

April 19, 2007
Revised November 16, 2007

Estimation of the SRM Using Specialized Software

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This paper was prepared for the National Science Foundation sponsored conference on “Intergroup Data as Modeled Using the Social Relations Model” held in Storrs CT on May 14-15, 2007. Thanks are due to Tessa West who made many helpful comments on a previous draft of this paper. The text was incorporated into Kenny, D. A., & Livi, S. (2009). A componential analysis of leadership using the Social Relations Model. In F. J. Yammarino & F. Dansereau (Eds.), *Multi-Level Issues in Organizational Behavior and Leadership* (Vol. 8 of *Research in Multi-level Issues*; pp. 147-191). Bingley, UK: Emerald (see pages 174-183).

Estimation of the SRM Using Specialized Software

The Social Relations Model (SRM) has been used for data in which people rate or interact with multiple partners. The basic SRM equation is that a score equals the mean plus actor plus partner plus relationship. The SRM equation for actor i with partner j in group k is:

$$X_{ijk} = m_k + a_{ik} + b_{jk} + g_{ijk}$$

where X_{ijk} is the score for person i rating (or behaving with) person j , m_k is the group mean, a_{ik} is person i 's actor effect, b_{jk} is person j 's partner effect, and g_{ijk} is the relationship effect. The terms m , a , b , and g , are random variables and there are the following variances are parameters of the model: σ_m^2 , σ_a^2 , σ_b^2 , and σ_g^2 . The SRM also specifies two different correlations between the SRM components of a variable, both of which can be viewed as reciprocity correlations. At the individual level, a person's actor effect can be correlated with that person's partner effect and can be denoted as σ_{ab} . At the dyadic level, the two members' relationship effects can be correlated and can be denoted as σ_{gg} . There are then six SRM parameters, four variances and two covariances.

Previously, almost all published papers used the method of moments, sometimes called ANOVA method, to estimate these variances and covariances. This method is described in some detail in Kenny, Kashy, and Cook (2006) in Chapter 9. A computer program for the estimation of these components called SOREMO has been developed. In this paper, we discuss how the SRM can be estimated by using conventional programs. We consider first the estimation of a restricted version of the SRM using multilevel modeling. We then show how some multilevel modeling programs can estimate the full SRM. Finally we show how structural equation modeling programs can estimate the model.

As an example, we use data gathered by Lord, Phillips and Rush (1980). They had a total of 24 4-person groups and measure how much each person in the group stated the other member contributed to the group on a rating scale from 1 to 6. The data structure is called a round robin design, which has a $n \times n$ structure in which the diagonal is missing.

Table 1 presents a summary of the results from the computer program SOREMO. Table 2 presents the actual SOREMO output. The raw data can be obtained as www.davidakenny.net/doc/contribute.sav. SOREMO does not provide an estimate of group variance, but it equals the variance of the group means minus the (actor variance + partner variance + 2(actor-partner covariance))/n + (relationship variance + relationship covariance)/[n(n - 1)] where n is the number of persons per group. For the example, we obtain -.091.

In the remainder of the paper, we consider how conventional software can estimate the SRM variances and covariances.

Conventional Multilevel Modeling: SAS and SPSS

Increasingly, multilevel models can estimate models with cross-classified variables. In these models, the actor-partner covariance is assumed to be zero which is a major limitation of this method. We describe this approach in three steps and describe how both SAS and SPSS can be used to estimate the model.

Step 1: Data Organization and Preparation

Create a data set in which each record is the response of one person in the dyad on all variables (for example, Person A's rating of Person B on extroversion, talkativeness, and intelligence). For a round robin of 5, there would be 20 records, assuming no self ratings are included. Make sure the following variables are on each record a unique actor number. For example, for group 1, the actor numbers would range from 1 to 5, and for group 2 the actor

numbers would range from 6 to 10. There would also need to be a unique partner number and a unique dyad number. For a five-person group, there are 10 dyads. Finally there would need to be a unique group number

Step 2: Syntax.

We first present the syntax for SAS and then for SPSS. Note again that the actor-partner covariance is not modeled.

The syntax for SAS is as follows:

```
PROC MIXED COVTEST;  
  
    CLASS ACTOR PARTNER DYAD GROUP;  
  
    MODEL LEAD = /S DDFM=SATTERTH NOTEST;  
  
    RANDOM INTERCEPT /TYPE=VC SUB=ACTOR;  
  
    RANDOM INTERCEPT /TYPE=VC SUB=PARTNER;  
  
    RANDOM INTERCEPT /TYPE=VC SUB=GROUP;  
  
    REPEATED /TYPE=CS SUB=DYAD;
```

The syntax for SPSS is as follows:

```
MIXED  
  
    LEAD BY GROUP  
  
    /FIXED =  
  
    /PRINT = SOLUTION TESTCOV  
  
    /RANDOM INTERCEPT | SUBJECT(GROUP) COVTYPE(VC) .  
  
    /RANDOM INTERCEPT | SUBJECT(ACTOR) COVTYPE(VC)  
  
    /RANDOM INTERCEPT | SUBJECT(PARTNER) COVTYPE(VC)  
  
    /RANDOM INTERCEPT | SUBJECT(DYAD) COVTYPE(VC) .
```

Note that with SPSS, the REPEATED statement cannot be used for dyad, and so one must presume that the dyadic covariance is positive. Note that for SPSS error variance equals the dyad variance plus the error variance, and the dyadic correlation equals the dyad variance divided by the sum of the dyad variance plus the error variance.

Table 3 presents the SAS and SPSS output. As can be seen in Table 1, the SAS and the SPSS output yield the same results. They would be different would be when the reciprocity covariance were negative. In that case, it would be estimated as zero by SPSS and properly estimated by SAS. Note also that the estimates are different from SOREMO. The major reason for the difference is the assumption of the zero actor-partner covariance. Because that covariance is small, the differences are small.

MLwiN with Dummy Variables

The approach described here was initially proposed by Snijders and Kenny (1999). With this approach $2n$ dummy variables are created and constraints are made on the variance-covariance matrix of those dummy variables. We describe their approach in three steps.

Step 1: Data Organization and Preparation

We create an observation data set, one record for each data point. For each observation, have a variable the designate what group the person is in, what dyad the person is in, and what observation.

We create the following dummy variables:

A(1) through A(n) where n is the largest group size. For a dummy variable A(i), if the actor is person i , the dummy equals 1, 0 otherwise.

P(1) through P(n) where n is the largest group size. For a dummy variable P(i), if the partner is person i, the dummy equals 1, 0 otherwise.

O(1) and O(2) where for member 1 of the dyad, O(1) = 1 and O(2) = 0 and for member 2 of the dyad, O(1) = 0 and O(2) = 0.

Step 2: Levels

The multilevel model has three levels. Level 3 is group, level 2 is dyad, and level 1 is observation.

Step 3: Model Specification

Intercept at level 1, no random variance

O(1) and O(2) random at level 2, with zero means and a nonzero covariance.

A(1) through A(n) random at level 3 with a zero mean and no covariance.

P(1) through P(n) random at level 3 with a zero mean and no covariance.

A(1) correlated with P(1) and in general A(i) correlated with P(i); all other covariances set to zero.

Equality constraints

Variations of A(1) through A(n)

Variations of P(1) through P(n)

Covariances of A(i) with P(i)

Variations of O(1) and O(2)

In Table 4, we have the MLwiN output which is also summarized in Table 1. Note there are some differences between these estimates and SOREMO. We suspect the results would have been the same had the group variance been non-negative.

SAS with Dummy Variables

This approach is the same as above, just a different program. We create $2n$ dummy variables. There are three steps.

Step 1: Data Organization and Preparation

Create a where each record refers to a data point or $n(n - 1)$ data points where n is the group size (assuming no self data). For each observation, have a variable that designates what group the person is in, what dummy, and what observation. We create the following two sets of dummy variables:

A(1) through A(n) where n is the largest group size. For a dummy variable A(i),
if the actor is person i , the dummy equals 1, 0 otherwise.

P(1) through P(n) where n is the largest group size. For a dummy variable P(i), if
the partner is person i , the dummy equals 1, 0 otherwise.

The SAS code that might be used to create the dummy variables for a four-person round robin in which there is a variable for actor and partner that goes from 1 to 4:

```
A1=0; A2=0; A3=0; A4=0;
IF ACT=1 THEN A1=1;
IF ACT=2 THEN A2=1;
IF ACT=3 THEN A3=1;
IF ACT=4 THEN A4=1;
P1=0; P2=0; P3=0; P4=0;
IF PART=1 THEN P1=1;
IF PART=2 THEN P2=1;
IF PART=3 THEN P3=1;
IF PART=4 THEN P4=1;
```

Step 2: Force Constraints

A data file, in this case called G, is created to set the n actor variances (parameter 1) equal, the n partner variances (parameter 2) equal, and the n actor-partner covariances (parameter 3) equal. The structure of the file for a four-person group is as follows.

```
DATA G;
```

```
INPUT PARM ROW COL VALUE;
```

```
DATALINES;
```

```
1 1 1 1
```

```
1 2 2 1
```

```
1 3 3 1
```

```
1 4 4 1
```

```
2 5 5 1
```

```
2 6 6 1
```

```
2 7 7 1
```

```
2 8 8 1
```

```
3 1 5 1
```

```
3 2 6 1
```

```
3 3 7 1
```

```
3 4 8 1
```

```
4 9 9 1
```

```
;
```

The structure of each record in the data file is parameter number (e.g., 1 refers to actor), row of the variance-covariance matrix, column of the matrix, and value in the matrix. The last line in the data file refers to the group variance.

Step 3

Below is the SAS code for PROC MIXED:

```
PROC MIXED COVTEST;  
  
    CLASS DYAD GROUP;  
  
    MODEL LEAD = GROUP /S DDFM=SATTERTH NOTEST;  
  
    RANDOM A1 A2 A3 A4 P1 P2 P3 P4 INTERCEPT  
          /G SUB=GROUP TYPE=LIN(4) LDATA=G;  
  
    REPEATED /TYPE=CS SUB=DYAD(GROUP);
```

(I thank Andrew Knight for suggesting using DYAD(GROUP) and not just DYAD.) Note that “LDATA = G” statement in the RANDOM statement sets the equality constraints. Note also that there nine terms in the RANDOM statement, A1 through INTERCEPT, and they are ordered as in G.

As seen in Tables 5 and 1, SAS with dummy variables and MLwiN yield essentially the same estimates even though they use somewhat different estimation methods.

Structural Equation Modeling

This method is a generalization of the method developed by Olsen and Kenny (2006) for dyadic analysis. I thank Joe Olsen who provided several helpful hints.

Step 1: Data Preparation

Group is the unit of analysis. If n members are in the largest group size, there would be $n(n - 1)$ scores read per group. For $n = 4$, the variables would be X12, X13, X14, X21, X23,

X24, X31, X32, X34, X41, X42, and X43. The order does not matter and scores can be missing. There must be two more groups than the number of variables. However, within Amos there can be fewer groups than individual. One tells the program to allow for non-positive definite input matrices.

Step 2: Latent Variables

There would be n actor factors and n partner factors. Parallel actor and partner effects would be correlated. Thus, the actor factor for person 1 would be correlated with partner factor for person 1. Additionally, there would be correlations between pairs of errors, e.g., the errors of X12 and X21.

Step 3: Equality Constraints

To achieve an identified model, many equality constraints would be made. The $n(n - 1)$ means would be set equal, the n actor variances, the n partner variances, the $n(n - 1)$ relationship variances, the n actor-partner covariances, and the $n(n - 1)/2$ error covariances. The total number of equality constraints would be $n(3 + 5(n - 1)/2)$. The number of elements in the moment matrix is $n(n - 1)([n(n - 1) + 1]/2 + 1)$ making the degrees of freedom of the model be $n[(n - 1)([n(n - 1) + 1]/2 - 3/2) - 3]$. So if n is 4, the model has 21 equality constraints, 78 elements in the matrix and 57 degrees of freedom in the model.

Step 4: Model Testing

The fit of the model does not matter. It is treated at the I-SAT model as described by Olsen and Kenny (2006). Also note that the estimates are maximum likelihood estimates and not restricted maximum likelihood or generalized least squared estimates obtained in the multilevel modeling program.

We used the program Amos to estimate the model. We have had difficulty using AmosBasic as the model appeared to be too big. Using AmosGraphics worked, but there are so many variables and constraints in the model that it was difficult to implement and determine if it was correct. We suggest outputting the “implied moments,” to determine if the constraints were successfully implemented.

Using SAS and SPSS for Block Designs

The previous discussion has presumed that the design is round robin. However, block designs can be used to estimate SRM variances and covariances. In a block design, the group is divided into two subgroups and each group rates or interacts members of the other subgroup.

Half Block

In this design, just one of the groups rates members of the other group. Because the data are one-sided, there are no actor-partner or dyadic covariances. See above for creation of the variables of actor and partner. The syntax for SAS is as follows:

```
PROC MIXED COVTEST;  
  
    CLASS ACTOR PARTNER GROUP;  
  
    MODEL LEAD = /S DDFM=SATTERTH NOTEST;  
  
    RANDOM INTERCEPT /TYPE=VC SUB=ACTOR;  
  
    RANDOM INTERCEPT /TYPE=VC SUB=PARTNER;  
  
    RANDOM INTERCEPT /TYPE=VC SUB=GROUP;
```

The syntax for SPSS is as follows:

```
MIXED  
  
    LEAD BY GROUP  
  
    /FIXED =
```

```

/PRINT = SOLUTION TESTCOV

/RANDOM INTERCEPT | SUBJECT(GROUP) COVTYPE(VC) .

/RANDOM INTERCEPT | SUBJECT(ACTOR) COVTYPE(VC)

/RANDOM INTERCEPT | SUBJECT(PARTNER) COVTYPE(VC)

```

Asymmetric Block

For this design, both subgroups rate or interact members of the other subgroup. We need to create unique identifiers for members of the two subgroups. We denote them as G and H. We create two indicator (0 and 1) variables: one for G participants as actors and H as partners) which is denoted as GH and the other with H participants as actors and G as partners which is denoted as HG.

The syntax for SAS is

```

PROC MIXED CL COVTEST;

CLASS G H GH HG GROUP ;

MODEL LEAD = GH HG /NOINT S ;

RANDOM GH HG / TYPE=CSH SUB=GROUP;

RANDOM GH HG / TYPE=CSH SUB=G(GROUP) ;

RANDOM GH HG / TYPE=CSH SUB=H(GROUP) ;

REPEATED GH HG / TYPE=CSH SUBJECT=G*H(GROUP);

```

The syntax for SPSS is

```

MIXED

LEAD BY G H GROUP WITH GH HG

/FIXED = GH HG | NOINT

/PRINT = SOLUTION TESTCOV

```

```
/RANDOM GH HG | COVTYPE(CSH) SUBJECT(GROUP)
```

```
/RANDOM GH HG | COVTYPE(CSH) SUBJECT(G)
```

```
/RANDOM GH HG | COVTYPE(CSH) SUBJECT(H)
```

```
/REPEATED GH HG | COVTYPE(CSH) SUBJECT(G*H*GROUP) .
```

Symmetric Block

For this design, both subgroups rate or interact members of the other subgroup and there are presumed to be no differences between members of the two subgroups. This design is best treated as a round robin design with missing data. Note that we could compare the fit of the symmetric and asymmetric designs to determine if the asymmetry makes an empirical difference.

Comparison of Different Methods

I believe that the dummy variable estimates would be the same as SOREMO with equal groups sizes and no missing data and if the variances were greater than equal to zero. SEM results are slightly biased because the program uses maximum likelihood estimation. Note that SOREMO and SEM do allow for negative variances. With MLwiN, one has the option of allowing for negative variances. If this is done for the example, we obtain the value of -0.091.

There are several advantages in using conventional software over using SOREMO. First, There can be missing data. Moreover groups can contain fewer than the minimum of four people. Second, when group sizes are unequal, the results from different groups are optimally weighted. Third, one can estimate specialized models, such as a model that sets group variance to zero, a model that sets the actor-partner and relationship covariances are zero, or that actor and partner variances equal. So for instance using SAS with dummy variables and setting the group variance to zero yields: actor variance of 0.1989, partner variance of 0.2056, actor-partner covariance of 0.04404, dyadic covariance of 0.03828, dyadic variance of 0.2098, and intercept of

3.8640. The major advantage of SOREMO is that it can estimate in a single run the variance and correlations for a large number of variables.

We have considered in this paper only univariate models. We do note that we used the dummy variable approach with SAS to estimate a bivariate model (Kenny, West, Cillessen, Coie, Dodge, Hubbard, & Schwartz, 2007). We constructed two additional dummy variables for the means of each variable and fixed to error variance to a very small value, essentially zero. Tessa West have also used the SEM approach to estimate a path model in which the actor and partner caused self-ratings but those analyses never were published.

References

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Table 1

Summary of Results Using Different Programs

<u>Term</u>	<u>Symbol</u>	<u>SOREMO</u>	<u>SAS I</u>	<u>SPSS</u>	<u>MLwiN</u>	<u>SAS II</u>	<u>SEM</u>
Mean	m	3.868	3.868	3.868	3.868	3.868	3.868
Actor Variance	σ_a^2	0.233	0.198	0.198	0.198	0.198	0.233
Partner Variance	σ_b^2	0.240	0.192	0.192	0.204	0.204	0.240
Group Variance	σ_m^2	-0.091	0.000	0.000	0.000	0.000	-0.094
A-P Covariance	σ_{ab}	0.059	----- ^a	----- ^a	0.024	0.024	0.059
Error Variance	σ_g^2	0.222	0.237	0.237	0.230	0.230	0.222
Error Covariance	σ_{gg}	0.014	0.032	0.032	0.022	0.022	0.014

^aFixed to zero.

Table 2

SOREMO Output

MEANS FOR THE DYADIC VARIABLES

contribute
3.8681

ABSOLUTE VARIANCE PARTITIONING

VARIABLE	ACTOR	PARTNER	RELATIONSHIP
contribute	.233	.240	.222

RECIPROCITY CORRELATIONS

VARIABLE	ACTOR-PARTNER	RELATIONSHIP
contribute	.250	.062

Table 3

SAS and SPSS Output Using Multilevel Modeling with Actor-Partner Covariance Set to Zero

SAS:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	Actor	0.1923	0.04553	4.22	<.0001
Intercept	Partner	0.1982	0.04630	4.28	<.0001
Intercept	Group	0	.	.	.
CS	Dyad	0.03186	0.03201	1.00	0.3195
Residual		0.2053	0.03347	6.13	<.0001

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	3.8681	0.07072	118	54.69	<.0001

SPSS:

Estimates of Covariance Parameters(b)

Parameter	Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Residual	.2053170	.0334712	6.134	.000	.1491627	.2826113
Intercept [subject = Actor] Variance	.1922936	.0455315	4.223	.000	.1208972	.3058534
Intercept [subject = Partner] Variance	.1981666	.0462966	4.280	.000	.1253628	.3132506
Intercept [subject = Group] Variance	.0000000(a)	.0000000
Intercept [subject = Dyad] Variance	.0318737	.0320114	.996	.319	.0044520	.2281981

a This covariance parameter is redundant. The test statistic and confidence interval cannot be computed.
 b Dependent Variable: I1.

Estimates of Fixed Effects(a)

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	3.8680556	.0707216	117.846	54.694	.000	3.7280056	4.0081055

a Dependent Variable: I1.

Table 4

MLwiN Output with Dummy Variables

$$\beta_{0k} = 3.868(0.075) + v_{0k}$$

$$\begin{bmatrix} v_{0k} \\ v_{1k} \\ v_{2k} \\ v_{3k} \\ v_{4k} \\ v_{5k} \\ v_{6k} \\ v_{7k} \\ v_{8k} \end{bmatrix} \sim N(0, \Omega_v) : \Omega_v = \begin{bmatrix} 0.000(0.000) & & & & & & & & \\ 0 & 0.198(0.046) & & & & & & & \\ 0 & 0 & 0.198(0.046) & & & & & & \\ 0 & 0 & 0 & 0.198(0.046) & & & & & \\ 0 & 0 & 0 & 0 & 0.198(0.046) & & & & \\ 0 & 0.024(0.032) & 0 & 0 & 0 & 0 & & & \\ 0 & 0 & 0.024(0.032) & 0 & 0 & 0 & & & \\ 0 & 0 & 0 & 0.024(0.032) & 0 & 0 & & & \\ 0 & 0 & 0 & 0 & 0 & 0.024(0.032) & 0 & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.024(0.032) & & \end{bmatrix}$$

$$\begin{bmatrix} u_{9jk} \\ u_{10jk} \end{bmatrix} \sim N(0, \Omega_u) : \Omega_u = \begin{bmatrix} 0.230(0.031) & \\ 0.022(0.031) & 0.230(0.031) \end{bmatrix}$$

Table 5

SAS Output with Dummy Variables

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
LIN(1)	Group	0.1978	0.04541	4.36	<.0001
LIN(2)	Group	0.2037	0.04619	4.41	<.0001
LIN(3)	Group	0.02368	0.03392	0.70	0.4851
LIN(4)	Group	0	.	.	.
CS	Dyad	0.02199	0.03250	0.68	0.4986
Residual		0.2083	0.03472	6.00	<.0001

Solution for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	3.8681	0.07451	53.2	51.91	<.0001

Table 6

Estimates of Using Structural Equation Modeling

Intercepts: (Group number 1 - Model 1)

	Estimate	S.E.	C.R.	P	Label
x12	3.868	.057	68.449	***	mm
x13	3.868	.057	68.449	***	mm
x14	3.868	.057	68.449	***	mm
x21	3.868	.057	68.449	***	mm
x23	3.868	.057	68.449	***	mm
x24	3.868	.057	68.449	***	mm
x31	3.868	.057	68.449	***	mm
x32	3.868	.057	68.449	***	mm
x34	3.868	.057	68.449	***	mm
x41	3.868	.057	68.449	***	mm
x42	3.868	.057	68.449	***	mm
x43	3.868	.057	68.449	***	mm

Covariances: (Group number 1 - Model 1)

	Estimate	S.E.	C.R.	P	Label
actor1 <--> partner1	.059	.042	1.396	.163	ap
partner2 <--> actor2	.059	.042	1.396	.163	ap
partner3 <--> actor3	.059	.042	1.396	.163	ap
actor4 <--> partner4	.059	.042	1.396	.163	ap
rel12 <--> rel21	.014	.030	.458	.647	r
rel13 <--> rel31	.014	.030	.458	.647	r
rel14 <--> rel41	.014	.030	.458	.647	r
rel23 <--> rel32	.014	.030	.458	.647	r
rel24 <--> rel42	.014	.030	.458	.647	r
rel34 <--> rel43	.014	.030	.458	.647	r

Variances: (Group number 1 - Model 1)

	Estimate	S.E.	C.R.	P	Label
actor1	.233	.056	4.180	***	a
actor2	.233	.056	4.180	***	a
actor3	.233	.056	4.180	***	a
actor4	.233	.056	4.180	***	a
partner1	.240	.057	4.218	***	p
partner2	.240	.057	4.218	***	p

	Estimate	S.E.	C.R.	P	Label
partner3	.240	.057	4.218	***	p
partner4	.240	.057	4.218	***	p
mean	-.094	.042	-2.227	.026	
rel12	.222	.030	7.325	***	e
rel13	.222	.030	7.325	***	e
rel14	.222	.030	7.325	***	e
rel21	.222	.030	7.325	***	e
rel23	.222	.030	7.325	***	e
rel24	.222	.030	7.325	***	e
rel31	.222	.030	7.325	***	e
rel32	.222	.030	7.325	***	e
rel34	.222	.030	7.325	***	e
rel41	.222	.030	7.325	***	e
rel42	.222	.030	7.325	***	e
rel43	.222	.030	7.325	***	e