## VilLain: Unsupervised Node Embedding on Hypergraphs via Virtual Label Propagation (Online Appendix)

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## **ABSTRACT**

Groupwise interactions arise in various scenarios in real-world systems: collaborations of researchers, co-purchases of products, and discussions in online Q&A sites, to name a few. Such higher-order relations are naturally modeled as hypergraphs, which consist of hyperedges (i.e., any-sized subsets of nodes). A popular and promising approach for analyzing such a hypergraph is to represent the nodes in it as structure-preserving embeddings (i.e., low-dimensional vectors), which can be readily used for various downstream tasks, such as node classification and hyperedge prediction. Importantly, it is desirable that such embeddings can be obtained even with minimal requirements, precisely, without relying on labels, features, augmentations, and negative samples. However, previous methods resort to additional information or manipulation of the data, which can be problematic in realistic setups.

In this work, we propose VilLain, a novel hypergraph embedding method based on the propagation of virtual labels (v-labels). Aiming to reproduce higher-order homogeneity, which we observe in real-world hypergraphs, VilLain first learns, for each node, the probability distribution over v-labels. Then, VilLain obtains embeddings by propagating the distributions over the hypergraph. With additional schemes for automatic combination of multiple embeddings while reducing redundancy, VilLain is: (a) Requirement-free: not

requiring extra information (e.g., labels and features) or data manipulation (e.g., augmentation and negative sampling), **(b) Versatile:** giving embeddings that are not specialized to specific tasks but generalizable to diverse downstream tasks, **(c) Accurate:** being up to 64.8% and 27.5% more accurate than its competitors for node classification and hyperedge prediction tasks, respectively.

- 1 INTRODUCTION
- 2 RELATED WORK
- 3 PROBLEM STATEMENT
- 4 PROPOSED METHOD
- 5 EXPERIMENTAL RESULTS
- 6 CONCLUSIONS

## **REFERENCES**

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