School of Computing and Information Systems

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Contrastive General Graph Matching with Adaptive Augmentation Sampling

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Presenter:

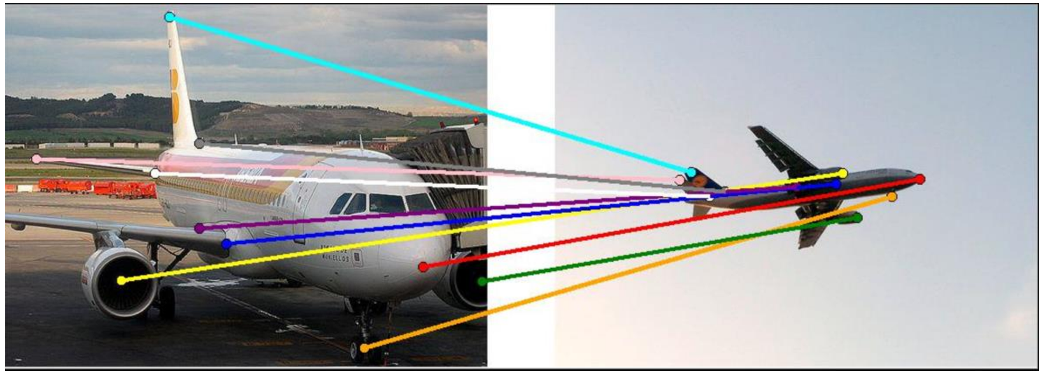
Jianyuan Bo

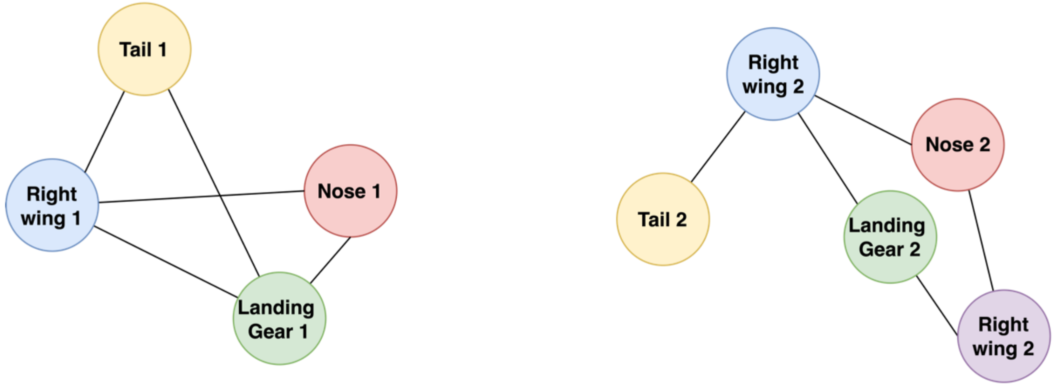
Overview

- Introduction
- Proposed Method
- Experiments

Introduction

- **Graph Matching**
  - one-to-one **correspondence** between the **nodes of two graphs**
  - computer vision, social network alignment, etc





Example of visual graph matching between two images of airplane

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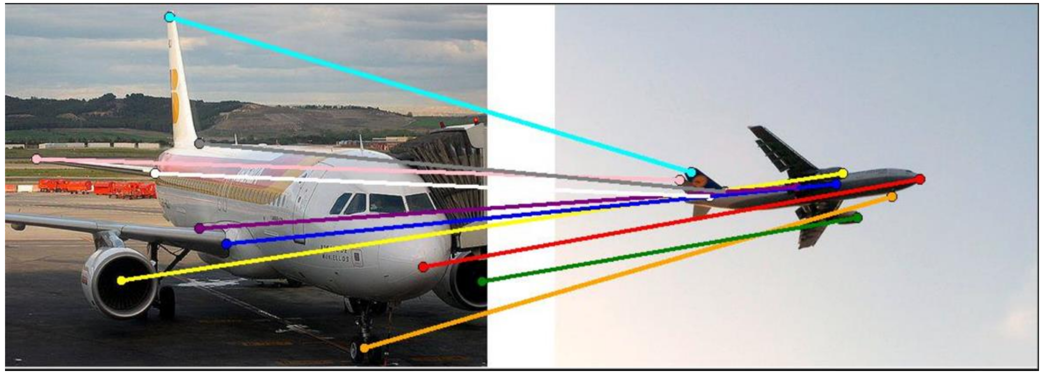
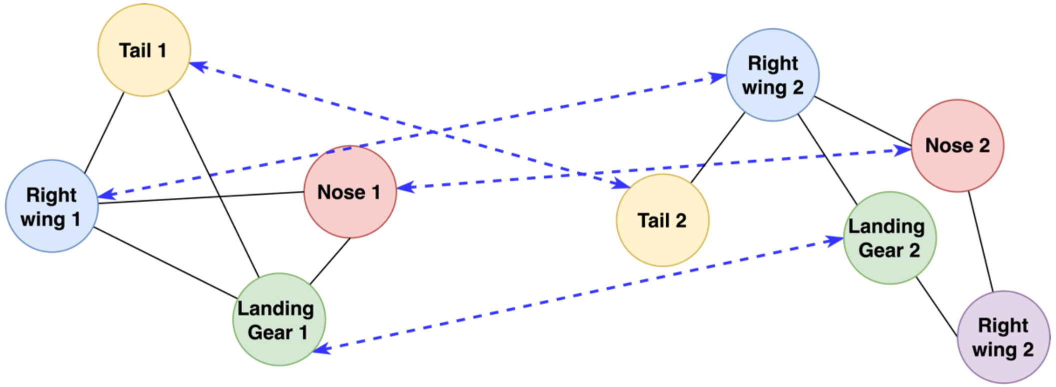
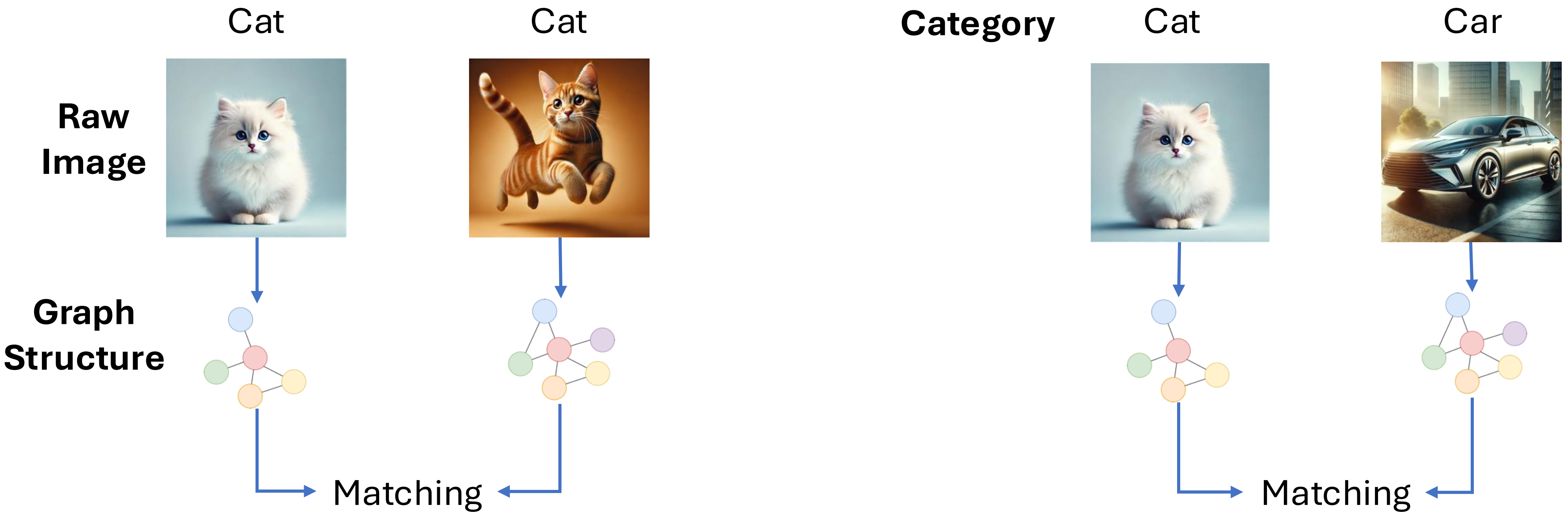




Example of visual graph matching between two images of airplane

Limitations of Existing Methods

- **Assumption of Side Information in SSL GM**
    - SCGM (Liu et al., 2022) requires **raw images**
    - GANN-GM (Wang et al., 2023) requires **matchable graph pairs based on category information**



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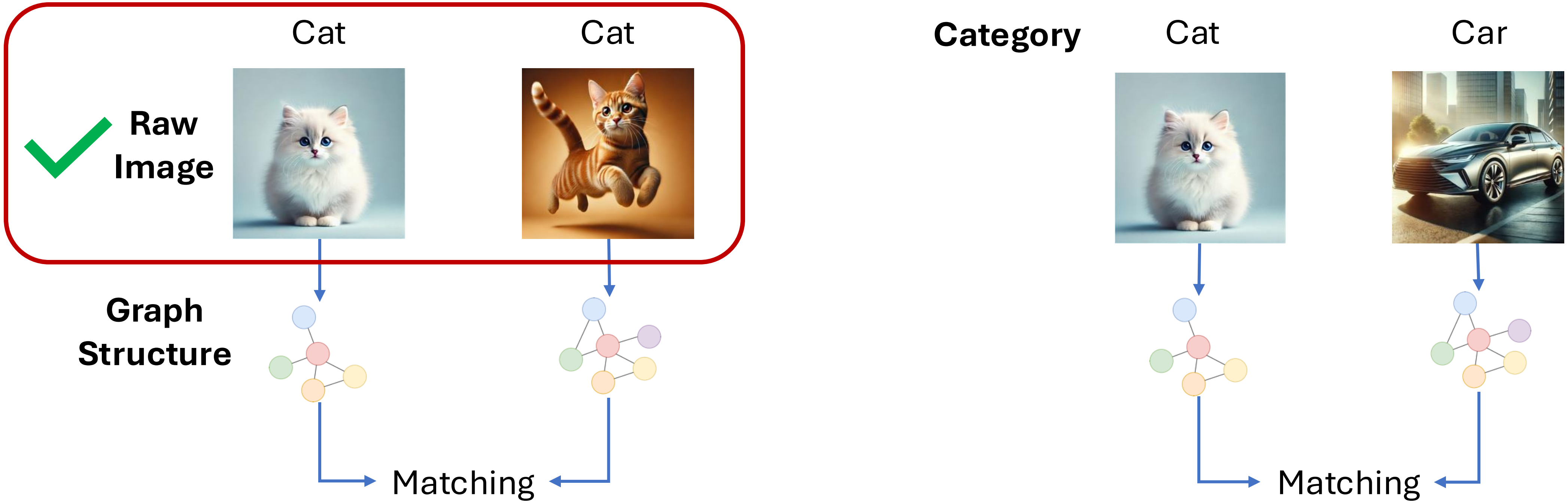

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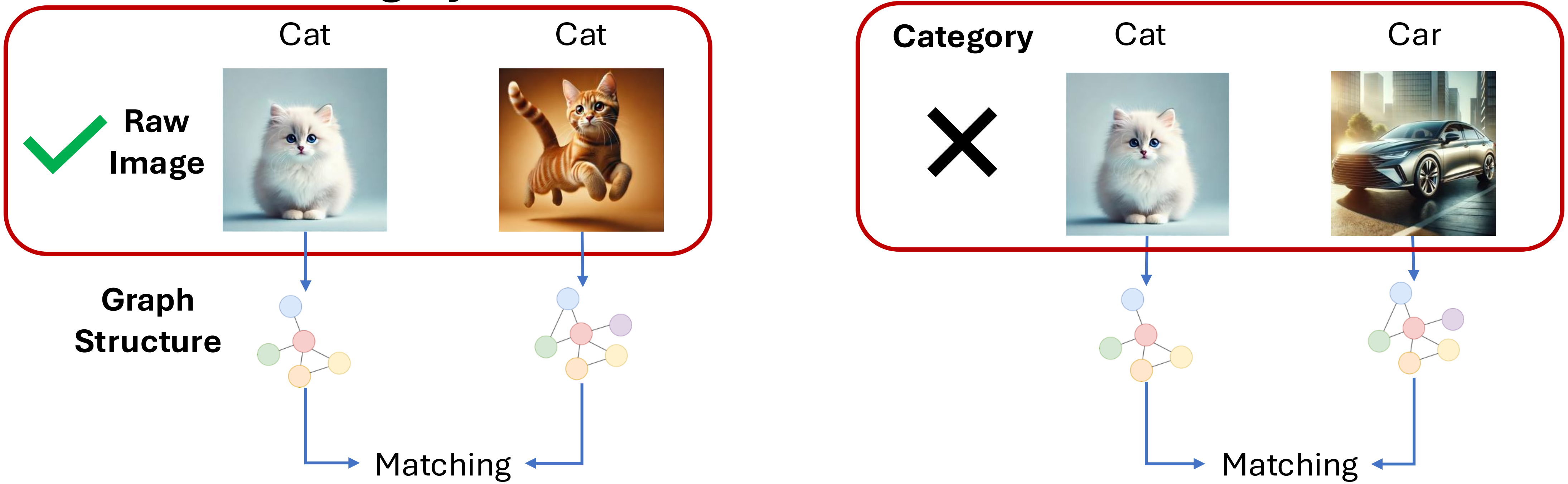

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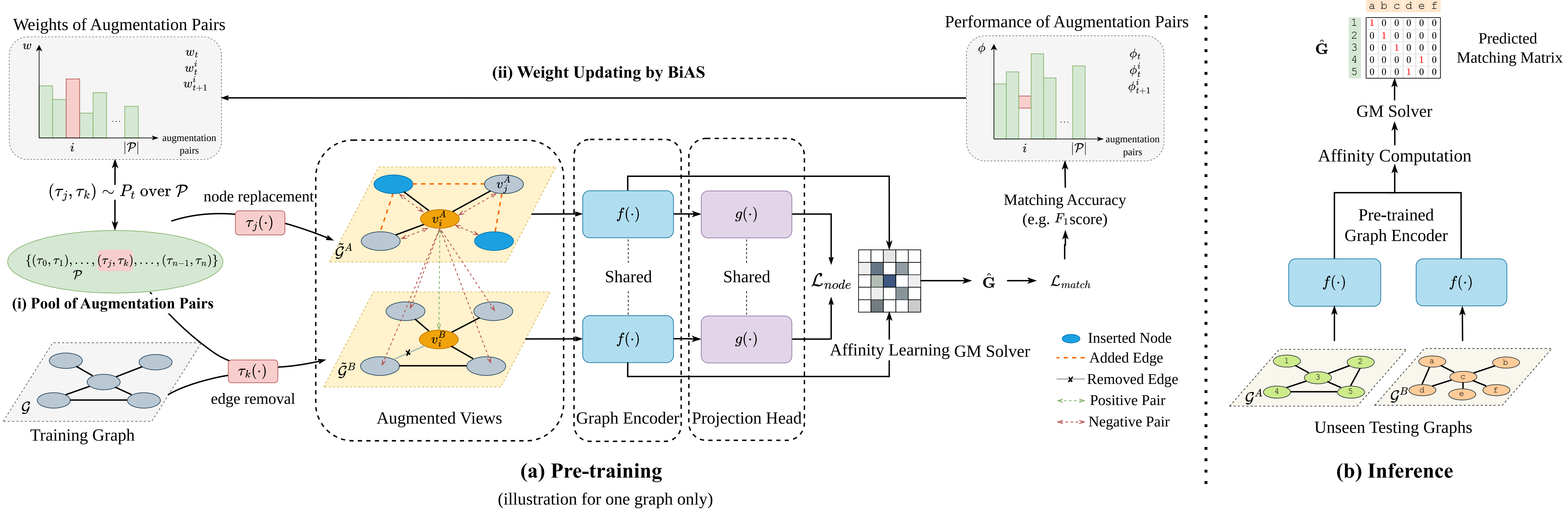
Limitations of Existing Methods

- **Graph contrastive learning (GCL)**
  - node-classification (Zhu et al., 2020)
  - graph-classification (You et al., 2020)
  - link prediction (Sun et al., 2019)
  - and **graph matching** (Liu et al., 2022)
- **Challenges with Augmentations in GCL**
  - design and selection of effective graph augmentations
  - effectiveness varies by dataset and task (You et al., 2020)
  - extensive augmentation tuning (You et al., 2021)

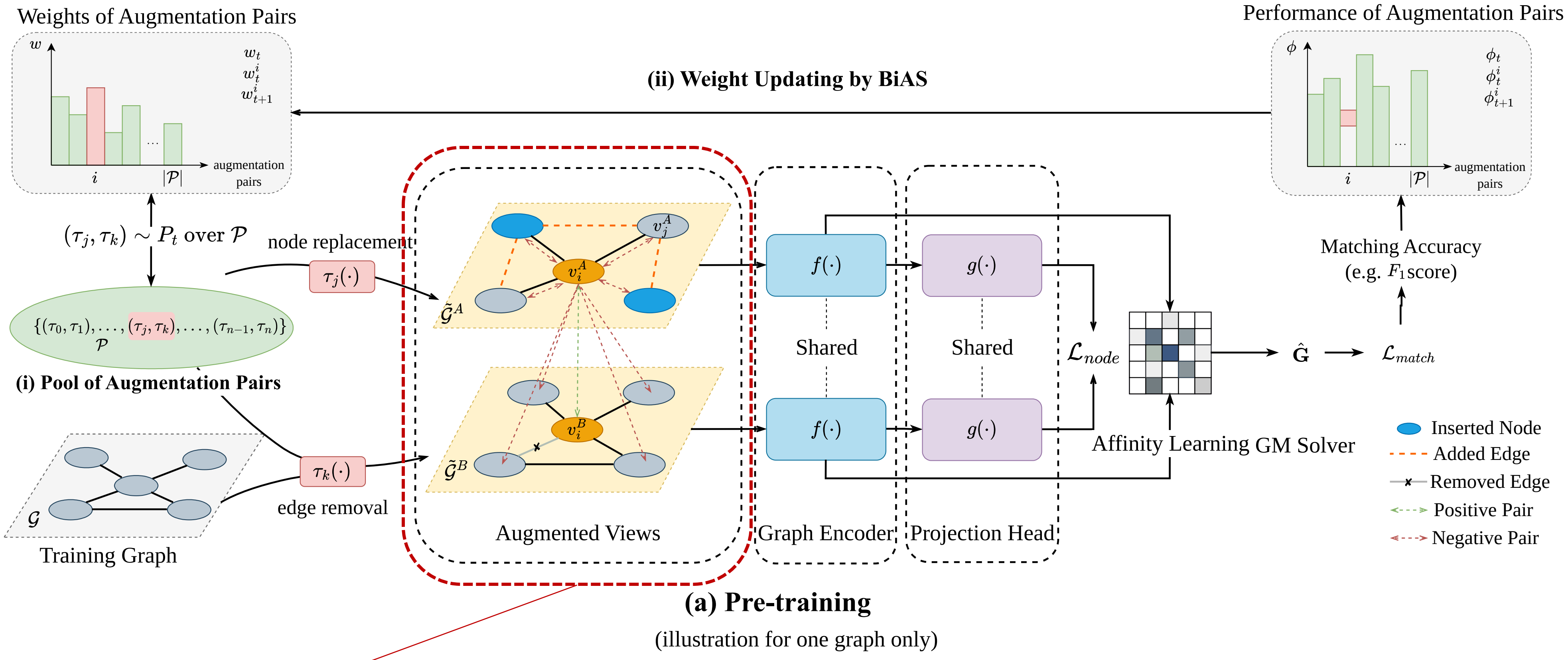
Sun, F.Y., Hoffman, J., Verma, V., Tang, J.: Infograph: Unsupervised and semi-supervised graph-level representation learning via mutual information maximization. ICLR (2019)
Zhu, Y., Xu, Y., Yu, F., Liu, Q., Wu, S., Wang, L.: Deep graph contrastive representation learning. arXiv preprint (2020)
You, Y., Chen, T., Sui, Y., Chen, T., Wang, Z., Shen, Y.: Graph contrastive learning with augmentations NeurIPS (2020)
You, Y., Chen, T., Shen, Y., Wang, Z.: Graph contrastive learning automated. ICML (2021)

Proposed Method



Graph-centric **C**ontrastive framework for **G**raph **M**atching (**GCGM**) with **B**oosting-inspired Adaptive **A**ugmentation **S**ampling (**BiAS**)

GCGM



Node-level Contrastive learning

Augmentations

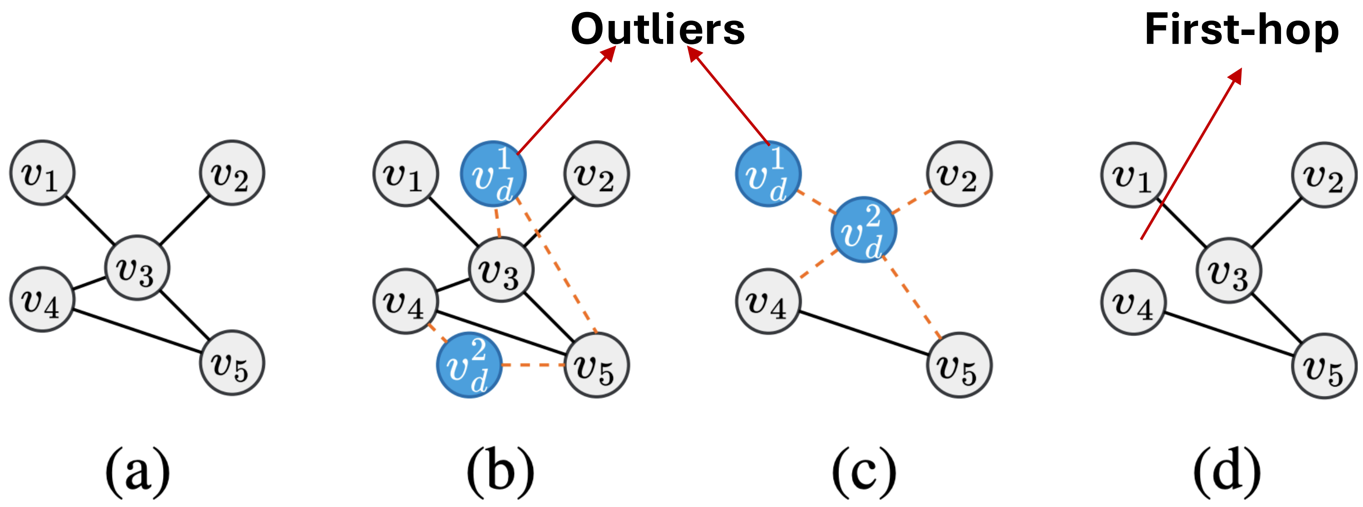
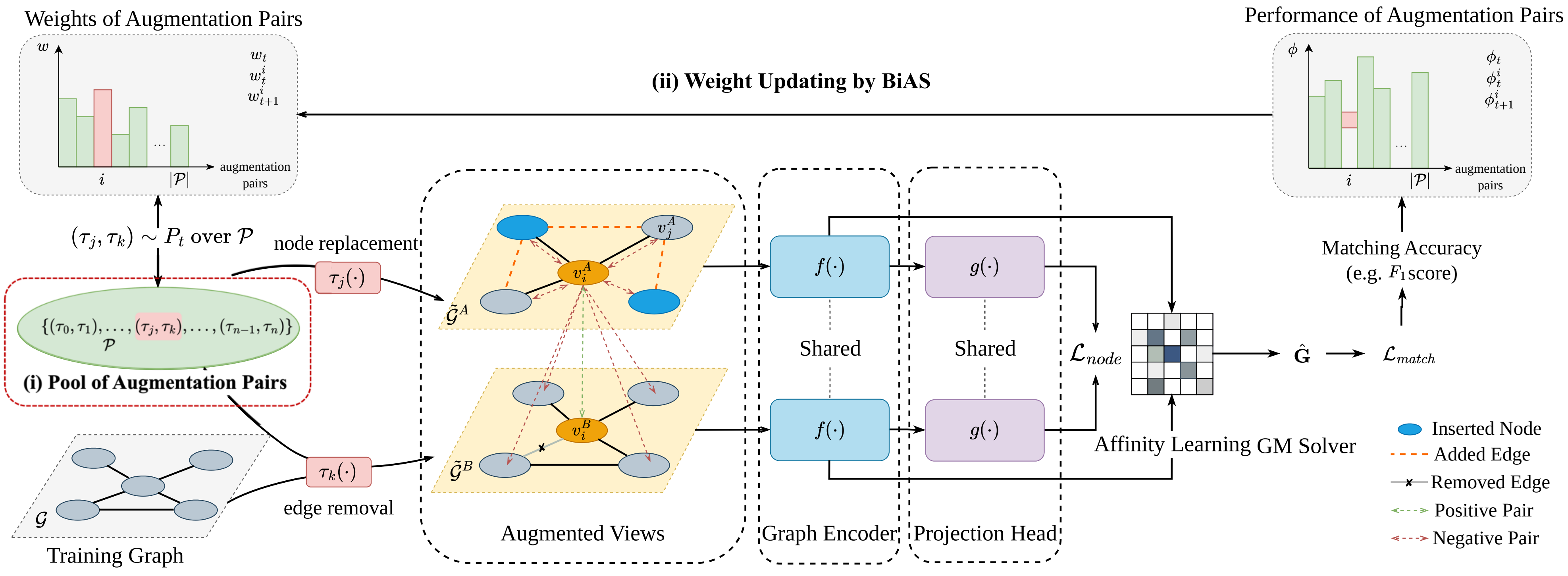


Figure 2: Graph augmentation: **(a)** input graph; **(b)** node insertion; **(c)** node replacement; **(d)** edge removal. The blue node represents the inserted node, and the dotted edge indicates the added edge.

Node insertion

- $Frac\ of\ nodes\ inserted = 0.25$
- $Size\ of\ subset\ = 2$
- $Aggregation\ =\ \max$
- $\#\ of\ Edges\ Inserted\ =\ 3$

1) Pool of Augmentations Pairs



(a) Pre-training

(illustration for one graph only)

1) Pool of Augmentations Pairs

$$\underbrace{\{(\tau_0, \tau_1), \ldots, (\tau_j, \tau_k), \ldots, (\tau_{n-1}, \tau_n)\}}_{\mathcal{P}}$$

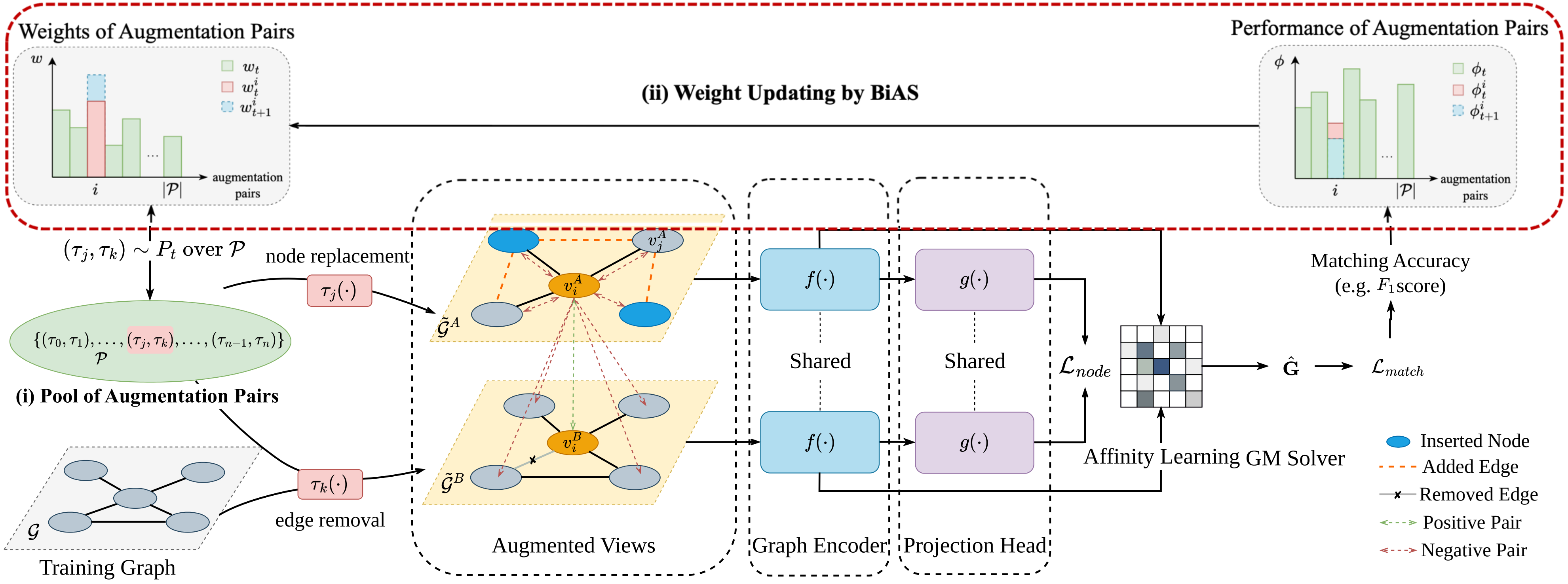
(i) Pool of Augmentation Pairs

- **Set of Randomly Initialized Augmentations**

$$I = \{NI_1, NI_2, \ldots, NI_k, NR_1, NR_2, \ldots, NR_k, ER_1, ER_2, \ldots, ER_k, \ldots\}$$

- **Pool of Augmentation Pairs** $P = I^2$

2) BiAS



(a) Pre-training

(illustration for one graph only)

2) BiAS

Algorithm 1 Training of GCGM with BiAS

Require: Augmentation pairs pool $\mathcal{P}$, Initial weight for each augmentation pair $w_i^0 = e^{\alpha}$, Hyperparameters α, λ

1: **for** t in training steps **do**

2: $P_t(i) = \frac{w_t^i}{\sum_{j \in S} w_t^j}, \forall i \in |\mathcal{P}|$ *# probability distribution*

3: **for** each graph $\mathcal{G}$ in batch of graphs $\{\mathcal{G}_1, \ldots, \mathcal{G}_N\}$ **do**

4: $(\tau_j, \tau_k) \sim P_t$ over $\mathcal{P}$ *# sample augmentation pairs*

5: $\tilde{\mathcal{G}}^A \leftarrow \tau_j(\mathcal{G}), \tilde{\mathcal{G}}^B \leftarrow \tau_k(\mathcal{G})$ *# augment graph*

6: $F_1 \leftarrow$ Match between $\tilde{\mathcal{G}}^A$ and $\tilde{\mathcal{G}}^B$

7: **end for**

8: $w_{t+1}^i = \lambda w_t^i + (1-\lambda) e^{\alpha(1-\phi_t^i)}$ *# update weights*

9: Update $\mathcal{P}$ with the new weights

10: **end for**

Ensure: Trained model

$\lambda = 0.6, \alpha = 2$

w_t	ϕ_t	w_{t+1}
1	0.9	1.09
1	0.4	**1.93**

Experiment

- Real-world Datasets
- Synthetic Dataset
- Ablation and Model Analyses

Real-world Datasets

Methods	Pascal VOC Intsec	Pascal VOC Unfilt	Willow Intsec	SPair-71k Intsec	SPair-71k Unfilt
CIE (SUP)	66.8±0.4	-	82.6±0.2	69.3±0.3	-
BBGM (SUP)	77.3±0.1	55.0±0.1	96.2±0.1	77.7±0.2	48.4±0.2
NGMv2 (SUP)	76.8±0.1	56.7±0.1	94.5±0.3	76.6±0.2	49.8±0.08
IPFP	45.8±0.02	31.5±0.002	80.1±0.06	57.0±0.04	31.7±0.01
RRWM	47.2±0.02	31.7±0.001	83.4±0.09	58.6±0.05	32.3±0.01
SM	46.2±0.03	30.4±0.002	81.3±0.08	57.7±0.04	30.3±0.01
GANN-GM^	34.5±0.3	23.4±0.2	89.3±0.1	34.7±0.4	19.4±0.3
SCGM+BBGM	54.8±0.05	36.6±0.04	93.1±0.08	60.2±0.05	34.1±0.01
SCGM+NGMv2	50.8±0.1	32.9±0.03	84.2±0.1	59.8±0.1	30.5±0.3
GCGM+BBGM	56.8±0.02	36.2±0.01	94.4±0.3	60.6±0.1	**35.9**±0.07
GCGM+NGMv2	**57.3**±0.11	**37.4**±0.07	**95.0**±0.1	**62.6**±0.02	35.4±0.07

- **Solver Compatibility**
  - BBGM
  - NGMv2
- **Consistency in Challenging Settings**
  - Intersection: no outliers
  - Unfiltered: more challenging with outliers

Synthetic Dataset

Methods	Synthetic Intsec	Synthetic Unfilt
GANN-GMˆ	11.2±0.04	10.2±0.03
SCGM + BBGM	33.5±2.0	24.3±1.2
SCGM + NGMv2	35.2±0.6	25.0±0.4
GCGM	**58.1**±0.5	**39.9**±0.4

Table 3: Performance (%) of SSL methods on the synthetic dataset.

- **Superior Performance**
- **Graph-Centric Advantage**
  - not dependent on visual inputs
  - enhance robustness

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Alation Study on Graph Augmentations

Augmentation Set	Pascal VOC Intsec	Pascal VOC Unfilt	Willow Intsec	SPair-71k Intsec	SPair-71k Unfilt	Synthetic Intsec	Synthetic Unfilt
$\mathcal{T}\backslash$NI	56.9	36.6	94.8	61.8	34.9	57.9	**40.5**
$\mathcal{T}\backslash$NR	56.5	36.5	**95.1**	61.8	34.4	57.8	40.0
$\mathcal{T}\backslash$ER	57.3	37.2	95.0	59.8	32.5	57.9	40.0
$\mathcal{T}\backslash$FS	**57.5**	37.2	95.0	62.1	35.1	57.8	40.3
$\mathcal{T}$	57.3	**37.4**	95.0	**62.6**	**35.4**	**58.1**	39.9

Table 4: Ablation study on graph augmentations.

- **Node Insertion (NI) and Node Replacement (NR)**
  - Pascal VOC and SPair-71k
- **Edge Removal (ER)**
  - **SPair-71k:** significant viewpoint and scale variability

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Effect of BiAS and Augmentation Pool

Settings	$\mathcal{P}$	Pascal VOC			Willow		SPair-71k		
		Intsec	Unfilt	Time/h	Intsec	Time/h	Intsec	Unfilt	Time/h
Random	✗	55.0	35.9	0.26	93.8	0.04	61.4	35.2	0.38
Tuning	✗	55.9	36.8	23.76	94.8	4.54	61.5	35.6	31.96
Tuning + BiAS	✗	55.8	37.0	23.95	**95.4**	4.54	61.9	**36.0**	31.88
Uniform	✓	56.9	36.7	0.32	94.7	0.05	62.0	34.8	0.35
BiAS	✓	**57.3**	**37.4**	0.39	95.0	0.05	**62.6**	35.4	0.34

Table 5: Performance of different initialization of augmentations and the use of augmentation pool. Time (hour) represents the total wall clock time spent on tuning the augmentations (for ‘Tuning’ methods) and training the model. The ‘$\mathcal{P}$’ column indicates if a pool of augmentation pairs is used.

Summary

- **General Graph Matching**
    - without the reliance on side information
- **Robust Augmentation Strategy**
    - a comprehensive pool of graph augmentations
- **Adaptive Augmentation Sampler**
    - dynamically selects challenging augmentations
- **Superior Performance and Efficiency**
    - outperforms other SSL methods

Thank you!