# UniGAD: Unifying Multi-level Graph Anomaly Detection

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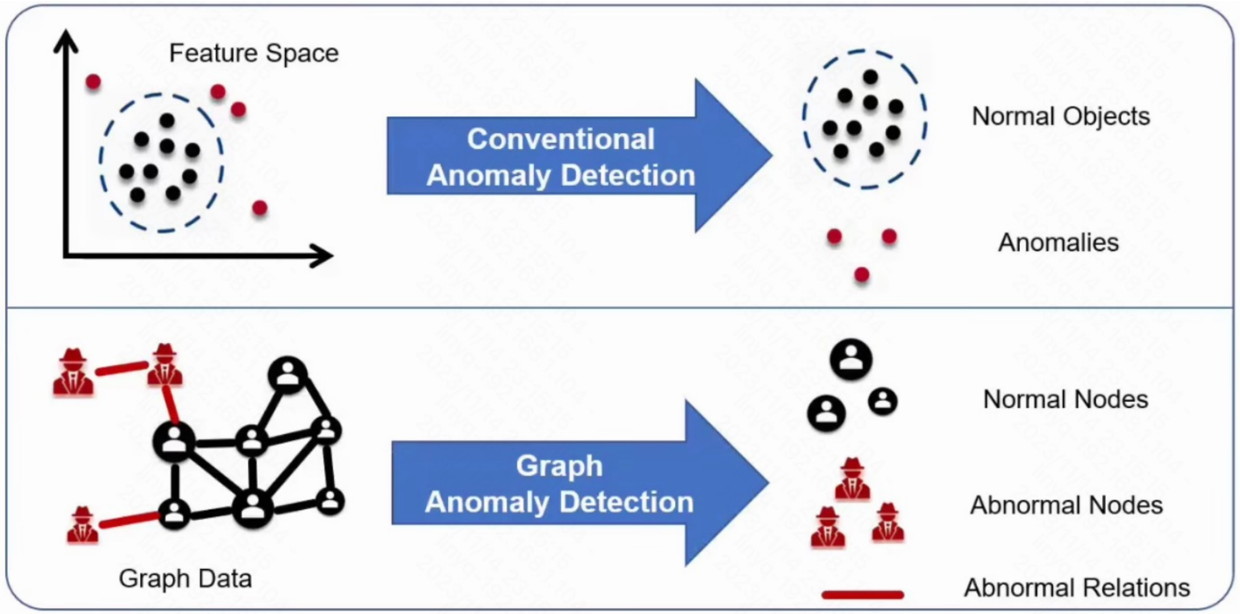
# Background

## Graph Anomaly Detection (GAD)

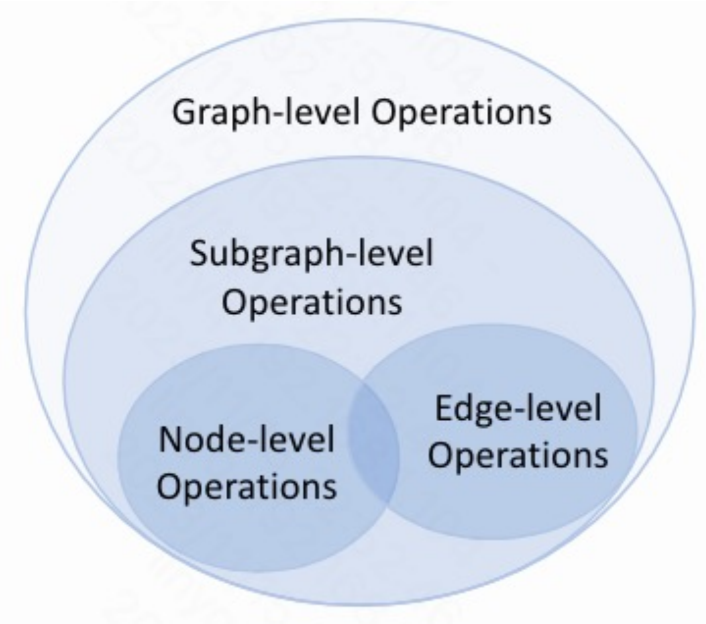
- Graph information often plays a vital role in identifying fraudulent users or activities.
- For example, transaction records on a financial platform.




Transaction Network

# Motivation

- **Anomaly Graph Task**
  - Node-level, Edge-level, Graph-level.
- **Exist Problem**
  - overlook the inherent connections among different object types of graph anomalies.
  - A money laundering transaction & an abnormal account.



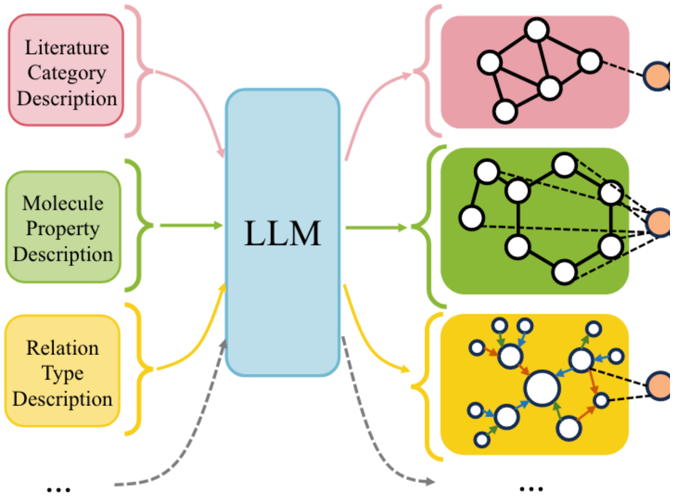

- **A unified framework for detecting anomalies at node, edge, and graph levels jointly.**

**Definition 2.1** (Multi-level GAD). *Given a training set $\mathcal{T}r(\mathcal{N}, \mathcal{E}, \mathcal{G})$ containing nodes, edges, and graphs with arbitrary labels at any of these levels, the goal is to train a unified model to predict anomalies in a test set $\mathcal{T}e(\mathcal{N}, \mathcal{E}, \mathcal{G})$, which also contains arbitrary labels at any of these levels.*

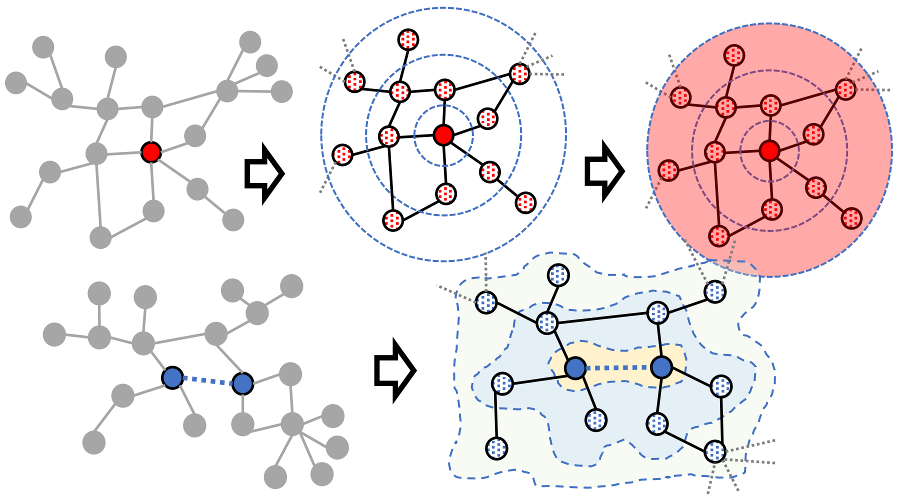
# Challenge 1

## ➢ How to unify multi-level formats?

- ❑ Node-level, edge-level and graph-level models exist inherent differences.
- ❑ large language models (LLMs) or graph prompt tuning.




LLMs

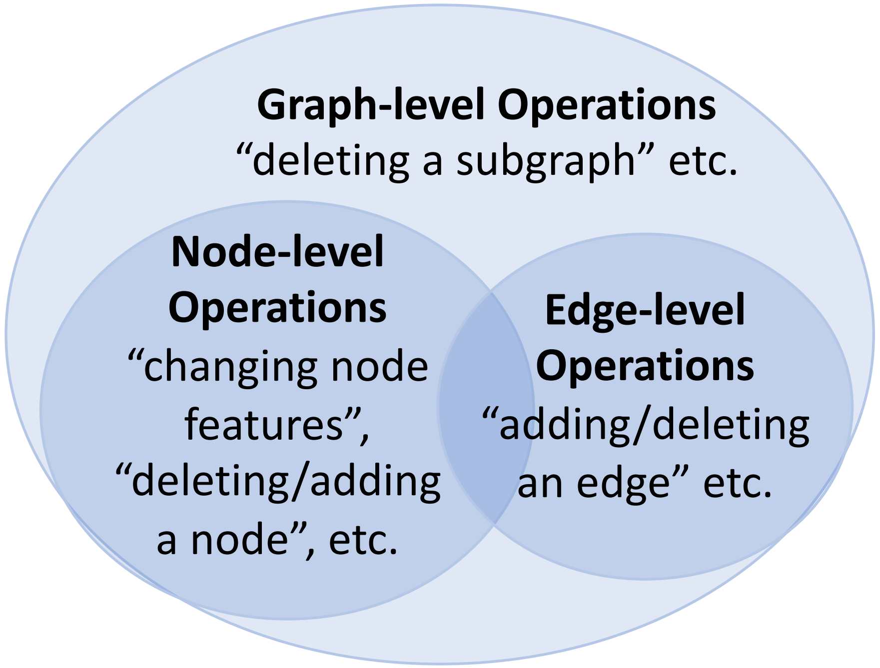


graph prompt

**BUT** they not specifically tailored to anomaly data,
resulting in inappropriate node selections that 'erase' critical anomaly information.

# Challenge 2

- **How to unify multi-level training?**
  - Transferring information between different levels.
  - Achieving a balanced training of these level tasks.



# UniGAD

## Overall Pipeline

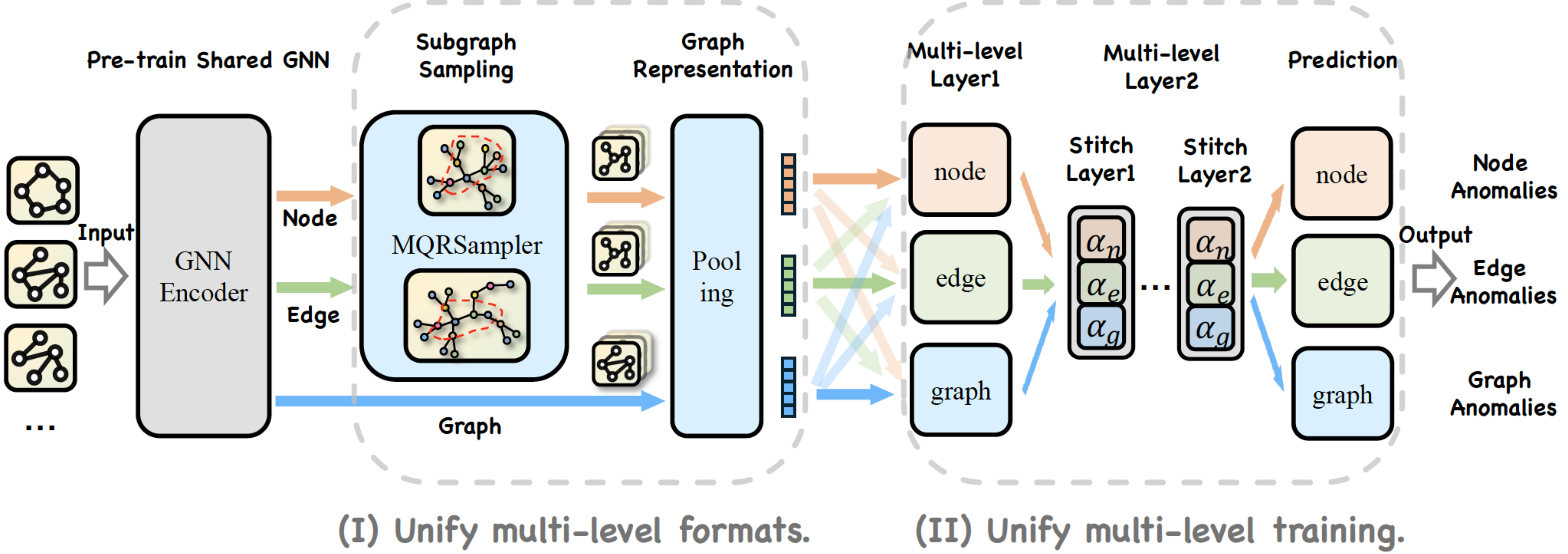



Figure 1: The overall framework of UniGAD.

# MRQSampler for Unifying Multi-level Formats

## Maximum Rayleigh Quotient Subgraph

- We formulate this as the following optimization problem:

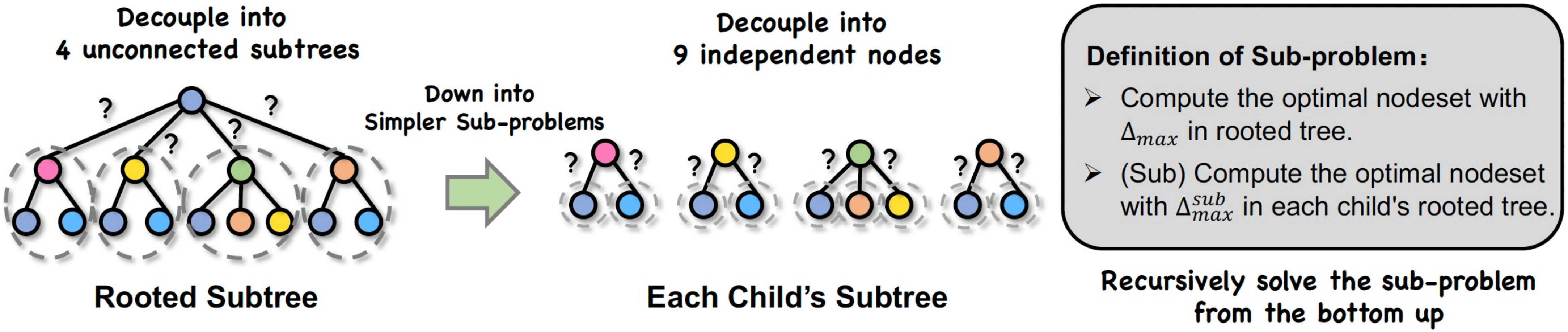
$$\mathcal{S}^{\star} = \underset{\mathcal{S}\subseteq\mathcal{G}}{\arg\max} \quad \frac{\sum_{(p,q)\in\mathcal{E}_{\mathcal{S}}}(x_p - x_q)^2}{\sum_{p\in\mathcal{S}} x_p^2},$$
$$\text{s.t.} \quad v \in \mathcal{S},$$
$$\forall v_p \in \mathcal{S},\ (v, v_p) \text{ is accessible.}$$

- Identify the induced subgraph with the highest Rayleigh quotient containing the most anomaly information.
- Generally, similar selecting subgraphs in this manner is considered an NP-Hard problem.

# MRQSampler for Unifying Multi-level Formats

## MRQSampler Algorithm

- Leveraging the properties of trees
- We uses dynamic programming (DP) to find the optimal solution.



# GraphStitch for Unifying Multi-level Training

- **GraphStitch Network**

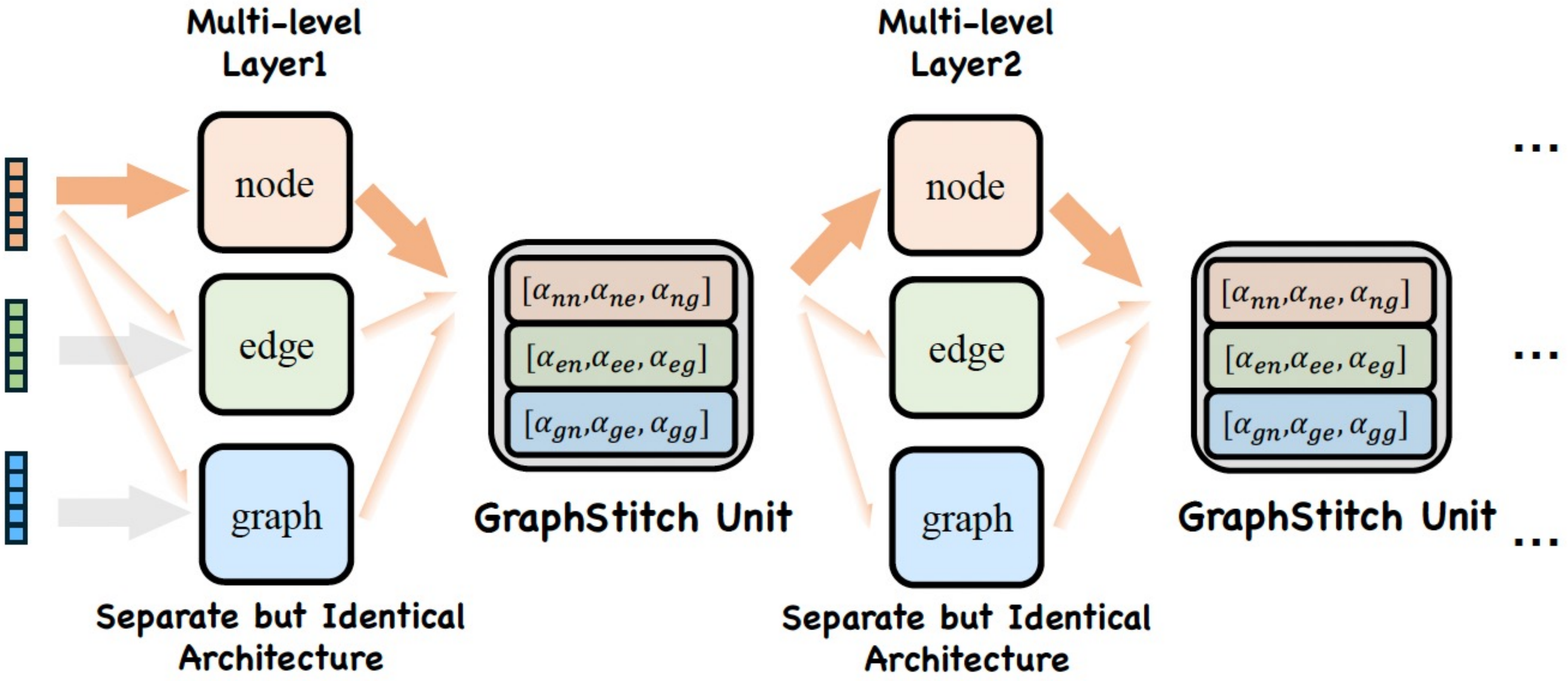


Figure 4: GraphStitch network structure in UniGAD. Node level is highlighted.

# Experiments

## ➢ Multi-Level Performance Comparison (RQ1) (Node/Edge)

Table 2: Comparison of unified performance (AUROC) at both node and edge levels with different single-level methods, multi-task methods, and our proposed method.

| | **Dataset** | **Reddit** | | **Weibo** | | **Amazon** | | **Yelp** | | **Tolokers** | | **Questions** | | **T-Finance** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Task-level** | **Node** | **Edge** | **Node** | **Edge** | **Node** | **Edge** | **Node** | **Edge** | **Node** | **Edge** | **Node** | **Edge** | **Node** | **Edge** |
| Node-Level | GCN | 62.60 | / | 97.97 | / | 82.37 | / | 57.62 | / | 75.21 | / | 70.15 | / | 90.70 | / |
| | GIN | 65.59 | / | 95.64 | / | 92.17 | / | 74.46 | / | 75.15 | / | 69.13 | / | 86.43 | / |
| | GraphSAGE | 62.25 | / | 94.45 | / | 84.53 | / | 82.12 | / | 79.74 | / | 72.47 | / | 78.16 | / |
| | SGC | 52.12 | / | 97.71 | / | 80.24 | / | 53.03 | / | 69.51 | / | 70.59 | / | 74.21 | / |
| | GAT | 65.87 | / | 94.40 | / | 96.24 | / | 77.40 | / | 78.90 | / | 71.38 | / | 90.60 | / |
| | BernNet | 66.68 | / | 93.93 | / | 96.62 | / | 81.48 | / | 76.68 | / | 70.28 | / | 92.37 | / |
| | PNA | 65.28 | / | 97.43 | / | 81.41 | / | 71.81 | / | 75.82 | / | 71.78 | / | 68.17 | / |
| | AMNet | 68.31 | / | 94.17 | / | 97.31 | / | 81.42 | / | 76.67 | / | 68.63 | / | 93.58 | / |
| | BWGNN | 64.65 | / | 97.42 | / | 97.80 | / | 83.11 | / | 80.51 | / | 70.25 | / | 96.03 | / |
| Edge-level | GCNE | / | 63.10 | / | 99.03 | / | 78.63 | / | 57.80 | / | 73.59 | / | 79.05 | / | 87.63 |
| | GINE | / | 67.36 | / | 98.09 | / | 79.74 | / | 67.58 | / | 69.27 | / | 80.75 | / | 79.05 |
| | GSAGEE | / | **67.52** | / | 98.67 | / | 78.92 | / | 73.30 | / | **76.98** | / | **87.51** | / | 77.14 |
| | SGCE | / | 53.36 | / | 98.55 | / | 76.41 | / | 52.02 | / | 70.59 | / | 74.24 | / | 69.01 |
| | GATE | / | 67.07 | / | 97.92 | / | 90.20 | / | 72.96 | / | 71.92 | / | 81.64 | / | 83.09 |
| | BernE | / | 65.57 | / | 97.87 | / | 89.60 | / | 73.93 | / | 73.39 | / | 84.78 | / | 87.80 |
| | PNAE | / | 64.15 | / | 99.10 | / | 75.71 | / | 67.98 | / | 75.09 | / | 84.05 | / | 83.91 |
| | AME | / | 66.73 | / | 97.08 | / | 89.36 | / | 73.69 | / | 71.99 | / | 84.93 | / | 86.19 |
| | BWE | / | 67.39 | / | 98.93 | / | 91.61 | / | 75.63 | / | 75.66 | / | 85.00 | / | 92.27 |
| Multi-task | GraphPrompt-U | 50.03 | 49.78 | 55.29 | 50.71 | 50.01 | 50.96 | 49.83 | 49.56 | 51.24 | 49.66 | 55.16 | 50.01 | OOT | OOT |
| | All-in-One-U | 51.35 | 54.10 | 48.61 | 52.63 | 56.11 | 54.80 | 49.77 | 49.13 | 50.41 | 49.29 | 51.49 | 64.24 | OOT | OOT |
| UniGAD (Ours) | UniGAD - GCN | **71.65** | 65.46 | 99.02 | **99.13** | 82.92 | 80.04 | 63.22 | 61.74 | 77.26 | 72.89 | **73.92** | 74.72 | 95.68 | 93.75 |
| | UniGAD - BWG | 64.42 | 53.60 | **99.07** | 99.10 | **97.84** | **92.18** | **86.23** | **79.05** | **80.62** | 74.85 | 70.97 | 73.45 | **96.49** | **94.32** |

# Experiments

## ➢ Multi-Level Performance Comparison (RQ1) (Node/Graph)

Table 3: Comparison of unified performance (AUROC) at both node and graph levels with different single-level methods, multi-task methods, and our proposed method.

| | Dataset | BM-MN | | BM-MS | | BM-MT | | MUTAG | | MNIST0 | | MNIST1 | | T-Group | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Task-level** | **Node** | **Graph** | **Node** | **Graph** | **Node** | **Graph** | **Node** | **Graph** | **Node** | **Graph** | **Node** | **Graph** | **Node** | **Graph** |
| Node-level | GCN | 86.31 | / | 90.17 | / | 92.30 | / | 99.38 | / | 94.10 | / | 93.84 | / | 91.81 | / |
| | GIN | 56.73 | / | 50.41 | / | 54.90 | / | 99.39 | / | 93.55 | / | 93.49 | / | 61.51 | / |
| | GraphSAGE | 50.00 | / | 50.00 | / | 49.95 | / | 99.26 | / | **99.99** | / | **99.99** | / | 64.15 | / |
| | SGC | 50.27 | / | 50.87 | / | 49.44 | / | 89.19 | / | 86.97 | / | 86.97 | / | 82.55 | / |
| | GAT | 58.47 | / | 62.52 | / | 65.72 | / | 99.42 | / | 99.90 | / | **99.99** | / | 78.17 | / |
| | BernNet | 60.06 | / | 65.58 | / | 59.18 | / | 98.97 | / | **99.99** | / | **99.99** | / | 93.85 | / |
| | PNA | 72.96 | / | 55.19 | / | 75.61 | / | 98.76 | / | 99.80 | / | 99.87 | / | 55.66 | / |
| | BWGNN | 93.05 | / | 87.22 | / | 88.97 | / | 99.50 | / | **99.99** | / | **99.99** | / | 94.81 | / |
| Graph-level | OCGIN | / | 98.46 | / | 81.97 | / | 58.05 | / | 89.50 | / | 57.24 | / | 86.15 | / | 64.53 |
| | OCGTL | / | 98.48 | / | 83.17 | / | 59.99 | / | 92.19 | / | 59.35 | / | 93.45 | / | 46.77 |
| | GLocalKD | / | 92.36 | / | 77.25 | / | 53.23 | / | 72.77 | / | 66.69 | / | 57.42 | / | 78.53 |
| | iGAD | / | 91.68 | / | 96.68 | / | 99.14 | / | 96.28 | / | 98.93 | / | 99.50 | / | 64.44 |
| | GmapAD | / | 50.00 | / | 50.00 | / | 50.00 | / | 75.48 | / | OOM | / | OOM | / | OOM |
| | RQGNN | / | **98.79** | / | 97.98 | / | 99.83 | / | 96.41 | / | 96.62 | / | 95.57 | / | 73.90 |
| Multi-task | GraphPrompt-U | 51.59 | 46.85 | 50.54 | 48.67 | 51.42 | 49.38 | 97.08 | 68.23 | 81.16 | 83.88 | 81.37 | 6.16 | 47.40 | 50.81 |
| | All-in-One-U | 67.87 | 3.21 | 54.70 | 19.42 | 69.70 | 45.89 | 50.63 | 48.98 | OOT | OOT | OOT | OOT | OOT | OOT |
| UniGAD (Ours) | UniGAD - GCN | **99.75** | 94.29 | **99.60** | **99.67** | **99.63** | **99.99** | 99.50 | 96.33 | 97.93 | 98.99 | 98.11 | 99.59 | 95.57 | 88.73 |
| | UniGAD - BWG | 92.60 | 68.74 | 93.30 | 68.55 | 90.76 | 56.01 | **99.54** | **96.73** | **99.99** | **99.61** | **99.99** | **99.98** | **96.19** | **88.78** |

# Experiments

## ➢ The Transferability in Zero-Shot Learning (RQ2)

Table 4: Zero-shot transferability (AUROC) at node and edge levels.

| Methods | Reddit | | Weibo | | Amazon | | Yelp | | Tolokers | | Questions | | T-Finance | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N→E | E→N | N→E | E→N | N→E | E→N | N→E | E→N | N→E | E→N | N→E | E→N | N→E | E→N |
| GraphPrompt-U | 54.06 | 47.43 | 57.03 | 42.85 | 49.76 | 50.26 | 49.97 | 49.94 | 48.56 | 51.08 | 54.26 | 51.97 | OOT | OOT |
| All-in-One-U | 49.23 | 49.93 | 52.22 | 54.30 | 52.61 | 42.35 | 49.48 | 44.50 | 48.34 | 50.22 | 49.83 | 51.97 | OOT | OOT |
| UniGAD - GCN | **59.67** | **59.46** | **98.31** | **98.59** | 76.20 | 82.38 | 58.28 | 60.92 | 71.45 | 73.35 | 69.54 | **65.37** | 91.63 | 90.17 |
| UniGAD - BWG | 53.32 | 57.63 | 94.71 | 96.87 | **82.64** | **96.41** | **75.56** | **84.08** | **74.04** | **78.49** | **71.02** | 62.72 | **93.60** | **95.68** |

Table 5: Zero-shot transferability (AUROC) at node and graph levels.

| Methods | BM-MN | | BM-MS | | BM-MT | | MUTAG | | MNIST0 | | T-Group | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N→G | G→N | N→G | G→N | N→G | G→N | N→G | G→N | N→G | G→N | N→G | G→N |
| GraphPrompt-U | 50.60 | 51.57 | 51.97 | 46.95 | 46.62 | 48.06 | 59.62 | 64.26 | 83.98 | **88.06** | 58.28 | 58.35 |
| All-in-One-U | **94.39** | 65.69 | 52.63 | 40.88 | 44.86 | 34.27 | 61.63 | 36.13 | OOT | OOT | OOT | OOT |
| UniGAD - GCN | 72.82 | **87.63** | **81.49** | **90.83** | **62.85** | **79.26** | **72.79** | **88.53** | **85.24** | 70.57 | **86.86** | **75.89** |
| UniGAD - BWG | 64.61 | 57.56 | 65.33 | 51.34 | 55.78 | 53.41 | 66.92 | 87.03 | 74.23 | 63.70 | 86.81 | 64.81 |

# Conclusion

- We presents the first unified graph anomaly detection framework UniGAD.
- MRQSampler unifies different graph object formats for nodes, edges, and graphs.
- The GraphStitch Network unifies multi-level training.
- UniGAD not only surpasses existing models in various tasks but also exhibits strong zero-shot transferability capabilities.

# Q&A

## The End, Thanks!