Certifiable Robustness in Graph Classification via Community-Aware Randomized Smoothing

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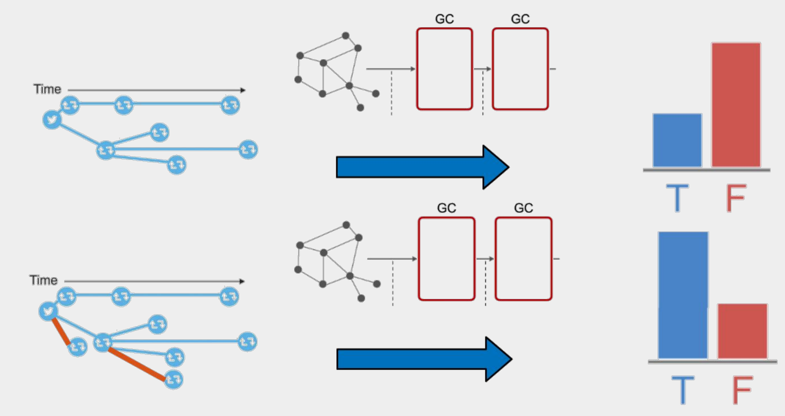
Motivation

Graph Neural Networks (GNNs) are effective in many graph-related tasks, but are **vulnerable to designed adversarial attacks**. Under adversarial attacks, the victimized samples are perturbed in such a way that they are not easily noticeable, but they lead to **wrong predictions**. This limitation of GNNs has arisen immense concerns on adopting them in **safety-critical applications**. Our main objective is to **introduce robustness certificates** in our graph classification model.



Framework

- Let $f : \mathcal{X} \to \mathcal{Y}$ be a trained classifier, we define a **certified radius** R as:

$$f(x) = c \text{ for } c \in \mathcal{Y} \implies \forall \tilde{x} \in \mathcal{B}_{||.||_0}(x, R), f(\tilde{x}) = c$$

- We transform our classifier f into a **smoothed classifier** g defined as:

$$g(x) = \underset{c \in \mathcal{Y}}{\arg\max}\, \mathbb{P}_{X \sim \phi(x)}(f(X) = c)$$

- The current classical perturbation $\phi(x)$ for graph is a **Bernoulli noise** over the edges

$$\phi(x) = x \oplus \epsilon \text{ with } \forall i \in [N], \epsilon_i \sim Bern(p)$$

- Given a perturbation $\phi(x)$ a certified radius R can be computed for every graph for the smoothed model $g(x)$

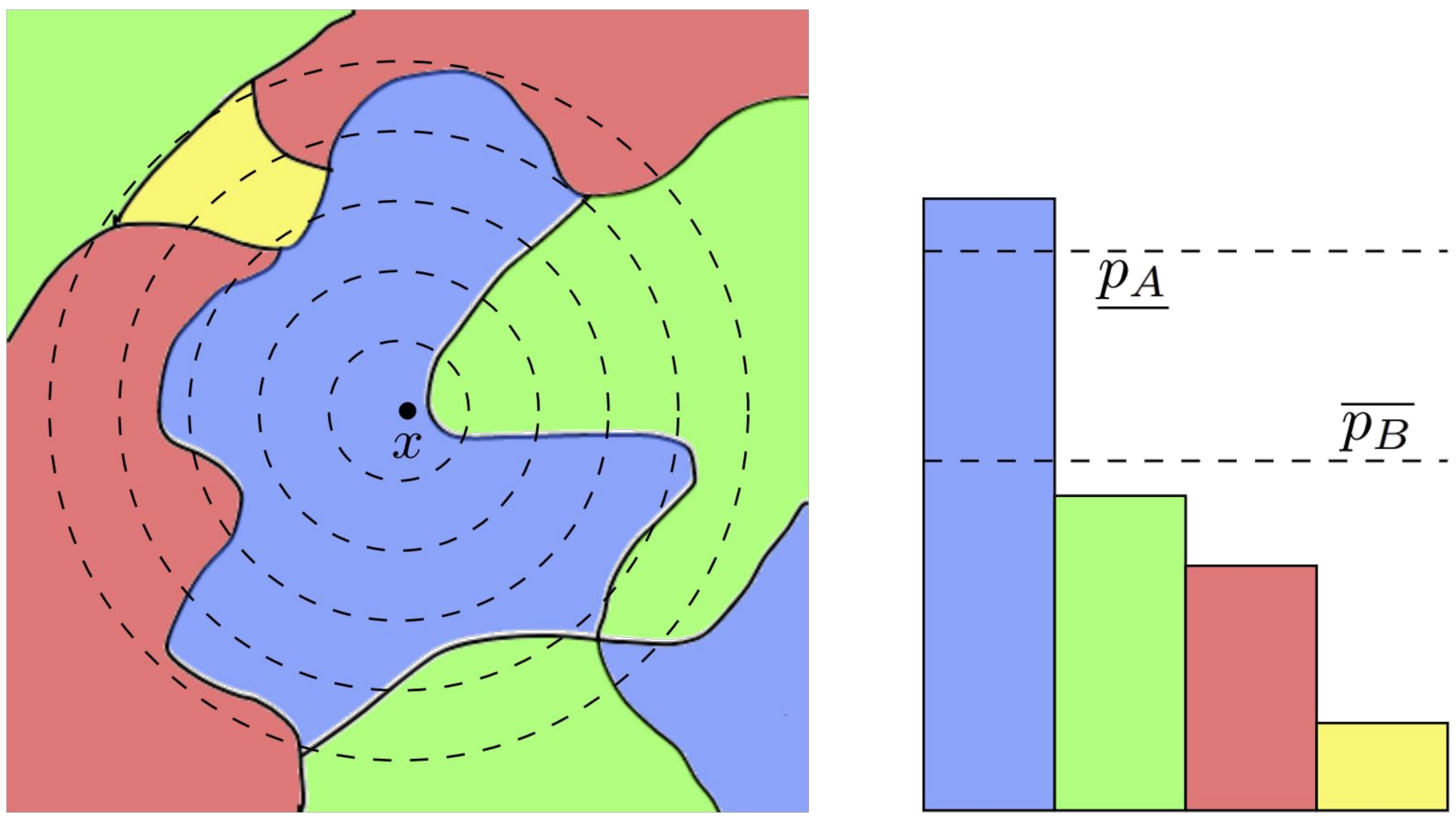
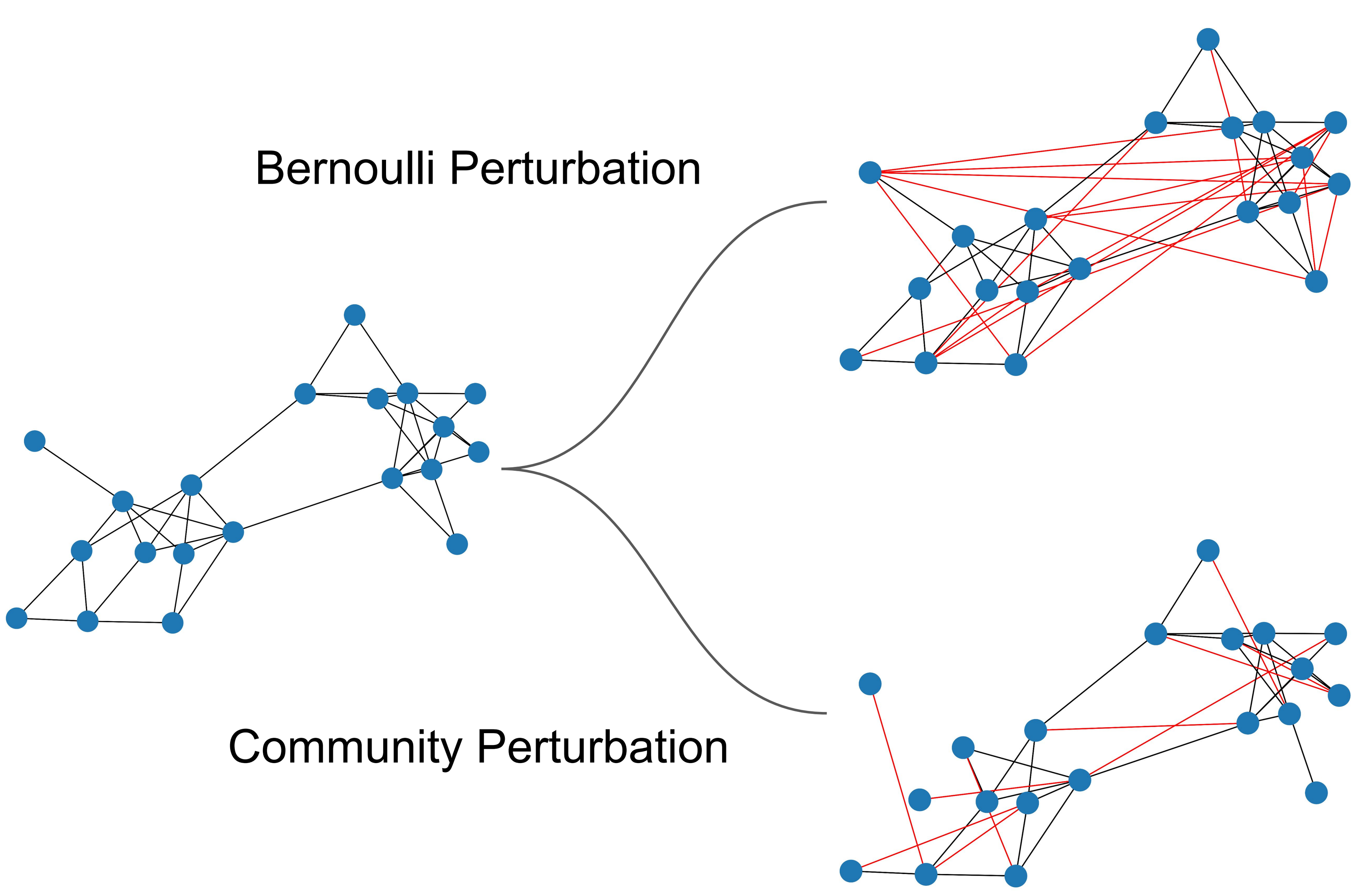


Illustration of a smoothed classifier: at every point x a neighborhood vote is performed according to a distribution $\phi(x)$ centered on x.

Method

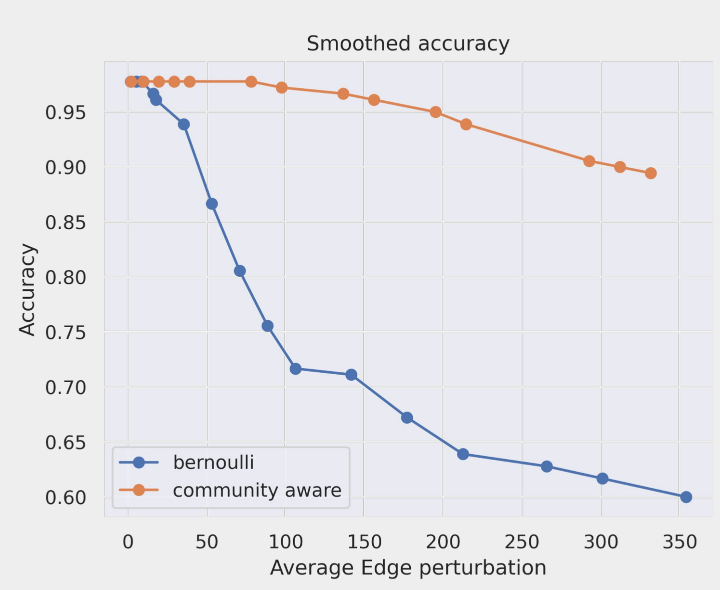
- We introduce a new perturbation method with edge dependency relying on the **community structure** of the graph:

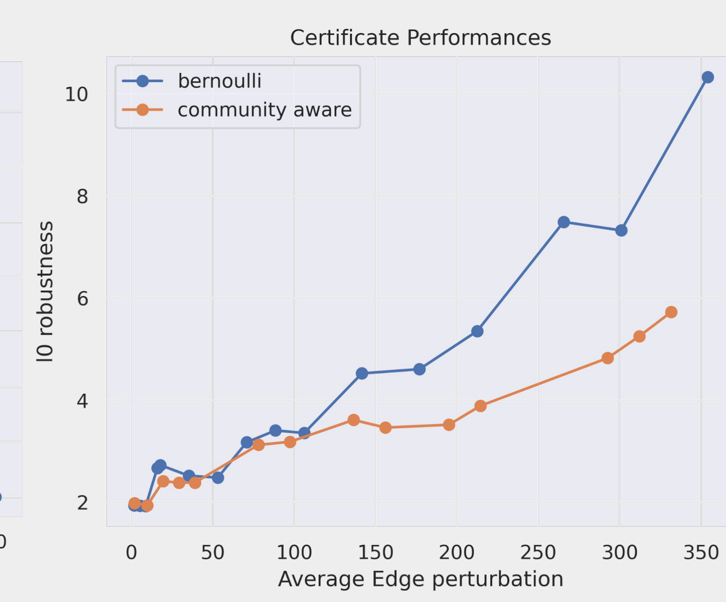
$$\forall i, j \in [L], \forall e \in C_{i,j}, P(\phi(x)_e \neq x_e) = p_{i,j}$$

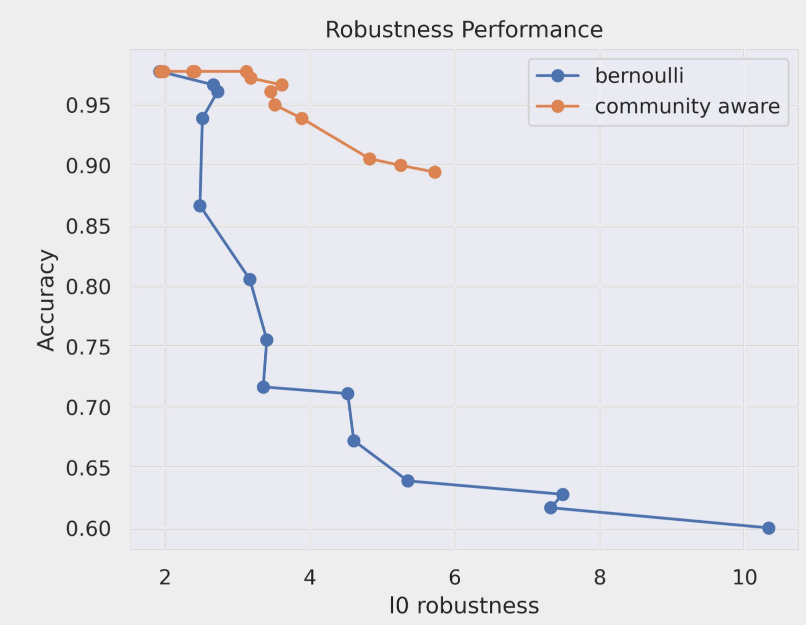


Result

- We test our new method on a synthetic dataset: Our dataset consists of graphs generated by a Stochastic Block Model (SBM) and Erdős–Rényi model (ER). A GNN is pre-trained on a task consisting in distinguishing the type of graphs.
- We achieve a higher average ℓ_0 robust radii for a given model accuracy.







References

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