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One should also assess the selection of the metaparameters more thoroughly. This could be based on grid-search and cross-validation (CV) [7], although we encountered challenges with both LOO-CV and fold-based CV techniques with the random basis in [8, 9].

An interesting future direction would certainly be to derive a weighted distance measure based on the sampled accuracy of the features. Furthermore, sampling could be replaced or directed using analytical methods, because the simple form of the distance-based basis allows straightforward computation of the feature saliency similarly to [7].

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