On the Role of Edge Dependency in Graph Generative Models

Sudhanshu Chanpuriya, Cameron Musco,
Konstantinos Sotiropoulos, Charalampos Tsourakakis

Graph Generative Models

Given a graph, we want to create a model that generates novel but similar graphs.

Why novel graphs?

- Test scalability & robustness of models and algorithms.
- Study networks under privacy.
- Drug discovery.

How similar?

- Match the input graph's structure and statistics as well as possible...
- But not to the point of reproducing the same edges!

How can we analyze the inherent trade-o between expressiveness and variety?

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Quantifying Graph Variety

To concretize *variety*, prior work defines the **overlap** of a random graph model G:

$$\mathrm{Ov}(G) := \frac{\mathbb{E}_{G_1, G_2 \sim G} |E(G_1) \cap E(G_2)|}{\mathbb{E}_{G \sim G} |E(G)|}.$$

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Consider common **edge-independent** graph models: some probability matrix $P \in [0, 1]^{n \times n}$ and the distribution $\mathcal{G}$ on graphs where each edge is added independently with probability P_{ij}.

It is shown that edge-independent models with low overlap are inherently limited in representing dense subgraph structure: the max expected triangle count **shrinks cubically in overlap**!

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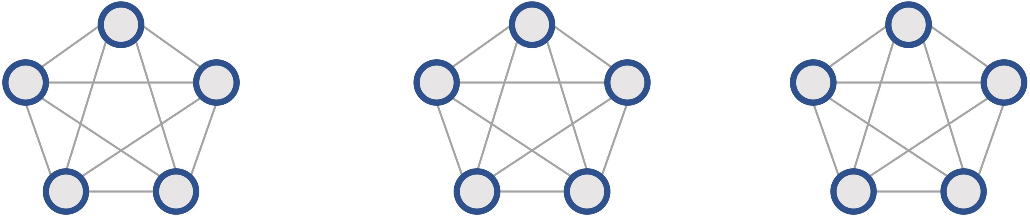
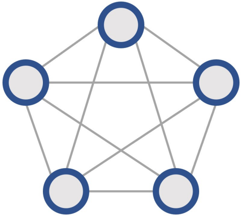
This is very constraining. In this work, we explore what happens beyond edge independence.

Beyond Edge Independence

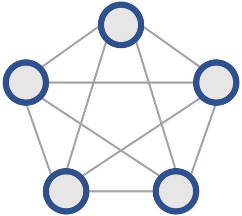


Beyond Edge Independence

Edge Activation



Node Activation



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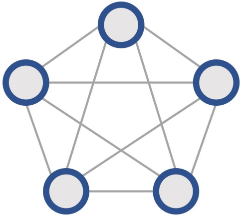

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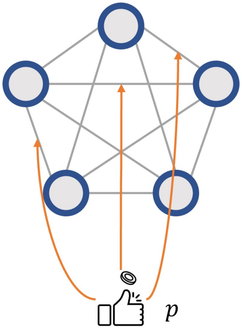

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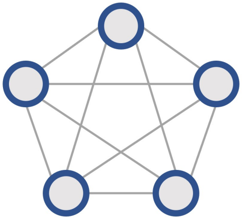

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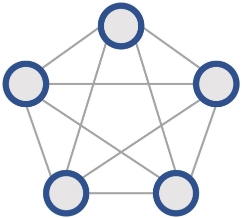

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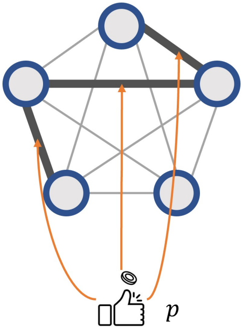

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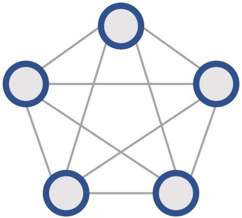

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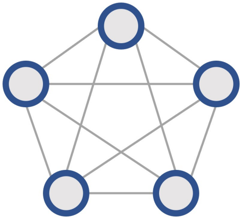

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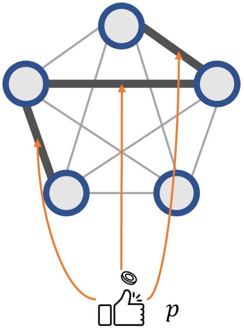

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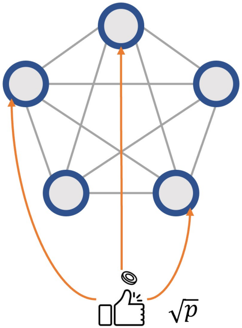

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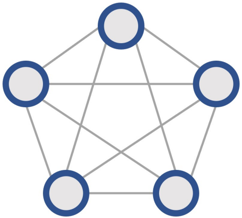

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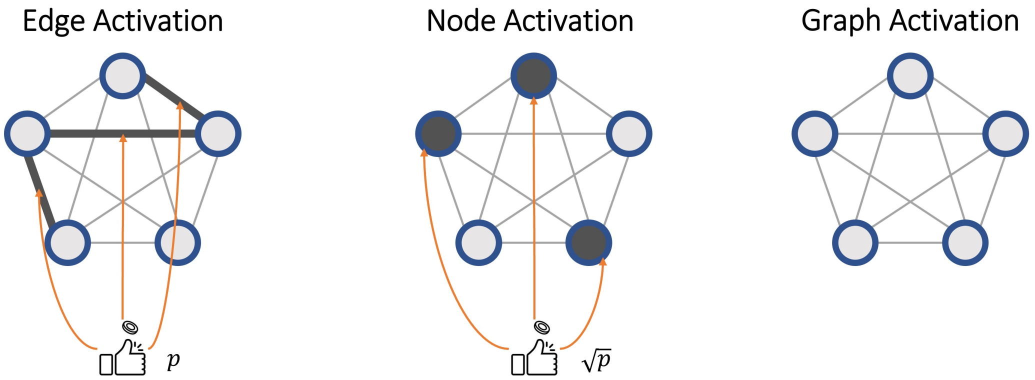

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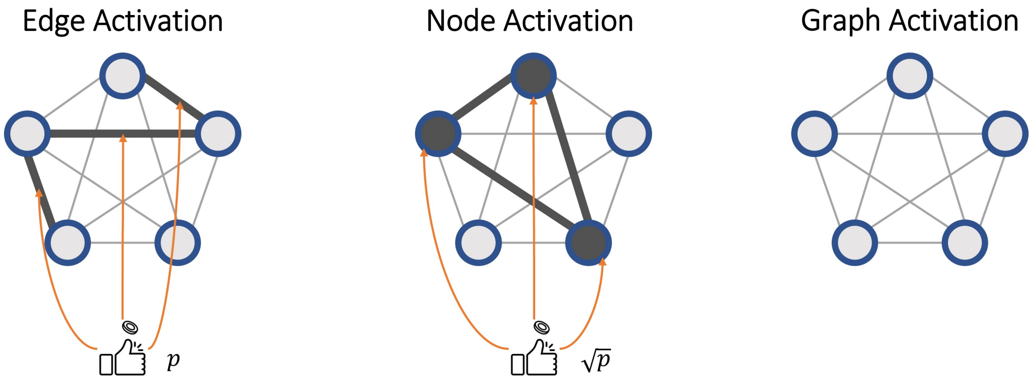

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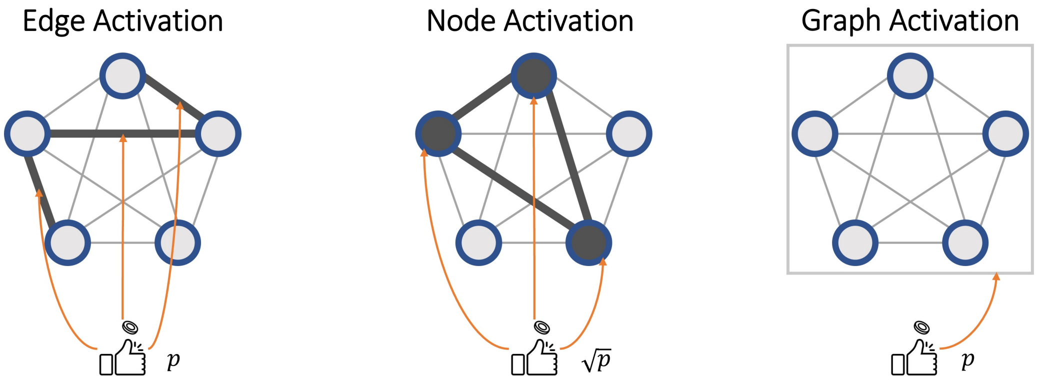

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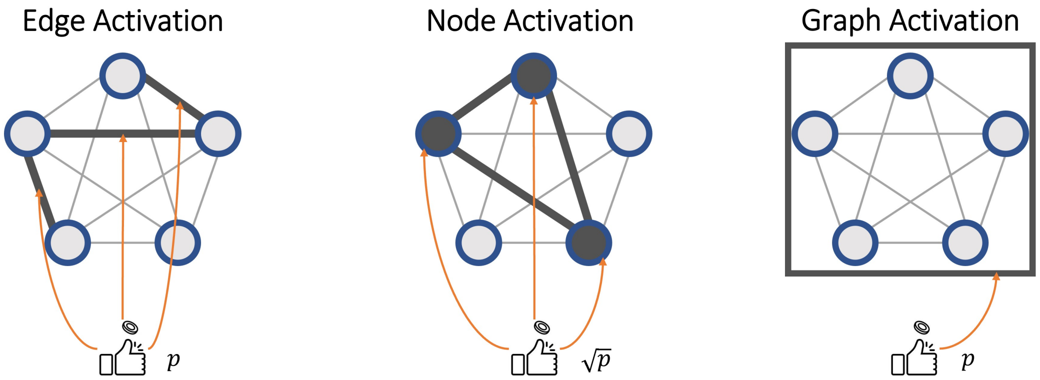

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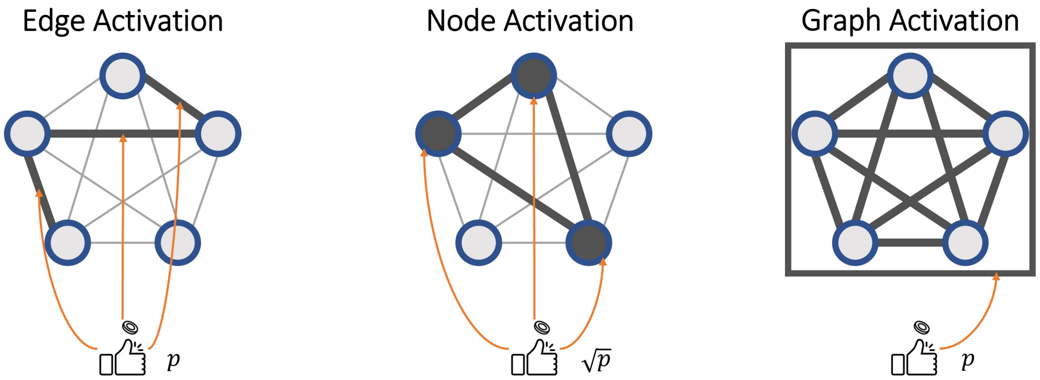

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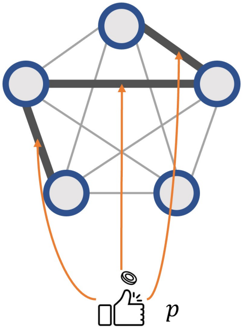
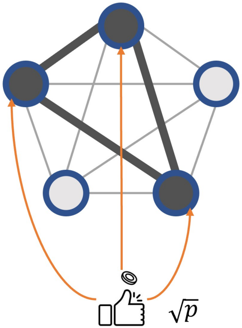


$\Pr(—) = p$

Node Activation



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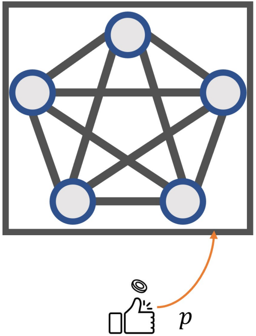

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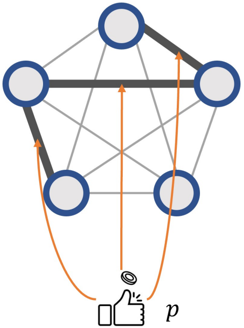

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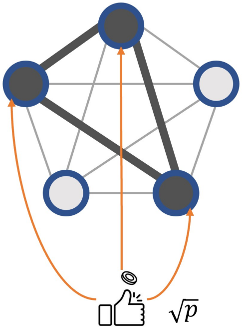

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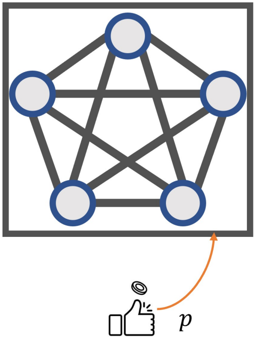

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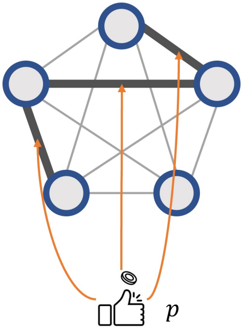

$$\text{Overlap} = p$$
$$\Pr(\Delta) = p^3$$

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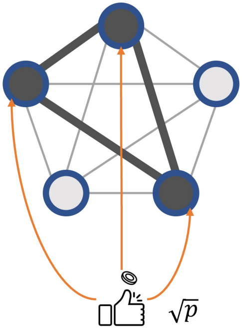

$$\text{Overlap} = p$$
$$\Pr(\Delta) = p^{1.5}$$

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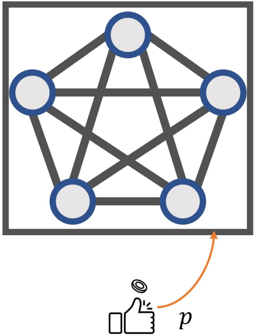

$$\text{Overlap} = p$$
$$\Pr(\Delta) = p^1$$

A Nested Hierarchy of Edge Dependence

We introduce the *node independent* model: Each node is given an independent distribution over representation vectors.

Definition (Node Independent Graph Model)

Distribution over $A = \quad (XY^{>})$ for some random node representation matrices X and Y, where $[X; Y]$'s rows are mutually independent.

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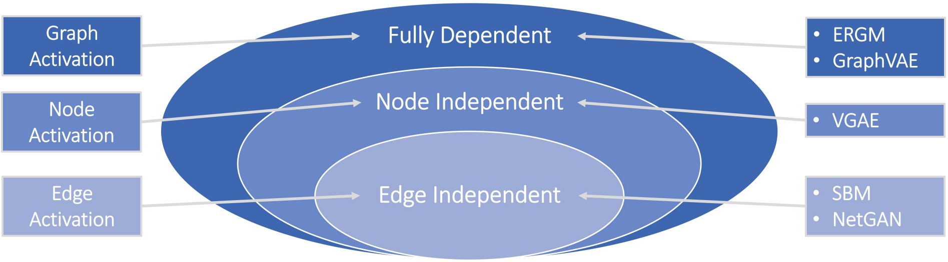

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Bounds for Edge Dependent Graph Models

We can prove bounds on the capabilities of models with edge dependency:

Model	Upper Bound on $=n^3$	Examples
Edge Independent	$\text{Ov}(A)^{3:0}$	SBM, NetGAN
Node Independent	$\text{Ov}(A)^{1:5}$	VGAE
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Empirical Contributions

We further explore empirical implications of our theoretical work:

- We motivate evaluation of graph generative models using not only error on matching graph statistics, but also overlap.
- We introduce three simple baselines inspired by {edge/node/graph} activation.
- We compare our baselines against modern deep-learning based models, and we find they are often competitive at matching graph statistics at the same levels of overlap.

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