This talk discusses two seemingly unrelated data analysis methodologies: kernel clustering and graphical models. Clustering is an unsupervised learning technique for general data where kernel methods are known for their discriminating power. Graphical models such as Markov Random Fields (MRF) and related continuous geometric methods represent common image segmentation methodologies. While both clustering and regularization models are very widely used in machine learning and computer vision, they could not be combined before due to significant differences in the corresponding optimization, e.g., spectral relaxation vs. combinatorial optimization methods. This talk reviews the general properties of kernel clustering and graphical models, discusses their limitations (including newly discovered "density biases" in kernel methods), and proposes a general easy-to-implement algorithm based on iterative bound optimization. In particular, we show that popular MRF potentials introduce principled geometric and contextual constraints into clustering, while standard kernel methodology allows graphical models to work with arbitrary high-dimensional features (e.g., RGBD, RGBDXY, deep, etc.).