# Benign overfitting : analysis of the generalisation paradox

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Recent extensive numerical experiments in high scale machine learning have allowed to uncover a quite counterintuitive phase transition, as a function of the ratio between the sample size and the number of parameters in the model. As the number of parameters $p$ approaches the sample size $n$, the generalisation error (a.k.a. testing error) increases, but in many cases, it starts decreasing again past the threshold $p = n$. This surprising phenomenon, brought to the theoretical community attention by Belkin and co-authors, has been thoroughly investigated lately, more specifically for simpler models than deep neural networks, such as the linear model when the parameter is taken to be the minimum norm solution to the least-square problem, mostly in the asymptotic regime when $p$ and $n$ tend to infinity. In the present work, we propose a finite sample analysis of non-linear models of ridge type, where we investigate the overparametrised regime of the double descent phenomenon for both the *estimation problem* and the prediction problem. Our results provide a precise analysis of the distance of the best estimator from the true parameter as well as a generalisation bound which complements recent works of Bartlett and co-authors and Chinot and co-authors. Our analysis is based on efficient but elementary tools closely related to the continuous Newton method.