

Bibliography

- [1] E. Anderson, Z. Bai, C. Bischof, L. S. Blackford, J. Demmel, J. Dongarra, J. Du Croz, A. Greenbaum, S. Hammarling, A. McKenney, and D. C. Sorensen. *LAPACK Users' Guide*, 3rd ed. SIAM, Philadelphia, 1999.
- [2] ANSI/IEEE 754. *Binary Floating Point Arithmetic*. IEEE, New York, 1985.
- [3] R. Baeza-Yates and B. Ribeiro-Neto. *Modern Information Retrieval*. ACM Press, Addison-Wesley, New York, 1999.
- [4] Z. Bai, J. Demmel, J. Dongarra, A. Ruhe, and H. van der Vorst, eds. *Templates for the Solution of Algebraic Eigenvalue Problems: A Practical Guide*. SIAM, Philadelphia, 2000.
- [5] R. Barrett, M. Berry, T. F. Chan, J. Demmel, J. Donato, J. Dongarra, V. Eijkhout, R. Pozo, C. Romine, and H. van der Vorst. *Templates for the Solution of Linear Systems: Building Blocks for Iterative Methods*. SIAM, Philadelphia, 1994.
- [6] B. Bergeron. *Bioinformatics Computing*. Prentice-Hall, New York, 2002.
- [7] P. Berkin. A survey on PageRank computing. *Internet Math.*, 2:73–120, 2005.
- [8] M. Berry and M. Browne. Email surveillance using non-negative matrix factorization. *Comput. Math. Organization Theory*, 11:249–264, 2005.
- [9] M. W. Berry, S. T. Dumais, and G. W. O'Brien. Using linear algebra for intelligent information retrieval. *SIAM Rev.*, 37:573–595, 1995.
- [10] M. J. A. Berry and G. Linoff. *Mastering Data Mining. The Art and Science of Customer Relationship Management*. John Wiley, New York, 2000.
- [11] M. W. Berry, ed. *Computational Information Retrieval*. SIAM, Philadelphia, 2001.
- [12] M. W. Berry and M. Browne. *Understanding Search Engines. Mathematical Modeling and Text Retrieval*, 2nd ed. SIAM, Philadelphia, 2005.

- [13] M. W. Berry, M. Browne, A. Langville, V. P. Pauca, and R. J. Plemmons. *Algorithms and Applications for Approximate Nonnegative Matrix Factorization*. Technical report, Department of Computer Science, University of Tennessee, 2006.
- [14] Å. Björck. *Numerical Methods for Least Squares Problems*. SIAM, Philadelphia, 1996.
- [15] Å. Björck. The calculation of least squares problems. *Acta Numer.*, 13:1–51, 2004.
- [16] K. Blom and A. Ruhe. A Krylov subspace method for information retrieval. *SIAM J. Matrix Anal. Appl.*, 26:566–582, 2005.
- [17] V. D. Blondel, A. Gajardo, M. Heymans, P. Senellart, and P. Van Dooren. A measure of similarity between graph vertices: Applications to synonym extraction and web searching. *SIAM Rev.*, 46:647–666, 2004.
- [18] C. Boutsidis and E. Gallopoulos. *On SVD-Based Initialization for Nonnegative Matrix Factorization*. Technical Report HPCLAB-SCG-6/08-05, University of Patras, Patras, Greece, 2005.
- [19] S. Brin and L. Page. The anatomy of a large-scale hypertextual web search engine. *Comput. Networks ISDN Syst.*, 30:107–117, 1998.
- [20] J.-P. Brunet, P. Tamayo, T. R. Golub, and J. P. Mesirov. Metagenes and molecular pattern discovery using matrix factorization. *PNAS*, 101:4164–4169, 2004.
- [21] M. C. Burl, L. Asker, P. Smyth, U. Fayyad, P. Perona, L. Crumpler, and J. Aubele. Learning to recognize volcanoes on Venus. *Machine Learning*, 30:165–195, 1998.
- [22] P. A. Businger and G. H. Golub. Linear least squares solutions by Householder transformations. *Numer. Math.*, 7:269–276, 1965.
- [23] R. Chelappa, C. L. Wilson, and S. Sirohey. Human and machine recognition of faces: A survey. *Proc. IEEE*, 83:705–740, 1995.
- [24] N. Christianini and J. Shawe-Taylor. *An Introduction to Support Vector Machines*. Cambridge University Press, London, 2000.
- [25] K. J. Cios, W. Pedrycz, and R. W. Swiniarski. *Data Mining. Methods for Knowledge Discovery*. Kluwer, Boston, 1998.
- [26] J. M. Conroy, J. D. Schlesinger, D. P. O’Leary, and J. Goldstein. Back to basics: CLASSY 2006. In *DUC 02 Conference Proceedings*, 2006. Available at <http://duc.nist.gov/pubs.html>.
- [27] T. A. Davis. *Direct Methods for Sparse Linear Systems*. Fundamentals of Algorithms 2. SIAM, Philadelphia, 2006.

- [28] S. Deerwester, S. Dumais, G. Furnas, T. Landauer, and R. Harsman. Indexing by latent semantic analysis. *J. Amer. Soc. Inform. Sci.*, 41:391–407, 1990.
- [29] J. W. Demmel. *Applied Numerical Linear Algebra*. SIAM, Philadelphia, 1997.
- [30] I. S. Dhillon and D. S. Modha. Concept decompositions for large sparse text data using clustering. *Machine Learning*, 42:143–175, 2001.
- [31] R. O. Duda, P. E. Hart, and D. G. Storck. *Pattern Classification*, 2nd ed. Wiley-Interscience, New York, 2001.
- [32] L. Eldén. Partial least squares vs. Lanczos bidiagonalization I: Analysis of a projection method for multiple regression. *Comput. Statist. Data Anal.*, 46:11–31, 2004.
- [33] L. Eldén. Numerical linear algebra in data mining. *Acta Numer.*, 15:327–384, 2006.
- [34] L. Eldén, L. Wittmeyer-Koch, and H. Bruun Nielsen. *Introduction to Numerical Computation—Analysis and MATLAB Illustrations*. Studentlitteratur, Lund, 2004.
- [35] U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, eds. *Advances in Knowledge Discovery and Data Mining*. AAAI Press/The MIT Press, Menlo Park, CA, 1996.
- [36] J. H. Fowler and S. Jeon. *The Authority of Supreme Court Precedent: A Network Analysis*. Technical report, Department of Political Science, University of California, Davis, 2005.
- [37] Y. Gao and G. Church. Improving molecular cancer class discovery through sparse non-negative matrix factorization. *Bioinform.*, 21:3970–3975, 2005.
- [38] J. T. Giles, L. Wo, and M. W. Berry. GTP (General Text Parser) software for text mining. In *Statistical Data Mining and Knowledge Discovery*, H. Bozdogan, ed., CRC Press, Boca Raton, FL, 2003, pp. 455–471.
- [39] N. Goharian, A. Jain, and Q. Sun. Comparative analysis of sparse matrix algorithms for information retrieval. *J. System. Cybernet. Inform.*, 1, 2003.
- [40] G. H. Golub and C. Greif. An Arnoldi-type algorithm for computing pagerank. *BIT*, 46:759–771, 2006.
- [41] G. Golub and W. Kahan. Calculating the singular values and pseudo-inverse of a matrix. *SIAM J. Numer. Anal. Ser. B*, 2:205–224, 1965.
- [42] G. H. Golub and C. F. Van Loan. *Matrix Computations*, 3rd ed. Johns Hopkins Press, Baltimore, 1996.
- [43] D. Grossman and O. Frieder. *Information Retrieval: Algorithms and Heuristics*. Kluwer, Boston, 1998.

- [44] Z. Gyöngyi, H. Garcia-Molina, and J. Pedersen. Combating web spam with TrustRank. In *Proc., 30th International Conference on Very Large Databases*, Morgan Kaufmann, 2004, pp. 576–587.
- [45] J. Han and M. Kamber. *Data Mining: Concepts and Techniques*. Morgan Kaufmann, San Francisco, 2001.
- [46] D. Hand, H. Mannila, and P. Smyth. *Principles of Data Mining*. MIT Press, Cambridge, MA, 2001.
- [47] T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning. Data Mining, Inference and Prediction*. Springer, New York, 2001.
- [48] T. H. Haveliwala and S. D. Kamvar. *An Analytical Comparison of Approaches to Personalizing PageRank*. Technical report, Computer Science Department, Stanford University, Stanford, CA, 2003.
- [49] M. Hegland. Data mining techniques. *Acta Numer.*, 10:313–355, 2001.
- [50] N. J. Higham. *Accuracy and Stability of Numerical Algorithms*, 2nd ed. SIAM, Philadelphia, 2002.
- [51] I. C. F. Ipsen and S. Kirkland. Convergence analysis of a PageRank updating algorithm by Langville and Meyer. *SIAM J. Matrix Anal. Appl.*, 27:952–967, 2006.
- [52] E. R. Jessup and J. H. Martin. Taking a new look at the latent semantic analysis approach to information retrieval. In *Computational Information Retrieval*, M. W. Berry, ed., SIAM, Philadelphia, 2001, pp. 121–144.
- [53] S. D. Kamvar, T. H. Haveliwala, and G. H. Golub. Adaptive methods for the computation of pagerank. *Linear Algebra Appl.*, 386:51–65, 2003.
- [54] S. D. Kamvar, T. H. Haveliwala, C. D. Manning, and G. H. Golub. *Exploiting the Block Structure of the Web for Computing PageRank*. Technical report, Computer Science Department, Stanford University, Stanford, CA, 2003.
- [55] S. D. Kamvar, T. H. Haveliwala, C. D. Manning, and G. H. Golub. Extrapolation methods for accelerating PageRank computations. In *Proc., 12th International World Wide Web Conference*, Budapest, 2003, pp. 261–270.
- [56] J. M. Kleinberg. Authoritative sources in a hyperlinked environment. *J. Assoc. Comput. Mach.*, 46:604–632, 1999.
- [57] A. N. Langville and C. D. Meyer. Deeper inside PageRank. *Internet Math.*, 1:335–380, 2005.
- [58] A. N. Langville and C. D. Meyer. A survey of eigenvector methods for web information retrieval. *SIAM Rev.*, 47:135–161, 2005.

- [59] A. N. Langville and C. D. Meyer. *Google's PageRank and Beyond: The Science of Search Engine Rankings*. Princeton University Press, Princeton, NJ, 2006.
- [60] L. De Lathauwer, B. De Moor, and J. Vandewalle. A multilinear singular value decomposition. *SIAM J. Matrix Anal. Appl.*, 21:1253–1278, 2000.
- [61] C. L. Lawson and R. J. Hanson. *Solving Least Squares Problems*. Classics in Appl. Math. 15. SIAM, Philadelphia, 1995. Revised republication of work first published in 1974 by Prentice–Hall.
- [62] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proc. IEEE*, 86:2278–2324, Nov. 1998.
- [63] D. Lee and H. Seung. Learning the parts of objects by non-negative matrix factorization. *Nature*, 401:788–791, Oct. 1999.
- [64] R. B. Lehoucq, D. C. Sorensen, and C. Yang. *ARPACK Users' Guide: Solution of Large-Scale Eigenvalue Problems with Implicitly Restarted Arnoldi Methods*. SIAM, Philadelphia, 1998.
- [65] R. Lempel and S. Moran. Salsa: The stochastic approach for link-structure analysis. *ACM Trans. Inform. Syst.*, 19:131–160, 2001.
- [66] O. Mangasarian and W. Wolberg. Cancer diagnosis via linear programming. *SIAM News*, 23:1,18, 1990.
- [67] I. Mani. *Automatic Summarization*. John Benjamins, Amsterdam, 2001.
- [68] *Matlab User's Guide*. Mathworks, Inc., Natick, MA, 1996.
- [69] J. Mena. *Data Mining Your Website*. Digital Press, Boston, 1999.
- [70] C. D. Meyer. *Matrix Analysis and Applied Linear Algebra*. SIAM, Philadelphia, 2000.
- [71] C. Moler. The world's largest matrix computation. *Matlab News and Notes*, Oct. 2002, pp. 12–13.
- [72] J. L. Morrison, R. Breitling, D. J. Higham, and D. R. Gilbert. Generank: Using search engine technology for the analysis of microarray experiment. *BMC Bioinform.*, 6:233, 2005.
- [73] P. Paatero and U. Tapper. Positive matrix factorization: A non-negative factor model with optimal utilization of error estimates of data values. *Environmetrics*, 5:111–126, 1994.
- [74] L. Page, S. Brin, R. Motwani, and T. Winograd. *The PageRank Citation Ranking: Bringing Order to the Web*. Stanford Digital Library Working Papers, Stanford, CA, 1998.

- [75] C. C. Paige and M. Saunders. LSQR: An algorithm for sparse linear equations and sparse least squares. *ACM Trans. Math. Software*, 8:43–71, 1982.
- [76] H. Park, M. Jeon, and J. Ben Rosen. Lower dimensional representation of text data in vector space based information retrieval. In *Computational Information Retrieval*, M. W. Berry, ed., SIAM, Philadelphia, 2001, pp. 3–23.
- [77] H. Park, M. Jeon, and J. B. Rosen. Lower dimensional representation of text data based on centroids and least squares. *BIT*, 43:427–448, 2003.
- [78] V. P. Pauca, J. Piper, and R. Plemmons. Nonnegative matrix factorization for spectral data analysis. *Linear Algebra Appl.*, 416:29–47, 2006.
- [79] Y. Saad. *Numerical Methods for Large Eigenvalue Problems*. Manchester University Press, Manchester, UK, 1992.
- [80] Y. Saad. *Iterative Methods for Sparse Linear Systems*, 2nd ed. SIAM, Philadelphia, 2003.
- [81] G. Salton, C. Yang, and A. Wong. A vector-space model for automatic indexing. *Comm. Assoc. Comput. Mach.*, 18:613–620, 1975.
- [82] B. Savas. *Analyses and Test of Handwritten Digit Algorithms*. Master’s thesis, Mathematics Department, Linköping University, 2002.
- [83] J. D. Schlesinger, J. M. Conroy, M. E. Okurowski, H. T. Wilson, D. P. O’Leary, A. Taylor, and J. Hobbs. Understanding machine performance in the context of human performance for multi-document summarization. In *DUC 02 Conference Proceedings*, 2002. Available at <http://duc.nist.gov/pubs.html>.
- [84] S. Serra-Capizzano. Jordan canonical form of the Google matrix: A potential contribution to the PageRank computation. *SIAM J. Matrix Anal. Appl.*, 27:305–312, 2005.
- [85] F. Shahnaz, M. Berry, P. Pauca, and R. Plemmons. Document clustering using nonnegative matrix factorization. *J. Inform. Proc. Management*, 42:373–386, 2006.
- [86] P. Simard, Y. Le Cun, and J. S. Denker. Efficient pattern recognition using a new transformation distance. In *Advances in Neural Information Processing Systems 5*, J. D. Cowan, S. J. Hanson, and C. L. Giles, eds., Morgan Kaufmann, San Francisco, 1993, pp. 50–58.
- [87] P. Y. Simard, Y.A. Le Cun, J. S. Denker, and B. Victorri. Transformation invariance in pattern recognition—tangent distance and tangent propagation. *Internat. J. Imaging System Tech.*, 11:181–194, 2001.
- [88] L. Sirovich and M. Kirby. Low dimensional procedures for the characterization of human faces. *J. Optical Soc. Amer. A*, 4:519–524, 1987.

- [89] M. Sjöström and S. Wold. SIMCA: A pattern recognition method based on principal component models. In *Pattern Recognition in Practice*, E. S. Gelsema and L. N. Kanal, eds., North-Holland, Amsterdam, 1980, pp. 351–359.
- [90] P. Smaragdis and J. Brown. Non-negative matrix factorization for polyphonic music transcription. In *Proc., IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, 2003, pp. 177–180.
- [91] A. Smilde, R. Bro, and P. Geladi. *Multi-way Analysis: Applications in the Chemical Sciences*. John Wiley, New York, 2004.
- [92] G. W. Stewart. *Matrix Algorithms: Basic Decompositions*. SIAM, Philadelphia, 1998.
- [93] G. W. Stewart. *Matrix Algorithms Volume II: Eigensystems*. SIAM, Philadelphia, 2001.
- [94] G. W. Stewart and J.-G. Sun. *Matrix Perturbation Theory*. Academic Press, Boston, 1990.
- [95] J. B. Tenenbaum and W. T. Freeman. Separating style and content with bilinear models. *Neural Comput.*, 12:1247–1283, 2000.
- [96] M. Totty and M. Mangalindan. As Google becomes Web’s gatekeeper, sites fight to get in. *Wall Street Journal*, 39, Feb. 26, 2003.
- [97] L. N. Trefethen and D. B. Bau, III. *Numerical Linear Algebra*. SIAM, Philadelphia, 1997.
- [98] L. R. Tucker. The extension of factor analysis to three-dimensional matrices. In *Contributions to Mathematical Psychology*, H. Gulliksen and N. Frederiksen, eds., Holt, Rinehart and Winston, New York, 1964, pp. 109–127.
- [99] L. R. Tucker. Some mathematical notes on three-mode factor analysis. *Psychometrika*, 31:279–311, 1966.
- [100] M. A. Turk and A. P. Pentland. Eigenfaces for recognition. *J. Cognitive Neurosci.*, 3:71–86, 1991.
- [101] G. van den Bergen. *Collision Detection in Interactive 3D Environments*. Morgan Kaufmann, San Francisco, 2004.
- [102] M. A. O. Vasilescu. Human motion signatures: Analysis, synthesis, recognition. In *Proc., International Conference on Pattern Recognition (ICPR ’02)*, Quebec City, Canada, 2002.
- [103] M. A. O. Vasilescu and D. Terzopoulos. Multilinear analysis of image ensembles: Tensorfaces. In *Proc., 7th European Conference on Computer Vision (ECCV ’02)*, Copenhagen, Denmark, Lecture Notes in Computer Science 2350, Springer-Verlag, New York, 2002, pp. 447–460.

- [104] M. A. O. Vasilescu and D. Terzopoulos. Multilinear image analysis for facial recognition. In *Proc., International Conference on Pattern Recognition (ICPR '02)*, Quebec City, Canada, 2002, pp. 511–514.
- [105] M. A. O. Vasilescu and D. Terzopoulos. Multilinear subspace analysis of image ensembles. In *Proc., IEEE Conference on Computer Vision and Pattern Recognition (CVPR '03)*, Madison, WI, 2003, pp. 93–99.
- [106] P. Å. Wedin. Perturbation theory for pseudoinverses. *BIT*, 13:344–354, 1973.
- [107] J. H. Wilkinson. Global convergene of tridiagonal qr algorithm with origin shifts. *Linear Algebra Appl.*, 1:409–420, 1968.
- [108] I. H. Witten and E. Frank. *Data Mining. Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann, San Francisco, 2000.
- [109] H. Wold. Soft modeling by latent variables: The nonlinear iterative partial least squares approach. In *Perspectives in Probability and Statistics, Papers in Honour of M. S. Bartlett*, J. Gani, ed., Academic Press, London, 1975.
- [110] S. Wold, A. Ruhe, H. Wold, and W. J. Dunn, III. The collinearity problem in linear regression. The partial least squares (PLS) approach to generalized inverses. *SIAM J. Sci. Stat. Comput.*, 5:735–743, 1984.
- [111] S. Wold, M. Sjöström, and L. Eriksson. PLS-regression: A basic tool of chemometrics. *Chemometrics Intell. Lab. Systems*, 58:109–130, 2001.
- [112] S. Wolfram. *The Mathematica Book*, 4th ed. Cambridge University Press, London, 1999.
- [113] D. Zeimpekis and E. Gallopoulos. Design of a MATLAB toolbox for term-document matrix generation. In *Proc., Workshop on Clustering High Dimensional Data and Its Applications*, I. S. Dhillon, J. Kogan, and J. Ghosh, eds., Newport Beach, CA, 2005, pp. 38–48.
- [114] H. Zha. Generic summarization and keyphrase extraction using mutual reinforcement principle and sentence clustering. In *Proc., 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, Tampere, Finland, 2002, pp. 113–120.

Index

- 1-norm, 17
 - matrix, 19
 - vector, 17
- 2-norm, 17, 61
 - matrix, 19
 - vector, 17
- 3-mode array, 91
- absolute error, 17
- adjacency matrix, 159
- Aitken extrapolation, 159
- algebra, multilinear, 91
- all-orthogonality, 95
- ALS, *see* alternating least squares
- alternating least squares, 106
- angle, 18
- animation, 10
- approximation
 - low-rank, 63, 89, 109, 135, 139, 145, 168
 - rank-1, 164
 - rank- k , 135, 165
- Arnoldi
 - decomposition, 203
 - method, 159, 203, 204, 208
 - implicitly restarted, 205
 - recursion, 203
- ARPACK, 72, 208
- array
 - n -mode, 91
 - n -way, 91
- ATLAS, 207
- authority, 159
 - score, 159
- backward
 - error, 9, 46, 54
 - analysis, 27
 - stability, 54
- band matrix, 29
- bandwidth, 29
- basis, 20, 37
 - matrix, 99
 - orthogonal, 50
 - orthonormal, 38, 65
 - vector, 14, 165, 173
- bidiagonal matrix, 81, 196
- bidiagonalization
 - Householder, 81
 - Lanczos–Golub–Kahan, 80, 84, 85, 142, 146, 201, 206
 - partial, 206
- bilinear form, 172
- bioinformatics, 3, 108
- BLAS, 14, 207
- breast cancer diagnosis, 103
- bulge, 195
- cancellation, 11, 43, 76
- cancer, 103
- centroid, 102, 114, 139
 - approximation, 146
- chemometrics, 92, 94
- Cholesky decomposition, 26, 30, 207
- classification, 75, 114, 120, 127, 172–174
- cluster, 101, 114, 139
 - coherence, 102
- clustering, 139, 165
- coherence, cluster, 102
- column pivoting, 72, 165
- column-stochastic matrix, 150
- complete orthogonal decomposition, 72
- compressed column storage, 200

- compressed row storage, 199
- computer games, 10
- computer graphics, 10
- concept vector, 139
- condition number, 26, 34, 35, 69
- coordinates, 14, 50, 89, 103, 165, 173
- core tensor, 95, 170
- cosine distance, 18, 114, 132, 136, 140, 141
- data
 - compression, 63, 100, 175
 - matrix, 66
 - deflated, 66
 - quality, 37
 - reduction, 20
- decomposition
 - Cholesky, 26, 30, 207
 - eigenvalue, 182, 200
 - LDL^T , 25
 - LU, 24, 207
 - tridiagonal, 30
 - QR, 49, 161, 207
 - column pivoting, 72, 165
 - thin, 49
 - Schur, 182, 197, 200, 207
 - complex, 183
 - partial, 182, 204
 - real, 182
 - singular value, 57, 116, 135, 207
 - thin, 59
- dense matrix, 31, 42, 179, 185
- dependent variable, 75
- determinant, 179
- diagonal matrix, 12
- digits, handwritten, 6, 91, 97, 113–128
- distance
 - cosine, 18, 114, 132, 136, 140, 141
 - Euclidean, 17, 113, 122
 - tangent, 122, 124
- document
 - clustering, 108, 139
 - weighting, 132, 162
- dominant eigenvalue, 152
- e-business, 3
- eigenfaces, 169
- eigenspace, 182
- eigenvalue, 150
 - decomposition, 182, 200
 - dominant, 152
 - perturbation, 181, 183
 - problem, 7
 - sensitivity, 180
 - similarity transformation, 180
- eigenvector, 150, 196
 - perturbation, 181, 184
- email surveillance, 108
- equation, polynomial, 179
- equivalent vector norms, 17
- error
 - absolute, 17
 - backward, 9, 46, 54
 - backward analysis, 27
 - floating point, 9, 46, 53
 - forward, 9
 - relative, 9, 17
- Euclidean
 - distance, 17, 113, 122
 - norm, 123
 - vector norm, 17, 19
- explanatory variable, 75
- face recognition, 172
- FIFA, 4, 79, 105
- finite algorithm, 190
- floating point
 - arithmetic, 9, 46, 155, 190, 196
 - error, 9, 46, 53
 - operation, 8
 - overflow, 10, 156
 - standard (IEEE), 9
 - underflow, 10, 156
- flop, 8
 - count, 45, 53, 195, 197
- football, 4, 80, 110
- forward error, 9
- frequency, term, 132
- Frobenius norm, 19, 40, 64, 92, 99
- fundamental subspace, 62

- Gauss transformation, 23
- Gaussian elimination, 23
- generank, 159
- Gilbert–Johnson–Keerthi algorithm, 10
- Givens rotation, *see* plane rotation
- Google, 4, 7, 79, 104, 109, 147
 - matrix, 153
- Gram–Schmidt, 90
- graph
 - Internet, 148
 - link, 7, 149
 - strongly connected, 152
- GTP, *see* text parser

- handwritten digits, 6, 91, 97, 113–128
 - classification, 6, 91
 - U.S. Postal Service database, 6, 97, 113, 114, 121, 122, 128
- Hessenberg matrix, 197
- HITS, *see* hypertext induced topic search
- Hooke’s law, 31
- HOSVD, 94, 170
 - thin, 96, 170
 - truncated, 175
- Householder
 - bidiagonalization, 81
 - matrix, 43
 - transformation, 43, 46, 47, 53, 80, 188, 196, 197
- HTML, 132, 161
- hub, 159
 - score, 159
- hypertext induced topic search, 159

- IEEE arithmetic, 9
 - double precision, 9
 - floating point standard, 9
 - single precision, 9
- ill-conditioned matrix, 27
- implicit Q theorem, 194
- implicit shift, 194, 197
- index, 130, 137
 - inverted, 130
- infinity norm
 - matrix, 19
- information retrieval, 3, 4, 103, 129, 133, 161, 200
- initialization, SVD, 108
- inlink, 7, 148, 159
- inner product, 15, 17, 92
- Internet, 3, 4, 7, 147, 164
 - graph, 148
- invariant subspace, 182
- inverse document frequency, 132
- inverse iteration, 186, 196, 198
- inverse matrix, 21, 31
- inverted index, 130
- irreducible matrix, 151

- k -means algorithm, 102, 139
- Kahan matrix, 74
- Karhunen–Loewe expansion, 58
- Krylov subspace, 80, 89, 201, 203

- Lanczos method, 72, 208
 - bidiagonalization, 84, 85
 - tridiagonalization, 206, 207
 - implicitly restarted, 206, 207
- Lanczos–Golub–Kahan bidiagonalization, 80, 84, 85, 142, 146, 201, 206
- LAPACK, 14, 72, 179, 189, 207
- latent semantic analysis, 135
- latent semantic indexing, 130, 135, 146
- L^AT_EX, 161, 163
- LDL^T decomposition, 25
- least squares, 31, 85
 - alternating, 106
 - method, 32
 - nonnegative, 106
 - normal equations, 33, 54
 - perturbation, 69
 - prediction, 75
 - problem, 32, 51, 66, 85, 117
 - solution
 - minimum norm, 70
 - QR decomposition, 51
 - SVD, 68
- lexical scanner, 163
- library catalogue, 129
- linear independence, 20

- linear operator, 5
- linear system, 23
 - overdetermined, 23, 31, 32, 51, 66
 - perturbation theory, 26
 - underdetermined, 71
- link, 4, 148
 - farm, 154
 - graph, 7, 149
 - matrix, 7, 200
- low-rank
 - approximation, 63, 89, 109, 135, 139, 145, 168
 - matrix, 63
- LSA, *see* latent semantic analysis
- LSI, *see* latent semantic indexing
- LU decomposition, 24, 207
 - tridiagonal, 30
- machine learning, 161
- manifold, 123
- mark-up language, 161
- Markov chain, 150
- Mathematica, 8, 208
- MATLAB, 8
- matrix, 4
 - 2-norm, 19
 - adjacency, 159
 - approximation, 63–65, 116
 - band, 29
 - basis, 99
 - bidiagonal, 81, 196
 - column-stochastic, 150
 - dense, 31, 42, 179, 185
 - diagonal, 12
 - factorization
 - nonnegative, 102, 106, 141, 146, 161, 165, 168
 - Google, 153
 - Hessenberg, 197
 - Householder, 43
 - ill-conditioned, 27
 - inverse, 21, 31
 - irreducible, 151
 - Kahan, 74
 - link graph, 7, 200
 - low-rank, 63
 - multiplication, 15, 93
 - outer product, 16
 - nonsingular, 21
 - null-space, 61
 - orthogonal, 39
 - permutation, 24, 72, 165
 - positive, 152
 - positive definite, 25
 - range, 61, 182
 - rank, 21
 - rank-1, 21, 152
 - rank-deficient, 70
 - rectangular, 23
 - reducible, 151
 - reflection, 43
 - rotation, 40, 47, 55, 197
 - sparse, 5, 132, 163, 185, 198, 200, 208
 - storage, 199, 200
 - symmetric, 25
 - term-document, 4, 91, 104, 130, 131, 135
 - term-sentence, 162
 - transition, 150
 - triangular, 23
 - tridiagonal, 29, 188, 197, 205
 - upper quasi-triangular, 182
 - upper triangular, 47
- matrix norm, 18
 - 1-norm, 19
 - 2-norm, 61
 - Frobenius, 19, 40, 64
 - infinity norm, 19
- matrix-vector multiplication, 13
- max-norm, 17
 - vector, 17
- medical abstracts, 129
- Medline, 129, 136, 140, 142, 144, 145
- microarray, 159
- mode, 91
- model, reduced rank, 77, 115
- MPI, 207
- multilinear algebra, 91
- multiplication
 - i -mode, 92
 - matrix, 15, 93

- matrix-vector, 13
 - tensor-matrix, 92
- music transcription, 108
- mutual reinforcement principle, 162
- n -way array, 91
- natural language processing, 161
- Netlib, 207
- network analysis, 159
- noise
 - reduction, 145
 - removal, 63
- nonnegative least squares, 106
- nonnegative matrix factorization, 102, 106, 141, 146, 161, 165, 168
- nonsingular matrix, 21
- norm
 - 1-norm, 17
 - Euclidean, 123
 - matrix, 18
 - 1-norm, 19
 - 2-norm, 61
 - Frobenius, 19, 40, 64
 - infinity, 19
 - maximum, 17
 - operator, 18
 - p -norm, 17
 - tensor, 92
 - Frobenius, 92, 99
 - vector, 17
 - Euclidean, 17, 19
- normal equations, 33, 54
- null-space, 61
- numerical rank, 63, 72, 76
- operator norm, 18
- orthogonal
 - basis, 50
 - decomposition, complete, 72
 - matrix, 39
 - similarity transformation, 180, 187
 - transformation, floating point, 46
 - vectors, 18, 38
- orthonormal
 - basis, 38, 65
 - vectors, 38
- outer product, 16, 59
- outlink, 7, 148, 159
- overdetermined system, 23, 31, 32, 51, 66
- overflow, 10, 156
- p -norm, vector, 17
- pagerank, 147–159, 161
- parser, text, 132, 161, 163
- partial least squares, *see* PLS
- partial pivoting, 23, 30
- pattern recognition, 6
- PCA, *see* principal component analysis
- performance modeling, 133
- permutation matrix, 24, 72, 165
- Perron–Frobenius theorem, 152
- personalization vector, 154
- perturbation
 - eigenvalue, 181, 183
 - eigenvector, 181, 184
 - least squares, 69
 - theory, 26, 28, 180
- plane rotation, 40, 46, 47, 55, 197
- PLS, *see* projection to latent structures
- polynomial equation, 179
- Porter stemmer, 131
- positive definite matrix, 25
- positive matrix, 152
- power method, 150, 154, 185, 201, 204
- precision, 133
- prediction, 75
- preprocessing, 130
- principal component
 - analysis, 66, 169
 - regression, 78, 144
- projection to latent structures, 80, 89, 142
- pseudoinverse, 71
- psychometrics, 92, 94
- QR algorithm, 179, 180
 - convergence, 194, 198
 - nonsymmetric, 197
 - symmetric, 190, 192

- QR decomposition, 49, 161, 207
 column pivoting, 72, 165
 thin, 49
 updating, 54
- qr function, 50
- query, 5, 79, 129–147, 159
 matching, 132–146
- random
 surfer, 150
 walk, 150
- range, 61, 182
- rank, 21
 numerical, 63, 72, 76
- rank-1
 approximation, 164
 matrix, 21, 152
- rank-deficient matrix, 70
- rank- k approximation, 135, 165
- ranking, 4, 147, 148, 159
 vector, 148
- recall, 134
- rectangular matrix, 23
- reduced rank model, 77, 115
- reducible matrix, 151
- reflection matrix, 43
- regression, principal component, 78, 144
- relative
 error, 9, 17
 residual, 75
- reorthogonalization, 90, 204
- residual
 relative, 75
 vector, 32, 117
- rotation
 Givens, 40
 plane, 40, 46, 47, 55, 197
- rotation matrix, 55, 197
- rounding error, 9
- saliency score, 162
- SAS, 208
- SAXPY, 14, 15
- ScaLAPACK, 207
- Schur decomposition, 182, 197, 200, 207
 partial, 182, 204
- search engine, 3, 7, 130, 147, 161
- semantic structure, 135
- shift, 186
 implicit, 194, 197
 Wilkinson, 190
- SIMCA, 121
- similarity transformation, orthogonal, 180, 187
- singular
 image, 116
 value, 58, 163
 i-mode, 95
 tensor, 95
 vector, 58, 163
- singular value decomposition, 57, 94, 116, 130, 135, 163, 165, 168, 169, 200, 206, 207
 computation, 72, 196
 expansion, 59
 Lanczos–Golub–Kahan method, 108, 206
 outer product form, 59
 tensor, 94
 thin, 59
 truncated, 63, 78, 136
- slice (of a tensor), 93
- software, 207
- sparse matrix, 5, 132, 163, 185, 198, 200, 208
 storage, 199, 200
- spectral analysis, 108
- spring constant, 31
- SPSS, 208
- stemmer, Porter, 131
- stemming, 130, 161
- stop word, 130, 161
- strongly connected graph, 152
- subspace
 fundamental, 62
 invariant, 182
 Krylov, 80, 89, 201, 203
- summarization, text, 161–168
- Supreme Court precedent, 159

- surfer, random, 150
- SVD, *see* singular value decomposition
- svd function, 60, 72
- svds function, 72, 108, 207
- symmetric matrix, 25
- synonym extraction, 159

- tag, 161
- tangent
 - distance, 122, 124
 - plane, 123
- teleportation, 153, 164
- tensor, 11, 91–100, 169–176
 - core, 95, 170
 - SVD, 94
 - unfolding, 93
- TensorFaces, 169
- term, 130, 162
 - frequency, 132
 - weighting, 132, 162
- term-document matrix, 4, 91, 104, 130, 131, 135
- term-sentence matrix, 162
- test set, 114–116
- text mining, 103, 129–146
- text parser, 132, 161
 - GTP, 131
 - TMG, 163
- Text Retrieval Conference, 145
- text summarization, 161–168
- theorem
 - implicit Q, 194
 - Perron–Frobenius, 152
- thin
 - HOSVD, 96, 170
 - QR, 49
 - SVD, 59
- TMG, *see* text parser
- trace, 19, 92
- training set, 91, 114–116, 120, 127
- transformation
 - diagonal hyperbolic, 126
 - Gauss, 23
 - Householder, 43, 46, 47, 53, 80, 188, 196, 197
 - orthogonal, floating point, 46
 - parallel hyperbolic, 126
 - rotation, 125
 - scaling, 126
 - similarity, orthogonal, 180, 187
 - thickening, 127
 - translation, 125
- transition matrix, 150
- TREC, *see* Text Retrieval Conference
- triangle inequality, 17, 18
- triangular matrix, 23
- tridiagonal matrix, 29, 188, 197, 205
- truncated HOSVD, 175
- truncated SVD, 63, 78, 136
- Tucker model, 94

- underdetermined system, 71
- underflow, 10, 156
- unfolding, 93
- unit roundoff, 9, 27, 46, 192, 196
- updating QR decomposition, 54
- upper quasi-triangular matrix, 182
- upper triangular matrix, 47
- U.S. Postal Service database, 6, 97, 113, 114, 121, 122, 128

- variable
 - dependent, 75
 - explanatory, 75
- vector
 - basis, 14, 173
 - concept, 139
 - norm, 17
 - 1-norm, 17
 - 2-norm, 17
 - equivalence, 17
 - Euclidean, 17, 19
 - max-norm, 17
 - personalization, 154
 - ranking, 148
 - residual, 117
 - singular, 163
- vector space model, 130, 146, 161
- vectors
 - orthogonal, 18, 38
 - orthonormal, 38

volcanos on Venus, 3

Web page, 4

Web search engine, *see* search engine

weighting

 document, 132, 162

 term, 132, 162

Wilkinson shift, 190

XML, 132

Yale Face Database, 170

zip code, 113