CONNECTIONS 22(2): 50-60

A General Permutation-Based QAP Analysis Approach for Dyadic Data from Multiple Groups[1]

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The QAP approach has been extended from the analysis of bivariate correlations to multiple regressions, and is assuming the "workhorse" role for social network analysis analogous to that played by the OLS linear regression for non-network analysis. But there are severe limitations to current implementations, namely the restriction to one group at a time, and to linear regressions. Contemporary computing power makes feasible an implementation that has neither of these restrictions. This paper describes the various alternatives to such an implementation, makes public a user-friendly program for linear and non-linear QAP regressions for data that may come from more than one group, and illustrates its use with an example that sheds some light on the dynamics of influence processes in naturally occurring groups.

THE PROBLEM OF CORRELATED ERROR STRUCTURES AND LIMITATIONS TO EXISTING ROUTINES

As network researchers are painfully aware, the standard errors of model estimates that are normally produced by statistical packages to conduct tests of statistical significance are usually invalid for dyadic data. This is because most derivations of the standard errors require the assumption that all error terms are independent of one another, so that the covariation of any two errors is zero (Hanushek and Jackson 1977: 53). But given dyadic data, each person will contribute to (N-1) dyads, and hence it is quite likely to be the case that the "error" that characterizes one dyad involving ego is similar to the error characterizing another dyad involving ego, or that the errors are "autocorrelated." In this case, the formula giving the variances of the estimates is incorrect, even if the estimates themselves are correct. Therefore, statistical inferences based on network data are likely to be wrong. It is this problem that the Quadratic Assignment Procedure (QAP) attempts to solve.

While the Quadratic Assignment Procedure (Hubert and Schultz 1976; Baker and Hubert 1981; Hubert 1985) is a general--and complex--analytic strategy, it is most commonly implemented for network data in a form analogous to an exact test; we use the observed data to generate a distribution of possible alternative outcomes; we then compute the statistical significance of our observation against this distribution. While certain usages of QAP may in fact be biased (Krackhardt 1992), Krackhardt's (1987, 1988) simulations show that QAP analyses are more likely to discriminate between significant and insignificant correlations than are conventional OLS (Ordinary Least Squares) statistics.

QAP multiple regressions have been incorporated in UCINET (Borgatti, Everett and Freeman 1992), the most popular general network program. But the existing implementations have two limitations. First, one cannot simultaneously fit models to more than one group at a time. (If we were to use a standard QAP package, it would attempt to permute members into groups in which they could not possibly belong, leading to an overwhelming amount of missing data.) Second, models for data with dependent variables that are dichotomous (e.g. logistic or probit regression), and models for data with dependent variables that take on only a few small non-negative integer values (e.g. Poisson or negative binomial regression) cannot be fit. These limitations close off many avenues of investigation to network researchers. There are a number of existing techniques that can be used to handle one or the other of these limitations; in the next section, I briefly review these, and then go on to present a general QAP framework for the analysis of multiple networks, and compare the results obtained via this program to those obtained via other techniques.

OTHER OPTIONS

Multiple Networks

The first limitation discussed was that existing QAP implementations are unable to analyze data from more than one group at a time. But it is possible to do separate analyses for each network, and then summarize the results in a meta-analytic procedure (for example, see Krackhardt and Porter 1986). In addition to doing a meta-analytic test of the significance of dyadic-level covariates, one may conduct a second model at the group level, by regressing the constants on group-level variables (for a two-stage analysis of network data using somewhat similar reasoning, see Blau and Alba 1982). Such a procedure has certain advantages; for example, by separating the groups, the biases that are associated with mixed level models are avoided. However, this procedure has drawbacks. Most importantly, we are unable to constrain the coefficients to be equal across groups; while the meta-analysis may still allow us to pass judgement as to the significance of some coefficient in the sample as a whole, we are not able to use the multiple groups to attain any precision in the estimation of this coefficient.

Correlated Error Structures

The other limitation of the standard QAP implementation has to do with the restriction to linear regression, as opposed to other models specifically designed for dichotomous dependent variables or counts with low means. Since dichotomous data appear frequently in network research (often, relations are either present or absent), and because the problems of using a linear model for dichotomous dependent variables (namely that predicted probabilities can be greater than one or less than zero) are more severe than those that come from fitting a linear model to data that may be Poisson distributed, I focus on the former case for the rest of this section, and discuss existing ways of fitting logistic (or probit) regression models to network data. There are many approaches to correlated error structures for logistic models, but these approaches are in general not applicable. That is because they generally assume that the correlations are across a set units, all of which are hierarchically nested within a some categorical schema (for example, given nonlinear models such as logistic models, see Goldstein 1991, Longford 1994). But there are recent models for network data that in some cases can be used to produce logistic regressions.

The *p** Model

First, there has been an explosion of work extending the Holland-Leinhardt (1981) p_1 model to handle situations of where the dyads are not independent after conditioning on node characteristics. While this approach begins from the “one tie” case, it can be extended to cover the relation between two dyadic variables. For a simple example, given two dichotomous relations **X** and **Y**, (=0,1), a graph statistic $G=\sum x_{ij}y_{ij}$ may be used as the basis for an estimate of a parameterization of the association between the two relations (Wasserman and Pattison 1996: 421). Thus the simplest "positive association" model can easily be incorporated as a form of dyadic dependence of **X** on **Y** restricted to those dyads $x_{ij,}$ y_{kl} in which i=k and j=l. Pattison and Wasserman (forthcoming) extend this to a more complete multivariate framework, and they suggest a wide class of dependence models for such data. Finally, this approach may also be extended to multiple networks (Anderson, Wasserman, and Crouch 1999: 55).

The *p** approach has the advantages of generality and flexibility; however, there are some disadvantages. Many of the disadvantages also apply to most rigorous network studies, such as the absence of a direct retrieval of standard errors of the estimates of parameters, or the assumption (required for pseudo-likelihood estimation) regarding the independence of observations. As this latter assumption can also be stated as an assumption that all dependencies between observations have been taken into account in the model, it is actually an assumption made by other models, including a QAP model. Perhaps of greater practical importance, then, is the exponential complexity that results when a number of relations, especially polychotomous, are taken as predictors of another relation (see Robins, Pattison and Wasserman, forthcoming, for an extension to valued data). While it should be possible in principle to extend the model to include continuous dyadic covariates, this has not yet been done.

The p_2 Model
A different extension of the p_1 framework is found in the p_2 model of van Duijn and Snijders (forthcoming); also see Lazega and van Duijn (1997). In essence, the (fixed but unknown) expansiveness and attractiveness parameters of the p_1 model are made linear functions of a set of individual level covariates and random errors. The p_2 model also parameterizes the density and the reciprocity as a function of dyadic parameters. As a result, the p_2 model can be used to study logistic regressions between dyadic variables. Like the QAP framework (and unlike the p_1 model), there is an explicit introduction of correlated errors associated with each person, leading to correlation of errors across dyads, but the p_2 model differs from a QAP implementation in a number of ways.

For example, given a dependent variable **Y** and two independent variables **X** and **Z**, within the p_2 framework we model the density of **Y** $\mu_{ij}=\mu + X_{ij}\delta_1 + Z_{ij}\delta_2$. (For simplicity of exposition, I ignore the possibility of modeling the reciprocity parameter, and instead, constrain this parameter to be zero in the logarithmic metric.) Covariates on the individual level (such as those employed in the example below) are taken into account separately. Because of the random error structure assumed for the residual attractiveness and expansiveness not explained by covariates, the resulting model is quite close to a QAP logistic model. So while p_2 can allow for the fitting of logistic models with continuous covariates that are difficult to fit within the *p** framework, it cannot fit other models, and its use is restricted to those with GAUSS. It is also not implemented for sets of dyads from more than one network.

A GENERALIZED QAP FRAMEWORK

In sum, there is no convenient way to fit logistic and related models to network data, especially not to multiple networks. As a result, I introduce a generalized QAP framework that allows for the fitting of linear and non-linear models to data from multiple networks. This approach is made actual in a program for Windows NT/95/98, Dyadic Analysis for Multiple Networks. In addition to linear regressions, the program DAMN fits logistic, probit, poisson, and negative-binomial regressions.[2] I first discuss the larger QAP routine, then the model fitting, and then particularities.

The outer shell of the algorithm is a QAP permutation routine, which randomly permutes individuals within their own group. In other words, we reconceive the QAP procedure as reproducing a distribution in which it is impossible that persons could have been in different groups. From this reconstructed distribution, an unbiased estimate of an exact test can be retrieved. This means that any given number of permutations may be more (or less) adequate to characterize this distribution for groups that are smaller (or larger) than others. Otherwise, the basic approach is the same as for a single group. For each permutation, the model in question is fit, and a tally kept of how many times coefficients equal to or larger than those found in the actual data are observed, leading to a p-value.[3]

When we fit data from more than one group, our model is technically a multilevel model. As is well known, the standard errors for group level variables in such models tend to be biased due to autocorrelation problems (Mason et al. 1983, DiPrete and Forristal 1994). But the QAP test for such group level variables is wholly meaningless, since all the permutations occur *within* groups. Thus neither the conventional test nor the QAP test gives us a good measure of such group level variables. The methods for correcting such models (see Bryk and Raudenbush 1992) require the covariance matrix for the parameters, which the permutation test does not produce. As a result, there is no good test of the significance of such group level variables, nor whether the multilevel nature of the model biases other coefficients, most importantly, interactions between dyadic and group level variables. An extremely conservative test would be a fixed effects model, in which we add a dummy variable for each group save one. Such a fixed effects model is automated in DAMN for when one wants to carry out “worst case” comparisons.

The model fit for each permutation may be either a conventional linear regression, or a logistic, probit, Poisson, or negative binomial regression. Each of these requires iterative fitting, and hence leads to a dramatic increase in the time necessary to complete a QAP analysis, in contrast to the linear regression, which has a closed form solution.[4] For large data sets, the time required can be significant (on the order of 10s of minutes, say).[5] Further, with such iterative fitting, different statistical routines can lead to different coefficient estimates. Hence the results obtained from this program may differ from those obtained from other programs. These differences may arise due to differences in standards of tolerance for convergence, differences in the way that near-infinite estimates are treated, and the precise nature of the maximization routine. Such differences are likely to be largest when *N*s are small but coefficients are large, such as when some data are extremely skewed. In such cases, the likelihood surface may be rather flat, in that there is a range of parameter values which produce more or less the same predicted frequencies. In such cases, results differ greatly according to the algorithm used. Experience suggests that the logistic routine is more robust than the probit routine in such circumstances.

The combination of multiple permutations and iterative fitting can lead to a lengthy process when data from a number of different groups are analyzed at one time. In such cases, doing the traditional 3000 or 5000 permutations can bog down a computer for something easily on the order of half an hour. However, it is possible to avoid such a lengthy process in many cases, since it may be that after just 300 permutations we are close to the true p-value. The problem is, of course, that we do not know in advance when 300 permutations are adequate and when we need 3000 or more. DAMN solves this by compartmentalizing its permutation results into separate logical “bins,” and comparing the p-values across bins. When the range is less than some specified amount, it considers its process to have “converged.” Further savings in time can be made by ignoring the coefficients for the constant and the fixed effects discussed above. Finally, since we are often interested in certain critical tests (such as p<.05 as opposed to p>.05), DAMN can restrict its attention to those coefficients which seem to be straddling some critical test value. Other p-values are ignored, which is especially helpful as it is non-significant coefficients which are most likely to change with sampling-via-permutations. As a result, it is sometimes the case that a complex model can be fit without too long a wait.

Other Features of the Program

DAMN is intended as a general platform for dealing with dyadic data from multiple networks, but not for manipulating the data. Recoding and similar transformations must be done in another environment, and the final file saved in a standard tab delimited ASCII file with variable names. However, to avoid the production of large data files, DAMN will automatically flip independent variables around, so that they refer to alter's reports, and not ego's reports. This can be done with the dependent variable as well, to determine reciprocity effects. DAMN not only carries out the analyses discussed above, but can be used to generate network files that can be read by other programs (such as UCINET and KRACKPLOT). In addition, DAMN permits the viewing of the data for each group, both as a matrix and as a graph.

EXAMPLE

For purposes of brief illustration, I take some illustrative data from the Urban Communes Data Set (Zablocki 1980), a set of network data from over 40 naturally occurring communities in the 1970s.[6] I will first use one group of 18 persons, and then a combined set of 40 groups, to examine some of the sources of social influence. Respondents were asked to name those in the group that they thought were "influential"; for any dyad, then, either ego did or did not name alter as influential. Were such attributions of influentiality tied to a *hierarchical* ordering of persons, or was there a tendency towards *mutuality* of such attributions?

Table 1
Results for Commune 57

	Model 1	Model 2	Model 3
Ego's Status	-0.429	0.35	0.999
	[p=.540]	[p=.324]	[p=.227]
	{rg=.400}	{rg=.100}	{rg=.100}
Alter's Status	3.733***	2.955**	2.921*
	[p<.001]	[p=.032]	[p=.024]
		{rg=.030}	{rg=.017}
Ego Defers to Alter		1.714***	1.713***
		[p<.001]	[p<.001]
Alter Claims Power		1.124**	1.108***
		[p=.002]	[p<.001]
		{rg=.010}	

Reciprocity			-152.848
			[p=1.000]
Constant	-3.568	-4.363	-4.292
Log-Likelihood	-43.388	-39.12	-38.82

If attributions of influentiality are tied to persons' positions in a strictly *hierarchical* order, we would assume that those alters who are of higher status would be more likely to receive attributions of influentiality than those of lower status. To measure status, I use that latent measure that is retrieved by the "symmetric" model for observed responses to a question on the balance of interpersonal power that is discussed in Martin (1998). I note that such a case can be treated within the p_2 model, but not within the p^* (because of the continuous covariates). Our first model has attributions of influentiality as a dependent variable, and ego's and alter's statuses as independent variables. The results are displayed in Table 1, Model 1.

For each coefficient, we have the value in logarithmic terms, the QAP p-value, and, for coefficients that were not taken into account in the convergence decision, the "range" of estimated p-values across bins. Thus the coefficient for ego's status is clearly not significant, and while the estimates of the exact p-value varied widely (over a range of .4), none fell on the other side of the line p=.1. While ego's status is not related to influentiality, then, alter's status most decidedly *is*. The p-value here was actually *zero*—no permutations had values for this coefficient as great as that which was observed. It does seem that there is a strong hierarchical component to influentiality—high status people are more likely to be chosen as influential.

Of course, there is a possible confounding factor, since an $(N-1)^{th}$ part of the measure of alter's status is ego's power relation with alter. (This is because the alter's status measure is based on the set of N-1 dyadic power relationships between alter and the other members of the group.) It might be that it is simply the dyadic relation between ego and alter that is important, and not alter's overall standing within the group. To test this, model 2 adds dummy variables for ego deferring to alter (saying alter has more power than ego), and alter claiming to have more power than ego. Hence we have two closely related measures of the existence of a power relation between ego and alter. As we find out, both of these measures are indeed related to the likelihood that ego will see alter as influential—the dyadic power relation *does* matter. But it does not make the effect of alter's status insignificant, though it is decreased slightly. I note that while the same general pattern of findings is retrieved by the p_2 model (constrained to have no reciprocity effects), the coefficients are not always twice their standard errors.[7]

In other words, in this commune, we find a strong hierarchical component to the organization of influence. But what about the effects of reciprocity? Do these also exist? It is, after all, possible that there are both hierarchical and reciprocal effects. Model 3 enters this effect, which produces a preposterous logged coefficient of –152. This is because there simply are no dyads with mutual attributions of influentiality in this group. In general, this would seem a strong finding. But influentiality is a relatively rare attribution (with 14 attributions in the group as a whole, there is less than one per member on average). Unless there was a strong tendency towards mutuality, we might never see it with simply this one group, since by chance, there are unlikely to be mutual attributions even were there no negative effect. (And the p-value of 1.00 confirms that this large number is more or less meaningless.[8])

But if we assume that the magnitude of the effects is the same across all 40 groups in this sample, by pooling the dyads, we can get an answer to the question of a tendency towards reciprocity in attributions of influentiality. Table 2 contains replications of models 1-3 for this larger set of around 3500 (asymmetric) dyads. Model 1 demonstrates that while the effect for alter's status is more or less the same in all groups together as it is in the one group examined, the net effect of ego's status in the larger sample seems to be mildly, but quite significantly, positive. Model 2 also confirms that while adding measures of the dyadic power relation reduces the magnitude of the coefficient for alter's status, it does not eliminate it. Finally, Model 3 enters the reciprocity effect, and it is significantly positive. While not as large as the effect of alter's status, it is roughly of the magnitude of the effect of the dyadic power relation (ego deferring to alter). Further, because we have controlled for ego and alter's status, we know that this is not actually a "ceiling" effect masking itself as reciprocity. (That is, if alter's status, but not ego's status, led to a high probability of ego attributing influentiality to alter, there would be an apparent reciprocity effect since the high status members would have no one else to choose but each other.)

In sum, by pooling the dyads, we are able to get considerable insight as to the dynamics by which group members perceive others as influential, though we might not be able to determine these by examining one single group.

Table 2
Results for 40 Combined Groups

	Model 1	**Model 2**	**Model 3**
Ego's Status	.455***	.974***	.649*
	[p<.001]	[p<.001]	[p=.010]
			{rg=.010}
Alter's Status	2.444***	1.784***	1.801***
	[p<.001]	[p<.001]	[p<.001]
Ego Defers to Alter		.975***	.938***
		[p<.001]	[p<.001]
Alter Claims Power Reciprocity		.531**	.532**
		[p=.002]	[p=.008]
			.942***
			[p<.001]
Constant	-2.247	-2.61	-2.745
Log-Likelihood	-1154.61	-1116.58	-1097.85

CONCLUSION

Increases in computing power make possible the substitution of processor-hungry routines for mathematically elegant ones. For social network researchers, this means that it is possible to use a permutation-based test for the significance of coefficients for a wide variety of models which otherwise might not be applied. A freely-available and user-friendly program allows the implementation of the most widely used models for single dependent variable regression type models.[9]

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Appendix A

Sample Input File for DAMN

GROUP	EGO	ALTER	INFLUE	STATUS	STATUSA	EGODEFER	BLANK
19	172	173	0	.4633	-.2325	0	.5
19	172	174	0	.4633	.501	0	.5
19	172	175	0	.4633	-.04	0	.5
19	172	176	0	.4633	-.6918	0	.5
19	173	172	1	-.2325	.4633	1	.5
19	173	174	1	-.2325	.501	1	.5
19	173	175	0	-.2325	-.04	1	.5
19	173	176	0	-.2325	-.6918	0	.5
19	174	172	0	.501	.4633	0	.5
19	174	173	0	.501	-.2325	0	.5
19	174	175	0	.501	-.04	0	.5
19	174	176	0	.501	-.6918	0	.5
19	175	172	0	-.04	.4633	0	.5
19	175	173	0	-.04	-.2325	0	.5
19	175	174	0	-.04	.501	0	.5
19	175	176	0	-.04	-.6918	0	.5
19	176	172	0	-.6918	.4633	0	.5
19	176	173	0	-.6918	-.2325	0	.5
19	176	174	0	-.6918	.501	0	.5
19	176	175	0	-.6918	-.04	0	.5
42	196	197	1	.6011	.1988	0	.5
42	196	198	0	.6011	-.5532	0	.5
42	196	199	0	.6011	-.4858	0	.5
42	196	200	0	.6011	.239	0	.5
42	197	196	0	.1988	.6011	1	.5
42	197	198	0	.1988	-.5532	0	.5
42	197	199	0	.1988	-.4858	0	.5
42	197	200	0	.1988	.239	0	.5
42	198	196	1	-.5532	.6011	1	.5
42	198	197	0	-.5532	.1988	0	.5
42	198	199	0	-.5532	-.4858	0	.5
42	198	200	0	-.5532	.239	1	.5
42	199	196	0	-.4858	.6011	1	.5
42	199	197	1	-.4858	.1988	1	.5
42	199	198	1	-.4858	-.5532	0	.5
42	199	200	0	-.4858	.239	0	.5
42	200	196	0	.239	.6011	0	.5
42	200	197	0	.239	.1988	0	.5
42	200	198	0	.239	-.5532	0	.5
42	200	199	1	.239	-.4858	0	.5

Appendix B

Sample Output File for DAMN

```
Logfile for DAMN program.
DATE : 11/10/1999
TIME : 1:33PM
+-----------------+
|      DAMN       |
+-----------------+
Data Analysis for Multiple Networks.
Version BETA.2
(This version fixes permutation for low numbers)


Load data file ex2gp.DAT?
Press to read in   40 cases; otherwise enter a different
number
Reading file ex2gp.DAT


Press to read in   4 variables; otherwise enter a
different number
Reading  4 variables.
DAMN read  40 dyads from   2 groups.
Choose one of the following:
(F) Create a set of group-level files
(A) Analyze using QAP
(N) New Data File
(D) Pass on DOS commands
(X) Exit
> a
Do only some groups?
?
** ANALYSIS MENU **
(R) Linear Regression
(L) Logistic Regression
(P) Probit Regression
(S) Poisson Regression (the S is for Simeon Denis)
(N) Negative Binomial Regression
(C) Change settings
(G) Just change group being analyzed
(X) Exit to main menu.
> L
QAP modeling done by default--type 'N' to override.
?
Select a dependent variable to use.
> influe
Input IVs by name; separate with blanks; ignore
end of line (don't press until all done).
> status statusa
Do fixed effects model?
?
Converged at permutation      50
```

```
*** REGRESSION PARAMETERS ***
STATUS    coefficient=  -0.86009  p-value=0.20000
 range=0.20000
STATUSA   coefficient=   0.63684  p-value=0.38000
 range=0.10000
constant  coefficient=  -1.64139  p-value=0.40000
Final Likelihood:      -17.776853

** ANALYSIS MENU **
(R) Linear Regression
(L) Logistic Regression
(P) Probit Regression
(S) Poisson Regression (the S is for Simeon Denis)
(N) Negative Binomial Regression
(C) Change settings
(G) Just change group being analyzed
(X) Exit to main menu.
> L
QAP modeling done by default--type 'N' to override.
?
Select a dependent variable to use.
Press to re-use the following (or enter new):
influe
>
Press to re-use the following (or enter new):
STATUS STATUSA
> STATUS STATUSA egodefer
Do fixed effects model?
?
Maximum estimate deviation is 0.200000 at permutation
number 50
Maximum estimate deviation is 0.200000 at permutation
number 100
{****etc.}
Maximum estimate deviation is 0.094737 at permutation
number 950
Converged at permutation    1000

*** REGRESSION PARAMETERS ***
STATUS    coefficient=  -0.20313  p-value=0.37500
 range=0.05000
STATUSA   coefficient=  -0.62174  p-value=0.29300
range=0.09500
EGODEFER  coefficient=   2.52461  p-value=0.00100
range=0.00500
constant  coefficient=  -2.34395  p-value=0.14100
Final Likelihood: -15.379511

** ANALYSIS MENU **
(R) Linear Regression
(L) Logistic Regression
(P) Probit Regression
(S) Poisson Regression (the S is for Simeon Denis)
(N) Negative Binomial Regression
(C) Change settings
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(G) Just change group being analyzed
(X) Exit to main menu.
> x
Choose one of the following:
(F) Create a set of group-level files
(A) Analyze using QAP
(N) New Data File
(D) Pass on DOS commands
(X) Exit
> x
Session ended relatively normally
```