Orlicz Fourier Features*

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Abstract

Kernel methods provide highly flexible tools with successful applications at virtually all sub-fields of machine learning and statistics. The random Fourier feature approach (RFF) is probably the most widely-used and popular idea to combine this representational power of kernels with computational efficiency. While the RFF technique has been analyzed in the context of objectives with function values, in numerous recent applications taking into account high-order derivatives is of paramount interest. Unfortunately, the understanding of the RFF scheme in this case is quite limited due to the challenging polynomial growing nature of the underlying function class in the empirical process: available results only allow consistency for 'small'-order (e.g., for the Gaussian kernel at most 2nd order) derivatives. We show that handling the complementary domain of high ($\geq \alpha$)-order derivatives is feasible under a finite α-exponential Orlicz norm assumption on the spectral measure associated to the kernel (with $\alpha > 0$, including the inverse multiquadric ($\alpha = 1$) or the Gaussian kernel ($\alpha = 2$)).

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