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SerpilKılıç (Faculty of Arts and Sciences, Department of Statistics, Yıldız Technical University, Davutpasa Campus, 34220, Esenler, İstanbul)

Ahmet Mete Çilingirtürk (Faculty of Economics and Administrative Sciences, Marmara University, Bahçelievler Campus, 34180, Bahçelievler, İstanbul)

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Author (s)

SerpilKılıç
Res. Assist., Faculty of Arts and Sciences, Department of Statistics, Yıldız Technical University, Davutpasa Campus, 34220, Esenler, İstanbul.
E-mail: serkilic@yildiz.edu.tr

Ahmet Mete Çilingirtürk
Prof. Dr., Faculty of Economics and Administrative Sciences, Marmara University, Bahçelievler Campus, 34180, Bahçelievler, İstanbul.
E-mail: acilingi@marmara.edu.tr

Abstract

Longitudinal studies involving binary responses are widely applied in medical, health and economic science research, have focused increasingly on how various independent variables affect responses over time. These studies involve repeated observations on a subject and thus correlation within each subject is expected. Correct inferences can only be obtained by taking into account the correct specification of within-subject correlation structure between repeated observations. In recent years, non-normal longitudinal data is analyzed by Generalized Estimating Equations (GEE) method. Goodness-of-fit statistics have been suggested for selecting an appropriate working correlation structure in GEE with longitudinal binary data. The purpose of this article to provide an overview of the GEE approach for analyzing correlated binary data and to choose the structure of the correlation matrix between repeated observations for model comparison, using data from Istanbul Stock Exchange (ISE) to increase on the return.

Keywords: Working Correlation Structures; Generalized Estimating Equations; Longitudinal Binary Data; Entropy

JEL Codes: C33, G00

Introduction

Generalized estimating equations (GEE) approach which extends generalized linear models is a very popular for the situation of correlated data obtained longitudinal studies. Although GEE models can be used for continuous responses, they have often become for analysis of categorical and count responses. GEE models use quasi-likelihood estimation and full likelihood of the data is not necessary. It does not need multivariate distributions, because GEE assumes only a functional relationship for marginal distribution at each time point. (Hedeker and Gibbons, 2006, 135). This approach is complex to interpret and implement from classical analysis approach. Despite the many benefits of classical analysis, it has some constraints. These are: (1) it does not model the mean response changes across time on each subject; (2) it has some assumptions about the variance-covariance matrix. For example; in the classical regression model, a single observation of the response variable is considered as the observational unit. Therefore, the statistical modeling assumes independence between observations (Lee et al., 2007, 188). But the assumption of independence is not usually used in longitudinal studies, because the relationship between repeated observations over time on the same subject can be correlated; (3) it does not consider about the structure of dependence between repeated observations obtained from the same subject. For these reasons, the classical approaches are insufficient.

The structure of correlation is important to produce efficiency (i.e., statistical power) in the estimation of the regression parameter. However, the loss of efficiency is lessened as the number of subjects gets large. If the correlation data is correctly identified, the inferences about hypothesis tests and confidence intervals will be valid and correct.

In this study, we consider to correlated binary data and compare several criteria that can be obtained the final selection of working correlation structure.

Generalized Estimating Equations

A review of GEE method

GEE models are used for analyzing longitudinal binary studies involve binary responses for each subject and a set of covariates varying with or without time. Consider a longitudinal binary data set comprising (X_{it},Y_{it}) for i=1,…,n; t=1,…,n_i. For the i^{th} subject, there are n_i repeated binary response variables. Define a n_ix1 binary response vector as $Y_i=(Y_{i1},…,Y_{in_i})'$ and a $n_i$xp covariate matrix as $X_i=(X_{i1},…,X_{in_i})'$ with a p-dimensional covariate vector X_{it}. The binary response variable Y_{it}=1 at time t, if the subject i has response 1, success and Y_{it}=0 if otherwise. It is assumed that n_i=m for all i and N=mn (Lin et al., 2008, 4428).

The most important problem in this method is to determine the (co)variance structure. Even if the covariance structure has been misspecified in longitudinal studies, GEE method yields asymptotically normal and consistent for estimated parameters. GEE specifications are similar to generalized linear model (GLM), but those of GLM with one addition are comprised by GEE approach. There are three specifications in this model. First, the linear predictor is given as

$$\eta_{it} = X'_{it}\beta \qquad (1)$$

Then a link function is chosen in Equation2.

$$g(\mu_{it}) = \eta_{it} \qquad (2)$$

The common choices for link function are identity, logit, and log for continuous, binary and count data, respectively. The variance is described as a function of the mean,

$$V(y_{it}) = \phi \upsilon(\mu_{it}) \quad (3)$$

where $\upsilon(\mu_{it})$ is a variance function and ϕ is a scale or distribution parameter. When each subject is measured at all m time points, the working correlation matrix of the repeated observations is of size mxm. If a subject has been measured at $n_i$timepoints (n_i<m), each subject's correlation matrix R_i will be of size $n_i x n_i$. α is a vector of association parameters which are assumed to be the same for all subjects. (Hedeker and Gibbons, 2006, 135)

Working Correlation Structures

There are some possible correlation structures to be appropriate to use in GEE. These structures are independent, exchangeable, autoregressive, m-dependent and unstructured. The most commonly used working correlation structures and estimators are given in the Table 1.

If data is balanced and there are clusters with small number of observations, the unstructured correlation matrix is recommended. An exchangeable correlation matrix may be most appropriate for datasets with clustered observations, which may not have a logical ordering at observations within a cluster. When the observations have been mistimed, it may be appropriate to regard a model where the M-dependent or autoregressive correlation is a function of the time between observations. Any estimation of α is not performed for both the independence and fixed working correlation structures (Horton and Lipsitz, 1999, 161).

This paper presents the use of entropy for working correlation matrix, which supports an unstructured dependence within the time points. Although the word "entropy" originated in the literature of thermodynamics, its usage has penetrated almost all disciplines due to its association with the concept of information as envisaged by Claude Shannon.

If the probabilities can be used rather than raw results, entropy can be calculated for one variable and can also be used for researching dependence between two or more variables. Due to this future of entropy, it could be a possible alternative for correlation coefficient. Because of the importance of working correlation matrix in GEE, it is crucial to use different working correlation structure in order to obtain efficient results. Therefore, entropy matrix could be the possible alternative for common working correlation matrix.

The entropy and entropy correlation coefficient(ρ_{H_1}, ρ_{H_2}) formulations are given in Equation 4-8.

$$H(X) = -\sum_{i=1}^{n} p_i \log(p_i) \quad (4)$$

$$H(X,Y) = -\sum_i \sum_j p(i,j) \log\big(p(i,j)\big) \quad (5)$$

$$I(X,Y) = H(X) + H(Y) - \ldots\ldots\ldots(6)$$

$$\rho_{H_1} = \sqrt{2\left(I(X,Y)\right)/H(X)} \ldots\ldots\ldots(7)$$

$$\rho_{H_2} = I(X,Y)/H(X,Y) \ldots\ldots(8)$$

GEE Estimation

The working covariance matrix for Yi equals $V_i = \phi A_i^{1/2} R_i(\alpha) A_i^{1/2}$ ....(9)

where A_i is mxm diagonal matrix with $V(\mu_{it})$ as the t^{th} diagonal element. ϕ is an overdispersion parameter that can be estimated as follows:

$$\hat{\phi} = (1/N - p)\sum_{i=1}^{n}\sum_{t=1}^{n_i}(Y_{it} - \mu_{it})/\sqrt{V(\mu_{it})} .(10)$$

where N is the total number of observations and p is the number of regression parameters. The square root of the overdispersion parameter is called the scale parameter.

The GEE estimator of β is the solution of $S(\beta) = \sum_{i=1}^{N} D_i' V_i^{-1}(Y_i - \mu_i) = 0$....(11)

where Di is the matrix of derivatives

$$\partial\mu_i/\partial\beta \ldots\ldots\ldots\ldots\ldots\ldots(12)$$

Iterative process for GEE's is given the following:

1. Start with R_i=independent (i.e., identity) and ϕ =1: estimate β.
2. Use estimates to calculated fitted values: $\hat{\mu}_i = g^{-1}(X_i\beta)$
3. Residuals: $Y_i - \hat{\mu}_i$
4. These are used to estimate A_i, R_i and ϕ
5. Then the GEE's are solved again to obtain improved estimates of β.

$$\beta_{r+1} = \beta_r + \left[\sum_{i=1}^{N}(\partial\mu_i'/\partial\beta)V_i^{-1}(\partial\mu_i/\partial\beta)\right]^{-1}$$

$$\left[\sum_{i=1}^{N}(\partial\mu_i'/\partial\beta)V_i^{-1}(Y_i - \mu_i)\right] \ldots\ldots\ldots(13)$$

6. Between step 2 and 5 are repeated to converge to a value of β (Kılıç and Çilingirtürk, 2011, 327).

Model Selection and Goodness of Fit Tests

This paper examines three model selection criteria which are Marginal R^2, QIC and QIC_U estimates.

Repeated observations are correlated over time points, therefore residuals are not independent. R^2 in the ordinary least squares method cannot be used for GEE directly. An extension of R^2 statistics in GLM is called as Marginal R^2 for GEE (Zheng, 2000, 1268). It can be calculated as shown below.

$$R_{Mrj}^2 = 1 - \left[\left(\sum_{t=1}^{n_t}\sum_{i=1}^{n}(Y_{it} - \hat{Y}_{it})^2\right)/\left(\sum_{t=1}^{n_t}\sum_{i=1}^{n}(Y_{it} - \bar{Y}_{it})^2\right)\right] \ldots(14)$$

Marginal R^2 is a statistical measure which is often interpreted as the proportion of response variation "explained" by the fitted model. SAS PROC GENMOD could not be given Marginal R^2, so this measurement is calculated with the macro %SelectGEE.

One of the goodness-of-fit statistics, Akaike's Information Criterion (AIC), can be used for comparing competitive models. But this criteria could not be used for GEE method. Because GEE is not a likelihood-based method. In this reason, Pan (2001) introduced a selection method which named as Ouasilikelihood under the Independence Model Criterion (QIC). QIC is similar to AIC. The formulas AIC and QIC are given as follows: $AIC = -2L + 2p$..............(15)

where L is the log likelihood and p is the dimension of β.

$QIC = -2Q(\hat{\beta}(R); I, D) + 2trace(\hat{\Omega}_I \hat{V}_r)$...

....(16)

$-2Q(\hat{\beta}(R); I, D)$

Is quasi likelihood computed using R, Ω^_I is the inverse of the variance matrix by fitting an independence model and $\hat{V}_r$ is modified sandwich estimate of variance from the model with R in Equation 16.

When $trace(\hat{\Omega}_I \hat{V}_r)$ approximates p, Pan (2001) also proposed QIC_U which could be useful in variable selection, but it is not used for model comparison. QIC_U's formula is given in Equation 17 (Hardin and Hilbe, 2003,

139). $QIC_U = -2Q(\hat{\beta}(R); I, D) + 2p$...(17)

Marginal R^2, QIC and QIC_U are the criteria of the evaluation of choosing the best model. In this process, the model with lower value of QIC and QIC_U and higher value of Marginal R^2 should be taken into account.

These criteria are obtained by special macro software in the SAS 9.2 program (support.sas.com/resources/papers/proceedings09/251-2009.pdf, 2011, 5).

Stock Price Change Model

The significance and purpose of this study

The purpose of this study is to model the ISE Stock Price Change and to present the entropy working correlation matrix. The model will have a technical analyses approach, because it takes just the increase signal in a quarterly base. According to goodness-of-fit criteria, appropriate working correlation structures in the GEE analysis of longitudinal studies with binary responses is determined. Furthermore, it is showed that which variables is the most effective on stock prices. One of the most thought in investors is to predict the future direction of stock prices. Stock prices have more volatility than the other investments. The most commonly used analyses in evaluating of the stock prices are fundamental and technical analysis. Fundamental analysis is a method of evaluating securities by attempting to measure the intrinsic value of a stock. Fundamental analysts study everything from the overall economy and industry conditions to the financial condition and management of companies. Technical analysis is the evaluation of securities by means of studying statistics generated by market activity, such as past prices and volume. Technical analysts do not attempt to measure a security's intrinsic value but instead use stock charts to identify patterns and trends that may suggest what a stock will do in the future" (http://www.investopedia.com/ask/answers/131.asp, 2011).

Data Sources

Using 100 transactions data chosen ISE between 2008/12 and 2010/12 quarterly, we estimate parameter estimates and the corresponding standard errors under exchangeable, AR(1), M(2) dependent, unstructured and entropy correlation structures via GEE method. We compare the criteria for choosing between these structures. In this study, response variable is stock price. According to the technical analysis, it is coded 1 if it increases according to the previous 3-month period, otherwise 0. Covariate variables are transaction volume, stock dividend, cash dividend, increase of capital, price index, exchange rate of dollar, Nomenclature Generale des Activites Economiques dans I'Union Europeenne, NACE, (General Name for Economic Activities in the European Union) Codes and time. Transaction volume and dividend paid in cash are coded 1 if it increases according to the previous 3-month period, otherwise 0. The effects of NACE, increase of capital and stock dividend of these factors on stock return are not statistically significant. We take the transaction volume and dividend paid in cash as the covariate variables.

Findings and Results

Let μ_{it} denote the mean, the probability of increasing stock prices for i=1,…,100 stocks and t=3 (baseline), 6, 9, 12, 15, 18, 21, 24 months. logit link function for binary responses can be shown as follows:

$$logit(\mu_{it}) = \beta_0 + \beta_1 TV + \beta_2 DC + \beta_3 TIME \ldots(18)$$

where β_0, β_1, β_2, β_3 are the regression coefficient parameters for intercept, the size of transaction volume, dividend paid in cash and time respectively. Table 2 presents the results of the GEE models using several various working correlations. The analysis results are similar in the estimated parameters for all structures. The negative sign of the regression coefficient of time variable indicates that decreasing on stock prices is stronger at the beginning of the follow-up period. From the results, high the size of transaction volume and dividend paid in cash have significantly positive effect on increasing stock prices. However, as shown in Table 2, p-values imply that there are statistically significant effects on these variables. Table 3 summarizes the results of the analysis with different working correlation structures. Although QIC and Marginal R^2 have selected the best fitting model, these criteria are very close for all structures. The M(2) dependent structure is found to have the smallest QIC in all other structures and thus is selected as the preferred working correlation structures. For without time dependent data set, this structure is used to consider as a function of time between observations, M(2) dependent is preferred.

Conclusions

We have discussed selecting the working correlation structure in GEE with longitudinal binary response. An application of longitudinal studies to data on stock price is used as an example. GEE is relatively new method for the analysis of longitudinal studies on stock price. GEE method yields the estimates of regression coefficients and their variances from different correlation structures that can be sensitivity to incorrect specification. $\hat{\beta}$ will be estimated asymptotically normal and consistently, even when the working correlation structure is misspecified. The choice of R_i will influence the efficiency for estimates of parameters and variances. It is more efficient to use R_i that is chosen correct specification. For this study, the results of the correlation structure M-dependent and AR(1) are more similar. If the repeated observations across subjects are measured at equally spaced in time, AR(1) structure is preferred in longitudinal data (Shults et al., 2009, 2353). M-dependent structure is used to consider as a function of time between observations for without time dependent data set. According to Marginal R^2, QIC and QIC_U of selection criteria, M(2) dependent structure is preferred in this study. However, one of the main points of this study is to compare the efficiency of the entropy matrix as a working correlation structure to other structures. According to Marginal R^2, QIC and QIC_U of selection criteria (lower QIC and OIC_U values and higher Marginal R^2 value), entropy matrix is preferred instead of unstructured correlation matrix. This result showed that entropy matrix could be used as a working correlation structure instead of unstructured correlation matrix in this study. In order to determine the status of the stock price, financial ratios are calculated by balance sheets, financial and income statements of companies. Further studies are needed to investigate how to affect these ratios as covariate variables when more common working correlation structures are used.

Table 1.Commonly used working correlation structures and estimators

Working Correlation Structures	**Definition**	**Example**	**The number of parameters**	**Estimators**
Independent	$Corr\left(Y_{ij},Y_{ik}\right)=\begin{cases}1 & \text{j=} \\ 0 & \text{j}\neq\end{cases}$	$\begin{pmatrix}1 & 0 & .. & 0\\ 0 & 1 & .. & 0\\ .. & .. & .. & ..\\ 0 & 0 & .. & 1\end{pmatrix}$	0	In this case, working correlation is not estimated.
Exchangeable	$Corr\left(Y_{ij},Y_{ik}\right)=\begin{cases}1 & \text{j=} \\ \alpha & \text{j}\neq\end{cases}$	$\begin{pmatrix}1 & \alpha & .. & \alpha\\ \alpha & 1 & .. & \alpha\\ .. & .. & .. & ..\\ \alpha & \alpha & .. & 1\end{pmatrix}$	1	$\hat{\alpha}=\frac{1}{\left(N^{*}-p\right)\phi}\sum_{i=1}^{K}\sum_{j\neq k}e_{ij}e_{ik}$ $N^{*}=\sum_{i=1}^{K}n_i\left(n_i-1\right)$
Unstructured	$Corr\left(Y_{ij},Y_{ik}\right)=\begin{cases}1 & \text{j=k} \\ \alpha_{jk} & \text{j}\neq\end{cases}$	$\begin{pmatrix}1 & \alpha_{12} & .. & \alpha_{1t}\\ \alpha_{12} & 1 & .. & \alpha_{2t}\\ .. & .. & .. & ..\\ \alpha_{1t} & \alpha_{2t} & .. & 1\end{pmatrix}$	$t\left(t-1\right)/2$	$\hat{\alpha}_{jk}=\frac{1}{\left(K-p\right)\phi}\sum_{i=1}^{K}e_{ij}e_{ik}$
Autoregressive of first order [AR(1)]	$Corr\left(Y_{ij},Y_{i,j+t}\right)=\alpha^{t}$ t=0,1,...,n_i-j	$\begin{pmatrix}1 & \alpha & .. & \alpha^{t-1}\\ \alpha & 1 & .. & \alpha^{t-2}\\ .. & .. & .. & ..\\ \alpha^{t-1} & \alpha^{t-2} & .. & 1\end{pmatrix}$	1	$\hat{\alpha}=\frac{1}{\left(K_1-p\right)\phi}\sum_{i=1}^{K}\sum_{j\leq n_i-1}e_{ij}e_{i,j}$ $K_1=\sum_{i=1}^{K}\left(n_i-1\right)$
M-dependent	$Corr\left(Y_{ij},Y_{ik}\right)=\begin{cases}1 & \text{t=0}\\ \alpha_t & \text{t=1,2,...}\\ 0 & \text{t>m}\end{cases}$	$\begin{pmatrix}1 & \alpha_1 & .. & \alpha_{t-1}\\ \alpha_1 & 1 & .. & \alpha_{t-2}\\ .. & .. & .. & ..\\ \alpha_{t-1} & \alpha_{t-2} & .. & 1\end{pmatrix}$	$0<M\leq t-$	$\hat{\alpha}_t=\frac{1}{\left(K_t-p\right)\phi}\sum_{i=1}^{K}\sum_{j\leq n_i-t}e_{ij}e_{i,}$ $K_t=\sum_{i=1}^{K}\left(n_i-t\right)$
Fixed	$Corr\left(Y_{ij},Y_{ik}\right)=r_{jk}$	$\begin{pmatrix}1 & r_{12} & .. & r_{1t}\\ r_{12} & 1 & .. & r_{2t}\\ .. & .. & .. & ..\\ r_{1t} & r_{2t} & .. & 1\end{pmatrix}$	0 (User specified)	In this case, working correlation is not estimated.

Table 2.Analysis of the GEE parameter and standard error (SE) estimates, using various working correlation structures

Parameter	Exchangeable		AR(1)		M(2) Dependent		Unstructured		Entropy 1		Entropy 2	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	0.5627*	0.1656	0.5809*	0.1650	0.5770*	0.1651	0.7169*	0.1579	0.7040*	0.1580	0.5788*	0.1633
The size of transaction volume, (TV)	1.4247*	0.1630	1.4235*	0.1650	1.4293*	0.1649	1.1946*	0.1519	1.2612*	0.1579	1.3955*	0.1614
Dividend paid in cash, (DC)	0.9203*	0.3657	0.9602*	0.3720	0.9491*	0.3700	0.7953*	0.3142	0.7459**	0.3308	0.8497**	0.3534
Time	-0.1302*	0.0373	-0.1347*	0.0369	-0.1337*	0.0370	-0.1754*	0.0331	-0.1538*	0.0353	-0.1321*	0.0368
Marginal R^2	0.13108		0.13118		0.13118		0.12443		0.12919		0.13092	
QIC	882.305		882.264		882.262		889.705		884.828		882.617	
QIC_U	882.379		882.427		882.412		888.163		883.950		882.416	

*p<0,01 ** p<0,05

Table 3.Estimated working correlation matrices for various structures

Exchangeable	Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8
Time 1	1.000	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017
Time 2	-0.017	1.000	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017
Time 3	-0.017	-0.017	1.000	-0.017	-0.017	-0.017	-0.017	-0.017

Unstructured	Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8
Time 1	1.000	-0.038	-0.201	-0.102	-0.185	-0.040	-0.172	-0.195
Time 2	-0.038	1.000	0.074	-0.105	0.168	-0.143	0.200	0.077
Time 3	-0.201	0.074	1.000	0.054	0.006	-0.008	0.229	0.104

Time 4	-0.017	-0.017	-0.017	1.000	-0.017	-0.017	-0.017	-0.017
Time 5	-0.017	-0.017	-0.017	-0.017	1.000	-0.017	-0.017	-0.017
Time 6	-0.017	-0.017	-0.017	-0.017	-0.017	1.000	-0.017	-0.017
Time 7	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	1.000	-0.017
Time 8	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	1.000

Time 4	-0.102	-0.105	0.054	1.000	-0.167	0.270	-0.040	-0.089
Time 5	-0.185	0.168	0.006	-0.167	1.000	-0.188	0.232	0.036
Time 6	-0.040	-0.143	-0.008	0.270	-0.188	1.000	-0.231	-0.084
Time 7	-0.172	0.200	0.229	-0.040	0.232	-0.231	1.000	0.120
Time 8	-0.195	0.077	0.104	-0.089	0.036	-0.084	0.120	1.000

AR(1)	Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8
Time 1	1.000	-0.059	0.003	0.000	0.000	0.000	0.000	0.000
Time 2	-0.059	1.000	-0.059	0.003	0.000	0.000	0.000	0.000
Time 3	0.003	-0.059	1.000	-0.059	0.003	0.000	0.000	0.000
Time 4	0.000	0.003	-0.059	1.000	-0.059	0.003	0.000	0.000
Time 5	0.000	0.000	0.003	-0.059	1.000	-0.059	0.003	0.000
Time	0.00	0.00	0.00	0.00	-0.05	1.00	-0.05	0.00

Entropy 1	Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8
Time 1	1.000	0.091	0.047	0.117	0.032	0.139	0.082	0.111
Time 2	0.091	1.000	0.037	0.079	0.187	0.057	0.252	0.055
Time 3	0.047	0.037	1.000	0.096	0.101	0.102	0.339	0.038
Time 4	0.117	0.079	0.096	1.000	0.128	0.093	0.021	0.071
Time 5	0.032	0.187	0.101	0.128	1.000	0.017	0.142	0.058
Time	0.13	0.05	0.10	0.09	0.01	1.00	0.03	0.07

6	0	0	0	3	9	0	9	3
Time 7	0.000	0.000	0.000	0.000	0.003	-0.059	1.000	-0.059
Time 8	0.000	0.000	0.000	0.000	0.000	0.003	-0.059	1.000

6	9	7	2	3	7	0	2	2
Time 7	0.082	0.252	0.339	0.021	0.142	0.032	1.000	0.107
Time 8	0.111	0.055	0.038	0.071	0.058	0.072	0.107	1.000

M(2) Dependent	Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8
Time 1	1.000	-0.058	0.024	0.000	0.000	0.000	0.000	0.000
Time 2	-0.058	1.000	-0.058	0.024	0.000	0.000	0.000	0.000
Time 3	0.024	-0.058	1.000	-0.058	0.024	0.000	0.000	0.000
Time 4	0.000	0.024	-0.058	1.000	-0.058	0.024	0.000	0.000
Time 5	0.000	0.000	0.024	-0.058	1.000	-0.058	0.024	0.000
Time 6	0.000	0.000	0.000	0.024	-0.058	1.000	-0.058	0.024
Time 7	0.000	0.000	0.000	0.000	0.024	-0.058	1.000	-0.058
Time 8	0.000	0.000	0.000	0.000	0.000	0.024	-0.058	1.000

Entropy 2	Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8
Time 1	1.000	0.004	0.001	0.007	0.000	0.010	0.003	0.006
Time 2	0.004	1.000	0.001	0.003	0.018	0.002	0.033	0.001
Time 3	0.001	0.001	1.000	0.005	0.005	0.005	0.061	0.001
Time 4	0.007	0.003	0.005	1.000	0.008	0.004	0.000	0.003
Time 5	0.000	0.018	0.005	0.008	1.000	0.000	0.010	0.002
Time 6	0.010	0.002	0.005	0.004	0.000	1.000	0.001	0.003
Time 7	0.003	0.033	0.061	0.000	0.010	0.001	1.000	0.006
Time 8	0.006	0.001	0.001	0.003	0.002	0.003	0.006	1.000

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