Inductive Graph Unlearning

Cheng-Long Wang[1,4], Mengdi Huai[2], Di Wang[1,3,4]
[1]King Abdullah University of Science and Technology
[2]Iowa State University [3]Computational Bioscience Research Center
[4]SDAIA-KAUST Center of Excellence in Data Science and Artificial Intelligence

Machine Unlearning: Bridging Law and Technology

Legislation: Right to be forgotten/right to delete

General Data Protection Regulation (GDPR) [1]	EU	2016
California Consumer Privacy Act (CCPA) [2]	USA	2018
Personal Information Protection Law (PIPL) [3]	CHINA	2021
Consumer Privacy Protection Act (CPPA) [4]	CANADA	2022
Personal Data Protection Law (PDPL) [5]	KSA	2023

[1] https://gdpr.eu/article-17-right-to-be-forgotten/
[2] https://oag.ca.gov/privacy/ccpa#sectiond
[3] http://en.npc.gov.cn.cdurl.cn/2021-12/29/c_694559.htm
[4] https://www.parl.ca/DocumentViewer/en/44-1/bill/C-27/first-reading
[5] https://sdaia.gov.sa/en/SDAIA/about/Documents/Personal%20Data%20English%20V2-23April2023-%20Reviewed-.pdf

Machine Unlearning: Challenges

Legislation： Right to be forgotten/right to delete

Gap between the law concept to technical problem in the ML age

- Memorization: Hard to locate/delete data in a complex ML system
- Privacy Paradox: ML Application Utility VS Aligning with Data Unlearning Requirements
- Computation: Multi-times unlearning adds significantly to training time.
- Governance: Auditing black box models is difficult

Machine Unlearning on Dynamic Graph

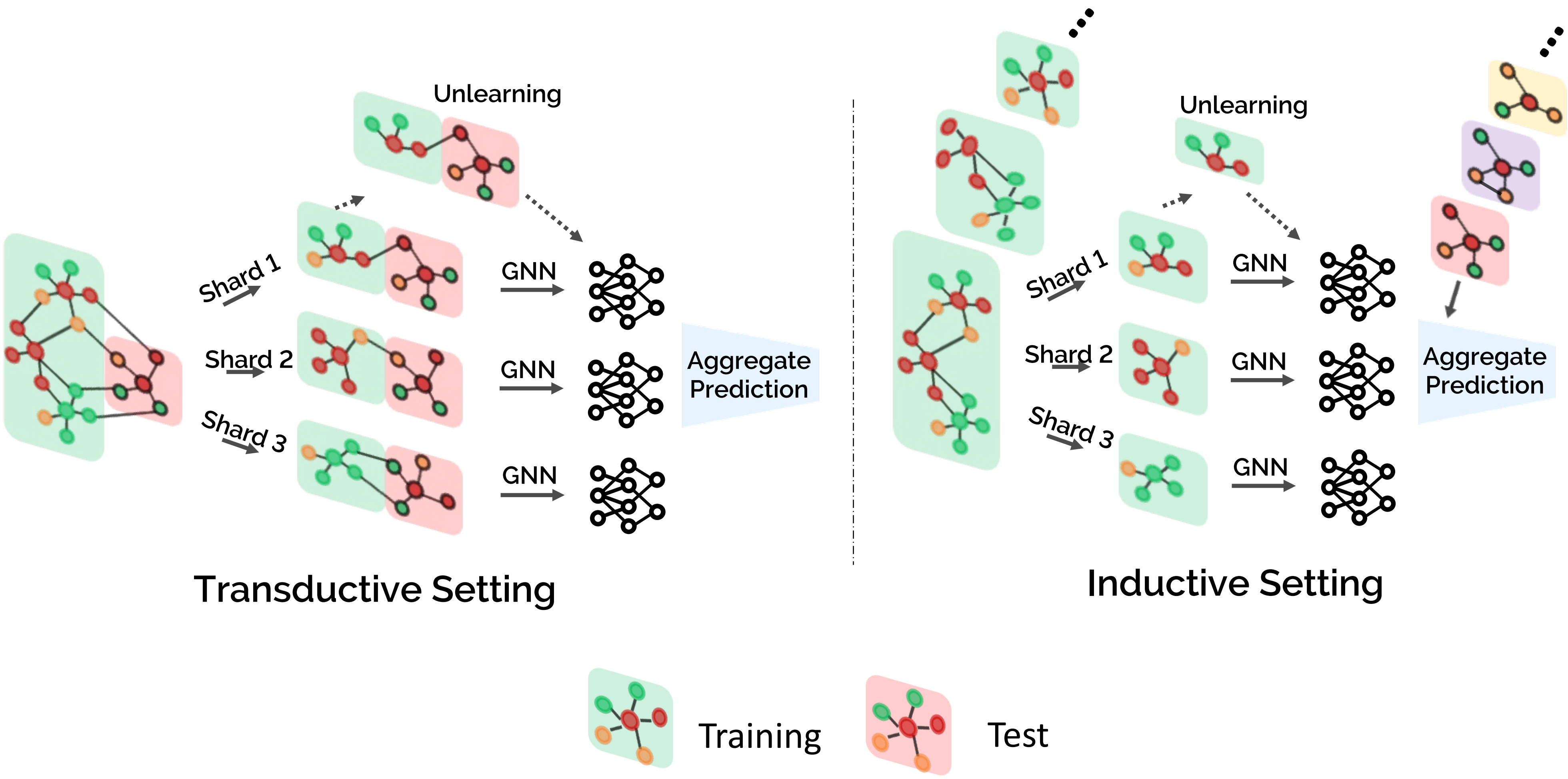
Legislation： Right to be forgotten/right to delete

Gap between the law concept to technical problem in the ML age

Towards practical framework of Graph Machine Learning applications

- Applicable to Evolving graphs / Multi graphs / Unseen graphs
- Efficiency to multi-times unlearning
- Parallelization of Unlearning requests
- Transparency to Governance

Motivation for Inductive Graph Unlearning



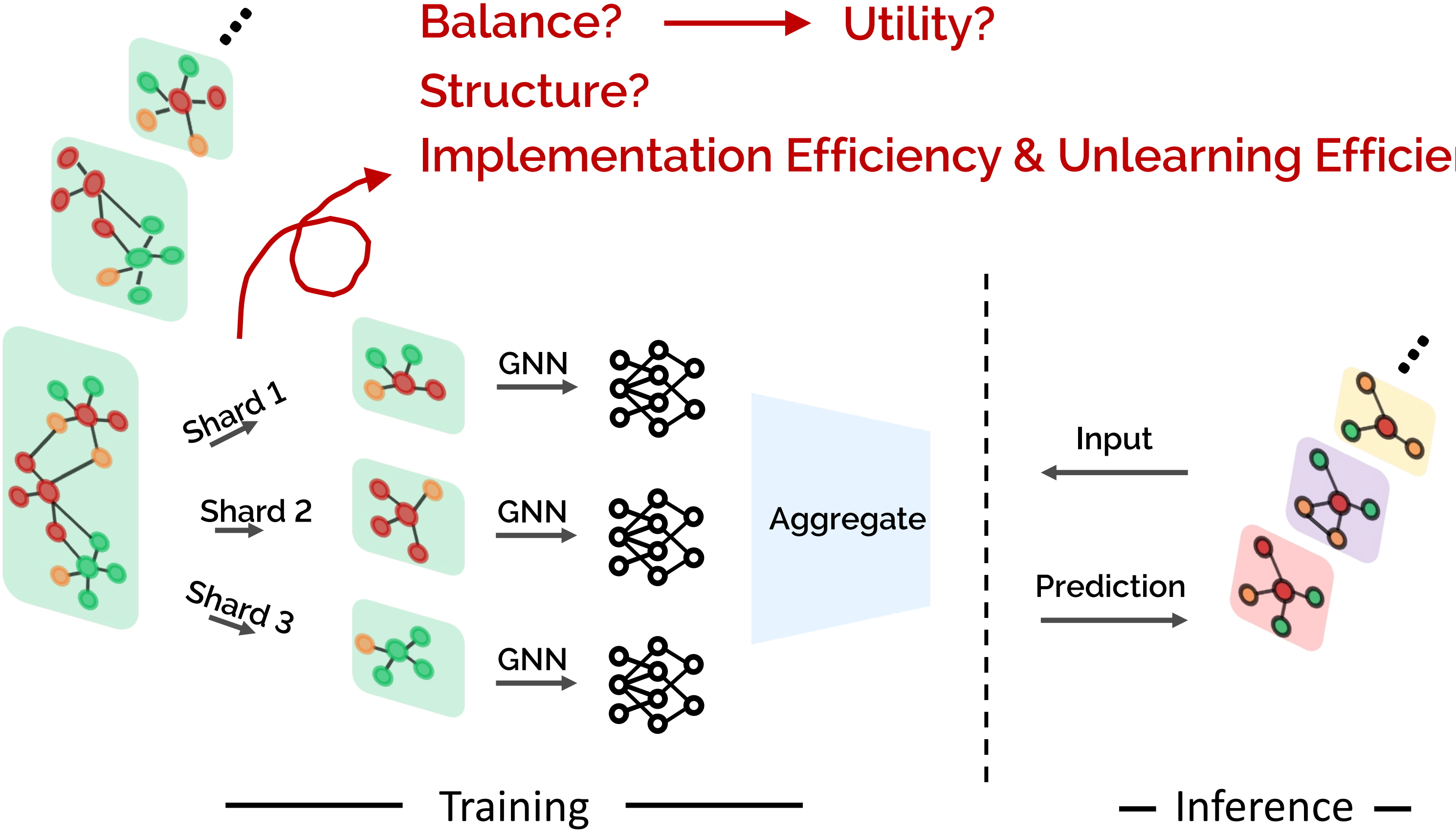
Motivation for Inductive Graph Unlearning

Fairness?

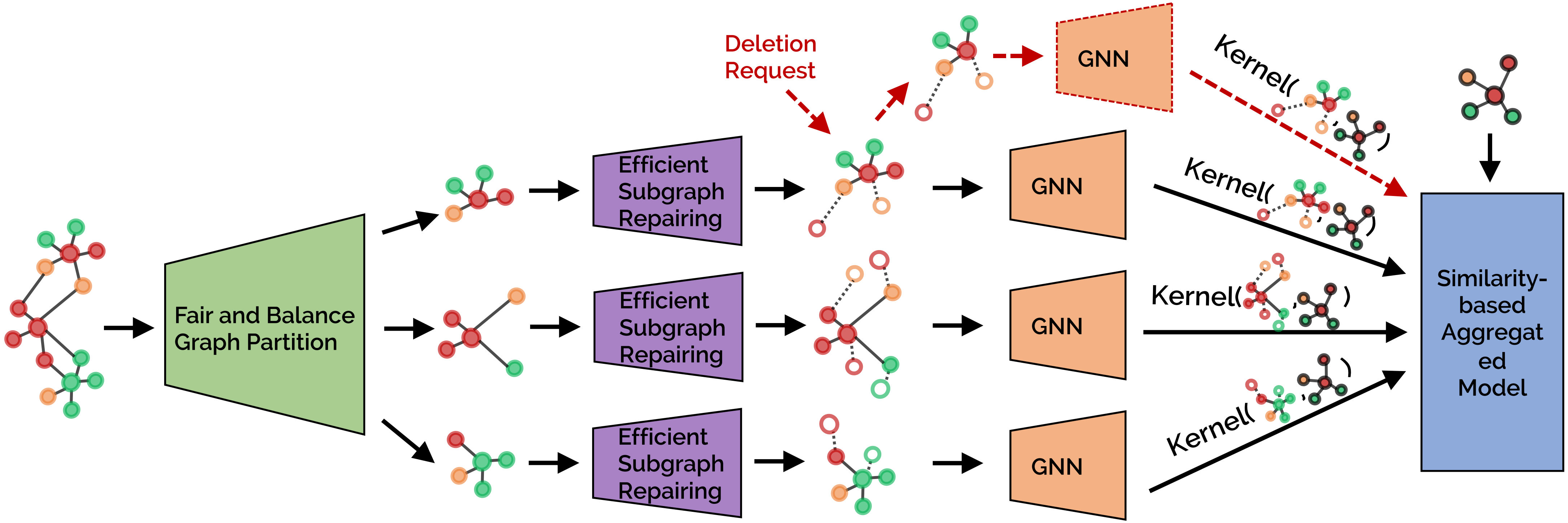
Balance? ⟶ Utility?

Structure?

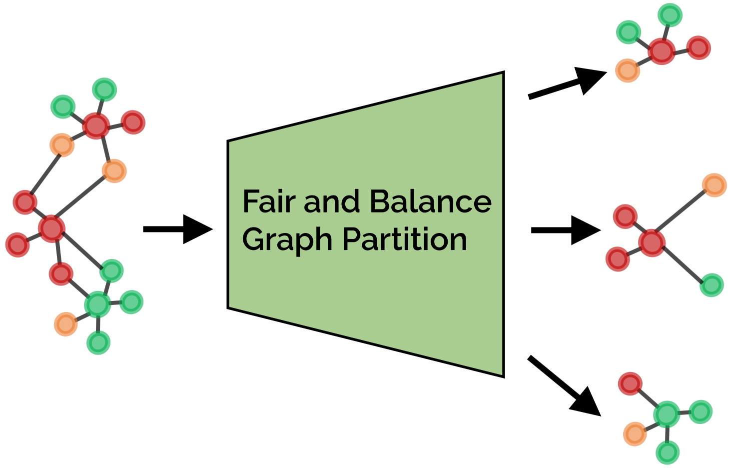
Implementation Efficiency & Unlearning Efficiency?



GUided InDuctivE Graph Unlearning Framework



Guided Graph Partition with Fairness and Balance

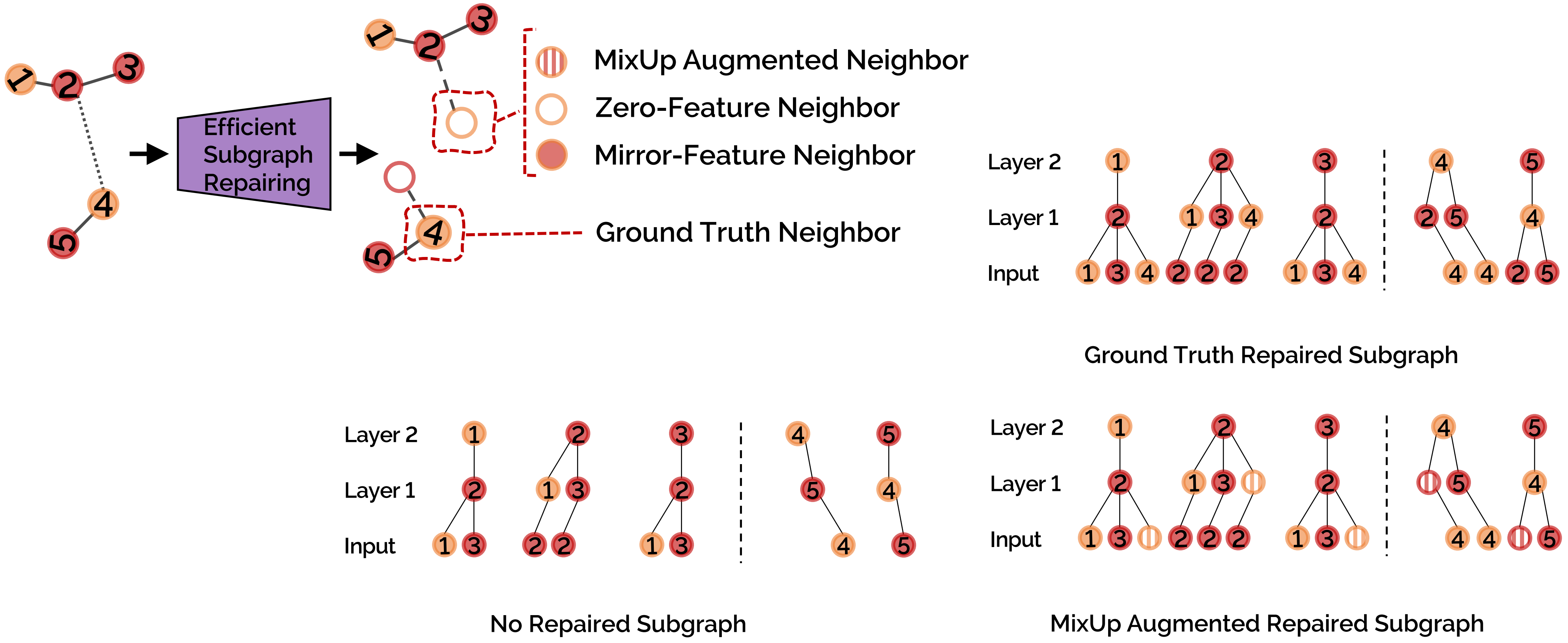


Theorem 2 (Transformation of Fairness and Balance Constraints on Embedding Matrix **H**). *Denote the normalized balanced and fair guided matrix by* $\widetilde{\mathbf{M}} \in \mathbb{R}^{h\times v}$, *i.e.,* $\widetilde{\mathbf{M}}_{s,j} = \frac{|C_s|}{\sqrt{nv}}$.

For a partition $\mathcal{V} = \dot{\cup}_{i\in[v]} \mathcal{V}_i$, *it is fair and balanced if and only if* $\mathbf{F}^\intercal\mathbf{H} = \widetilde{\mathbf{M}}$, *where* $\mathbf{H}$ *is the normalized group-membership indicator matrix of the partition which has the form in (8).*[2]

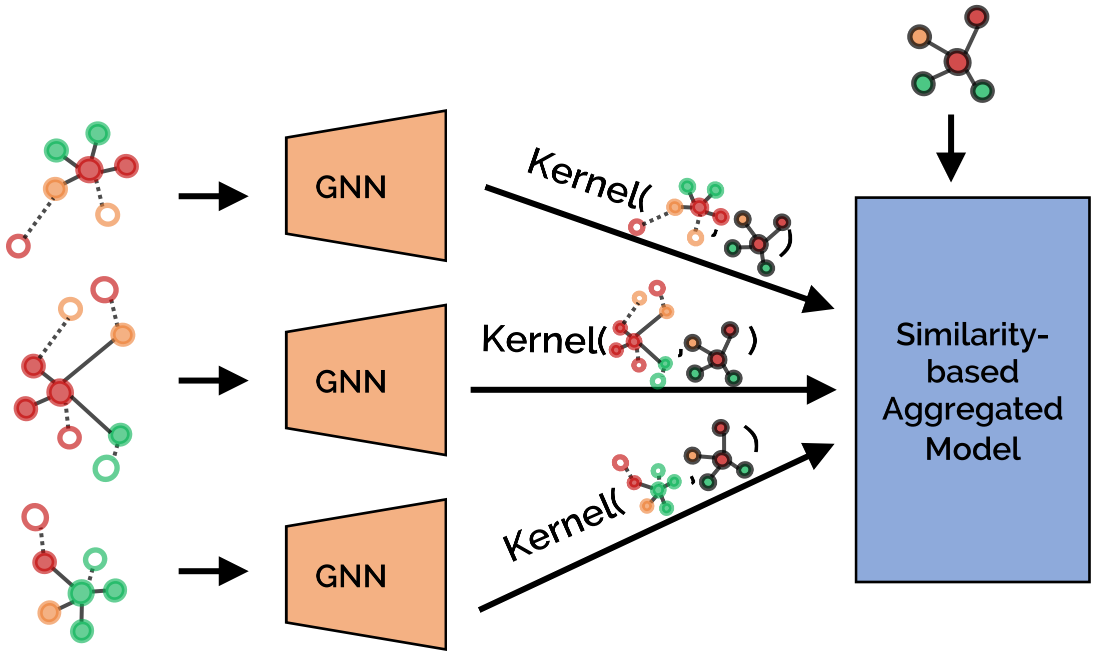
$$\begin{aligned}
\min_{\mathbf{H},\mathbf{Y}} \quad & Tr(\mathbf{H}^\intercal\mathbf{L}\mathbf{H}) + \alpha\|\mathbf{F}^\intercal\mathbf{H} - \widetilde{\mathbf{M}}\|_2^2 + \\
& \beta\|\mathbf{H}\mathbf{R} - \mathbf{D}^{-\frac{1}{2}}\mathbf{Y}(\mathbf{Y}^\intercal\mathbf{D}\mathbf{Y})^{-\frac{1}{2}}\|_2^2 \quad . \\
s.t. \quad & \mathbf{H}^\intercal\mathbf{H} = \mathbf{I}, \mathbf{R}^\intercal\mathbf{R} = \mathbf{I}
\end{aligned}$$

Efficient Subgraph Repairing



Similarity-based Aggregation

- The importance score of each sub-model should be
  - Independent to each other
  - Applicable to inference on new graphs



Results 1: Fair and Balanced Partition

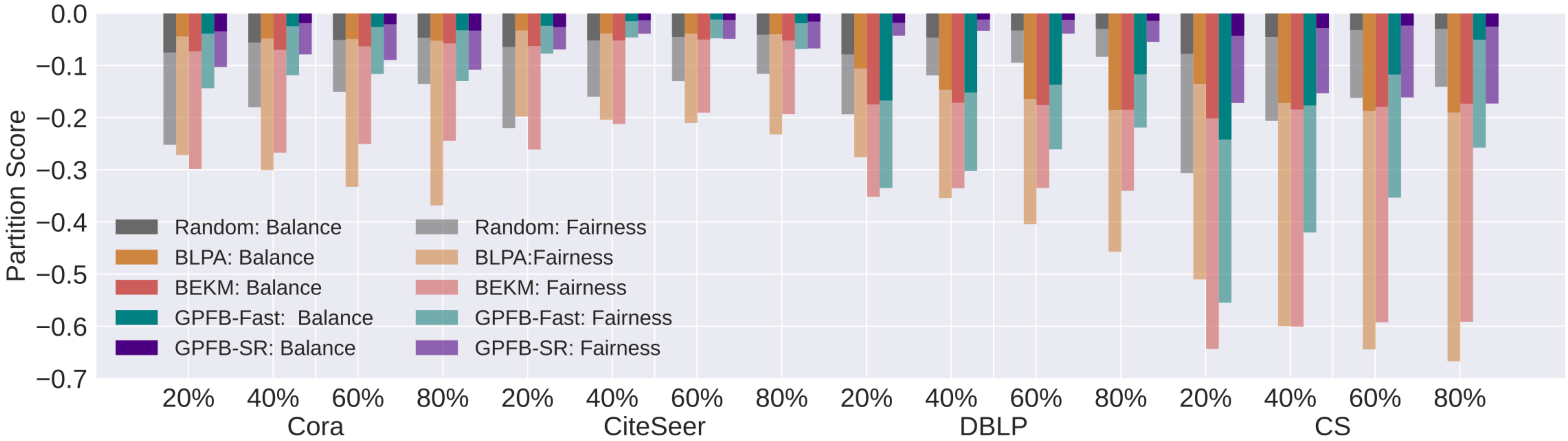


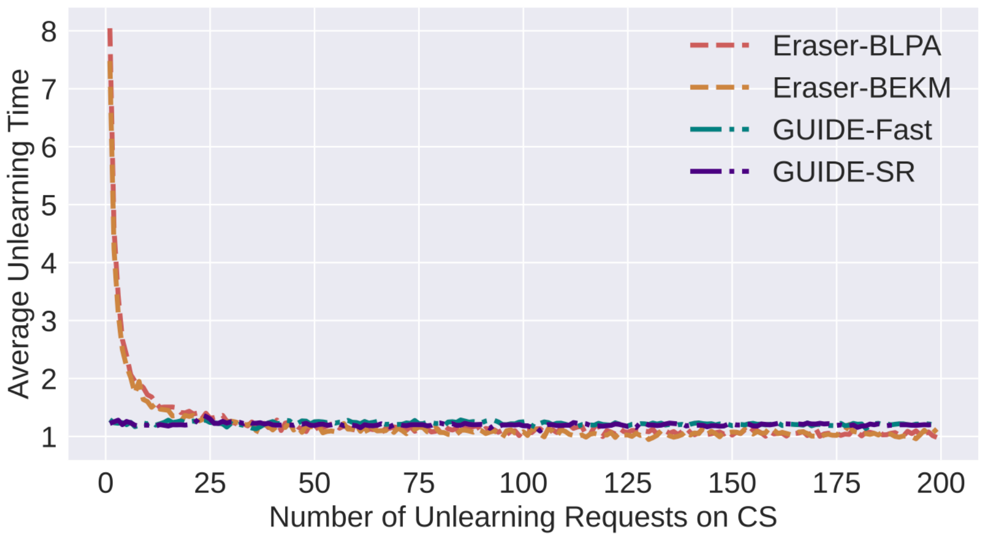
Figure 6: Partition scores of 5 methods on different datasets.

Fair enough and balance enough

Results 2: Efficient Implementation and Unlearning

Table 1: Graph partition time of 4 methods(s).

Dataset	BLPA	BEKM	GPFB-Fast	GPFB-SR
Cora	5.41	10.10	**0.24**	2.85
CiteSeer	6.36	14.56	**0.31**	3.54
CS	38.77	5454.36	**15.71**	40.02
DBLP	37.30	5182.10	**14.44**	33.52
Elliptic	303.02	1089.72	**26.19**	201.99



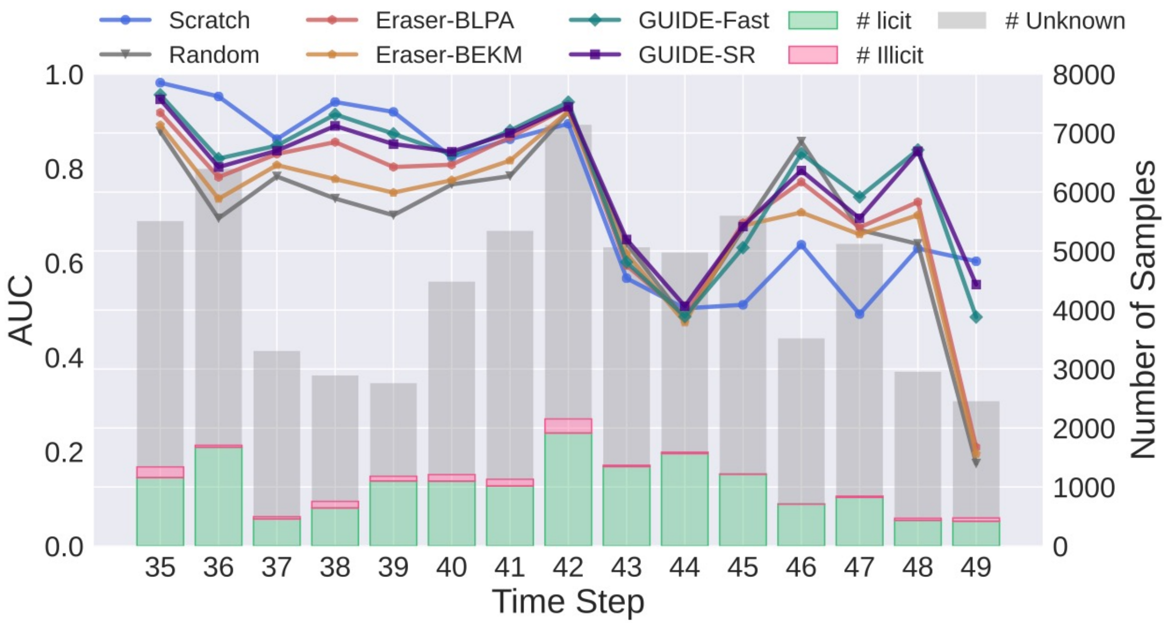
Fast enough

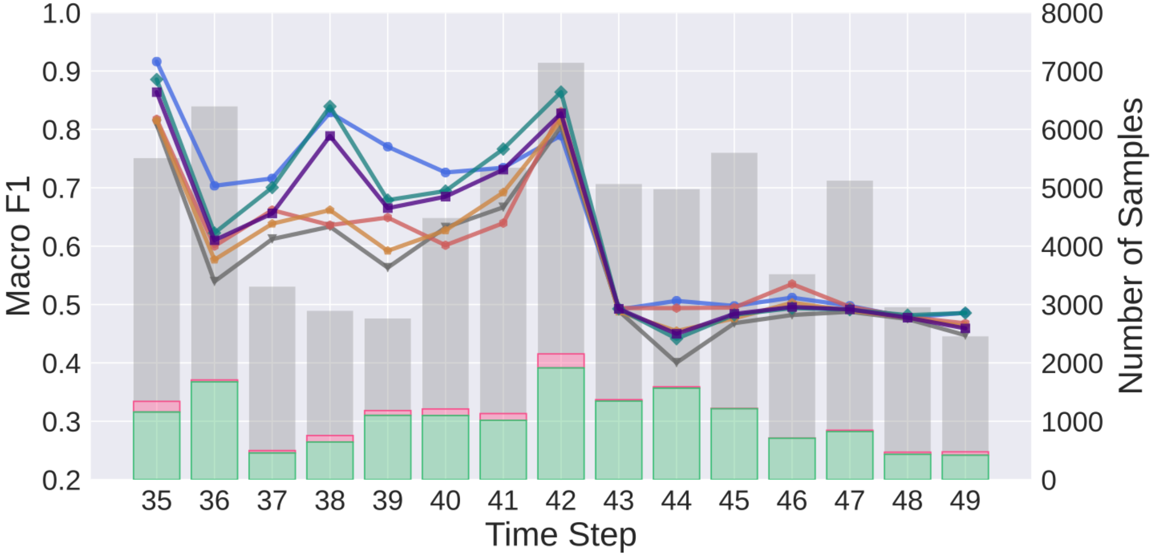
Results 3: Simple but Efficient Subgraph Repair

Table 3: Results of different subgraph repairing strategies on Cora(%)

Partition Method	Model	Ground Truth	No Repairing	Mirror Feature	Zero Feature	MixUp
GPFB-Fast	SAGE	77.26±0.04	59.98±0.19	63.22±0.08	73.55±0.05	71.33±0.10
	GIN	79.26±0.04	70.09±0.05	77.13±0.07	72.07±0.06	76.40±0.05
	GAT	70.52±0.10	49.63±0.08	62.90±0.09	66.52±0.07	66.25±0.09
GPFB-SR	SAGE	77.78±0.02	59.98±0.09	65.67±0.08	74.38±0.04	72.26±0.04
	GIN	78.96±0.02	69.28±0.14	75.16±0.09	72.20±0.06	77.06±0.06
	GAT	70.85±0.06	50.00±0.20	65.18±0.09	67.08±0.08	66.40±0.09
Normalized Score		100.00	0.00	54.09	62.32	73.65

Results 4: Superior Utility on Evolving Graphs





Results 5: Superior Utility on Inductive Graphs

Table 2: Node classification accuracy of 5 graph unlearning methods with 6 inductive GNN models (%).

Dataset	Model	Scratch	Random	Eraser-BLPA	Eraser-BEKM	GUIDE-Fast	GUIDE-SR
Cora	SuperGAT	89.17±0.00	31.57±0.04	41.74±0.16	44.92±0.57	65.69±0.04	**66.49±0.12**
	GATv2	88.94±0.00	31.22±0.04	43.83±0.68	36.62±0.55	66.80±0.08	**68.10±0.16**
	SAGE	92.73±0.00	53.68±0.18	44.20±0.37	53.57±0.60	71.33±0.10	**72.26±0.04**
	GIN	87.07±0.13	56.49±0.26	67.84±0.14	65.55±0.29	76.40±0.05	**77.06±0.06**
	GAT	88.97±0.00	31.90±0.07	38.91±0.36	34.10±0.34	66.25±0.09	**66.40±0.09**
	APPNP	85.96±0.03	51.28±0.13	38.02±0.26	46.38±0.12	64.14±0.07	**64.56±0.05**
CiteSeer	SuperGAT	79.33±0.00	25.44±1.34	53.31±1.15	45.98±0.48	70.66±0.02	**71.17±0.02**
	GATv2	79.53±0.00	25.88±1.45	58.50±0.36	41.04±1.58	70.78±0.02	**71.26±0.02**
	SAGE	83.08±0.00	69.10±0.05	66.90±0.06	69.25±0.05	**72.71±0.02**	72.38±0.01
	GIN	81.20±0.06	58.02±0.41	66.29±0.11	64.21±0.13	69.64±0.07	**69.67±0.04**
	GAT	79.61±0.00	26.32±1.46	58.57±0.64	43.46±1.17	70.66±0.02	**71.02±0.02**
	APPNP	77.49±0.00	72.98±0.02	66.33±0.40	71.29±0.04	73.09±0.03	73.43±0.02
DBLP	SuperGAT	84.21±0.00	44.67±0.00	70.27±0.01	69.84±0.01	**71.67±0.01**	69.29±0.01
	GATv2	83.93±0.00	44.67±0.00	70.23±0.01	69.06±0.05	**71.69±0.01**	69.10±0.00
	SAGE	86.72±0.00	60.38±0.02	70.13±0.00	69.70±0.00	71.92±0.01	**72.16±0.01**
	GIN	87.35±0.01	67.76±0.02	**79.09±0.02**	75.78±0.09	77.11±0.03	77.51±0.00
	GAT	84.05±0.00	44.67±0.00	70.41±0.01	68.51±0.08	**71.39±0.01**	68.70±0.01
	APPNP	83.80±0.00	67.53±0.00	71.56±0.01	70.96±0.01	**73.62±0.01**	72.84±0.01
CS	SuperGAT	87.57±0.00	22.79±0.01	53.01±0.02	41.98±0.25	**69.63±0.00**	69.53±0.01
	GATv2	86.98±0.00	22.79±0.01	53.58±0.04	40.08±0.29	**73.28±0.01**	73.15±0.01
	SAGE	91.79±0.00	71.96±0.02	57.37±0.04	74.38±0.01	**80.68±0.00**	80.67±0.00
	GIN	83.69±0.18	36.70±0.01	75.42±0.15	**83.65±0.01**	79.24±0.01	79.73±0.02
	GAT	87.37±0.00	22.79±0.01	53.24±0.01	43.17±1.04	**69.55±0.01**	69.45±0.01
	APPNP	78.70±0.01	58.03±0.01	48.24±0.10	47.81±0.09	74.38±0.01	**74.44±0.01**
Normalized Score		100.00	0.00	20.42	23.71	59.52	59.40

Method	Normalized Score
Random	0.00
Eraser-BLPA	20.42
Eraser-BEKM	23.71
GUIDE-Fast	59.52
GUIDE-SR	59.40
Scratch	100.00

Results 6: Low Unlearning Privacy Risk

Table 5: AUC of membership inference attack on GUIDE(%).

Dataset	SAGE	GAT	GIN
Cora	51.34±0.08	49.78±0.02	53.57±0.19
CiteSeer	53.36±0.10	50.97±0.12	50.70±0.08
DBLP	53.34±0.07	51.22±0.19	55.83±0.7
CS	50.34±0.14	51.27±0.14	48.09±0.14

GUided InDuctivE Graph Unlearning Framework

- GUIDE can be efficiently implemented on the inductive graph learning and unlearning tasks for its low graph partition cost, no matter on computation or structure information.

https://github.com/Happy2Git/GUIDE