<u>Paper review:</u>

This document presents my review of the paper: **[Simultaneous Missing Value Imputation and Structure Learning with Groups (Morales-Alvarez et al., 2022)]**

Summary:

This paper introduces VISL (missing value imputation with structural learning), a structure learning method which simultaneously learns relations between groups of variables and performs missing value imputations. VISL was applied on three datasets in the context of education. Extensive experiments were conducted to evaluate the efficacy of the proposed methods showing improvements in the performance of both structure learning and missing data imputation in comparison to recent approaches in these tasks.

The authors proposed a model based on a variational auto-encoder (VAE) architecture where:

- The encoder learns to map input samples X_n into latent representations Z_n, where Z_n is partitioned into M groups, defining a group-wise structured latent space. Here, M MLPs are used to map M groups of observations to the latent space.
- The decoder (generator) takes local latent variables Z_n and global graph structure G as inputs, and reconstructs observations X_n. This generation phase is done in two main steps:
  (1) GNN message passing with respect to the learned graph G between latent variables
  (2) Final read-out layer to generate X_n

Novelty:

Even though the proposed method doesn't introduce a strong theoretical contribution, I found its novelty in the combination of interesting ideas for structure learning and missing value imputation. In addition, the authors tackled an important application in the education domain, aiming to (1) predicting students' responses to un-answered questions, and (2) exploring the relationships between different topics, which I do think it is important for education experts. Through extensive experiments, the proposed approach showed improvements in performance with respect to popular approaches.

Writing:

Overall, the paper is well-written and easy to read. I appreciate Section 2 which describes the proposed model and associated maths rigorously, as well as Section 4 which clearly presents experiments and discusses them.

Evaluation protocol and experimental results:

The authors evaluated VISL on three different datasets: one is synthetic, the second is semi-synthetic which was simulated from a real-world problem, while the third is a real-world education setting. The authors carefully defined the experimental settings as to have fair comparison with baselines. For instance, they selected five methods from the literature to evaluate the structure discovery task, while only working with fully observed training data since those baselines cannot deal with missing values in data. Then they chose 5 other popular baselines to evaluate the missing data imputation task.

The authors clearly defined the metrics. For the imputation performance, RMSE and accuracy where mainly used. To quantify the structure discovery performance, they measure recall, precision and F1-score metrics on the adjacency and orientation.

Results were presented and discussed separately and clearly for each dataset. Overall, in comparison to baselines, the proposed method in this paper showed superior or comparable results in both tasks and in all datasets, which supports the contributions of this paper.