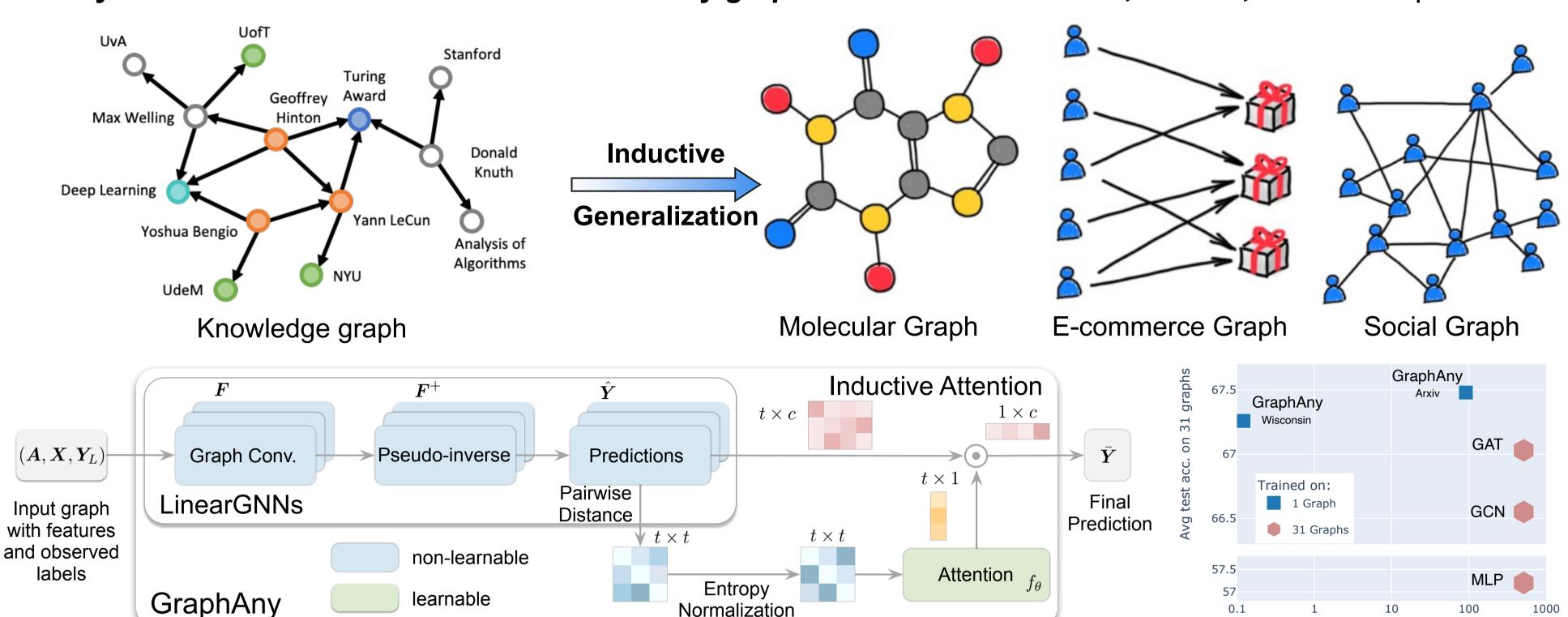
Fully-inductive Node Classification on Arbitrary Graphs

Jianan Zhao, Mikhail Galkin, Hesham Mostafa, Michael Bronstein, **Zhaocheng Zhu, Jian Tang**





Fully Inductive Generalization: Inference on any graph with unseen structure, feature, and label spaces.



Normalization

The GraphAny Architecture

Node Classification Performance

Total training labeled nodes (k)

LinearGNN

Training-free inference on *any graph* with an analytical solution.

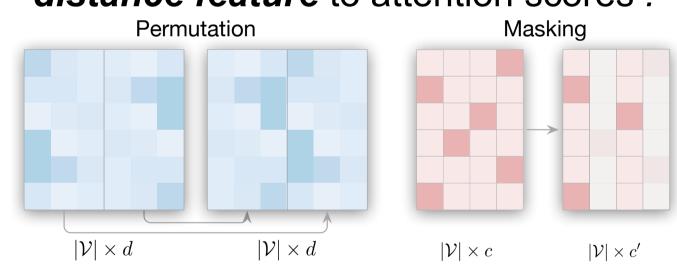
$$egin{aligned} \hat{m{Y}} &= m{F}m{W}, \quad m{W}^* = rg \min_{m{W}} \left\| \hat{m{Y}}_L - m{Y}_L
ight\|^2, \ m{W}^* &= m{F}_L^+ m{Y}_L, \quad \hat{m{Y}} = m{F}m{F}_L^+ m{Y}_L. \end{aligned}$$

- Precomputed propagated feature F, e.g. AX, A^2X .
- Weights $oldsymbol{W}^*$ are given in analytical form, optimizing the meansquared error (MSE) loss.
- Solving $oldsymbol{W}^*$ takes $O\left(|V_L|\right)$ complexity.
- Provides fast and training-free inductive inference with reasonably good performance.

Inductive Attention

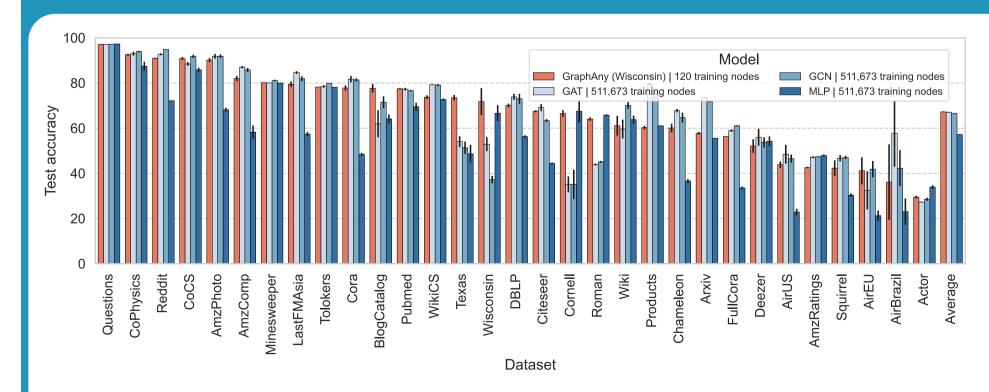
An inductive function that maps *entropy-normed* distance feature to attention scores.

0.1



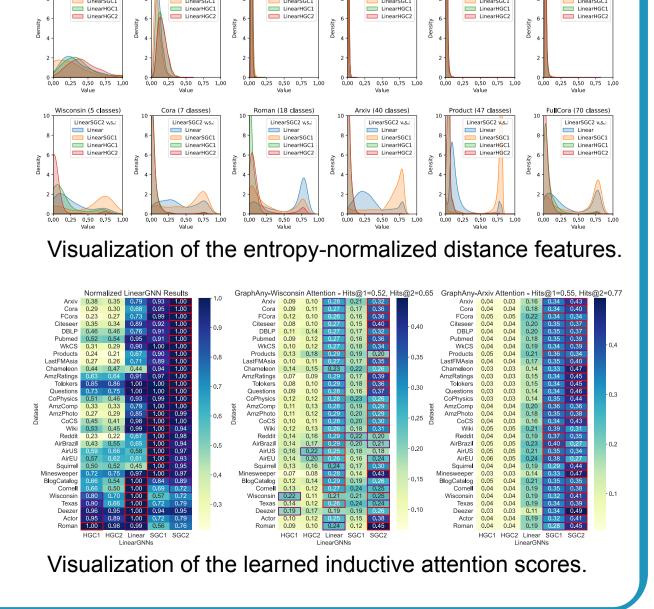
- A fully-inductive inductive function should satisfy: Permutation Invariance and Dimensional Robustness across diverse feature/label dimensions.
- We propose *entropy-normalized distance features* to compute attention scores that adaptively fuse LinearGNN predictions.

Experiments



- Inference on any graph: GraphAny trained on one graph, e.g. Wisconsin with 120 labeled nodes, generalizes to 30 new graphs and outperforms transductive baselines.
- Effectiveness: Training with 2.95x speed up on a single V100 or even on your laptop!

Model	Pre-processing	Optimization	Inference	Total Wall Time (31 graphs)
GCN	0	$O(\mathcal{E})$	$O(\mathcal{E})$	18.80 min
LinearGNN	$O(\mathcal{E})$	$O(\mathcal{V}_L)$	$O(\mathcal{V})$	$1.25 \min (15.04 \times)$
GraphAny	$O(\mathcal{E})$	$O(\mathcal{V}_L)$	$O(\mathcal{V})$	6.37 min (2.95×)





Paper



Code