Localized kernel method in signal processing and machine learning

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Many applications in signal processing and machine learning requires the use of intrinsically global data for obtaining local analysis of the objects involved. For example, the problem of separation of stationary signals can be formulated as recuperation of a finitely supported measure on the complex unit circle using finitely many Fourier coefficients of the measure. One way to mitigate the curse of dimensionality in machine learning is to apply local learning based on a random sample taken from an unknown probability distribution. For example, assuming the data lies on a compact metric measure space, we may wish to develop a network so that different subnetworks are responsible for the data on different parts of the metric space. Motivated by such applications, we have developed a family of localized kernels based on different global orthogonal systems in various settings: the complex unit circle, Jacobi and spherical polynomials, multivariate Hermite polynomials, manifolds etc. We state a Tauberian theorem that gives a general construction for such kernels, and illustrate the use of the localized kernels in various theoretical and practical settings.