Exposure Mapping Function Learning for Peer Effect Estimation

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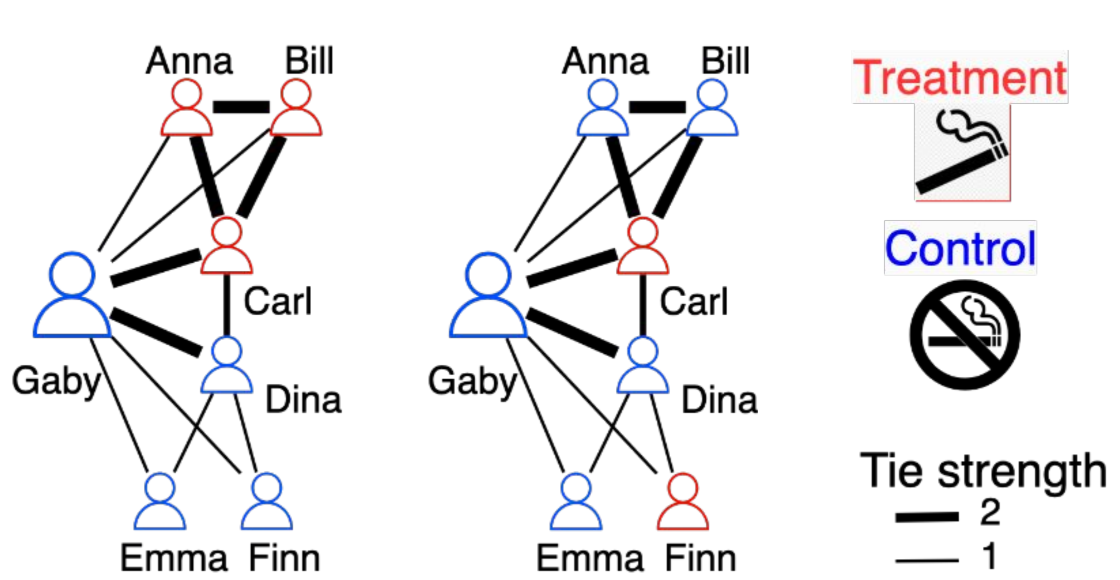
Introduction

- ***Peer effect***: difference in counterfactual outcomes of an individual for different levels of *peer exposure*
- ***Peer exposure:*** aggregated peer treatment, the extent to which an individual is exposed to the treatments or actions of peers
- ***Exposure mapping function***: maps peer treatments and relevant contexts to peer exposure representation

Existing research assumes that the exposure mapping function is known a priori. In reality, it is often unknown and can be misspecified.

Observed (Factual) peer treatments — Counterfactual peer treatments



Variety of possible peer exposures for Gaby's ego network

Exposure mapping function	Peer exposure	
	Factual	Counterfactual
Binary (at least one peer treated)	1	1
Fraction of treated peers	3/6	2/6
Linear threshold (40%)	1	0
Weighted fraction (tie strengths)	4/8	3/8
Weighted fraction (attribute similarity: female)	1/3	0/3
Local structure: Clustering coefficient of treated peers	1	0
Local structure: Structural diversity of treated peers (connected components)	1	2

Research Goal

To learn the exposure mapping function to capture underlying peer influence mechanisms for robust peer effect estimation.

Causal Inference Problem Setup

- Attributed network $G=(\mathbf{V},\boldsymbol{\mathcal{E}})$ with node attributes $\mathbf{X}$, edge attributes $\mathbf{Z}$, and $N=|\mathbf{V}|$ nodes
- Treatment random variables $\mathbf{T} =< T_1, ..., T_i, ..., T_N >$ with assignments $\boldsymbol{\pi} =< \pi_1, ..., \pi_i, ..., \pi_N >$
- Outcome $\mathbf{Y}=<Y_1, ..., Y_i, ..., Y_N>$

- Individual Peer effect (**IPE**) for node v_i due to peer treatments $T_{N(i)}=\boldsymbol{\pi}_{N(i)}$ vs $T_{N(i)}=\boldsymbol{\pi}'_{N(i)}$ on outcome Y_i conditioned on *effect modifiers* $\mathbf{C}_i$
  $\delta_i = E[Y_i(T_i=\pi_i, P_{N(i)}=\varphi_e(\boldsymbol{\pi}_{N(i)},G,\mathbf{Z}))|\mathbf{C}_i] - E[Y_i(T_i=\pi_i, P_{N(i)}=\varphi_e(\boldsymbol{\pi}'_{N(i)},G,\mathbf{Z})|\mathbf{C}_i]$, where
  - $P_{N(i)}$ is a random variable for peer exposure
  - φ_e is an *exposure mapping function*
  - $\mathbf{C}_i= \varphi_f(G,\mathbf{X},\mathbf{Z})$ is a feature mapping function that captures confounders and effect modifiers

- Assuming *unconfoundedness, consistency*, and *positivity*, peer effects can be estimated as:
  $\delta_i = E[Y_i|T_i=\pi_i, P_{N(i)}=\varphi_e(\boldsymbol{\pi}_{N(i)},G,\mathbf{Z}),\mathbf{C}_i] - E[Y_i|T_i=\pi_i, P_{N(i)}=\varphi_e(\boldsymbol{\pi}'_{N(i)},G,\mathbf{Z}),\mathbf{C}_i]$

Experimental Setup

Evaluation:

Setting: Observed peer treatments versus flipped peer treatments

Metric: Precision in the estimation of heterogeneous effect (PEHE)

$\varepsilon_{PEHE}= \sqrt{\frac{1}{N}\sum_i(\delta_i - \hat{\delta}_i)^2}$

Baselines:

Handling influence mechanisms due to local neighborhood structures

- ***GNN_TARNet_MOTIFS*** (Yuan et al., WWW'21)
- ***INE_TARNet*** (Adhikari and Zheleva, Machine Learning Journal 2025)

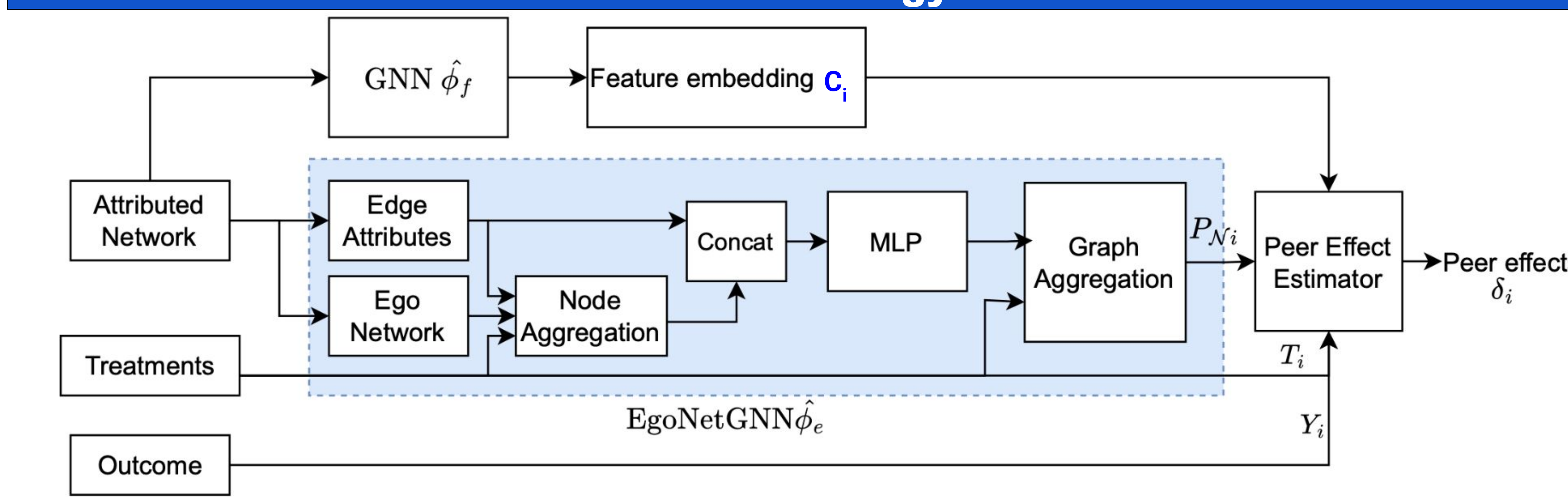
Potentially misspecified peer exposure mapping

- ***1GNN_HSIC*** (Ma et al., AISTATS'21)
- ***DWR*** (Zhao et al., TKDD'24)

Homogeneous exposure mapping based on fraction of treated peers

- ***TNet*** (Chen et al., ICML'24)
- ***NetEstimator*** (Jiang and Sun, CIKM'22)

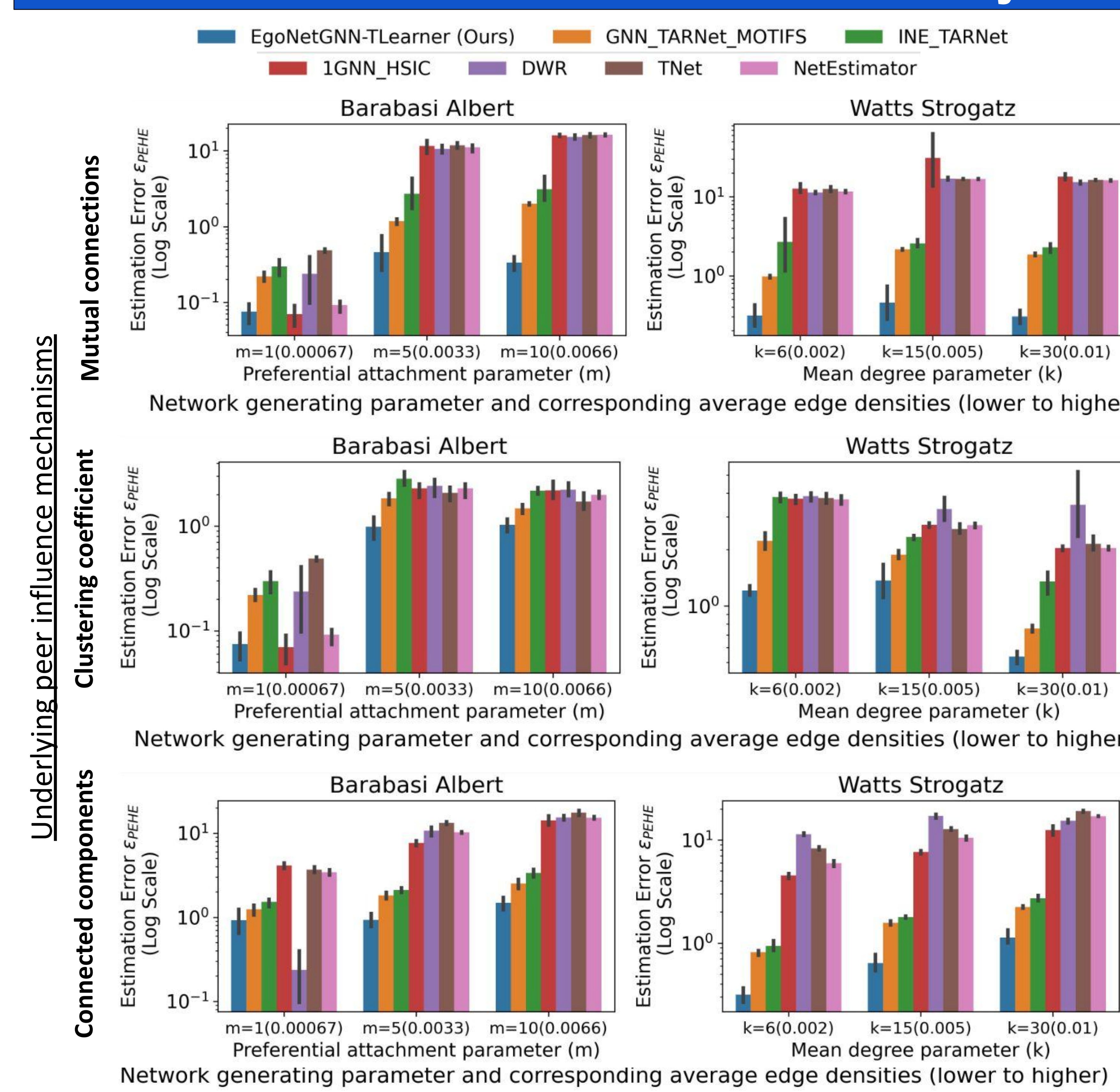
Methodology



An overview of the proposed EgoNetGNNmodel to learn exposure mapping function for peer effect estimation

- EgoNetGNN extracts ego networks, for each node, with peer treatments as node attributes and existing edge attributes.
- Node-level aggregation, encoder MLP, and graph-level aggregation capture relevant local neighborhood contexts.
- Any peer effect estimator (e.g., Treatment Agnostic Representation Network (TARNet)) can be used to get peer effects.

Results and Takeaways



- ***EgoNetGNN significantly outperforms all baselines showing its capability to count triangles in the ego network.***
- ***EgoNetGNN is better than all the baselines when the underlying peer exposure mechanism can be explained by causal motif counts.***
- ***EgoNetGNN performs well compared to all baselines when underlying peer exposure mechanism cannot be explained totally with motif structures only.***

Conclusion

EgoNetGNN improves the estimation of peer effects compared to state-of-the-art baselines by learning an exposure mapping function that captures unknown underlying peer influence mechanisms accounting for peer treatments, unknown edge weights and neighborhood structure.