Fast Rate Conditions in Statistical Learning
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Abstract

We study conditions under which the order of convergence of algorithms in statistical learning can be improved from $O_P(n^{-1/2})$ to $O_P(n^{-1})$ (up to logarithmic factors) in the number of data points. If excess losses are bounded, it is known that two conditions, called Bernstein's and strong central condition, are equivalent and lead to fast rates both for Empirical Risk Minimization and for randomized algorithms. If the excess losses are unbounded, they are no longer equivalent and are known to lead to faster rates either under additional assumptions or for specific randomized algorithms. We investigate their relation in the unbounded case and show weak, realistic assumptions under which they become equivalent. Furthermore, in this regime we show tighter bounds than those presented in the literature.