

Stochastic blockmodels

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Outline

Stochastic blockmodelling
Stochastic equivalence

Statistical model
Estimation
Posterior probabilities of interblock relations

Fitting stochastic blockmodels using BLOCKS in StocNet

Selecting number of blocks

Example 1: the political network
Example 2: work frequency and importance in an organisation
Example 3: collaboration in a law firm

Other latent variable models for networks
Latent space model
Latent ultrametric model

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A posteriore stochastic blockmodels (Nowicki & Snijders, 2001)

Assume that:

Actors are associated with *unobserved* classes, or groups (represented by different *colours*)

the probability that a dyad has a particular relational “pattern” depends only on the (unobserved) colours of the actors
possible patterns define an *alphabet* of possibilities
actors with the same colour have the same pattern probabilities and hence are *stochastically equivalent*

dyads are *conditionally independent*, given the colours of the actors

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More formally

Let Z_i be a variable denoting the *colour* of actor i and assume that the Z_i are iid random variables with probability $\Pr(Z_i = k) = \theta_k$

Also assume that $\Pr(\mathbf{D}_{ij} = \mathbf{a} | \mathbf{Z} = \mathbf{z}) = \eta_{\mathbf{a}}(z_i, z_j)$ where:

\mathbf{D}_{ij} is a vector of relational variables for the dyad (i, j)

\mathbf{a} is a vector of possible values for the dyad variables (a *pattern* in the *alphabet*), and

$\eta_{\mathbf{a}}(z_i, z_j)$ is the colour-dependent probability of observing the pattern \mathbf{a}

Also assume that the dyads are conditionally dependent given the colours \mathbf{Z} , so that:

the joint distribution of the \mathbf{D}_{ij} given \mathbf{Z} is the product of the conditional dyad probabilities

$$\Pr(\mathbf{D}, \mathbf{Z}) = \Pr(\mathbf{D} | \mathbf{Z}) \Pr(\mathbf{Z})$$

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Estimation

Nowicki and Snijders developed a Bayesian approach to estimation of θ and η using Gibbs sampling (an iterative sampling scheme for approximating posterior distribution)

They also compute posterior probabilities that:

two actors have the same colour

a dyad has a particular relational pattern

interblock ties have a particular relational pattern

Implemented in BLOCKS within Stocnet

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Example 1: political network

Data file: Doreian_mat.txt

```
00110010000010
00000001110100
10010110000001
10101110000100
00010100000000
00111000000101
10110000000000
01000000110110
01000001010010
01000001100010
00000000000100
01010101001010
10000001110100
00100100000000
```

Some BLOCKS preliminary output

Data file is named
<C:\stocnet\temp\~Doreian_mat.txt>.
Preliminary inspection of first line of the data file:
Data file contains 14 vertices.

The following options were chosen:
Number of colors to be analyzed ranges from 2 to 4.
3 Gibbs sequences for each color.

Set of symmetric relations is
1 (0, 0) (63 dyads)
2 (1, 1) (28 dyads)
No asymmetric relations.
Total number of relations is 2.

Number of dyads with observed values is 91.
Number of dyads with missing values is 0.

Entropy of empirical dyad distribution = 0.61724

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How many classes?

No of classes	information I_y	H_x
2	.46	.19
3	.43	.45
4	.41	.45
5	.40	.43

Values averaged over 3 runs (all within .01)

I_y is the **information** in the observed relations, conditional on the class structure and the inter- and intra-class probabilities (smaller values mean that observed relations are more determined by model parameters)

H_x measures the extent to which the class distribution defines a **clear-cut partition** of actors into classes (smaller values signify clearer partitions, max value of 1 corresponds to the case where all classes are equally likely for any actor)

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Two-block solution: Permutation of data

A new ranking of the vertices was determined to bring out the block structure.

New ranking is

```
1 2 3 4 5 6 7 8 9 10 11 12 13 14
1 3 4 5 6 7 14 2 8 9 10 11 12 13
```

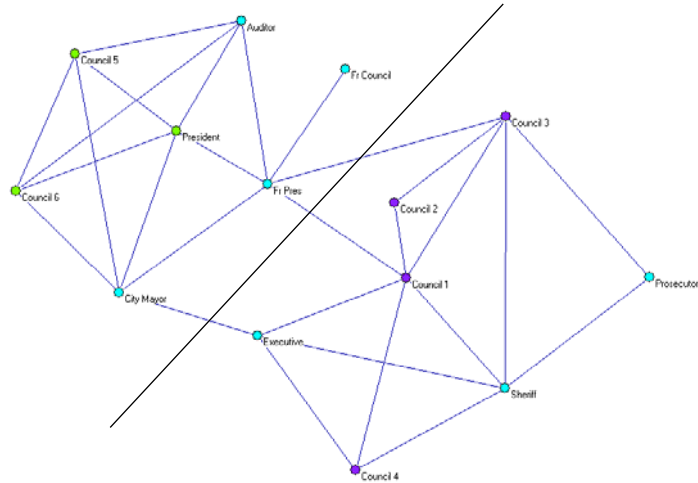
Recoded observed adjacency matrix in new ranking is as follows:

```

      1      1 1 1 1
      1 3 4 5 6 7 4 2 8 9 0 1 2 3
1     2 2 1 1 2 1 1 1 1 1 1 1 2
3     2  2 1 2 2 2 1 1 1 1 1 1 1
4     2 2  2 2 2 1 1 1 1 1 1 2 1
5     1 1 2  2 1 1 1 1 1 1 1 1 1
6     1 2 2 2  1 2 1 1 1 1 1 2 1
7     2 2 2 1 1  1 1 1 1 1 1 1 1
14    1 2 1 1 2 1  1 1 1 1 1 1 1
2     1 1 1 1 1 1 1 2 2 2 1 2 1
8     1 1 1 1 1 1 1 2  2 2 1 2 2
9     1 1 1 1 1 1 1 2 2  2 1 1 2
10    1 1 1 1 1 1 1 2 2 2  1 1 2
11    1 1 1 1 1 1 1 1 1 1 1  2 1
12    1 1 2 1 2 1 1 2 2 1 1 2  2
13    2 1 1 1 1 1 1 1 2 2 2 1 2
```

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Doreian (1988) political network colour codes vote (aqua = non-voting)



Posterior probabilities that two actors have the same colour

Matrix of pairwise color equality

```

=====
          1      1 1 1 1
1      1 3 4 5 6 7 4 2 8 9 0 1 2 3
3      9 9 9 9 9 9 0 0 0 0 4 1 0
4      9 9 9 9 9 9 0 0 0 0 4 1 0
5      9 9 9 9 9 9 0 0 0 0 4 1 0
6      9 9 9 9 9 9 0 0 0 0 4 1 0
7      9 9 9 9 9 9 9 0 0 0 0 4 1 0
14     9 9 9 9 9 9 9 0 0 0 0 4 1 0
2      0 0 0 0 0 0 0 0 9 9 9 6 9 9
8      0 0 0 0 0 0 0 0 9 9 9 6 9 9
9      0 0 0 0 0 0 0 0 9 9 9 6 9 9
10     0 0 0 0 0 0 0 0 9 9 9 6 9 9
11     4 4 4 4 4 4 4 4 6 6 6 6 7 6 Former council member
12     1 1 1 1 1 1 1 1 9 9 9 9 7 9 Former President
13     0 0 0 0 0 0 0 0 9 9 9 9 6 9
    
```

Posterior probabilities of dyadic relations

Probabilities of relation 1 = (0, 0) between vertices													Probabilities of relation 2 = (1, 1) between vertices																	
	1	3	4	5	6	7	4	2	8	9	0	1	2	3		1	3	4	5	6	7	4	2	8	9	0	1	2	3	
1		5	5	5	5	5	5	9	9	9	9	8	9	9	1	5	5	5	5	5	5	1	1	1	1	2	1	1		
3		5		5	5	5	5	5	9	9	9	9	8	9	1	5		5	5	5	5	1	1	1	1	2	1	1		
4		5	5		5	5	5	5	9	9	9	9	8	9	1	5	5		5	5	5	1	1	1	1	2	1	1		
5		5	5	5		5	5	5	9	9	9	9	8	9	1	5	5	5		5	5	1	1	1	1	2	1	1		
6		5	5	5	5		5	5	9	9	9	9	8	9	1	5	5	5	5		5	1	1	1	1	2	1	1		
7		5	5	5	5	5		5	9	9	9	9	8	9	1	5	5	5	5	5		5	1	1	1	1	2	1	1	
14		5	5	5	5	5	5		9	9	9	9	8	9	1	5	5	5	5	5	5		1	1	1	1	2	1	1	
2		9	9	9	9	9	9	9		3	3	3	6	4	3	2	1	1	1	1	1	1	1	1	7	7	7	4	6	7
8		9	9	9	9	9	9	9	3		3	3	6	4	3	8	1	1	1	1	1	1	7	7	7	4	6	7	7	
9		9	9	9	9	9	9	9	3	3		3	6	4	3	9	1	1	1	1	1	1	7	7	7	4	6	7	7	
10		9	9	9	9	9	9	9	3	3	3		6	4	3	10	1	1	1	1	1	1	7	7	7	4	6	7	7	
11		8	8	8	8	8	8	8	6	6	6	6		5	6	11	2	2	2	2	2	2	4	4	4	4	5	4	4	
12		9	9	9	9	9	9	9	4	4	4	4	5		4	12	1	1	1	1	1	1	6	6	6	6	5	6	6	
13		9	9	9	9	9	9	9	3	3	3	3	6	4		13	1	1	1	1	1	1	7	7	7	7	4	6	6	

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Vertex-by-vertex analysis of fit

Overall maximum pairwise value for vertices in different classes is 0.360
 Overall minimum pairwise value for vertices in the same class is 0.645

Classes now are labeled 1 to 2.

Vertices, as far as not thrown out, with their class number, their maximum pairwise value for vertices in a different class, and their minimum pairwise value for vertices in the same class;

and, if this vertex were to be deleted: the overall maximum pairwise value for vertices in different classes, and the overall minimum pairwise value for vertices in the same class:

1	1	0.357	0.989	0.360	0.645
2	2	0.010	0.646	0.360	0.645
3	1	0.354	0.991	0.360	0.645
4	1	0.355	0.991	0.360	0.645
5	1	0.360	0.985	0.357	0.645
6	1	0.351	0.991	0.360	0.645
7	1	0.353	0.990	0.360	0.645
8	2	0.009	0.646	0.360	0.645
9	2	0.009	0.645	0.360	0.646
10	2	0.009	0.646	0.360	0.645
11	2	0.360	0.645	0.113	0.893
12	2	0.113	0.747	0.360	0.645
13	2	0.010	0.646	0.360	0.645
14	1	0.351	0.985	0.360	0.645

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BLOCKS appraisal of vertex-by-vertex analysis of fit

In @6:

Vertex for which throwing it out improves the fit most is 11;
this vertex now is thrown out.

...

Permuted data array, showing *post hoc* block structure

Recoded adjacency matrix with block structure

```

          1 .          1 1 1 1
1  1 3 4 5 6 7 4 . 2 8 9 0 1 2 3
3  2  2 1 2 2 2 . 1 1 1 1 1 1 1
4  2 2  2 2 2 1 . 1 1 1 1 1 2 1
5  1 1 2  2 1 1 . 1 1 1 1 1 1 1
6  1 2 2 2  1 2 . 1 1 1 1 1 2 1
7  2 2 2 1 1  1 . 1 1 1 1 1 1 1
14 1 2 1 1 2 1  . 1 1 1 1 1 1 1
.....
2  1 1 1 1 1 1 1 . 2 2 2 1 2 1
8  1 1 1 1 1 1 1 . 2  2 2 1 2 2
9  1 1 1 1 1 1 1 . 2 2  2 1 1 2
10 1 1 1 1 1 1 1 . 2 2 2  1 1 2
11 1 1 1 1 1 1 1 . 1 1 1 1  2 1
12 1 1 2 1 2 1 1 . 2 2 1 1 2  2
13 2 1 1 1 1 1 1 . 1 2 2 2 1 2

```


Example 2: Work frequency and work importance in an organisation

Crosstabulation of frequency and importance categories:

work frequency * work importance Crosstabulation

Count		work importance				Total
		Critical	Important	None	Routine	
work frequency	Daily	53	49		37	139
	Hourly	38	5		6	49
	Monthly	32	67	1	79	179
	None			100		100
	Weekly	48	104		58	210
Total		171	225	101	180	679

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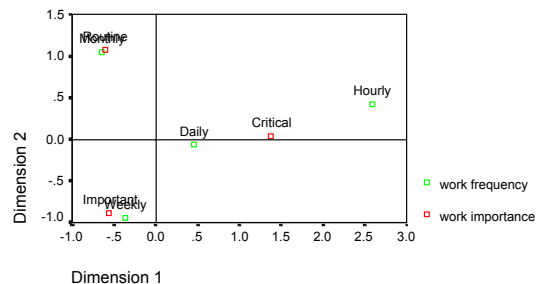
Correspondence analysis for frequency and importance of non-null work ties

Summary

Dimension	Singular Value	Inertia	Chi Square	Sig.	Proportion of Inertia		Confidence Singular Value	
					Accounted for	Cumulative	Standard Deviation	Correlation
1	.381	.130			.862	.862	.041	
2	.144	.021			.138	1.000	.043	.034
Total		.151	86.936	.000*	1.000	1.000		

a. 6 degree of freedom

Category Quantifications



A stochastic blockmodel for work ties

Code work ties as:

0 = none

1 = work interactions (at least monthly, at least routinely)

2 = critically important work interactions, occurring at least daily

Alphabet for dyadic relations:

1 = (0,0)

2 = (1,1)

3 = (0,1)

4 = (0,2)

5 = (1,2)

6 = (1,0)

7 = (2,0)

8 = (2,1)

note that (2,2) did not occur!

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How many classes?

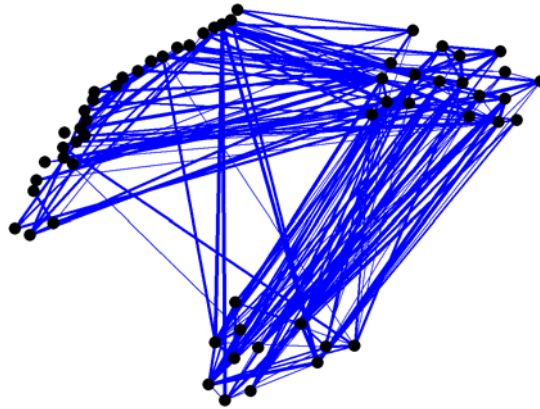
No of classes	information I_y	H_x
2	.4940	.2463
3	.4727	.4219
4	.4694	.4349
5	.4639	.4247

I_y is the information in the observed relations, conditional on the class structure and the inter- and intra-class probabilities (smaller values mean that observed relations are more determined by model parameters)

H_x measures the extent to which the class distribution defines a clear-cut partition of actors into classes (smaller values signify clearer partitions, max value of 1 corresponds to the case where all classes are equally likely for any actor)

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Organisational networks



Frequency of work interactions

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Relationship between 2- and 3-class solutions

2-class solution

class 1

class 2

*3-class
solution*

class 1

1,3,4,8,11,12,16,17
19,21,26,31,34,38,39
40,43,46,47,48,54,55
55,57,58,59,60

10,24,52

class 2

2,5,7,9,14,15,18
20,22,23,27,29
30,36,37,41,49,
50,53,56

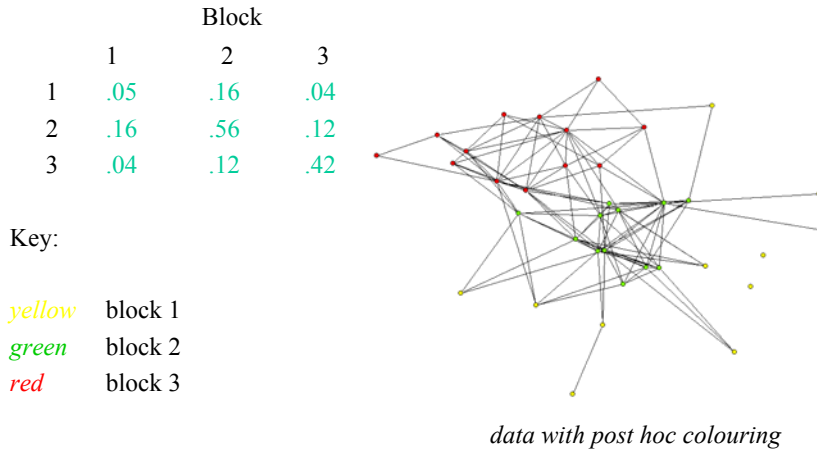
class 3

6,13,25,28,32,33,42,44

35,45,51

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Example 3: collaboration among partners in a law firm: average posterior probabilities for blocks based on *post hoc* colouring (Lazega)



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Other latent variable formulations (for positive “association” relational forms)

Latent space model (Handcock, Hoff & Raftery, 2002)

Nodes have (latent) locations in a k -dimensional Euclidean space
 Tie probabilities are conditionally independent, given latent locations
 Bayesian estimation of unobserved locations (and their uncertainty)

Latent ultrametric model (Schweinberger & Snijders, 2003)

Every pair of nodes is associated with a (latent) distance in an ultrametric space (corresponding to a hierarchy of “settings”)
 Tie probabilities are conditionally independent, given latent ultrametric distances
 Bayesian estimation for unobserved ultrametric distances (and hence setting hierarchy)

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References

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- Schweinberger, M., & Snijders, T. A. B. (2003). Settings in social networks: a measurement model. *Sociological Methodology*, *33*, 307-341.