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XI'AN·CHINA

MGNN: A Multimodal Graph Neural Network for Predicting the Survival of Cancer Patients

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中南大學 CENTRAL SOUTH UNIVERSITY

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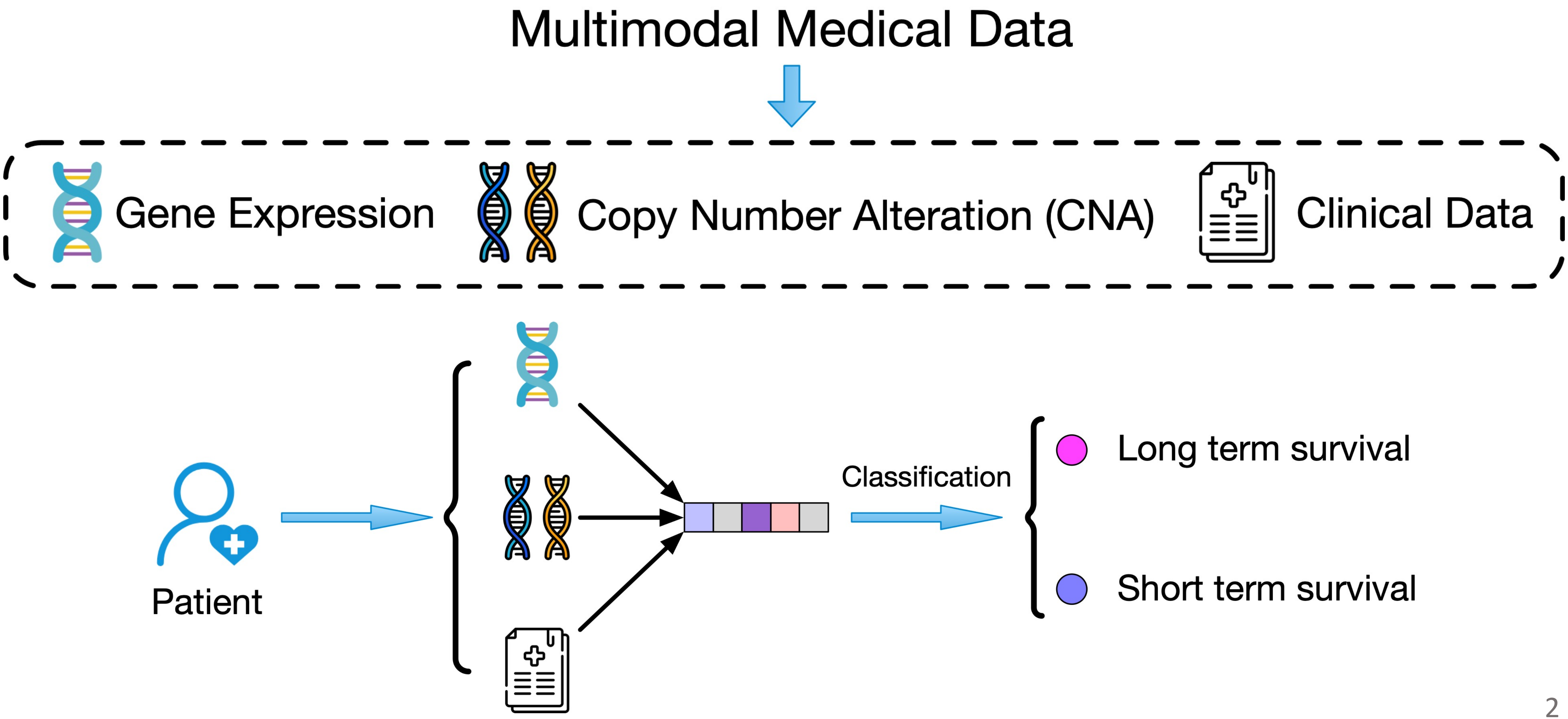
Alibaba Group

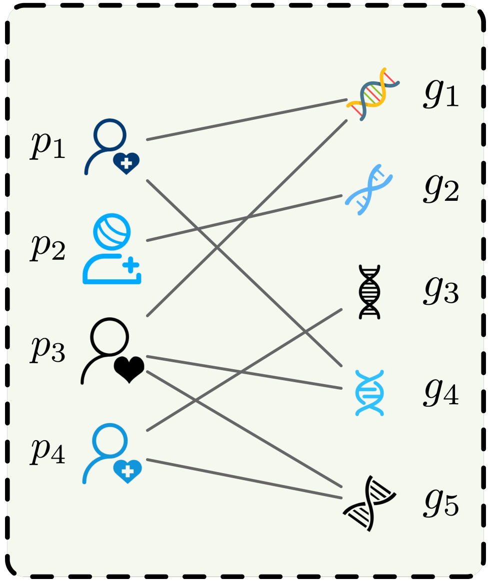
Task: Predicting the Survival of Cancer Patients

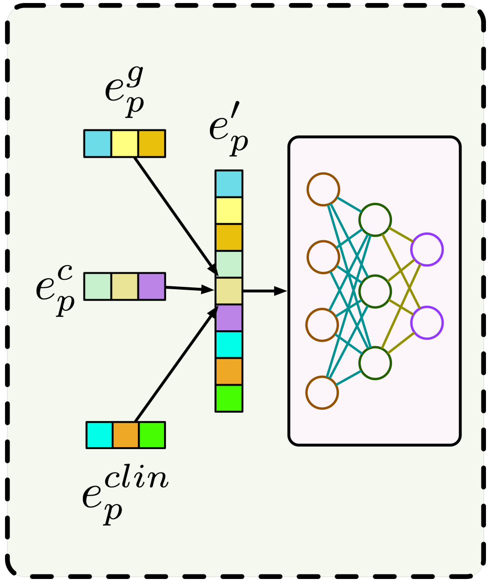


Motivation

➢ Problems:

- Cancer prognosis prediction: critical, complex and urgent tasks
- The structure information between patients and multimodal medical data
- The features of medical data from different modalities

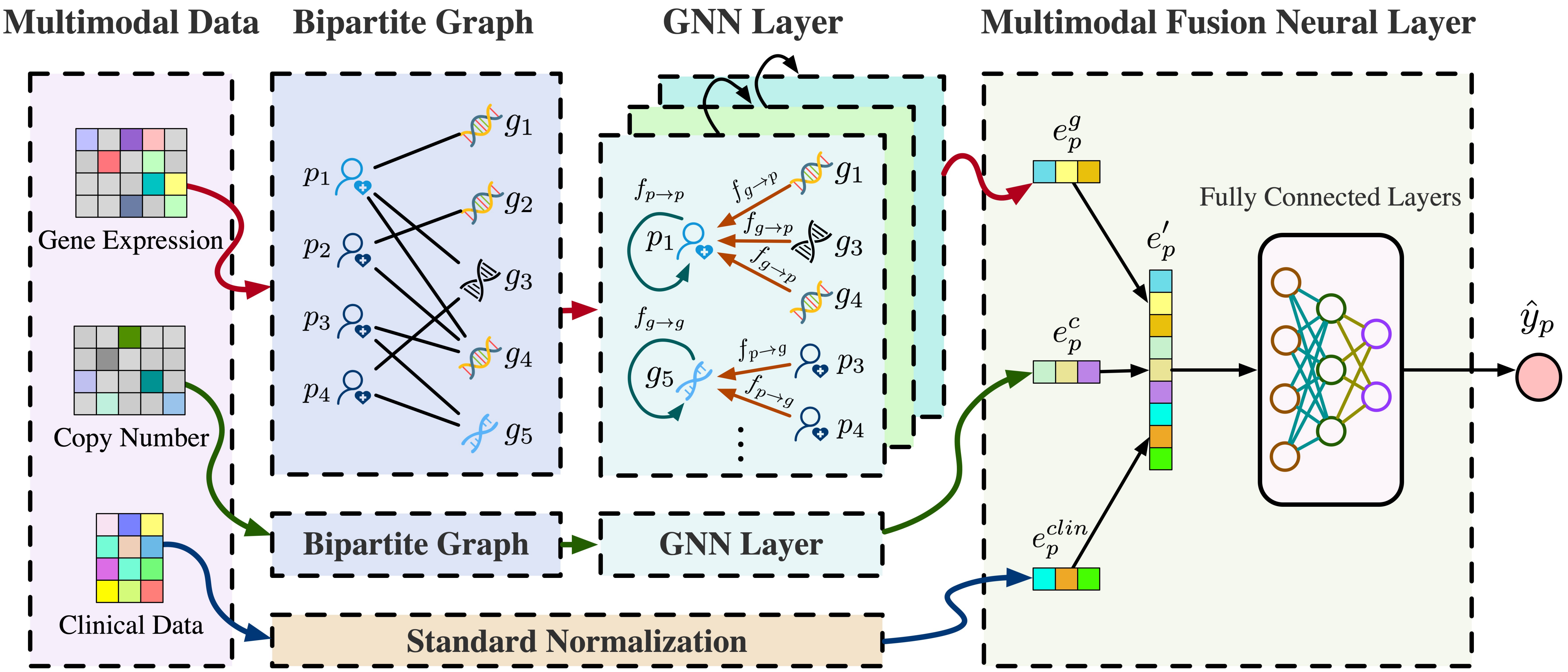




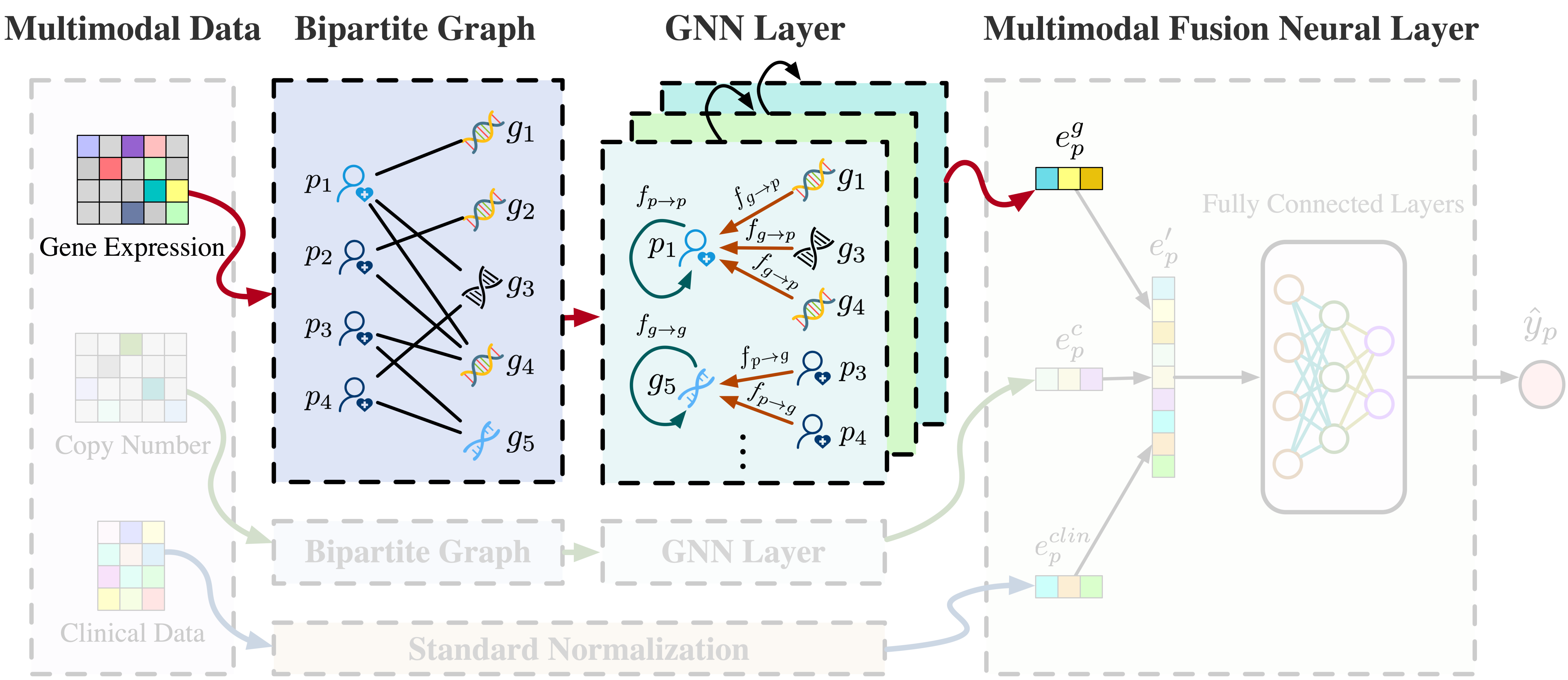
➢ Solutions:

- Building the graph
- Multimodal fusion representation

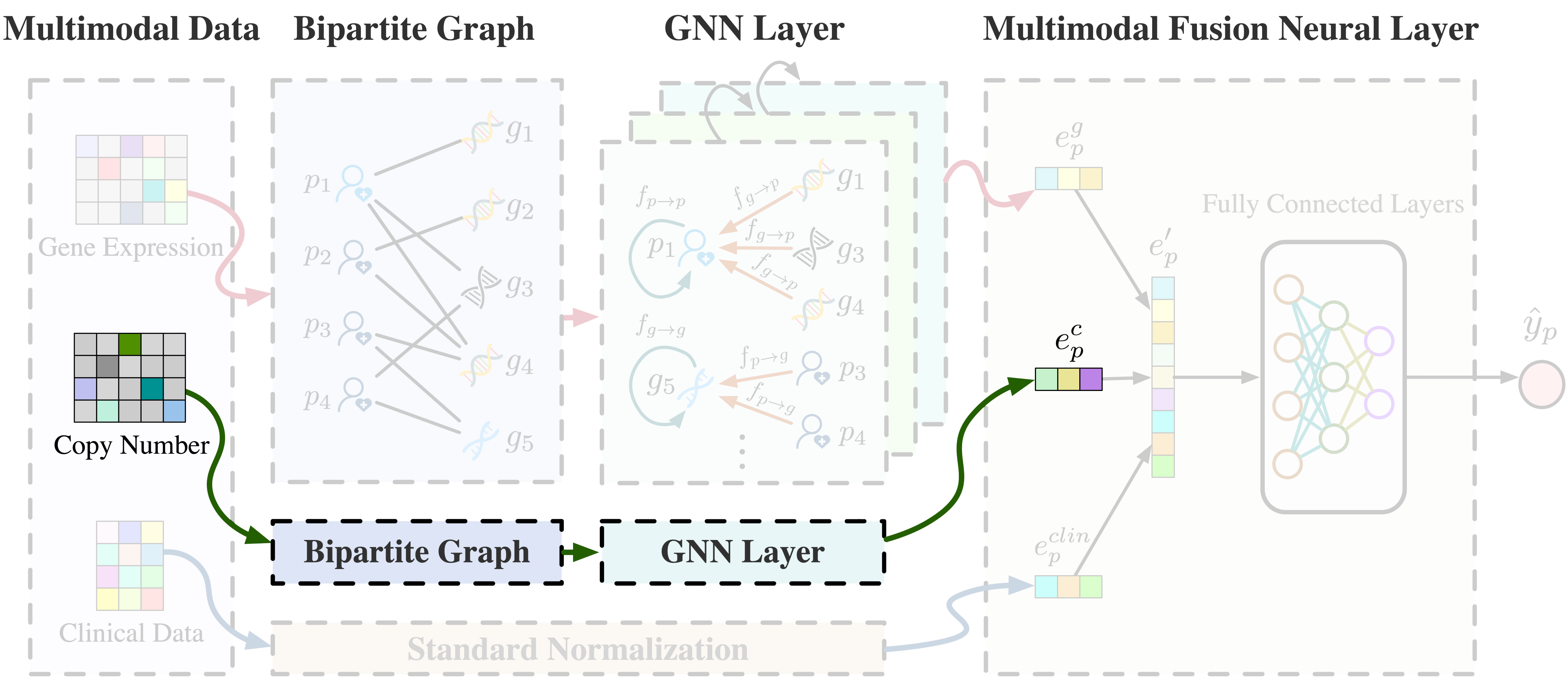
Framework of MGNN



Framework of MGNN



Framework of MGNN



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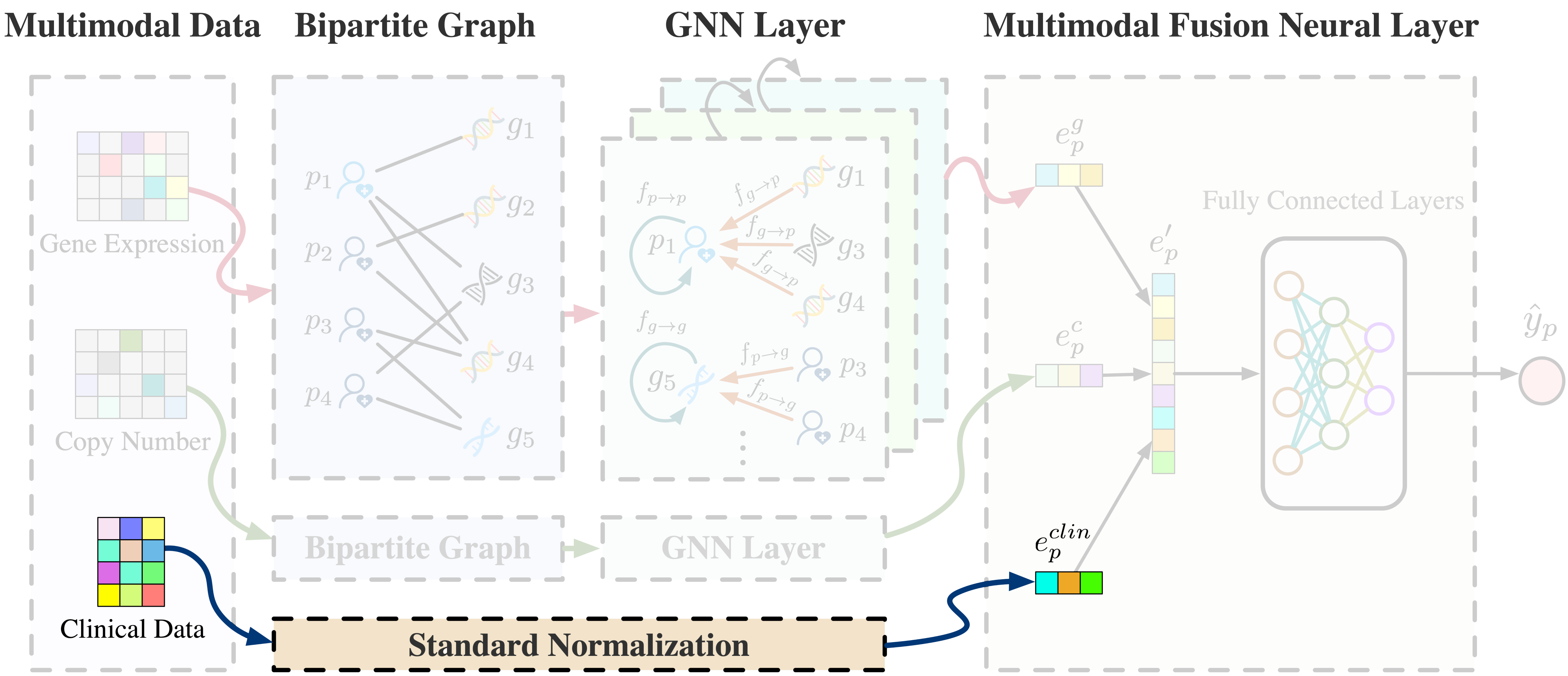

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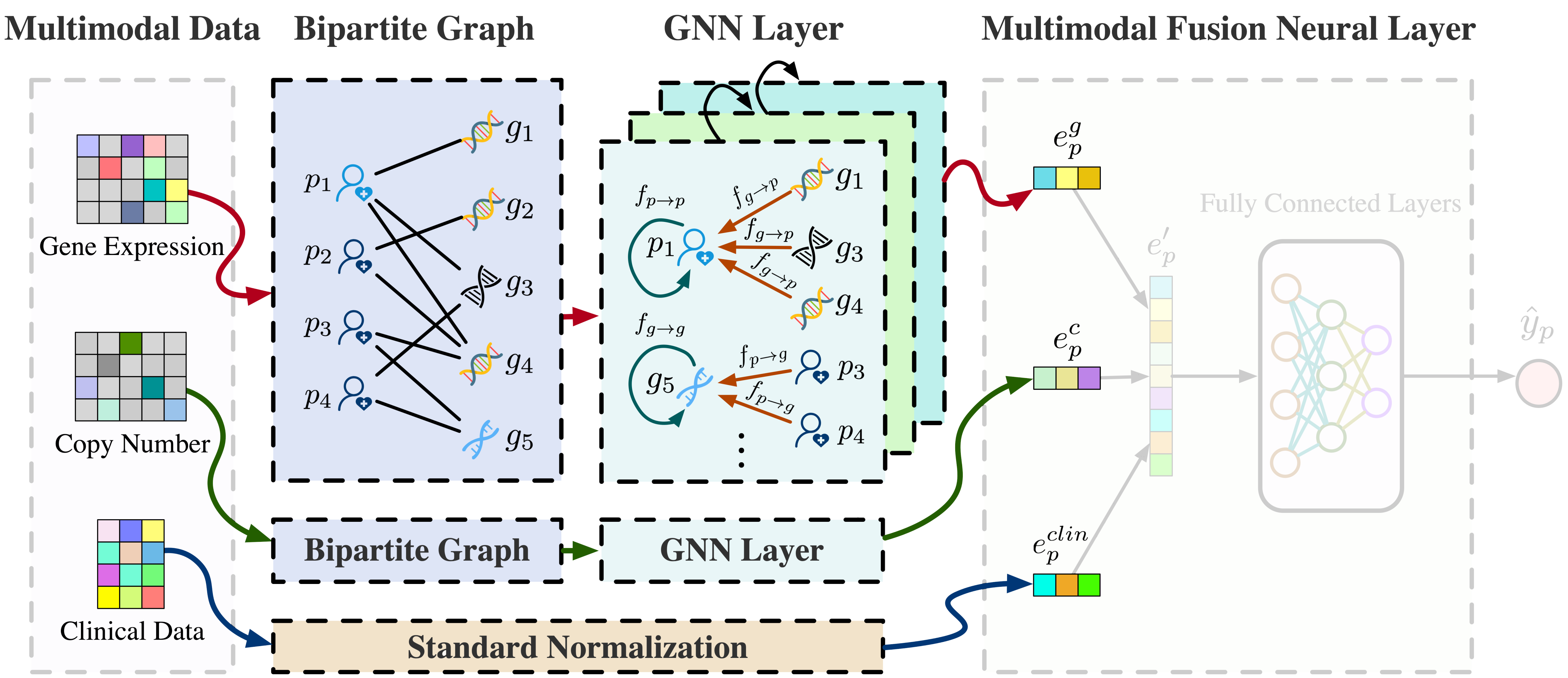

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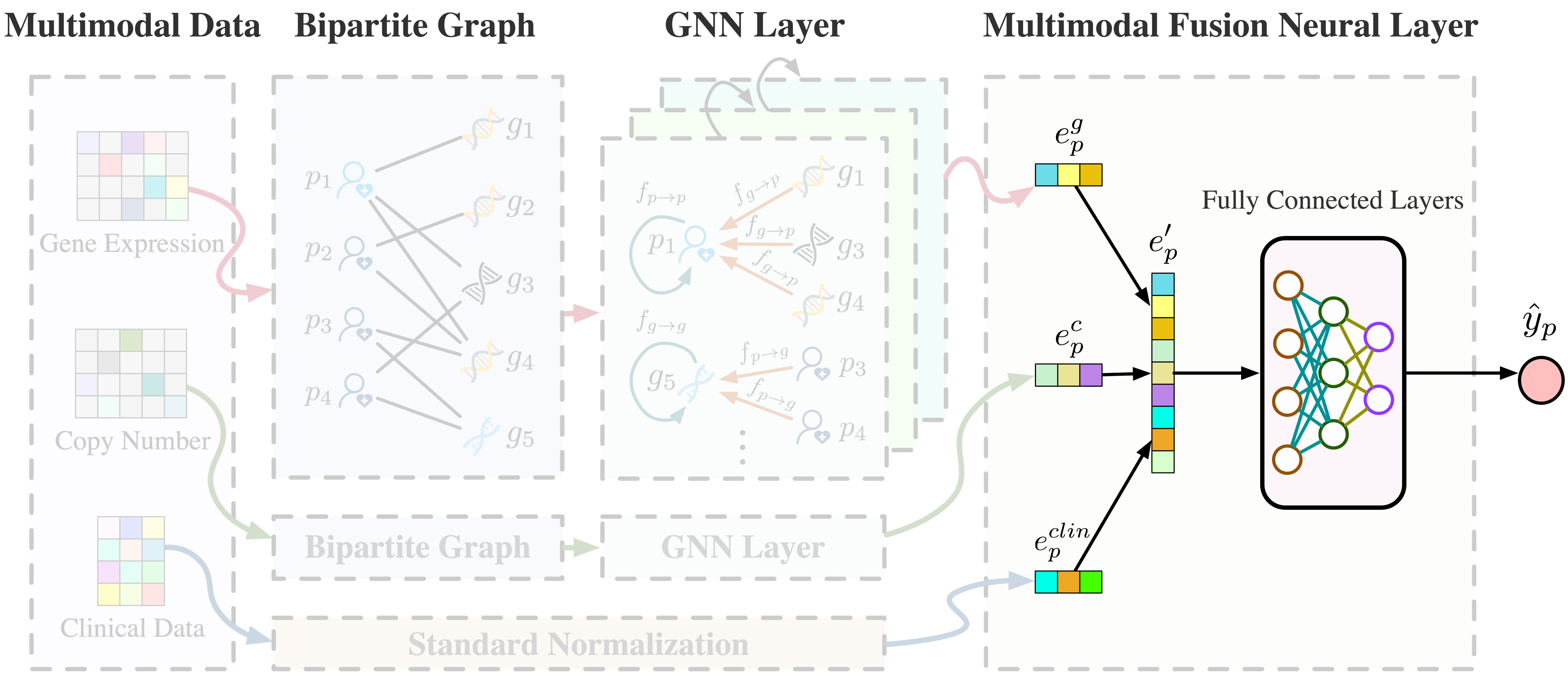
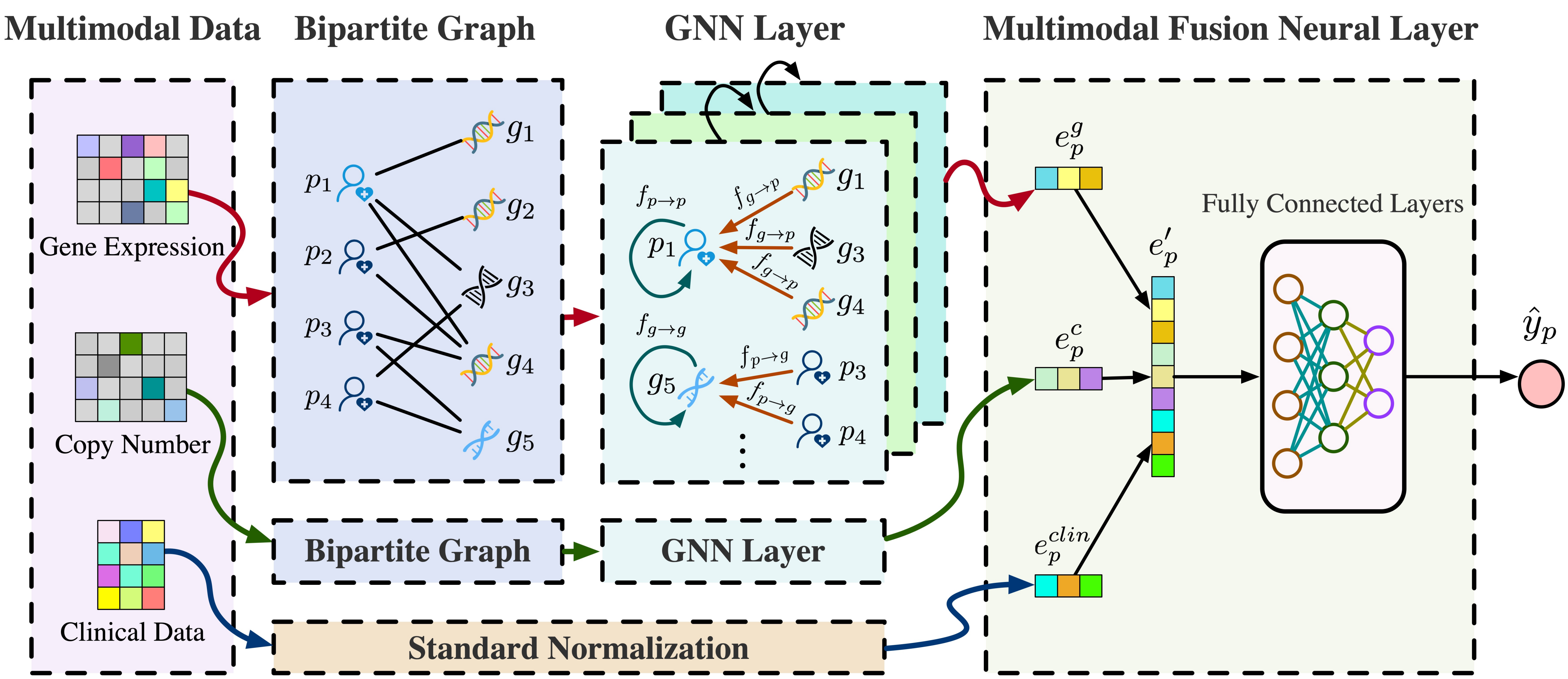
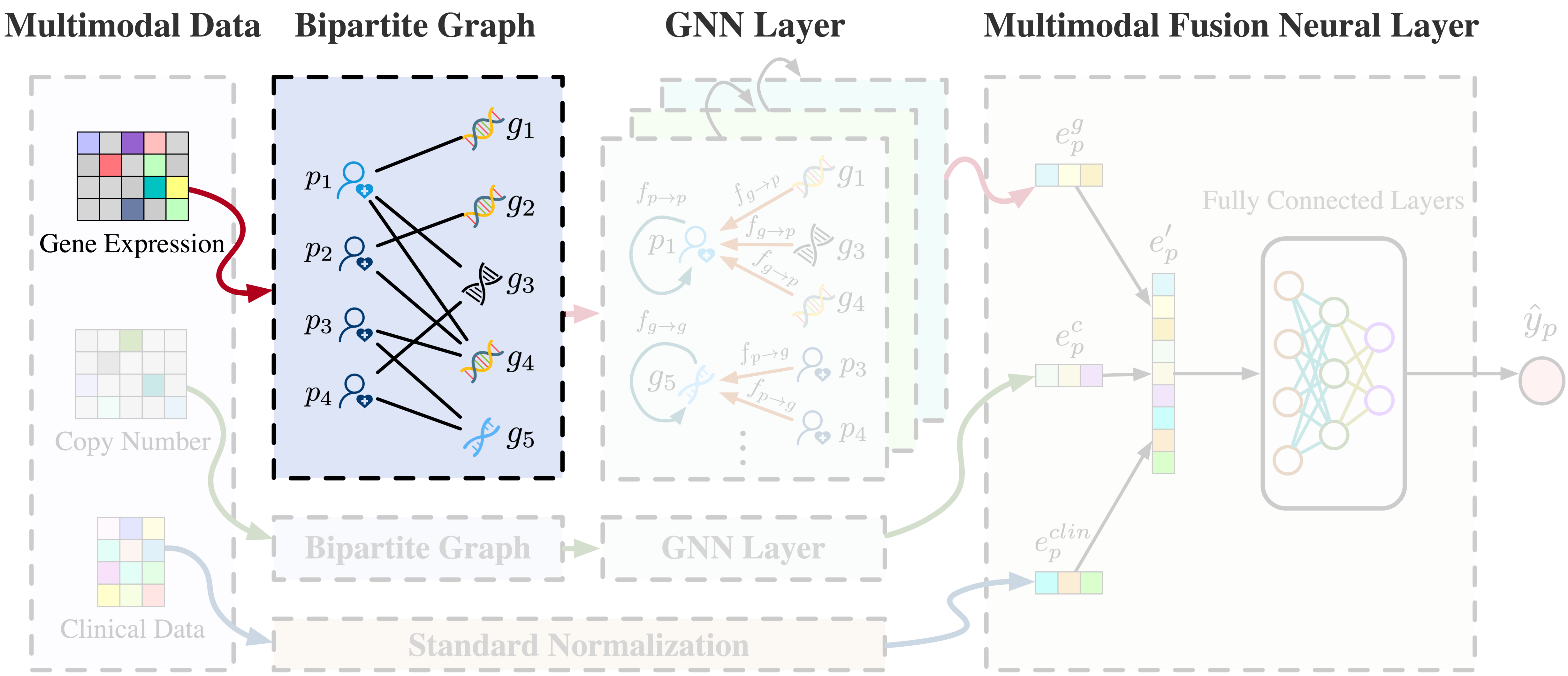


Framework of MGNN



Step 1: Building the Bipartite Graph



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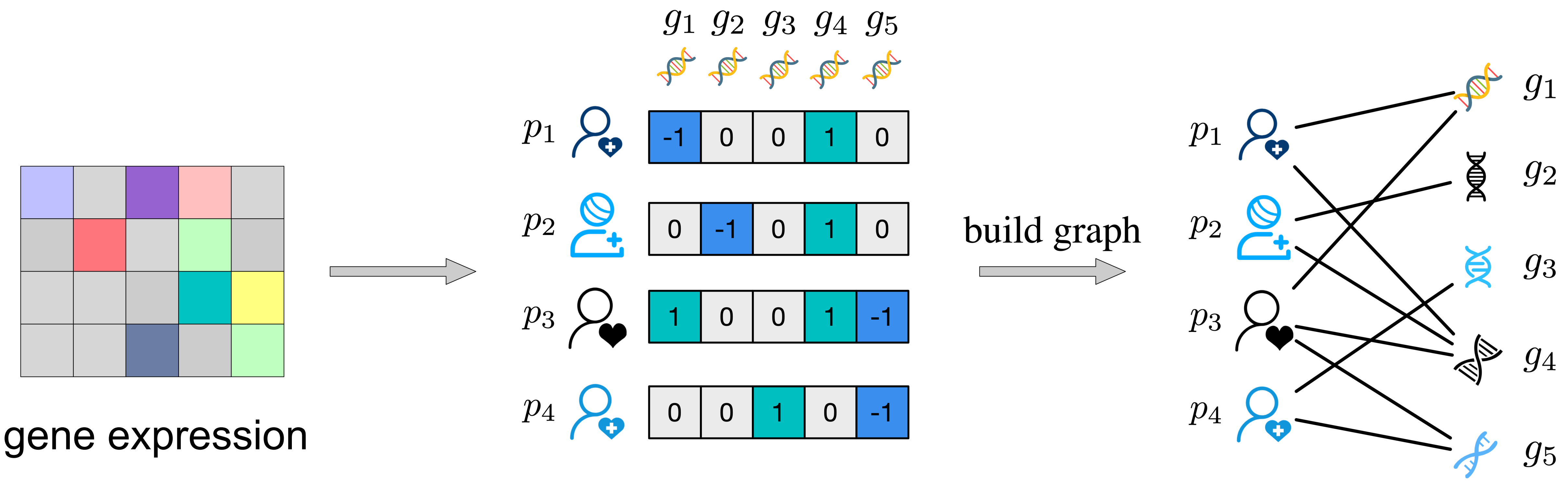
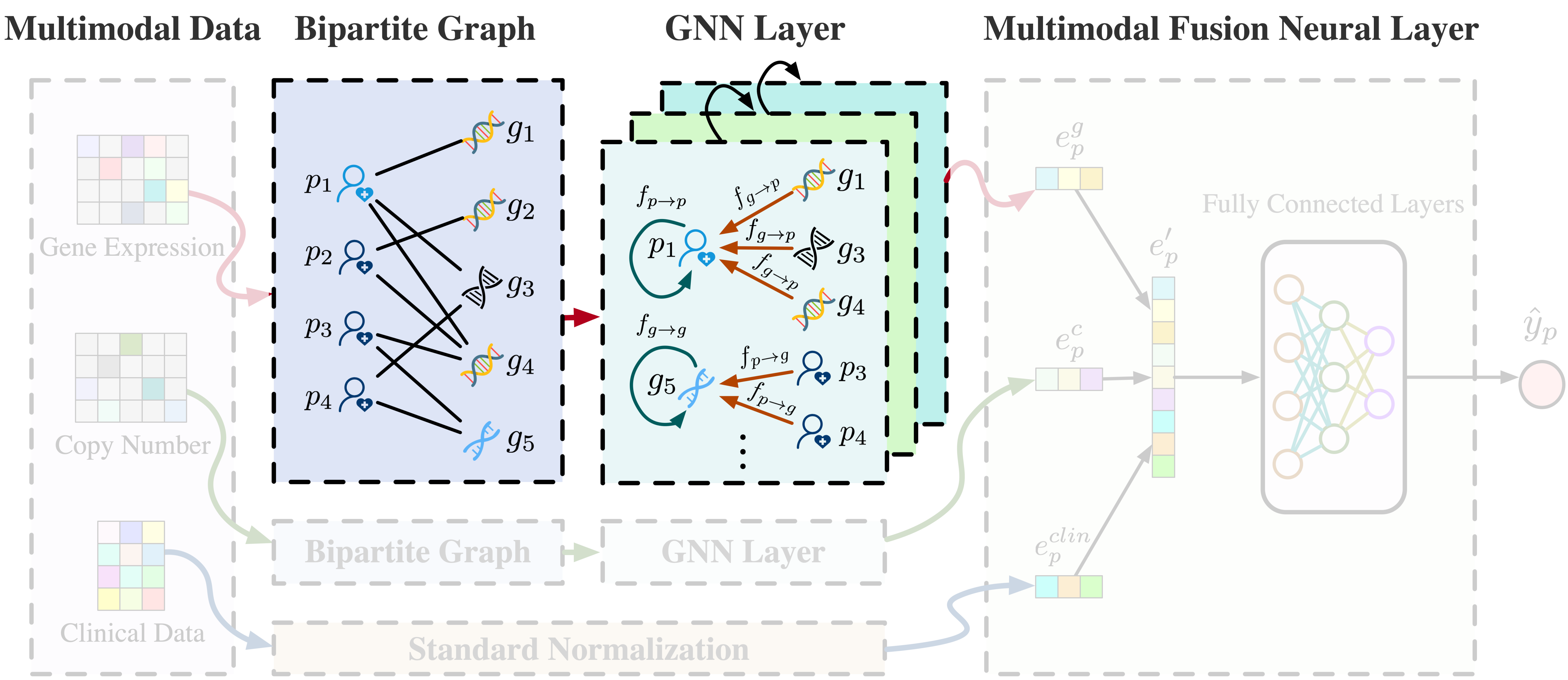


Step 2: Messages Propagation



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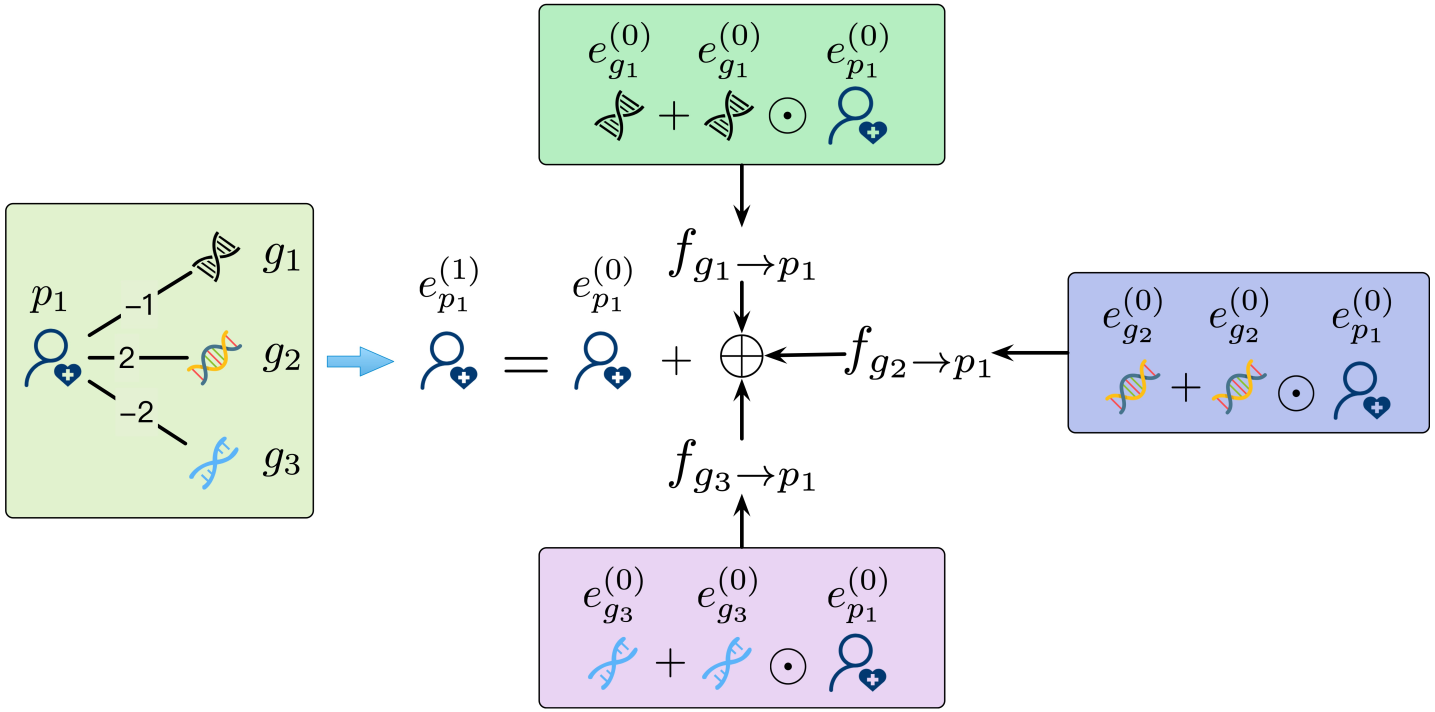
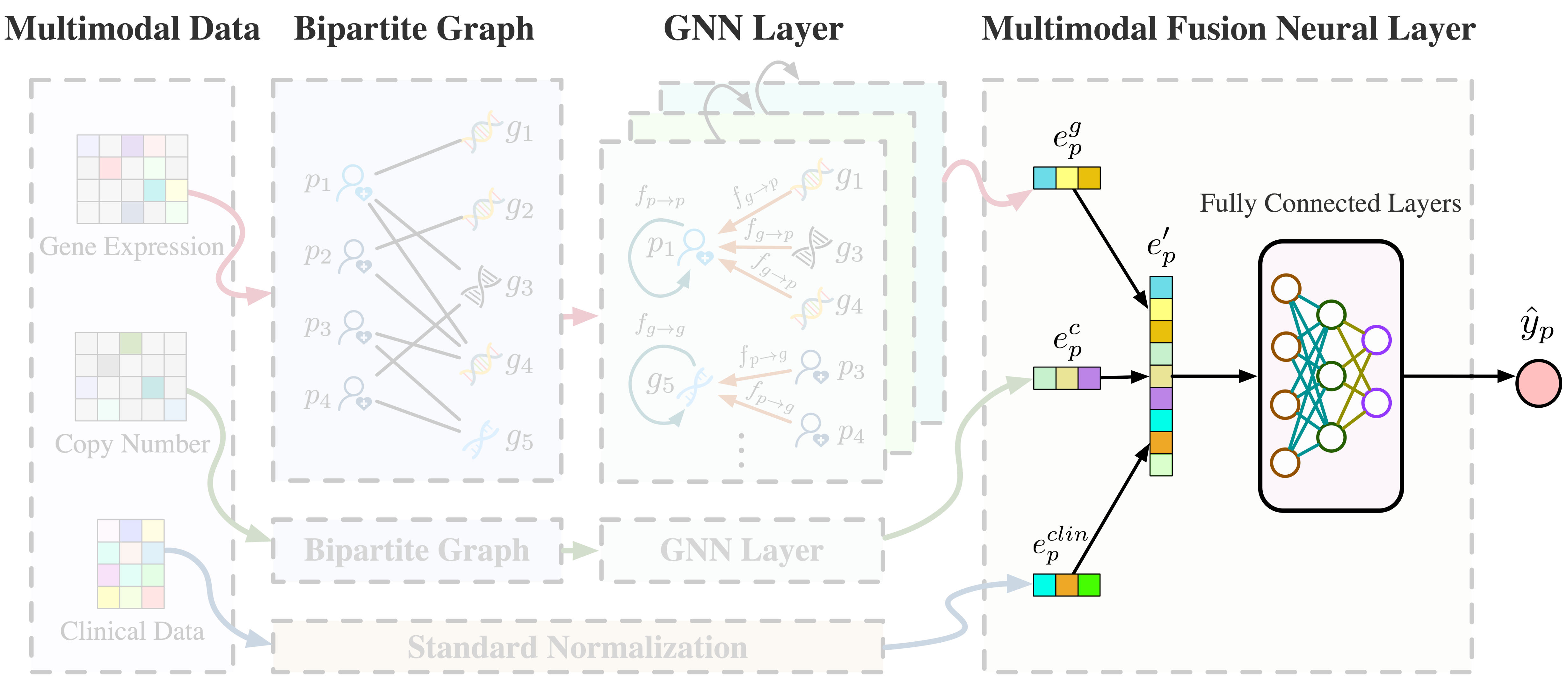


$$e_p^{(l+1)} = \sigma\left(f_{p\to p}(e_p^{(l)}) + \sum_{g \in \mathcal{N}_p} f_{g\to p}(e_p^{(l)}, e_g^{(l)})\right)$$

$$\begin{cases} f_{p\to p}(e_p^{(l)}) = W_1^{(l)} e_p^{(l)} \\ f_{g\to p}(e_p^{(l)}, e_g^{(l)}) = (W_1^{(l)} e_g^{(l)} + W_2^{(l)} (e_g^{(l)} \odot e_p^{(l)})) \end{cases}$$

Step 3: Multimodal Fusion Representation



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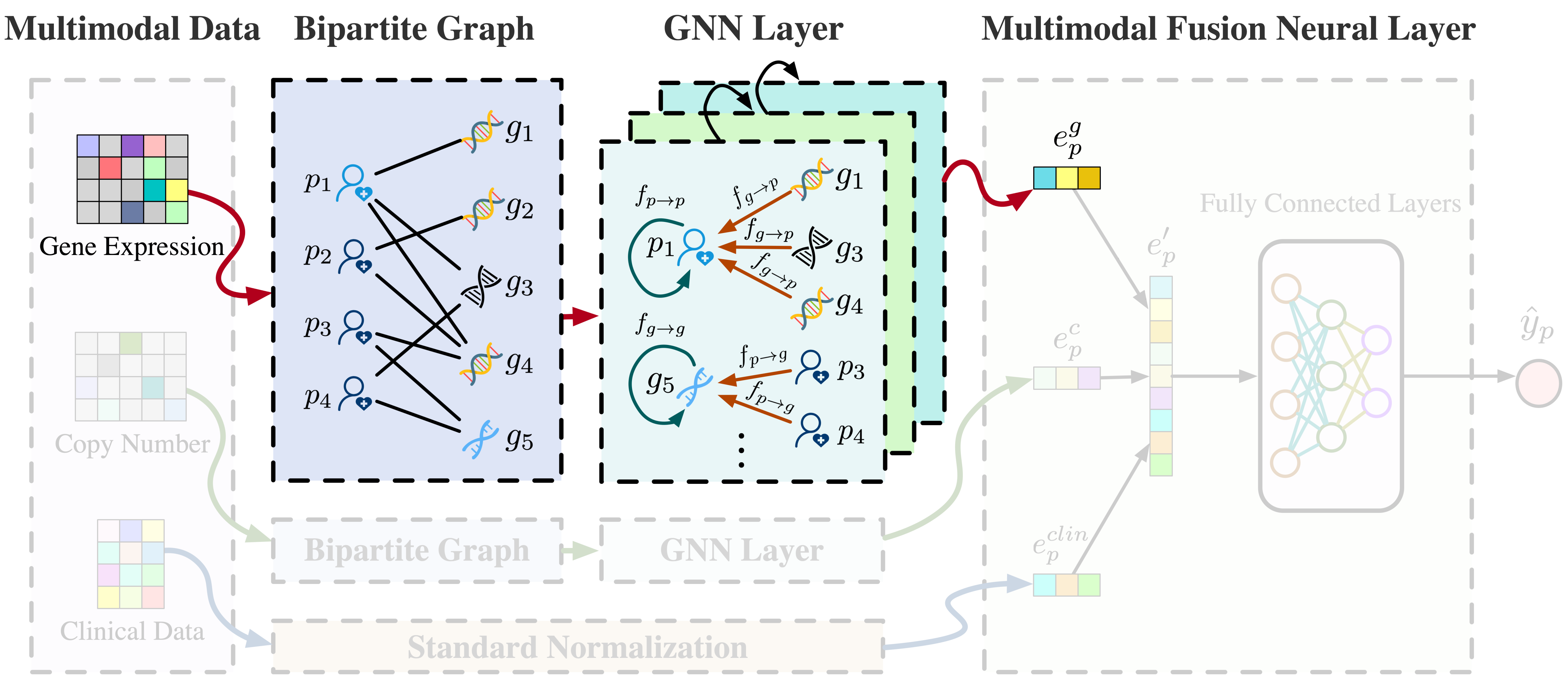

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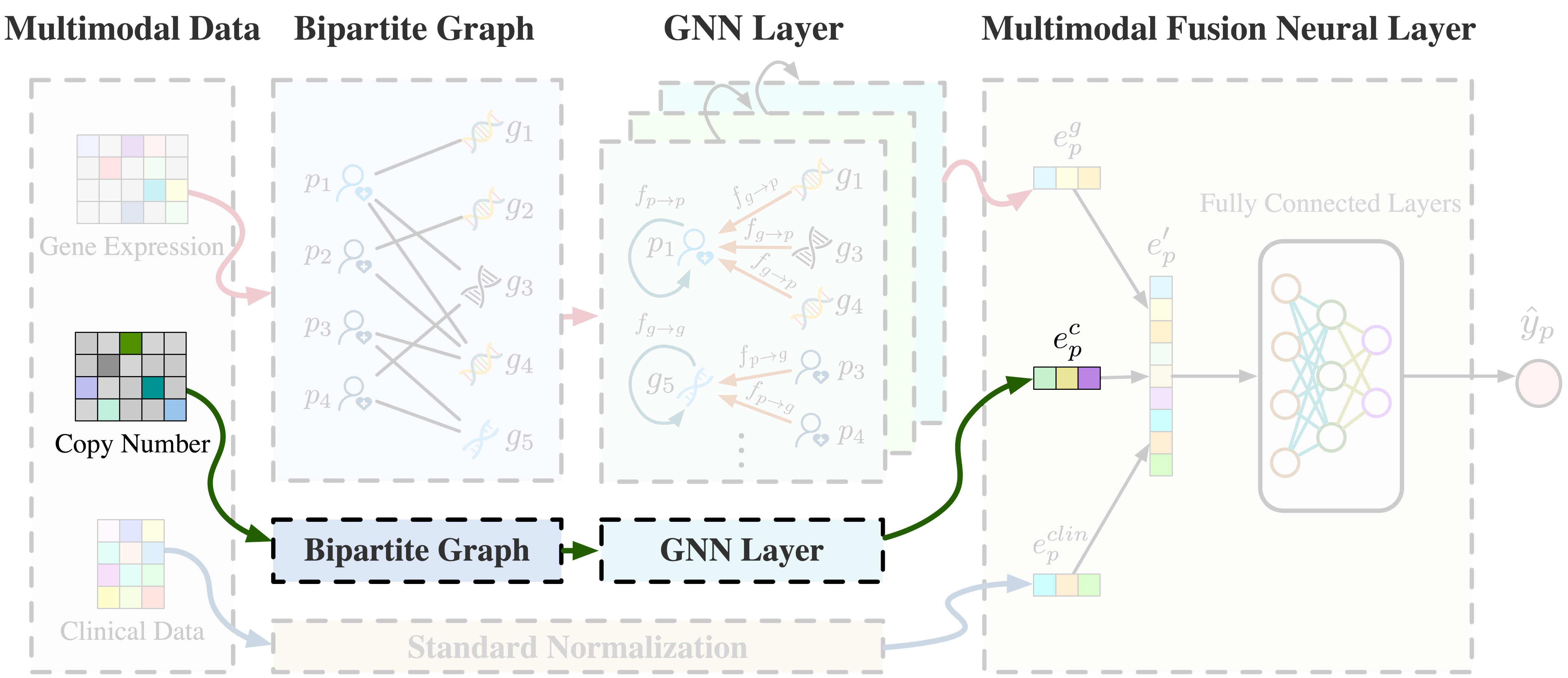

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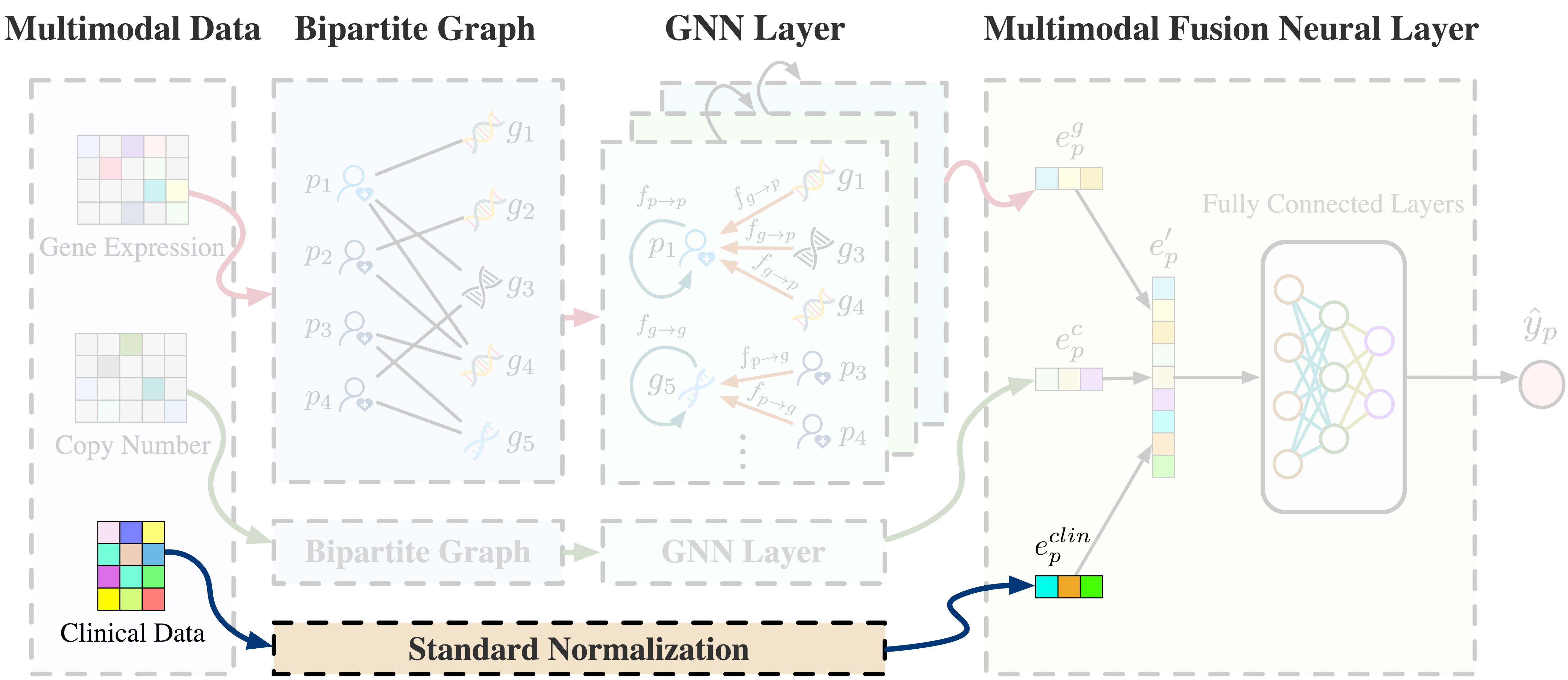

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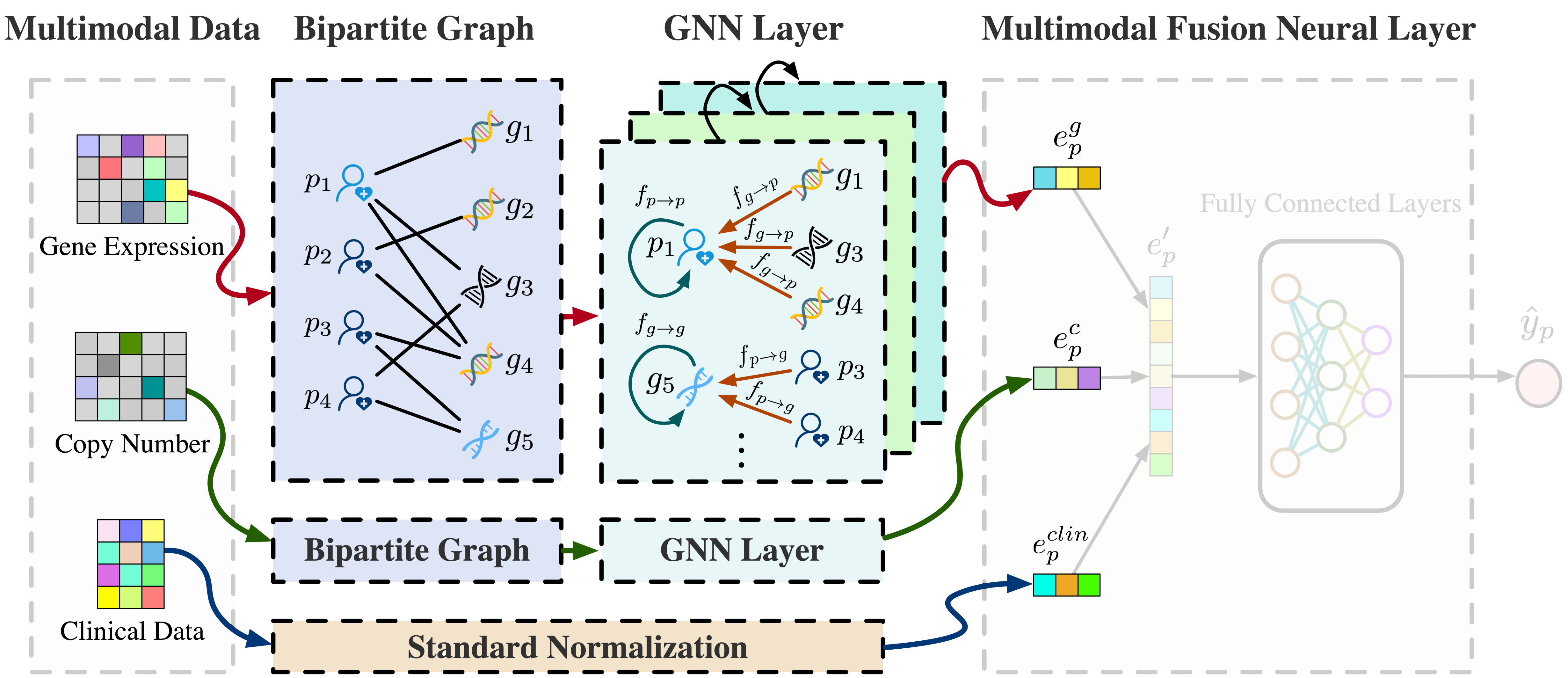

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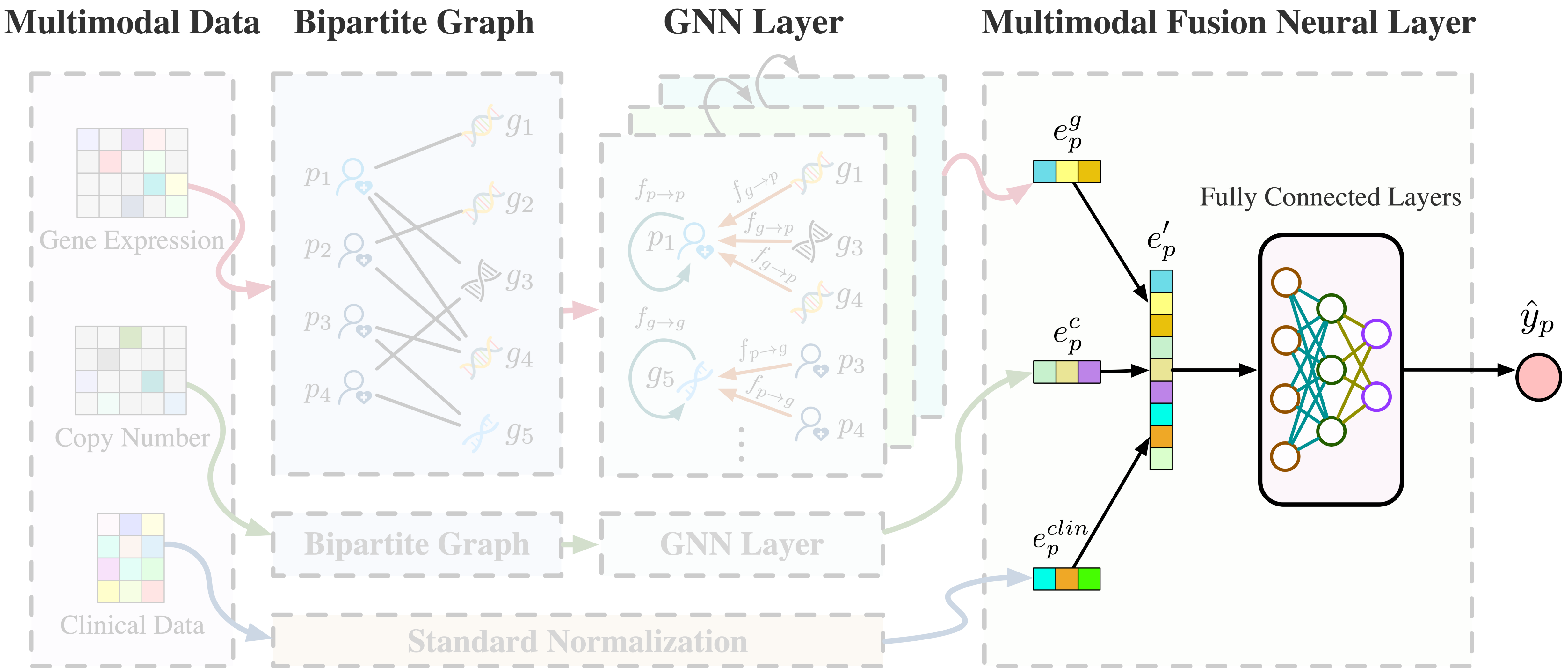


Experiments & Results

➢ Performance Comparison

- We compare our results with MDNNMD[1], SVM, RF and LR on breast cancer dataset[2].

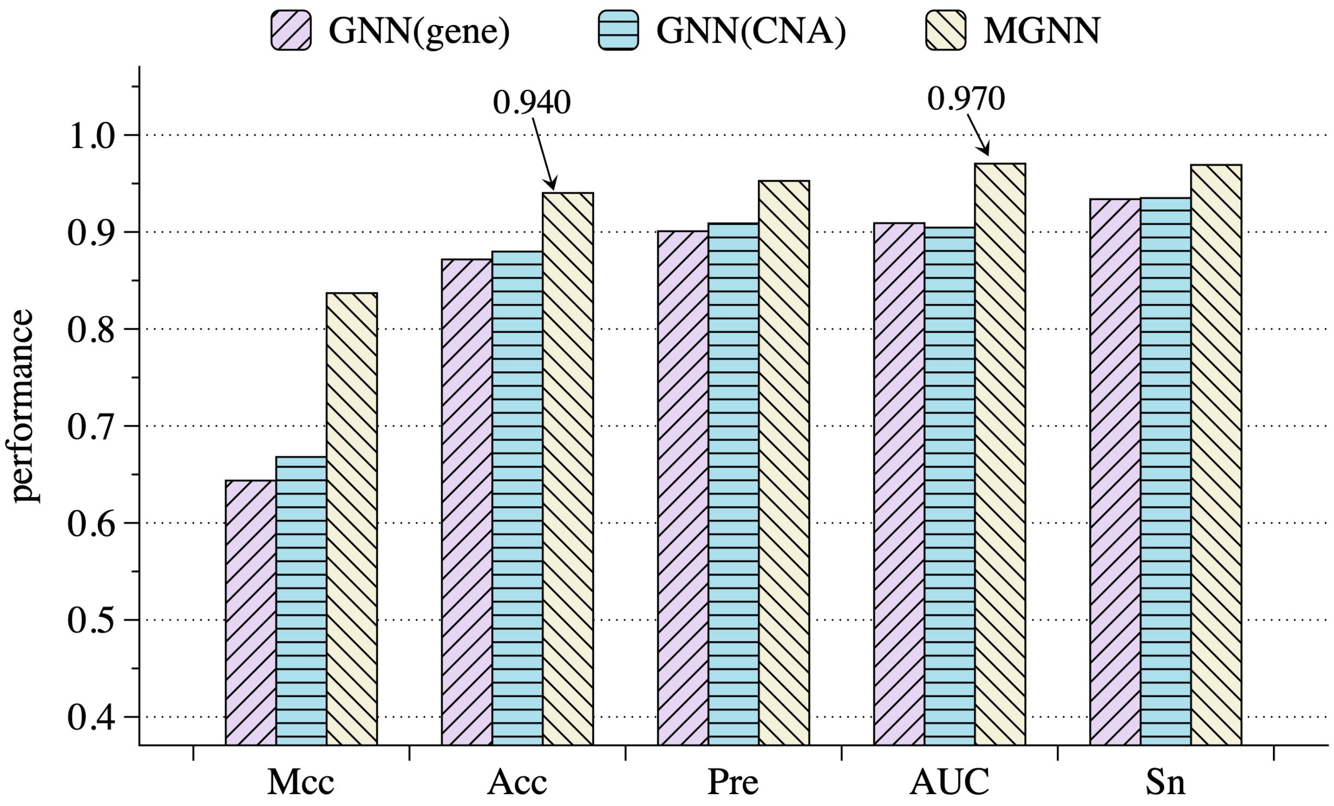
Methods	Acc	Pre	Sn	Mcc	AUC
LR	0.760	0.549	0.183	0.209	0.663
RF	0.791	0.766	0.226	0.337	0.801
SVM	0.805	0.708	0.365	0.407	0.810
MDNNMD	0.826	0.749	0.450	0.486	0.845
MGNN	**0.940**	**0.953**	**0.969**	**0.837**	**0.970**

[1]Dongdong Sun, et al. A multimodal deep neural network for human breast cancer prognosis prediction by integrating multi-dimensional data. TCBB, 16(3):841– 850, 2018.
[2]Datasets are available at https://www.cbioportal.org/

Experiments & Results

➢ Ablation Test

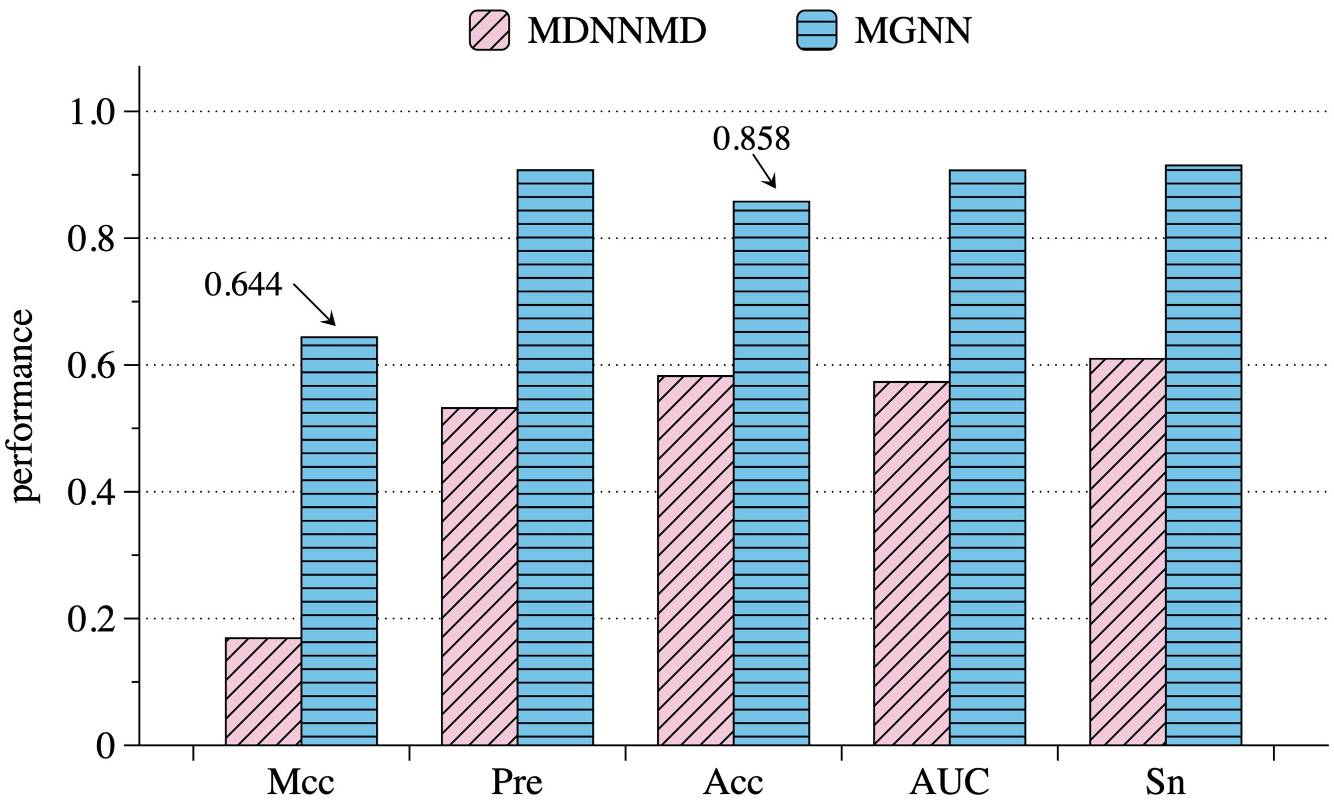
- MGNN: multimodal fusion representation
- GNN (gene) and GNN (CNA): single multimodality



Experiments & Results

➢ Robustness Verification

- MGNN: multimodal fusion representation for lung cancer patients[3]
- MDNNMD: Compared method



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Summarization

- highlight the critical importance of explicitly exploiting the multimodal data, and structure information between patients and multimodal medical data.

- propose a unified framework for cancer survival prediction.

- Achieve state-of-the-art results on cancer survival prediction.

Thank You