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Vegetation Monitoring with Gaussian Processes and Latent Force Models

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Monitoring vegetation by biophysical parameter retrieval from Earth observation data is a challenging problem, where machine learning is currently a key player. Neural networks, kernel methods, and Gaussian Process (GP) regression have excelled in parameter retrieval tasks at both local and global scales. GP regression is based on solid Bayesian statistics, yield efficient and accurate parameter estimates, and provides interesting advantages over competing machine learning approaches such as confidence intervals. However, GP models are hampered by lack of interpretability, that prevented the widespread adoption by a larger community. In this presentation we will summarize some of our latest developments to address this issue.

We will review the main characteristics of GPs and their advantages in vegetation monitoring standard applications. Then, three advanced GP models will be introduced. First, we will derive sensitivity maps for the GP predictive function that allows us to obtain feature ranking from the model and to assess the influence of examples in the solution. Second, we will introduce a Joint GP (JGP) model that combines in situ measurements and simulated radiative transfer data in a single GP model. The JGP regression provides more sensible confidence intervals for the predictions, respects the physics of the underlying processes, and allows for transferability across time and space. Finally, a latent force model (LFM) for GP modeling that encodes ordinary differential equations to blend data-driven modeling and physical models of the system is presented. The LFM performs multi-output regression, adapts to the signal characteristics, is able to cope with missing data in the time series, and provides explicit latent functions that allow system analysis and evaluation. Empirical evidence of the performance of these models will be presented through illustrative examples.