Generalization of Graph Neural Networks on latent random graphs (Abstract of Invited Talk)

Nicolas Keriven[1]

[1] *CNRS, IRISA 263 av du Général Leclerc 35000 Rennes*

Abstract

This extended abstract accompanies an invited talk presented at STAF 2026.

This talk will present recent works around the statistical analysis of Graph Neural Networks on latent position random graphs. We will establish links with regular Machine Learning on independent data, and emphasize the difference in the graph case.

Keywords

Graph Machine Learning, Generalization theory, Graph Neural Networks

In many scientific domains, graphs are the objects of choice to represent structured data: from molecules to social networks, power grids, protein interaction networks, the internet, and so on [1, 2]. Machine Learning on graphs (GML) is thus a fast-growing field, with Graph Neural Networks (GNN) currently at the front of it.

However, the theoretical framework of GML does not fall under the hood of traditional statistical ML analysis on independent data, as nodes within graphs are by nature dependent. As a result, it is not clear how to properly analyze GNNs, characterize their limitations and how to fix them.

The purpose of this invited talk is to broadly introduce the field of GML and GNNs, and outline a potential fundamental framework to express the generalization capabilities of GML algorithms, with an emphasis on the similarities and difference with traditional ML. We will then revisit notions of stability, concentration, and universality of GNNs in this framework. In particular, statistical GML will necessary call for models of *random* graphs, a vast, established field from which we will be able to borrow many mathematical tools.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

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nicolas.keriven@cnrs.fr (N. Keriven)

https://nkeriven.github.io (N. Keriven)

0000-0002-3846-8763 (N. Keriven)

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