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New machine-learning paradigm provides advantages for remote sensing

Gustavo Camps-Valls

Kernel methods increase the accuracy of remote-sensing data processing, including specific land-cover identification, biophysical parameter estimation, and feature extraction.

The problems in remote-sensing data processing typically involve identifying specific land-covers, estimating biophysical parameters, and extracting features. This variety of problems gives rise to a complex scenario for data analysis.

Kernel methods constitute a machine learning paradigm for building nonlinear methods (classification, regression, clustering) from linear ones.[1,2] Kernel methods intrinsically cope with nonlinearities in a very flexible way, are robust to uncertainty and noise, and are effective when dealing with low numbers of high-dimensional samples. Here we review recent advances in kernel methods for remote sensing data analysis.

Survey of kernel methods for remote sensing

The support vector machine (SVM)[1] kernel method has been successfully used in hyperspectral image classification.[3] Nevertheless, SVMs must be adapted to the specific needs of the field. Inclusion of contextual information in the classifier is necessary to produce more spatially homogeneous classification maps.[4] Multi-sensor and multi-temporal information has been also synergetically combined with kernels.[5] Another kernel method, the one-class SVM, is aimed at identifying samples of one particular class and rejecting the others. The method was originally introduced for anomaly detection,[6,7] then used for dealing with incomplete and unreliable training data,[8] and recently reformulated for change detection.[5] Specifically-designed kernel-based target detection methods have also been presented.[9] Lately, semi-supervised kernel-based classifiers—for example, the transductive SVM[10] and the Laplacian SVM[11]—have been introduced to exploit the wealth of unlabeled data in the image.

In the field of regression, powerful kernel developments have been published recently: support vector regression (SVR) methods have been used for parameter estimation,[12–14] a fully-constrained kernel least squares method provides abundance estimation,[15] and a kernel-based bidirectional reflection distribution function model inversion method can be used for land surface parameter retrieval.[16]

Nonlinear feature extraction with kernels is sometimes used to improve posterior classification or regression, and some techniques have been presented including the kernel orthogonalized partial least squares (KOPLS)[17] and the unsupervised kernel principal component analysis (PCA).[18]

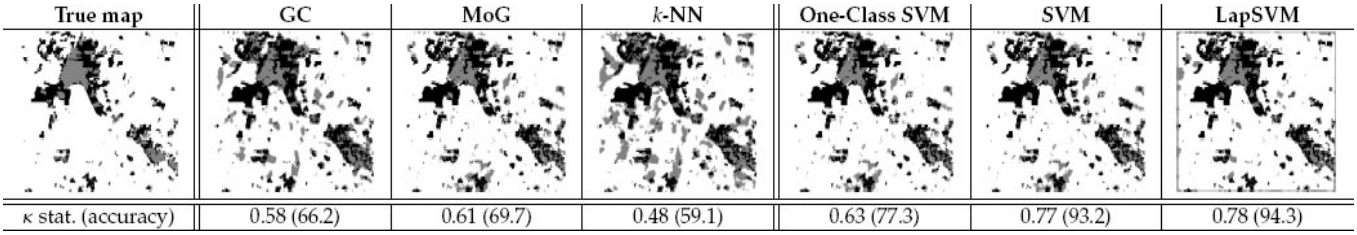

Figure 1. *The true map for Rome (1999), and classification maps obtained with various kernel methods: The Gaussian classifier (GC), mixtures of Gaussians (MoG), k-nearest neighbours (k-NN), one-class support vector machine (SVM), supervised SVM, and Laplacian SVM kernel methods. In the maps, non-urban areas are white, urban areas are gray, and unknown class areas are black.*

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Table 1. *Leaf Area Index (LAI) estimation test results: Mean error (ME), root mean-squared error (RMSE), mean absolute error (MAE), and correlation coefficient (r). n_p is the number of extracted features.*

Model	ME	RMSE	MAE	r
ε-SVR	-0.003	0.721	0.501	0.884
L_2-loss SVR	-0.004	0.711	0.502	0.882
PLS	0.051	0.886	0.708	0.851
KPLS, $n_p = 1$	0.056	0.940	0.742	0.832
KPLS, $n_p = 5$	0.026	0.803	0.598	0.879
KPLS, $n_p = 10$	0.005	0.749	0.544	0.896
KOPLS, $n_p = 1$	-0.003	0.758	0.525	0.893

Applications of kernel methods in remote sensing

Here we discuss the performance of representative kernel-based methods for key remote-sensing applications. First, we illustrate the potential of the presented methods in the complex classification problem of urban monitoring with multi-source data. We consider the test site of Rome (Italy), where images from Earth Resources Satellite 2 (ERS2) synthetic aperture radar (SAR) and Landsat Thematic Mapper (TM) sensors were acquired in 1995 and 1999 as part of the Urbex project. Figure 1 shows the classification maps and improved accuracies with standard and supervised, one-class, and semi-supervised kernel methods.[5,8,11]

Second, we conducted feature extraction and estimation of the Leaf Area Index (LAI) from hyperspectral satellite images, a problem characterized by high levels of noise and uncertainty. We used data from the Spectra Barrax Campaign (SPARC) project.[19] Table 1 shows the results obtained via different regression kernel-based methods: SVR, kernel partial least squares (KPLS), and KOPLS.[17] The results show a clear improvement with use of kernel-based methods rather than linear methods.[17]

Conclusions

The field of kernel methods for addressing remote-sensing learning problems is vast. We showed performance in two challenging real scenarios: multi-source and multi-temporal image classification, and nonlinear feature extraction and regression. The field is evolving constantly and further improvements are expected in the near future.

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