



### Keyulu Xu, Mozhi Zhang, Stefanie Jegelka, Kenji Kawaguchi





# **Optimization of Graph Neural Networks:** Implicit Acceleration by Skip Connections and More Depth



## Background: theory of GNNs

# Optimization

Can gradient descent find a global minimum for GNNs? What affects the speed of convergence?

### **Expressive Power**

(Xu et al. 2019, Sato et al 2020, Chen et al 2019, 2020, Maron et al 2019, Keriven et al 2019, Loukas 2020, Balcilar et al 2021, Morris et al 2020, Azizian et al 2021, Vignac et al 2020)

### **Generalization** (interpolation & extrapolation)

(Scarselli et al. 2018, Verma et al 2019, Du et al 2019, Garg et al 2020, Xu et al 2020, 2021)

## Analysis of gradient dynamics

Linearized GNNs with and without skip connections (non-convex):

$$f(X, W, B) = \sum_{l=0}^{H} W_{(l)} X_{(l)},$$
$$X_{(l)} = B_{(l)} X_{(l-1)} S.$$

Trajectory of gradient descent (flow) training:

$$\frac{d}{dt}W_t = -\frac{\partial L}{\partial W}(W_t, B_t), \quad \frac{d}{dt}B_t = -\frac{\partial L}{\partial B}(W_t, B_t)$$



### JK-Net

(Xu et al 2018)

### Global convergence

### Theorem (XZJK'21) Gradient descent training of a linearized GNN, with or without skip connections, converges to a *global minimum* at a linear rate.



## **Convergence** in practice

Linear convergence for linearized and ReLU GNNs:



Rates for GIN vs. GCN:

10<sup>3</sup> -10-5 10<sup>-13</sup> -10-20



### Implicit acceleration

# Theorem (XZJK'21) and/or a good label distribution.



(a) Multiscale vs. non-multiscale.



(b) Depth.

(c) Signal vs. noise.

2. Deep GNNs with skip connections are promising:

- more expressive & helps with over-smoothing
- faster convergence

More information: https://people.csail.mit.edu/keyulux/

### 1. Global convergence implies more powerful GNNs better fit the training data