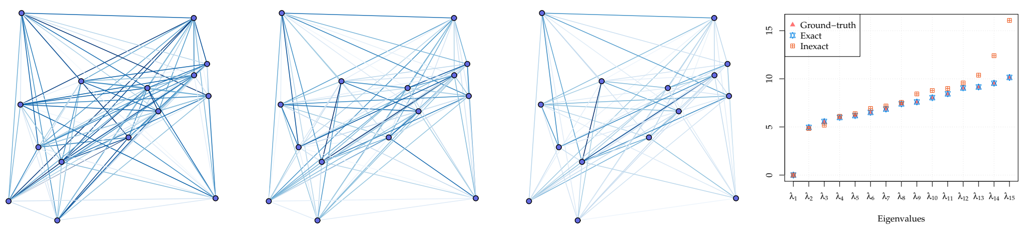
Authors Feedback Paper ID: 6220

We thank the reviewers for their valuable comments and for acknowledging the novelty of our work. We hope to address adequately the concerns raised by the reviewers.

1) *"Visual inspection"* For the cancer data set, we agree that we should have included a numerical result. We apologize for overlooking this. Here are the values for clustering accuracy (ACC)[50], (SGL=0.99875, CLR=0.9862). For the animal data set, visualization of the animal connections is a standard practice to evaluate a graph learning algorithm [26, 63, 65], and the performance can be judged based on the intuition that similar animals should be strongly connected.

2) *"Different Spectral Constraints"* As a concrete example, we reported a detailed analysis of the most used case of k-components eq (4) and single component graph eq (5). Following reviewer's suggestion, we implement the 4th case eq (7) in Figure 1 presented below.



(a) Ground truth (b) Constraint eq (7) (c) Constraint eq (5) (d) Eigenvalues

Figure 1: Experiment for a connected graph with $p = 15$ nodes and $n/p = 10$. (a) True graph; (b) Graph learned with exact spectral constraint (RE= 0.19, FS=0.97); (c) Graph learned with only connected graph spectral constraint (RE= 0.34, FS=0.87). This demonstrates that more spectral information helps improve the graph estimation results.

3) *"What practical relevance can a k-component graph have?"* k-component graph is a widely studied graph structure, found in a variety of applications, e.g., spectral graph theory, clustering, classification, community detection, and pattern matching [6, 7, 18, 39, 41, 42, 44, 45, 50]. $k-$component SGL is an unsupervised learning technique for clustering data and learning the connections. Such a method can be used for simultaneous clustering and graph learning: a much-needed tool for a variety of applications including gene classification and their pathways analysis [6,7].

4) *"term structured graph learning is potentially somewhat misleading"* The framework requires a prior knowledge about the underlying graph structure to be estimated. Erdos Renyi and Grid graphs are estimated under connected constraint eq(5).

5) *"Other points"* A new formulation eq(8) with graph Laplacian operator is a new numerical implementation, which simplifies the design of the algorithm. The sub problem in eq(9) is convex with respect to $\mathbf{w}$, but it is difficult to find a convex formulation for eq(8), due to the eigenvalue constraint. We proposed a graph learning framework viable to several graph structures by considering different eigenvalue constraints. Nuclear norm regularization in our situation could only apply to k-component graph learning, while our current formulation is more flexible. $\alpha||\mathcal{L}\mathbf{w}||_1$= tr$(\mathcal{L}\mathbf{w}\mathbf{H})$ is a useful identity which is proposed in [26].

The major computational complexity of our algorithm is the eigenvalue decomposition. Thus our algorithm would be applicable to problems where eigenvalue decomposition can be performed–which nowadays are possible for large scale problems. The parameter 'k' could be determined by some prior knowledge according to specific applications, e.g., via model selection. More interestingly, it is observed in Fig. 7(in the supplementary file) that the result is still acceptable when 'k' is inaccurate. It is observed in k-component graph learning experiments that the estimated graph always has exactly k components for both synthetic and real-world data, though the original problem is relaxed. In addition, we can see in Fig. 5 that the algorithm achieves a good performance in terms of Average RE by setting a sufficiently large β, and the performance remains stable for larger β but with a decrease in convergence speed.

Preprint. Work in progress.