Graph Neural Differential Equations in the Infinite-Node Limit

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What theoretical principles govern the generalization of graph-based learning models as graph size varies? In this talk, we address this question in the context of Graph Neural Differential Equations (GNDEs)—a class of models that combine the inductive bias of Graph Neural Networks (GNNs) with the continuous-depth dynamics of Neural ODEs. To this end, we introduce Graphon Neural Differential Equations (Graphon-NDEs), which serve as infinite-node limits of GNDEs. Leveraging tools from graphon theory and dynamical systems, we establish the well-posedness of Graphon-NDEs and prove the trajectory-wise convergence of GNDE solutions to their Graphon-NDE counterparts as graph size increases. In addition, we obtain explicit convergence rates for both weighted and unweighted graphs. These results lead to size transferability bounds that provide theoretical justification for applying GNDE models trained on moderate-sized graphs to larger, structurally similar graphs without retraining. Our theoretical findings are supported by numerical experiments.

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