Effective modeling of high dimensional data is crucial in information processing and machine learning. Classical subspace methods have been very effective in such applications. However, over the past few decades, there has been considerable research towards the development of new modeling paradigms that go beyond subspace methods. This dissertation focuses on the study of sparse models and their interplay with modern machine learning techniques such as manifold, ensemble and graph-based methods, along with their applications in image analysis and recovery. By considering graph relations between data samples while learning sparse models, graph-embedded codes can be obtained for use in unsupervised, supervised and semi-supervised problems. Using experiments on standard datasets, it is demonstrated that the codes obtained from the proposed methods outperform several baseline algorithms. In order to facilitate sparse learning with large scale data, the paradigm of ensemble sparse coding is proposed, and different strategies for constructing weak base models are developed. Experiments with
image recovery demonstrate that these ensemble models perform better when compared to conventional sparse coding frameworks. When examples from the data manifold are available, manifold constraints can be incorporated with sparse models and two approaches are proposed to combine sparse coding with manifold projection. The improved performance of the proposed techniques in comparison to sparse coding approaches is demonstrated using several image recovery experiments.

In addition to these approaches, it might be required in some applications to combine multiple sparse models with different regularizations. In particular, combining an unconstrained sparse model with non-negative sparse coding is important in image analysis, and it poses several algorithmic and theoretical challenges. A convex and an efficient greedy algorithm for recovering combined representations are proposed. Theoretical guarantees on sparsity thresholds for exact recovery using these algorithms are derived and recovery performance is also demonstrated using simulations on synthetic data. Finally, the problem of non-linear compressive sensing, where the measurement process is carried out in feature space obtained using non-linear transformations, is considered. An optimized non-linear measurement system is proposed, and improvements in recovery performance are demonstrated in comparison to using random measurements as well as optimized linear measurements.