RCOX models: Graphical Gaussian models with edge and vertex symmetries

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and

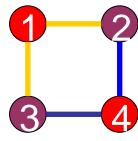
Sren Hjsgaard, Sören Höjsgaard, Særen Hæjsgaard and S???ren H???jsgaard



Take-home message and Outline

- New types of graphical Gaussian models
 - With colours; as in the logo
 - Attribute specific meanings to the colours
- An R-package (gRc) for inference in these models
- Motivation
- RCO'X' models: RCON, RCOR, RCOP
- Estimation algorithms
- Software

Idea...

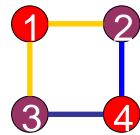


- Apply graphical (Gaussian) models to large matrices, e.g. in gene expression
- Problem: d >>n, many genes few replicates

Graphical model for $Y \sim N_d(0,\Sigma)$

- When d >n, MLE of Σ does not exist (in saturated model)
- Impose restrictions on $K=\Sigma^{-1}$ to achieve more parsimonious model;
- In addition to conditional independence, restrict parameters to being identical

Concentration and derived quantities



- Model for $y \sim N_d(0, \Sigma)$, $K = (k^{ij}) = \Sigma^{-1}$.
- The partial (conditional) covariance :

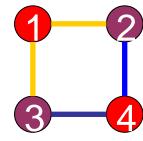
$$cov(y_i, y_j | rest) = \frac{-k^{ij}}{\det K^{ij}} \text{ where } K^{ij} = \begin{bmatrix} k^{ii} & k^{ij} \\ k^{ij} & k^{jj} \end{bmatrix}$$

• The partial (conditional) correlation:

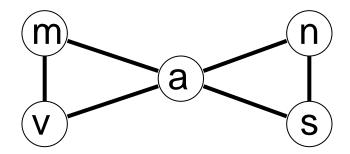
$$cor(y_i, y_j | rest) = \rho^{ij} = \frac{-k^{ij}}{\sqrt{k^{ii}k^{jj}}}$$

• Conditional independence: $y_i \perp \!\!\!\perp y_j | rest$ iff $k^{ij} = 0$

Example: Mathematics marks

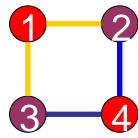


- Mathmark data (Mardia, Kent, Bibby): 88 students marks on (a) Igebra, a(n) alysis, (m) echanics, (v) ectors and (s) tatistics
- Stepwise backward selection gives butterfly model



- Convention: Black and white are neutral colours
 - corresponding parameters are unrestricted.

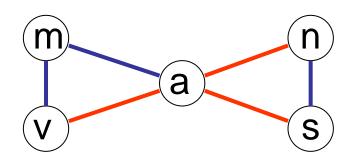
Concentrations for mathmarks



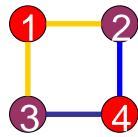
Concentrations ($\times 1000$):

	mechanics	vectors	algebra	analysis	statistics
mechanics	5.24	-2.44	-2.74	0.01	-0.14
vectors	-2.44	10.43	-4.71	-0.79	-0.17
algebra	-2.74	-4.71	26.95	-7.05	-4.70
analysis	0.01	-0.79	-7.05	9.88	-2.02
statistics	-0.14	-0.17	-4.70	-2.02	6.45

- Some concentrations ≈0
- Some concentrations ≈ identical



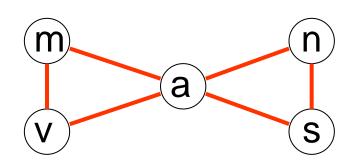
Partial correlations for mathmarks



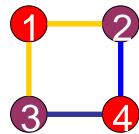
Partial correlations:

	mechanics	vectors	algebra	analysis	statistics
(m)echanics	1.00	-0.30	-0.20	0.00	0.00
(v)ectors	-0.30	1.00	-0.30	-0.10	0.00
(a)lgebra	-0.20	-0.30	1.00	-0.40	-0.40
a(n)alysis	0.00	-0.10	-0.40	1.00	-0.30
(s)tatistics	0.00	0.00	-0.40	-0.30	1.00
Partial variances	190.67	95.91	37.10	101.18	155.04

 Some partial correlations ≈ identical



RCON (Restricted CONcentration) models

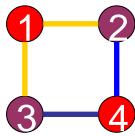


Model: $Y \sim N_d$ (0, Σ)

$$K = \Sigma^{-1} = \begin{bmatrix} k^{11} & k^{12} & k^{13} & 0 \\ k^{12} & k^{22} & 0 & k^{24} \\ k^{13} & 0 & k^{33} & k^{34} \\ 0 & k^{24} & k^{34} & k^{44} \end{bmatrix}$$

- Markov properties as for graphical Gaussian model
- Entries of K with same colour restricted to being identical → 4 rather than 8 parameters.

Implied restrictions (I): Equal contributions in regression



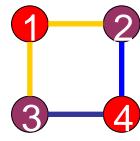
Regressing y₁ on y₂, y₃, y₄

$$y_1 = a_1 - (k^{12}/k^{11}) y_2 - (k^{13}/k^{11}) y_3$$

- so y_2 and y_3 contribute equally because $k^{12} = k^{13}$

$$K = \Sigma^{-1} = \begin{bmatrix} k^{11} & k^{12} & k^{13} & 0 \\ k^{12} & k^{22} & 0 & k^{24} \\ k^{13} & 0 & k^{33} & k^{34} \\ 0 & k^{24} & k^{34} & k^{44} \end{bmatrix}$$

Implied restrictions (II): Parallel regressions

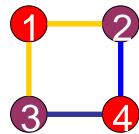


Regressions of y₂,y₃ on y₁,y₄ are parallel

$$\begin{bmatrix} y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} a_2 \\ a_3 \end{bmatrix} - \begin{bmatrix} k^{22} & 0 \\ 0 & k^{33} \end{bmatrix}^{-1} \begin{bmatrix} k^{21} & k^{24} \\ k^{31} & k^{34} \end{bmatrix} \begin{bmatrix} y_1 \\ y_4 \end{bmatrix}$$
$$= \begin{bmatrix} a_2 \\ a_3 \end{bmatrix} - \begin{bmatrix} k^{21}/k^{22} & k^{24}/k^{22} \\ k^{31}/k^{33} & k^{34}/k^{33} \end{bmatrix} \begin{bmatrix} y_1 \\ y_4 \end{bmatrix}$$

- because $k^{12}=k^{13}$, $k^{24}=k^{34}$ and $k^{22}=k^{33}$

Implied restrictions (III): Partial covariances and concentrations



This RCON model has also identical partial covariances

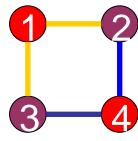
$$cov(y_1, y_2|y_3, y_4) = \frac{-k^{12}}{|K^{12}|} = \frac{-k^{13}}{|K^{13}|} = cov(y_1, y_3|y_2, y_4)$$

– and identical partial correlations

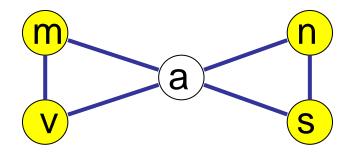
$$cor(y_1, y_2|y_3, y_4) = \frac{-k^{12}}{\sqrt{k^{11}k^{22}}} = \frac{-k^{13}}{\sqrt{k^{11}k^{33}}} = cor(y_1, y_3|y_2, y_4)$$

$$\mathsf{K} = \Sigma^{-1} = \begin{bmatrix} \mathbf{k}^{11} & \mathbf{k}^{12} & \mathbf{k}^{13} & \mathbf{0} \\ \mathbf{k}^{12} & \mathbf{k}^{22} & \mathbf{0} & \mathbf{k}^{24} \\ \mathbf{k}^{13} & \mathbf{0} & \mathbf{k}^{33} & \mathbf{k}^{34} \\ \mathbf{0} & \mathbf{k}^{24} & \mathbf{k}^{34} & \mathbf{k}^{44} \end{bmatrix} \quad \begin{array}{l} \mathsf{Not} \\ \mathsf{generally} \\ \mathsf{the \ case!!!} \\ \mathsf{the \ case!!!} \\ \mathsf{nor \ } \\ \mathsf{nor \$$

Example – mathematics marks



- Focus on butterfly model
 - EdgeColourClass: Edges with same colour
 - VertexColourClass: Vertices with same colour
- Note: Black and white are neutral colours; no restrictions
- Successively apply (with LR-test, 5% level)
 - JoinEdgeColourClasses()
 - JoinVertexColourClasses()

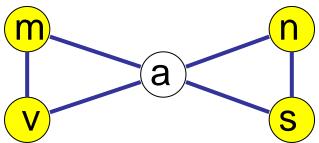


Mathematics marks...

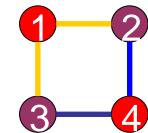
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Estimated / observed concentrations (\times 1000) are

Concentrations	mechanics	vectors	algebra	analysis	statistics
mechanics	7.58	-3.49	-3.49	0.00	0.00
vectors	-3.49	7.58	-3.49	0.00	0.00
algebra	-3.49	-3.49	20.76	-3.49	-3.49
analysis	0.00	0.00	-3.49	7.58	-3.49
statistics	0.00	0.00	-3.49	-3.49	7.58
mechanics	5.24	-2.44	-2.74	0.01	-0.14
vectors	-2.44	10.43	-4.71	-0.79	-0.17
algebra	-2.74	-4.71	26.95	-7.05	-4.70
analysis	0.01	-0.79	-7.05	9.88	-2.02
statistics	-0.14	-0.17	-4.70	-2.02	6.45

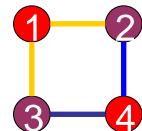


RCOR (Restricted CORrelation) models



- Restricting concentrations not scale-invariant: Identical concentrations of y ~ N(0,Σ) not generally preserved for Ay ~ N(0,AΣA), where A is diagonal
- Hence RCON models are only of interest in cases where the scale of measurement for different variables are comparable
- Alternatively: Focus on restricted partial correlations

RCOR (restricted correlation) models



Write -K as

$$\begin{bmatrix} \eta^{11} & 0 & 0 & 0 \\ 0 & \eta^{22} & 0 & 0 \\ 0 & 0 & \eta^{33} & 0 \\ 0 & 0 & 0 & \eta^{44} \end{bmatrix} \begin{bmatrix} 1 & \rho^{12} & \rho^{13} & 0 \\ \rho^{12} & 1 & 0 & \rho^{24} \\ \rho^{13} & 0 & 1 & \rho^{34} \\ 0 & \rho^{24} & \rho^{34} & 1 \end{bmatrix} \begin{bmatrix} \eta^{11} & 0 & 0 & 0 \\ 0 & \eta^{22} & 0 & 0 \\ 0 & 0 & \eta^{33} & 0 \\ 0 & 0 & 0 & \eta^{44} \end{bmatrix}$$

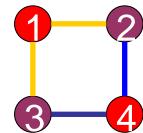
$$= A_{\eta} C_{\rho} A_{\eta}$$
 where

 $A_{\boldsymbol{\eta}}$: diagonal with positive entries (inverse partial standard deviations)

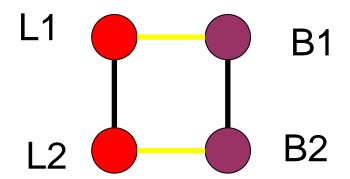
 C_p : has 1s on diagonal (partial correlations)

- Entries of (A_η, C_ρ) restricted according to colouring
- Scale invariant if vertices with same colour are rescaled identically

RCOP models ('P' for permution symmetry)



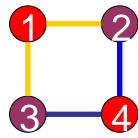
Fret's head: Length and breadth of head of first and second son:



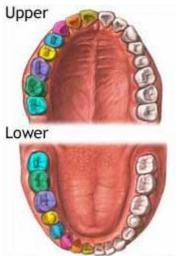
Complete symmetry between first and second son

- Both RCON and RCOR
- RCOP-model (defined by permutations)
- Studied by Helene Neufeld (poster session)

Symmetry models in nature

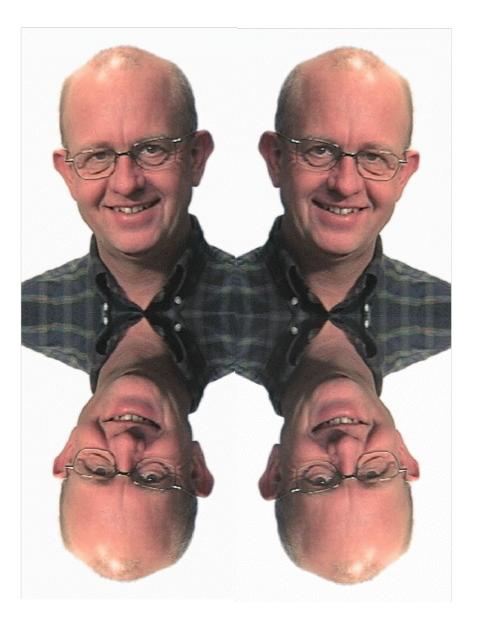


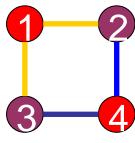






Further...

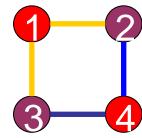




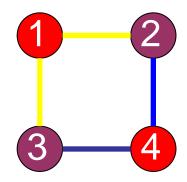
A bigger picture... Relationships between models **RCOR RCON** Scale invariant Linear in K

Also linear in Σ

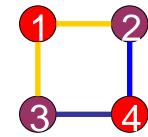
Specification of RCON / RCOR models



- Generators of model
 - Edge colour classes:
 EC = {{1,2}{1,3}} {{2,4}{3,4}}
 - Vertex colour classes:
 VC = {1,4}{2,3}
- (EC,VC) specifies RCON/RCOR model



RCON Estimation - Sufficient statistics



For EdgeCC $s=\{\{1,2\}\{1,3\}\}$

Let W ~ Wishart(
$$f,\Sigma$$
)

$$T^s = \begin{vmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{vmatrix}$$

RCON regular exponential family; linear in K:

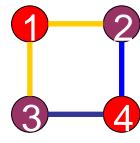
For vertexCC s={1,4}

2 log L = f log
$$|K|$$
 - tr(KW)
= f log $|K|$ - $\sum_{s} \theta_{s}$ tr(TsW)

So {ts=tr(Ts W)} is a set of sufficient statistics

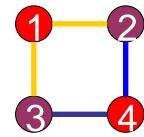
Equated with expectations $\{t^s\} = \{f tr(T^s\Sigma)\}$

Estimation in RCON models - Modified Newton



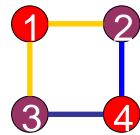
- Use convergent (!) algorithm of Jensen, Johansen and Lauritzen (1991):
- Maximize 1/L (instead of logL) cyclically over one parameter at the time by Newton iteration.
- In exponential families we have
 - $\exp(t(y)\theta-\psi(\theta))$
 - $I^* = 1/L = \exp(-t(y)\theta + \psi(\theta))$

Modified Newton



- Let $\Delta = E(t(y)) t(y)$.
- Then
 - $(I^*)' = \exp(-t(y)\theta + \psi(\theta))\Delta$
 - $(I^*)'' = \exp(-t(y)\theta + \psi(\theta))[Var(t(y)) + \Delta^2]$
- Newton step becomes:
- $\bullet \quad <- \quad \theta \quad \quad (I^*)'/ \quad (I^*)'' = \theta \quad \quad \Delta \quad / \quad (Var(t(y)) \quad + \quad \Delta^2)$
- For RCON models
 - $E(T^sW) = f tr(T^s\Sigma)$
 - $Var(T^sW) = f tr(T^s\Sigma T^s\Sigma)$

Estimation – RCOR - short version



RCOR model is generally not a linear exponential family

$$logL = f/2 log |C_{\rho}| + f log |A_{\eta}| - tr(A_{\eta} C_{\rho} A_{\eta} W)/2$$

Linear exponential family for fixed η ; likelihood equations quadratic for fixed ρ .

Existence/uniqueness of MLE not clear. But unique maximum in ρ for fixed η and unique maximum in η for fixed ρ .

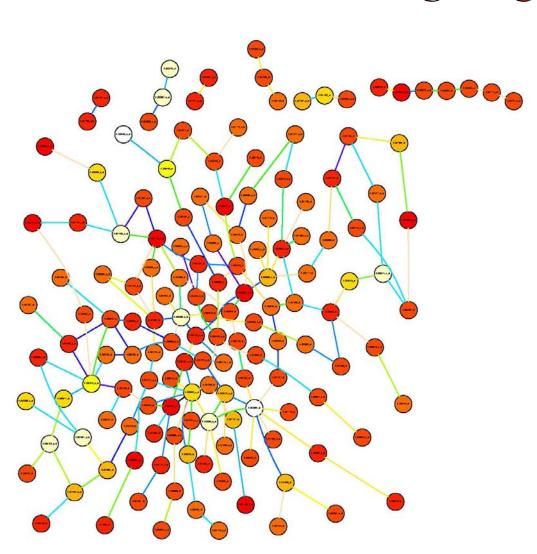
Suggests alternating algorithm

- For given η, estimate ρ using modified Newton as for RCON
- 2. For given ρ , estimate η by solving system of 2nd degree equations (cyclically)

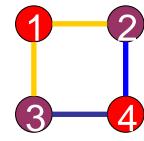
Larger model: Breast cancer genes

1 2 3 4

- 58 cases, 150 genes
- 7 VCC, 10 ECC: 17 parameters
- Fitting with gRc: 0.3 sec
- 380 parms
- Fitting with gRc: 1.1 sec
- Model selection is a big issue...



Summing up



- SH +Lauritzen: Graphical Gaussian models with edge and vertex symmetries. (RSSB, To appear)
- SH + Lauritzen (2007). Inference in graphical Gaussian models with edge and vertex symmetries with the gRc package for R (J. Stat. Soft)
- gRc package in R ('c' for colour) on CRAN