1135-65-2261 **Matthew Dunlop*** (mdunlop@caltech.edu), **Dejan Slepčev**, **Andrew Stuart** and **Matthew Thorpe**. *Graph-based learning as a Bayesian inverse problem.*

A common task in machine learning is to divide a set of data points, such as images, into a number of classes. The data points may be viewed as vertices of a graph, with edges weighted according to some similarity measure between points, from which a graph Laplacian L can be constructed. The spectral properties of L can contain a significant amount of clustering information. If the classes for a small number of points are known, the problem is to propagate these class labels to all of the data points in an appropriate manner; combining the known labels with L is a natural approach to this. In the Bayesian approach, a prior distribution is constructed from L, and Bayes' theorem is used to condition it upon the labeled data. Classification, and quantification of uncertainty associated with it, can then be found via integration with respect to this conditioned distribution. We study large data limits of this problem. Subject to appropriate scaling, the graph Laplacian converges to a certain differential operator; properties of this operator then provide heuristics for selection of parameters underlying the prior when the number of data points is large but finite. We also consider hierarchical Bayesian approaches, in which these parameters are learned from the labeled data. (Received September 25, 2017)