In the nervous system of humans and animals, sensory data are represented as combinations of elementary data components. While for data such as sound waveforms the elementary components combine linearly, other data can better be explained by non-linear forms of component superpositions. Using examples of visual data and auditory spectrogram data, I will motivate and define probabilistic generative models of super-position non-linearities. In benchmark applications the non-linear approaches are quantitatively compared to state-of-the-art approaches for component extraction.

Crucial for the applicability of the models are efficient learning procedures. I briefly introduce a novel learning scheme before discussing two main application domains of non-linear models: (A) Computational Neuroscience and (B) Computer Vision.

In the first application I study predictions of non-linear models for information processing in primary visual cortex. New results on predicted response properties of cortical neurons are presented and are compared to predictions of linear models and experimental findings. In Computer Vision, applications of non-linear models to the autonomous learning of objects are discussed, and recent results are presented.