Multiresolution Gaussian Processes
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A key challenge in many time series applications is efficiently capturing potentially long-range, non-Markovian dependencies. One method of addressing this challenge is through employing a Gaussian process (GP) with an appropriate (non-band-limited) kernel function. However, the smoothness of the GP random functions can blur key elements of the signal if abrupt changes occur. Likewise, a changepoint model between smooth functions cannot capture long-range dependencies. Instead, we propose a multiresolution GP that hierarchically couples a collection of smooth GPs, each defined over an element of a random nested partition. Long-range dependencies are captured by the top-level GP while the partition points define the abrupt changes in the time series. Due to the inherent conjugacy of the GPs, one can analytically marginalize the GPs and compute the conditional probability of the observations given the partition tree. This allows for efficient inference of the partition itself, for which we employ graph-theoretic techniques. We analyze the theoretical properties of the multiresolution GP, as well as applying it to the analysis of Magnetoencephalography (MEG) recordings of brain activity.