# Bayesian inference for Gaussian models: Inverse problems and evolution equations

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# Stellingen

behorende bij het proefschrift

**Bayesian Inference for Gaussian Models: Inverse Problems and Evolution Equations**

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(i) A general theorem on posterior contraction rates can be constructed with a family of reconstruction operators (Theorem 4.10). This approach can be flexibly adjusted for particular models, by specifying the reconstruction operators (e.g. Theorem 6.1, Theorem 8.6, etc.).

(ii) In the general theorems on Bayesian inverse problems (Theorem 6.1, Theorem 8.6), the contraction rate is derived from the requirement that the prior puts enough mass on the elements with good approximation accuracy, and the condition that the rate is not smaller than the maximum of the direct rate amplified by the inverse nature and the approximation accuracy of the true parameter.

(iii) Random series priors are in general adaptive (up to a logarithmic factor) in Gaussian linear inverse problems (Theorem 6.5, Theorem 8.10), because the random truncation from the prior construction enables to search for the true smoothness.

(iv) Simple Gaussian priors are in general non-adaptive in Gaussian linear inverse problems (Theorem 6.7, Theorem 8.11), because each Gaussian prior is fixed to one smoothness. This limitation can be removed by introducing another prior on the hyperparameter of Gaussian priors, which leads to a prior known as Gaussian mixtures (Theorem 6.11, Theorem 8.13).

(v) When the observation and the noise are both smoothed, whitening the observed signal leads back to the standard Gaussian sequence model (The proof of Theorem 10.5).

(vi) The structure of inverse problems is determined together by: the space of the original signal, the space of observations, and the mapping operator.

(vii) The curse of dimensionality not only lowers convergence rates, but it also gives the complication that functions may (and most likely will) behave dissimilarly in the many different directions in multidimensional space.

(viii) One difficulty in nonparametric statistics is to find explicit and tractable representations for abstract objects.

(ix) Examples that are concrete and yet not trivial at the same time are much more difficult to find than expected.

(x) One challenge in research is to keep the momentum to proceed, while technicality is good at slowing the progress down.