Dynamic Relation-Attentive Graph Neural Networks for Fraud Detection

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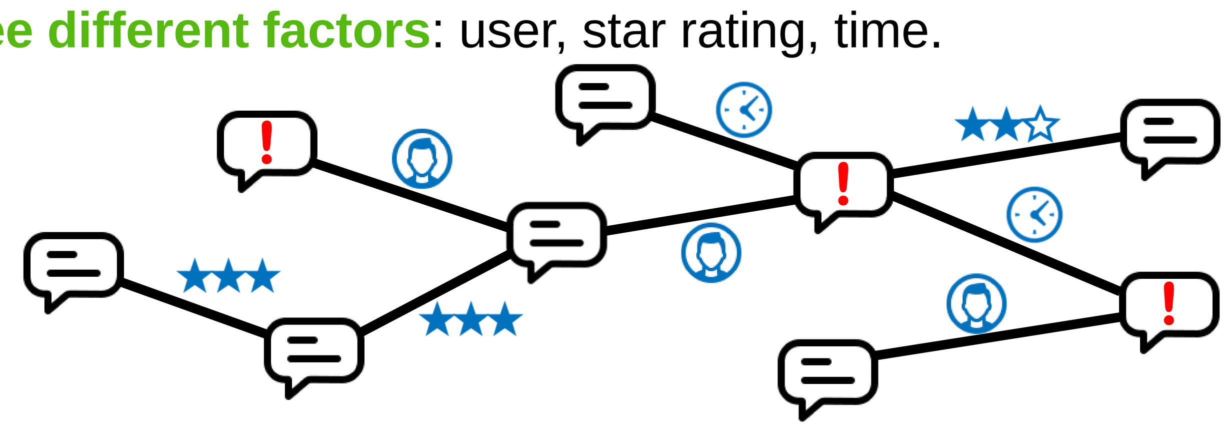
Main Contributions

- Propose **D**ynamic **R**elation-**A**ttentive **G**raph Neural Networks (**DRAG**) to detect fraudsters on **graphs with heterophily**.
  - Learn a node representation **per relation** and aggregate the representations by assigning a different attention coefficient to each relation.
  - Combine the intermediate representations of **each layer** using a learnable attention function to consider both the local and global structures.
  - By employing **a dynamic attention mechanism** in all the aggregation processes, DRAG computes the attention coefficients for each node.
- DRAG outperforms state-of-the-art graph-based fraud detection methods.

Graph-based Fraud Detection

- **Fraud detection** aims to discover fraudsters deceiving other users.
  - e.g., Discovering fake reviews or abnormal transactions.
- **Graph-based fraud detection** methods represent objects that should be determined to be **fraud or benign** as **nodes**.
  - e.g., In YelpChi dataset, nodes are reviews and **edges are created based on three different factors**: user, star rating, time.



Dynamic Attention Mechanism

- **The dynamic attention** swaps **the order of operations** of applying a linear projection layer and the non-linear function.

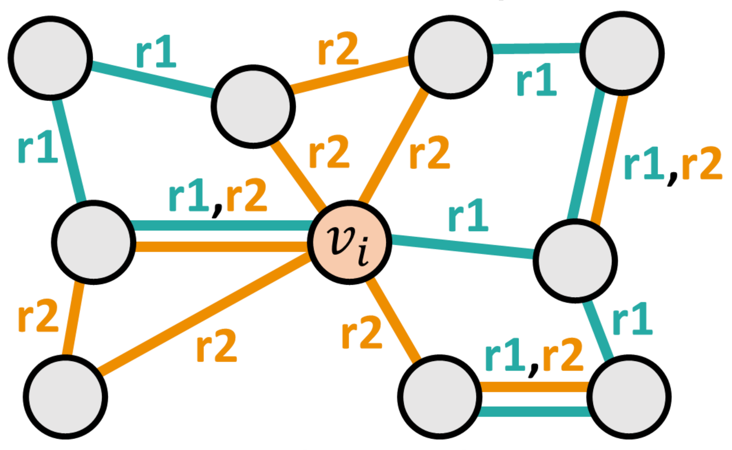
$$\mathbf{h}_i^{(l)} = \sigma\left(\sum_{v_j\in\mathcal{N}_i} \alpha_i \mathbf{P}^{(l)}\mathbf{h}_j^{(l)}\right)$$

$$\alpha_i = \frac{\exp(\mathbf{a}^{(l)}\sigma(\mathbf{W}^{(l)}[\mathbf{h}_i^{(l)}||\mathbf{h}_j^{(l)}]))}{\sum_{v_{j'}\in\mathcal{N}_i}\exp(\mathbf{a}^{(l)}\sigma(\mathbf{W}^{(l)}[\mathbf{h}_i^{(l)}||\mathbf{h}_{j'}^{(l)}]))}$$

- By utilizing the dynamic attention mechanism, attention coefficients can vary **depending on each target node**.

Overview of DRAG

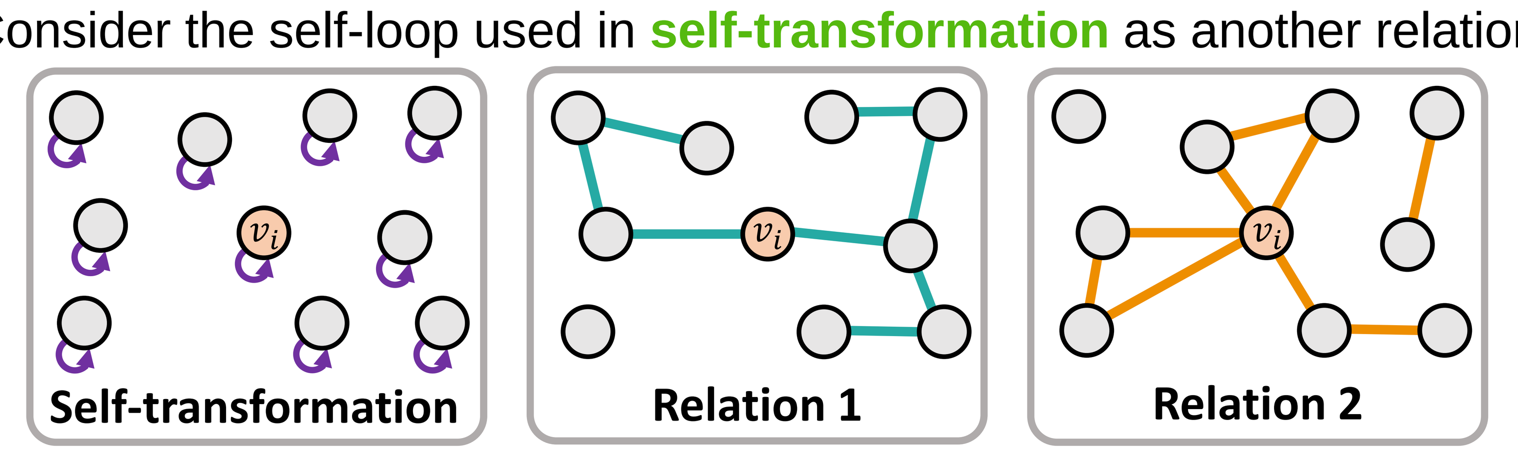
- Many real-world graphs include **different types of relations**.
  - **Relation-aware approaches** have shown superior performance over the fraud detection methods that ignore relations.
  - Under heterophily, it is helpful to explicitly consider **the local and global neighbors** to solve a node classification problem.



- DRAG computes node representations using **relation-wise** and **layer-wise** dynamic attention mechanisms.

Relation-attentive Aggregation

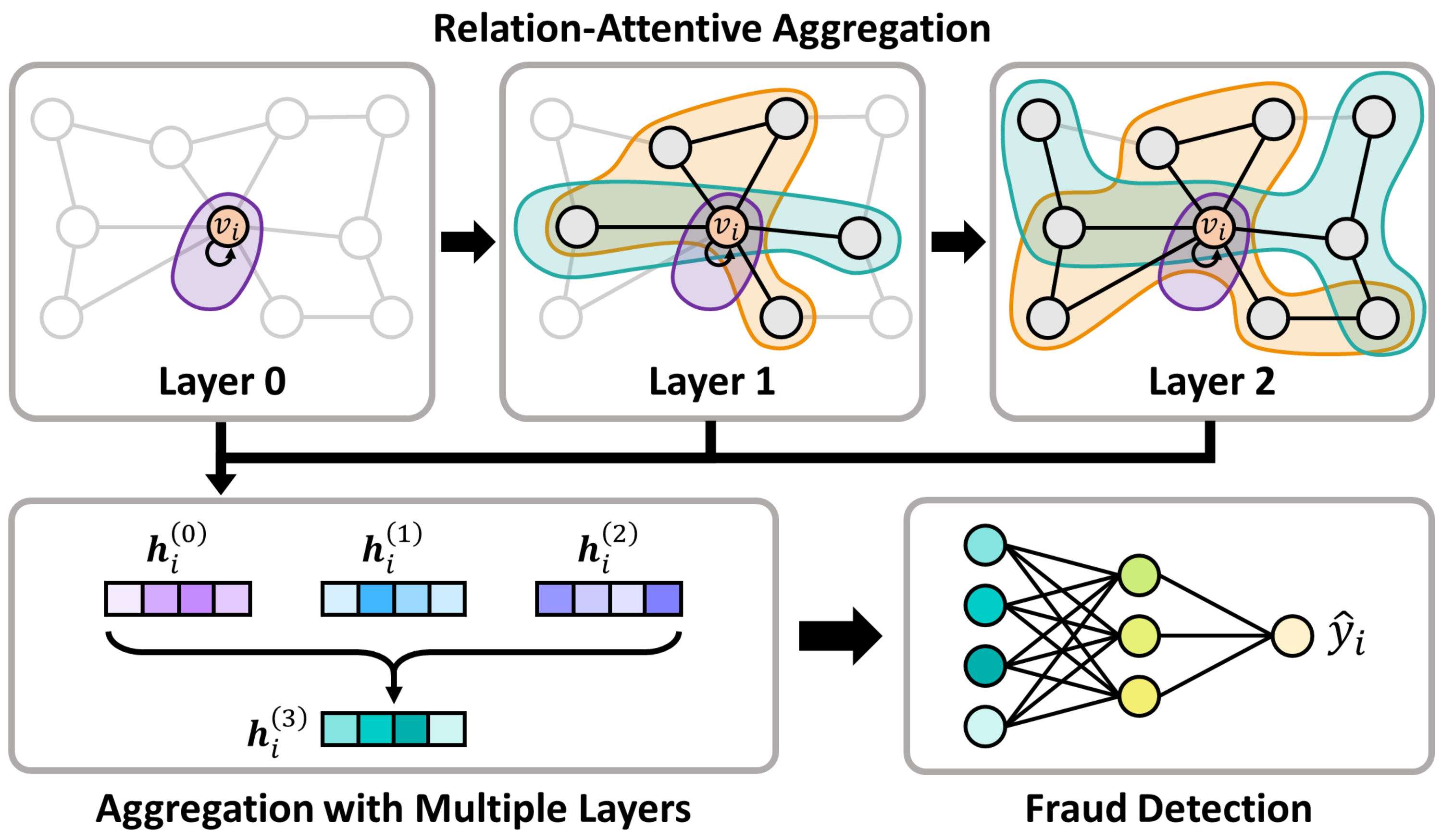
- DRAG decomposes the original graph by relations to learn a node representation **per relation** along with a **self-transformation**.
  - Consider the self-loop used in **self-transformation** as another relation.



- At each layer, DRAG aggregates the **multiple node representations** for each node with different learnable weights for the **relations**.

Aggregation with Multiple Layers

- The final node representation is computed by aggregating **intermediate node representations** from **different layers**.
  - Attention coefficients learn the importance of **each layer's representation**.
- Using the final representation of each node, DRAG predicts the node label.



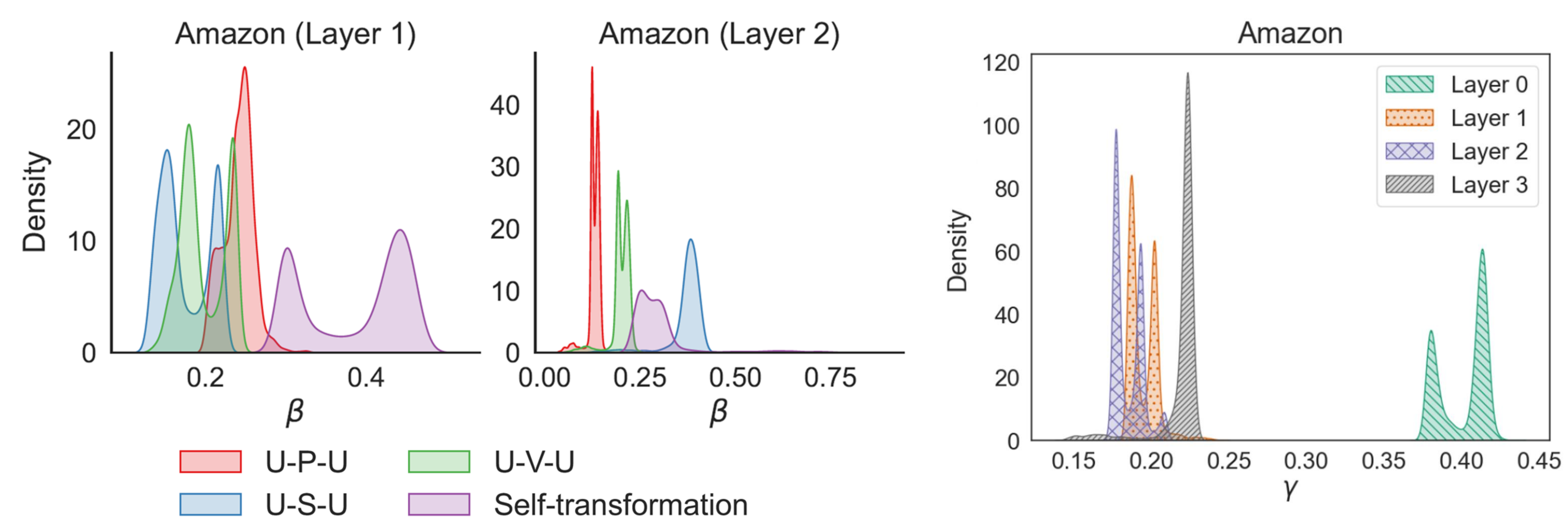
Experiments

- **Baseline Methods**: MLP, GraphSAGE, GAT, GATv2, FRAUDRE, CARE-GNN, PC-GNN, BWGNN-Homo, BWGNN-Hetero
- **Fraud Detection on Benchmark Datasets**
  - The results using **different percentage of labels** (1%, 40%) are reported.

		1%		40%	
		F1-macro (↑)	AUC (↑)	F1-macro (↑)	AUC (↑)
YelpChi	CARE-GNN	0.6151	0.7290	0.6943	0.8316
	PC-GNN	0.6335	0.7412	0.7202	0.8495
	BWGNN	0.6558	0.7764	0.7176	0.9026
	DRAG	**0.6884**	**0.8279**	**0.7988**	**0.9233**
Amazon	CARE-GNN	0.9024	**0.9235**	0.9025	0.9539
	PC-GNN	0.8838	0.9031	0.8792	0.9524
	BWGNN	0.8024	0.8759	0.8791	0.9692
	DRAG	**0.9028**	0.9172	**0.9130**	**0.9701**

Qualitative Analysis and Ablation Studies

- **Distributions of the Attention Coefficients**
  - The attention coefficient values are **not concentrated** on specific values, and some of their distributions are **multimodal**.



Attention Coefficients of Relations | Attention Coefficients of Layers

- **Ablation Studies**
  - AUC scores on YelpChi using different percentages of labels

	1%	40%
DRAG	0.8279	0.9233
without relation types	0.7200	0.8716
without layer aggregation	0.7153	0.8775
with only a single layer	0.8214	0.9076

Conclusion & Future Work

- Propose **DRAG**, a **dynamic attention-based fraud detection** method, performing **relation-wise** and **layer-wise** attentive aggregations.
- By **dynamically adapting** the attention coefficients for individual nodes, DRAG is especially effective in fraud detection on **graphs with heterophily**.
- Plan to extend DRAG to handle **evolving graphs** where new nodes appear and new edges are formed over time.