

Contents

List of Contributors XV

1	Using the DiffCorr Package to Analyze and Visualize Differential Correlations in Biological Networks	1
	<i>Atsushi Fukushima and Kozo Nishida</i>	
1.1	Introduction	1
1.1.1	An Introduction to Omics and Systems Biology	1
1.1.2	Correlation Networks in Omics and Systems Biology	1
1.1.3	Network Modules and Differential Network Approaches	2
1.1.4	Aims of this Chapter	4
1.2	What is DiffCorr?	4
1.2.1	Background	4
1.2.2	Methods	5
1.2.3	Main Functions in DiffCorr	5
1.2.4	Installing the DiffCorr Package	6
1.3	Constructing Co-Expression (Correlation) Networks from Omics Data – Transcriptome Data set	8
1.3.1	Downloading the Transcriptome Data set	8
1.3.2	Data Filtering	9
1.3.3	Calculation of the Correlation and Visualization of Correlation Networks	11
1.3.4	Graph Clustering	15
1.3.5	Gene Ontology Enrichment Analysis	17
1.4	Differential Correlation Analysis by DiffCorr Package	21
1.4.1	Calculation of Differential Co-Expression between Organs in Arabidopsis	21
1.4.2	Exploring the Metabolome Data of Flavonoid-Deficient Arabidopsis	26
1.4.3	Avoiding Pitfalls in (Differential) Correlation Analysis	29
1.5	Conclusion	30
	Acknowledgments	30
	Conflicts of Interest	30
	References	30

2	Analytical Models and Methods for Anomaly Detection in Dynamic, Attributed Graphs 35
	<i>Benjamin A. Miller, Nicholas Arcolano, Stephen Kelley, and Nadya T. Bliss</i>
2.1	Introduction 35
2.2	Chapter Definitions and Notation 36
2.3	Anomaly Detection in Graph Data 37
2.3.1	Neighborhood-Based Techniques 37
2.3.2	Frequent Subgraph Techniques 38
2.3.3	Anomalies in Random Graphs 39
2.4	Random Graph Models 41
2.4.1	Models with Attributes 41
2.4.2	Dynamic Graph Models 43
2.5	Spectral Subgraph Detection in Dynamic, Attributed Graphs 44
2.5.1	Problem Model 44
2.5.2	Filter Optimization 46
2.5.3	Residuals Analysis in Attributed Graphs 47
2.6	Implementation in R 50
2.7	Demonstration in Random Synthetic Backgrounds 51
2.8	Data Analysis Example 55
2.9	Summary 58
	Acknowledgments 58
	References 59
3	Bayesian Computational Algorithms for Social Network Analysis 63
	<i>Alberto Caimo and Isabella Gollini</i>
3.1	Introduction 63
3.2	Social Networks as Random Graphs 64
3.3	Statistical Modeling Approaches to Social Network Analysis 64
3.3.1	Exponential Random Graph Models (ERGMs) 65
3.3.2	Latent Space Models (LSMs) 65
3.4	Bayesian Inference for Social Network Models 66
3.4.1	R-Based Software Tools 67
3.5	Data 67
3.5.1	Bayesian Inference for Exponential Random Graph Models 68
3.5.2	Bayesian Inference for Latent Space Models 71
3.5.3	Predictive Goodness-of-Fit (GoF) Diagnostics 76
3.6	Conclusions 80
	References 81
4	Threshold Degradation in R Using iDEMO 83
	<i>Chien-Yu Peng and Ya-Shan Cheng</i>
4.1	Introduction 83
4.2	Statistical Overview: Degradation Models 85
4.2.1	Wiener Degradation-Based Process 85
4.2.1.1	Lifetime Information 86

4.2.1.2	Log-Likelihood Function	87
4.2.2	Gamma Degradation-Based Process	88
4.2.2.1	Lifetime Information	88
4.2.2.2	Log-Likelihood Function	89
4.2.3	Inverse Gaussian Degradation-Based Process	89
4.2.3.1	Lifetime Distribution	90
4.2.3.2	Log-Likelihood Function	91
4.2.4	Model Selection Criteria	91
4.2.5	Choice of $\Lambda(t)$	91
4.2.6	Threshold Degradation	92
4.3	iDEMO Interface and Functions	92
4.3.1	Overview of the Package iDEMO Functionality	93
4.3.2	Data Input Format	93
4.3.3	Starting the iDEMO	93
4.3.3.1	Import Data	94
4.3.3.2	Basic Information	95
4.3.3.3	Degradation Model Selection	96
4.3.4	Single Degradation Model Analysis	96
4.3.4.1	Parameter Estimation	97
4.3.4.2	Lifetime Information	98
4.3.5	Odds and Ends	101
4.3.6	Computational Details	101
4.4	Case Applications	101
4.4.1	Laser Example	102
4.4.2	Fatigue Example	106
4.4.3	ADT Example	112
4.5	Concluding Remarks	122
	References	122
5	Optimization of Stratified Sampling with the R Package SamplingStrata: Applications to Network Data	125
	<i>Marco Ballin and Giulio Barcaroli</i>	
5.1	Networks and Stratified Sampling	125
5.2	The R Package SamplingStrata	126
5.2.1	General Setting	126
5.2.2	A General Procedure for the Optimization of Strata in a Frame	130
5.2.3	An Example	132
5.3	Application to Networks	139
5.3.1	Use of Networks as Frames	139
5.3.2	Sampling Massive Networks	145
5.4	Conclusions	149
	References	149

6	Exploring the Role of Small Molecules in Biological Systems Using Network Approaches 151
	<i>Rajarshi Guha and Sourav Das</i>
6.1	The Role of Networks in Drug Discovery 152
6.2	R for Network Analyses 153
6.3	Linking Small Molecules to Targets, Pathways, and Diseases 154
6.3.1	Drug–Target Networks 154
6.3.2	Disease Networks 155
6.3.3	SAR Networks 156
6.3.4	Assay Networks 157
6.3.5	Scaffold Networks 158
6.3.6	Scaffold-Document Networks 159
6.4	R as a Platform for Network Analyses in Drug Discovery 162
6.5	Discussion 165
	Acknowledgments 165
	References 166
7	Performing Network Alignments with R 173
	<i>Qiang Huang and Ling-Yun Wu</i>
7.1	Introduction 173
7.2	Problems, Models, and Algorithms 175
7.2.1	Problems 176
7.2.1.1	Pairwise Network Alignment 176
7.2.1.2	Network Querying 178
7.2.1.3	Multiple Network Alignment 179
7.2.2	Models and Algorithms 180
7.2.3	Comparison and Challenges 180
7.2.3.1	NQ Versus PNA 180
7.2.3.2	PNA Versus MNA 182
7.2.3.3	Challenges 182
7.3	Algorithms Based on Conditional Random Fields 183
7.3.1	CNetQ for Network Querying 183
7.3.1.1	General Framework 183
7.3.1.2	Feature Function 185
7.3.1.3	Gap Penalty 185
7.3.1.4	Network Simplification 186
7.3.1.5	Real Examples 186
7.3.2	CNetA for Pairwise Network Alignment 186
7.3.2.1	Iterative Bidirectional Mapping Strategy 187
7.3.2.2	Simulated Data 188
7.3.2.3	Comparison 188
7.3.2.4	Evaluation Measures 189
7.3.3	CNetMA for Multiple Network Alignment 189
7.3.3.1	Græmlin 189
7.3.3.2	IsoRank 190

7.3.3.3	MNA Examples	190
7.3.3.4	CNetMA	191
7.4	Performing Network Alignments with R	193
7.4.1	Installation	193
7.4.1.1	CRF Package	193
7.4.1.2	Corbi Package	193
7.4.2	Usage	193
7.4.2.1	Input File Format	194
7.4.2.2	Output File Format	194
7.4.2.3	Arguments	194
7.4.3	Examples	195
7.4.3.1	Network Querying	195
7.4.3.2	Pairwise Network Alignment	195
7.4.4	Web Services and Tool Functions	196
7.5	Discussion	196
	References	197
8	ℓ_1-Penalized Methods in High-Dimensional Gaussian Markov Random Fields	201
	<i>Luigi Augugliaro, Angelo M. Mineo, and Ernst C. Wit</i>	
8.1	Introduction	201
8.2	Graph Theory: Terminology and Basic Topological Notions	202
8.3	Probabilistic Graphical Models	203
8.4	Markov Random Field	204
8.4.1	Ising Model and Extensions	205
8.4.2	Gaussian Markov Random Fields	206
8.5	Sparse Inference in High-dimensional GMRFs	207
8.5.1	Neighborhood Selection	207
8.5.2	The R Package <i>simone</i>	209
8.5.3	Osteolytic Lesions Data Set: An Analysis by Neighborhood Selection Method	210
8.5.4	Graphical Lasso Estimator	215
8.5.5	The R Package <i>glasso</i> : Computing the Gradient and Coefficient Solution Path on a Simulated Data Set	217
8.5.6	Computational Aspects of the <i>glasso</i> Estimator: the Block-Coordinate Descent Algorithm	223
8.5.7	Faster Computation via Exact Covariance Thresholding	225
8.5.8	Lung Cancer Microarray Data: An Analysis by <i>glasso</i> Estimator	227
8.5.9	The Joint Graphical Lasso	233
8.5.10	Computational Aspects of the <i>jglasso</i> Estimator: ADMM Algorithm	235
8.5.11	The R Package <i>JGL</i>	239
8.5.12	Lung Cancer Microarray Data: An Analysis by <i>jglasso</i> Estimator	241
8.5.13	Structured Graphical Lasso	243

8.5.13.1	Computational Aspects of the <i>sglasso</i> Estimator: Cyclic Coordinate Algorithms	246
8.5.14	The R Package <i>sglasso</i>	248
8.5.15	<i>Neisseria meningitidis</i> Data Set: An Analysis by <i>fglasso</i> Estimator	250
8.6	Selecting the Optimal Value of the Tuning Parameter	252
8.7	Summary and Conclusion	256
	References	259
9	Cluster Analysis of Social Networks Using R	267
	<i>Malika Charrad</i>	
9.1	Introduction	267
9.2	Cluster Analysis in Social Networks	268
9.2.1	Social Network Data	268
9.2.1.1	The Data as a Graph	268
9.2.1.2	The Data as a Matrix	269
9.2.2	Clustering in Social Networks	269
9.3	Cluster Analysis in Social Networks Using R	270
9.3.1	R Packages for Cluster Analysis	270
9.3.2	Data Loading and Formatting	270
9.3.2.1	Removing Zero Edges	271
9.3.2.2	Coercing the Data into a Graph Object	271
9.3.2.3	Creating Social and Task Subgraphs	272
9.3.3	Agglomerative Hierarchical Clustering	274
9.3.3.1	Measuring Similarity/Dissimilarity	274
9.3.3.2	Clustering	275
9.3.3.3	Cluster Validity	276
9.3.4	Edge Betweenness Clustering Algorithm	279
9.3.5	Fast Greedy Modularity Optimization Algorithm	281
9.3.6	Walktrap Algorithm	283
9.4	Discussion and Further Readings	285
	References	286
10	Inference and Analysis of Gene Regulatory Networks in R	289
	<i>Ricardo de M. Simoes, Matthias Dehmer, Constantine Mitsiades, and Frank Emmert-Streib</i>	
10.1	Introduction	289
10.2	Multiple Myeloma	290
10.3	Installation of Required R Packages from CRAN and Bioconductor	291
10.4	Data Preprocessing	292
10.5	Bc3net Gene Regulatory Network Inference	294
10.6	Retrieving and Generating Gene Sets for a Functional Analysis	297
10.7	Pathway and Other Gene Set Collections	298
10.7.1	Functional Enrichment Analysis of Gene Regulatory Networks	300

10.8	Conclusion	302
	References	303
11	Visualization of Biological Networks Using NetBioV	307
	<i>Shailesh Tripathi, Salissou Moutari, Matthias Dehmer, and Frank Emmert-Streib</i>	
11.1	Introduction	307
11.2	Network Visualization	310
11.3	NetBioV	313
11.3.1	Global Network Layouts	313
11.3.2	Modular Network Layout	316
11.3.3	Layered Network (Multiroot) Layout	317
11.3.4	Other Features	318
11.3.4.1	Information Flow	318
11.3.4.2	Spiral View	318
11.3.4.3	Color Schemes, Node Labeling	318
11.3.4.4	Interface to R and Customization	319
11.4	Example: Visualization of Networks Using NetBioV	319
11.4.1	Loading Library and Data	320
11.4.2	Global Layout Style	320
11.4.2.1	R Code in Figure 11.4	320
11.4.3	Modular Layout Style	322
11.4.3.1	R Code in Figure 11.5	322
11.4.4	Layered Layout Style	323
11.4.4.1	R Code in Figure 11.6	323
11.5	Conclusion	325
11.6	Appendix	326
11.6.1	R Code for the Visualization in Figures 11.2 and 11.3	326
11.7	Spiral View	329
11.7.1	Spiral Layout Style in Figure 11.7	329
	References	330
	Index	335

