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. 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) kernel method has been successfully used in hyperspectral image classification. 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. Multi-sensor and multi-temporal information has been also synergistically combined with kernels. 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, then used for dealing with incomplete and unreliable training data, and recently reformulated for change detection. Specifically-designed kernel-based target detection methods have also been presented. Lately, semi-supervised kernel-based classifiers—for example, the transductive SVM and the Laplacian SVM—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, a fully-constrained kernel least squares method provides abundance estimation, and a kernel-based bidirectional reflection distribution function model inversion method can be used for land surface parameter retrieval. 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) and the unsupervised kernel principal component analysis (PCA).

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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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.

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). np is the number of extracted features.

<table>
<thead>
<tr>
<th>Model</th>
<th>ME</th>
<th>RMSE</th>
<th>MAE</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>ε-SVR</td>
<td>0.003</td>
<td>0.721</td>
<td>0.501</td>
<td>0.884</td>
</tr>
<tr>
<td>L2-loss SVR</td>
<td>0.004</td>
<td>0.711</td>
<td>0.502</td>
<td>0.882</td>
</tr>
<tr>
<td>PLS</td>
<td>0.051</td>
<td>0.886</td>
<td>0.708</td>
<td>0.851</td>
</tr>
<tr>
<td>KPLS, np = 1</td>
<td>0.056</td>
<td>0.940</td>
<td>0.742</td>
<td>0.832</td>
</tr>
<tr>
<td>KPLS, np = 5</td>
<td>0.026</td>
<td>0.803</td>
<td>0.598</td>
<td>0.879</td>
</tr>
<tr>
<td>KPLS, np = 10</td>
<td>0.005</td>
<td>0.749</td>
<td>0.544</td>
<td>0.896</td>
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<tr>
<td>KOPLS, np = 1</td>
<td>-0.003</td>
<td>0.758</td>
<td>0.525</td>
<td>0.893</td>
</tr>
</tbody>
</table>

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Gustavo Camps-Valls is an associate professor in the Department of Electronics Engineering at the University of Valencia. He is the author of 50 journal papers and more than 60 international conference papers as well as the editor of several books, a referee for international journals, and a member of several scientific committees. In particular, he has been a member of the technical committee of SPIE Europe since 2003, acting as referee, chair, and presenter.

References


