MODELLO D (inglese)			
General Information	AA 2020-2021		
Academic subject	Numerical Methods for Computer Science		
Degree course	Master Degree in Computer Science		
Curriculum			
ECTS credits	9		
Compulsory attendance	No		
Language	English		
Subject teacher	Name Surname	Mail address	SSD
	Mazzia Francesca; Antonella Falini	francesca.mazzia@uniba.it antonella.falini@uniba.it	MAT/08– Numerical Analysis
ECTS credits details	7	2	
Basic teaching activities	Lectures	Programming laboratory	
Class schedule			
Period	First term		
Year	First year		
Type of class	Lectures- Programming laboratory		
Time management			
Hours	86		
Hours of lectures	56		
Tutorials and lab	30		
Academic calendar			
Class begins	October 5, 2020		
Class ends	January 13, 2021		
Syllabus			
Prerequisites/requirements	Basic knowledge of methods in Numerical Analysis		
Expected learning outcomes (according to Dublin Descriptors) (it is recommended that they are congruent with the learning outcomes contained in A4a, A4b, A4c tables of the SUA-CdS)	*Knowledge and understanding* Knowledge and understanding of numerical linear algebra techniques useful for treating structured data. Application of optimization methods for solving problems in data mining, image processing and information retrieval. *Applying knowledge and understanding* Acquiring the main numerical linear algebra techniques for treating real world problems. Ability to design efficient numerical codes implementing numerical techniques for solving problems in data mining, image processing and information retrieval. Mastering basic and advanced numerical linear algebra techniques to model real world problems. Ability to design and to implement efficient algorithms for the treatment of data-mining and image processing applications. *Making informed judgements and choices* Judgment autonomy is acquired through critical study and interpretation of texts. The achievement of an adequate autonomy is verified through the exercises, which are held during the		

	teaching programme and with the final written and oral examinations. *Communicating knowledge and understanding* Students are able to express the topics included in the teaching programme by employing the specific lexicon of the discipline. *Lifelong learning skills* Learning an appropriate studying methodology, supported by text consultation and implementation of the techniques proposed during the course.
Contents	• Numerical Linear Algebra Basic and Advanced Notions • Systems of nonlinear equations and optimization. • Least squared approximation methods. • Low Rank matrix approximation techniques and dimensionality reduction methods. • Mathematical methods for information retrieval.
Course program	Numerical Linear Algebra: Space of matrices. Operation with matrices. Properties of square and rectangular matrices. Vector spaces and subspaces. Spanning sets. Range and Null spaces. Basis of subspaces. Rank, connectivity and graphs. Properties of AA^T and A^TA. Linear Transformations. Similarity. Structured matrices and their properties. Norms, scalar product and orthogonality. Applications to reconstruction error functions in image processing. Gram-Schmidt ortho-normalization algorithm. QR factorization. Eigenvalues, eigenvectors and their properties. QR method. Power method, Singular Value Decomposition. Eckart-Young Theorem. Truncated SVD. Principal Component Analysis. Eigenvalues applications: Pagerank algorithm and eigenface model, image compression. Unconstrained optimization. Line search method. Gradient descent methods Basics of Vector Calculus (2D and 3D). Newton methods. Least squares problems. System of normal equations and their properties. Least squares line and the optimization problem related. Support vector machines and their formulation as an optimization problem. Optimization and machine learning. Stochastic gradient descent method. Latent Semantic Indexing. Mathematical Models and Text Retrieval. Eigenbased methods for web information retrieval.
Bibliography	1. C. Meyer, Matrix Analysis and Applied Linear Algebra, SIAM, 2003.

	2. Lars Eldèn, Matrix Methods in Data Mining and Pattern Recognition, SIAM 2007 3. A. N. Langville, C. D. Meyer: Google's PageRank and beyond. Princeton Univ. Press, 2006. 4. D. G. Luenberger, Y. Ye: Linear and Nonlinear Programming. Forth Edition, Springer. 5. M. W. Berry, M. Browne. Understanding Search Engines: Mathematical Models and Text Retrieval. SIAM, 1999. 6. A. Cichocki, R. Zdunek, A.H. Phan, S.I Amari, Nonnegative Matrix and Tensor Factorizations, Wiley, 2009 7. M. Turk and A. Pentland. Eigenfaces for recognition. Journal of Cognitive Neuroscience 3(1): 71–86. doi:10.1162/jocn.1991.3.1.71 (1991)
Notes	All the references will be integrated by suggested readings, slides and notes provided during the lectures
Teaching methods	Lectures. Laboratory experiments with open source software and available datasets.
Assessment methods (indicate at least the type written, oral, other)	Written and oral examinations.
Evaluation criteria (Explain for each expected learning outcome what a student has to know, or is able to do, and how many levels of achievement there are).	Students will be evaluated on the basis of the level of their knowledge concerning the various topics included in the syllabus.
Further information	