

# Polynomial Graph Neural Networks and the Effect of Graph Noise

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# Motivation

## Background

- Graph neural networks (GNNs) are state-of-the-art for graph learning
- Empirical evidence suggests deeper networks  $\neq$  “better”
- Lack theoretical understanding of the role of network depth

## Key questions

- Do deeper networks = better performance for GNNs?
- What is the fundamental limit of GNN performance?
- How does graph noise affect classification?

# Motivation

- Vinas and Amini attempt to answer some of these questions and their work<sup>1</sup> is the focus of this presentation
- Emphasis on the results that use arguments from matrix perturbation theory and random matrix theory

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<sup>1</sup>Vinas and Amini, *Sharp Bounds for Poly-GNNs and the Effect of Graph Noise*, 2024

# SSNC with GNNs

In the task of semi-supervised node classification (SSNC) one is given an adjacency matrix  $A \in \{0, 1\}^{n \times n}$  and is asked to make predictions using a partially observed set of labels

# SSNC with GNNs

## Input:

- Graph:  $A \in \{0, 1\}^{n \times n}$
- Node features:  $X \in \mathbb{R}^{n \times d}$  where the  $i$ -th row is  $x_i^\top$  (i.e., the feature vector of node  $i$ )
- Partial labels:  $y_i$  where  $i \in \mathcal{O} \subset [n]$

## Goal:

- Predict the unseen labels  $y_i$ ,  $i \in \mathcal{O}^c$

# SSNC with GNNs

The prototypical GNN is defined (layer-wise) where, for  $Z^{(0)} = X$ , the intermediate feature  $Z^{(l+1)}$  is

$$Z^{(l+1)} = \varphi \left( AZ^{(l)} W^{(l)} \right)$$

Here,

- $l = 0, 1, \dots, k - 1$  denotes the layer index,
- $\varphi : \mathbb{R} \rightarrow \mathbb{R}$  is a non-linear function applied elementwise, and
- $W^{(l)} \in \mathbb{R}^{d_l} \times \mathbb{R}^{d_{l-1}}$  is the weight matrix for layer  $l$

# SSNC with GNNs

- If we take  $\varphi$  to be the identity map, then we obtain
$$Z^{(k)} = A^k X W^{(0)} \dots W^{(k-1)}$$
- We reparameterize and obtain the **poly-GNN**

$$Z^{(k)} = A^k X W \tag{1}$$

# SSNC with GNNs

To train a classifier for (1), we form the graph-aggregated features  $\phi^{(k)} := A^k X \in \mathbb{R}^{n \times d}$  and then train a linear classifier on the observed pairs

$$\left( (\phi^{(k)})_{i\star}, y_i \right), \quad i \in \mathcal{O},$$

where  $(\cdot)_{i\star}$  denotes the operator that extracts the  $i$ -th row of a matrix



# SSNC with GNNs

To explain the performance of  $\phi^{(k)}$ , we use the **signal-to-noise ratio** (SNR):

$$\frac{1}{\rho^{(k)}} := \min_{i,j:y_i \neq y_j} \frac{\left\| \mathbb{E} [\phi_i^{(k)}] - \mathbb{E} [\phi_j^{(k)}] \right\|_2}{\left( \frac{1}{n} \sum_i \left\| \phi_i^{(k)} - \mathbb{E} [\phi_i^{(k)}] \right\|_2^2 \right)^{1/2}}, \quad (2)$$

where  $\phi_i^{(k)}$  is the  $i$ -th row of  $\phi^{(k)}$  viewed as a column vector

# Contextual Stochastic Block Model

- A suitable model is the **contextual stochastic block model** (CSBM)
- Network data  $(A, X)$  is CSBM-generated if, for some cluster centers  $\mu_1, \dots, \mu_L \in \mathbb{R}^d$  and a connectivity matrix  $B \in \mathbb{R}^{L \times L}$ , the data follows

$$x_i | y_i \sim \mu_{y_i} + \epsilon_i \quad \text{and} \quad A_{ij} | y_i, y_j \sim \text{Bern}(B_{y_i y_j}),$$

with  $\epsilon_i \sim \text{SG}(\sigma)$  being a zero-mean, sub-Gaussian random variable with parameter  $\sigma$

# Noise Decomposition

- We want to control the noise deviation in (2):

$$\bar{D} := \left( \frac{1}{n} \sum_i \left\| \phi_i^{(k)} - \mathbb{E} [\phi_i^{(k)}] \right\|_2^2 \right)^{1/2} = \left( \frac{1}{n} \sum_{i,m} D_{im}^2 \right)^{1/2}$$

- For  $k$ -hop aggregated features  $\phi_{im}^{(k)} = (A^k X)_{im}$ , we have

$$D_{im} = \underbrace{\sum_j \left( (A^k)_{ij} - \mathbb{E} [A^k]_{ij} \right) x_{jm}}_{=:\Delta_{im} \text{ (graph noise)}} + \underbrace{\sum_j \mathbb{E} [A^k]_{ij} \epsilon_{jm}}_{=:\Delta_{im}^\epsilon \text{ (feature noise)}}$$

# Notation

- Define  $\tilde{\mu}_l^{(k)} := \mathbb{E}\phi_l^{(k)}$  to be the ideal center of  $\mathcal{C}_l = \{j : y_j = l\}$  (i.e., the set of indices corresponding to the  $l$ -th class)
- Then, (2) becomes

$$\frac{1}{\rho^{(k)}} := \frac{\min_{l \neq l'} \left\| \tilde{\mu}_l^{(k)} - \tilde{\mu}_{l'}^{(k)} \right\|_2}{\left( \frac{1}{n} \sum_i \left\| \phi_i^{(k)} - \mathbb{E} \left[ \phi_i^{(k)} \right] \right\|_2^2 \right)^{1/2}} = \min_{l \neq l'} \frac{S(l, l')}{\bar{D}},$$

where  $S(l, l') := \left\| \tilde{\mu}_l^{(k)} - \tilde{\mu}_{l'}^{(k)} \right\|_2$ ,  $\bar{D}$  defined as before

# Notation

- Let  $p_{ij} = \mathbb{E}[A_{ij}]$  and let  $\nu_n := np_{\max}$ , where  $p_{\max} := \max_{i,j} p_{ij} = \max_{l,l'} B_{ll'}$
- For cluster  $\mathcal{C}_l$  let  $\pi_l = \frac{|\mathcal{C}_l|}{n}$  and  $\pi = (\pi_1, \dots, \pi_L)$
- Let  $\mu = [\mu_1, \dots, \mu_L] \in \mathbb{R}^{d \times L}$  where  $\mu_l = \mathbb{E}[x_i]$  for class  $l$
- Define  $\bar{\xi}_l^{(k)} = \mu \left( \Pi \frac{nB}{\nu_n} \right)^k e_l$  where  $\Pi := \text{diag}(\pi) \in \mathbb{R}^{L \times L}$

# Assumptions

## Sparsity structure

- (A1) For every class  $l$ , we have  $nB_{ll'} \geq c_B \nu_n$  and  $nB_{ll'} \leq C_B \nu_n^{1-\delta}$  where  $c_B, C_B > 0$  and  $\delta \in (0, \infty]$
- (A2)  $\nu_n \leq (1 - c_\nu)n$ ,  $c_\nu \in (0, 1)$

## Class balance

- (A3)  $L\pi_l \geq c_\pi$  and  $\sqrt{L}\|\pi\|_2 \leq C_\pi$

## Feature separation

- (A4)  $\|\mu\| \leq C_\mu \sqrt{d}$
- (A5)  $\left\| \bar{\xi}_l^{(k)} - \bar{\xi}_{l'}^{(k)} \right\|_2 \geq c_\xi \sqrt{d}$ , where  $c_\xi \leq 1$

# Additional Conditions

## Sparsity growth

$$\blacksquare \text{ (C1) } \nu_n \gtrsim \max \left\{ \log n, \frac{LC_\mu^2 C_k^2}{c_\pi c_\xi^2} \right\}$$

## Sample size

$$\blacksquare \text{ (C2) } \min \left\{ \frac{n}{k}, \frac{\nu_n^\delta}{C_B} \right\} \geq \frac{4C_\mu L}{c_\pi c_\xi}$$

## Moment control

$$\blacksquare \text{ (C3) } r_n(\epsilon) \geq 4 \text{ where } r_n \text{ controls moment growth}$$

# Main Result (Formal)

## Theorem 1 (Signal bound)

*Assume (A3)–(A5), and (C1). Then, for  $l \neq l'$ ,*

$$\frac{c_\xi}{2} \sqrt{d} \nu_n^k \leq S(l, l') \leq \sqrt{8d} C_\mu C_\pi^k \nu_n^k.$$

In other words, the signal  $S(l, l')$  grows precisely at the rate  $\nu_n^k$



# Main Result (Formal)

## Theorem 2 (Noise upper bound)

*Assume  $\nu_n \geq ke^{2(k-1)}$  and  $r_n(\epsilon) \geq 2$ . Then, for all real  $r \in [2, r_n(\epsilon)]$ ,*

$$\mathbb{E} \left[ |\bar{D}|^r \right] \leq \left( \kappa_3 \sqrt{8dr} \nu_n^{k-1/2} \right)^r.$$

*Moreover, for  $u \geq 8de$ ,*

$$\mathbb{P} \left( \bar{D} \geq \kappa_3 \nu_n^{k-1/2} \sqrt{u} \right) \leq \exp \left( -\frac{1}{2} \min \left\{ \frac{u}{4de}, r_n \right\} \right).$$

# Main Result (Formal)

## Theorem 3 (Noise lower bound)

*Assume (A1)–(A3), (A5), and (C2)–(C3). Then, for any  $\eta \in (0, 1)$ ,*

$$\mathbb{P}\left(\bar{D} \geq \sqrt{\eta \kappa_1 d} \nu_n^{k-1/2}\right) \geq (1 - \eta)^2 \frac{\kappa_1^2}{\kappa_2^2}.$$

Combined with Theorem 2, we see that the noise  $\bar{D}$  grows precisely at the rate  $\nu_n^{k-1/2}$

# Main Result (Informal)

Combining Theorems 1–3, the SNR grows at the precise rate  $\nu_n^{1/2}$  independent of  $k$

## Theorem 4 (SNR bound)

*Let  $(A, X)$  be generated from an  $L$ -class CSBM satisfying (A1)–(A5) with  $\nu_n \gtrsim \log n$  and  $n$  sufficiently large. Then, for any  $k \geq 1$ , with high probability,*

$$\sqrt{\nu_n} \rho^{(k)} \leq C c_\xi^{-1}$$

*for a constant  $C$  independent of  $n$  and  $k$ . Furthermore, with probability bounded away from zero,*

$$\sqrt{\nu_n} \rho^{(k)} \geq c c_\xi$$

*for a constant  $c > 0$  independent of  $n$  and  $k$ .*

# Signal Analysis

We introduce some notation:

- $P := ZBZ^\top$ , where  $Z \in \{0, 1\}^{n \times L}$  is the cluster membership matrix for  $y$
- $M := \mu ZT^\top \in \mathbb{R}^{d \times n}$
- $\tilde{S}(l, l')$  where  $\tilde{S}(l, l') \asymp \nu_n^k$  (signal proxy)

# Signal Analysis

- We now show that  $\tilde{S}(l, l')$  is close to the signal deviation  $\left\| \tilde{\mu}_l^{(k)} - \tilde{\mu}_{l'}^{(k)} \right\|_2$
- Using a Banach-valued mean value theorem, we obtain the following lemmas:

## Lemma 5

$$\left\| \mathbb{E}[A]^k - p^k \right\| \leq \frac{k\nu_n^k}{n}.$$

# Signal Analysis

## Lemma 6 (Concentration inequality for $A^k$ )

*Suppose that  $\nu_n \geq c'_\nu \log n \geq 1$  for some constant  $c'_\nu > 0$ . Then, for any integer  $k \geq 1$ , the spectrum of  $A$  concentrates as*

$$\mathbb{E} \left\| A^k - \mathbb{E}[A]^k \right\| \leq C_k \nu_n^{k-1/2},$$

*where  $C_k = k 2^k \left( C + \sqrt{\left( \frac{c}{c'_\nu} \right) (k+1)} \right)^k$  for some universal constants  $C > 1$  and  $c > 0$ .*

# Signal Analysis

## Proof sketch of Theorem 1.

By Lemmas 5 and 6,  $\|\mathbb{E}[A^k] - P^k\| \leq 2C_k \nu_n^{k-1/2}$ . Then, we have

$$\begin{aligned} \left| \left\| \tilde{\mu}_l^{(k)} - \tilde{\mu}_{l'}^{(k)} \right\| - \tilde{S}(l, l') \right| &\leq \left\| M \left( \mathbb{E}[A^k] - P^k \right) w \right\|_2 \\ &\vdots \\ &\leq \sqrt{8dL/c_\pi} C_\mu C_k \nu_n^{k-1/2} \end{aligned}$$

By (C1) we obtain  $1 \geq \frac{c_\xi}{2} \geq \sqrt{8L/c_\pi} C_\mu C_k \nu_n^{-1/2}$ , hence

$$\frac{c_\xi}{2} \sqrt{d} \nu_n^k \leq S(l, l') \leq \sqrt{8d} C_\mu C_\pi^k \nu_n^k$$

as desired. □

# Noise Analysis

There are two main ingredients for proving Theorems 2 and 3:

- 1 Walk analysis (walk sequences, trees)
- 2 High-order moment bounds



# Noise Analysis

Recall that  $D_{im} =: \Delta_{im} + \Delta_{im}^\epsilon$

- We can upper-bound the  $r$ -th moment of the noise as

$$\mathbb{E}(\bar{D})^r \leq \frac{d^{r/2-1}}{n} \sum_{i,m} \mathbb{E} D_{im}^r \quad (3)$$

- We have for  $r \in 2\mathbb{N}$ ,

$$D_{im}^r \leq 2^{r-1} (\Delta_{im}^r + (\Delta_{im}^\epsilon)^r) \quad (4)$$

- We first control  $\mathbb{E} (\Delta_{im}^\epsilon)^r$

# Noise Analysis

- Recall  $\epsilon_{im} \sim \text{SG}(\sigma)$
- It follows that  $\Delta_{im}^\epsilon \sim \text{SG}\left(\sqrt{\sigma^2 \sum_j \mathbb{E}[A^k]_{ij}^2}\right)$
- We have also the following lemma<sup>2</sup>:

## Lemma 7

If  $Z$  is sub-Gaussian with parameter  $\sigma$ , then  $\mathbb{E}|Z|^r \leq \left(C_1 \sigma r^{1/2}\right)^r$  where  $C_1$  is a numerical constant.

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<sup>2</sup>Vershynin, *High-Dimensional Probability: An Introduction with Applications in Data Science*, 2018

# Noise Analysis

We have

$$\begin{aligned} \left(\mathbb{E}[A^k]_{ij}^2\right)^{1/2} &\leq \mathbb{E}[A^k]_{ii} + \sqrt{n} \max_{j \neq i} \mathbb{E}[A^k]_{ij} \\ &\vdots \\ &\leq 4\nu_n^{k-1/2} \end{aligned}$$

Applying Lemma 7 gives

$$\mathbb{E}(\Delta_{im}^\epsilon)^r \leq \left(4C_1 \sigma \nu_n^{k-1/2} r^{1/2}\right)^r, \quad (5)$$

hence  $\Delta_{im}^\epsilon$  is sub-Gaussian with parameter  $\lesssim \sigma \nu_n^{k-1/2}$

# Noise Upper Bound

We have the following lemma:

## Lemma 8

*Let  $\eta > 0$  and  $r_0 \in 2\mathbb{R} \cup \{\infty\}$ . Assume that for all even integers  $r \leq r_0$ , we have*

$$\mathbb{E} [|\Delta|^r] \leq (K(C\eta r)^\eta)^r. \quad (6)$$

*Then, (6) holds for all real  $r \in [2, r_0]$  with  $C$  replaced with  $2C$ . Moreover, if  $x \geq 4\eta C e$ , then*

$$\mathbb{P} (|\Delta| \geq Kx^\eta) \leq \exp \left( -\min \left\{ \frac{x}{2Ce}, \eta r_0 \right\} \right).$$

# Noise Upper Bound

## Proof sketch of Theorem 2.

Combining (3) and (4), we have

$$\mathbb{E}(\bar{D})^r \leq \frac{d^{r/2-1}}{n} \sum_{i,m} 2^{r-1} (\mathbb{E}[\Delta_{im}^r] + \mathbb{E}(\Delta_{im}^\epsilon)^r)$$

We use a walk analysis to bound the first term and (5) to bound the second. Applying Lemma 8 with specific choices of constants, we obtain

$$\mathbb{E} \left[ |\bar{D}|^r \right] \leq \left( \kappa_3 \sqrt{8dr} \nu_n^{k-1/2} \right)^r.$$



# Noise Lower Bound

We have the following lemmas to help prove Theorem 3:

## Lemma 9

*Assume (C2)–(C3) and  $r_n \geq 2$ . Then,*

$$\mathbb{E}(\bar{D})^2 \geq \kappa_1 d \nu_n^{2k-1}.$$

## Lemma 10

*Under the assumptions of Lemma 9, further assume  $r_n \geq 4$ . Then,*

$$\frac{(\mathbb{E} \bar{D}^2)^2}{\mathbb{E} \bar{D}^4} \geq \frac{\kappa_1^2}{\kappa_2}.$$

# Noise Lower Bound

## Proof of Theorem 3.

Applying the Paley-Zygmund inequality to the non-negative quantity  $\bar{D}^2$  yields

$$\mathbb{P}\left(\bar{D}^2 \geq \eta \mathbb{E} \bar{D}^2\right) \geq (1 - \eta^2) \frac{(\mathbb{E} \bar{D}^2)^2}{\mathbb{E} \bar{D}^4}.$$

Using Lemma 9 on the LHS and Lemma 10 on the RHS, we obtain

$$\mathbb{P}\left(\bar{D} \geq \sqrt{\eta \kappa_1 d} \nu_n^{k-1/2}\right) \geq (1 - \eta)^2 \frac{\kappa_1^2}{\kappa_2^2}.$$



# Consequences

- $\rho^{(k)}$  is rate invariant to the Poly-GNN depth  $k$
- Graph aggregation by GNNs does help at the rate  $\sqrt{\nu_n}$
- Oversmoothing does not affect SNR rate
- The rate optimal choice for SNR is obtained at  $k = 1$



# Future Work: A CLT for GNNs

- Consider 1-D node features  $x \in \mathbb{R}^n$
- Define  $\xi_i^{(k)} = \nu_n^{1/2-k} \left( (A^k x)_i - \mathbb{E}[(A^k x)_i] \right)$
- We look at the empirical distribution of  $\{\xi_i^{(k)}\}_{i=1}^n$ :

$$\mathbb{P}_n^{(k)} := \frac{1}{n} \sum_{i=1}^n \delta_{\xi_i^{(k)}}$$

- One can show  $\mathbb{P}_n^{(k)}$  leads to

$$\mathbb{G} := \sum_{l=1}^L \pi_l N(0, \sigma_l^2),$$

i.e., a scale-mixture of Gaussians

# References I



Vershynin, Roman. *High-Dimensional Probability: An Introduction with Applications in Data Science*. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press, 2018, pp. 11–37.



Vinas, Luciano and Arash A. Amini. *Sharp Bounds for Poly-GNNs and the Effect of Graph Noise*. 2024. arXiv: 2407.19567 [cs.LG]. URL: <https://arxiv.org/abs/2407.19567>.