Stability of Graph Neural Network with respect to different types of topological perturbations

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Background

- Graph Neural Networks
- Perturbations negatively impact the stability
- This work analyses the impact of different types of perturbations
- Future research can use these results to inform GNN design

Methodology

- Train model on unperturbed data
- Perturb the graph
- Compare the output of the perturbed and unperturbed graph

Measuring stability

Matrix presentation of a graph S
Euclidean distance between outputs:

$$||y - y_p||/||y||$$

Error matrix:

$$\mathbf{E} = |\mathbf{S} - \mathbf{S_p}|$$

Stability bound:

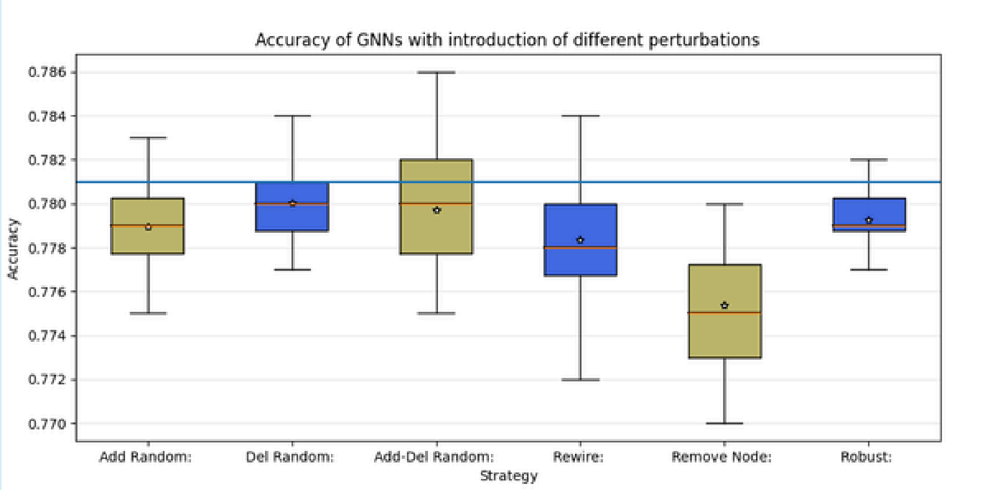
$$C \geq ||y - y_p||/||\mathbf{E}||$$

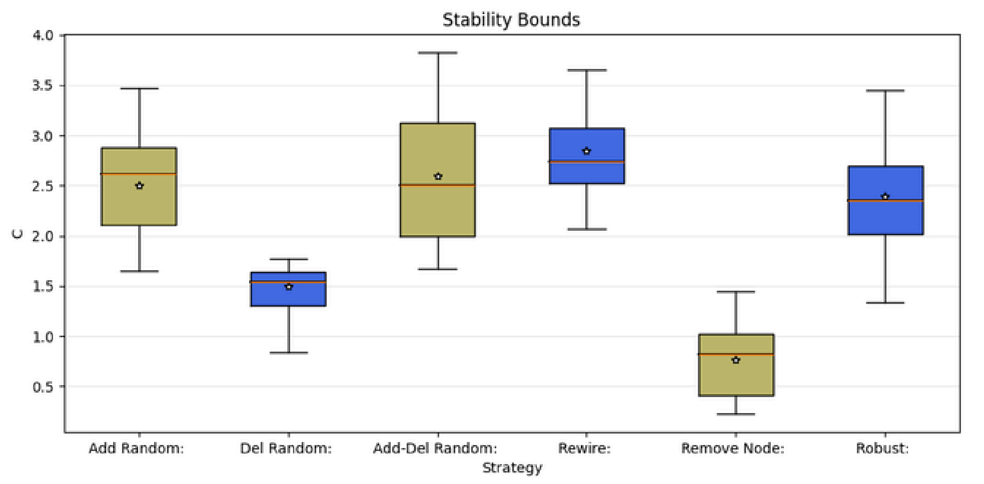
Experiments

- Accuracy, relative distance and stability bound for all the strategies
- Influence of the degree of adjacent nodes

Cora dataset with a GNN using TAGConv layers[1,2].

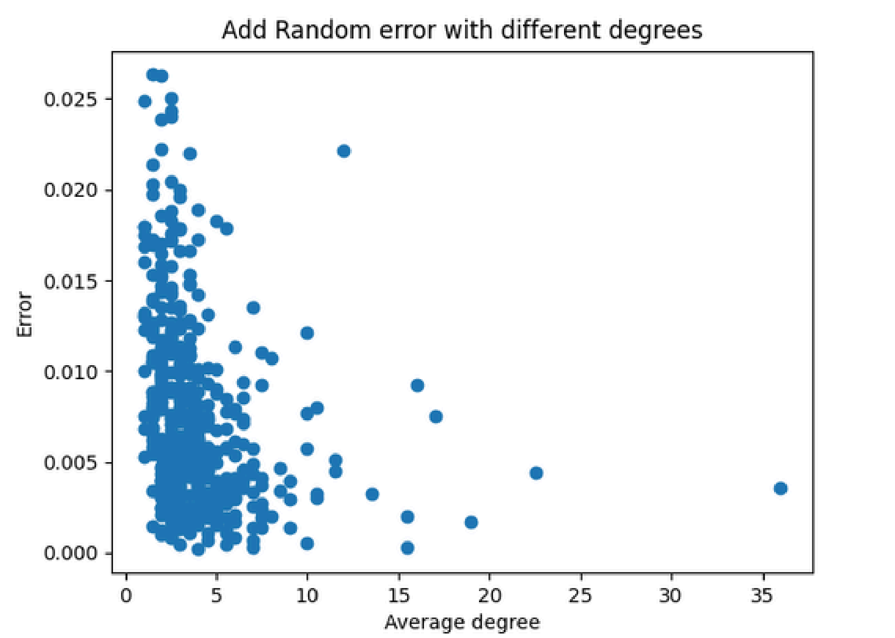
Strategies considered: Add Random, Delete Random, Add-Delete Random, Rewire, Remove Node, Robust





Results

- Some perturbations can increase the performance of the GNN
- Deleting edges is better than adding edges to the graph.
- Larger operations have more variation
- Delete Random and Remove node have the smallest stability bound
- Edges adjacent to nodes with a lower degree have more impact on stability



Future work

Consider more types of perturbations
Verify that the results of these random strategies correspond to domain applications