Learning Smoothly Varying Bayesian Network Structures Under Similar Contexts

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Recently, attention has been given to the problem of learning multiple Bayesian networks from similar tasks [2,3]. We extend this multi-task problem to cover groups of tasks with arbitrary similarity relationships, i.e. the tasks need not be all directly related to each other. In particular, we propose a novel algorithm for learning Bayesian network structures from experimental data when several experimental conditions exist.

For example, the gene expression network of yeast may be observed under different environmental stresses such as starvation or heat shock. From these two conditions, four different environments can be realized: starvation with heat shock, starvation alone, heat shock alone, and the control environment. Thus, we could learn four different networks, but we expect these networks to have structural similarities. Often the amount of data available to learn these networks is limited, thus it is advantageous to leverage the full dataset across the contexts. We may also estimate networks under contexts for which there is little or no data available by using data from similar contexts.

For a given collection of contexts, an undirected graph is constructed where each vertex is a context and edges represent similarity between two contexts (the **similarity graph**). The goal is to learn a Bayesian network structure for each context. Our new algorithm learns a network for each context by optimizing a weighted combination of the likelihood of the data and the similarity of learned structures across the similarity graph. To do this, we introduce a new regularization penalty into the structure score while searching over the space of graphs. This penalty is a distance metric between neighboring networks in the similarity graph and is applied in addition to the common-practice complexity penalty for each individual network [1]. This new score trades-off the relative importance of similarity between learned network structures and the fit of each individual structure to its training data. This framework is quite flexible, allowing for both direct and indirect transfer of learning between contexts through the similarity graph, as well as providing a mechanism, through the choice of distance metric, for learning related networks with different sets of vertices.

In addition to using synthetic data, we apply our algorithm to learning the functional network of brain activity from imaging data, specifically the fMRI data from the Pittsburgh Brain Activity Interpretation Competition (PBAIC).

Topic: graphical models, learning algorithms
Preference: poster

References

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