Nonparametric and high-dimensional models, due to their high flexibility, are widely used in statistics to find a better approximation for the underlying mechanism generating the observed data. There exists a huge number of statistical methods to make inference on these models.

In this thesis we focus on four important statistical inference problems: estimation, posterior contraction, structure recovery (in a weak sense) and uncertainty quantification, by using empirical Bayes and penalization methods. The main contribution of this thesis is development of a general robust framework for addressing the above mentioned inference problems and applying these to a number of various examples of high-dimensional and nonparametric models and structures, under possible misspecification.

In Chapter 1, we give a brief introduction to some important theoretical notions and concepts which we are going to use in the sequel.

In Chapter 2, we obtain novel results for the grand problem of uncertainty quantification (on the way solving other inference problems as well) for possibly sparse sequences.

In Chapter 3, we consider empirical Bayesian inference in the many normal means model in the situation when the high-dimensional mean vector is multilevel sparse.

In Chapter 4, by using the penalization method, we study the following inference problems in the biclustering model: estimation, structure recovery (in a weak sense) and uncertainty quantification.

Finally, in Chapter 5, we develop the general framework of projection structures and study the above mentioned inference problems within this framework by using empirical Bayes and penalization methods.

This thesis is mainly based on the following publications:


