Modality-Free Graph In-Context Alignment

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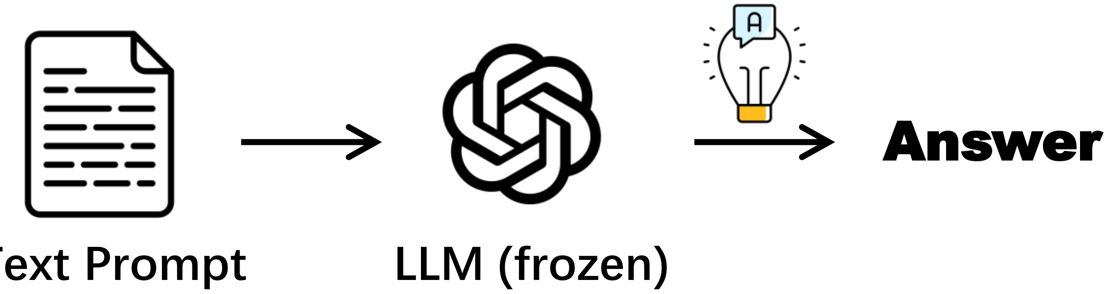
Can we achieve the generality of LLM In-Context Learning (ICL) on Graphs?

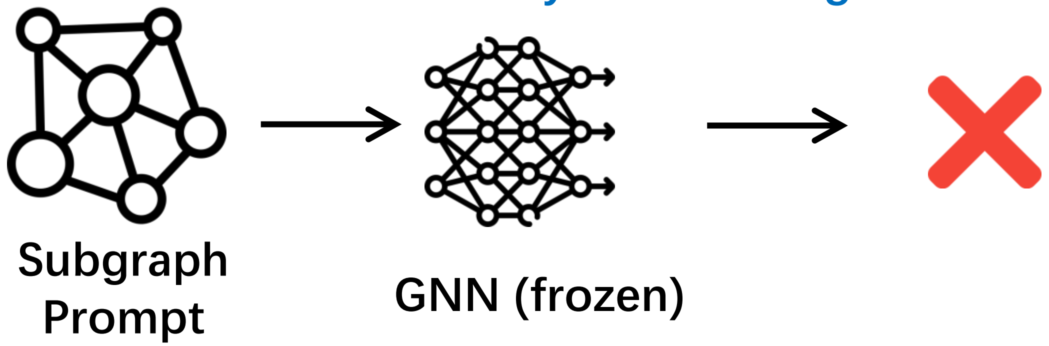
LLM: Universal In-Context Learning

Task defined by context, not weights



GNNs: Domain Specific & Modality Locked

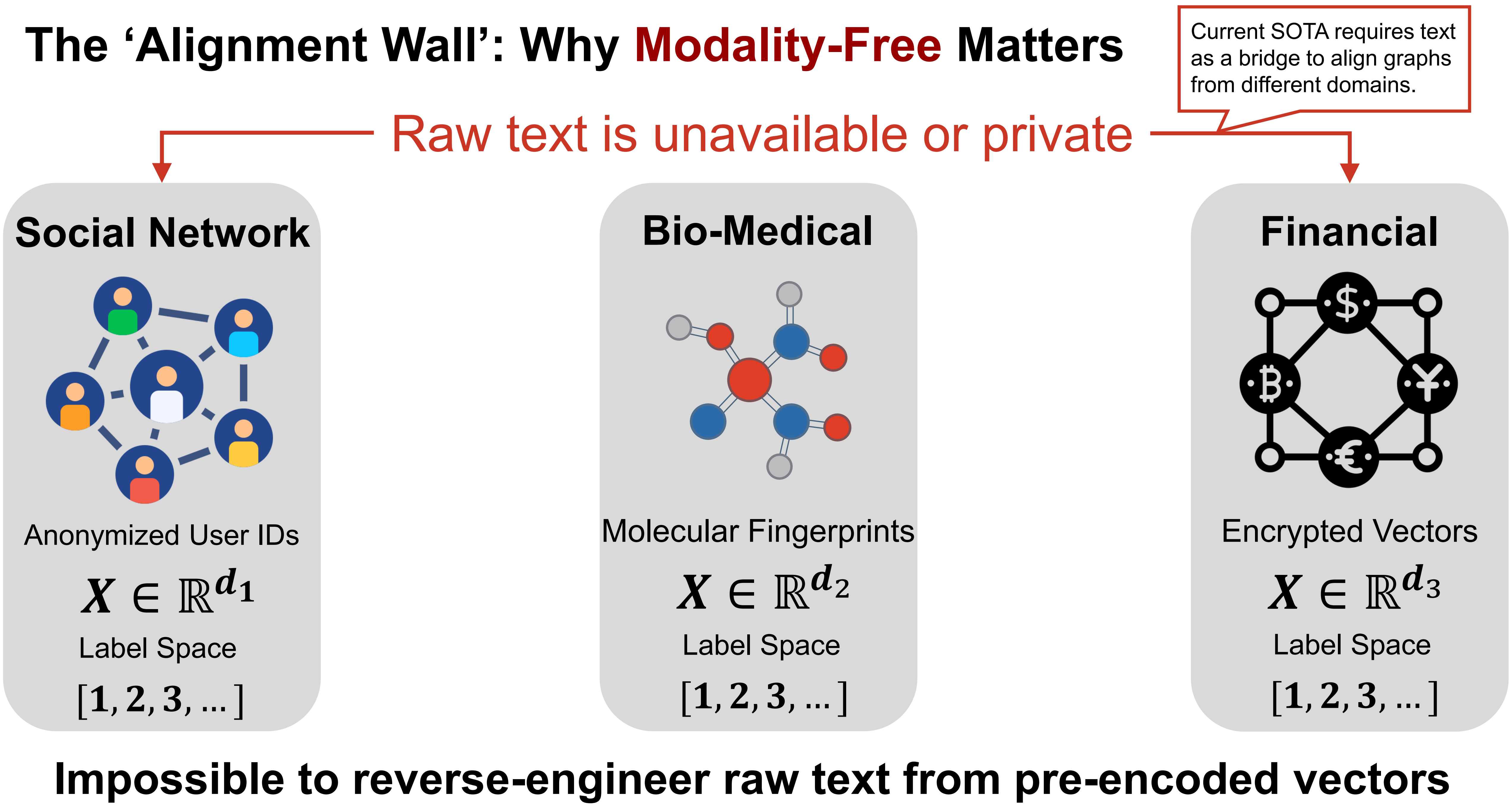
Task defined by trained weights

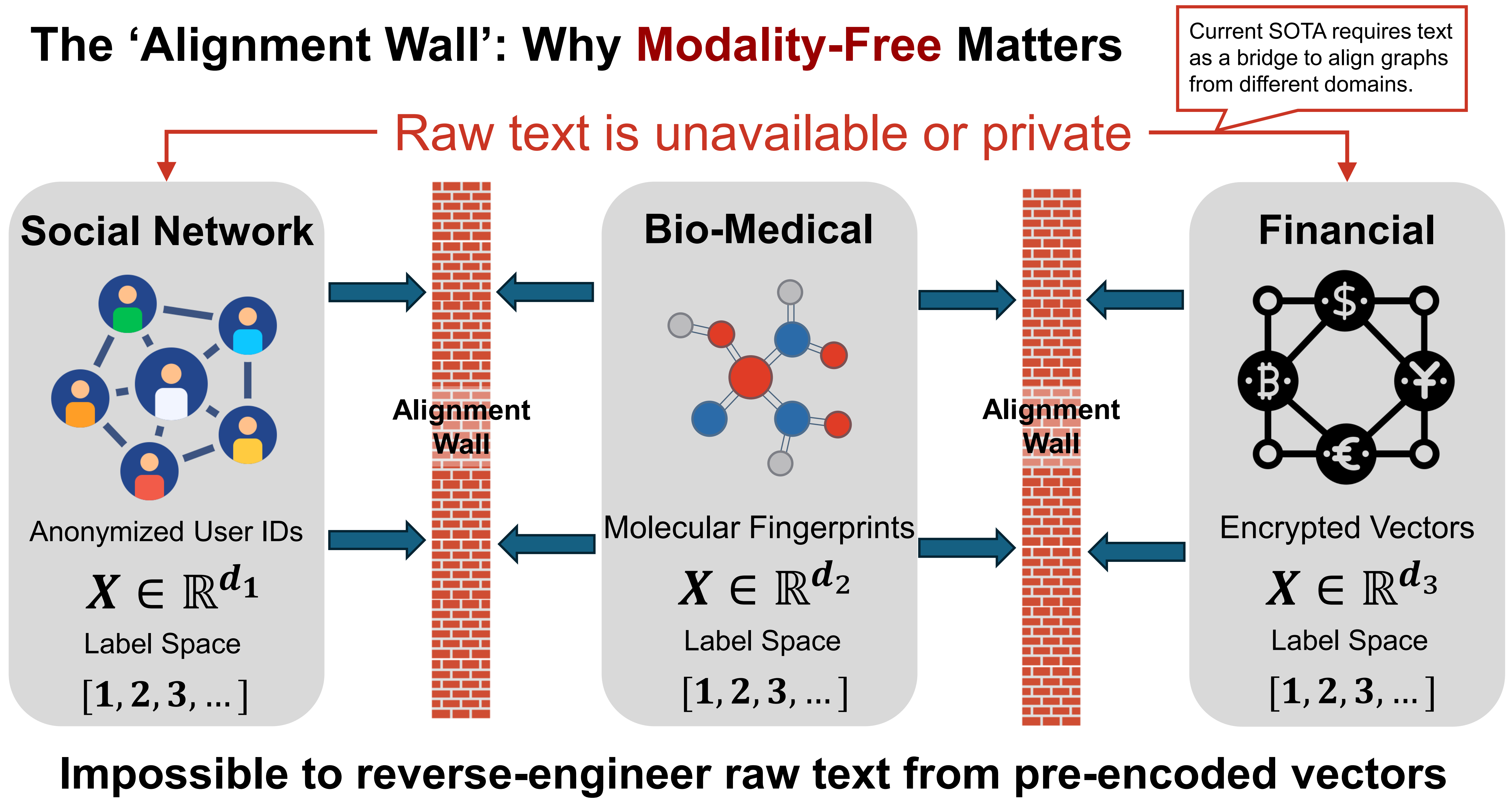


The Evidence

True Graph ICL requires meeting three criteria

Method	Tuning-Free	Domain Alignment	Modality-Free
SSL-GNN	✗	✗	✓
All in One	✗	✗	✓
GPF	✓	✗	✓
GCOPE	✗	✓	✓
GFT	✗	✓	✗
Prodigy	✓	✗	✓
UniGraph	✓	✓	✗
OFA	✓	✓	✗
AutoGFM	✗	✓	✗
MF-GIA	✓	✓	✓


The 'Alignment Wall': Why Modality-Free Matters
Current SOTA requires text as a bridge to align graphs from different domains.
Raw text is unavailable or private
Social Network
Anonymized User IDs
$X \in \mathbb{R}^{d_1}$
Label Space
$[1, 2, 3, \ldots]$
Bio-Medical
Molecular Fingerprints
$X \in \mathbb{R}^{d_2}$
Label Space
$[1, 2, 3, \ldots]$
Financial
Encrypted Vectors
$X \in \mathbb{R}^{d_3}$
Label Space
$[1, 2, 3, \ldots]$
Impossible to reverse-engineer raw text from pre-encoded vectors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The MF-GIA Framework

= Trainable
= Frozen

1. Modality-Free Alignment

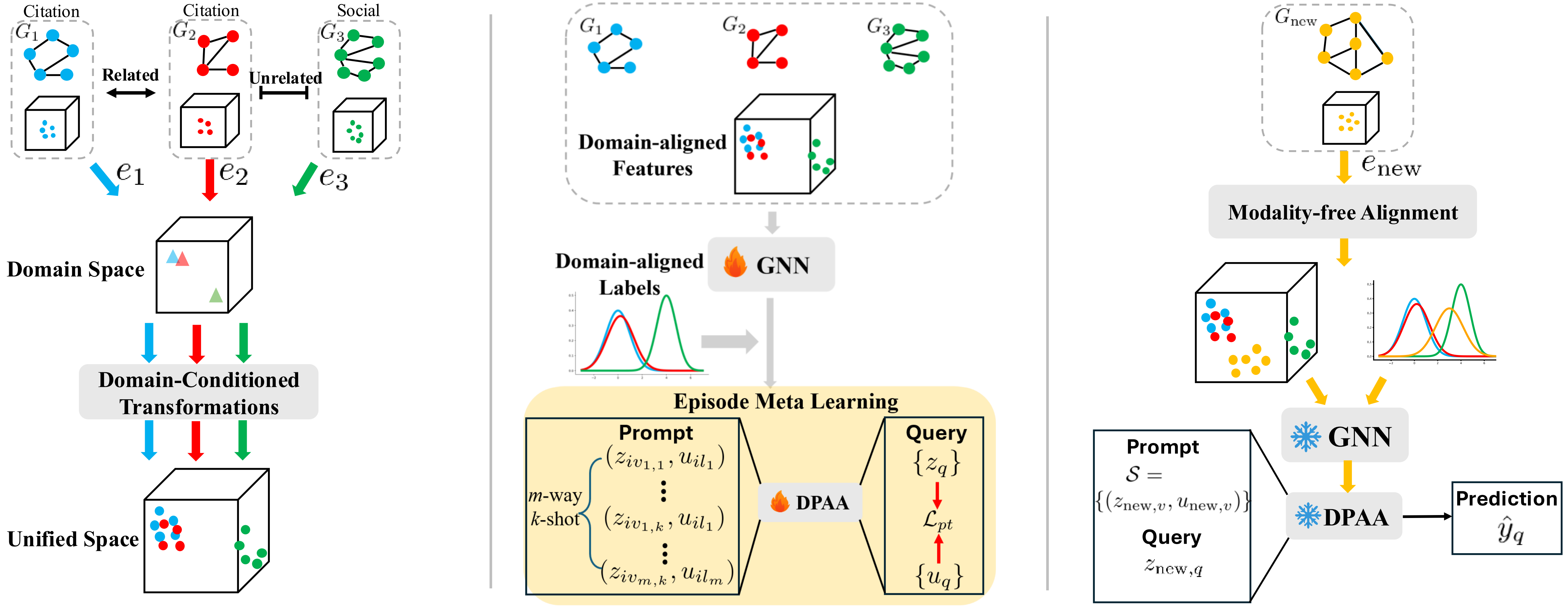
Maps heterogeneous domains to a unified space using gradient fingerprints.

2. Episodic Pretraining

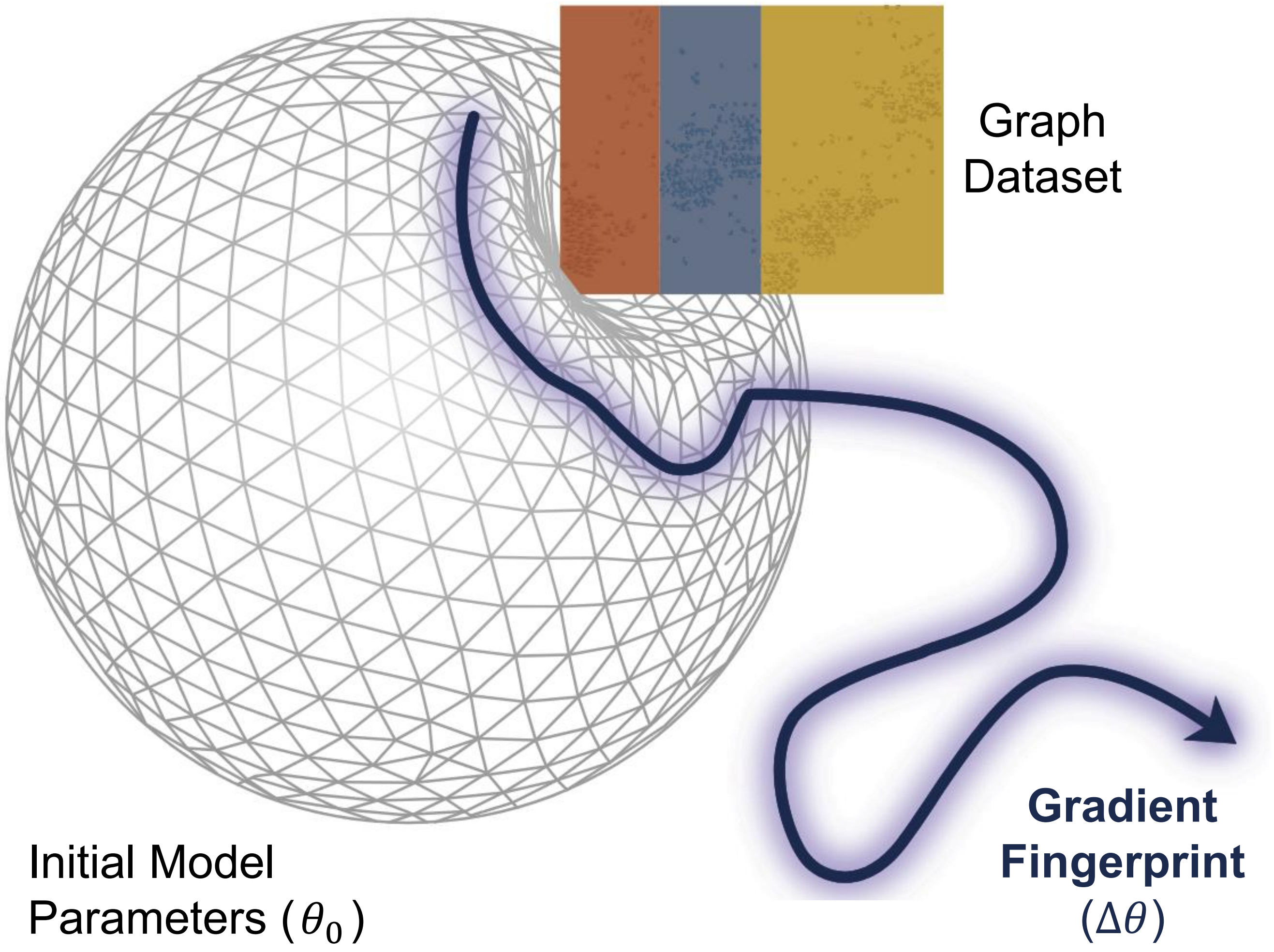
Learns to “read” the prompt using Dual Prompt-Aware Attention (DPAA).

3. In-Context Prediction

Performs parameter-update-free inference on unseen domains.



Domain Embedder: Gradient Fingerprints

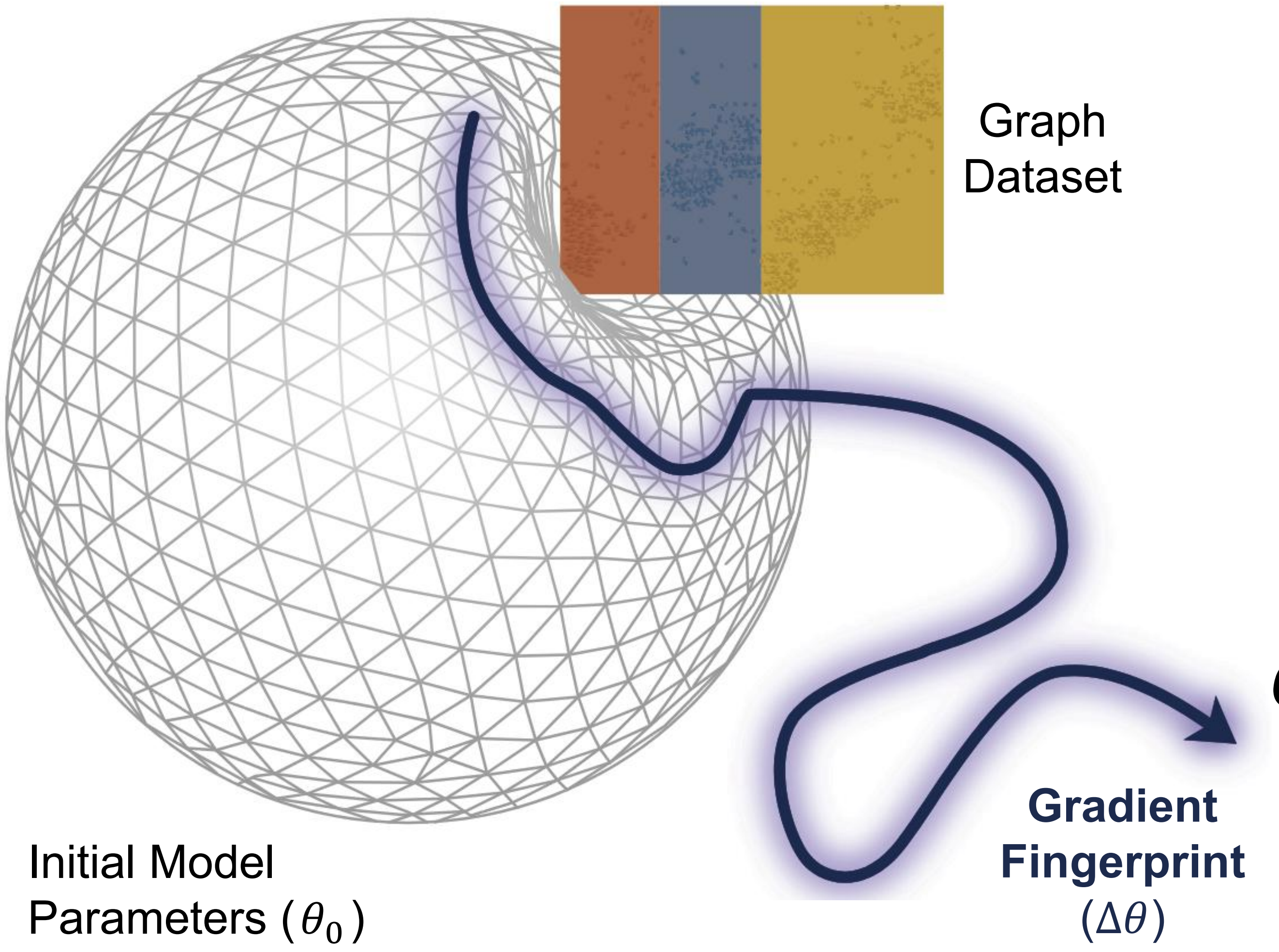


Gradient Fingerprint 🫆 **:**

$$\Delta\theta_i = \nabla L_i(\theta_0)$$

The gradient update captures how structure, features, and labels *jointly* influence the model, creating a unique identity for the domain.

Domain Embedder: Gradient Fingerprints



Gradient Fingerprint :

$$\Delta\boldsymbol{\theta}_i = \nabla L_i(\boldsymbol{\theta}_0)$$

Domain Embedding:

$$\boldsymbol{e}_i = \mathbf{MLP}(\mathbf{Conv2D}(\Delta\, \boldsymbol{\theta}_i))$$

The gradient update captures how structure, features, and labels *jointly* influence the model, creating a unique identity for the domain.

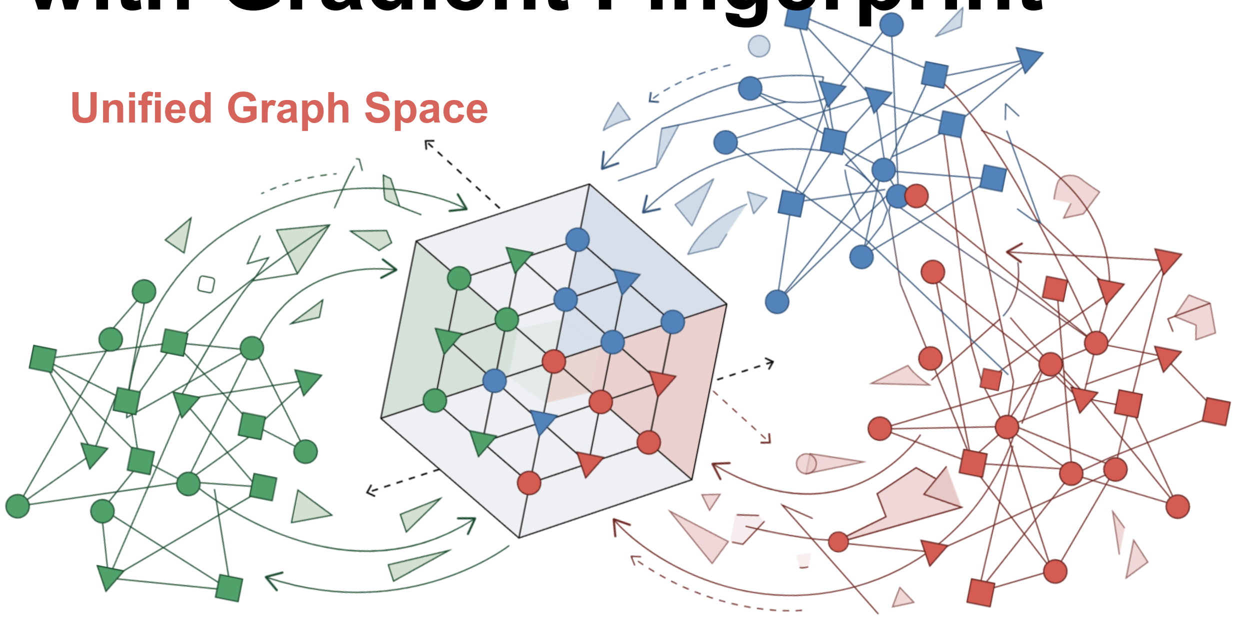
Modality-Free Alignment with Gradient Fingerprint

Feature-wise Linear Modulation (FiLM)

Feature Alignment:

$$\gamma(\boldsymbol{e}_i) \odot \boldsymbol{x} + \beta(\boldsymbol{e}_i)$$

The domain embedding modulates the feature space, warping disparate domains into geometric alignment.



Modality-Free Alignment with Gradient Fingerprint

Feature-wise Linear Modulation (FiLM)

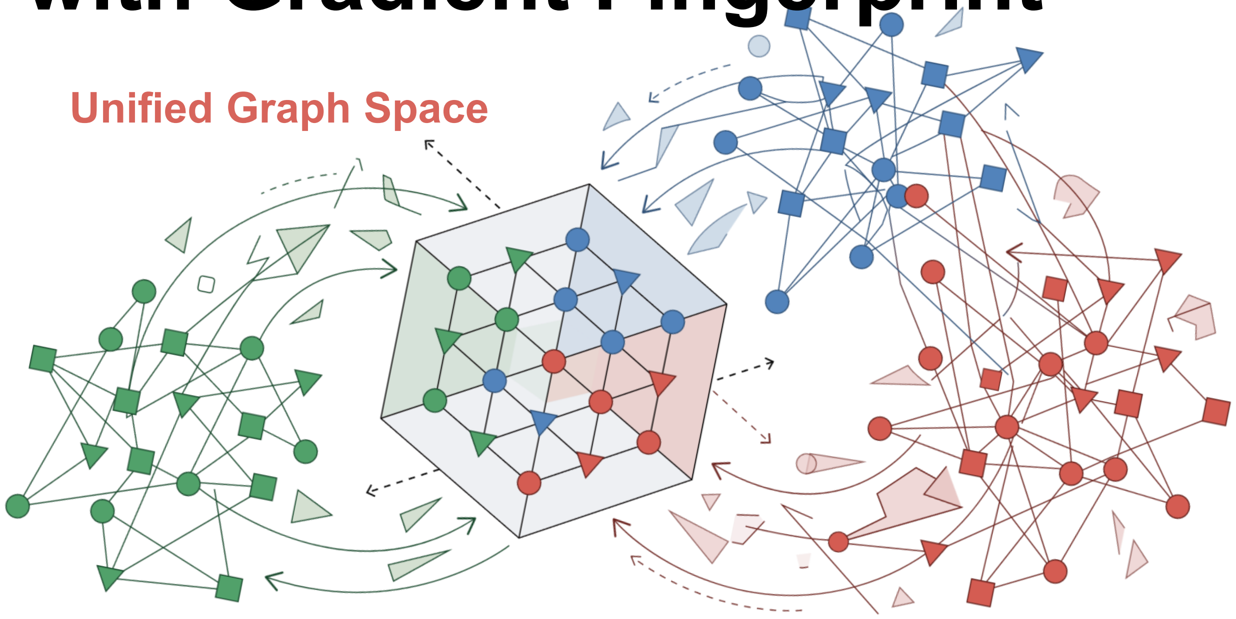
Feature Alignment:

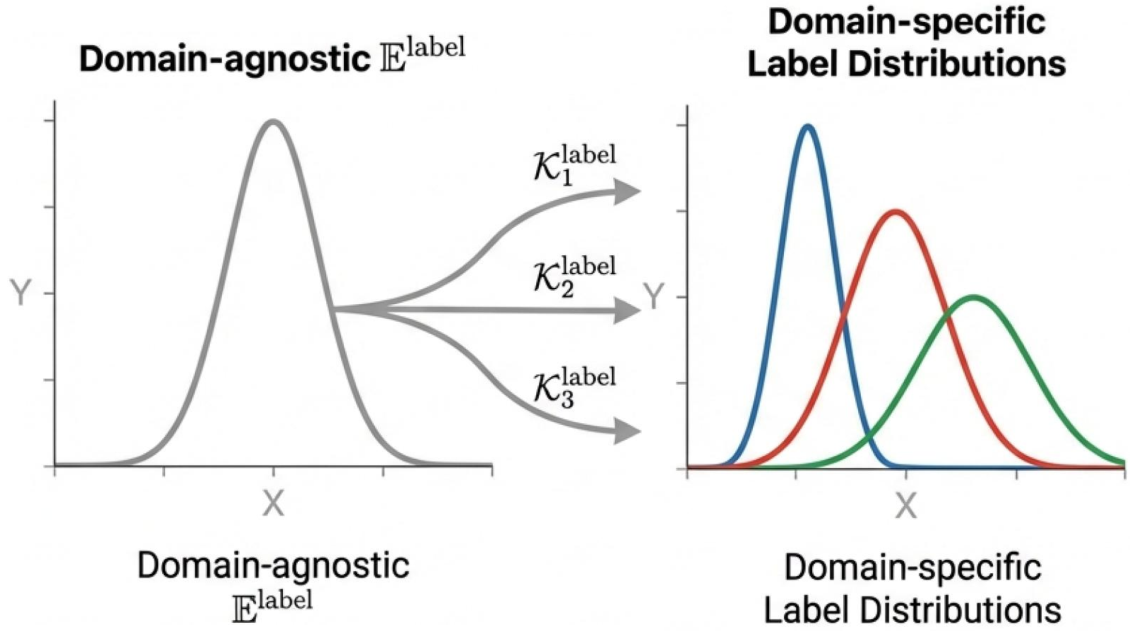
$$\gamma(\boldsymbol{e}_i) \odot \boldsymbol{x} + \beta(\boldsymbol{e}_i)$$

The domain embedding modulates the feature space, warping disparate domains into geometric alignment.

Label Alignment:

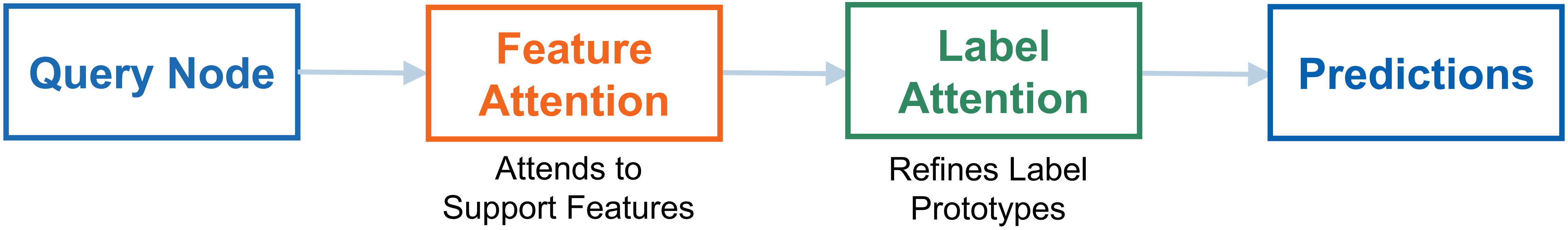
Shared label prototypes are shifted and scaled to match the local domain semantics.





Episodic Pretraining: Learning to Read Prompt

Dual Prompt-Aware Attention (DPAA)



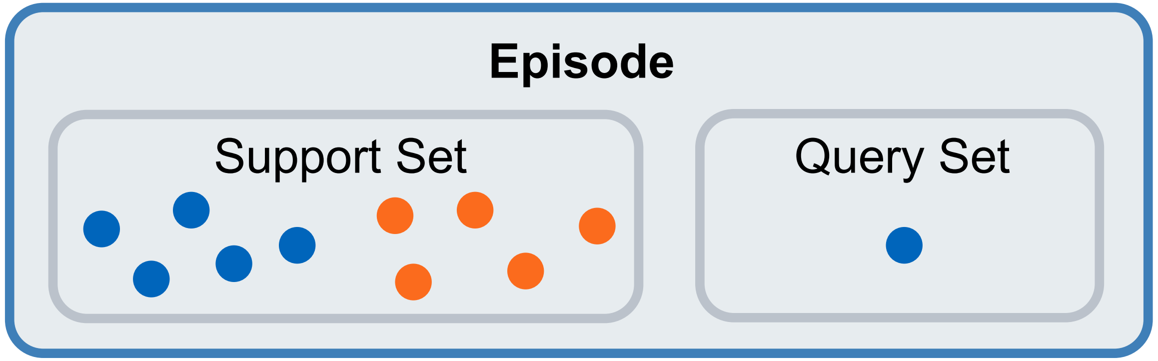
Episodic Pretraining: Learning to Read Prompt

Dual Prompt-Aware Attention (DPAA)

Query Node → **Feature Attention** → **Label Attention** → **Predictions**

Feature Attention: Attends to Support Features

Label Attention: Refines Label Prototypes



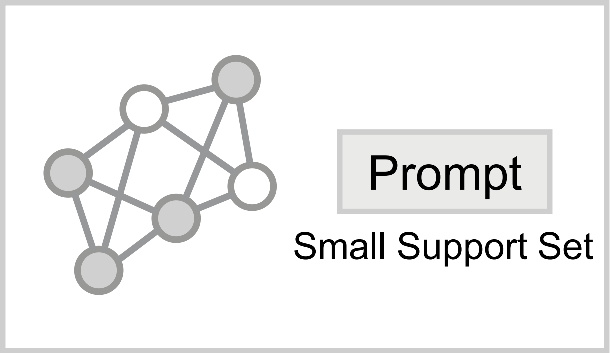
$\boldsymbol{m}$-way $\boldsymbol{k}$-shot episodes

Episodic Objective

Simulates the few-shot scenarios faced at test time. The model learns a in-context reasoning strategy, not dataset memorization.

In-Context Prediction
on Graphs from Unseen Domains

Fully Frozen Parameters



Input (Unseen Domain)

In-Context Prediction
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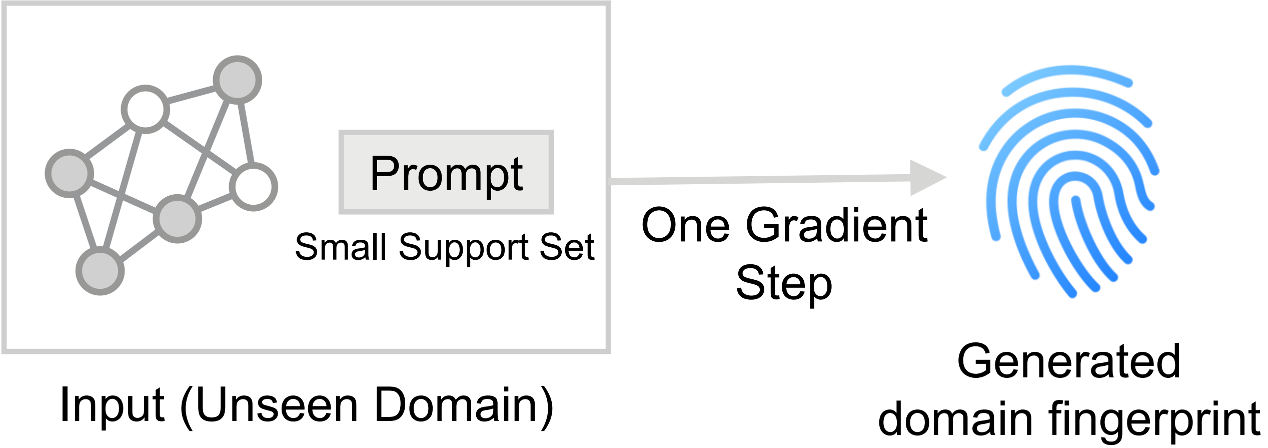
Fully Frozen Parameters



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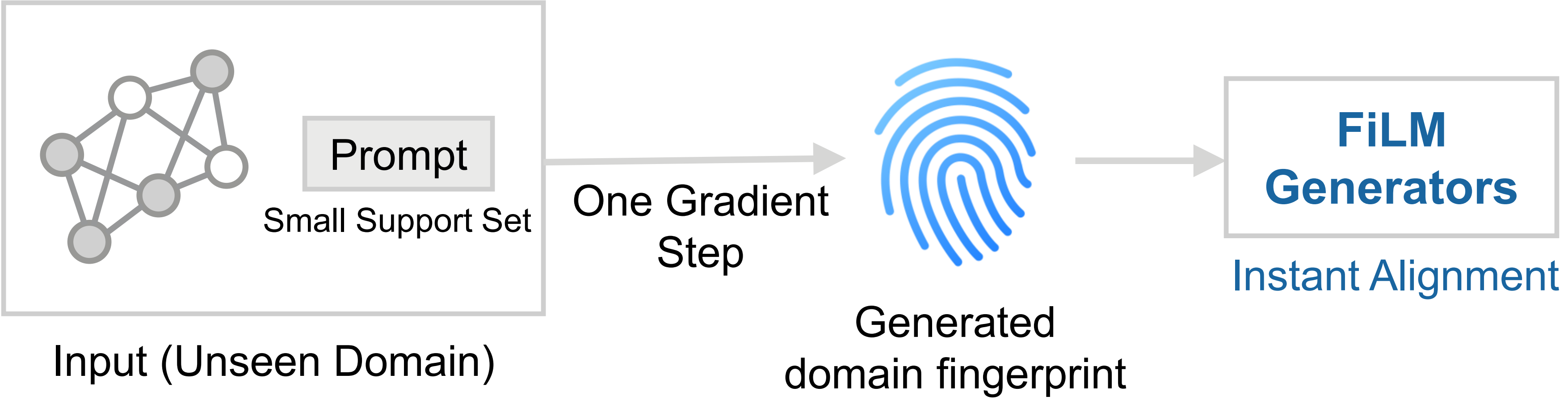

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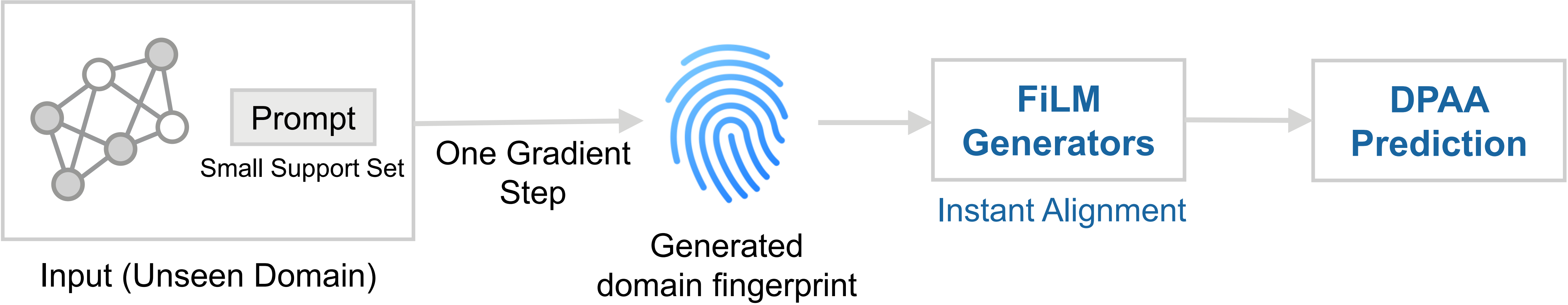

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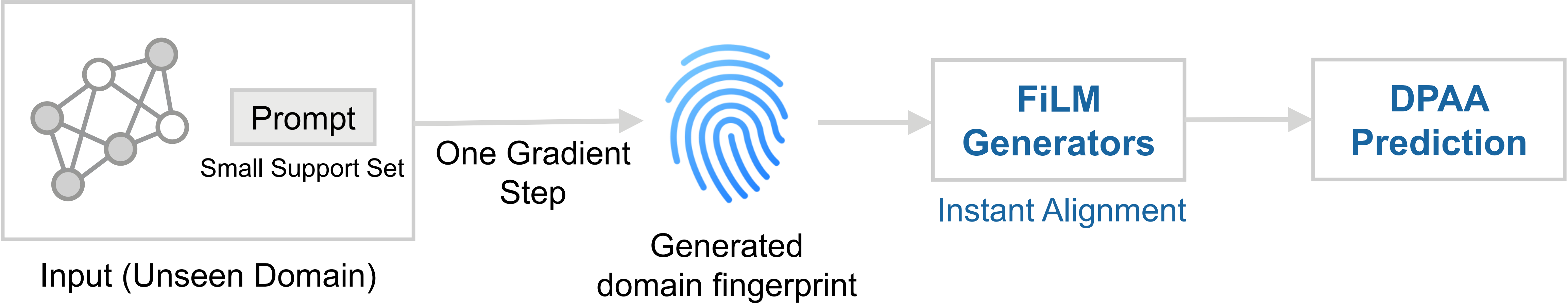

True In-Context Learning:

- Tuning-free ✓
- Cross-domain alignment ✓
- Modality-free ✓

The fingerprint automatically triggers the correct alignment for the new semantics of the unseen domain.

Few-shot Node-level Tasks

Model	Products (E-Commerce)	Physics (Co-Author)	BlogCatalog (Social Media)
SAGE+FT	9.42	77.36	58.03
Prodigy	11.46	79.47	53.44
GFT	15.43	--	--
OFA	8.66	--	--
MF-GIA	**22.61**	**88.92**	**67.31**

Few-shot Node-level Tasks

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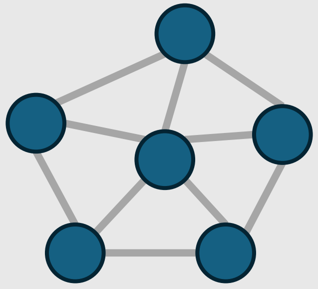
Existing TAG-based models cannot run on pre-encoded graphs without raw text data.

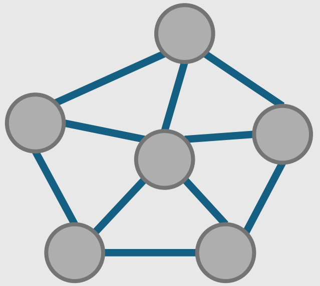
Generalization Beyond Task Types (Node → Edge)

Node
Classification



Task Transfer via
Line Graph Conversion

Edge
Classification

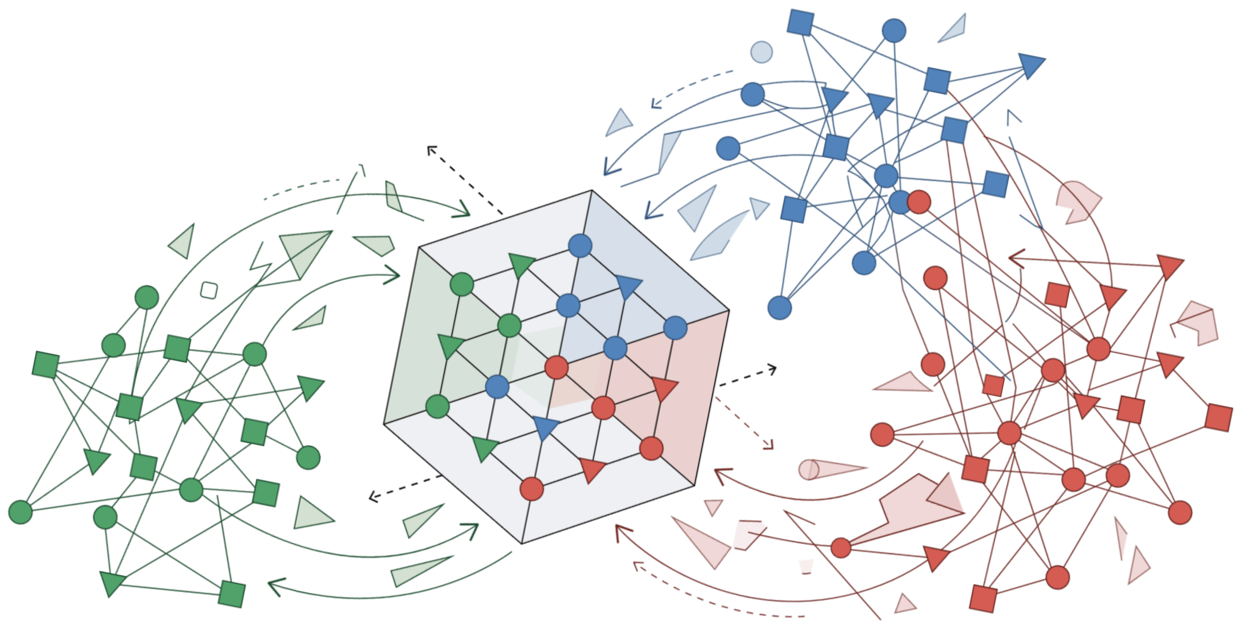


Pretraining: Node Tasks Only
Testing: Link Tasks (FB15K237, WN18RR)

Model	**Accuracy**
MAML	63.13%
Prodigy	71.45%
MF-GIA	**91.38%**

MF-GIA generalizes to entirely new structural reasoning tasks it never saw during pretraining.

Summary



Modality-Free
First framework to align graphs without metadata or TAG conversion.

Cross-Domain Alignment
Mapping heterogeneous cross-domain graphs to a unified space.

True Graph ICL
Requiring no fine-tuning or prompt learning at test time.

SOTA Performance
Superior performance on unseen graphs and across unseen tasks.