M2 internship/PhD

Revisiting Graph U-net through the lens of Graph Coarsening

In recent years, **Graph Machine Learning** has gained increasing attention, with applications in chemistry, biology, recommender systems, and social networks. Many of these approaches draw inspiration from deep learning on images, adapting its core principles to graph-structured data. Following the success of convolutional models on graphs such as **Graph Convolutional Networks** (GCNs) [4], it was natural to look toward more advanced architectures. The U-Net [5], originally designed for biomedical image segmentation, quickly emerged as a strong candidate for adaptation to the graph domain.

The proposed **Graph U-net**[1], aims to capture hierarchical and multiscale information using **pooling mechanisms** such as DiffPool[6]. However, the unpooling stage remains less well understood, and relies on debatable heuristics (see figure 3 of [1] initializing the unpooled nodes as zeros). Despite promising early results, this architecture has seen limited adoption in practice, with most modern graph models favoring simpler message-passing schemes.

Inspired by recent results on **Graph Coarsening** [3, 2], we propose in this internship to explore how the unpooling part could be better addressed to achieve a more fine-grained graph reconstruction. Graph coarsening consists in reducing the size of a graph through a coarsening and a lifting matrix. The interplay between these two matrices have been recently discussed in [3]. In light of this result, the goal of this internship is to investigate the interaction between the pooling and unpooling schemes.

Graph U-net could be used for **node-task** on graph and to learn **new graph representation** for graph-task. For the former, it covers mainly middle size graph with thousands nodes such Cora and Citeseer. Scaling it to larger graph would require to rethink the architecture to be memory efficient and would not be addressed in the internship.

While this internship can be supported by some theoric approaches inspired from [2, 3], empirical experiments remains essential and benchmarking against other architecture is expected. The coding framework will be developped with pytorch geometric allowing a better understanding of this library.

Info. Location: IRISA, Rennes, France. Starting date in 2026. This M2 internship could be potentially followed by a PhD funded by ERC MALAGA `nkeriven.github.io/malaga/`.

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References

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[2] Antonin Joly and Nicolas Keriven. Graph coarsening with message-passing guarantees. *Advances in Neural Information Processing Systems*, 37:114902–114927, 2024.

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