

Titel:

"Improved Classification Rates for Localized Algorithms under Margin Conditions".

Abstract:

One of the main characteristics of localized support vector machines which solve SVMs on many spatially defined small chunks is, besides the computational benefit compared to global SVMs, the freedom of choosing arbitrary kernel and regularization parameter on each cell. We take advantage of this observation to derive global learning rates for localized SVMs with Gaussian kernels and hinge loss.

Under certain assumptions the rates we obtain outperform known classification rates for localized SVMs, for global SVMs, and other learning algorithms based on e.g., plug-in rules, trees, or DNNs. These rates are achieved under a set of margin conditions that describe the behavior of the data-generating distribution, where no assumption on the existence of a density is made. We observe that a crucial assumption is a margin condition that relates the distance to the decision boundary to the amount of noise. The analysis relies on a careful analysis of the excess risk which includes a separation of the input space into a subset which is close to the decision boundary and into a subset that is sufficiently far away. In order to illustrate this technique, we apply it in a first step to the histogram rule. We show that the obtained learning rates outperform learning rates obtained by global SVMs under a suitable set of assumptions.