- [1] L. Adamic, E. Adar, Friends and neighbors on the web. Soc. Network. **25**(3), 211–230 (2003)
- [2] E.M. Airoldi, D.M. Blei, S.E. Fienberg, E.P. Xing, Mixed membership stochastic blockmodels. J. Mach. Learn. Res. **9**, 1981–2014 (2008)
- [3] M. Al Hasan, M.J. Zaki, A survey of link prediction in social networks. In *Social Network Data Analytics* (Springer, New York, 2011), pp. 243–275
- [4] D. Aldous, Exchangeability and related topics. In *École d'Été de Probabilités de Saint-Flour XIII—1983*, (Springer, Berlin, 1985), pp. 1–198
- [5] T. Anderson, *An Introduction to Multivariate Statistical Analysis*, 2nd edn. (Wiley, New York, 1984)
- [6] R. Anderson, R. May, *Infectious Diseases of Humans: Dynamics and Control* (Oxford University Press, Oxford, 1991)
- [7] J. Bader, A. Chaudhuri, J. Rothberg, J. Chant, Gaining confidence in high-throughput protein interaction networks. Nat. Biotechnol. **22**(1), 78–85 (2004)
- [8] A. Barabási, R. Albert, Emergence of scaling in random networks. Science **286**(5439), 509–512 (1999)
- [9] A. Barrat, M. Barthélemy, A. Vespignani, *Dynamical Processes on Complex Networks* (Cambridge University Press, New York, 2008)
- [10] D.S. Bassett, E. Bullmore, Small-world brain networks. Neuroscientist **12**(6), 512–523 (2006)
- [11] Y. Benjamini, Y. Hochberg, Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. Roy. Stat. Soc. Ser. B **57**(1), 289–300 (1995)
- [12] J. Besag, Spatial interaction and the statistical analysis of lattice systems. J. Roy. Stat. Soc. Ser. B **36**(2), 192–236 (1974)
- [13] J. Besag, Statistical analysis of non-lattice data. The Statistician **24**(3), 179–195 (1975)
- [14] S. Bialonski, M.-T. Horstmann, K. Lehnertz, From brain to earth and climate systems: small-world interaction networks or not? Chaos Interdiscipl. J. Nonlinear Sci. **20**(1), 013134 (2010)

- [15] B. Bollobás, *Modern Graph Theory* (Springer, New York, 1998)
- [16] B. Bollobás, *Random Graphs*, 2nd edn. (Cambridge University Press, New York, 2001)
- [17] B. Bollobás, O. Riordan, Mathematical results on scale-free random graphs. In *Handbook of Graphs and Networks: From the Genome to the Internet*, ed. by S. Bornholdt, H. Schuster (Wiley-VCH, Weinheim, 2002), pp. 1–34
- [18] B. Bollobás, O. Riordan, The diameter of a scale-free random graph. Combinatorica **24**(1), 5–34 (2004)
- [19] B. Bollobás, O. Riordan, J. Spencer, G. Tusnady, The degree sequence of a scale-free random graph process. Random Struct. Algorithm. **18**(3), 279–290 (2001)
- [20] P. Bonacich, Factoring and weighting approaches to status scores and clique identification. J. Math. Socio. **2**(1), 113–120 (1972)
- [21] K. Boyack, R. Klavans, K. Börner, Mapping the backbone of science. Scientometrics **64**(3), 351–374 (2005)
- [22] U. Brandes, T. Erlebach (eds.), *Network Analysis: Methodological Foundations*. Lecture Notes in Computer Science, vol. 3418 (Springer, New York, 2005)
- [23] J. Cao, D. Davis, S. Wiel, B. Yu, Time-varying network tomography: router link data. J. Am. Stat. Assoc. **95**(452), 1063–1075 (2000)
- [24] P.C. Caragea, M.S. Kaiser, Autologistic models with interpretable parameters. J. Agr. Biol. Environ. Stat. **14**(3), 281–300 (2009)
- [25] H. Carey, *Principles of Social Science* (Lippincott, Philadelphia, 1858)
- [26] R. Castro, M. Coates, R. Nowak, Likelihood-based hierarchical clustering. IEEE Trans. Signal Process. **52**(8), 2308–2321 (2004)
- [27] R. Castro, M. Coates, G. Liang, R. Nowak, B. Yu, Network tomography: recent developments. Stat. Sci. 19(3), 499–517 (2004)
- [28] F. Chung, *Spectral Graph Theory* (American Mathematical Society, Providence, 1997)
- [29] F. Chung, L. Lu, *Complex Graphs and Networks* (American Mathematical Society, Providence, 2006)
- [30] A. Clauset, M. Newman, C. Moore, Finding community structure in very large networks. Phys. Rev. E **70**(6), 66111 (2004)
- [31] W. Cleveland, The Elements of Graphing Data (Wadsworth, Monterey, 1985)
- [32] W. Cleveland, *Visualizing Data* (Hobart Press, Summit, 1993)
- [33] M. Coates, R. Castro, R. Nowak, M. Gadhiok, R. King, Y. Tsang, Maximum likelihood network topology identification from edge-based unicast measurements. Proceedings of the 2002 ACM SIGMETRICS International Conference on Measurement and Modeling of Computer Systems, 2002, pp. 11–20
- [34] A. Coja-Oghlan, A. Lanka, Finding planted partitions in random graphs with general degree distributions. SIAM J. Discrete Math. **23**(4), 1682–1714 (2009)
- [35] T. Cormen, C. Leiserson, R. Rivest, C. Stein, *Introduction to Algorithms* (MIT Press, Cambridge, 2003)
- [36] M. Crawley, *The R Book* (Wiley, New York, 2007)

- [37] N. Cressie, Statistics for Spatial Data (Wiley, New York, 1993)
- [38] N. Cristianini, J. Shawe-Taylor, A. Elisseeff, J. Kandola, On kernel-target alignment. In *Advances in Neural Information Processing Systems*, vol. 14 (MIT Press, Cambridge, 2002)
- [39] N. Cristianini, J. Kandola, A. Elisseeff, J. Shawe-Taylor, On kernel-target alignment. In *Innovations in Machine Learning: Theory and Applications*, ed. by D. Holmes, L. Jain (Springer, New York, 2006)
- [40] D. Daley, J. Gani, *Epidemic Modeling* (Cambridge University Press, New York, 1999)
- [41] J.-J. Daudin, F. Picard, S. Robin, A mixture model for random graphs. Stat. Comput. **18**(2), 173–183 (2008)
- [42] G. Davidson, B. Wylie, K. Boyack, Cluster stability and the use of noise in interpretation of clustering. *IEEE Symposium on Information Visualization*, 2002, pp. 23–30
- [43] J. Davis, S. Leinhardt, The structure of positive interpersonal relations in small groups. In *Sociological Theories in Progress*, vol. 2, ed. by J. Berger (Houghton-Mifflin, Boston, 1972)
- [44] W. Deming, F. Stephan, On a least squares adjustment of a sampled frequency table when the expected marginal totals are known. Ann. Math. Stat. **11**(4), 427–444 (1940)
- [45] A. Dempster, Covariance selection. Biometrics **28**(1), 157–175 (1972)
- [46] G. di Battista, P. Eades, R. Tamassia, I. Tollis, *Graph Drawing* (Prentice Hall, Englewood Cliffs, 1999)
- [47] R. Diestel, *Graph Theory*, 3rd edn. (Springer, Heidelberg, 2005)
- [48] S. Dorogovtsev, J. Mendes, A. Samukhin, Structure of growing networks with preferential linking. Phys. Rev. Lett. **85**(21), 4633–4636 (2000)
- [49] D. Easley, J. Kleinberg, *Networks, Crowds, and Markets* (Cambridge University Press, Cambridge, 2010)
- [50] P. Erdős, A. Rényi, On random graphs. Publ. Math. Debrecen **6**(290), 290–297 (1959)
- [51] P. Erdős, A. Rényi, On the evolution of random graphs. Publ. Math. Inst. Hung. Acad. Sci. 5, 17–61 (1960)
- [52] P. Erdős, A. Rényi, On the strength of connectedness of a random graph. Acta. Math. Acad. Sci. Hung. 12, 261–267 (1961)
- [53] G. Fagiolo, Clustering in complex directed networks. Phys. Rev. E **76**(2), 026107 (2007)
- [54] J. Faith, B. Hayete, J. Thaden, I. Mogno, J. Wierzbowski, G. Cottarel, S. Kasif, J. Collins, T. Gardner, Large-scale mapping and validation of *Escherichia coli* transcriptional regulation from a compendium of expression profiles. PLoS Biol. 5(1), e8 (2007)
- [55] J. Felsenstein, *Inferring Phylogenies* (Sinear Associates, Sunderland, 2004)
- [56] M. Fiedler, Algebraic connectivity of graphs. Czech. Math. J. **23**(98), 298–305 (1973)
- [57] M. Fischer, S. Gopal, Artificial neural networks: a new approach to modeling interregional telecommunication flows. J. Reg. Sci. **34**(4), 503–527 (1994)

[58] O. Frank, D. Strauss, Markov graphs. J. Am. Stat. Assoc. 81(395), 832–842 (1986)

- [59] L. Freeman, A set of measures of centrality based on betweenness. Sociometry **40**(1), 35–41 (1977)
- [60] T. Fruchterman, E. Reingold, Graph drawing by force-directed placement. Software Pract. Ex. **21**(11), 1129–1164 (1991)
- [61] F. Gerhard, G. Pipa, B. Lima, S. Neuenschwander, W. Gerstner, Extraction of network topology from multi-electrode recordings: is there a small-world effect? Front. Comput. Neurosci. **5**, 4 (2011)
- [62] C. Geyer, E. Thompson, Constrained Monte Carlo maximum likelihood for dependent data. J. Roy. Stat. Soc. Ser. B 54(3), 657–699 (1992)
- [63] E. Gilbert, Random graphs. Ann. Math. Stat. **30**(4), 1141–1144 (1959)
- [64] C. Godsil, G. Royle, *Algebraic Graph Theory* (Springer, New York, 2001)
- [65] D. Goldberg, F. Roth, Assessing experimentally derived interactions in a small world. Proc. Natl. Acad. Sci. **100**(8), 4372–4376 (2003)
- [66] S. Gopal, The evolving social geography of blogs. In *Societies and Cities in the Age of Instant Access*, ed. by H. Miller (Springer, Berlin, 2007), pp. 275–294
- [67] J. Gross, J. Yellen, *Graph Theory and Its Applications* (Chapman & Hall/CRC, Boca Raton, 1999)
- [68] M. Handcock, Assessing degeneracy in statistical models of social networks. Technical Report No. 39, Center for Statistics and the Social Sciences, University of Washington, 2003
- [69] S. Hanneke, E.P. Xing, Discrete temporal models of social networks. In *Statistical Network Analysis: Models, Issues, and New Directions* (Springer, New York, 2007), pp. 115–125
- [70] S. Hanneke, W. Fu, E.P. Xing, Discrete temporal models of social networks. Electron. J. Stat. **4**, 585–605 (2010)
- [71] T. Hastie, R. Tibshirani, J. Friedman, *The Elements of Statistical Learning* (Springer, New York, 2001)
- [72] P. Hoff, Multiplicative latent factor models for description and prediction of social networks. Comput. Math. Organ. Theor. (2007)
- [73] P. Hoff, Modeling homophily and stochastic equivalence in symmetric relational data. *Advances in Neural Information Processing Systems, NIPS* (MIT Press, Cambridge, 2008)
- [74] P. Holland, S. Leinhardt, A method for detecting structure in sociometric data. Am. J. Socio. 70, 492–513 (1970)
- [75] S. Holmes, Phylogenies: an overview. In *Statistics and Genetics*, ed. by E. Halloran, S. Geisser. IMA, vol. 81 (Springer, New York, 1999)
- [76] S. Holmes, Statistics for phylogenetic trees. Theor. Popul. Biol. **63**, 17–32 (2003)
- [77] D.N. Hoover, Row-column exchangeability and a generalized model for probability. In *Exchangeability in Probability and Statistics* (North-Holland, Amsterdam, 1982), pp. 81–291

[78] D. Hunter, Curved exponential family models for social networks. Soc. Network. **29**(2), 216–230 (2007)

- [79] D. Hunter, M. Handcock, Inference in curved exponential family models for networks. J. Comput. Graph. Stat. **15**(3), 565–583 (2006)
- [80] E. Ising, Beitrag zur theorie des ferromagnetismus Zeit. fur Physik **31**, 253–258 (1925)
- [81] M. Jackson, *Social and Economic Networks* (Princeton University Press, Princeton, 2008)
- [82] A. Jain, M. Murty, P. Flynn, Data clustering: a review. ACM Comput. Surv. **31**(3), 264–323 (1999)
- [83] X. Jiang, N. Nariai, M. Steffen, S. Kasif, E. Kolaczyk, Integration of relational and hierarchical network information for protein function prediction. BMC Bioinform. **9**, 350 (2008)
- [84] R. Johnson, D. Wichern, *Applied Multivariate Statistical Analysis*, 5th edn. (Pearson Eduction, Upper Saddle River, 2001)
- [85] T. Kamada, S. Kawai, An algorithm for drawing general undirected graphs. Inform. Process. Lett. **31**(1), 7–15 (1989)
- [86] B. Karrer, M.E. Newman, Stochastic blockmodels and community structure in networks. Phys. Rev. E **83**(1), 016107 (2011)
- [87] N. Kashtan, S. Itzkovitz, R. Milo, U. Alon, Efficient sampling algorithm for estimating subgraph concentrations and detecting network motifs. Bioinformatics **20**(11), 1746–1758 (2004)
- [88] L. Katz, A new status index derived from sociometric analysis. Psychometrika **18**(1), 39–43 (1953)
- [89] M. Kaufmann, D. Wagner (eds.), *Drawing Graphs* (Springer, Berlin, 1998)
- [90] J. Kleinberg, Authoritative sources in a hyperlinked environment. J. ACM **46**(5), 604–632 (1999)
- [91] E. Kolaczyk, Statistical Analysis of Network Data: Methods and Models (Springer, New York, 2009)
- [92] D. König, *Theorie der Endlichen und Unendlichen Graphen* (American Mathematical Society, New York, 1950)
- [93] P. Krapivsky, S. Redner, F. Leyvraz, Connectivity of growing random networks. Phys. Rev. Lett. **85**(21), 4629–4632 (2000)
- [94] P.N. Krivitsky, M.S. Handcock, A separable model for dynamic networks. J. Roy. Stat. Soc. Ser. B (Stat. Meth.) (2013)
- [95] A. Lancichinetti, S. Fortunato, Community detection algorithms: a comparative analysis. Phys. Rev. E **80**(5), 056117 (2009)
- [96] G. Lanckriet, N. Cristianini, P. Bartlett, L. El Ghaoui, M. Jordan, Learning the kernel matrix with semidefinite programming. J. Mach. Learn. Res. 5, 27–72 (2004)
- [97] S. Lauritzen, *Graphical Models* (Oxford University Press, Oxford, 1996)
- [98] E. Lazega, *The Collegial Phenomenon: The Social Mechanisms of Cooperation Among Peers in a Corporate Law Partnership* (Oxford University Press, Oxford, 2001)

[99] E. Lazega, P. Pattison, Multiplexity, generalized exchange and cooperation in organizations: a case study. Soc. Network. **21**(1), 67–90 (1999)

- [100] S. Li, Markov Random Field Modeling in Computer Vision (Springer, New York, 1995)
- [101] D. Liben-Nowell, J. Kleinberg, The link prediction problem for social networks. In *Proceedings of the 12th International Conference on Information and Knowledge Management*, 2003
- [102] Y. Lin, H. Zhang, Component selection and smoothing in multivariate non-parametric regression. Ann. Stat. **34**(5), 2272–2297 (2006)
- [103] R. Little, D. Rubin, *Statistical Analysis with Missing Data*, 2nd edn. (Wiley, New York, 2002)
- [104] L. Lü, T. Zhou, Link prediction in complex networks: a survey. Phys. A Stat. Mech. Appl. **390**(6), 1150–1170 (2011)
- [105] D. Lusher, J. Koskinen, G. Robins, Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications (Cambridge University Press, Cambridge, 2012)
- [106] S. Martin, W. Brown, R. Klavans, K. Boyack, DrL: distributed recursive (graph) layout. SAND Reports, Technical Report 2936, 2008
- [107] P. McCullagh, J. Nelder, Generalized Linear Models (Chapman & Hall/CRC, London, 1989)
- [108] J. McDonald, P. Smith, J. Forster, Markov chain Monte Carlo exact inference of social networks. Soc. Network. **29**, 127–136 (2007)
- [109] G. McLachlan, T. Krishnan, *The EM Algorithm and Extensions*, vol. 382 (Wiley, New York, 2007)
- [110] N. Meinshausen, P. Bühlmann, High-dimensional graphs and variable selection with the Lasso. Ann. Stat. **34**(3), 1436–1462 (2006)
- [111] R. Milo, S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, U. Alon, Network motifs: simple building blocks of complex networks. Science **298**(5594), 824–827 (2002)
- [112] M. Mitzenmacher, A brief history of generative models for power law and lognormal distributions. Internet Math. 1(2), 226–251 (2004)
- [113] B. Mohar, The Laplacian spectrum of graphs. In *Graph Theory, Combinatorics, and Applications*, vol. 2, ed. by Y. Alavi, G. Chartrand, O. Oellermann, A. Schwenk (Wiley, New York, 1991), pp. 871–898
- [114] J. Moody, D. McFarland, S. Bender-deMoll, Dynamic network visualization. Am. J. Socio. **110**(4), 1206–1241 (2005)
- [115] L. Négyessy, T. Nepusz, L. Kocsis, F. Bazsó, Prediction of the main cortical areas and connections involved in the tactile function of the visual cortex by network analysis. Eur. J. Neurosci. 23(7), 1919–1930 (2006)
- [116] M. Newman, Mixing patterns in networks. Phys. Rev. E **67**(2), 26126 (2003)
- [117] M. Newman, Finding community structure in networks using the eigenvectors of matrices. Phys. Rev. E **74**(3), 36104 (2006)
- [118] M. Newman, *Networks: An Introduction* (Oxford University Press, Oxford, 2010)

[119] M. Newman, M. Girvan, Finding and evaluating community structure in networks. Phys. Rev. E **69**(2), 26113 (2004)

- [120] A. Noor, E. Serpedin, M. Nounou, H. Nounou, N. Mohamed, L. Chouchane, An overview of the statistical methods used for inferring gene regulatory networks and protein–protein interaction networks. Adv. Bioinformatics 2013, 953814 (2013)
- [121] K. Nowicki, T. Snijders, Estimation and prediction for stochastic blockstructures. J. Am. Stat. Assoc. **96**(455), 1077–1087 (2001)
- [122] P. Pattison, G. Robins, Neighborhood-based models for social networks. Socio. Meth. **32**(1), 301–337 (2002)
- [123] A. Popescul, L. Ungar, Statistical relational learning for link prediction. In *Proceedings of the Workshop on Learning Statistical Models from Relational Data at IJCAI-2003*, 2003
- [124] J. Roberts, Simple methods for simulating sociomatrices with given marginal totals. Soc. Network. **22**(3), 273–283 (2000)
- [125] G. Robins, M. Morris, Advances in exponential random graph (p*) models. Soc. Network. **29**(2), 169–172 (2007)
- [126] G. Robins, P. Pattison, Y. Kalish, D. Lusher, An introduction to exponential random graph (p*) models for social networks. Soc. Network. **29**(2), 173–191 (2007)
- [127] G. Sabidussi, The centrality index of a graph. Psychometrika **31**, 581–683 (1966)
- [128] B. Schölkopf, A. Smola, Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond (MIT Press, Cambridge, 2002)
- [129] J. Scott, *Social Network Analysis: A Handbook*, 2nd edn. (Sage Publications, Newbury Park, 2004)
- [130] A. Sen, T. Smith, *Gravity Models of Spatial Interaction Behavior* (Springer, Berlin, 1995)
- [131] J. Shawe-Taylor, N. Cristianini, *Kernel Methods for Pattern Analysis* (Cambridge University Press, Cambridge, 2004)
- [132] A. Smola, R. Kondor, Kernels and regularization on graphs. In *Proceedings* of the 16th Annual Conference on Learning Theory (COLT), 2003
- [133] T. Snijders, Enumeration and simulation methods for 0-1 matrices with given marginal totals. Psychometrika **57**, 397–417 (1991)
- [134] T. Snijders, P. Pattison, G. Robins, M. Handcock, New specifications for exponential random graph models. Socio. Meth. **36**(1), 99–153 (2006)
- [135] T.A. Snijders, G.G. Van de Bunt, C.E. Steglich, Introduction to stochastic actor-based models for network dynamics. Soc. Network. **32**(1), 44–60 (2010)
- [136] J. Stewart, An inverse distance variation for certain social influences. Science **93**(2404), 89–90 (1941)
- [137] B. Taskar, M. Wong, P. Abbeel, D. Koller, Link prediction in relational data. In *Advances in Neural Information Processing Systems*, vol. 16 (MIT Press, Cambridge, 2004)

[138] R. Tibshirani, Regression shrinkage and selection via the lasso. J. Roy. Stat. Soc. Ser. B **58**, 267–288 (1996)

- [139] E. Tufte, *The Visual Display of Quantitative Information* (Graphics Press, Cheshire, 1983)
- [140] J. Tukey, Exploratory Data Analysis (Addison-Wesley, New York, 1977)
- [141] P. Vanhems, A. Barrat, C. Cattuto, J.-F. Pinton, N. Khanafer, C. Régis, B.-a. Kim, B. Comte, N. Voirin, Estimating potential infection transmission routes in hospital wards using wearable proximity sensors. PloS One 8(9), e73970 (2013)
- [142] Y. Vardi, Network tomography: estimating source-destination traffic intensities from link data. J. Am. Stat. Assoc. **91**(433), 365–377 (1996)
- [143] W. Venables, D. Smith, *An Introduction to R*. (Network Theory Ltd, Bristol, 2009)
- [144] S. Wasserman, K. Faust, *Social Network Analysis: Methods and Applications* (Cambridge University Press, New York, 1994)
- [145] S. Wasserman, P. Pattison, Logit models and logistic regressions for social networks: I. An introduction to Markov graphs and p^* . Psychometrika **61**(3), 401–425 (1996)
- [146] D. Watts, S. Strogatz, Collective dynamics of 'small-world' networks. Nature 393(6684), 440–442 (1998)
- [147] J. Whittaker, *Graphical Models in Applied Multivariate Statistics* (Wiley, Chichester, 1990)
- [148] A. Wille, P. Zimmermann, E. Vránova, A. Fürholz, O. Laule, S. Bleuler, L. Hennig, A. Prelić, P. Rohr, L. Thiele et al., Sparse graphical Gaussian modeling of the isoprenoid gene network in arabidopsis thaliana. Genome Biol. 5(11), R92 (2004)
- [149] W. Zachary, An information flow model for conflict and fission in small groups. J. Anthropol. Res. **33**(4), 452–473 (1977)
- [150] H. Zhang, Y. Lin, Component selection and smoothing for nonparametric regression in exponential families. Statistica Sinica **16**, 1021–1042 (2006)
- [151] Y. Zhang, M. Roughan, C. Lund, D. Donoho, An information-theoretic approach to traffic matrix estimation. In *Proceedings of SIGCOMM'03*, 2003
- [152] A. Zuur, E. Ieno, E. Meesters, *A Beginner's Guide to R* (Springer, New York, 2009)

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