## How to Use the Script

# For Items of Two Categories (Binary Items)

Model, How to Use the Script, and Listings Yasuharu Okamoto, 2018

#### Model

The coefficient of reliability calculated in this study is based on a psychological model, which is called Thurstonian model, or is known as Samejima's model in item response theory (IRT). According to Thurstonian modeling, categorical response  $Y_{ij}$  on item j of person i is generated by categorizing a latent continuous response  $U_{ij}$  on item j of person i (Okamoto, 2017). The latent continuous response  $U_{ij}$  consists of a true value  $\mu_j + \lambda_j F_i$  and an error  $E_{ij}$ , that is,

$$(1) U_{ij} = \mu_j + \lambda_j F_i + E_{ij}$$

Strength of the psychological concept to measure of person i is represented by  $F_i$ . For model (1), the true value is defined to correspond to the psychological concept to measure.

The observed categorical score  $Y_{ij}$  on categorical item j of person i is given by categorization of  $U_{ij}$ , that is,

$$(2) Y_{ij} = k, if C_{k-1} \le U_{ij} < C_{k,}$$

where  $C_{k_i}$  is category boundary.

A score of a psychological scale of M categorical items of person i is given by the sum  $Y_i$ , where

$$(3) Y_i = \sum_{j=1}^M Y_{ij}.$$

For the model given by Equations (1) to (3), relation of a true value  $\mu_j + \lambda_j F_i$ , more specifically  $F_i$ , and the observed scale score  $Y_i$  can be represented by the following regression models:

$$(4) Y_i = a_F + b_F F_i + \varepsilon_F$$

or

$$(5) F_i = a_U + b_U Y_i + \varepsilon_U$$

Reliability of the scale, which represents strength of the relation between the observed score  $Y_i$  and the true value  $F_i$ , can be given by the coefficient of determination  $R^2$ -

index, which is given by squared correlation of  $Y_i$  and  $F_i$ , the common value for regression models (4) and (5). This coefficient of reliability given by  $R^2$ -index is denoted by  $R^2$  (Okamoto (2016)) or  $\rho_{cat}$  (Okamoto (2017)), and given by

(6) 
$$R^2 = \rho_{cat} = [Cor(Y_i, F_i)]^2$$

Reliability coefficient  $R^2$  or  $\rho_{cat}$  represents strength of the relation between an observed score  $Y_i$  and the true value  $F_i$  of the psychological concept to measure. The popular coefficient of reliability  $\alpha$ , which can be considered to be a coefficient of statistical reliability, tends to overestimate  $R^2$  or  $\rho_{cat}$  (Okamoto, 2016, 2017). On distinction of statistical reliability and psychological reliability, see the discussion of the website from this document was downloaded.

Python scripts to estimate  $\rho_{cat}$  (that is,  $R^2$ ) are available below. Formulae of the calculation are given in appendix of Okamoto (2017) and rather complex. However, it should be noted that in general, the following simpler equation is wrong:

(7) 
$$Cov(X,Y) = \int_{-\infty}^{+\infty} Cov(X,Y|\theta)p(\theta)d\theta$$
, (Wrong Equation)

where  $Cov(X,Y|\theta)$  denotes covariance of X and Y conditional on  $\theta$ , and  $p(\theta)$  is a probability density function of  $\theta$ .

The following example shows that Equation (7) is wrong.

Set two variables *X* and *Y* as follows:

$$X = F$$
,  $F \sim N(0,1)$  a standard normal distribution  $Y = a + bX$ 

Then, denoting expectations of X and Y by  $\overline{X}$  and  $\overline{Y}$ , we have

$$Cov(X,Y) = E((X - \overline{X})(Y - \overline{Y})) = E(XY) - \overline{X}\overline{Y}$$

Since

$$\overline{X} = E(F) = 0$$
,

we have

$$\overline{X}\overline{Y}=0.$$

We also have

$$E(XY) = E(aX + bX^{2}) = a\overline{X} + bE(F^{2}) = bVar(F) = b$$

Hence, we have

(8) 
$$Cov(X,Y) = b$$
.

On the other hand, denoting expectations of X and Y conditional on F by  $\overline{X}|F$  and  $\overline{Y}|F$ , and variables X and Y conditional on F by X|F and Y|F, we have

(9) 
$$Cov(X,Y|F) = E[(X|F - \overline{X}|F)(Y|F - \overline{Y}|F)]|F$$
$$= E[(F - F)((a + bF) - (a + bF))]|F$$

$$= 0$$
,

where  $E[\cdot]|F|$  denotes expectation conditional on F.

Hence, we have

(10) 
$$\int_{-\infty}^{+\infty} Cov(X,Y|F)\phi(F)dF = 0,$$

where  $\phi(F)$  is a density function of N(0,1).

Equations (8) and (10) shows that Equation (7) does not hold.

Python scripts with Stan script were developed. The models (1) and (2) give probabilities of categorical responses as follows:

(11) 
$$P(Y_{ij} = k \mid \mathbf{F}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\psi}, \boldsymbol{C})$$

$$= P(C_{k-1} \leq U_{ij} < C_k \mid \mathbf{F}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\psi}, \boldsymbol{C})$$

$$= \Phi\left(\frac{C_k - (\mu_j + \lambda_j F_i)}{\psi_i}\right) - \Phi\left(\frac{C_{k-1} - (\mu_j + \lambda_j F_i)}{\psi_i}\right)$$

Equation (11) shows that an origin and a unit of the scale are arbitrary. To identify parameter values, some restrictions of parameters are needed (Okamoto, 2017). The Stan script was developed with the following restrictions for model identification.

For binary items, there is only one category boundary. The origin is set by the following condition

(12) 
$$C_1 = 0$$

Under this condition (12), we have

(13) 
$$P(Y_{ij} = 1 | \mathbf{F}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\psi}, \boldsymbol{C})$$
$$= \Phi\left(\frac{-(\mu_j + \lambda_j F_i)}{\psi_j}\right)$$
$$= \Phi\left(-\left\{\frac{\mu_j}{\psi_j} + \frac{\lambda_j}{\psi_j} F_i\right\}\right)$$
$$= \Phi\left(-\left\{\mu_{bj} + \lambda_{bj} F_i\right\}\right),$$

where

$$\mu_{bj} = \frac{\mu_j}{\psi_i}$$
 and  $\lambda_{bj} = \frac{\lambda_j}{\psi_i}$ .

Equation (13) shows that for binary items, parameters can be estimated under condition (12) and

$$(14) \psi_i = 1$$

Condition (14) sets the units of the items (Okamoto, 2017).

The Stan script for binary items is shown in Listing 1 below.

#### How to use the program

The main script is MainTwoCat.py (Figure 1). Run this script, then a file name of

```
PS T:\(\frac{1}{2}\)paper2017J\(\text{WU}\)_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1}{2}\)WU_f\(\frac{1
```

Figure 1

the input data file is asked. After typing in the input data file name, an output data file name will be asked. Any text file name can be used.

Format of an input data file is as that as shown in Figure 2.

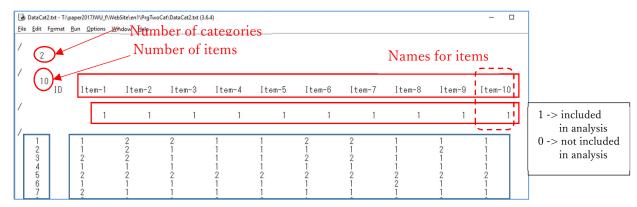


Figure 2

In the next line after the first one with a slash / at the head, the number of categories

is written.

In the next line after the second one with a slash / at the head, the number of items is written, and in the succeeding line, a name of a person identification variable and names of items are written.

In the next line after the third one with a slash / at the head, integers, 0 or 1, are arranged. Integer 1 indicates that the corresponding item is included in the analysis, and integer 0 indicates that the corresponding item is not included in the analysis.

After the fourth line with a slash / at the head, scores on items are written following the format in which an identification string and one set of scores of a person is written in one line, each line starts with the person identification string. Scores in items of K categories should be integers from 1 to K (Okamoto, 2017). An integer out of this range 1 to K is treated as a missing value.

The next line after the last data must have a slash at the head, by which the end of the data is shown (Figure 3).

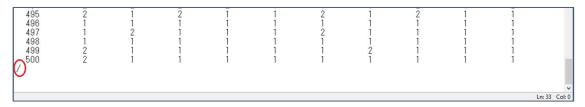


Figure 3

After typing in the output file name, the Stan script will run. When execution of the Stan script ends, the coefficient of reliability  $\rho_{cat}$  will be calculated using the medians of the posterior distributions of the parameters. In Figure 4, the estimated value  $\hat{\rho}_{cat} \approx 0.704$  is shown as Est\_Rho\_cat by Meds.

```
Medians of Cs...
Med_C[1] = 0.000

Calculating Rho_cat...

Est_Rho_cat by Meds = 0.806

Do you estimate the distribution of Rho_cat? Y(es) or N(o) = Y.
```

Figure 4

After showing the estimated value of the coefficient of reliability using the medians of the parameters, whether you want the distribution of the reliability coefficient or not will be asked. If you type in character 'N', the program ends. But, you type in character 'Y', the program starts estimating the posterior distribution. Calculation of this distribution will be

done using 100 samples of set of parameters, which are randomly selected from the samples generated by the Stan script, and executed by multiprocessing with four processes, each of which will display a window with the current step of calculation shown (Figure 5).

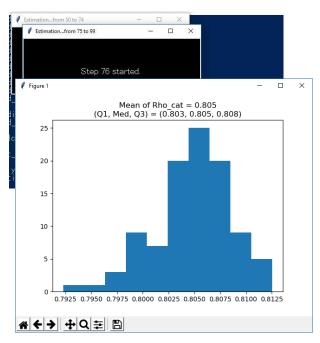
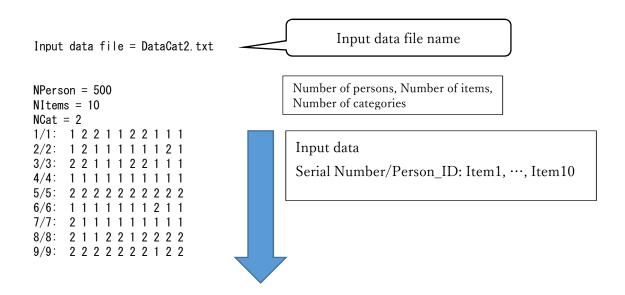


Figure 6

After the calculation ends, a histogram of the distribution of the 100 samples of the coefficient of reliability  $\rho_{cat}$  will be displayed (Figure 6). If you want a histogram of more than 100 samples, you can get the one by modifying the script.

Click the icon X at the upper right corner to close the window, then the program will end. After the program ends, you can open the output file by any editor. An example of the content of an output file is as follows:



```
10/10: 1 2 1 1 1 1 1 1 1 1
11/11: 2 2 2 2 2 1 2 2 1 1
495/495: 2 1 2 1 1 2 1 2 1 1
496/496:
          11111111111
497/497:
          1211121111
498/498:
         11111111111
499/499: 2 1 1 1 1 1 2 1 1 1
500/500: 2 1 1 1 1 1 1 1 1 1
Reconstructed data for the Stan script...
1/5000 IDpsn/1 IDitm/1 Res/1
                                            Serial Number Person ID Item ID Response
2/5000 IDpsn/1
                 IDitm/2
                           Res/2
3/5000
        IDpsn/1
                 IDitm/3
                           Res/2
4/5000
        IDpsn/1
                 IDitm/4
                           Res/1
5/5000
        IDpsn/1
                 IDitm/5
                           Res/1
6/5000
        IDpsn/1
                 IDitm/6
                           Res/2
        IDpsn/1
7/5000
                 IDitm/7
                          Res/2
4995/5000
           IDpsn/500
                       IDitm/5
                                Res/1
4996/5000
                       IDitm/6
           IDpsn/500
                                Res/1
4997/5000
           IDpsn/500
                       IDitm/7
                                Res/1
4998/5000
           IDpsn/500
                       IDitm/8
                                Res/1
4999/5000
           IDpsn/500
                       IDitm/9
                                Res/1
5000/5000
           IDpsn/500
                       IDitm/10
                                 Res/1
                                              The coefficient of reliability \alpha
Coeff alpha = 0.859
fit...
Inference for Stan model: anon_model_9a2ebcb00cdae47628541165bafa808c.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.
            mean se mean
                                   2.5%
                                           25%
                                                   50%
                                                          75% 97.5%
                                                                       n eff
                                                                               Rhat
                              ba
Lambda [0]
                            0.09
                                          0.74
                                                  0.81
                                                         0.87
                                                                 1.0
            0.81 1.5e-3
                                   0.63
                                                                        4000
                                                                                1.0
Lambda[1]
                  2. 4e-3
                            0.12
                                   0.89
                                           1.03
                                                                        2588
            1. 11
                                                  1.11
                                                         1.19
                                                                1.36
                                                                                1.0
Lambda [2]
                  2. 3e-3
                            0.12
                                   0.88
                                           1.01
                                                  1.09
                                                         1.17
                                                                1.36
                                                                        2643
             1.1
                                                                                1.0
Lambda[3]
            1.35
                  3. 0e-3
                            0.14
                                    1.1
                                           1.25
                                                  1.34
                                                         1.45
                                                                1.65
                                                                        2284
                                                                                1.0
                                   2.28
Lambda [4]
            3.32
                     0.04
                            0.89
                                           2.8
                                                  3.14
                                                         3.63
                                                                5. 21
                                                                         404
                                                                               1.01
                  2. 0e-3
Lambda [5]
            0.89
                             0.1
                                    0.7
                                           0.82
                                                  0.89
                                                         0.95
                                                                 1.09
                                                                        2449
                                                                                1.0
Lambda[6]
            0.72
                  1. 4e-3
                            0.09
                                   0.57
                                                                        4000
                                          0.66
                                                  0.72
                                                         0.78
                                                                 0.9
                                                                                1.0
Lambda [7]
            1. 02
                  2. 2e-3
                            0.11
                                   0.81
                                          0.94
                                                  1.01
                                                         1.09
                                                                 1.25
                                                                        2623
                                                                                1.0
Lambda[8]
            1. 59
                  4. 0e-3
                            0.18
                                   1.27
                                           1.47
                                                  1.58
                                                          1. 7
                                                                1.98
                                                                        1920
                                                                                1.0
Lambda [9]
                  7. 2e-3
             2. 2
                            0.28
                                   1.71
                                           2.01
                                                  2.18
                                                         2.36
                                                                2.81
                                                                        1516
                                                                                1.0
mu[0]
            0.07
                  1. 2e-3
                            0.07 -0.08
                                          0.02
                                                  0.07
                                                                        4000
                                                         0.12
                                                                0.21
                                                                                1.0
mu[1]
            0.16 3.1e-3
                            0.08-5.0e-3
                                                  0.16
                                                         0.22
                                                                0.33
                                                                         725
                                           0.1
                                                                                1.0
                            0.08 -0.02
mu[2]
            0.14 2.9e-3
                                           0.08
                                                  0.14
                                                          0.2
                                                                0.31
                                                                         825
                                                                                1.0
            0.14 3.6e-3
                                 -0.05
                                          0.07
                                                  0.14
                                                                0.33
                                                                         696
mu[3]
                             0.1
                                                          0.2
                                                                                1.0
mu[4]
            0.27 9.9e-3
                             0. 2
                                 -0.11
                                          0.14
                                                  0.26
                                                         0.39
                                                                         426
                                                                 0.7
                                                                               1.01
mu[5]
           -0. 22 2. 4e-3
                            0.07
                                  -0.37
                                         -0.27
                                                 -0.22
                                                        -0.17
                                                               -0.07
                                                                         950
                                                                                1.0
                                 -0. 31
                                         -0. 22
mu[6]
           -0.17 1.1e-3
                            0.07
                                                -0.18
                                                       -0.13 -0.04
                                                                        4000
                                                                                1.0
                                        -0. 21
                            0.08 -0.32
mu[7]
           -0. 16 2. 6e-3
                                                -0.16 -0.11-3.3e-3
                                                                         919
                                                                                1.0
           -0. 18 4. 2e-3
                                  -0.38
                                        -0. 25
                                                -0.18 -0.11
mu[8]
                            0.11
                                                                0.03
                                                                         638
                                                                                1.0
                            0.14 - 0.71 - 0.51 - 0.42 - 0.32 - 0.17
mu[9]
           -0. 42 6. 0e-3
                                                                         521
                                                                               1.01
```

```
psi[0]
              1.0
                      0.0
                              0.0
                                     1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
psi[1]
              1.0
                      0.0
                              0.0
                                     1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
psi[2]
              1.0
                      0.0
                              0.0
                                      1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
psi[3]
                      0.0
                              0.0
                                             1.0
                                                     1.0
                                                                          4000
              1.0
                                      1.0
                                                            1.0
                                                                    1.0
                                                                                   nan
psi[4]
                      0.0
                              0.0
                                      1.0
                                             1.0
                                                     1.0
                                                                          4000
              1.0
                                                            1.0
                                                                    1.0
                                                                                   nan
psi[5]
              1.0
                      0.0
                              0.0
                                      1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
psi[6]
              1.0
                      0.0
                              0.0
                                      1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
psi[7]
              1.0
                      0.0
                              0.0
                                      1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
                      0.0
                              0.0
                                     1.0
psi[8]
              1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
                                                                                   nan
              1.0
                      0.0
                              0.0
                                     1.0
                                             1.0
                                                     1.0
                                                            1.0
                                                                    1.0
                                                                          4000
psi[9]
                                                                                   nan
                      0.0
                              0.0
                                     0.0
                                             0.0
                                                    0.0
                                                            0.0
                                                                   0.0
                                                                          4000
C[0]
              0.0
                                                                                   nan
                           23.59
            -2476
                     1.09
                                   -2524 -2492 -2476 -2460 -2431
                                                                           472
                                                                                  1.01
lp__
```

Samples were drawn using NUTS at Thu Mar 1 10:59:33 2018. For each parameter, n\_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence. Rhat=1).

```
Median of Lambdas..

Med_Lambda[1] = 0.806

Med_Lambda[2] = 1.111

Med_Lambda[3] = 1.089

Med_Lambda[4] = 1.345

Med_Lambda[5] = 3.145

Med_Lambda[6] = 0.886

Med_Lambda[7] = 0.719

Med_Lambda[8] = 1.012

Med_Lambda[9] = 1.581

Med_Lambda[10] = 2.175
```

Medians of mus...

Med\_mu[1] = 0.068

Med\_mu[2] = 0.159

Med\_mu[3] = 0.142

Med\_mu[4] = 0.138

Med\_mu[5] = 0.261

Med\_mu[6] = -0.217

Med\_mu[7] = -0.175

Med\_mu[8] = -0.161

Med\_mu[9] = -0.180

Med\_mu[10] = -0.417

Medians of psis...

Med\_psi[1] = 1.000

Med\_psi[2] = 1.000

Med\_psi[3] = 1.000

Med\_psi[4] = 1.000

Med\_psi[5] = 1.000

Med\_psi[6] = 1.000

Med\_psi[7] = 1.000

Med\_psi[8] = 1.000

Med\_psi[9] = 1.000

Med\_psi[10] = 1.000

Medians of Cs...  $Med_C[1] = 0.000$ 

 $\rho_{cat}$ : calculated with the medians

 $Est_Rho_cat$  by Meds = 0.806

```
Mean of Rho_cat = 0.805

Median of Rho_cat = 0.805

[Q1, Q3] = [0.803, 0.808]

Statistics of the sample distribution of \rho_{cat}
```

### Listings of scripts

The zip file PrgTwoCat.zip, which is available at the website, contains the files shown in Figure 7. Listigns 1 and 2 below show the Stan script ctt\_TwoCat.stan, which do MCMC sampling for the model explained above, and the main Python script, which calls the Stan script and calculate the coefficient of reliability  $\rho_{cat}$  using the class CalcRhoPreRhoYYP included in SubModule.py.

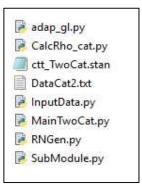


Figure 7

**Listing 1.** The Stan script ctt\_TwoCat.stan for estimation of parameter values.

```
Yasuharu Okamoto, 2017.07
//
    int \langle lower = 2, upper = 2 \rangle K;
                                                             //
                                                                      Number of categories = 2
    int Npsn;
                                                          Number of persons
    int Nitm;
                                                          Number of items
    int Ntot;
                                                          Number of data,
                                                                           Ntot <= Nprn * Nitm
    int<lower = 1, upper = Npsn> IDpsn[Ntot];
                                                  //
                                                          Person ID
    int<lower = 1, upper = Nitm> IDitm[Ntot];
                                                          Item ID
    int<lower = 1, upper = K> Res[Ntot];
                                                           Response-> An integer value between 1
and K
parameters {
        real<lower = 0.0> Lambda[Nitm];
        real mu[Nitm];
        real F[Npsn];
transformed parameters {
    vector[K] p[Ntot];
    real C[K-1];
    real psi[Nitm];
    C[1] = 0.0;
    for (j in 1:Nitm){
            psi[j] = 1.0;
    for (i in 1:Ntot) {
        p[i][K] = Phi(((mu[IDitm[i]] + (Lambda[IDitm[i]] * F[IDpsn[i]])) - C[K - 1]) /
```

```
psi[IDitm[i]]);
    p[i][1] =1.0 - p[i][K];
}

model {
    for (i in 1:Npsn)
        F[i] ~ normal(0.0, 1.0);
    for (i in 1:Ntot)
        Res[i] ~ categorical(p[i]);
}
```

#### **Listing 2.** The main Python script MainTwoCat.py.

```
import pystan
from pystan import StanModel
import pickle
from multiprocessing.pool import Pool
import numpy as np
import matplotlib.pyplot as plt
from InputData import *
from SubModule import *
from CalcRho_cat import *
from RNGen import *
if __name__ == '__main__':
    #
             Prepare the input data file
    fn_in = input("Input data file = ")
    f_{in} = open(f_{in}, "r")
    #
             Prepare the output file
    fn_out = input("Output data file = ")
    f_out = open(fn_out, "w")
    f_out.write("Input data file = " + fn_in + "\u00e4n")
    NPerson, NItems, NCat, ID, X = ReadData(f_in, f_out)
    f_out.write('\format(NPerson))
f_out.write('\format(NItems))
f_out.write('\format(NItems))
f_out.write('\format(NCat))
    for i in range(len(ID)):
         f_{out.write('Yn\{0\}/\{1\}: '.format((i + 1), ID[i]))}
         for v in X[i]:
             f_out.write(' {}'.format(v))
    if (NCat != 2):
```

```
print('\forall nNumber of Categories is not two !')
    raise Exception('This programm is for items with two categries.')
K = NCat
Ntot = 0
IDpsn = []
IDitm = []
Res = []
for i in range (NPerson):
    for j in range (NItems):
        if (X[i][j] >= 1) and (X[i][j] \le K):
             IDpsn. append(i + 1)
             IDitm.append(j + 1)
             Res. append (X[i][j])
             Ntot += 1
f out.write('\forall n\forall n\forall constructed data for the Stan script...')
for t in range (Ntot):
    f_{out.write}('Y_{n}{0}/{1} IDpsn/{2} IDitm/{3} Res/{4}'.format(
        (t + 1), Ntot, IDpsn[t], IDitm[t], Res[t]))
coeff_alpha = CalcAlpha(X, NCat, NPerson, NItems)
if coeff_alpha < 0.0:
    print('\forall nA missing value was found in the dataset.')
    print('The coefficient alpha was not calculated.')
    f_out.write('\frac{Yn}{n} \text{missing value was found in the dataset. f')
    f_out.write('The coefficient alpha was not calculated.\u00e4n')
else:
    print('YnCoeff alpha = \{0: 3f\}Yn', format(coeff alpha))
    f_{out.write}('YnYnCoeff_alpha = \{0:.3f\}Yn'.format(coeff_alpha))
Data = {'K': NCat, 'Npsn': NPerson, 'Nitm': NItems, 'Ntot': Ntot,
         'IDpsn': IDpsn, 'IDitm': IDitm, 'Res': Res}
iLmbd = []
imu = []
for i in range (NItems):
    iLmbd. append (1.0)
    imu. append (0.0)
def f init():
    return dict(Lambda = iLmbd, mu = imu)
fit = pystan.stan(file = 'ctt_TwoCat.stan', data = Data,
                   init = f_init, seed = 999,
                   pars = ['Lambda', 'mu', 'psi', 'C'], n_jobs = 1)
sm = StanModel(file = 'ctt TwoCat.stan')
with open ('model.pkl', 'wb') as f:
    pickle.dump(sm, f)
fit = sm. sampling(data = Data, seed = 999,
                   pars = ['Lambda', 'mu', 'psi', 'C'], n_jobs = 1)
```

```
with open('fit.pkl', 'wb') as g:
pickle.dump(fit, g)
sm = pickle.load(open('model.pkl', 'rb'))
fit = pickle.load(open('fit.pkl', 'rb'))
print(fit)
f out.write('\forall n\forall nfit...\forall n')
f_out.write('{}'.format(fit))
LImbd = fit['Lambda']
Lmu = fit['mu']
Lpsi = fit['psi']
tempLC = fit['C']
LC = []
for v in tempLC:
    LC. append([v])
RawNSamples = len(Llmbd)
rn = RNp2to191()
LSamplesID = []
for i in range (RawNSamples):
    LSamples ID. append ([])
    LSamples ID[i]. append(i)
    LSamples ID[i]. append (rn. uni ())
LSamplesID.sort(key = lambda v: v[1])
MCMCSmpl_Imbd = []
for i in range(NItems):
    MCMCSmpI_Imbd. append([])
for v in Llmbd:
    for i in range (NItems):
         MCMCSmpl_Imbd[i].append(v[i])
MCMCSmpl_mu = []
MCMCSmpl_psi = []
MCMCSmpl_C = []
for i in range(NItems):
    MCMCSmpl_mu.append([])
    MCMCSmpl_psi.append([])
for i in range(NCat - 1):
    MCMCSmpI_C. append([])
for v in Lmu:
    for i in range (NItems):
         MCMCSmpl_mu[i].append(v[i])
for v in Lpsi:
    for i in range (NItems):
         MCMCSmpl_psi[i].append(v[i])
```

```
for v in LC:
    for i in range (NCat -1):
         MCMCSmpI_C[i]. append(v[i])
for i in range (NItems):
    MCMCSmpl Imbd[i].sort()
    MCMCSmpl_mu[i].sort()
    MCMCSmpl_psi[i].sort()
for i in range (NCat - 1):
    MCMCSmpI_C[i].sort()
Med Lmbd = []
for i in range (NItems):
    Med Lmbd.append(MCMCSmpl lmbd[i][int(len(MCMCSmpl lmbd[i]) / 2.0)])
Med mu = []
for i in range (NItems):
    Med mu. append (MCMCSmpl mu[i][int(len(MCMCSmpl mu[i]) / 2.0)])
Med_psi = []
for i in range (NItems):
    Med_psi.append(MCMCSmpl_psi[i][int(len(MCMCSmpl_psi[i]) / 2.0)])
Med C = []
for i in range (NCat - 1):
    Med_C. append (MCMCSmpl_C[i][int(len(MCMCSmpl_C[i]) / 2.0)])
print('\forall nMedians of Lambdas...')
for i in range (NItems):
    print("Med_Lambda[\{0\}] = \{1:.3f\}".format((i + 1), Med_Lmbd[i]))
print('\forall nMedians of mus...')
for i in range (NItems):
    print('Med_mu[\{0\}] = \{1:.3f\}'.format((i + 1), Med_mu[i]))
print('\forall nMedians of psis...')
for i in range (NItems):
    print('Med_psi[\{0\}] = \{1:.3f\}'.format((i + 1), Med_psi[i]))
print('\forall nMedians of Cs...')
for i in range (NCat - 1):
    print('Med_C[\{0\}] = \{1:.3f\}'.format((i + 1), Med_C[i]))
f out.write('\footnote{n}\text{YnYnMedian of Lambdas...\footnote{n}\)
for i in range (NItems):
    f_{\text{out. write}}(\text{Med\_Lambda}[\{0\}] = \{1:.3f\} \text{Yn}''. \text{format}((i + 1), \text{Med\_Lmbd}[i]))
f_out.write('\forall nMedians of mus...\forall n')
for i in range (NItems):
    f_{\text{out.write}}(Med_{\text{mu}}[\{0\}] = \{1:.3f\} Yn'.format((i + 1), Med_{\text{mu}}[i]))
f_out.write('\forall nMedians of psis...\forall n')
for i in range (NItems):
    f_{out.write('Med_psi[\{0\}] = \{1:.3f\}Yn'.format((i + 1), Med_psi[i]))}
f_out.write('\forall nMedians of Cs...\forall n')
for i in range (NCat - 1):
    f_{\text{out. write}}(Med_C[\{0\}] = \{1:.3f\} Yn'. format((i + 1), Med_C[i]))
print('\forallow \text{MCalculating Rho_cat...')
calc_rhos = CalcRhoPreRhoYYP( NCat, NItems, Med_mu, Med_Lmbd, Med_psi, Med_C )
print('YnEst_Rho_cat by Meds = \{0:.3f\}'.format(calc_rhos.GetRhoPre()))
f_out.write('\forall nEst_Rho_cat by Meds = \{0:.3f\}\forall n'.format(calc_rhos.GetRhoPre()))
```

```
print('\u00e4nDo you estimate the distribution of Rho_cat? Y(es) or N(o) = ', end = '')
    ck est = input()
    if (ck_est[0] == 'Y') or (ck_est[0] == 'y'):
        print('Estimation started.')
        StartPos = 0
        StopPos = 9
        param0 = {'NCat': NCat, 'NItems': NItems, 'StartPos': StartPos, 'StopPos': StopPos,
                    'LSamplesID': LSamplesID, 'LImbd': LImbd, 'Lmu': Lmu, 'Lpsi': Lpsi, 'LC':
LC}
        n_proc = 4;
        params = []
        NEstRhos = None
        if (RawNSamples > 100):
            NEstRhos = 100
        else:
            NEstRhos = RawNSamples
        for iproc in range (n proc):
            param_t = param0.copy()
            param_t['StartPos'] = int(iproc * NEstRhos / n_proc)
            param_t['StopPos'] = int(((iproc + 1) * NEstRhos / n_proc) - 1)
            params. append (param_t)
        pool = Pool()
        Results = pool.map(EstDistriRho_cat, params)
        SamplesRho cat = []
        for u in Results:
            for v in u:
                SamplesRho cat. append (v)
        sum = 0.0
        for v in SamplesRho_cat:
            sum += v
        meanRho_cat = sum / len(SamplesRho_cat)
        SamplesRho_cat.sort()
        medRho cat = SamplesRho cat[int(len(SamplesRho cat) / 2)]
        Q1Rho_cat = SamplesRho_cat[int(len(SamplesRho_cat) / 4)]
        Q3Rho_cat = SamplesRho_cat[int(len(SamplesRho_cat) * 3 / 4)]
        print('[Q1, Q3] = [\{0:.3f\}, \{1:.3f\}]'.format(Q1Rho_cat, Q3Rho_cat))
        f_{out.write}('YnYnMean of Rho_cat = {0:.3f}Yn'.format(meanRho_cat))
        f_out.write('Median of Rho_cat = \{0:.3f\}\format(medRho_cat))
        f_{\text{out.write}}('[Q1, Q3] = [\{0:.3f\}, \{1:.3f\}] + n'.format(Q1Rho_cat, Q3Rho_cat))
        title_str = 'Mean of Rho_cat = \{0:.3f\}\footnote{\text{Y}}n' + \footnote{\text{Y}}
                         (Q1, Med, Q3) = (\{1:.3f\}, \{2:.3f\}, \{3:.3f\})
        title_str = title_str.format(meanRho_cat, Q1Rho_cat, medRho_cat, Q3Rho_cat)
        plt. title(title str)
        plt.hist(SamplesRho cat, bins = 10)
        plt. show()
```

f\_out.close()

#### References

- Okamoto, Y. (2016). Reliability coefficients for ordinal categorical items: Actual relation of observed and true scores. *Japan Women's University Journal: Faculty of Integrated Arts and Social Sciences*, 2016, 27, 113-122.
- Okamoto, Y. (2017). Bayesian estimation of ordinal categorical items' reliability coefficients: Relationship between true values and observed values. *Japan Women's University Journal: Faculty of Integrated Arts and Social Sciences*, 2017, ??, ??????.