1.	Record Nr.	UNINA9910139774103321
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	Titolo	Kernel methods for remote sensing data analysis / / edited by Gustavo Camps-Valls, Lorenzo Bruzzone
	Pubbl/distr/stampa	Chichester, West Sussex ; ; Hoboken, NJ, : Wiley, 2009
	ISBN	1-282-29170-X 9786612291708 0-470-74899-0 0-470-74900-8
	Descrizione fisica	1 online resource (444 p.)
	Altri autori (Persone)	BruzzoneLorenzo
	Disciplina	621.36/780285631
	Soggetti	Remote sensing Geography
	Lingua di pubblicazione	Inglese
	Formato	Materiale a stampa
	Livello bibliografico	Monografia
	Note generali	Description based upon print version of record.
	Nota di bibliografia	Includes bibliographical references and index.
	Nota di contenuto	Kernel Methods for Remote Sensing Data Analysis; Contents; About the editors; List of authors; Preface; Acknowledgments; List of symbols; List of abbreviations; I Introduction; 1 Machine learning techniques in remote sensing data analysis; 1.1 Introduction; 1.1.1 Challenges in remote sensing; 1.1.2 General concepts of machine learning; 1.1.3 Paradigms in remote sensing; 1.2 Supervised classification: algorithms and applications; 1.2.1 Bayesian classification strategy; 1.2.2 Neural networks; 1.2.3 Support Vector Machines (SVM); 1.2.4 Use of multiple classifiers; 1.3 Conclusion; Acknowledgments References2 An introduction to kernel learning algorithms; 2.1 Introduction; 2.2 Kernels; 2.2.1 Measuring similarity with kernels; 2.2.2 Positive definite kernels; 2.2.3 Constructing the reproducing kernel Hilbert space; 2.2.4 Operations in RKHS; 2.2.5 Kernel construction; 2.2.6 Examples of kernels; 2.3 The representer theorem; 2.4 Learning with kernels; 2.4.1 Support vector classification; 2.4.2 Support vector regression; 2.4.3 Gaussian processes; 2.4.4 Multiple kernel learning; 2.4.5 Structured prediction using kernels; 2.4.6 Kernel principal component analysis 2.4.7 Applications of support vector algorithms2.4.8 Available

software; 2.5 Conclusion; References; II Supervised image classification; 3 The Support Vector Machine (SVM) algorithm for supervised classification of hyperspectral remote sensing data; 3.1 Introduction; 3.2 Aspects of hyperspectral data and its acquisition; 3.3 Hyperspectral remote sensing and supervised classification; 3.4 Mathematical foundations of supervised classification; 3.4.1 Empirical risk minimization; 3.4.2 General bounds for a new risk minimization principle; 3.4.3 Structural risk minimization
3.5 From structural risk minimization to a support vector machine algorithm3.5.1 SRM for hyperplane binary classifiers; 3.5.2 SVM algorithm; 3.5.3 Kernel method; 3.5.4 Hyperparameters; 3.5.5 A toy example; 3.5.6 Multi-class classifiers; 3.5.7 Data centring; 3.6 Benchmark hyperspectral data sets; 3.6.1 The 4 class subset scene; 3.6.2 The 16 class scene; 3.6.3 The 9 class scene; 3.7 Results; 3.7.1 SVM implementation; 3.7.2 Effect of hyperparameter d; 3.7.3 Measure of accuracy of results; 3.7.4 Classifier results for the 4 class subset scene and the 16 class full scene
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4.5.2 Specific issues for SVM classification

Sommario/riassunto

Kernel methods have long been established as effective techniques in the framework of machine learning and pattern recognition, and have now become the standard approach to many remote sensing applications. With algorithms that combine statistics and geometry, kernel methods have proven successful across many different domains related to the analysis of images of the Earth acquired from airborne and satellite sensors, including natural resource control, detection and monitoring of anthropic infrastructures (e.g. urban areas), agriculture inventorying, disaster prevention and damage assessment