0.751
TRUE
14     FIN_KFOR 0.424     1     0     1     1     0     1  0.576   0.935
TRUE
16    FRN_Libya 0.223     1     1     0     0     0     0  0.670   0.898
TRUE
26     UK_Libya 0.069     1     1     0     0     0     0  0.670   0.936
TRUE
23     ITA_Afgh 0.025     1     1     0     1     0     0  0.670   0.898
TRUE
10    ESP_EURCA 0.041     1     1     1     0     0     0  0.767   0.920
TRUE
18   GER_Bosnia 0.031     1     1     1     0     0     0  0.670   0.800
TRUE
25   UK_DaeshIr 0.069     1     1     1     0     0     0  0.670   0.891
TRUE
1       DK_Afgh 0.005     1     1     1     1     0     0  0.670   0.884
TRUE
7      DK_Libya 0.483     1     1     1     1     0     0  0.517   0.950
TRUE
2     DK_Bosnia 0.011     1     1     1     1     0     0  0.909   0.696
FALSE
    Best MostDCOV
24 0.430     TRUE
15 0.330     TRUE
21 0.431     TRUE
3  0.330     TRUE
5  0.400    FALSE
```

```
11 0.293     TRUE
8  0.330    FALSE
9  0.330    FALSE
20 0.359     TRUE
6  0.170    FALSE
22 0.194    FALSE
19 0.330    FALSE
12 0.113     TRUE
4  0.317     TRUE
13 0.330    FALSE
17 0.344    FALSE
14 0.424    FALSE
16 0.330     TRUE
26 0.330     TRUE
23 0.330     TRUE
10 0.233     TRUE
18 0.330    FALSE
25 0.330    FALSE
1  0.330    FALSE
7  0.483    FALSE
2  0.091     TRUE
```

```
# deviant coverage - iir
dcoviir <- smmr(results = sol_nyp,
                outcome = "~PC",
                match = TRUE,
                cases = 4)
dcoviir
```

```
Matching Deviant Coverage-IIR Cases :
----------
           DCOV         IIR TT_PD TT_HR TT_PI TT_PF TT_RO TT_GP TT_DCV<=Y
Best
1  FRN_DaeshSyr   UK_Iraq03     0     1     0     0     1     0      TRUE
0.946
2    GER_Kosovo  UK_DaeshSy     0     1     1     0     0     0      TRUE
1.081
3     GER_EURCA GER_DaeshIr     1     0     1     0     0     1      TRUE
1.013
4     GER_EURCA   GER_EUSom     1     0     1     0     0     1      TRUE
1.032
5   FIN_DaeshIr     GER_Leb     1     0     1     1     0     1      TRUE
0.762
6      FIN_KFOR     GER_Leb     1     0     1     1     0     1      TRUE
0.928
7  GER_Atalanta     GER_Leb     1     0     1     1     0     1      TRUE
0.949
8     DK_Iraq91     GER_Leb     1     0     1     1     0     1      TRUE
0.955
9      ITA_Afgh   ITA_Libya     1     1     0     1     0     0      TRUE
```

```
0.762
10     ITA_Afgh  ITA_Iraq91     1     1     0     1     0     0      TRUE
0.763
```

The two SMMR designs for identifying missing conjuncts are implemented as follows:

```
# deviant consistency
dcons <- smmr(results = sol_nyp,
              outcome = "~PC",
              match = FALSE,
              cases = 3)
dcons

Deviant Consistency Cases :
----------
      Cases  Term TermMemb Outcome  Best MostDCONS
1  GER_Afgh PD*RO    0.670   0.000 0.660      TRUE
3  SLK_KFOR PD*RO    0.683   0.189 0.823     FALSE
2 ITA_Som92 PD*RO    0.566   0.084 0.952     FALSE

# deviant consistency - typical
typdcons <- smmr(results = sol_nyp,
                 outcome = "~PC",
                 match = TRUE,
                 cases = 3)
typdcons

Term PD*RO :
----------
           TYP    DCONS  Best MostTypTerm MostDCONS
1    DK_Serval GER_Afgh 0.670       FALSE      TRUE
2   FRN_Serval GER_Afgh 0.680        TRUE      TRUE
3 ESP_Atalanta GER_Afgh 0.713       FALSE      TRUE
4    BEL_Libya GER_Afgh 0.714       FALSE      TRUE
5      SLK_Leb GER_Afgh 0.714       FALSE      TRUE
```

4.2 Causal inference SMMR

The presence of conjuncts requires researchers to make a choice when aiming at causal inferences: do they want to solicit conceptual arguments and treat the conjunction as one set or do they want to treat each conjunct in the conjunction separately. The latter is the default options. The following code implements the three SMMR designs that operate on focal conjuncts.

```
# typical
typ_foc <- smmr(results = sol_nyp,
                outcome = "~PC",
                match = FALSE,
                cases = 2)
typ_foc
```

```
Typical Cases - Focal Conjunct PD :
----------
               FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best
ESP_Libya    0.67   0.944  0.937 0.670    1     FALSE  TRUE    TRUE 0.878
BEL_Libya    0.67   0.946  0.940 0.670    1     FALSE  TRUE    TRUE 0.882
FRN_Serval   1.00   0.980  0.975 0.975    2      TRUE FALSE    TRUE 0.065
DK_Serval    1.00   0.990  0.927 0.927    2      TRUE FALSE    TRUE 0.093
ESP_Atalanta 1.00   0.947  0.937 0.937    2      TRUE FALSE    TRUE 0.169
             MostTypFC MostTypTerm
ESP_Libya        FALSE       FALSE
BEL_Libya        FALSE       FALSE
FRN_Serval        TRUE       FALSE
DK_Serval        FALSE       FALSE
ESP_Atalanta     FALSE       FALSE

Typical Cases - Focal Conjunct RO :
----------
                FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best
FRN_Serval   0.975   0.980      1 0.975    1      TRUE  TRUE    TRUE 0.035
ESP_EUSom    0.937   0.942      1 0.937    1      TRUE  TRUE    TRUE 0.072
SLK_EUMali   0.930   0.935      1 0.930    1      TRUE  TRUE    TRUE 0.080
ESP_Atalanta 0.937   0.947      1 0.937    1      TRUE  TRUE    TRUE 0.082
FRN_Sangaris 0.885   0.894      1 0.885    1      TRUE  TRUE    TRUE 0.133
             MostTypFC MostTypTerm
FRN_Serval        TRUE       FALSE
ESP_EUSom        FALSE       FALSE
SLK_EUMali       FALSE       FALSE
ESP_Atalanta     FALSE       FALSE
FRN_Sangaris     FALSE       FALSE
```

```r
# typical - iir
typiir_foc <- smmr(results = sol_nyp,
                   outcome = "~PC",
                   match = TRUE,
                   cases = 2,
                   max_pairs = 10)
typiir_foc
```

```
Focal Conjunct PD :
----------
             TYP        IIR PairRank CleanCorr FC<=Y UniqCov GlobUncov  Best
232    ESP_Libya  UK_Iraq03        1       iir  both    TRUE      TRUE 1.532
227    BEL_Libya  UK_Iraq03        1       iir  both    TRUE      TRUE 1.536
142    ESP_Libya ITA_Kosovo        1       iir   typ    TRUE      TRUE 1.642
137    BEL_Libya ITA_Kosovo        1       iir   typ    TRUE      TRUE 1.646
202    ESP_Libya SLK_Kosovo        1       iir   typ    TRUE      TRUE 1.848
197    BEL_Libya SLK_Kosovo        1       iir   typ    TRUE      TRUE 1.853
229    DK_Serval  UK_Iraq03        2      both   iir    TRUE      TRUE 0.617
236   FRN_Serval  UK_Iraq03        2      both   iir    TRUE      TRUE 0.695
239      SLK_Leb  UK_Iraq03        2      both   iir    TRUE      TRUE 0.718
```

```
230 ESP_Atalanta  UK_Iraq03        2      both   iir    TRUE      TRUE 0.757
    MostTypFC MostTypTerm
232     FALSE       FALSE
227     FALSE       FALSE
142     FALSE       FALSE
137     FALSE       FALSE
202     FALSE       FALSE
197     FALSE       FALSE
229     FALSE       FALSE
236      TRUE        TRUE
239     FALSE       FALSE
230     FALSE       FALSE

Focal Conjunct RO :
----------
             TYP        IIR PairRank CleanCorr FC<=Y UniqCov GlobUncov  Best
116   FRN_Serval ITA_Iraq90        1      both  both    TRUE      TRUE 0.238
111    ESP_EUSom ITA_Iraq90        1      both  both    TRUE      TRUE 0.313
110 ESP_Atalanta ITA_Iraq90        1      both  both    TRUE      TRUE 0.318
118   SLK_EUMali ITA_Iraq90        1      both  both    TRUE      TRUE 0.328
176   FRN_Serval ITA_Sophia        1      both  both    TRUE      TRUE 0.340
109    DK_Serval ITA_Iraq90        1      both  both    TRUE      TRUE 0.392
171    ESP_EUSom ITA_Sophia        1      both  both    TRUE      TRUE 0.415
114  FRN_DaeshIr ITA_Iraq90        1      both  both    TRUE      TRUE 0.416
170 ESP_Atalanta ITA_Sophia        1      both  both    TRUE      TRUE 0.420
115 FRN_Sangaris ITA_Iraq90        1      both  both    TRUE      TRUE 0.422
    MostTypFC MostTypTerm
116      TRUE        TRUE
111     FALSE       FALSE
110     FALSE       FALSE
118     FALSE       FALSE
176      TRUE        TRUE
109     FALSE       FALSE
171     FALSE       FALSE
114     FALSE       FALSE
170     FALSE       FALSE
115     FALSE       FALSE

# typical - typical
typtyp_foc <- smmr(results = sol_nyp,
                   outcome = "~PC",
                   match = TRUE,
                   cases = 1)
typtyp_foc

Focal Conjunct PD :
----------
        TYP1       TYP2 PairRank CleanCorr FC<=Y UniqCov  Best MostTypFC
22 ESP_Libya  BEL_Libya        1      none  both    both 2.105      none
37 ESP_Libya DK_DaeshIr        2      typ2  typ1    both 2.418      none
```

```
32 BEL_Libya DK_DaeshIr        2      typ2  typ1    both 2.422      none
94 DK_Serval  ESP_Libya        3      typ1  typ2    both 1.203      none
19 DK_Serval  BEL_Libya        3      typ1  typ2    both 1.211      none
   MostTypTerm
22        none
37        none
32        none
94        none
19        none

Focal Conjunct RO :
----------
           TYP1     TYP2 PairRank CleanCorr FC<=Y UniqCov  Best MostTypFC
176   FRN_Serval ITA_Alba        1      both  both    both 0.673      typ1
171    ESP_EUSom ITA_Alba        1      both  both    both 0.747      none
170 ESP_Atalanta ITA_Alba        1      both  both    both 0.752      none
178   SLK_EUMali ITA_Alba        1      both  both    both 0.762      none
169    DK_Serval ITA_Alba        1      both  both    both 0.827      none
    MostTypTerm
176        typ1
171        none
170        none
178        none
169        none
```

If a researcher decides that good reasons exist to move up on the ladder of abstraction and treat the conjunction (in the current example $PD * RO$) as one set, then the following code implements this choice.

```
# typical
typ_term <- smmr(results = sol_nyp,
                 outcome = "~PC",
                 match = FALSE,
                 cases = 1)
typ_term

Typical Cases :
----------
           Case  Term  TermMemb   Outcome UniqCov       Best MostTyp
11   FRN_Serval PD*RO 0.9748652 0.9800000    TRUE 0.03540449    TRUE
6     ESP_EUSom PD*RO 0.9373178 0.9420202    TRUE 0.07208690   FALSE
13   SLK_EUMali PD*RO 0.9300000 0.9349026    TRUE 0.07980513   FALSE
5  ESP_Atalanta PD*RO 0.9373178 0.9468406    TRUE 0.08172771   FALSE
10 FRN_Sangaris PD*RO 0.8850000 0.8939132    TRUE 0.13282640   FALSE
9   FRN_DaeshIr PD*RO 0.9000000 0.9337101    TRUE 0.16742018   FALSE
1   BEL_DaeshIr PD*RO 0.8773462 0.9000000    TRUE 0.16796145   FALSE
4     DK_Serval PD*RO 0.9267515 0.9900000    TRUE 0.19974551   FALSE
14      SLK_Leb PD*RO 0.8951981 0.9458406    TRUE 0.20608675   FALSE
12     ITA_Alba PD*RO 0.8000000 0.8057869    TRUE 0.21157381   FALSE
15    SLK_UNDOF PD*RO 0.6832891 0.8806141    TRUE 0.71136086   FALSE
```

```
8       FIN_Leb PD*RO 0.6849579 0.9108743    TRUE 0.76687496   FALSE
7     ESP_Libya PD*RO 0.6700000 0.9440380    TRUE 0.87807605   FALSE
2     BEL_Libya PD*RO 0.6700000 0.9461180    TRUE 0.88223592   FALSE
3    DK_DaeshIr PD*RO 0.5560820 0.8974634    TRUE 1.12668081   FALSE
```

```
# typical - iir
typiir_term <- smmr(results = sol_nyp,
                    outcome = "~PC",
                    match = TRUE,
                    cases = 6,
                    max_pairs = 10)
typiir_term
```

```
Term PD*RO :
----------
            TYP        IIR UniqCov ConsIIR GlobUncov  Best MostTyp
1    FRN_Serval SLK_Iraq03    TRUE    TRUE       TRUE 0.062    TRUE
4     ESP_EUSom SLK_Iraq03    TRUE    TRUE       TRUE 0.136   FALSE
5  ESP_Atalanta SLK_Iraq03    TRUE    TRUE       TRUE 0.141   FALSE
9    SLK_EUMali SLK_Iraq03    TRUE    TRUE       TRUE 0.151   FALSE
18    DK_Serval SLK_Iraq03    TRUE    TRUE       TRUE 0.216   FALSE
21   FRN_Serval ITA_Iraq90    TRUE    TRUE       TRUE 0.239    TRUE
22  FRN_DaeshIr SLK_Iraq03    TRUE    TRUE       TRUE 0.240   FALSE
23 FRN_Sangaris SLK_Iraq03    TRUE    TRUE       TRUE 0.245   FALSE
33      SLK_Leb SLK_Iraq03    TRUE    TRUE       TRUE 0.266   FALSE
37  BEL_DaeshIr SLK_Iraq03    TRUE    TRUE       TRUE 0.274   FALSE
```

```
# typical - typical
typtyp_term <- smmr(results = sol_nyp,
                    outcome = "~PC",
                    match = TRUE,
                    cases = 5)
typtyp_term
```

```
Term PD*RO :
----------
            TYP1     TYP2 UniqCov  Best MostTyp
166   FRN_Serval ITA_Alba    both 0.673    typ1
31     ESP_EUSom ITA_Alba    both 0.747    none
55  ESP_Atalanta ITA_Alba    both 0.752    none
65    SLK_EUMali ITA_Alba    both 0.762    none
215    DK_Serval ITA_Alba    both 0.827    none
```

4.3 Chapter 4: M. R. Schneider, Schulze-Bentrop, and Paunescu (2010), necessary INUS condition

Sometimes, INUS conditions qualify as necessary conditions for the outcome. This must be taken into account in all causal inference SMMR designs that zoom in on the necessary focal conjunct. This is done by specifying the necessary INUS condition via the argument

`nec.cond =` in function `smmr()`. For illustration I use the study by M. R. Schneider, Schulze-Bentrop, and Paunescu (2010).

Outcome

- `EXPORT` = success in export of high-tech products

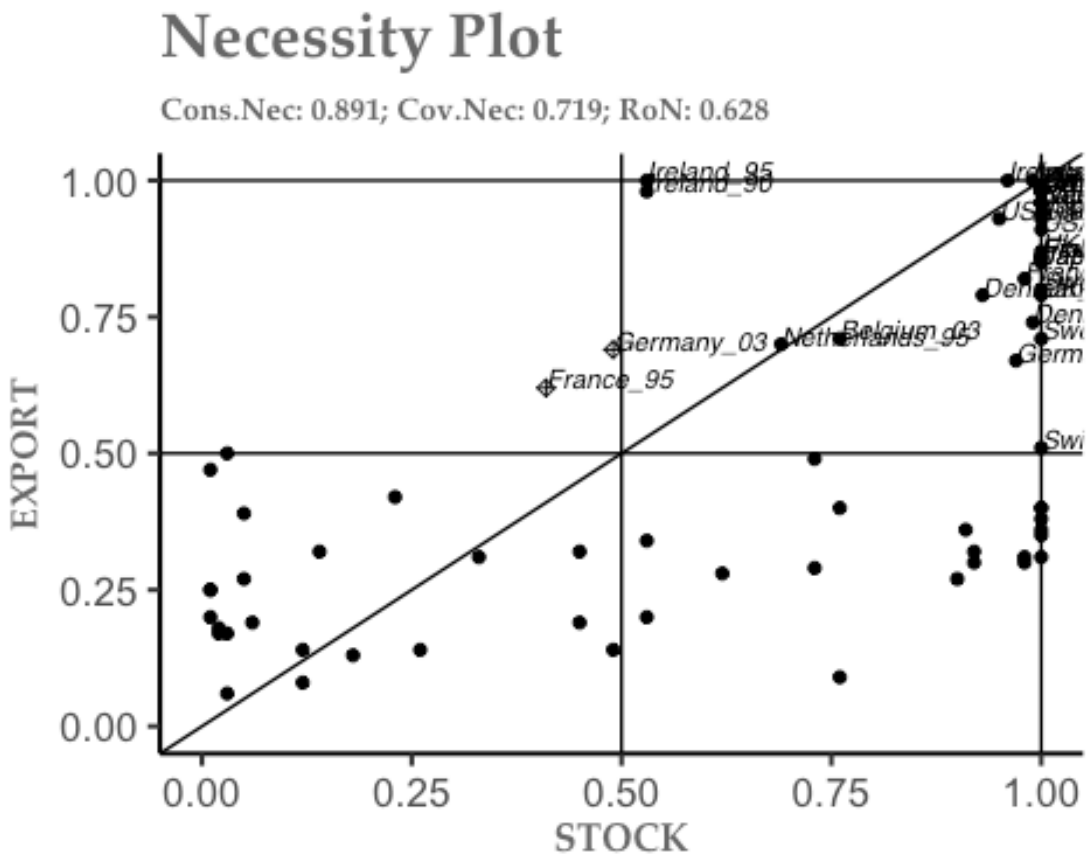
Conditions

- `EMP`= high employment protection
- `BARGAIN` = high collective bargaining
- `UNI` = a lot of university training
- `OCCUP` = a lot of occupational training
- `STOCK` = big stock market size
- `MA` = a lot of mergers and acquisitions

```
SCHF <- read.csv("Schneider_etal_10_fs.csv", row.names = 1)
```

We identify the necessary condition $STOCK$ and visualize it in an XY plot.

```
# Identify necessary condition
NEC <- superSubset(SCHF, outcome = "EXPORT",
            conditions = c("EMP","BARGAIN","UNI","OCCUP","STOCK", "MA"),
            incl.cut = .87,
            ron.cut = 0.5,
            cov.cut = 0.6,
            depth = 1)

NEC


          inclN   RoN   covN
------------------------------
1  STOCK  0.891  0.628  0.719
------------------------------

# Plot necessary condition

pimplot(SCHF,
        results = NEC,
        outcome = "EXPORT",
        necessity = TRUE)
```



In the next step, we identify the sufficient conditions. For this, we first produce the truth table. Since we do have a necessary condition, we must make sure that our sufficiency statements do not contradict this necessity claim. For this, we apply the Enhanced Standard Analysis (ESA). This means, we must block from being included in the logical minimization all those truth table rows that would contradict the necessity claim.

```
# Obtain truth table
TT_y <- truthTable(SCHF, outcome = "EXPORT",
                   conditions = c("EMP","BARGAIN","UNI","OCCUP","STOCK",
"MA"),
                   incl.cut = .9,
                   pri.cut = 0.5,
                   sort.by =c('OUT', 'incl'))
TT_y


  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

     EMP BARGAIN UNI OCCUP STOCK MA   OUT    n   incl  PRI
19    0     1     0    0     1   0     1     1   0.982 0.911
```

```
28    0     1     1     0     1    1     1     2    0.966 0.899
16    0     0     1     1     1    1     1     1    0.964 0.866
43    1     0     1     0     1    0     1     4    0.951 0.875
63    1     1     1     1     1    0     1     2    0.941 0.755
64    1     1     1     1     1    1     1     7    0.941 0.860
27    0     1     1     0     1    0     1     1    0.930 0.714
 8    0     0     0     1     1    1     1     3    0.930 0.776
60    1     1     1     0     1    1     1     4    0.929 0.796
11    0     0     1     0     1    0     1     6    0.920 0.849
32    0     1     1     1     1    1     1     4    0.910 0.765
29    0     1     1     1     0    0     0     1    0.900 0.333
56    1     1     0     1     1    1     0     5    0.894 0.653
62    1     1     1     1     0    1     0     1    0.883 0.267
12    0     0     1     0     1    1     0     10   0.880 0.789
61    1     1     1     1     0    0     0     2    0.844 0.228
55    1     1     0     1     1    0     0     2    0.835 0.297
57    1     1     1     0     0    0     0     1    0.824 0.214
 2    0     0     0     0     0    1     0     1    0.787 0.316
49    1     1     0     0     0    0     0     4    0.742 0.115
10    0     0     1     0     0    1     0     2    0.662 0.158
53    1     1     0     1     0    0     0     12   0.607 0.091
```

Since we do have a necessary condition, we must make sure that our sufficiency statements do not contradict this necessity claim. For this, we apply the Enhanced Standard Analysis (ESA). This means, we must block from being included in the logical minimization all those truth table rows that would contradict the necessity claim.

```
# Perform ESA by blocking all truth table rows that contain the negation of
the necessary condition STOCK
TT_yesa <- esa(oldtt = TT_y,
               nec_cond = "STOCK")
TT_yesa


  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

     EMP BARGAIN UNI OCCUP STOCK MA   OUT    n   incl  PRI
19    0     1     0    0     1    0     1     1   0.982 0.911
28    0     1     1    0     1    1     1     2   0.966 0.899
16    0     0     1    1     1    1     1     1   0.964 0.866
43    1     0     1    0     1    0     1     4   0.951 0.875
63    1     1     1    1     1    0     1     2   0.941 0.755
64    1     1     1    1     1    1     1     7   0.941 0.860
27    0     1     1    0     1    0     1     1   0.930 0.714
 8    0     0     0    1     1    1     1     3   0.930 0.776
60    1     1     1    0     1    1     1     4   0.929 0.796
11    0     0     1    0     1    0     1     6   0.920 0.849
```

```
32    0     1     1     1     1     1     1     4    0.910 0.765
29    0     1     1     1     0     0     0     1    0.900 0.333
56    1     1     0     1     1     1     0     5    0.894 0.653
62    1     1     1     1     0     1     0     1    0.883 0.267
12    0     0     1     0     1     1     0     10   0.880 0.789
61    1     1     1     1     0     0     0     2    0.844 0.228
55    1     1     0     1     1     0     0     2    0.835 0.297
57    1     1     1     0     0     0     0     1    0.824 0.214
 2    0     0     0     0     0     1     0     1    0.787 0.316
49    1     1     0     0     0     0     0     4    0.742 0.115
10    0     0     1     0     0     1     0     2    0.662 0.158
53    1     1     0     1     0     0     0     12   0.607 0.091
 1    0     0     0     0     0     0     0     0      -     -
 5    0     0     0     1     0     0     0     0      -     -
 6    0     0     0     1     0     1     0     0      -     -
 9    0     0     1     0     0     0     0     0      -     -
13    0     0     1     1     0     0     0     0      -     -
14    0     0     1     1     0     1     0     0      -     -
17    0     1     0     0     0     0     0     0      -     -
18    0     1     0     0     0     1     0     0      -     -
21    0     1     0     1     0     0     0     0      -     -
22    0     1     0     1     0     1     0     0      -     -
25    0     1     1     0     0     0     0     0      -     -
26    0     1     1     0     0     1     0     0      -     -
30    0     1     1     1     0     1     0     0      -     -
33    1     0     0     0     0     0     0     0      -     -
34    1     0     0     0     0     1     0     0      -     -
37    1     0     0     1     0     0     0     0      -     -
38    1     0     0     1     0     1     0     0      -     -
41    1     0     1     0     0     0     0     0      -     -
42    1     0     1     0     0     1     0     0      -     -
45    1     0     1     1     0     0     0     0      -     -
46    1     0     1     1     0     1     0     0      -     -
50    1     1     0     0     0     1     0     0      -     -
54    1     1     0     1     0     1     0     0      -     -
58    1     1     1     0     0     1     0     0      -     -
```

The logical minimization produces two enhanced most parsimonious solutions (aka model ambiguity). For illustration I focus on model 1. The insights and arguments on SMMR that follow remain unaffected by the presence of model ambiguity and the choice of model 1 for illustration.

```
# Logically minimize the enhanced truth table to obtain the enhanced most
parsimonious solution
sol_yp <- minimize(TT_yesa,
                       include = "?",
                       details = TRUE, show.cases = TRUE)

sol_yp
```

```
M1: BARGAIN*UNI*STOCK + ~OCCUP*STOCK*~MA + (~EMP*OCCUP*STOCK) -> EXPORT
M2: BARGAIN*UNI*STOCK + ~OCCUP*STOCK*~MA + (~BARGAIN*OCCUP*STOCK) -> EXPORT

                                                 ------------------
                          inclS   PRI   covS   covU   (M1)   (M2)
-------------------------------------------------------------------
1    BARGAIN*UNI*STOCK  0.796  0.665  0.497  0.183  0.187  0.250
2     ~OCCUP*STOCK*~MA  0.890  0.788  0.374  0.149  0.149  0.155
-------------------------------------------------------------------
3      ~EMP*OCCUP*STOCK  0.863  0.668  0.319  0.008  0.038
4  ~BARGAIN*OCCUP*STOCK  0.944  0.808  0.202  0.000         0.031
-------------------------------------------------------------------
                     M1  0.798  0.696  0.708
                     M2  0.807  0.707  0.701

                          cases
------------------------------
1     BARGAIN*UNI*STOCK  Denmark_95; Ireland_95,Australia_03;
Australia_95,Australia_99,Denmark_99,Denmark_03;
                          Spain_99,Sweden_99,Norway_03,Sweden_03;
Finland_95,France_03;

Belgium_99,Finland_99,France_99,Netherlands_99,Belgium_03,Finland_03,Netherla
nds_03
2      ~OCCUP*STOCK*~MA  Canada_90,USA_90,Canada_95,USA_95,Japan_03,USA_03;
Ireland_90;
                          Denmark_95; Japan_90,Japan_95,Japan_99,Spain_03
------------------------------
3      ~EMP*OCCUP*STOCK  Switzerland_90,Switzerland_95,Switzerland_03;
Switzerland_99;
                          Australia_95,Australia_99,Denmark_99,Denmark_03
4  ~BARGAIN*OCCUP*STOCK  Switzerland_90,Switzerland_95,Switzerland_03;
Switzerland_99
------------------------------
```

The empirical illustration consists of the three causal inference SMMR designs because only for them the focal conjunct principle applies. I illustrate using term 3 ($\sim OCCOP * STOCK * \sim MA$).

The best available typical case is found as follows. Note that argument `nec.cond =` specifies $STOCK$ as the necessary INUS condition.

```
# Best available typical case
typ_foc <- smmr(results = sol_yp,
     outcome = "EXPORT",
     match=FALSE,
     cases=2,
     term = 3,
```

```
     nec.cond = "STOCK")
typ_foc

Typical Cases - Focal Conjunct ~OCCUP :
----------
            FC Outcome CC_Min Term Rank CleanCorr FC<=Y UniqCov Best
MostTypFC
Japan_95   0.85    0.85   0.95 0.85    1      TRUE  TRUE    TRUE 0.15
TRUE
Japan_03   0.87    0.94   0.94 0.87    1     FALSE  TRUE    TRUE 0.27
FALSE
Japan_99   0.84    0.96   0.92 0.84    1     FALSE  TRUE    TRUE 0.40
FALSE
USA_03     0.97    0.98   0.83 0.83    2      TRUE  TRUE    TRUE 0.19
FALSE
Ireland_90 0.84    0.98   0.51 0.51    2      TRUE  TRUE    TRUE 0.77
FALSE
           MostTypTerm
Japan_95         FALSE
Japan_03         FALSE
Japan_99         FALSE
USA_03           FALSE
Ireland_90       FALSE

Typical Cases - Necessary Focal Conjunct STOCK :
----------
           FC Outcome CC_Min Term Rank CleanCorr FC>=Y UniqCov Best MostTypFC
USA_90   0.95    0.93   0.85 0.85    1      TRUE  TRUE    TRUE 0.19      TRUE
USA_03   1.00    0.98   0.83 0.83    1      TRUE  TRUE    TRUE 0.21     FALSE
Japan_99 1.00    0.96   0.84 0.84    1      TRUE  TRUE    TRUE 0.24     FALSE
Japan_03 1.00    0.94   0.87 0.87    1     FALSE  TRUE    TRUE 0.25     FALSE
USA_95   1.00    0.91   0.85 0.85    1     FALSE  TRUE    TRUE 0.33     FALSE
         MostTypTerm
USA_90         FALSE
USA_03         FALSE
Japan_99       FALSE
Japan_03       FALSE
USA_95         FALSE

Typical Cases - Focal Conjunct ~MA :
----------
            FC Outcome CC_Min Term Rank CleanCorr FC<=Y UniqCov Best
MostTypFC
USA_95     0.85    0.91   0.97 0.85    1      TRUE  TRUE    TRUE 0.27
FALSE
USA_90     0.85    0.93   0.95 0.85    1      TRUE  TRUE    TRUE 0.31
FALSE
USA_03     0.83    0.98   0.97 0.83    1     FALSE  TRUE    TRUE 0.47
FALSE
Ireland_90 0.51    0.98   0.53 0.51    1     FALSE  TRUE    TRUE 1.43
```

```
FALSE
Japan_03   0.94    0.94   0.87 0.87    2      TRUE  TRUE    TRUE 0.13
TRUE
          MostTypTerm
USA_95          FALSE
USA_90          FALSE
USA_03          FALSE
Ireland_90      FALSE
Japan_03        FALSE
```

The best available pairs - for each focal conjunct separately - of a typical and an iir case look as follows.

```
# Best available pair of typical and iir cases
typiir_foc <- smmr(results = sol_yp,
     outcome = "EXPORT",
     match=TRUE,
     cases=2,
     term = 3,
     nec.cond = "STOCK",
     max_pairs = 10)
typiir_foc

Focal Conjunct ~OCCUP :
----------
         TYP        IIR PairRank CleanCorr FC<=Y UniqCov GlobUncov Best
192 Japan_95   Italy_99        1      both  both    TRUE      TRUE 1.10
122 Japan_95 Finland_95        1      both  both    TRUE     FALSE 1.50
24  Japan_95 Denmark_90        1      both   typ    TRUE      TRUE 1.62
195 Japan_03   Italy_99        1       iir  both    TRUE      TRUE 1.12
194 Japan_99   Italy_99        1       iir  both    TRUE      TRUE 1.21
125 Japan_03 Finland_95        1       iir  both    TRUE     FALSE 1.52
124 Japan_99 Finland_95        1       iir  both    TRUE     FALSE 1.61
27  Japan_03 Denmark_90        1       iir   typ    TRUE      TRUE 1.64
26  Japan_99 Denmark_90        1       iir   typ    TRUE      TRUE 1.73
196   USA_03   Italy_99        2      both  both    TRUE      TRUE 0.75
    MostTypFC MostTypTerm
192      TRUE        TRUE
122      TRUE        TRUE
24       TRUE        TRUE
195     FALSE       FALSE
194     FALSE       FALSE
125     FALSE       FALSE
124     FALSE       FALSE
27      FALSE       FALSE
26      FALSE       FALSE
196     FALSE       FALSE

Necessary Focal Conjunct STOCK :
----------
```

```
           TYP            IIR PairRank CleanCorr FC>=Y UniqCov GlobUncov Best
210     USA_03      Norway_99        1      both  both    TRUE      TRUE 1.77
208   Japan_99      Norway_99        1      both  both    TRUE      TRUE 1.84
205     USA_90      Norway_99        1       iir  both    TRUE      TRUE 1.89
209   Japan_03      Norway_99        1       iir  both    TRUE      TRUE 1.93
207     USA_95      Norway_99        1       iir  both    TRUE      TRUE 2.00
206   Japan_95      Norway_99        1       iir  both    TRUE      TRUE 2.18
204 Ireland_90      Norway_99        2       iir   iir    TRUE      TRUE 2.78
21      USA_03     Belgium_90        3      both  both    TRUE      TRUE 0.78
19    Japan_99     Belgium_90        3      both  both    TRUE      TRUE 0.85
203     USA_03 New Zealand_99        3      both  both    TRUE      TRUE 1.06
    MostTypFC MostTypTerm
210     FALSE       FALSE
208     FALSE       FALSE
205      TRUE       FALSE
209     FALSE       FALSE
207     FALSE       FALSE
206     FALSE        TRUE
204     FALSE       FALSE
21      FALSE       FALSE
19      FALSE       FALSE
203     FALSE       FALSE

Focal Conjunct ~MA :
----------
       TYP            IIR PairRank CleanCorr FC<=Y UniqCov GlobUncov Best
184 USA_90      Canada_99        1      both  both    TRUE      TRUE 1.24
186 USA_95      Canada_99        1      both  both    TRUE      TRUE 1.24
212 USA_90       Spain_99        1      both  both    TRUE     FALSE 1.05
214 USA_95       Spain_99        1      both  both    TRUE     FALSE 1.05
247 USA_90      Norway_03        1      both  both    TRUE     FALSE 1.38
249 USA_95      Norway_03        1      both  both    TRUE     FALSE 1.38
219 USA_90   Australia_03        1      both  both    TRUE     FALSE 1.51
221 USA_95   Australia_03        1      both  both    TRUE     FALSE 1.51
142 USA_90 New Zealand_95        1      both   typ    TRUE      TRUE 0.93
144 USA_95 New Zealand_95        1      both   typ    TRUE      TRUE 0.93
    MostTypFC MostTypTerm
184     FALSE       FALSE
186     FALSE       FALSE
212     FALSE       FALSE
214     FALSE       FALSE
247     FALSE       FALSE
249     FALSE       FALSE
219     FALSE       FALSE
221     FALSE       FALSE
142     FALSE       FALSE
144     FALSE       FALSE
```

And the best pair of two typical cases is listed below.

```r
# Best available pair of two typical cases
typtyp_foc <- smmr(results = sol_yp,
                   outcome = "EXPORT",
                   match=TRUE,
                   cases=1,
                   term = 3,
                   nec.cond = "STOCK")
typtyp_foc
```

```
Focal Conjunct ~OCCUP :
----------
       TYP1       TYP2 PairRank CleanCorr FC<=Y UniqCov Best MostTypFC
38 Japan_95   Japan_03        1      typ1  both    both 1.26      typ1
31 Japan_95   Japan_99        1      typ1  both    both 1.37      typ1
34 Japan_03   Japan_99        1      none  both    both 1.39      none
45 Japan_95     USA_03        2      both  both    both 1.39      typ1
3  Japan_95 Ireland_90        2      both  both    both 1.84      typ1
   MostTypTerm
38        typ1
31        typ1
34        none
45        typ1
3         typ1

Necessary Focal Conjunct STOCK :
----------
       TYP1     TYP2 PairRank CleanCorr FC>=Y UniqCov Best MostTypFC
47 Japan_99   USA_03        1      both  both    both 1.15      none
44   USA_90   USA_03        1      typ2  both    both 1.20      typ1
30   USA_90 Japan_99        1      typ2  both    both 1.21      typ1
48 Japan_03   USA_03        1      typ2  both    both 1.24      none
34 Japan_03 Japan_99        1      typ2  both    both 1.25      none
   MostTypTerm
47        none
44        none
30        none
48        none
34        none

Focal Conjunct ~MA :
----------
     TYP1       TYP2 PairRank CleanCorr FC<=Y UniqCov Best MostTypFC
11 USA_95     USA_90        1      both  both    both 1.32      none
46 USA_95     USA_03        1      typ1  both    both 1.47      none
44 USA_90     USA_03        1      typ1  both    both 1.51      none
2  USA_90 Ireland_90        1      typ1  both    both 2.23      none
4  USA_95 Ireland_90        1      typ1  both    both 2.23      none
   MostTypTerm
11        none
46        none
```

44	none
2	none
4	none

5 Chapter 5: C. Q. Schneider and Makszin (2014)

In chapter 5, the example of C. Q. Schneider and Makszin (2014) is used for empirically illustrating different scenarios on the location of a case's membership in the within-case mechanism vis-a-vis its membership in the cross-case conditions and the outcome in a setting of full causal complexity (that is, a QCA solution that consists of a disjunction of conjunctions).

I start with model-refining, descriptive inference SMMR and then turn to causal inference SMMR.

```
MACRO.d <- read.csv('SchneiderMakszin2014.csv', row.names = 1)

# conditions
conds <- c("WC", "UN", "EP", "LM")

# truth table
tt_y <- truthTable(data = MACRO.d,
                   outcome = 'LPI',
                   conditions = conds,
                   incl.cut = 0.8,
                   sort.by = c('OUT', 'incl'),
                   complete = TRUE,
                   show.cases = TRUE)
tt_y


  OUT: output value
    n: number of cases in configuration
 incl: sufficiency inclusion score
  PRI: proportional reduction in inconsistency

     WC UN EP LM   OUT    n   incl  PRI
 4   0  0  1  1     1     4   0.911 0.871
 8   0  1  1  1     1     5   0.900 0.833
12   1  0  1  1     1     7   0.873 0.839
 3   0  0  1  0     1     9   0.825 0.744
14   1  1  0  1     1     2   0.825 0.698
11   1  0  1  0     1     2   0.818 0.730
16   1  1  1  1     1     6   0.800 0.663
15   1  1  1  0     0     5   0.781 0.683
13   1  1  0  0     0     4   0.769 0.666
 6   0  1  0  1     0     5   0.759 0.618
 7   0  1  1  0     0     5   0.754 0.576
 5   0  1  0  0     0     6   0.726 0.578
 2   0  0  0  1     0     1   0.686 0.476
 9   1  0  0  0     0     3   0.642 0.486
 1   0  0  0  0     0     12  0.537 0.399
10   1  0  0  1     ?     0     -     -
```

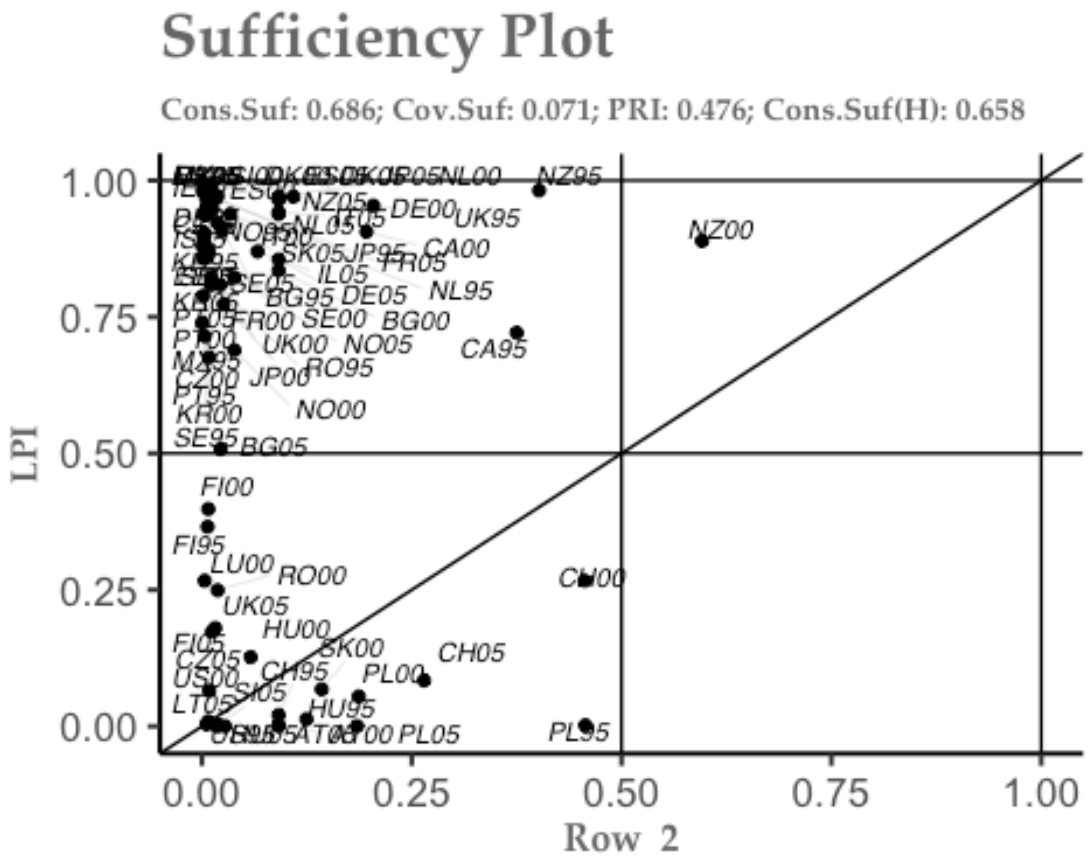
```
     cases
 4   FR00,FR05,ES95,ES00
 8   DK95,FI95,SI95,SE00,SE05
12   AT05,DE00,DE05,NL95,NL00,NL05,ES05
 3   EE05,KR05,LT05,MX95,MX00,MX05,PT95,PT00,PT05
14   DK00,IE00
11   KR95,KR00
16   AT00,FI00,FI05,DE95,NO95,SE95
15   IT00,NO00,NO05,SI00,SI05
13   CZ95,IS05,IT05,SK00
 6   CA95,DK05,HU95,NZ95,PL95
 7   BG95,BG00,LU00,RO95,RO00
 5   CA00,CZ00,HU00,IL05,UK95,UK00
 2   NZ00
 9   JP95,JP00,CH95
 1   CZ05,HU05,JP05,NZ05,PL00,PL05,SK05,CH00,CH05,UK05,US95,US00
10
```

```
# most parsimonious solution
sol_yp <- minimize(input = tt_y,
                   include = '?',
                   details = TRUE)
sol_yp


M1: WC*LM + ~UN*EP + EP*LM -> LPI

           inclS   PRI   covS   covU
-------------------------------------
1   WC*LM  0.813  0.760  0.257  0.044
2  ~UN*EP  0.859  0.828  0.414  0.208
3   EP*LM  0.868  0.835  0.346  0.056
-------------------------------------
       M1  0.839  0.804  0.598

           cases
----------------
1   WC*LM  AT05,DE00,DE05,NL95,NL00,NL05,ES05; DK00,IE00;
AT00,FI00,FI05,DE95,NO95,SE95
2  ~UN*EP  EE05,KR05,LT05,MX95,MX00,MX05,PT95,PT00,PT05; FR00,FR05,ES95,ES00;
KR95,KR00;
           AT05,DE00,DE05,NL95,NL00,NL05,ES05
3   EP*LM  FR00,FR05,ES95,ES00; DK95,FI95,SI95,SE00,SE05;
AT05,DE00,DE05,NL95,NL00,NL05,ES05;
           AT00,FI00,FI05,DE95,NO95,SE95
----------------

# missing disjuncts
dcov <- smmr(results = sol_yp,
             outcome = 'LPI',
```

```
               match = FALSE,
               cases = 4)
dcov

Deviant Coverage Cases :
----------
   Case   Sol TT_WC TT_UN TT_EP TT_LM TT_row Outcome TT<=Y  Best MostDCOV
18 NZ05 0.081     0     0     0     0  0.876   0.970  TRUE 0.124     TRUE
13 JP05 0.068     0     0     0     0  0.822   0.971  TRUE 0.178    FALSE
22 SK05 0.099     0     0     0     0  0.710   0.921  TRUE 0.290    FALSE
17 NZ00 0.009     0     0     0     1  0.596   0.889  TRUE 0.404     TRUE
24 UK95 0.002     0     1     0     0  0.658   0.954  TRUE 0.342     TRUE
8  IL05 0.052     0     1     0     0  0.625   0.870  TRUE 0.375    FALSE
5  CZ00 0.387     0     1     0     0  0.578   0.859  TRUE 0.422    FALSE
3  CA00 0.003     0     1     0     0  0.558   0.906  TRUE 0.442    FALSE
23 UK00 0.002     0     1     0     0  0.526   0.808  TRUE 0.474    FALSE
7  DK05 0.285     0     1     0     1  0.715   0.981  TRUE 0.285     TRUE
4  CA95 0.003     0     1     0     1  0.625   0.721  TRUE 0.375    FALSE
19 NZ95 0.005     0     1     0     1  0.598   0.982  TRUE 0.402    FALSE
1  BG00 0.394     0     1     1     0  0.606   0.835  TRUE 0.394    FALSE
2  BG95 0.472     0     1     1     0  0.528   0.909  TRUE 0.472    FALSE
20 RO95 0.071     0     1     1     0  0.929   0.822 FALSE 0.071     TRUE
14 JP95 0.324     1     0     0     0  0.676   0.967  TRUE 0.324     TRUE
12 JP00 0.108     1     0     0     0  0.613   0.773  TRUE 0.387    FALSE
9  IS05 0.005     1     1     0     0  0.909   0.937  TRUE 0.091     TRUE
6  CZ95 0.086     1     1     0     0  0.613   0.948  TRUE 0.387    FALSE
11 IT05 0.387     1     1     0     0  0.598   0.942  TRUE 0.402    FALSE
21 SI00 0.208     1     1     1     0  0.792   0.994  TRUE 0.208    FALSE
10 IT00 0.354     1     1     1     0  0.646   0.947  TRUE 0.354    FALSE
16 NO05 0.160     1     1     1     0  0.840   0.822 FALSE 0.160     TRUE
15 NO00 0.203     1     1     1     0  0.797   0.689 FALSE 0.203    FALSE
```

Eight truth table rows populated by deviant coverage cases. This signals high heterogeneity in data - something also illustrated by fact that there is just one remainder row (see truth table in chapter 1 ???). Another interesting observation: truth table row 2 (0001) has only deviant coverage case (NZ00) but no iir case. Why is the row not consistent enough to be included in the logical minimization? Let's plot it.

```
pimplot(data = MACRO.d,
        outcome = 'LPI',
        ttrows = c(2),
        results = sol_yp,
        all_labels = TRUE,
        jitter = TRUE,
        consH = TRUE)
```



The low consistency (.686) seems to be driven down by iir cases AND by skewed membership: with most cases being ttrow2 = 0, the few cases that are >0 have relatively more weight in the consistency formula.

Pairs of deviant coverage and iir cases:

```
dcov_iir <- smmr(results = sol_yp,
                 outcome = 'LPI',
                 match = TRUE,
                 cases = 4)
dcov_iir

Matching Deviant Coverage-IIR Cases :
----------
   DCOV  IIR TT_WC TT_UN TT_EP TT_LM TT_DCV<=Y  Best
1  NZ05 US95     0     0     0     0      TRUE 0.278
2  NZ05 HU05     0     0     0     0      TRUE 0.278
3  NZ05 US00     0     0     0     0      TRUE 0.287
4  JP05 US95     0     0     0     0      TRUE 0.384
5  JP05 HU05     0     0     0     0      TRUE 0.384
6  UK95 HU00     0     1     0     0      TRUE 1.157
7  CA00 HU00     0     1     0     0      TRUE 1.205
8  IL05 HU00     0     1     0     0      TRUE 1.242
```

```
9  CZ00 HU00     0     1     0     0      TRUE 1.252
10 UK00 HU00     0     1     0     0      TRUE 1.303
11 DK05 HU95     0     1     0     1      TRUE 0.652
12 NZ95 HU95     0     1     0     1      TRUE 0.835
13 NZ95 PL95     0     1     0     1      TRUE 0.934
14 DK05 PL95     0     1     0     1      TRUE 0.935
15 CA95 HU95     0     1     0     1      TRUE 1.042
16 BG00 RO00     0     1     1     0      TRUE 1.203
17 BG00 LU00     0     1     1     0      TRUE 1.220
18 BG95 RO00     0     1     1     0      TRUE 1.285
19 BG95 LU00     0     1     1     0      TRUE 1.303
20 RO95 RO00     0     1     1     0     FALSE 0.779
21 JP95 CH95     1     0     0     0      TRUE 0.702
22 JP00 CH95     1     0     0     0      TRUE 1.022
23 CZ95 SK00     1     1     0     0      TRUE 0.908
24 IS05 SK00     1     1     0     0      TRUE 0.920
25 IT05 SK00     1     1     0     0      TRUE 0.929
26 SI00 SI05     1     1     1     0      TRUE 0.526
27 IT00 SI05     1     1     1     0      TRUE 0.764
28 NO05 SI05     1     1     1     0     FALSE 0.698
29 NO00 SI05     1     1     1     0     FALSE 0.831
```

There are pairs of deviant coverage and iir cases in seven truth table rows (all but 0001 with NZ00).

5.1 Descriptive inference SMMR

For identifying missing conjuncts, we need to select among deviant consistency cases, either alone or in comparision with a typical case.

```
dcons <- smmr(results = sol_yp,
              outcome = 'LPI',
              match = FALSE,
              cases = 3)
dcons

Deviant Consistency Cases :
----------
   Cases   Term TermMemb Outcome  Best MostDCONS
21  LT05 ~UN*EP    0.939   0.003 0.125      TRUE
11  AT05 ~UN*EP    0.546   0.000 0.908     FALSE
12  AT00  EP*LM    0.550   0.003 0.903      TRUE
22  AT05  EP*LM    0.546   0.000 0.908     FALSE
31  FI95  EP*LM    0.676   0.366 1.014     FALSE
5   FI05  EP*LM    0.523   0.173 1.127     FALSE
41  FI00  EP*LM    0.602   0.398 1.194     FALSE
4   FI05  WC*LM    0.909   0.173 0.356      TRUE
3   FI00  WC*LM    0.799   0.398 0.801     FALSE
2   AT05  WC*LM    0.595   0.000 0.810     FALSE
1   AT00  WC*LM    0.550   0.003 0.903     FALSE
```

Case AT05 deviates in all 3 sufficient terms (and AT00 in 2 of them). This might indicate an idiosyncratic reason? For instance, membership in the outcome of AT00 and AT05 could be assigned erroneously (e.g. typo in the data).

Comparing deviant consistency and typical cases, we obtain the following list of best-available pairs:

```
typdcons <- smmr(results = sol_yp,
                 outcome = 'LPI',
                 match = TRUE,
                 cases = 3)
typdcons

Term WC*LM :
----------
   TYP DCONS  Best MostTypTerm MostDCONS
1 NL00  FI05 0.385       FALSE      TRUE
2 DE95  FI05 0.390       FALSE      TRUE
3 DE00  FI05 0.391       FALSE      TRUE
4 NL95  FI05 0.417        TRUE      TRUE
5 NL05  FI05 0.417        TRUE      TRUE

Term ~UN*EP :
----------
   TYP DCONS  Best MostTypTerm MostDCONS
1 ES95  LT05 0.130       FALSE      TRUE
2 MX05  LT05 0.136       FALSE      TRUE
3 ES05  LT05 0.139       FALSE      TRUE
4 MX00  LT05 0.142       FALSE      TRUE
5 ES00  LT05 0.154        TRUE      TRUE

Term EP*LM :
----------
   TYP DCONS  Best MostTypTerm MostDCONS
1 ES95  AT00 0.907        TRUE      TRUE
2 ES95  AT05 0.913        TRUE     FALSE
3 DK95  AT00 0.914       FALSE      TRUE
4 ES05  AT00 0.917       FALSE      TRUE
5 DK95  AT05 0.920       FALSE     FALSE
```

Note that only for one out of three terms do the most typical and most deviant pair also form the best available pair (ES95-AT00 for term $EP * LM$).

5.2 Causal inference SMMR

5.2.1 Single-case designs

All causal inference SMMR designs involve at least one typical case. Let's start with the single typical case SMMR design. Two options exist: either we focus on the entire term or on each conjunct in a term.

```
typ_term <- smmr(results = sol_yp,
                 outcome = 'LPI',
                 match = FALSE,
                 cases = 1)
typ_term

Typical Cases :
----------
    Case   Term  TermMemb   Outcome UniqCov       Best MostTyp
51  MX00 ~UN*EP 0.9569631 0.9837771    TRUE 0.09666497   FALSE
61  MX05 ~UN*EP 0.9403115 0.9896921    TRUE 0.15844974   FALSE
110 EE05 ~UN*EP 0.8732439 0.9034615    TRUE 0.18719124   FALSE
11  PT00 ~UN*EP 0.8131240 0.8798720    TRUE 0.32037199   FALSE
10  PT95 ~UN*EP 0.7005875 0.7391510    TRUE 0.37653941   FALSE
41  KR05 ~UN*EP 0.5344089 0.9452656    TRUE 1.28730450   FALSE
13  ES00 ~UN*EP 0.9597141 0.9713331   FALSE 0.06352398    TRUE
14  ES05 ~UN*EP 0.9639284 0.9860489   FALSE 0.08031256   FALSE
12  ES95 ~UN*EP 0.9560068 0.9954660   FALSE 0.12291156   FALSE
81  NL00 ~UN*EP 0.7835768 0.9704676   FALSE 0.59020474   FALSE
71  NL95 ~UN*EP 0.7550638 0.9385688   FALSE 0.61194620   FALSE
31  DE05 ~UN*EP 0.6658041 0.8552988   FALSE 0.71318534   FALSE
21  DE00 ~UN*EP 0.7101368 0.9647188   FALSE 0.79902730   FALSE
91  NL05 ~UN*EP 0.6344637 0.9385688   FALSE 0.97374651   FALSE
22  FR05  EP*LM 0.8612599 0.9721739    TRUE 0.36056792   FALSE
121 SE00  EP*LM 0.7912679 0.8798720    TRUE 0.38594041   FALSE
131 SE05  EP*LM 0.7507898 0.8698141    TRUE 0.48725896   FALSE
82  SI95  EP*LM 0.6935801 0.9007564    TRUE 0.72077262   FALSE
111 DK95  EP*LM 0.7332014 0.9887111    TRUE 0.77781802   FALSE
92  ES95  EP*LM 0.9762687 0.9954660   FALSE 0.06212602    TRUE
32  DE00  EP*LM 0.9047892 0.9647188   FALSE 0.21506996   FALSE
52  NL00  EP*LM 0.9047892 0.9704676   FALSE 0.22656763   FALSE
72  NO95  EP*LM 0.7917734 0.9367786   FALSE 0.49823702   FALSE
101 ES00  EP*LM 0.7469490 0.9713331   FALSE 0.70181906   FALSE
42  DE05  EP*LM 0.6658041 0.8552988   FALSE 0.71318534   FALSE
112 ES05  EP*LM 0.7131751 0.9860489   FALSE 0.83257252   FALSE
62  NL05  EP*LM 0.6344637 0.9385688   FALSE 0.97374651   FALSE
2   DE95  WC*LM 0.9086748 0.9657468    TRUE 0.20546926   FALSE
4   IE00  WC*LM 0.8438186 0.9793647    TRUE 0.42727353   FALSE
1   DK00  WC*LM 0.6128984 0.9860489    TRUE 1.13340252   FALSE
5   NL95  WC*LM 0.9086748 0.9385688   FALSE 0.15111329    TRUE
7   NL05  WC*LM 0.9086748 0.9385688   FALSE 0.15111329    TRUE
3   DE00  WC*LM 0.9086748 0.9647188   FALSE 0.20341334   FALSE
6   NL00  WC*LM 0.9086748 0.9704676   FALSE 0.21491101   FALSE
8   NO95  WC*LM 0.7917734 0.9367786   FALSE 0.49823702   FALSE
9   ES05  WC*LM 0.7131751 0.9860489   FALSE 0.83257252   FALSE
```

Focusing on the entire term is recommended only if there are theoretical and conceptual reasons to treat the term as one set. Short of this, each conjunct needs to be focussed on separately for causal inference.

```
typ_foc1 <- smmr(results = sol_yp,
                 outcome = 'LPI',
                 match = FALSE,
                 cases = 2,
                 term = 1)
typ_foc1
```

```
Typical Cases - Focal Conjunct WC :
----------
        FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best MostTypFC
DK00 0.613   0.986  0.998 0.613    1      TRUE  TRUE    TRUE 1.133     FALSE
NL95 0.909   0.939  0.991 0.909    1      TRUE  TRUE   FALSE 0.151      TRUE
NL05 0.909   0.939  0.962 0.909    1      TRUE  TRUE   FALSE 0.151      TRUE
DE00 0.909   0.965  0.972 0.909    1      TRUE  TRUE   FALSE 0.203     FALSE
DE95 0.909   0.966  0.971 0.909    1      TRUE  TRUE   FALSE 0.205     FALSE
     MostTypTerm
DK00       FALSE
NL95       FALSE
NL05       FALSE
DE00       FALSE
DE95       FALSE

Typical Cases - Focal Conjunct LM :
----------
        FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best MostTypFC
IE00 0.844   0.979  0.999 0.844    1      TRUE  TRUE    TRUE 0.427     FALSE
NO95 0.792   0.937  0.994 0.792    1      TRUE  TRUE   FALSE 0.498     FALSE
ES05 0.713   0.986  0.799 0.713    1     FALSE  TRUE   FALSE 0.833     FALSE
DK00 0.998   0.986  0.613 0.613    2      TRUE FALSE    TRUE 0.411     FALSE
DE95 0.971   0.966  0.909 0.909    2      TRUE FALSE   FALSE 0.101      TRUE
     MostTypTerm
IE00       FALSE
NO95       FALSE
ES05       FALSE
DK00       FALSE
DE95       FALSE
```

```
typ_foc2 <- smmr(results = sol_yp,
                 outcome = 'LPI',
                 match = FALSE,
                 cases = 2,
                 term = 2)
typ_foc2
```

```
Typical Cases - Focal Conjunct ~UN :
----------
        FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best MostTypFC
MX00 0.957   0.984  0.994 0.957    1      TRUE  TRUE    TRUE 0.097     FALSE
MX05 0.940   0.990  0.994 0.940    1      TRUE  TRUE    TRUE 0.158     FALSE
PT00 0.813   0.880  1.000 0.813    1      TRUE  TRUE    TRUE 0.320     FALSE
```

```
PT95 0.701   0.739  1.000 0.701    1      TRUE  TRUE    TRUE 0.377     FALSE
ES00 0.960   0.971  0.987 0.960    1      TRUE  TRUE   FALSE 0.064      TRUE
     MostTypTerm
MX00       FALSE
MX05       FALSE
PT00       FALSE
PT95       FALSE
ES00       FALSE

Typical Cases - Focal Conjunct EP :
----------
        FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best MostTypFC
EE05 0.873   0.903  0.988 0.873    1      TRUE  TRUE    TRUE 0.187     FALSE
KR05 0.534   0.945  0.988 0.534    1      TRUE  TRUE    TRUE 1.287     FALSE
DE05 0.666   0.855  0.839 0.666    1     FALSE  TRUE   FALSE 0.713     FALSE
NL05 0.634   0.939  0.876 0.634    1     FALSE  TRUE   FALSE 0.974     FALSE
NL00 0.905   0.970  0.784 0.784    2      TRUE  TRUE   FALSE 0.348     FALSE
     MostTypTerm
EE05       FALSE
KR05       FALSE
DE05       FALSE
NL05       FALSE
NL00       FALSE

typ_foc3 <- smmr(results = sol_yp,
                 outcome = 'LPI',
                 match = FALSE,
                 cases = 2,
                 term = 3)
typ_foc3

Typical Cases - Focal Conjunct EP :
----------
        FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best MostTypFC
SE00 0.791   0.880  0.988 0.791    1      TRUE  TRUE    TRUE 0.386     FALSE
DK95 0.733   0.989  1.000 0.733    1      TRUE  TRUE    TRUE 0.778     FALSE
DE00 0.905   0.965  0.972 0.905    1      TRUE  TRUE   FALSE 0.215     FALSE
NL00 0.905   0.970  0.988 0.905    1      TRUE  TRUE   FALSE 0.227     FALSE
DE05 0.666   0.855  0.959 0.666    1      TRUE  TRUE   FALSE 0.713     FALSE
     MostTypTerm
SE00       FALSE
DK95       FALSE
DE00       FALSE
NL00       FALSE
DE05       FALSE

Typical Cases - Focal Conjunct LM :
----------
        FC Outcome CC_Min  Term Rank CleanCorr FC<=Y UniqCov  Best MostTypFC
SI95 0.694   0.901  0.997 0.694    1      TRUE  TRUE    TRUE 0.721     FALSE
```

```
ES95 0.976   0.995  0.999 0.976    1      TRUE  TRUE   FALSE 0.062      TRUE
FR05 0.861   0.972  0.992 0.861    1      TRUE  TRUE   FALSE 0.361     FALSE
NO95 0.792   0.937  0.981 0.792    1      TRUE  TRUE   FALSE 0.498     FALSE
ES00 0.747   0.971  0.987 0.747    1      TRUE  TRUE   FALSE 0.702     FALSE
     MostTypTerm
SI95       FALSE
ES95       FALSE
FR05       FALSE
NO95       FALSE
ES00       FALSE
```

For all three terms and all conjuncts, close to ideal cases can be selected: uniquely covered, rank 1, consistent FC. Note that rarely are they the most typical for the term or FC, though, which is not a problem as such.

5.2.2 Comparative-case designs

To obtain the best available pairs of typical and iir cases when treating a conjunction as one set, the following command needs to be run.

```
typ_iir_term <- smmr(results = sol_yp,
                     outcome = 'LPI',
                     match = TRUE,
                     cases = 6,
                     max_pairs = 50)
typ_iir_term

Term WC*LM :
----------
     TYP  IIR UniqCov ConsIIR GlobUncov  Best MostTyp
20  DE95 PL95    TRUE    TRUE      TRUE 0.245   FALSE
25  DE95 LT05    TRUE    TRUE      TRUE 0.250   FALSE
33  DE95 HU95    TRUE    TRUE      TRUE 0.269   FALSE
46  DE95 PL00    TRUE    TRUE      TRUE 0.403   FALSE
53  IE00 PL95    TRUE    TRUE      TRUE 0.453   FALSE
54  IE00 LT05    TRUE    TRUE      TRUE 0.458   FALSE
56  IE00 HU95    TRUE    TRUE      TRUE 0.477   FALSE
74  DE95 HU00    TRUE    TRUE      TRUE 0.610   FALSE
75  IE00 PL00    TRUE    TRUE      TRUE 0.612   FALSE
92  IE00 HU00    TRUE    TRUE      TRUE 0.818   FALSE
125 DE95 LU00    TRUE    TRUE      TRUE 1.030   FALSE
138 DK00 PL95    TRUE    TRUE      TRUE 1.152   FALSE
139 DK00 LT05    TRUE    TRUE      TRUE 1.157   FALSE
141 DK00 HU95    TRUE    TRUE      TRUE 1.177   FALSE
149 IE00 LU00    TRUE    TRUE      TRUE 1.238   FALSE
152 DK00 PL00    TRUE    TRUE      TRUE 1.311   FALSE
161 DK00 HU00    TRUE    TRUE      TRUE 1.518   FALSE
170 DK00 LU00    TRUE    TRUE      TRUE 1.938   FALSE
28  DE95 US00    TRUE    TRUE     FALSE 0.267   FALSE
49  DE95 CZ05    TRUE    TRUE     FALSE 0.426   FALSE
```

```
55  IE00 US00    TRUE    TRUE     FALSE 0.475   FALSE
78  IE00 CZ05    TRUE    TRUE     FALSE 0.634   FALSE
89  DE95 UK05    TRUE    TRUE     FALSE 0.779   FALSE
100 DE95 CH00    TRUE    TRUE     FALSE 0.862   FALSE
117 DE95 RO00    TRUE    TRUE     FALSE 0.977   FALSE
119 IE00 UK05    TRUE    TRUE     FALSE 0.987   FALSE
128 IE00 CH00    TRUE    TRUE     FALSE 1.071   FALSE
140 DK00 US00    TRUE    TRUE     FALSE 1.174   FALSE
144 IE00 RO00    TRUE    TRUE     FALSE 1.186   FALSE
153 DK00 CZ05    TRUE    TRUE     FALSE 1.334   FALSE
165 DK00 UK05    TRUE    TRUE     FALSE 1.687   FALSE
167 DK00 CH00    TRUE    TRUE     FALSE 1.770   FALSE
169 DK00 RO00    TRUE    TRUE     FALSE 1.885   FALSE
13  DE95 PL05    TRUE   FALSE      TRUE 0.241   FALSE
39  DE95 SI05    TRUE   FALSE      TRUE 0.295   FALSE
51  IE00 PL05    TRUE   FALSE      TRUE 0.449   FALSE
58  IE00 SI05    TRUE   FALSE      TRUE 0.503   FALSE
135 DK00 PL05    TRUE   FALSE      TRUE 1.148   FALSE
145 DK00 SI05    TRUE   FALSE      TRUE 1.202   FALSE
14  DE95 US95    TRUE   FALSE     FALSE 0.241   FALSE
34  DE95 HU05    TRUE   FALSE     FALSE 0.270   FALSE
52  IE00 US95    TRUE   FALSE     FALSE 0.449   FALSE
57  IE00 HU05    TRUE   FALSE     FALSE 0.478   FALSE
71  DE95 SK00    TRUE   FALSE     FALSE 0.600   FALSE
82  DE95 CH05    TRUE   FALSE     FALSE 0.689   FALSE
91  IE00 SK00    TRUE   FALSE     FALSE 0.808   FALSE
108 DE95 CH95    TRUE   FALSE     FALSE 0.891   FALSE
110 IE00 CH05    TRUE   FALSE     FALSE 0.897   FALSE
129 IE00 CH95    TRUE   FALSE     FALSE 1.099   FALSE
134 DE95 FI95    TRUE   FALSE     FALSE 1.146   FALSE

Term ~UN*EP :
----------
     TYP  IIR UniqCov ConsIIR GlobUncov  Best MostTyp
49  MX00 HU00    TRUE    TRUE      TRUE 0.459   FALSE
57  MX05 HU00    TRUE    TRUE      TRUE 0.515   FALSE
70  EE05 HU00    TRUE    TRUE      TRUE 0.630   FALSE
87  MX00 RO00    TRUE    TRUE      TRUE 0.684   FALSE
92  MX00 LU00    TRUE    TRUE      TRUE 0.704   FALSE
98  MX05 RO00    TRUE    TRUE      TRUE 0.740   FALSE
100 MX05 LU00    TRUE    TRUE      TRUE 0.760   FALSE
103 PT00 HU00    TRUE    TRUE      TRUE 0.787   FALSE
115 EE05 RO00    TRUE    TRUE      TRUE 0.855   FALSE
123 EE05 LU00    TRUE    TRUE      TRUE 0.875   FALSE
147 PT95 HU00    TRUE    TRUE      TRUE 0.984   FALSE
152 PT00 RO00    TRUE    TRUE      TRUE 1.012   FALSE
157 PT00 LU00    TRUE    TRUE      TRUE 1.031   FALSE
183 MX00 FI95    TRUE    TRUE      TRUE 1.203   FALSE
185 PT95 RO00    TRUE    TRUE      TRUE 1.209   FALSE
193 PT95 LU00    TRUE    TRUE      TRUE 1.228   FALSE
```

```
197 MX05 FI95    TRUE    TRUE      TRUE 1.259   FALSE
203 MX00 FI00    TRUE    TRUE      TRUE 1.300   FALSE
211 MX05 FI00    TRUE    TRUE      TRUE 1.355   FALSE
216 EE05 FI95    TRUE    TRUE      TRUE 1.374   FALSE
237 EE05 FI00    TRUE    TRUE      TRUE 1.470   FALSE
241 PT00 FI95    TRUE    TRUE      TRUE 1.530   FALSE
253 PT00 FI00    TRUE    TRUE      TRUE 1.627   FALSE
258 KR05 HU00    TRUE    TRUE      TRUE 1.689   FALSE
260 PT95 FI95    TRUE    TRUE      TRUE 1.727   FALSE
269 PT95 FI00    TRUE    TRUE      TRUE 1.824   FALSE
276 KR05 RO00    TRUE    TRUE      TRUE 1.913   FALSE
279 KR05 LU00    TRUE    TRUE      TRUE 1.933   FALSE
292 KR05 FI95    TRUE    TRUE      TRUE 2.432   FALSE
293 KR05 FI00    TRUE    TRUE      TRUE 2.529   FALSE
9   MX00 US00    TRUE    TRUE     FALSE 0.140   FALSE
11  MX00 CH95    TRUE    TRUE     FALSE 0.156   FALSE
16  MX05 US00    TRUE    TRUE     FALSE 0.196   FALSE
18  MX05 CH95    TRUE    TRUE     FALSE 0.212   FALSE
34  EE05 US00    TRUE    TRUE     FALSE 0.311   FALSE
37  EE05 CH95    TRUE    TRUE     FALSE 0.327   FALSE
39  MX00 CH05    TRUE    TRUE     FALSE 0.346   FALSE
44  MX05 CH05    TRUE    TRUE     FALSE 0.402   FALSE
51  PT00 US00    TRUE    TRUE     FALSE 0.468   FALSE
54  PT00 CH95    TRUE    TRUE     FALSE 0.484   FALSE
58  EE05 CH05    TRUE    TRUE     FALSE 0.517   FALSE
68  MX00 FI05    TRUE    TRUE     FALSE 0.621   FALSE
76  MX00 UK05    TRUE    TRUE     FALSE 0.650   FALSE
80  PT95 US00    TRUE    TRUE     FALSE 0.665   FALSE
82  PT00 CH05    TRUE    TRUE     FALSE 0.674   FALSE
84  MX05 FI05    TRUE    TRUE     FALSE 0.677   FALSE
85  PT95 CH95    TRUE    TRUE     FALSE 0.680   FALSE
93  MX05 UK05    TRUE    TRUE     FALSE 0.706   FALSE
104 EE05 FI05    TRUE    TRUE     FALSE 0.792   FALSE
109 EE05 UK05    TRUE    TRUE     FALSE 0.821   FALSE

Term EP*LM :
----------
     TYP  IIR UniqCov ConsIIR GlobUncov  Best MostTyp
34  FR05 CH95    TRUE    TRUE      TRUE 0.431   FALSE
48  SE00 CH95    TRUE    TRUE      TRUE 0.549   FALSE
71  SE05 CH95    TRUE    TRUE      TRUE 0.660   FALSE
81  FR05 HU00    TRUE    TRUE      TRUE 0.735   FALSE
105 DK95 CH95    TRUE    TRUE      TRUE 0.832   FALSE
112 SE00 HU00    TRUE    TRUE      TRUE 0.853   FALSE
116 SI95 CH95    TRUE    TRUE      TRUE 0.863   FALSE
143 SE05 HU00    TRUE    TRUE      TRUE 0.964   FALSE
176 FR05 RO00    TRUE    TRUE      TRUE 1.117   FALSE
179 DK95 HU00    TRUE    TRUE      TRUE 1.136   FALSE
181 FR05 LU00    TRUE    TRUE      TRUE 1.148   FALSE
185 SI95 HU00    TRUE    TRUE      TRUE 1.167   FALSE
```

```
196 SE00 RO00    TRUE    TRUE      TRUE 1.235   FALSE
198 SE00 LU00    TRUE    TRUE      TRUE 1.266   FALSE
207 SE05 RO00    TRUE    TRUE      TRUE 1.346   FALSE
209 SE05 LU00    TRUE    TRUE      TRUE 1.377   FALSE
219 DK95 RO00    TRUE    TRUE      TRUE 1.518   FALSE
220 DK95 LU00    TRUE    TRUE      TRUE 1.549   FALSE
221 SI95 RO00    TRUE    TRUE      TRUE 1.549   FALSE
225 SI95 LU00    TRUE    TRUE      TRUE 1.580   FALSE
31  FR05 US00    TRUE    TRUE     FALSE 0.416   FALSE
47  SE00 US00    TRUE    TRUE     FALSE 0.533   FALSE
53  FR05 CZ05    TRUE    TRUE     FALSE 0.575   FALSE
65  FR05 CH05    TRUE    TRUE     FALSE 0.621   FALSE
69  SE05 US00    TRUE    TRUE     FALSE 0.645   FALSE
77  SE00 CZ05    TRUE    TRUE     FALSE 0.693   FALSE
83  SE00 CH05    TRUE    TRUE     FALSE 0.739   FALSE
99  SE05 CZ05    TRUE    TRUE     FALSE 0.804   FALSE
101 DK95 US00    TRUE    TRUE     FALSE 0.816   FALSE
108 SI95 US00    TRUE    TRUE     FALSE 0.847   FALSE
111 SE05 CH05    TRUE    TRUE     FALSE 0.851   FALSE
136 FR05 UK05    TRUE    TRUE     FALSE 0.925   FALSE
147 DK95 CZ05    TRUE    TRUE     FALSE 0.976   FALSE
153 SI95 CZ05    TRUE    TRUE     FALSE 1.007   FALSE
156 DK95 CH05    TRUE    TRUE     FALSE 1.022   FALSE
164 SE00 UK05    TRUE    TRUE     FALSE 1.043   FALSE
167 SI95 CH05    TRUE    TRUE     FALSE 1.053   FALSE
183 SE05 UK05    TRUE    TRUE     FALSE 1.154   FALSE
186 FR05 CH00    TRUE    TRUE     FALSE 1.170   FALSE
202 SE00 CH00    TRUE    TRUE     FALSE 1.288   FALSE
205 DK95 UK05    TRUE    TRUE     FALSE 1.326   FALSE
208 SI95 UK05    TRUE    TRUE     FALSE 1.357   FALSE
214 SE05 CH00    TRUE    TRUE     FALSE 1.399   FALSE
222 DK95 CH00    TRUE    TRUE     FALSE 1.571   FALSE
227 SI95 CH00    TRUE    TRUE     FALSE 1.602   FALSE
39  FR05 HU05    TRUE   FALSE      TRUE 0.471   FALSE
45  FR05 PL00    TRUE   FALSE      TRUE 0.513   FALSE
51  FR05 PL95    TRUE   FALSE      TRUE 0.566   FALSE
54  SE00 HU05    TRUE   FALSE      TRUE 0.589   FALSE
66  SE00 PL00    TRUE   FALSE      TRUE 0.630   FALSE
```

We see that for each term, several pairs tick the important boxes of `UniqCov` and `GlobUncov`.

Matching two typical cases when treating the conjunction as one set, generates the following results:

```
typ_typ_term <- smmr(results = sol_yp,
                     outcome = 'LPI',
                     match = TRUE,
                     cases = 5,
```

```
                     max_pairs = 50)
typ_typ_term

Term WC*LM :
----------
   TYP1 TYP2 UniqCov  Best MostTyp
13 DE95 IE00    both 1.334    none
81 DE95 DK00    both 1.585    none
56 IE00 DK00    both 1.793    none
18 DE95 NL00    typ1 1.242    none
12 DE95 NO95    typ1 1.258    none
65 IE00 NO95    typ1 1.466    none
49 DE95 ES05    typ1 1.485    none
35 IE00 ES05    typ1 1.693    none
20 NL05 DE95    typ2 1.201    typ1
75 NL95 DE95    typ2 1.201    typ1
78 DE00 DE95    typ2 1.227    none
14 NL95 IE00    typ2 1.307    typ1
66 NL05 IE00    typ2 1.307    typ1
24 DE00 IE00    typ2 1.333    none
51 NL00 IE00    typ2 1.339    none
58 NL05 DK00    typ2 1.558    typ1
63 NL95 DK00    typ2 1.558    typ1
57 DE00 DK00    typ2 1.584    none
52 NL00 DK00    typ2 1.590    none
53 NO95 DK00    typ2 1.907    none
69 ES05 DK00    typ2 2.192    none
21 NL95 NL05    none 1.120    both
74 NL05 NL95    none 1.120    both
19 NL95 DE00    none 1.198    typ1
39 NL05 DE00    none 1.198    typ1
11 NL05 NL00    none 1.215    typ1
38 NL95 NL00    none 1.215    typ1
33 NL05 NO95    none 1.231    typ1
79 NL95 NO95    none 1.231    typ1
17 DE00 NL00    none 1.241    none
50 DE00 NO95    none 1.257    none
34 NL00 NO95    none 1.263    none
32 NL95 ES05    none 1.458    typ1
70 NL05 ES05    none 1.458    typ1
31 DE00 ES05    none 1.484    none
59 NL00 ES05    none 1.489    none
71 NO95 ES05    none 1.806    none
1  <NA> <NA>    none    NA    none
2  <NA> <NA>    none    NA    none
3  <NA> <NA>    none    NA    none
4  <NA> <NA>    none    NA    none
5  <NA> <NA>    none    NA    none
6  <NA> <NA>    none    NA    none
7  <NA> <NA>    none    NA    none
```

```
8  <NA> <NA>    none    NA    none
9  <NA> <NA>    none    NA    none
10 <NA> <NA>    none    NA    none
15 <NA> <NA>    none    NA    none
16 <NA> <NA>    none    NA    none
22 <NA> <NA>    none    NA    none

Term ~UN*EP :
----------
    TYP1 TYP2 UniqCov  Best MostTyp
56  MX00 PT95    both 0.630    none
132 MX05 PT95    both 0.686    none
43  EE05 PT95    both 0.801    none
35  MX00 PT00    both 0.939    none
34  MX00 EE05    both 0.950    none
120 PT00 PT95    both 0.957    none
39  MX05 PT00    both 0.995    none
127 MX05 EE05    both 1.006    none
48  EE05 PT00    both 1.110    none
17  MX00 MX05    both 1.142    none
135 MX00 KR05    both 1.414    none
138 MX05 KR05    both 1.470    none
67  EE05 KR05    both 1.585    none
105 PT00 KR05    both 1.742    none
109 PT95 KR05    both 1.939    none
195 MX00 DE05    typ1 1.013    none
74  MX05 DE05    typ1 1.069    none
192 MX00 ES95    typ1 1.143    typ2
89  MX00 NL95    typ1 1.174    typ2
174 EE05 DE05    typ1 1.184    none
99  MX05 NL95    typ1 1.229    typ2
87  MX00 NL00    typ1 1.241    none
119 MX00 NL05    typ1 1.294    typ2
70  MX05 NL00    typ1 1.297    none
94  MX00 DE00    typ1 1.297    none
184 PT00 DE05    typ1 1.341    none
196 EE05 NL95    typ1 1.344    typ2
92  MX05 NL05    typ1 1.350    typ2
157 MX05 DE00    typ1 1.353    none
85  EE05 NL00    typ1 1.412    none
125 EE05 NL05    typ1 1.465    typ2
19  EE05 DE00    typ1 1.468    none
189 PT00 NL95    typ1 1.501    typ2
143 PT95 DE05    typ1 1.537    none
150 PT00 NL00    typ1 1.568    none
77  PT00 NL05    typ1 1.622    typ2
9   PT00 DE00    typ1 1.625    none
162 PT95 NL95    typ1 1.698    typ2
148 PT95 NL00    typ1 1.765    none
30  PT95 NL05    typ1 1.819    typ2
```

```
15  PT95 DE00    typ1 1.821    none
123 ES00 PT95    typ2 0.609    typ1
98  ES05 PT95    typ2 0.611    none
175 ES95 PT95    typ2 0.644    typ1
160 ES00 PT00    typ2 0.919    typ1
161 ES05 PT00    typ2 0.921    none
182 ES00 EE05    typ2 0.929    typ1
12  ES05 EE05    typ2 0.931    none
80  ES95 PT00    typ2 0.954    typ1
130 ES95 EE05    typ2 0.965    typ1

Term EP*LM :
----------
    TYP1 TYP2 UniqCov  Best MostTyp
48  FR05 SE00    both 1.237    none
21  FR05 SE05    both 1.247    none
112 SE00 SE05    both 1.365    none
105 FR05 SI95    both 1.397    none
102 SE00 SI95    both 1.515    none
149 FR05 DK95    both 1.621    none
41  SE05 SI95    both 1.626    none
31  SE00 DK95    both 1.739    none
143 SE05 DK95    both 1.850    none
168 SI95 DK95    both 2.053    none
49  FR05 DE05    typ1 1.288    none
133 SE00 DE05    typ1 1.406    none
120 FR05 NO95    typ1 1.407    none
13  SE05 DE05    typ1 1.518    none
30  SE00 NO95    typ1 1.525    none
61  FR05 ES00    typ1 1.555    typ2
85  FR05 NL05    typ1 1.570    typ2
117 FR05 ES05    typ1 1.633    none
14  SE05 NO95    typ1 1.636    none
25  SE00 ES00    typ1 1.673    typ2
4   SE00 NL05    typ1 1.687    typ2
47  SE00 ES05    typ1 1.751    none
155 SE05 ES00    typ1 1.784    typ2
94  SE05 NL05    typ1 1.799    typ2
154 SE05 ES05    typ1 1.862    none
65  DK95 NL05    typ1 1.970    typ2
19  SI95 NL05    typ1 2.001    typ2
66  DK95 ES05    typ1 2.034    none
76  SI95 ES05    typ1 2.065    none
147 ES95 SE00    typ2 0.915    typ1
88  ES95 SE05    typ2 0.925    typ1
3   ES95 SI95    typ2 1.075    typ1
167 DE00 SE00    typ2 1.099    none
101 NL00 SE00    typ2 1.104    none
139 DE00 SE05    typ2 1.109    none
152 NL00 SE05    typ2 1.115    none
```

```
124 ES95 FR05    typ2 1.122    typ1
15  DE00 SI95    typ2 1.259    none
50  NL00 SI95    typ2 1.265    none
109 ES95 DK95    typ2 1.300    typ1
161 DE00 FR05    typ2 1.306    none
98  NL00 FR05    typ2 1.311    none
75  DE00 DK95    typ2 1.483    none
163 NL00 DK95    typ2 1.489    none
95  NO95 SI95    typ2 1.570    none
79  ES00 SI95    typ2 1.739    typ1
54  NO95 DK95    typ2 1.794    none
141 DE05 SI95    typ2 1.867    none
158 ES00 DK95    typ2 1.963    typ1
53  DE05 DK95    typ2 2.091    none
```

For each of the three terms, pairs of uniquely covered typical cases can be found.

In the book I do not treat each conjunct as one set and, instead, apply the focal conjunct principle. I discuss only two of the three conjunctions: $LM * WC$ and $LM * EP$. Let's start with $LM * WC$.

```
typ_typ_foc1 <- smmr(results = sol_yp,
                     outcome = 'LPI',
                     match = TRUE,
                     cases = 1,
                     term = 1,
                     max_pairs = 50)
typ_typ_foc1

Focal Conjunct WC :
----------
   TYP1 TYP2 PairRank CleanCorr FC<=Y UniqCov  Best MostTypFC MostTypTerm
2  DE95 DK00        1      both  both    both 1.612      none        none
47 DE95 NL00        1      both  both    typ1 1.260      none        none
16 NL05 DE95        1      both  both    typ2 1.210      typ1        typ1
14 NL95 DE95        1      both  both    typ2 1.221      typ1        typ1
12 DE00 DE95        1      both  both    typ2 1.228      none        none
5  NL95 DK00        1      both  both    typ2 1.565      typ1        typ1
7  NL05 DK00        1      both  both    typ2 1.594      typ1        typ1
6  NL00 DK00        1      both  both    typ2 1.600      none        none
3  DE00 DK00        1      both  both    typ2 1.610      none        none
43 NL05 NL95        1      both  both    none 1.148      both        both
59 NL95 NL05        1      both  both    none 1.148      both        both
25 NL05 DE00        1      both  both    none 1.207      typ1        typ1
23 NL95 DE00        1      both  both    none 1.218      typ1        typ1
50 NL95 NL00        1      both  both    none 1.218      typ1        typ1
52 NL05 NL00        1      both  both    none 1.241      typ1        typ1
48 DE00 NL00        1      both  both    none 1.258      none        none
74 DE95 ES05        2      both  both    typ1 1.657      none        none
79 NL05 ES05        2      both  both    none 1.621      typ1        typ1
```

```
77 NL95 ES05        2      both  both    none 1.650      typ1        typ1
75 DE00 ES05        2      both  both    none 1.656      none        none
78 NL00 ES05        2      both  both    none 1.679      none        none
29 DE95 IE00        2      both  typ1    both 1.384      none        none
65 DE95 NO95        2      both  typ1    typ1 1.463      none        none
34 NL05 IE00        2      both  typ1    typ2 1.348      typ1        typ1
32 NL95 IE00        2      both  typ1    typ2 1.377      typ1        typ1
30 DE00 IE00        2      both  typ1    typ2 1.384      none        none
33 NL00 IE00        2      both  typ1    typ2 1.406      none        none
70 NL05 NO95        2      both  typ1    none 1.427      typ1        typ1
68 NL95 NO95        2      both  typ1    none 1.456      typ1        typ1
66 DE00 NO95        2      both  typ1    none 1.463      none        none
69 NL00 NO95        2      both  typ1    none 1.485      none        none
9  ES05 DK00        3      both  both    typ2 2.220      none        none
4  IE00 DK00        3      both  typ2    both 1.560      none        none
8  NO95 DK00        3      both  typ2    typ2 1.735      none        none
76 IE00 ES05        4      both  typ2    typ1 1.351      none        none
80 NO95 ES05        4      both  typ2    none 1.421      none        none
67 IE00 NO95        4      both  none    typ1 1.157      none        none

Focal Conjunct LM :
----------
   TYP1 TYP2 PairRank CleanCorr FC<=Y UniqCov  Best MostTypFC MostTypTerm
67 IE00 NO95        1      both  both    typ1 1.472      none        none
76 IE00 ES05        1      typ1  both    typ1 1.893      none        none
80 NO95 ES05        1      typ1  both    none 2.001      none        none
4  IE00 DK00        2      both  typ1    both 1.842      none        none
8  NO95 DK00        2      both  typ1    typ2 1.950      none        none
9  ES05 DK00        2      typ2  typ1    typ2 2.040      none        none
29 DE95 IE00        3      both  typ2    both 1.258      typ1        none
65 DE95 NO95        3      both  typ2    typ1 1.177      typ1        none
33 NL00 IE00        3      both  typ2    typ2 1.261      none        none
30 DE00 IE00        3      both  typ2    typ2 1.262      none        none
34 NL05 IE00        3      both  typ2    typ2 1.331      none        typ1
32 NL95 IE00        3      both  typ2    typ2 1.360      none        typ1
69 NL00 NO95        3      both  typ2    none 1.180      none        none
66 DE00 NO95        3      both  typ2    none 1.181      none        none
70 NL05 NO95        3      both  typ2    none 1.250      none        typ1
68 NL95 NO95        3      both  typ2    none 1.279      none        typ1
74 DE95 ES05        3      typ1  typ2    typ1 1.428      typ1        none
78 NL00 ES05        3      typ1  typ2    none 1.431      none        none
75 DE00 ES05        3      typ1  typ2    none 1.432      none        none
79 NL05 ES05        3      typ1  typ2    none 1.501      none        typ1
77 NL95 ES05        3      typ1  typ2    none 1.530      none        typ1
2  DE95 DK00        4      both  none    both 1.377      typ1        none
47 DE95 NL00        4      both  none    typ1 1.067      typ1        none
12 DE00 DE95        4      both  none    typ2 1.024      typ2        none
16 NL05 DE95        4      both  none    typ2 1.093      typ2        typ1
14 NL95 DE95        4      both  none    typ2 1.122      typ2        typ1
6  NL00 DK00        4      both  none    typ2 1.380      none        none
```

```
3  DE00 DK00        4      both  none    typ2 1.381      none        none
7  NL05 DK00        4      both  none    typ2 1.450      none        typ1
5  NL95 DK00        4      both  none    typ2 1.479      none        typ1
48 DE00 NL00        4      both  none    none 1.071      none        none
25 NL05 DE00        4      both  none    none 1.096      none        typ1
59 NL95 NL05        4      both  none    none 1.123      none        both
23 NL95 DE00        4      both  none    none 1.125      none        typ1
52 NL05 NL00        4      both  none    none 1.140      none        typ1
50 NL95 NL00        4      both  none    none 1.169      none        typ1
43 NL05 NL95        4      both  none    none 1.181      none        both
```

For focal conjunct *WC*: only one pair with both typical cases uniquely covered (DE95-DK00)

For focal conjunct *LM*: only pair in rank 2 with both uniquely covered (IE00 - DK00), but DK00 has inconsistent focal conjunct.

```
typ_typ_foc3 <- smmr(results = sol_yp,
                     outcome = 'LPI',
                     match = TRUE,
                     cases = 1,
                     term = 3,
                     max_pairs = 200)
typ_typ_foc3

Focal Conjunct EP :
----------
    TYP1 TYP2 PairRank CleanCorr FC<=Y UniqCov  Best MostTypFC MostTypTerm
12  SE00 DK95        1      both  both    both 1.751      none        none
51  SE00 DE05        1      both  both    typ1 1.436      none        none
77  SE00 NL05        1      both  both    typ1 1.714      none        none
66  DK95 NL05        1      both  both    typ1 2.008      none        none
148 NL00 SE00        1      both  both    typ2 1.105      none        none
146 DE00 SE00        1      both  both    typ2 1.116      none        none
5   NL00 DK95        1      both  both    typ2 1.501      none        none
3   DE00 DK95        1      both  both    typ2 1.512      none        none
4   DE05 DK95        1      both  both    typ2 2.132      none        none
42  DE00 DE05        1      both  both    none 1.163      none        none
44  NL00 DE05        1      both  both    none 1.185      none        none
55  DE00 NL00        1      both  both    none 1.273      none        none
68  DE00 NL05        1      both  both    none 1.441      none        none
70  NL00 NL05        1      both  both    none 1.463      none        none
69  DE05 NL05        1      both  both    none 2.042      none        none
168 SE00 SE05        1      typ1  both    both 1.527      none        none
159 DE00 SE05        1      typ1  both    typ2 1.254      none        none
161 NL00 SE05        1      typ1  both    typ2 1.276      none        none
13  SE05 DK95        1      typ2  both    both 2.024      none        none
52  SE05 DE05        1      typ2  both    typ1 1.650      none        none
78  SE05 NL05        1      typ2  both    typ1 1.934      none        none
103 SE00 SI95        2      both  typ1    both 1.893      none        none
```

90	SE00	NO95	2	both	typ1	typ1	1.709	none	none
129	SE00	ES00	2	both	typ1	typ1	1.739	none	none
142	SE00	ES05	2	both	typ1	typ1	1.767	none	none
131	DK95	ES05	2	both	typ1	typ1	2.061	none	none
16	DE00	FR05	2	both	typ1	typ2	1.365	none	none
18	NL00	FR05	2	both	typ1	typ2	1.387	none	none
94	DE00	SI95	2	both	typ1	typ2	1.620	none	none
96	NL00	SI95	2	both	typ1	typ2	1.642	none	none
95	DE05	SI95	2	both	typ1	typ2	2.215	none	none
81	DE00	NO95	2	both	typ1	none	1.437	none	none
83	NL00	NO95	2	both	typ1	none	1.459	none	none
120	DE00	ES00	2	both	typ1	none	1.466	none	none
122	NL00	ES00	2	both	typ1	none	1.488	none	none
133	DE00	ES05	2	both	typ1	none	1.494	none	none
135	NL00	ES05	2	both	typ1	none	1.516	none	none
134	DE05	ES05	2	both	typ1	none	2.089	none	none
104	SE05	SI95	2	typ2	typ1	both	1.842	none	none
91	SE05	NO95	2	typ2	typ1	typ1	1.659	none	none
130	SE05	ES00	2	typ2	typ1	typ1	1.688	none	none
143	SE05	ES05	2	typ2	typ1	typ1	1.716	none	none
145	FR05	SE00	3	both	typ2	both	1.051	none	none
2	FR05	DK95	3	both	typ2	both	1.447	none	none
8	SI95	DK95	3	both	typ2	both	1.834	none	none
41	FR05	DE05	3	both	typ2	typ1	1.073	none	none
67	FR05	NL05	3	both	typ2	typ1	1.358	none	none
73	SI95	NL05	3	both	typ2	typ1	1.745	none	none
152	ES95	SE00	3	both	typ2	typ2	0.873	typ1	typ1
9	ES95	DK95	3	both	typ2	typ2	1.269	typ1	typ1
10	ES00	DK95	3	both	typ2	typ2	1.559	none	none
7	NO95	DK95	3	both	typ2	typ2	1.612	none	none
48	ES95	DE05	3	both	typ2	none	0.930	typ1	typ1
35	ES95	DE00	3	both	typ2	none	1.007	typ1	typ1
61	ES95	NL00	3	both	typ2	none	1.031	typ1	typ1
49	ES00	DE05	3	both	typ2	none	1.186	none	none
74	ES95	NL05	3	both	typ2	none	1.208	typ1	typ1
46	NO95	DE05	3	both	typ2	none	1.238	none	none
76	ES05	NL05	3	both	typ2	none	1.462	none	none
75	ES00	NL05	3	both	typ2	none	1.470	none	none
72	NO95	NL05	3	both	typ2	none	1.522	none	none
158	FR05	SE05	3	typ1	typ2	both	0.969	none	none
165	ES95	SE05	3	typ1	typ2	typ2	1.021	typ1	typ1
93	FR05	SI95	4	both	none	both	1.335	none	none
80	FR05	NO95	4	both	none	typ1	1.152	none	none
119	FR05	ES00	4	both	none	typ1	1.181	none	none
132	FR05	ES05	4	both	none	typ1	1.209	none	none
138	SI95	ES05	4	both	none	typ1	1.300	none	none
22	ES95	FR05	4	both	none	typ2	1.132	typ1	typ1
101	ES00	SI95	4	both	none	typ2	1.218	none	none
98	NO95	SI95	4	both	none	typ2	1.361	none	none
100	ES95	SI95	4	both	none	typ2	1.387	typ1	typ1

```
140 ES00 ES05        4      both  none    none 1.093      none        none
87  ES95 NO95        4      both  none    none 1.204      typ1        typ1
124 NO95 ES00        4      both  none    none 1.207      none        none
126 ES95 ES00        4      both  none    none 1.233      typ1        typ1
137 NO95 ES05        4      both  none    none 1.235      none        none
139 ES95 ES05        4      both  none    none 1.261      typ1        typ1

Focal Conjunct LM :
----------
    TYP1 TYP2 PairRank CleanCorr FC<=Y UniqCov  Best MostTypFC MostTypTerm
93  FR05 SI95        1      both  both    both 1.403      none        none
80  FR05 NO95        1      both  both    typ1 1.418      none        none
119 FR05 ES00        1      both  both    typ1 1.560      none        none
132 FR05 ES05        1      both  both    typ1 1.635      none        none
138 SI95 ES05        1      both  both    typ1 2.072      none        none
100 ES95 SI95        1      both  both    typ2 1.077      typ1        typ1
22  ES95 FR05        1      both  both    typ2 1.129      typ1        typ1
98  NO95 SI95        1      both  both    typ2 1.586      none        none
101 ES00 SI95        1      both  both    typ2 1.749      none        none
87  ES95 NO95        1      both  both    none 1.103      typ1        typ1
126 ES95 ES00        1      both  both    none 1.245      typ1        typ1
139 ES95 ES05        1      both  both    none 1.320      typ1        typ1
124 NO95 ES00        1      both  both    none 1.735      none        none
137 NO95 ES05        1      both  both    none 1.816      none        none
140 ES00 ES05        1      both  both    none 1.978      none        none
158 FR05 SE05        2      both  both    both 1.413      none        none
165 ES95 SE05        2      both  both    typ2 1.098      typ1        typ1
2   FR05 DK95        2      both  typ1    both 1.658      none        none
145 FR05 SE00        2      both  typ1    both 1.674      none        none
8   SI95 DK95        2      both  typ1    both 2.095      none        none
67  FR05 NL05        2      both  typ1    typ1 1.694      none        none
41  FR05 DE05        2      both  typ1    typ1 1.736      none        none
73  SI95 NL05        2      both  typ1    typ1 2.131      none        none
9   ES95 DK95        2      both  typ1    typ2 1.344      typ1        typ1
152 ES95 SE00        2      both  typ1    typ2 1.360      typ1        typ1
7   NO95 DK95        2      both  typ1    typ2 1.820      none        none
10  ES00 DK95        2      both  typ1    typ2 1.996      none        none
35  ES95 DE00        2      both  typ1    none 1.111      typ1        typ1
61  ES95 NL00        2      both  typ1    none 1.154      typ1        typ1
74  ES95 NL05        2      both  typ1    none 1.379      typ1        typ1
48  ES95 DE05        2      both  typ1    none 1.422      typ1        typ1
72  NO95 NL05        2      both  typ1    none 1.856      none        none
46  NO95 DE05        2      both  typ1    none 1.899      none        none
75  ES00 NL05        2      both  typ1    none 2.031      none        none
49  ES00 DE05        2      both  typ1    none 2.074      none        none
76  ES05 NL05        2      both  typ1    none 2.150      none        none
104 SE05 SI95        3      both  both    both 1.646      none        none
91  SE05 NO95        3      both  both    typ1 1.640      none        none
130 SE05 ES00        3      both  both    typ1 1.794      none        none
143 SE05 ES05        3      both  both    typ1 1.875      none        none
```

103	SE00	SI95	3	both	typ2	both	1.564	none	none
131	DK95	ES05	3	both	typ2	typ1	1.536	none	none
90	SE00	NO95	3	both	typ2	typ1	1.557	none	none
129	SE00	ES00	3	both	typ2	typ1	1.712	none	none
142	SE00	ES05	3	both	typ2	typ1	1.793	none	none
96	NL00	SI95	3	both	typ2	typ2	1.178	none	none
94	DE00	SI95	3	both	typ2	typ2	1.179	none	none
18	NL00	FR05	3	both	typ2	typ2	1.219	none	none
16	DE00	FR05	3	both	typ2	typ2	1.220	none	none
95	DE05	SI95	3	both	typ2	typ2	1.733	none	none
83	NL00	NO95	3	both	typ2	none	1.171	none	none
81	DE00	NO95	3	both	typ2	none	1.172	none	none
122	NL00	ES00	3	both	typ2	none	1.326	none	none
120	DE00	ES00	3	both	typ2	none	1.327	none	none
135	NL00	ES05	3	both	typ2	none	1.407	none	none
133	DE00	ES05	3	both	typ2	none	1.408	none	none
134	DE05	ES05	3	both	typ2	none	1.963	none	none
13	SE05	DK95	4	both	typ1	both	1.419	none	none
78	SE05	NL05	4	both	typ1	typ1	1.455	none	none
52	SE05	DE05	4	both	typ1	typ1	1.497	none	none
168	SE00	SE05	4	both	typ2	both	1.172	none	none
159	DE00	SE05	4	both	typ2	typ2	1.014	none	none
161	NL00	SE05	4	both	typ2	typ2	1.014	none	none
12	SE00	DK95	4	both	none	both	1.418	none	none
66	DK95	NL05	4	both	none	typ1	1.080	none	none
77	SE00	NL05	4	both	none	typ1	1.453	none	none
51	SE00	DE05	4	both	none	typ1	1.496	none	none
5	NL00	DK95	4	both	none	typ2	1.259	none	none
3	DE00	DK95	4	both	none	typ2	1.260	none	none
148	NL00	SE00	4	both	none	typ2	1.275	none	none
146	DE00	SE00	4	both	none	typ2	1.276	none	none
4	DE05	DK95	4	both	none	typ2	1.472	none	none
55	DE00	NL00	4	both	none	none	1.071	none	none
68	DE00	NL05	4	both	none	none	1.295	none	none
70	NL00	NL05	4	both	none	none	1.295	none	none
44	NL00	DE05	4	both	none	none	1.337	none	none
42	DE00	DE05	4	both	none	none	1.338	none	none
69	DE05	NL05	4	both	none	none	1.372	none	none

For focal conjunct EP several pairs are fine (all involving case SE). The best-available pair even matches SE00 to SE05.

For focal conjunct LM only on pair from rank 1 with both uniquely covered and consistent focal conjuncts exists (FR0 - SI95).

5.3 Illustrating mechanisms

In the book, I empirically illustrate the location of the mechanism M vis-a-vis the two conjunctions $LM * WC$ and $LM * EP$. More often than not, data on the best-available pairs of typical and iir cases is not available and therefore the next best-available case pairs need

to be chosen. The following lines of command produce the graphs depicted in chapter 5 involving membership scores of cases in the mechanism.

```
MECH <- read.csv('micro_macro_best.csv', row.names = 1)
```

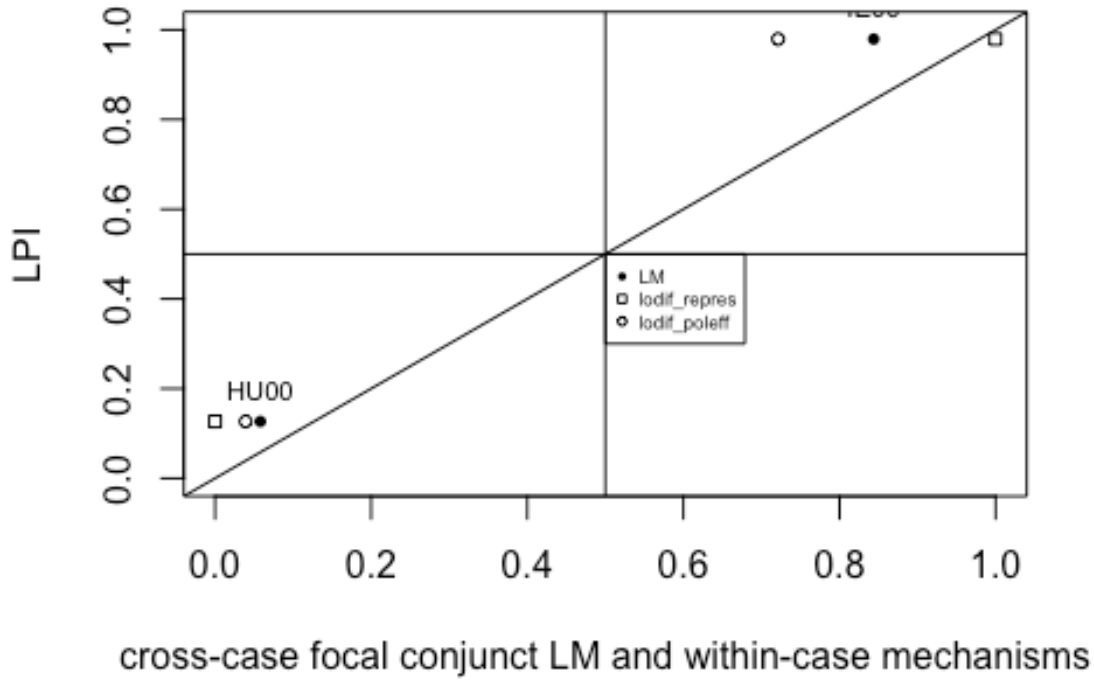
Let's start with term $LM * WC$ and there with focal conjunct WC.

```
MECH_test <- subset(MECH,
                    MECH$ID_mac %in%
                      c('DE95', 'PL95'))

with(MECH_test, plot(WC,LPI,
                     pch = 16, cex = .7,
                     xlim = c(0,1),
                     ylim = c(0,1),
                     xlab = "cross-case focal conjunct WC and within-case
mechanisms"))
text(MECH_test$WC, MECH_test$LPI, labels = MECH_test$ID_mac,
     cex = 0.7, pos = 3)
legend(x = 0.5, y = 0.5, #"bottomright",
       # Add legend to plot
       legend = c("WC", "lodif_repres", "lodif_poleff"),
       pch = c(16, 0, 1),
       cex = 0.5
)

abline(h=0.5, col="black")
abline(v=0.5, col="black")
abline(coef = c(0,1))

with(MECH_test, points(MECH_test$lorepres_diff,LPI,
                       pch = 0, cex = .7))
with(MECH_test, points(MECH_test$lopoleff_diff,LPI,
                       pch = 1, cex = .7))
```

And now focal conjunct LM in conjunction $LM * WC$

```
# get only two relevant cases
MECH_test <- subset(MECH,
                    MECH$ID_mac %in%
                      c('IE00', 'HU00'))


{with(MECH_test, plot(LM,LPI,
                     pch = 16, cex = .7,
                     xlim = c(0,1),
                     ylim = c(0,1),
                     xlab = "cross-case focal conjunct LM and within-case
mechanisms"))
```

```
text(MECH_test$LM, MECH_test$LPI, labels = MECH_test$ID_mac,
     cex = 0.7, pos = 3)
legend(x = 0.5, y = 0.5, #"bottomright",
       # Add legend to plot
       legend = c("LM", "lodif_repres", "lodif_poleff"),
       pch = c(16, 0, 1),
       cex = 0.5
)

abline(h=0.5, col="black")
abline(v=0.5, col="black")
abline(coef = c(0,1))

with(MECH_test, points(MECH_test$lorepres_diff,LPI,
                       pch = 0, cex = .7))
with(MECH_test, points(MECH_test$lopoleff_diff,LPI,
                       pch = 1, cex = .7))}
```



Turning to conjunction $LM * EP$, let's focus first on conjunct LM.

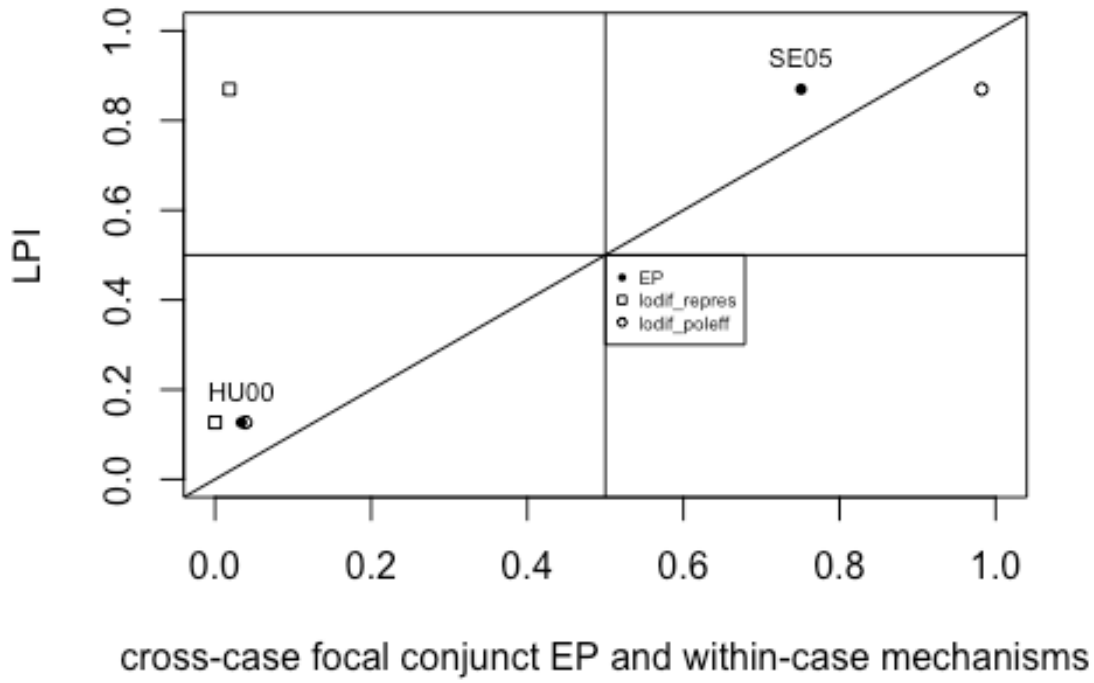
```
MECH_test <- subset(MECH,
                    MECH$ID_mac %in%
                      c('FR05', 'RO00'))
```

```
with(MECH_test, plot(LM,LPI,
                     pch = 16, cex = .7,
                     xlim = c(0,1),
                     ylim = c(0,1),
                     xlab = "cross-case focal conjunct LM and within-case
mechanisms"))
text(MECH_test$LM, MECH_test$LPI, labels = MECH_test$ID_mac,
     cex = 0.7, pos = 3)
legend(x = 0.5, y = 0.5, #"bottomright",
       # Add legend to plot
       legend = c("LM", "lodif_repres", "lodif_poleff"),
       pch = c(16, 0, 1),
       cex = 0.5
)

abline(h=0.5, col="black")
abline(v=0.5, col="black")
abline(coef = c(0,1))

with(MECH_test, points(MECH_test$lorepres_diff,LPI,
                       pch = 0, cex = .7))
with(MECH_test, points(MECH_test$lopoleff_diff,LPI,
                       pch = 1, cex = .7))
```

And finally, focal conjunct *EP*.

```
# term LM*EP focal conjunct EP < Y: SE05 - HU00

MECH_test <- subset(MECH,
                    MECH$ID_mac %in%
                      c('SE05', 'HU00'))

with(MECH_test, plot(EP,LPI,
                     pch = 16, cex = .7,
                     xlim = c(0,1),
                     ylim = c(0,1),
                     xlab = "cross-case focal conjunct EP and within-case
mechanisms"))
text(MECH_test$EP, MECH_test$LPI, labels = MECH_test$ID_mac,
     cex = 0.7, pos = 3)
legend(x = 0.5, y = 0.5, #"bottomright",
       # Add legend to plot
       legend = c("EP", "lodif_repres", "lodif_poleff"),
       pch = c(16, 0, 1),
       cex = 0.5
)
```

```
# plot the mechanism dots
abline(h=0.5, col="black")
abline(v=0.5, col="black")
abline(coef = c(0,1))

with(MECH_test, points(MECH_test$lorepres_diff,LPI,
                       pch = 0, cex = .7))
with(MECH_test, points(MECH_test$lopoleff_diff,LPI,
                       pch = 1, cex = .7))
```



cross-case focal conjunct EP and within-case mechanisms

6 Chapter 6: Bretthauer (2015)

In chapter 6, I use the study by Bretthauer (2015) on peace and conflict in resource-scarse countries to illustrate SMMR on necessity claims of various levels of complexity ($A \Leftarrow Y$, $A + B \Leftarrow Y$, and $A * B \Leftarrow Y$).

Outcome

- BDT = Conflict

Conditions

- PIN = Low Quality of Political Institutions
- COR = Political corruption
- EEX = Ethnic exclusion
- POV = Poverty
- DEP = Dependence on agriculture
- EDU = High tertiary education
- ECOD = Economic development

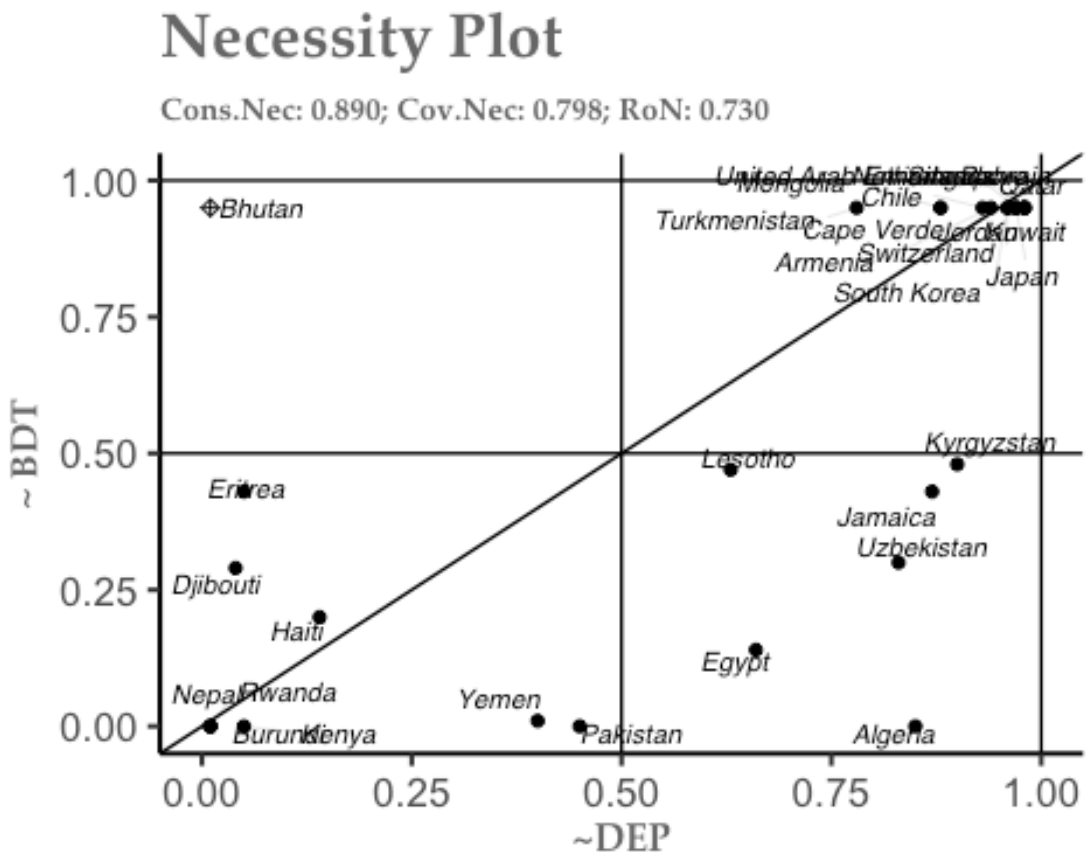
```
#load data
BRETT <- read.csv("Bretthauer_2014_fs.csv", row.names =1)

colnames(BRETT) <- toupper(colnames(BRETT))
```

6.1 $A \Leftarrow Y$

First, we identify the necessary condition $\sim DEP$ and visualize it via an X plot.

```
# Analysis of single necessity, outcome ~Y
NEC_ny <- superSubset(data = BRETT,
                      outcome = '~BDT',
                      conditions = c("POV", "DEP", "COR",  "PIN",  "EDU",
"EEX"),
                      incl.cut = 0.89,
                      ron.cut = 0.6,
                      cov.cut = 0.5,
                      depth = 1)
NEC_ny


         inclN   RoN   covN
----------------------------
1  ~DEP  0.890  0.730  0.798
----------------------------
```

```
# Visualization via XY plot
pimplot(data = BRETT,
        outcome = 'BDT',
        results = NEC_ny,
        necessity = TRUE,
        all_labels = TRUE,
        jitter = TRUE)
```



6.1.1 Descriptive inference SMMR

In the following, I show the four single-case and comparative SMMR designs with the goal of enhancing descriptive inferences.

I start with the best available deviant relevance case.

```
# For technical reasons, a solution object from function minimize() is
needed, even if one is not interested in an analysis of sufficiency. I
therefore produce a truth table analysis of sufficiency, outcome ~Y
sol_np <- minimize(BRETT,
                   outcome = "~BDT",
                   conditions = c("POV", "DEP", "ECOD",  "COR",  "PIN",
"EDU",  "EEX"),
                   incl.cut = 0.75,
                   pri.cut = 0.5,
```

```
                    details = TRUE,
                    include = "?",
                    row.dom = TRUE)

# Deviant relevance
drel <- smmr(nec.cond = "~DEP",
             results = sol_np,
             outcome = "~BDT",
             match = FALSE,
             cases = 3,
             necessity = TRUE)
drel

~DEP :
----------
         Case NecCond Outcome Best MostDREL
1     Algeria    0.85    0.00 0.30     TRUE
6  Uzbekistan    0.83    0.30 0.64    FALSE
4  Kyrgyzstan    0.90    0.48 0.68    FALSE
3     Jamaica    0.87    0.43 0.69    FALSE
2       Egypt    0.66    0.14 0.82    FALSE
5     Lesotho    0.63    0.47 1.21    FALSE
```

The best pairs of typical - deviant relevance cases are listed here.

```
# typical - deviant relevance
typdrel <- smmr(nec.cond = "~DEP",
                results = sol_np,
                outcome = "~BDT",
                match = TRUE,
                cases = 1,
                max_pairs = 10,
                necessity = TRUE)
typdrel

~DEP :
----------
                     TYP     DREL Best MostTyp MostDREL
3                 Jordan  Algeria  0.35    TRUE     TRUE
8            South Korea  Algeria  0.35    TRUE     TRUE
9            Switzerland  Algeria  0.35    TRUE     TRUE
1                Bahrain  Algeria  0.35   FALSE     TRUE
2                  Japan  Algeria  0.35   FALSE     TRUE
4                 Kuwait  Algeria  0.35   FALSE     TRUE
5            Netherlands  Algeria  0.35   FALSE     TRUE
6                  Qatar  Algeria  0.35   FALSE     TRUE
7              Singapore  Algeria  0.35   FALSE     TRUE
10 United Arab Emirates  Algeria  0.35   FALSE     TRUE
```

The best available deviant consistency cases are shown as below. As could be seen from the XY plot, there is just one such case in the data: Bhutan. What the output adds to this is information of the truth table row to which Bhutan belongs.

```
# deviant consistency
dcons <- smmr(nec.cond = "~DEP",
              results = sol_np,
              outcome = "~BDT",
              match = FALSE,
              cases = 2,
              necessity = TRUE)
dcons

~DEP :
----------
     Case NecCond TT_POV TT_DEP TT_ECOD TT_COR TT_PIN TT_EDU TT_EEX TT_row
1 Bhutan     0.01      1      1       0      0      0      1      1   0.72
  Outcome TT<=Y Best MostDCONS
1    0.95  TRUE 0.06      TRUE
```

The best available pair of typical and deviant consistency cases is shown below. As we see, no typical case shares with Bhutan the same truth table (minus the necessary condition $\sim DEP$, of course, in which both case types hold different membership scores, by definition).

```
# typical - deviant consistency
typdcons <- smmr(nec.cond = "~DEP",
                 results = sol_np,
                 outcome = "~BDT",
                 match = TRUE,
                 cases = 2,
                 max_pairs = 10,
                 necessity = TRUE)
typdcons

~DEP :
----------
[1] "There are no pairs in the same TT row"
```

6.1.2 Causal inference SMMR

Now I turn to the three causal inference SMMR designs.

I start with a single typical case.

```
# typical case
typ <- smmr(nec.cond = "~DEP",
            results = sol_np,
            outcome = "~BDT",
            match = FALSE,
            cases = 1,
```

```
            necessity = TRUE)
typ

~DEP :
----------
                    Case NecCond Outcome UniqCov Best MostTyp
3                 Jordan     0.96    0.95    TRUE 0.06    TRUE
8            South Korea     0.96    0.95    TRUE 0.06    TRUE
9            Switzerland     0.96    0.95    TRUE 0.06    TRUE
2                  Japan     0.97    0.95    TRUE 0.07   FALSE
5            Netherlands     0.97    0.95    TRUE 0.07   FALSE
10 United Arab Emirates     0.97    0.95    TRUE 0.07   FALSE
1                Bahrain     0.98    0.95    TRUE 0.08   FALSE
4                 Kuwait     0.98    0.95    TRUE 0.08   FALSE
6                  Qatar     0.98    0.95    TRUE 0.08   FALSE
7              Singapore     0.98    0.95    TRUE 0.08   FALSE
```

The best-matching pairs of typical and iir cases are listed below.

```
# typical - iir
typiir <- smmr(nec.cond = "~DEP",
               results = sol_np,
               outcome = "~BDT",
               match = TRUE,
               cases = 3,
               max_pairs = 10,
               necessity = TRUE)
typiir

~DEP :
----------
             TYP      IIR UniqCov GlobUncov Best MostTyp
3         Jordan  Burundi    TRUE      TRUE 0.13    TRUE
8    South Korea  Burundi    TRUE      TRUE 0.13    TRUE
9    Switzerland  Burundi    TRUE      TRUE 0.13    TRUE
23        Jordan    Nepal    TRUE      TRUE 0.13    TRUE
28   South Korea    Nepal    TRUE      TRUE 0.13    TRUE
29   Switzerland    Nepal    TRUE      TRUE 0.13    TRUE
43        Jordan   Rwanda    TRUE      TRUE 0.13    TRUE
48   South Korea   Rwanda    TRUE      TRUE 0.13    TRUE
49   Switzerland   Rwanda    TRUE      TRUE 0.13    TRUE
2          Japan  Burundi    TRUE      TRUE 0.14   FALSE
```

Finally, the list best-matching pairs of two typical cases looks as follows.

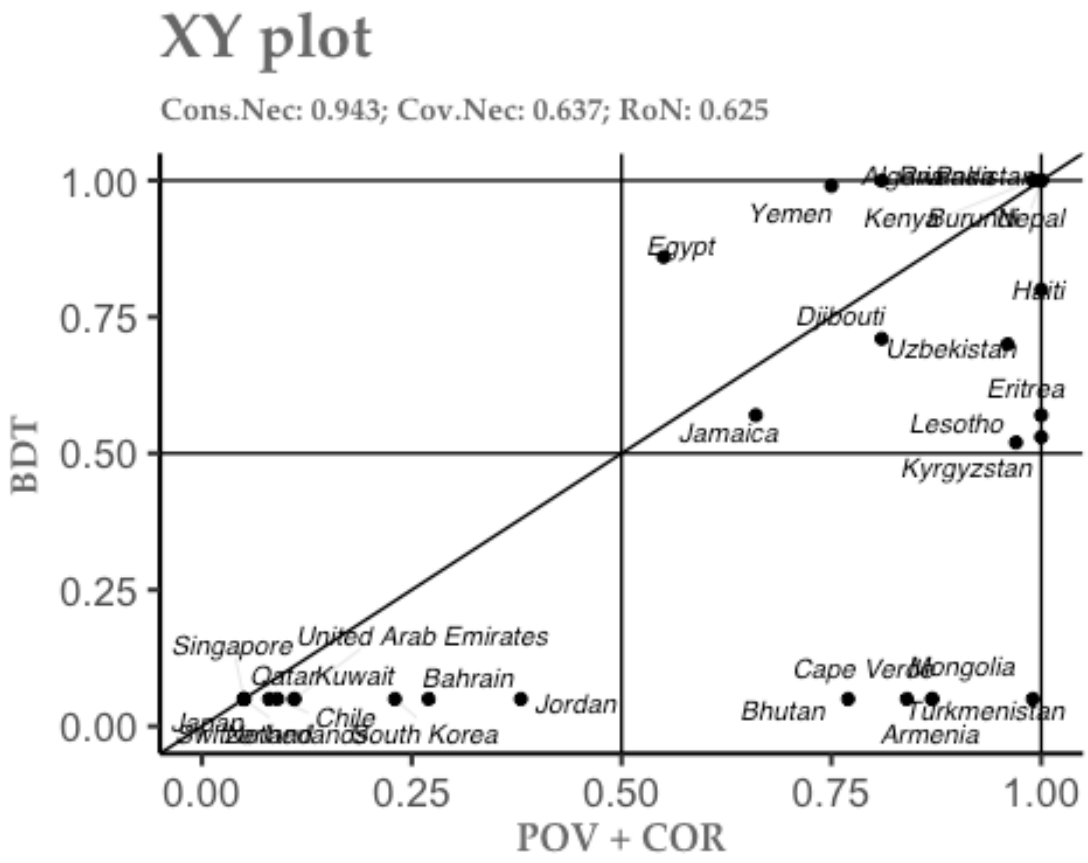
```
# two typical cases
typtyp <- smmr(nec.cond = "~DEP",
               results = sol_np,
               outcome = "~BDT",
               match = TRUE,
               cases = 4,
```

```
               max_pairs = 10,
               necessity = TRUE)
typtyp

~DEP :
----------
           TYP1         TYP2 UniqCov Best MostTyp
15 South Korea       Jordan     both 1.04    both
16 Switzerland       Jordan     both 1.04    both
49      Jordan  South Korea     both 1.04    both
50 Switzerland  South Korea     both 1.04    both
51      Jordan  Switzerland     both 1.04    both
52 South Korea  Switzerland     both 1.04    both
10      Jordan        Japan     both 1.07    typ1
12 South Korea        Japan     both 1.07    typ1
13 Switzerland        Japan     both 1.07    typ1
27      Jordan  Netherlands     both 1.07    typ1
```

6.2 $A + B \Leftarrow Y$

For illustrating SMMR in the presence of SUIN conditions, I continue with the example by Bretthauer (2015). Now the outcome consists in the presence of conflict (BDT). The necessity claim consisting of SUIN conditions looks as follows:

```
# Analysis of SUIN necessity, outcome BDT
SUIN_y <- superSubset(data = BRETT,
                      outcome = 'BDT',
                      conditions = c("POV", "DEP", "COR",  "PIN",  "EDU",
"EEX"),
                      incl.cut = 0.94,
                      ron.cut = 0.6,
                      cov.cut = 0.5,
                      depth = 2)
SUIN_y


              inclN   RoN   covN
---------------------------------
1  POV + COR  0.943  0.625  0.637
---------------------------------

#Visualize via XY plot
BRETT$POVCOR <- pmax(BRETT$POV, BRETT$COR)

xy.plot(data = BRETT,
        'POVCOR', 'BDT',
        necessity = TRUE,
        xlab = 'POV + COR',
        ylab = 'BDT',
        jitter = TRUE)
```



6.2.1 Descriptive inference SMMR

I start with descriptive inference SMMR designs, and here with the study of a deviant relevance case. As can be seen, they are automatically listed for each SUIN condition and for the disjunction fo SUIN conditions. This holds for all other SMMR designs involving SUIN conditions.

```
# For technical reasons, a solution object from function minimize() is
needed, even if one is not interested in an analysis of sufficiency. I
therefore produce a truth table analysis of sufficiency, outcome ~Y

sol_p<- minimize(BRETT, outcome = "BDT",
                   conditions = c("POV", "DEP", "ECOD",  "COR",  "PIN",
"EDU",  "EEX"),
                 incl.cut1 = 0.75,
                 pri.cut = 0.5,
                 include = "?",
                 details = TRUE,
                 row.dom = TRUE)

# deviant relevance
drel <- smmr(nec.cond = "POV+COR",
             results = sol_p,
```

```
             outcome = "BDT",
             match = FALSE,
             cases = 3,
             necessity = TRUE)
drel

POV :
----------
           Case NecCond Outcome Best MostDREL
5 Turkmenistan     0.99    0.05 0.07     TRUE
4     Mongolia     0.87    0.05 0.31    FALSE
3   Cape Verde     0.84    0.05 0.37    FALSE
2       Bhutan     0.77    0.05 0.51    FALSE
1      Armenia     0.55    0.05 0.95    FALSE

COR :
----------
           Case NecCond Outcome Best MostDREL
3 Turkmenistan     0.97    0.05 0.11     TRUE
1      Armenia     0.87    0.05 0.31    FALSE
2     Mongolia     0.79    0.05 0.47    FALSE

POV+COR :
----------
           Case NecCond Outcome Best MostDREL
5 Turkmenistan     0.99    0.05 0.07     TRUE
1      Armenia     0.87    0.05 0.31    FALSE
4     Mongolia     0.87    0.05 0.31    FALSE
3   Cape Verde     0.84    0.05 0.37    FALSE
2       Bhutan     0.77    0.05 0.51    FALSE
```

The best-matching pairs of typical and deviant relevance cases are the following.

```
# typical - deviant relevance
typdrel <- smmr(nec.cond = "POV+COR",
                results = sol_p,
                outcome = "BDT",
                match = TRUE,
                cases = 1,
                max_pairs = 6,
                necessity = TRUE)
typdrel

POV :
----------
        TYP          DREL UniqCov Best MostTyp MostDREL
39 Eritrea  Turkmenistan     TRUE 0.50   FALSE     TRUE
30 Eritrea      Mongolia     TRUE 0.74   FALSE    FALSE
21 Eritrea    Cape Verde     TRUE 0.80   FALSE    FALSE
12 Eritrea        Bhutan     TRUE 0.94   FALSE    FALSE
3  Eritrea       Armenia     TRUE 1.38   FALSE    FALSE
```

```
37 Burundi  Turkmenistan    FALSE 0.07    TRUE     TRUE

COR :
----------
           TYP          DREL UniqCov Best MostTyp MostDREL
16 Kyrgyzstan  Turkmenistan     TRUE 0.59   FALSE     TRUE
4  Kyrgyzstan       Armenia     TRUE 0.79   FALSE    FALSE
10 Kyrgyzstan      Mongolia     TRUE 0.95   FALSE    FALSE
15    Jamaica  Turkmenistan     TRUE 1.16   FALSE     TRUE
3     Jamaica       Armenia     TRUE 1.16   FALSE    FALSE
9     Jamaica      Mongolia     TRUE 1.16   FALSE    FALSE

POV+COR :
----------
         TYP          DREL Best MostTyp MostDREL
45  Burundi  Turkmenistan  0.07    TRUE     TRUE
52    Nepal  Turkmenistan  0.07    TRUE     TRUE
53 Pakistan  Turkmenistan  0.07    TRUE     TRUE
54   Rwanda  Turkmenistan  0.07    TRUE     TRUE
48    Haiti  Turkmenistan  0.27   FALSE     TRUE
1   Burundi       Armenia  0.31    TRUE    FALSE
```

Deviant consistency cases are listed for each truth table row that contains at least one such case type. While there are deviant consistency cases for POV and COR, respectively, there are none for the disjunction $POV + COR$.

```
# deviant Consistency
dcons <- smmr(nec.cond = "POV+COR",
              results = sol_p,
              outcome = "BDT",
              match = FALSE,
              cases = 2,
              necessity = TRUE)
dcons

POV :
----------
         Case NecCond TT_POV TT_DEP TT_ECOD TT_COR TT_PIN TT_EDU TT_EEX
TT_row
2      Egypt     0.16      0      0       0      1      0      0      1
0.55
1    Algeria     0.32      0      0       0      1      1      0      1
0.55
4 Kyrgyzstan     0.24      0      0       0      1      1      1      1
0.55
3    Jamaica     0.07      0      0       1      1      1      0      0
0.54
  Outcome GlobUncov TT<=Y Best MostDCONS
2    0.86     FALSE  TRUE 0.30      TRUE
1    1.00     FALSE  TRUE 0.32      TRUE
```

```
4    0.52     FALSE FALSE 0.72      TRUE
3    0.57     FALSE  TRUE 0.50      TRUE

COR :
----------
      Case NecCond TT_POV TT_DEP TT_ECOD TT_COR TT_PIN TT_EDU TT_EEX TT_row
1 Eritrea     0.21      1      1       0      0      0      0      0   0.79
  Outcome GlobUncov TT<=Y Best MostDCONS
1    0.57     FALSE FALSE 0.64      TRUE

POV+COR :
----------
[1] "No cases"
```

The comparison between typical and deviant consistency cases reveals that no such pair exists, except for one truth table row. The pair Eritrea - Haiti shares the same truth table row except for, by definition, membership in the focal disjunct COR.

```
# typical - deviant consistency
typdcons <- smmr(nec.cond = "POV+COR",
                 results = sol_p,
                 outcome = "BDT",
                 match = TRUE,
                 cases = 2,
                 max_pairs = 10,
                 necessity = TRUE)
typdcons
```

```
POV :
----------
[1] "There are no pairs in the same TT row"

COR :
----------
     DCONS    TYP TT_POV TT_DEP TT_ECOD TT_PIN TT_EDU TT_EEX UniqCov
GlobUncov
1 Eritrea  Haiti       1      1       0      0      0      0   FALSE
FALSE
  Best MostTyp MostDCONS
1 0.47    TRUE      TRUE

POV+COR :
----------
[1] "There are no pairs in the same TT row"
```

6.2.2 Causal inference SMMR

The best available typical case for each focal SUIN condition and for the disjunction are listed as follows.

```
# TYP
typ <- smmr(nec.cond = "POV+COR",
            results = sol_p,
            outcome = "BDT",
            match = FALSE,
            cases = 1,
            necessity = TRUE)
typ
```

```
POV :
----------
         Case NecCond Outcome UniqCov Best MostTyp
3     Eritrea    1.00    0.57    TRUE 0.86   FALSE
1     Burundi    1.00    1.00   FALSE 0.00    TRUE
6       Nepal    1.00    1.00   FALSE 0.00    TRUE
7    Pakistan    1.00    1.00   FALSE 0.00    TRUE
8      Rwanda    1.00    1.00   FALSE 0.00    TRUE
2    Djibouti    0.79    0.71   FALSE 0.37   FALSE
4       Haiti    1.00    0.80   FALSE 0.40   FALSE
9  Uzbekistan    0.96    0.70   FALSE 0.56   FALSE
5     Lesotho    1.00    0.53   FALSE 0.94   FALSE

COR :
----------
         Case NecCond Outcome UniqCov Best MostTyp
3     Jamaica    0.66    0.57    TRUE 0.52   FALSE
4  Kyrgyzstan    0.97    0.52    TRUE 0.93   FALSE
2       Haiti    0.97    0.80   FALSE 0.37    TRUE
1    Djibouti    0.81    0.71   FALSE 0.39   FALSE
6  Uzbekistan    0.96    0.70   FALSE 0.56   FALSE
5     Lesotho    0.81    0.53   FALSE 0.75   FALSE

POV+COR :
----------
          Case NecCond Outcome UniqCov Best MostTyp
1      Burundi    1.00    1.00    TRUE 0.00    TRUE
8        Nepal    1.00    1.00    TRUE 0.00    TRUE
9     Pakistan    1.00    1.00    TRUE 0.00    TRUE
10      Rwanda    1.00    1.00    TRUE 0.00    TRUE
2     Djibouti    0.81    0.71    TRUE 0.39   FALSE
4        Haiti    1.00    0.80    TRUE 0.40   FALSE
5      Jamaica    0.66    0.57    TRUE 0.52   FALSE
11 Uzbekistan    0.96    0.70    TRUE 0.56   FALSE
3      Eritrea    1.00    0.57    TRUE 0.86   FALSE
6   Kyrgyzstan    0.97    0.52    TRUE 0.93   FALSE
7      Lesotho    1.00    0.53    TRUE 0.94   FALSE
```

The best-matching pairs of typical and iir cases are shown below.

```
# TYP - IIR
typiir <- smmr(nec.cond = "POV+COR",
               results = sol_p,
               outcome = "BDT",
               match = TRUE,
               cases = 3,
               max_pairs = 7,
               necessity = TRUE)
typiir
```

```
POV :
----------
        TYP          IIR UniqCov GlobUncov Best MostTyp
3  Eritrea      Bahrain     TRUE      TRUE 1.39   FALSE
21 Eritrea        Japan     TRUE      TRUE 1.39   FALSE
39 Eritrea       Kuwait     TRUE      TRUE 1.39   FALSE
48 Eritrea  Netherlands     TRUE      TRUE 1.39   FALSE
57 Eritrea        Qatar     TRUE      TRUE 1.39   FALSE
66 Eritrea    Singapore     TRUE      TRUE 1.39   FALSE
75 Eritrea  South Korea     TRUE      TRUE 1.39   FALSE

COR :
----------
           TYP                   IIR UniqCov GlobUncov Best MostTyp
33    Jamaica                 Qatar     TRUE      TRUE 1.11   FALSE
45    Jamaica  United Arab Emirates     TRUE      TRUE 1.13   FALSE
27    Jamaica                Kuwait     TRUE      TRUE 1.17   FALSE
39    Jamaica           South Korea     TRUE      TRUE 1.41   FALSE
3     Jamaica               Bahrain     TRUE      TRUE 1.49   FALSE
34 Kyrgyzstan                 Qatar     TRUE      TRUE 1.57   FALSE
46 Kyrgyzstan  United Arab Emirates     TRUE      TRUE 1.59   FALSE

POV+COR :
----------
         TYP          IIR UniqCov GlobUncov Best MostTyp
23  Burundi        Japan     TRUE      TRUE  0.1    TRUE
30    Nepal        Japan     TRUE      TRUE  0.1    TRUE
31 Pakistan        Japan     TRUE      TRUE  0.1    TRUE
32   Rwanda        Japan     TRUE      TRUE  0.1    TRUE
56  Burundi  Netherlands     TRUE      TRUE  0.1    TRUE
63    Nepal  Netherlands     TRUE      TRUE  0.1    TRUE
64 Pakistan  Netherlands     TRUE      TRUE  0.1    TRUE
```

And the best pairs of two typical cases are the following.

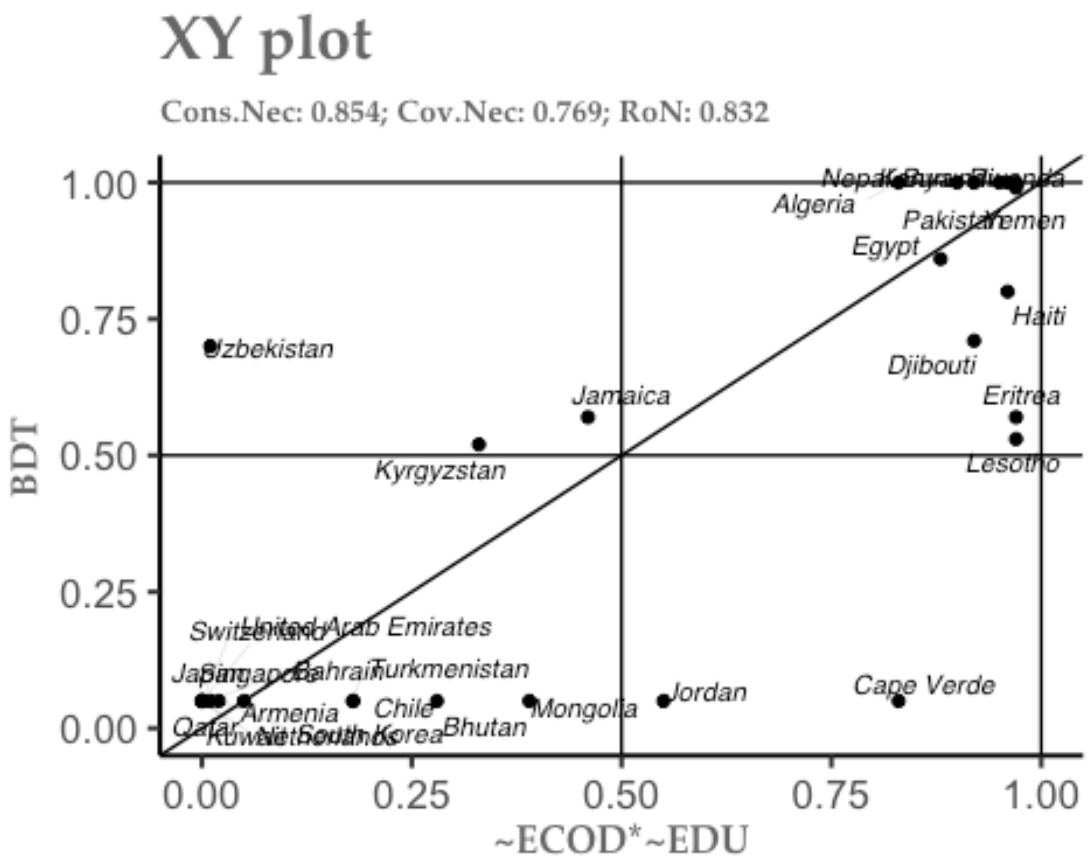
```
# TYP - TYP
typtyp <- smmr(nec.cond = "POV+COR",
               results = sol_p,
               outcome = "BDT",
               match = TRUE,
```

```
               cases = 4,
               max_pairs = 10,
               necessity = TRUE)
typtyp

POV :
----------
          TYP1      TYP2 UniqCov Best MostTyp
22    Eritrea   Lesotho     typ1 2.76    none
8     Burundi   Eritrea     typ2 1.43    typ1
11      Nepal   Eritrea     typ2 1.43    typ1
12   Pakistan   Eritrea     typ2 1.43    typ1
13     Rwanda   Eritrea     typ2 1.43    typ1
10      Haiti   Eritrea     typ2 2.03    none
9    Djibouti   Eritrea     typ2 2.09    none
14 Uzbekistan   Eritrea     typ2 2.29    none
4     Burundi  Djibouti     none 0.66    typ1
5       Nepal  Djibouti     none 0.66    typ1

COR :
----------
          TYP1        TYP2 UniqCov Best MostTyp
6     Jamaica  Kyrgyzstan     both 2.34    none
11    Jamaica     Lesotho     typ1 1.85    none
15    Jamaica  Uzbekistan     typ1 2.13    none
3       Haiti     Jamaica     typ2 0.98    typ1
2    Djibouti     Jamaica     typ2 1.09    none
5       Haiti  Kyrgyzstan     typ2 1.96    typ1
4    Djibouti  Kyrgyzstan     typ2 2.07    none
8  Uzbekistan  Kyrgyzstan     typ2 2.25    none
7     Lesotho  Kyrgyzstan     typ2 2.61    none
1       Haiti    Djibouti     none 1.29    typ1

POV+COR :
----------
        TYP1      TYP2 UniqCov Best MostTyp
21  Burundi   Jamaica     both 0.41    typ1
24    Nepal   Jamaica     both 0.41    typ1
25 Pakistan   Jamaica     both 0.41    typ1
26   Rwanda   Jamaica     both 0.41    typ1
4   Burundi  Djibouti     both 0.72    typ1
5     Nepal  Djibouti     both 0.72    typ1
6  Pakistan  Djibouti     both 0.72    typ1
7    Rwanda  Djibouti     both 0.72    typ1
1     Nepal   Burundi     both 1.00    both
2  Pakistan   Burundi     both 1.00    both
```

6.3 $A * B \Leftarrow Y$

I illustrate SMMR in the presence of a necessary conjunction with outcome BDT from the study by Bretthauer (2015). For illustrative purposes, let us accept the conjunction $\sim ECOD *\sim EDU$ as a necessary conjunction for outcome BDT.

```
# parameters of fit for conjunction
NEC_conj <- pof(data = BRETT,
    ~ECOD * ~EDU <- BDT)

NEC_conj


               inclN   RoN   covN
---------------------------------
1  ~ECOD*~EDU  0.854  0.832  0.769
---------------------------------

# create conjunction set in data set
BRETT$ECODEDU <- pmin(1-BRETT$ECOD, 1-BRETT$EDU)

# XY plot for conjunction
xy.plot(data = BRETT,
        'ECODEDU', 'BDT',
        necessity = TRUE,
        xlab = '~ECOD*~EDU',
        ylab = 'BDT',
        jitter = TRUE)
```



6.3.1 Descriptive inference SMMR

As before, I start with the four descriptive inference SMMR designs. Since the focal conjunct principle does not apply to descriptive inference SMMR designs, the output only shows cases for the conjunction, not each ININ condition separately.

As can be seen, there are only two deviant relevance cases.

```
# Deviant Rel.
drel <- smmr(nec.cond = "~ECOD*~EDU",
             results = sol_p,
             outcome = "BDT",
             match = FALSE,
             cases = 3,
             necessity = TRUE)
drel

~ECOD*~EDU :
----------
         Case NecCond Outcome Best MostDREL
1 Cape Verde     0.83    0.05 0.39     TRUE
2     Jordan     0.55    0.05 0.95    FALSE
```

There are more pairs of typical and deviant relevance cases, all of them involving, of course, the two deviant relevance cases of either Cape Verde and Jordan.

```
# TYP - DREL
typdrel <- smmr(nec.cond = "~ECOD*~EDU",
                results = sol_p,
                outcome = "BDT",
                match = TRUE,
                cases = 1,
                max_pairs = 10,
                necessity = TRUE)
typdrel

~ECOD*~EDU :
----------
         TYP        DREL Best MostTyp MostDREL
2     Egypt  Cape Verde  0.53    TRUE     TRUE
4     Haiti  Cape Verde  0.59   FALSE     TRUE
1  Djibouti  Cape Verde  0.68   FALSE     TRUE
3   Eritrea  Cape Verde  0.82   FALSE     TRUE
5   Lesotho  Cape Verde  0.86   FALSE     TRUE
7     Egypt      Jordan  1.09    TRUE    FALSE
9     Haiti      Jordan  1.15   FALSE    FALSE
6  Djibouti      Jordan  1.24   FALSE    FALSE
8   Eritrea      Jordan  1.38   FALSE    FALSE
10  Lesotho      Jordan  1.42   FALSE    FALSE
```

There are also just three deviant consistency cases. All three sit in different truth table rows.

```
# Deviant Cons.
dcons <- smmr(nec.cond = "~ECOD*~EDU",
              results = sol_p,
              outcome = "BDT",
              match = FALSE,
              cases = 2,
              necessity = TRUE)
dcons

~ECOD*~EDU :
----------
         Case NecCond TT_POV TT_DEP TT_ECOD TT_COR TT_PIN TT_EDU TT_EEX
TT_row
2 Kyrgyzstan     0.33      0      0       0      1      1      1      1
0.55
1    Jamaica     0.46      0      0       1      1      1      0      0
0.54
3 Uzbekistan     0.01      1      0       0      1      0      1      1
0.83
  Outcome TT<=Y Best MostDCONS
2    0.52 FALSE 0.81      TRUE
```

```
1    0.57  TRUE 0.89      TRUE
3    0.70 FALSE 0.31      TRUE
```

As the output below shows, no typical case shares the same truth table row with any of the three deviant consistency cases.

```
# TYP - DCN
typdcons <- smmr(nec.cond = "~ECOD*~EDU",
                 results = sol_p,
                 outcome = "BDT",
                 match = TRUE,
                 cases = 2,
                 max_pairs = 10,
                 necessity = TRUE)
typdcons

~ECOD*~EDU :
----------
[1] "There are no pairs in the same TT row"
```

6.3.2 Causal inference SMMR

For causal inference designs, the focal conjunct principle applies and the best available (pairs of) cases are listed for each ININ cause and the necessary conjunction separately.

Single typical cases are listed below.

```
# TYP
typ <- smmr(nec.cond = "~ECOD*~EDU",
            results = sol_p,
            outcome = "BDT",
            match = FALSE,
            cases = 1,
            necessity = TRUE)
typ

~ECOD :
----------
       Case NecCond Outcome Rank CleanCorr UniqCov Best MostTyp
2    Egypt    0.92    0.86    1     FALSE   FALSE 0.20    TRUE
4    Haiti    0.97    0.80    1     FALSE   FALSE 0.37   FALSE
3  Eritrea    0.98    0.57    1     FALSE   FALSE 0.84   FALSE
1 Djibouti    0.92    0.71    2      TRUE   FALSE 0.50   FALSE
5  Lesotho    0.97    0.53    2      TRUE   FALSE 0.91   FALSE

~EDU :
----------
       Case NecCond Outcome Rank CleanCorr UniqCov Best MostTyp
1 Djibouti    0.97    0.71    1     FALSE   FALSE 0.55   FALSE
2    Egypt    0.88    0.86    2      TRUE   FALSE 0.16    TRUE
4    Haiti    0.96    0.80    2      TRUE   FALSE 0.36   FALSE
```

```
3  Eritrea     0.97    0.57    2      TRUE   FALSE 0.83   FALSE
5  Lesotho     0.97    0.53    2      TRUE   FALSE 0.91   FALSE

~ECOD*~EDU :
----------
       Case NecCond Outcome UniqCov Best MostTyp
2    Egypt     0.88    0.86    TRUE 0.16    TRUE
4    Haiti     0.96    0.80    TRUE 0.36   FALSE
1 Djibouti     0.92    0.71    TRUE 0.50   FALSE
3  Eritrea     0.97    0.57    TRUE 0.83   FALSE
5  Lesotho     0.97    0.53    TRUE 0.91   FALSE
```

The best-matching pairs of typical and iir cases look as follows.

```
# TYP - IIR
typiir <- smmr(nec.cond = "~ECOD*~EDU",
               results = sol_p,
               outcome = "BDT",
               match = TRUE,
               cases = 3,
               max_pairs = 10,
               necessity = TRUE)
typiir

~ECOD :
----------
        TYP    IIR PairRank CleanCorr Best MostTyp UniqCov GlobUncov
2    Egypt  Chile         3      none 1.68    TRUE   FALSE      TRUE
4    Haiti  Chile         3      none 1.99   FALSE   FALSE      TRUE
3  Eritrea  Chile         3      none 2.70   FALSE   FALSE      TRUE
1 Djibouti  Chile         4       typ 2.22   FALSE   FALSE      TRUE
5  Lesotho  Chile         4      none 2.81   FALSE   FALSE      TRUE

~EDU :
----------
         TYP           IIR PairRank CleanCorr Best MostTyp UniqCov GlobUncov
1  Djibouti       Armenia         1       iir 0.97   FALSE   FALSE     FALSE
31 Djibouti  Turkmenistan         1       iir 1.23   FALSE   FALSE     FALSE
6  Djibouti        Bhutan         1       iir 1.43   FALSE   FALSE     FALSE
16 Djibouti      Mongolia         1       iir 1.67   FALSE   FALSE     FALSE
2     Egypt       Armenia         2      both 0.43    TRUE   FALSE     FALSE
4     Haiti       Armenia         2      both 0.68   FALSE   FALSE     FALSE
32    Egypt  Turkmenistan         2      both 0.69    TRUE   FALSE     FALSE
7     Egypt        Bhutan         2      both 0.89    TRUE   FALSE     FALSE
34    Haiti  Turkmenistan         2      both 0.94   FALSE   FALSE     FALSE
17    Egypt      Mongolia         2      both 1.13    TRUE   FALSE     FALSE

~ECOD*~EDU :
----------
         TYP           IIR UniqCov GlobUncov Best MostTyp
```

```
2     Egypt       Armenia     TRUE      TRUE 0.40    TRUE
12    Egypt         Chile     TRUE      TRUE 0.66    TRUE
22    Egypt  Turkmenistan     TRUE      TRUE 0.66    TRUE
4     Haiti       Armenia     TRUE      TRUE 0.66   FALSE
7     Egypt        Bhutan     TRUE      TRUE 0.86    TRUE
1  Djibouti       Armenia     TRUE      TRUE 0.89   FALSE
14    Haiti         Chile     TRUE      TRUE 0.92   FALSE
24    Haiti  Turkmenistan     TRUE      TRUE 0.92   FALSE
17    Egypt      Mongolia     TRUE      TRUE 1.08    TRUE
9     Haiti        Bhutan     TRUE      TRUE 1.12   FALSE
```

And the best available pairs of typical cases are listed below.

```
# TYP - TYP
typtyp <- smmr(nec.cond = "~ECOD*~EDU",
               results = sol_p,
               outcome = "BDT",
               match = TRUE,
               cases = 4,
               max_pairs = 7,
               necessity = TRUE)
typtyp

~ECOD :
----------
     TYP1      TYP2 PairRank CleanCorr Best MostTyp UniqCov
6  Egypt     Haiti         1      none 1.53    typ1    none
4  Egypt   Eritrea         1      none 1.80    typ1    none
5  Haiti   Eritrea         1      none 1.95    none    none
1  Egypt  Djibouti         2      typ2 1.48    typ1    none
2  Haiti  Djibouti         2      typ2 1.63    none    none
8  Egypt   Lesotho         2      typ2 1.81    typ1    none
10 Haiti   Lesotho         2      typ2 1.96    none    none

~EDU :
----------
       TYP1      TYP2 PairRank CleanCorr Best MostTyp UniqCov
3 Djibouti   Eritrea         2      typ2 2.24    none    none
7 Djibouti   Lesotho         2      typ2 2.27    none    none
1    Egypt  Djibouti         3      typ1 1.50    typ1    none
2    Haiti  Djibouti         3      typ1 1.81    none    none
6    Egypt     Haiti         4      both 1.43    typ1    none
4    Egypt   Eritrea         4      both 1.70    typ1    none
8    Egypt   Lesotho         4      both 1.73    typ1    none

~ECOD*~EDU :
----------
     TYP1      TYP2 UniqCov Best MostTyp
1  Egypt  Djibouti     both 1.35    typ1
6  Egypt     Haiti     both 1.38    typ1
```

```
2  Haiti  Djibouti     both 1.61    none
4  Egypt   Eritrea     both 1.64    typ1
8  Egypt   Lesotho     both 1.68    typ1
5  Haiti   Eritrea     both 1.90    none
10 Haiti   Lesotho     both 1.94    none
```

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