基于图神经网络的无线网络资源优化技术

RISTA前沿大讲堂

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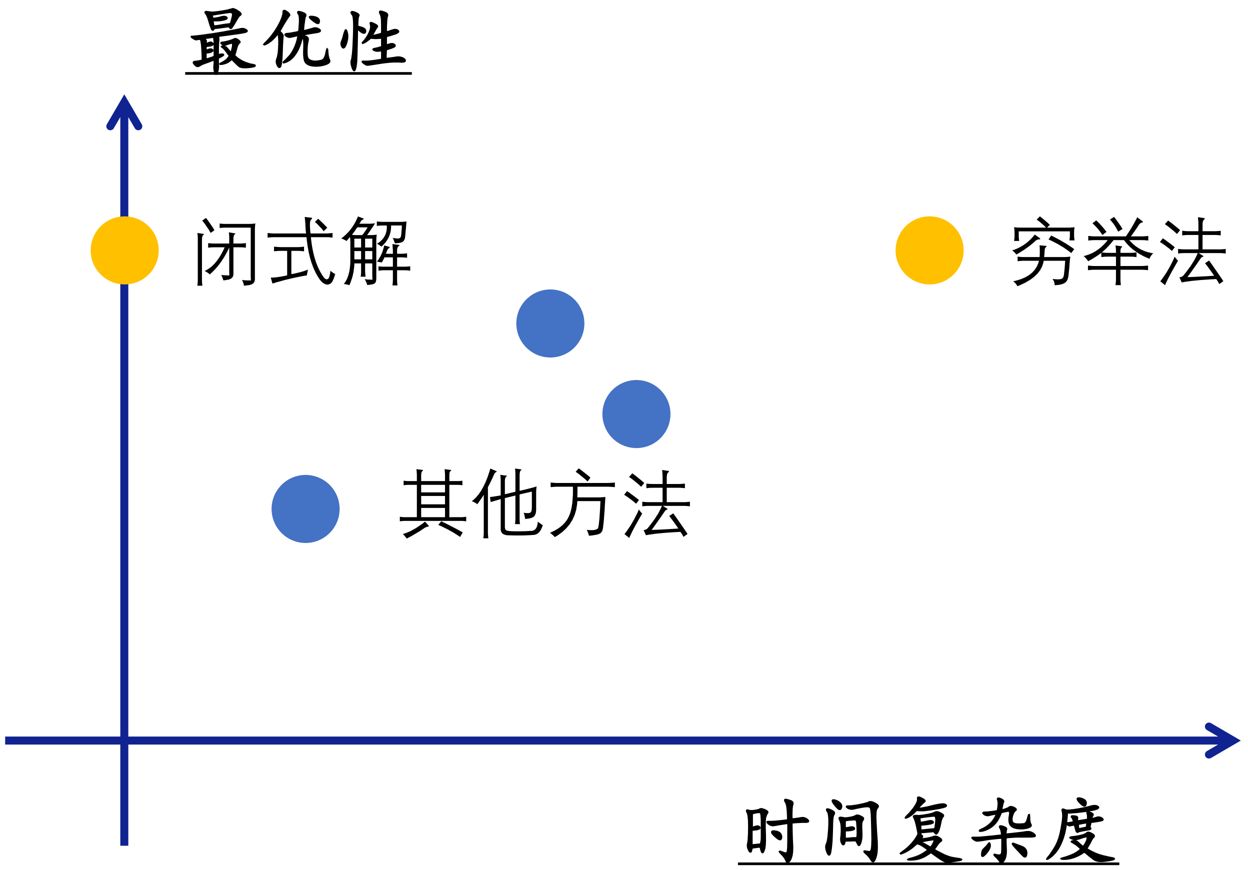
@Learning & Optimization in Networks Lab.

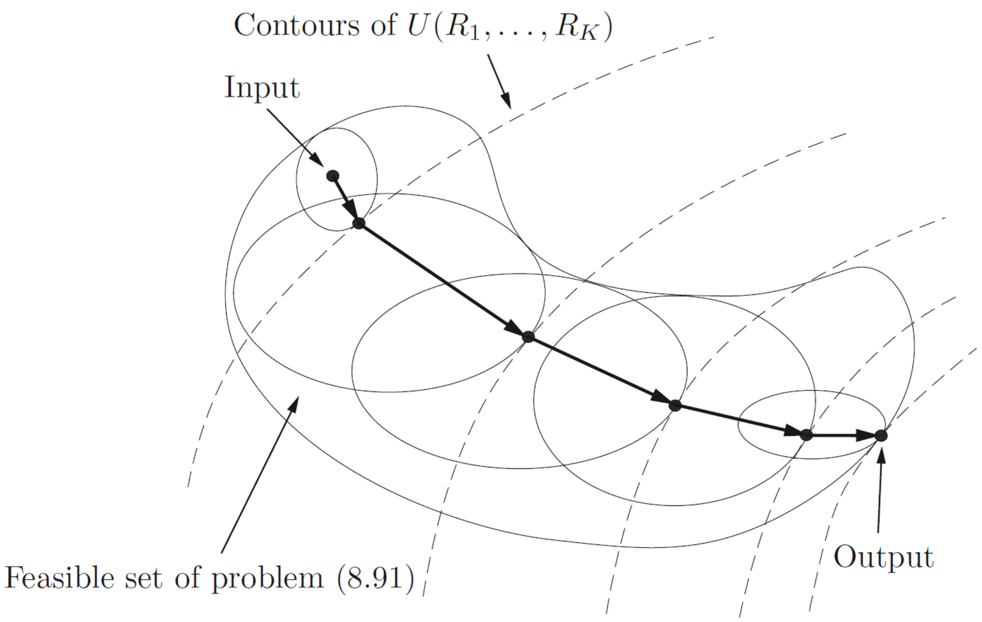
目录

1. **Y. Lu**, Y. Li, R. Zhang, W. Chen, B. Ai, and D. Niyato, “Graph neural networks for wireless networks: Graph representation, architecture and evaluation,” IEEE Wireless Communications Magazine, 2024.

1/ 无线资源分配问题与图神经网络

对于一个复杂优化问题：





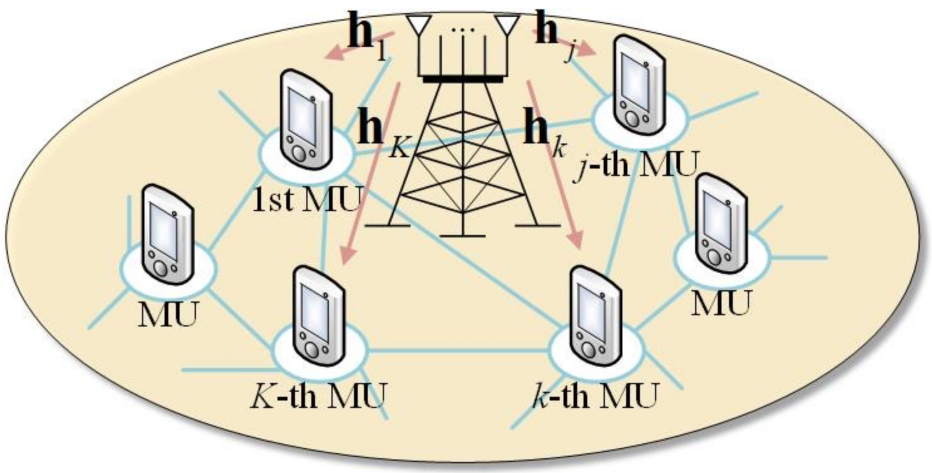
迭代次数

收敛结果

效率 VS 效果

无记忆方法很难兼顾
效果与效率

1/ 无线资源分配问题与图神经网络



典型MU-MISO系统

无线资源分配问题

$$\max_{\{\mathbf{w}_i\}} \mathrm{EE}\left(\{\mathbf{w}_i\}\right)$$

$$\text{s.t.} \ \ \|\mathbf{w}_i\|_2^2 \le P_i,$$

$$\mathbf{w}_i \in \mathbb{C}^{N_\mathrm{T}}, \forall i \in \mathcal{K}.$$

深度学习算法思路：
训练神经网络近似传统优化算法

万能近似定理（**Universal Approximation theorem**）：
神经网络可以以任意精度近似任何一个定义在实数空间中的有界闭集函数。

输入：信道状态信息 → 传统优化算法 → 输出：最优波束向量

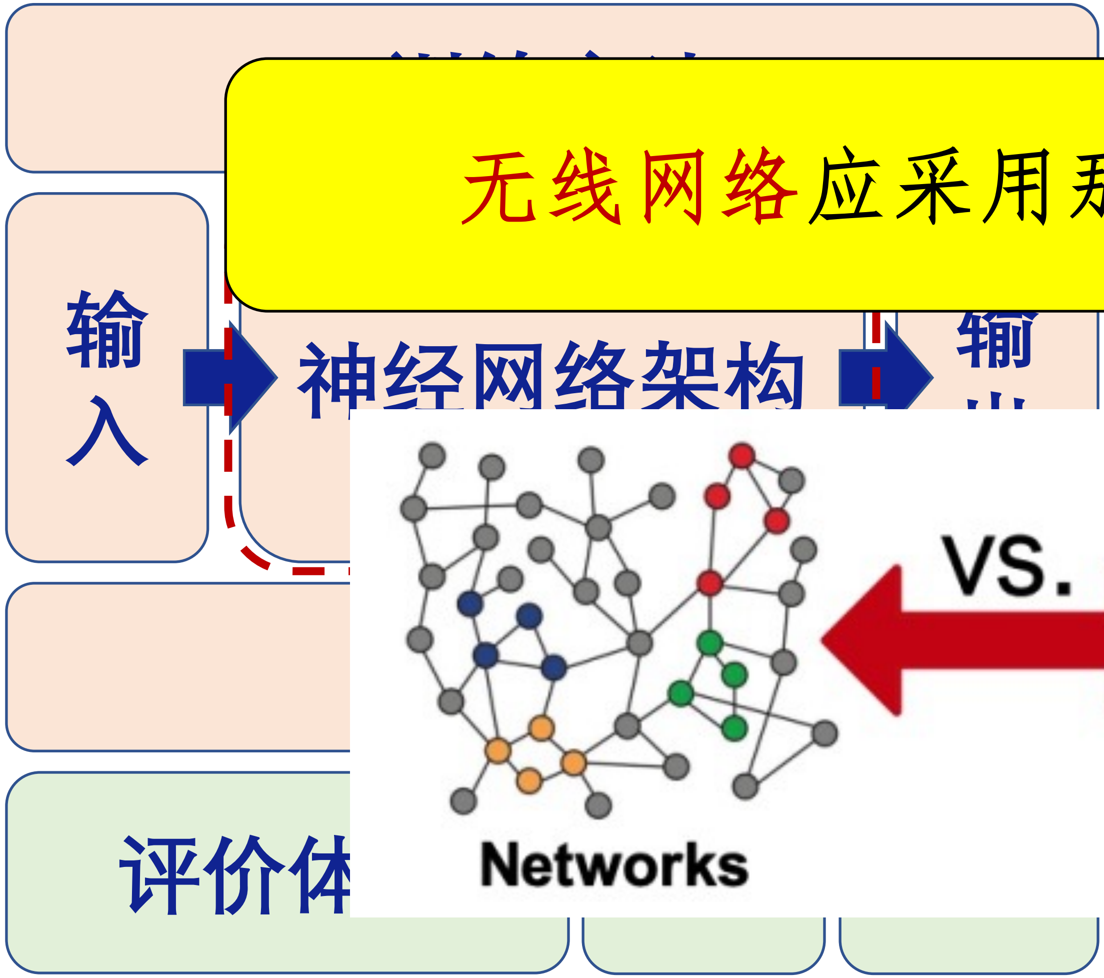
传统优化算法思路：
将非凸问题转化为凸问题，再使用迭代算法求解

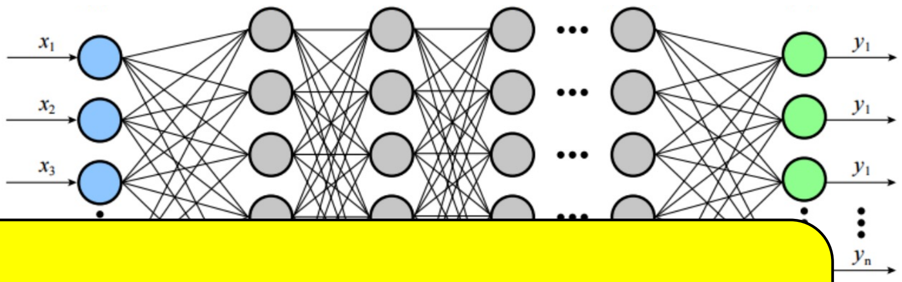
Algorithm 1: BSUM-based algorithm for Problem P_0

```
Initialize {w_i[0]} satisfying (4a);
Set t = 1;
while |Opt[t] − Opt[t − 1]|/Opt[t] > ε do
    Update k = (t − 1 mod K) + 1;
    Initialize λ[0] with F(λ[0]) ≥ 0;
    Set q = 0;
    while F(λ[q]) ≥ ε do
        Obtain w*_k[q] by solving Problem P_2;
        Update F(λ[q]) by (9). Update λ[q + 1] by (8);
        Update q = q + 1;
    Update w_k[t] = w*_k[q];
    Update w_j[t] = w_j[t − 1] for j ≠ k;
    Update Opt[t] = EE({w_i[t]});
    Update t = t + 1;
```

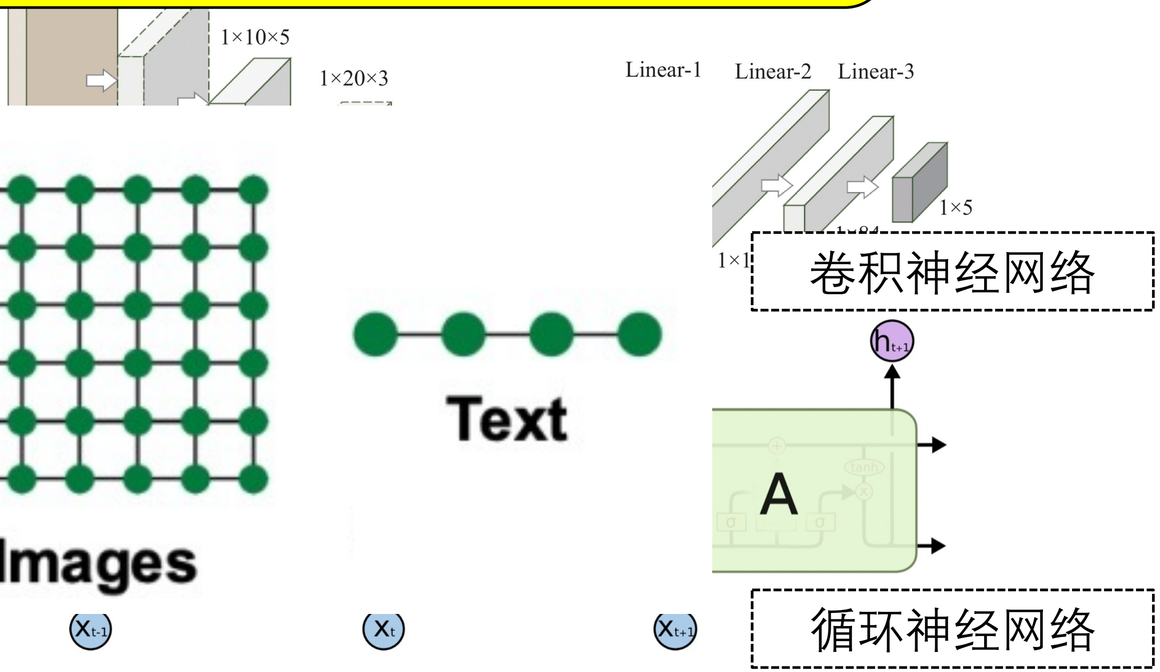
1/ 无线资源分配问题与图神经网络

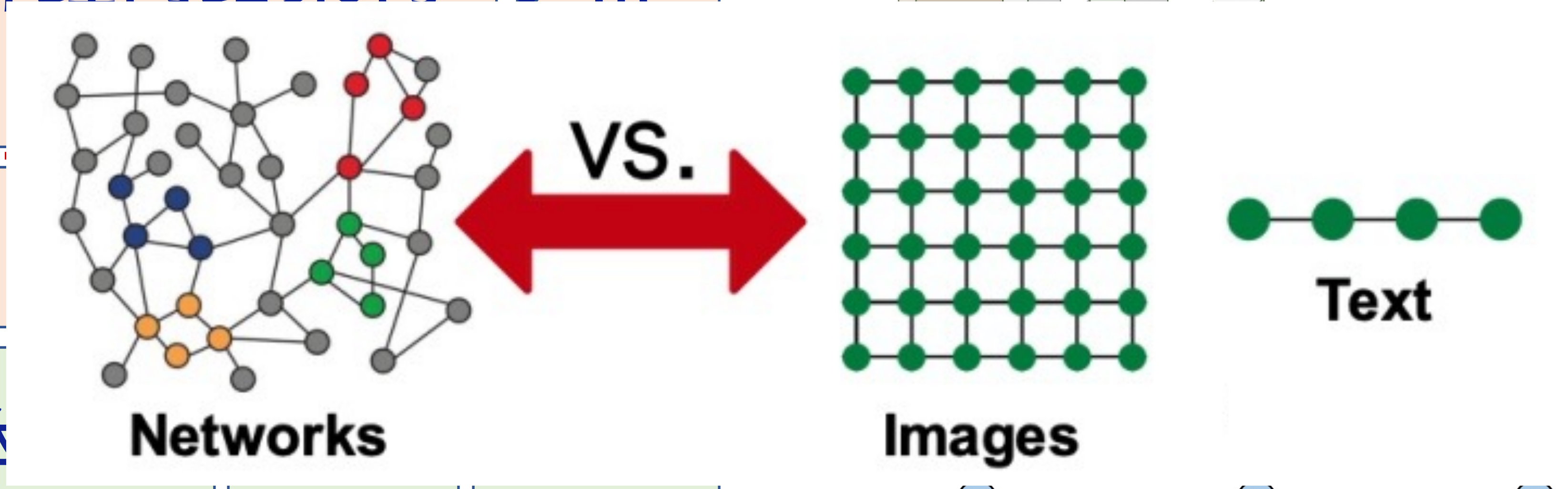
训练神经网络近似传统优化算法





无线网络应采用那种类型的神经网络？

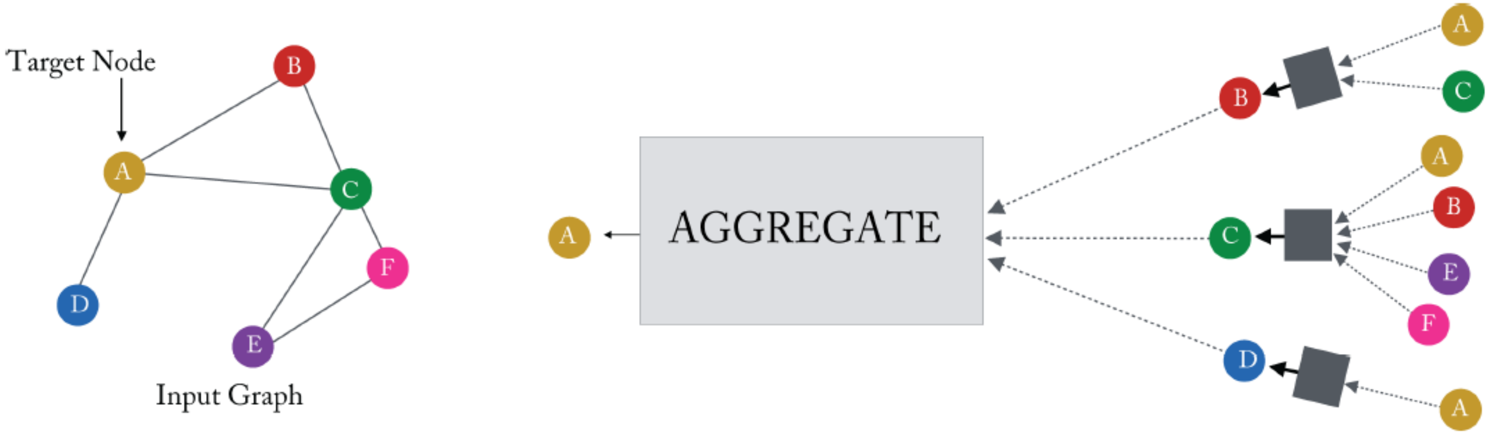




1/ 无线资源分配问题与图神经网络

什么是图神经网络？

The defining feature of a GNN is that it uses a form of ***neural message passing*** in which vector messages are exchanged between nodes and updated using neural networks[1].



点特征　　　　邻居节点

$$\mathbf{h}_u^{(k+1)} = \text{UPDATE}^{(k)}\left(\mathbf{h}_u^{(k)}, \underbrace{\text{AGGREGATE}^{(k)}(\{\mathbf{h}_v^{(k)}, \forall v \in \mathcal{N}(u)\})}\right)$$

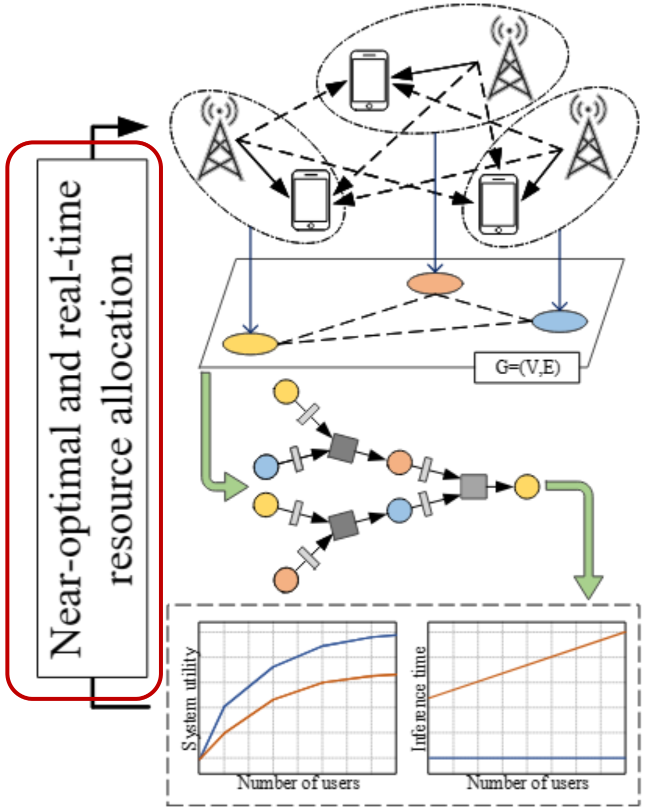
"Message" is **aggregated** from node's graph neighborhood.

消息传递（**message passing**）的两个核心步骤：聚合（**Aggregate**）和更新（**Update**）

1. W. L. Hamilton, Graph representation learning, Springer, 2020.

1/ 无线资源分配问题与图神经网络

为什么训练神经网络近似传统优化算法？



	Key steps
Wireless networks	System model, problem formulation, data pre-processing and training dataset generation
↓ Formulation	
Graph representation	Definition of graph, node features, edge features and adjacency matrix
↓ Input	
GNN-based model	Model architectures, activation function, loss function and hyperparameter tuning
↓ Output	
Evaluation	Test dataset generation, ablation experiment and result analysis

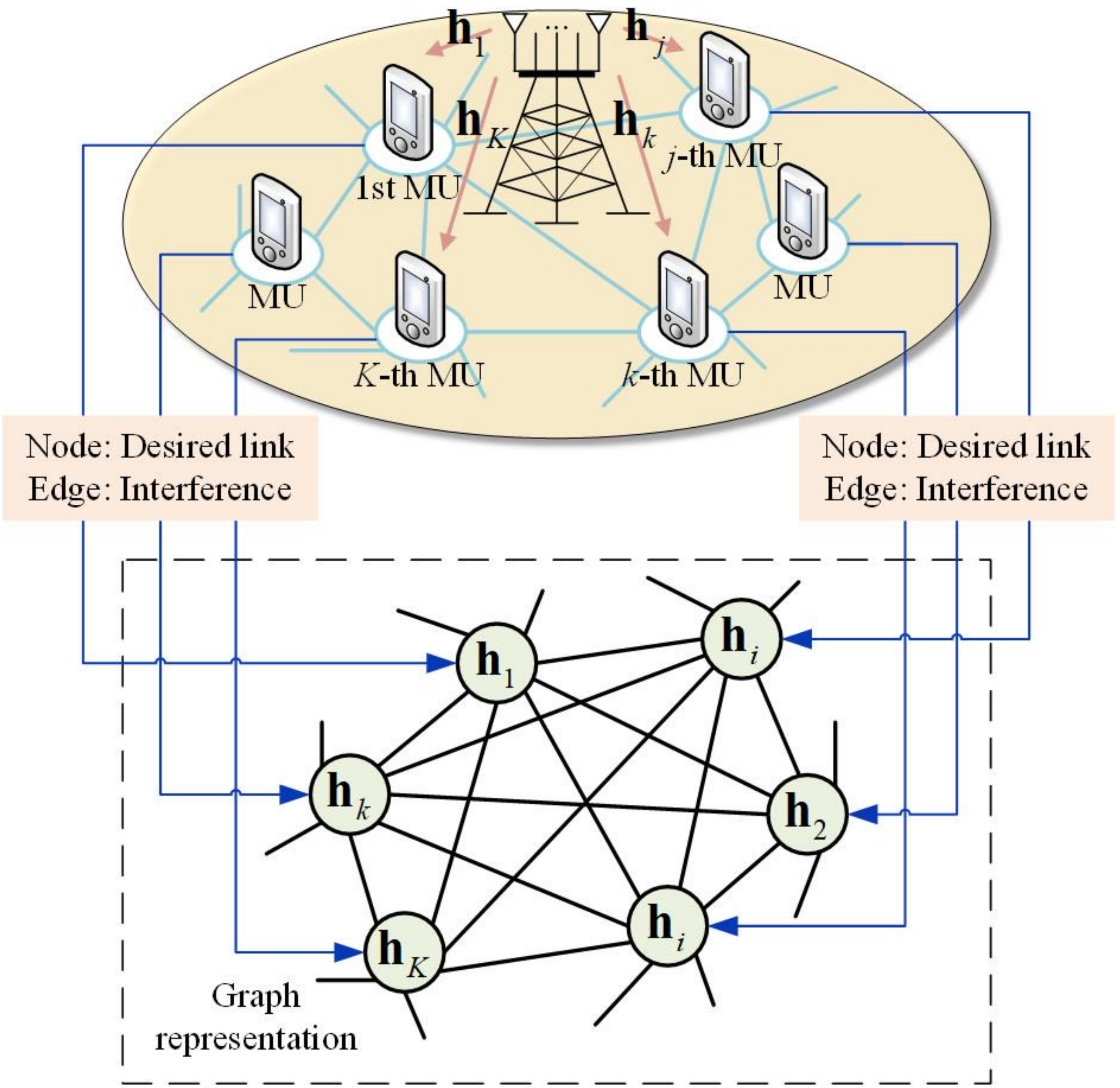
Challegnes

- Model capability improvement
- Over-smoothing issue
- Complicated constraints
- Complex input and output
- Dynamic wireless environment
- Scalability requirement
- Distributed implementation
- Transfer learning
- Meta learning
- Over-the-air computing
- High-quality dataset
- …

2/ 如何将无线网络输入图神经网络?

无线网络

图

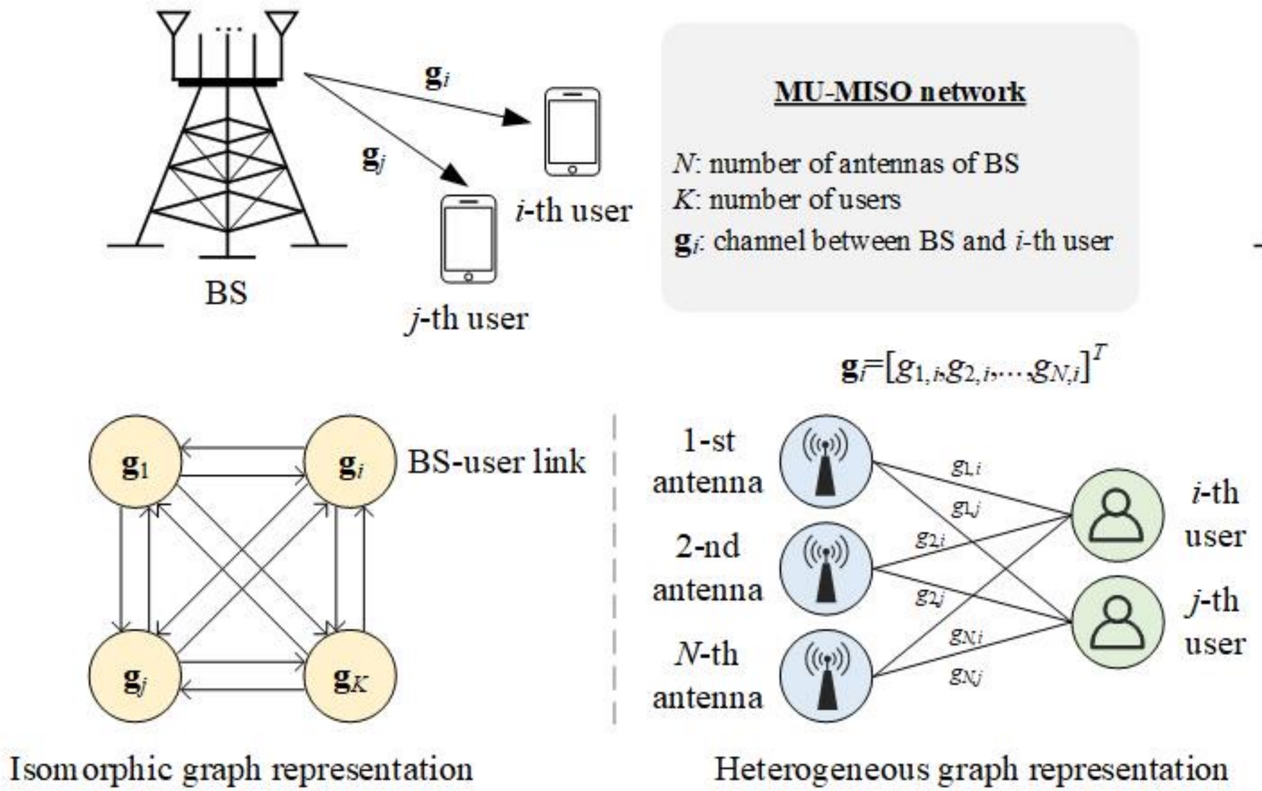


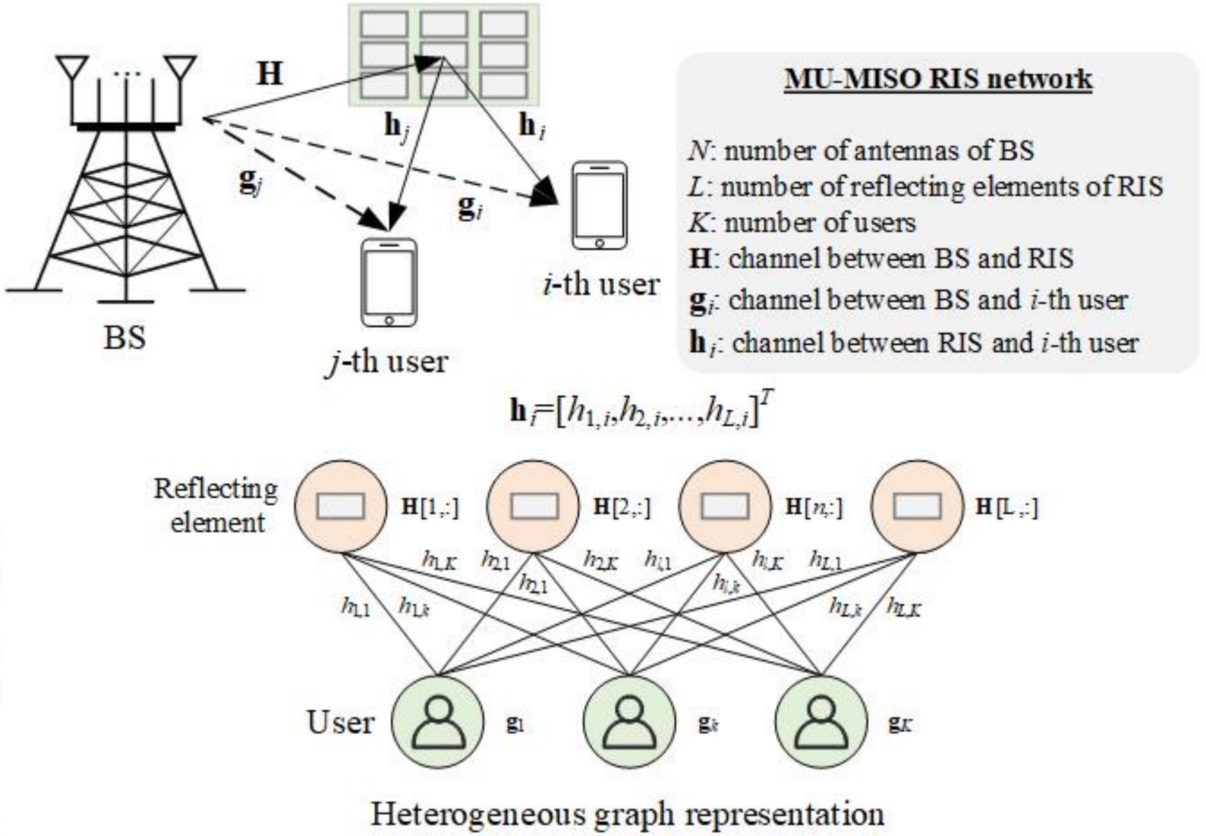
使用无线网络的系统参数（如信道状态信息等）构建图

Formally, a **graph** G = (V; E) is denoted by a set of **nodes** V and a set of **edges** E between these nodes.

Adjacency matrix
Node feature
Edge feature

2/ 如何将无线网络输入图神经网络?



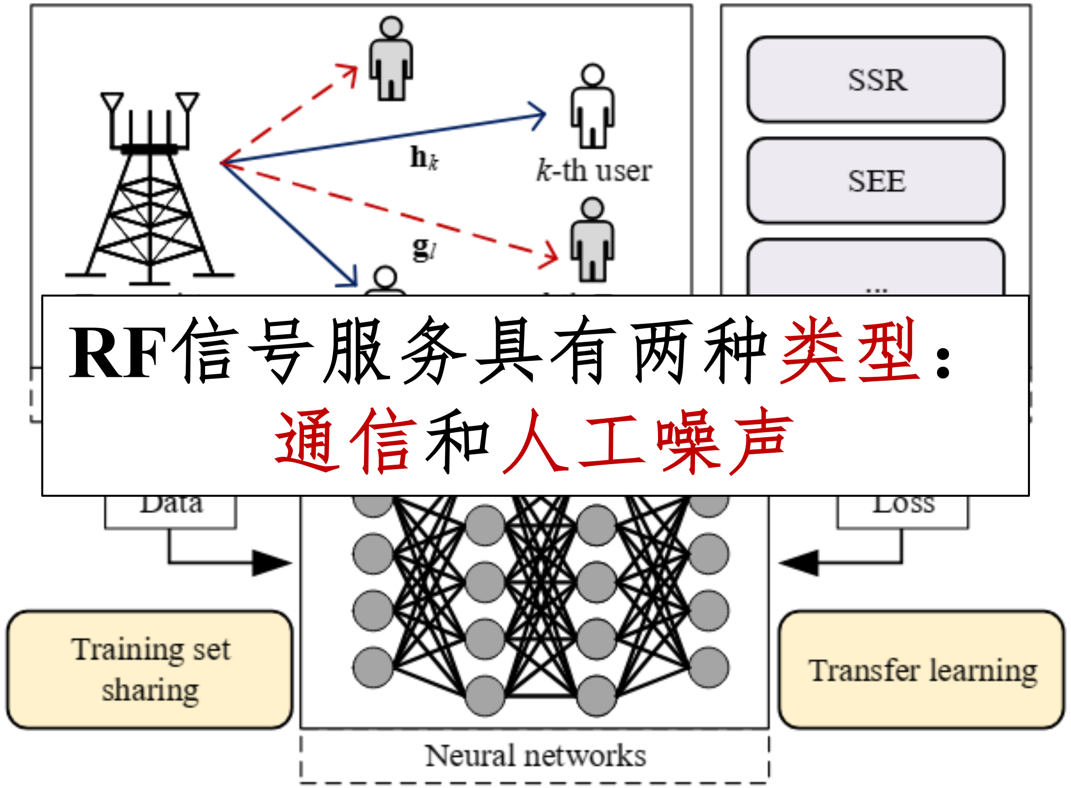


同构图表示

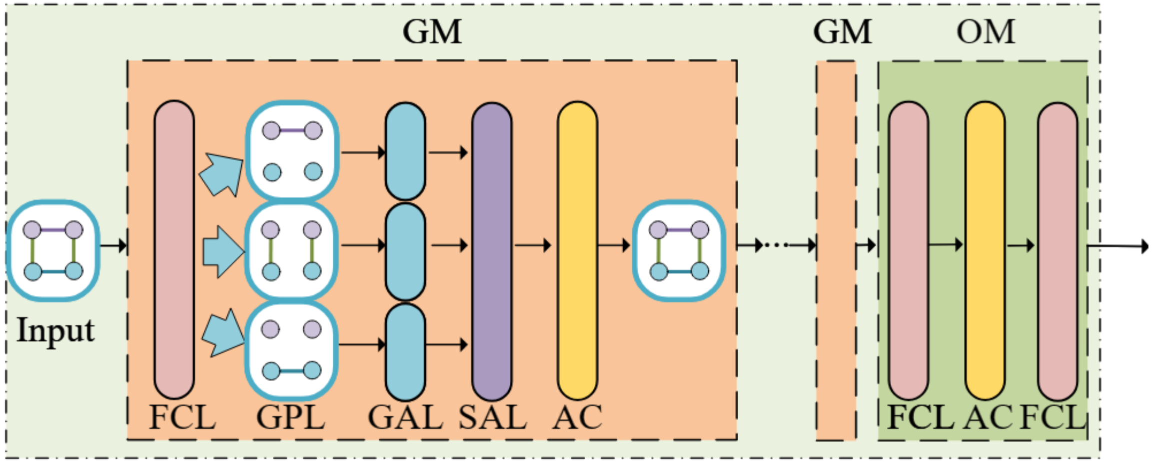
异构图表示

2/ 如何将无线网络**输入**图神经网络?

异构图学习示例：物理层安全[1]



RF信号服务具有两种类型：通信和人工噪声

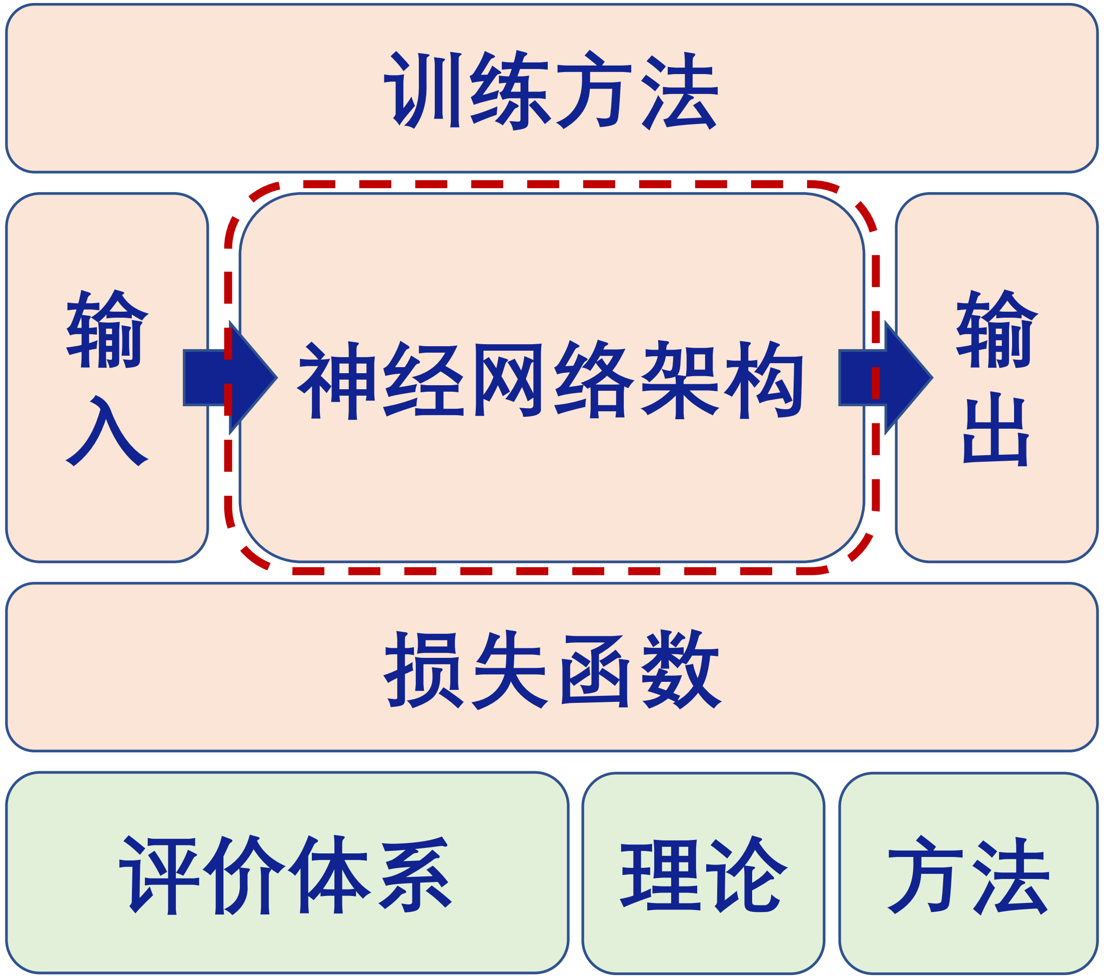


Utility	K_{Tr}	K_{Te}	Baseline				Proposed	
			CVX	MLP [3]	CNN [4]	GAT [9]	SecCNN	SecGNN
SSR	6	5	100%	50.3%	67.4%	46.4%	90.2%	88.7%
		6	100%	49.5%	61.9%	43.0%	84.7%	83.9%
		7	100%	×	×	40.7%	×	75.3%
Inference time			34.2 s	1.76 ms	6.15 ms	4.16 ms	7.00 ms	7.13 ms
SEE	6	5	100%	61.4%	67.6%	87.1%	93.5%	92.8%
		6	100%	56.8%	76.3%	84.4%	90.4%	90.6%
		7	100%	×	×	78.8%	×	85.8%
Inference time			46.9 s	1.73 ms	6.01 ms	4.10 ms	6.89 ms	6.97 ms

1. Z. Song, **Y. Lu***, X. Chen, B. Ai, Z. Zhong, D. Niyato. A deep learning framework for physical-layer secure beamforming [J]. IEEE Transactions on Vehicular Technology, 2024.

3/ 如何**提升**图神经网络性能?

训练神经网络近似传统优化算法



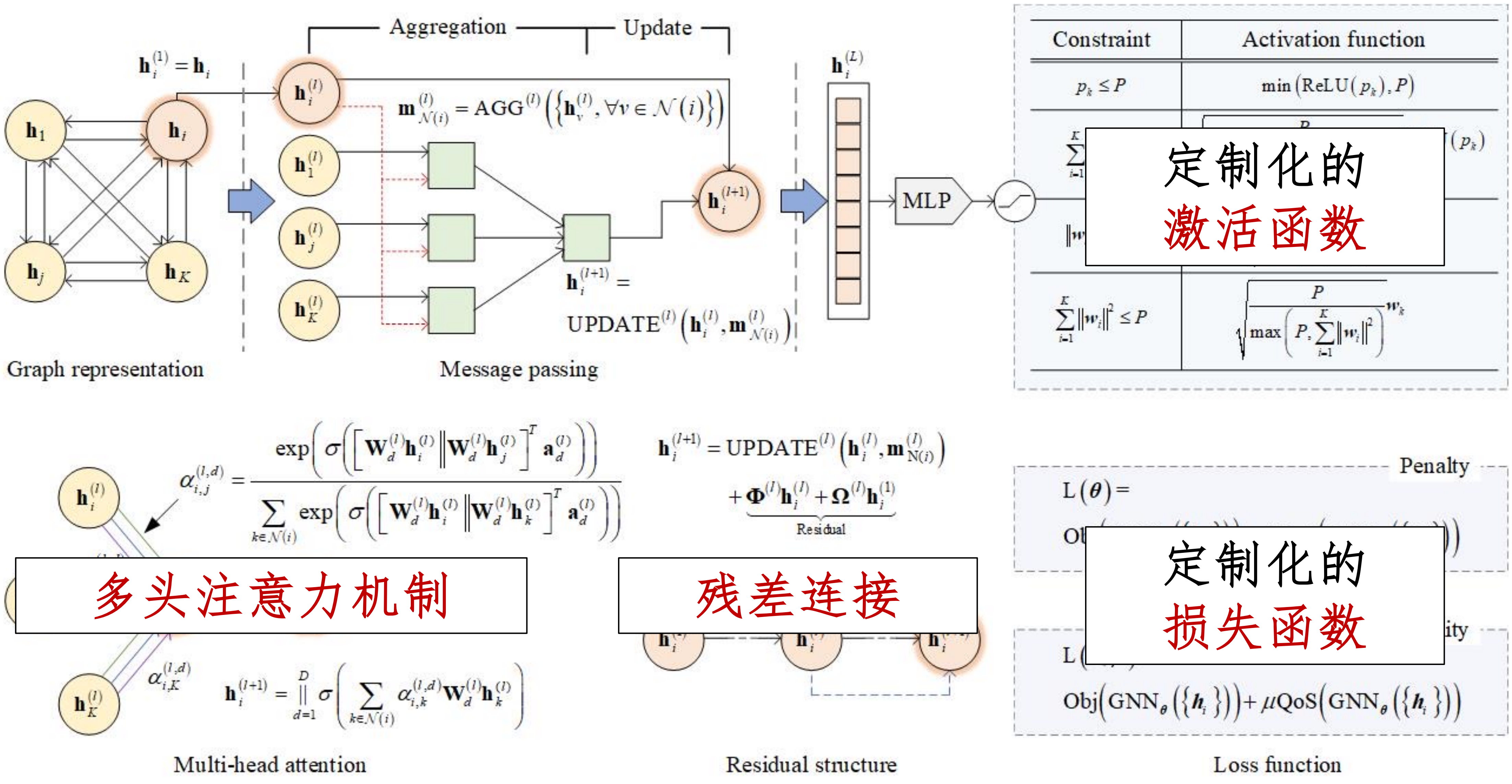
消息传递（**message passing**）的两个核心步骤：

- ➢ 聚合（**Aggregate**）
- ➢ 更新（**Update**）

$$\mathbf{h}_u^{(k+1)} = \text{UPDATE}^{(k)}\left(\mathbf{h}_u^{(k)}, \text{AGGREGATE}^{(k)}\left(\{\mathbf{h}_v^{(k)}, \forall v \in \mathcal{N}(u)\}\right)\right)$$

聚合的问题：邻居节点特征无区分
更新的问题：**over-smoothing**

3/ 如何提升图神经网络性能?



3/ 如何提升图神经网络性能?

图神经网络架构设计示例：消融实验

(a) Ablation experiment: Effectiveness of MP, AN and RD.

MP	AN	RD	SRM	EEM	MMR	Inference time
×	×	×	36.1%	17.9%	28.3%	0.88 ms
√	×	×	52.3%	71.9%	42.2%	1.02 ms
√	√	×	84.0%	79.1%	92.7%	1.85 ms
√	√	√	95.4%	96.5%	94.2%	2.41 ms

MP/AN/RD: message passing/attention/residual.

(b) Ablation experiment: Multi-head attention.

Task	Number of attention heads			
	1	4	7	10
SRM	80.1%	95.2%	95.5%	95.4%
EEM	68.7%	92.8%	95.1%	95.0%
MMR	53.3%	83.7%	88.0%	90.2%
Inference time	2.23 ms	2.28 ms	2.30 ms	2.34 ms

(c) Ablation experiment: Residual.

Task	RD	Depth			
		2	3	4	5
SRM	×	84.4%	84.0%	4.0%	4.0%
	√	84.9%	93.8%	95.4%	93.7%
EEM	×	85.4%	79.1%	51.9%	4.4%
	√	93.4%	96.5%	97.9%	96.6%
MMR	×	86.5%	92.7%	65.4%	2.5%
	√	87.3%	94.2%	95.9%	94.7%
Inference time	×	1.40 ms	1.89 ms	2.57 ms	4.12 ms
	√	1.60 ms	2.16 ms	3.05 ms	5.22 ms

典型MU-MISO网络波束赋形
设计问题

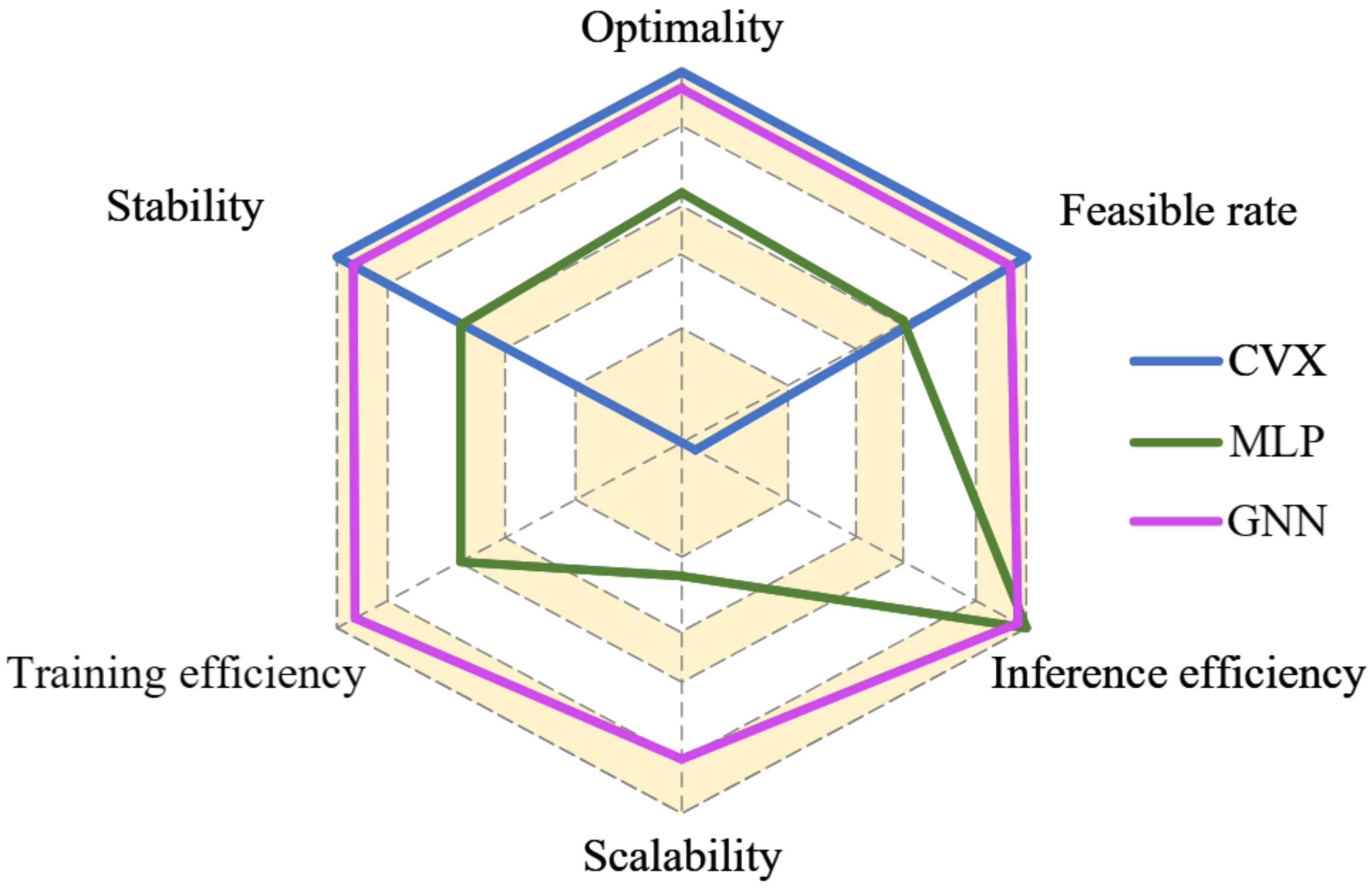
SRM: sum-rate max
EEM: energy efficiency max
MMR: max-min rate

Trade-off
推理能力与推理速度

随注意力头数饱和

随堆叠层数饱和

4/ 如何评价图神经网络资源优化算法?



多维度的评价体系

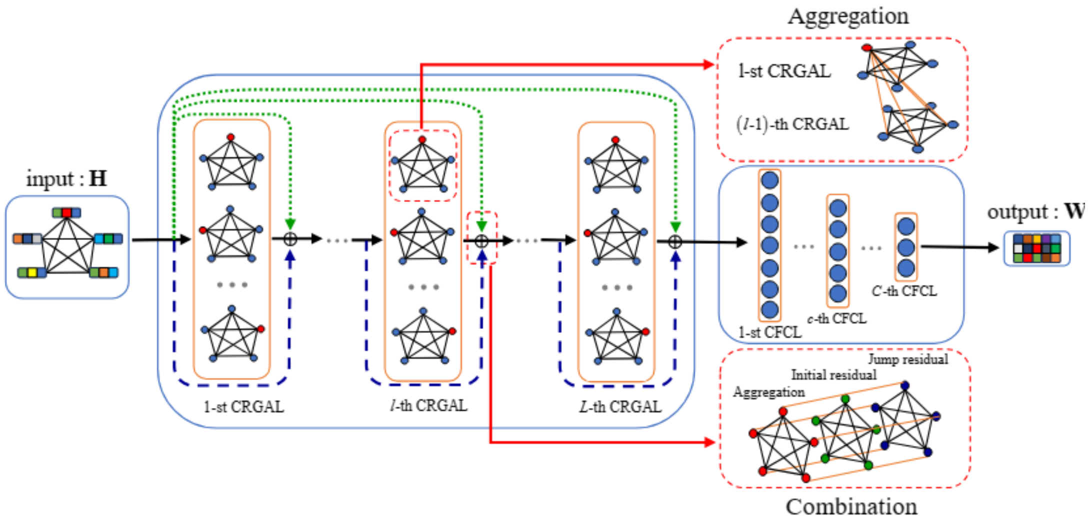
评价指标示例：和速率最大化[1]

$$\max_{\{\mathbf{w}_i\}} \sum_{k=1}^{K} R_k\left(\{\mathbf{w}_i\}\right)$$

$$\text{s.t.} \sum_{k=1}^{K} \|\mathbf{w}_k\|_2^2 \leq P_{\mathrm{Max}},$$

$$R_k\left(\{\mathbf{w}_i\}\right) \geq R_{\mathrm{Req}},$$

$$\mathbf{w}_i \in \mathbb{C}^{N_{\mathrm{T}}}, \forall i, k \in \mathcal{K},$$



1. Y. Li, **Y. Lu***, B. Ai, O. Dobre, Z. Ding, D. Niyato. GNN-based beamforming for sum-rate maximization in MU-MISO networks [J]. IEEE Transactions on Wireless Communications, 2024.

4/ 如何评价图神经网络资源优化算法?

☐ Optimality:

$$\mathrm{OP} = \frac{1}{\left|\mathcal{M}_{\mathrm{Te}}^{\mathrm{Fe}}\right|} \sum\nolimits_{m \in \mathcal{M}_{\mathrm{Te}}^{\mathrm{Fe}}} \frac{\sum_{k=1}^{K} \widehat{R}_k\left(\widehat{\mathbf{W}}_{(m)} | \boldsymbol{\theta}\right)}{\mathrm{OPT}_{(m)}^{\mathrm{CVX}}} \times 100\%$$

☐ Feasibility rate:

$$\mathrm{FR} = \frac{\left|\mathcal{M}_{\mathrm{Te}}^{\mathrm{Fe}}\right|}{M_{\mathrm{Te}}} \times 100\%$$

☐ Inference time:

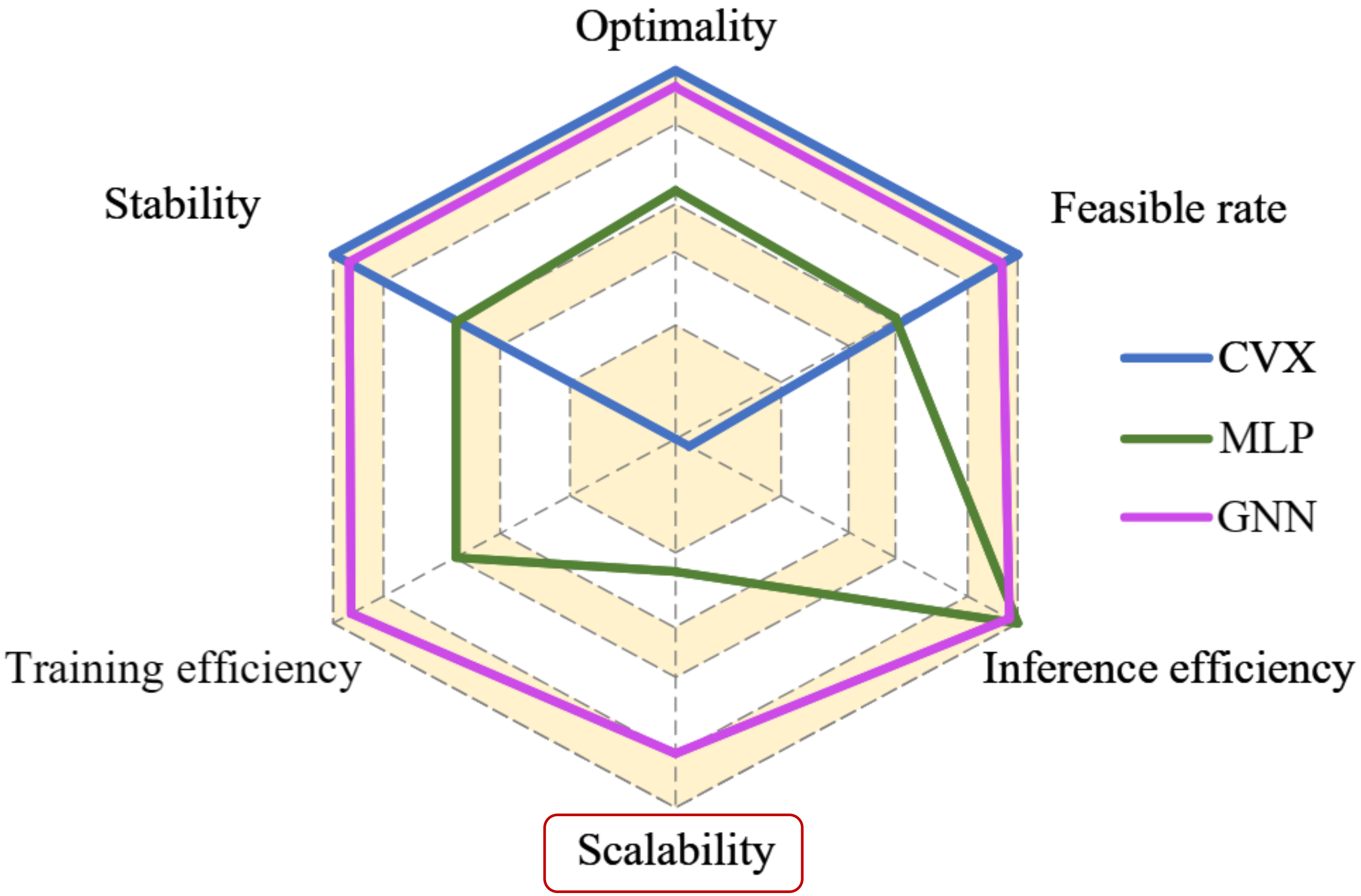
$$\mathrm{IT} = \frac{1}{\left|\mathcal{M}_{\mathrm{Te}}^{\mathrm{Fe}}\right|} \sum\nolimits_{m \in \mathcal{M}_{\mathrm{Te}}^{\mathrm{Fe}}} \mathrm{time}_{(m)}^{\mathrm{In}} - \mathrm{time}_{(m)}^{\mathrm{Out}}$$

Advanced Metrics

1) **Model effectiveness**: Evaluate the efficacy of the model based on the basic metrics, where the settings of the **test set** and the **training set** are **identical**.
2) **Scalability**: Evaluate the efficacy of the learning-based approach on the **test set** with **different** settings from the **training set**.
3) **Adaptability**: Evaluate the efficacy of the **activation function** and the **loss function** with different system parameters.

1. Y. Li, **Y. Lu***, B. Ai, O. Dobre, Z. Ding, D. Niyato. GNN-based beamforming for sum-rate maximization in MU-MISO networks [J]. IEEE Transactions on Wireless Communications, 2024.

4/ 如何评价图神经网络资源优化算法?

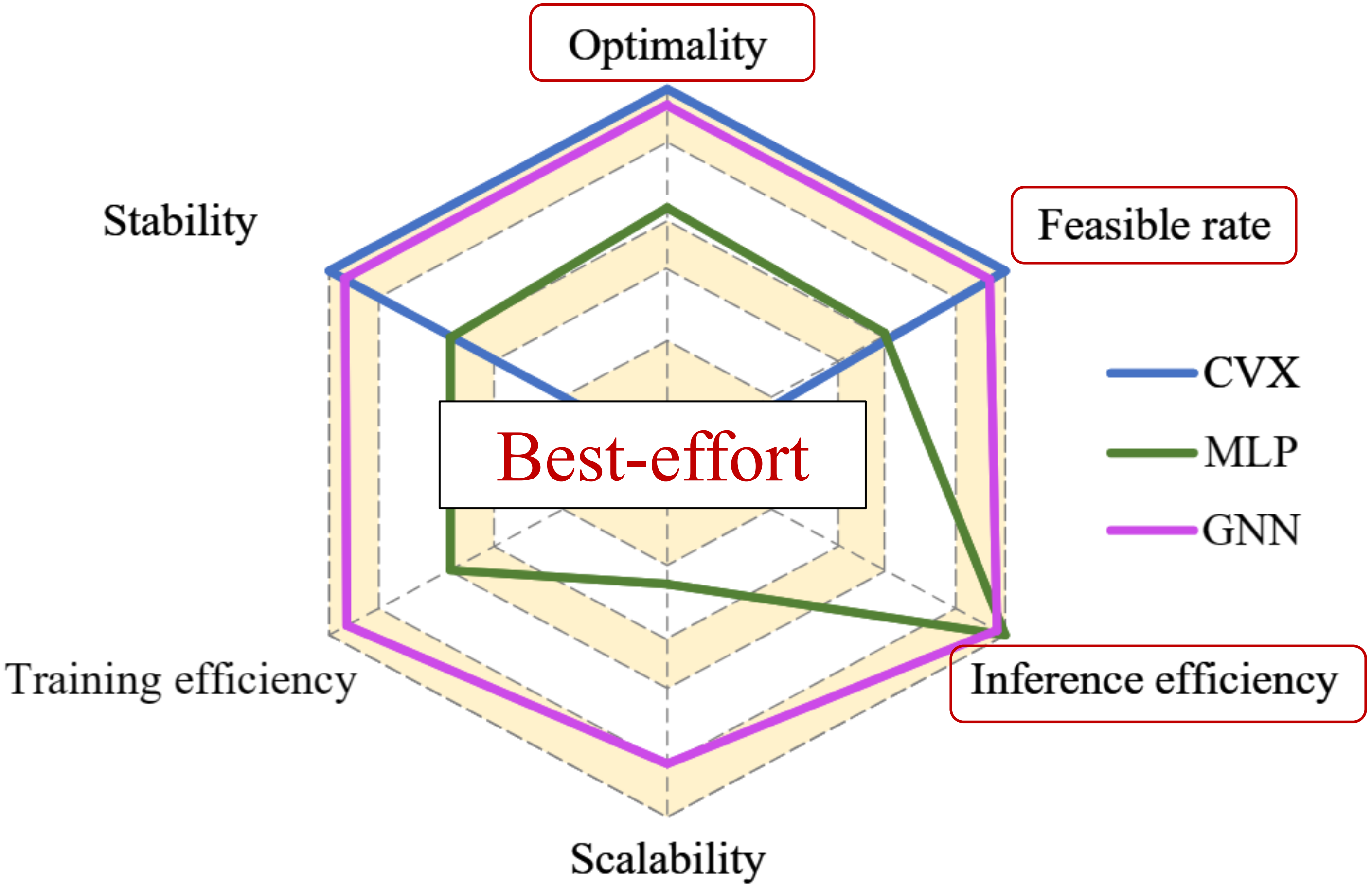


Scalability性能测试

N_{T}	K_{Tr}	K_{Te}	Model	OP	FR
8	4	3	CGCN	82.7%	100%
			CGAT	86.4%	100%
			CTGCN	89.0%	100%
			CRGAT	96.0%	100%
		5	CGCN	78.8%	92.7%
			CGAT	82.6%	98.2%
			CTGCN	77.8%	94.3%
			CRGAT	92.2%	99.5%
16	8	7	CGCN	55.9%	99.8%
			CGAT	84.8%	100%
			CTGCN	47.8%	98.3%
			CRGAT	95.3%	100%
		9	CGCN	52.2%	95.9%
			CGAT	82.5%	99.6%
			CTGCN	45.0%	92.7%
			CRGAT	94.6%	100%

1. Y. Li, **Y. Lu***, B. Ai, O. Dobre, Z. Ding, D. Niyato. GNN-based beamforming for sum-rate maximization in MU-MISO networks [J]. IEEE Transactions on Wireless Communications, 2024.

4/ 如何评价图神经网络资源优化算法?



Optimality/Feasible rate/Inference time性能测试

N_T	K	Approach	OP	FR	IT
8	4	Beam-SCA	100%	100%	1.99s
		MRT-SCA	46.6%	100%	1.29s
		ZF-SCA	99.1%	100%	1.12s
		CMLP	79.7%*	0%	0.93ms
		CGCN	84.5%	99.3%	0.90ms
		CGAT	91.0%	99.6%	1.66ms
		CTGCN	85.0%	99.2%	2.42ms
		CRGAT	97.1%	100%	2.73ms
16	8	Beam-SCA	100%	100%	8.48s
		MRT-SCA	40.6%	100%	1.86s
		ZF-SCA	98.9%	100%	2.14s
		CMLP	36.1%*	0%	0.94ms
		CGCN	52.3%	98.5%	0.92ms
		CGAT	84.0%	99.9%	1.71ms
		CTGCN	45.0%	92.7%	2.46ms
		CRGAT	95.4%	100%	2.81ms

1. Y. Li, **Y. Lu***, B. Ai, O. Dobre, Z. Ding, D. Niyato. GNN-based beamforming for sum-rate maximization in MU-MISO networks [J]. IEEE Transactions on Wireless Communications, 2024.

4/ 如何评价图神经网络资源优化算法?

有监督学习还是无监督学习？

$$\mathbf{P}_0 : \max_{\{\mathbf{w}_i\}} \mathrm{EE}\left(\{\mathbf{w}_i\}\right)$$
$$\text{s.t.} \quad \|\mathbf{w}_i\|_2^2 \le P_i,$$
$$\mathbf{w}_i \in \mathbb{C}^{N_\mathrm{T}}, \forall i \in \mathcal{K}.$$

$$L_N(\boldsymbol{\theta}) = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{\mathrm{EE}\left(\left\{\phi\left(\mathbf{w}_k^{(C)}\right)\right\}^{(n)} | \boldsymbol{\theta}\right) - \mathrm{EE}_n^{\mathrm{BSUM}}}{\mathrm{EE}_n^{\mathrm{BSUM}}}\right|$$

$$L_N(\boldsymbol{\theta}) = -\frac{1}{N}\sum_{n=1}^{N}\mathrm{EE}\left(\left\{\phi\left(\mathbf{w}_k^{(C)}\right)\right\}^{(n)} | \boldsymbol{\theta}\right)$$

(f) Comparison of supervised and unsupervised learning.

Task	K_{Train}	K_{Test}	SL	USL	Diff.
SRM	8	7	95.1%	94.2%	-0.9%
		8	95.3%	94.3%	-1.0%
		9	94.4%	93.3%	-1.1%
EEM	8	7	96.0%	96.1%	-1.0%
		8	96.5%	96.5%	0.0%
		9	94.9%	94.9%	0.0%
MMR	8	7	89.3%	89.8%	0.5%
		8	87.8%	88.7%	0.9%
		9	83.9%	84.9%	1.0%

SL/USL: supervised learning/unsupervised learning.

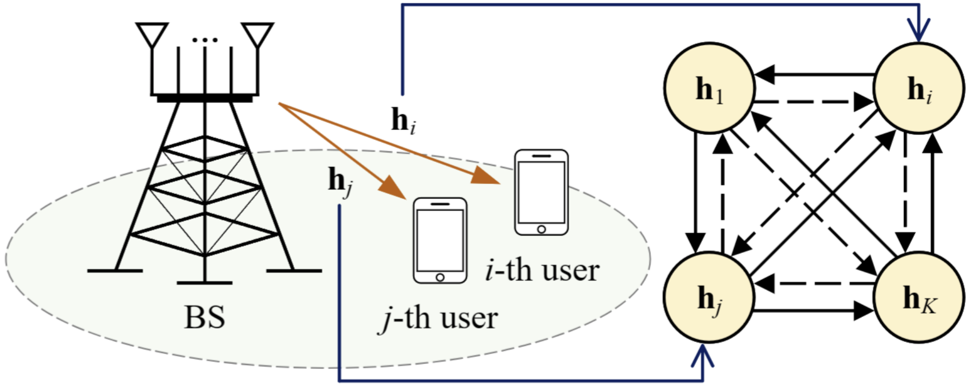
5/ Case Study

- □Case I: 图神经网络与传统优化算法对比
- □Case II: 基于先验知识的大规模网络传输
- □Case III: 基于OTA的分布式图神经网络方法
- □Case IV: 面向SWIPT的图神经网络与迁移学习
- □Case V: 面向HBF的同构图与异构图学习
- □Case VI: 图神经网络与通感一体化
- □Case VII: 图神经网络与可重构天线

5/ Case Study I：图神经网络与传统优化算法对比

显示特征　节点表示：基站与用户的信道

隐式特征　边表示：干扰



针对传统优化算法可求解问题，图神经网络算法具备近似最优、实时、高扩展能力

$$\mathbf{P_0}:\max_{\{\mathbf{w}_i\}} \mathrm{EE}(\{\mathbf{w}_i\})$$

$$\text{s.t.}\quad \|\mathbf{w}_i\|_2^2 \le P_i,$$

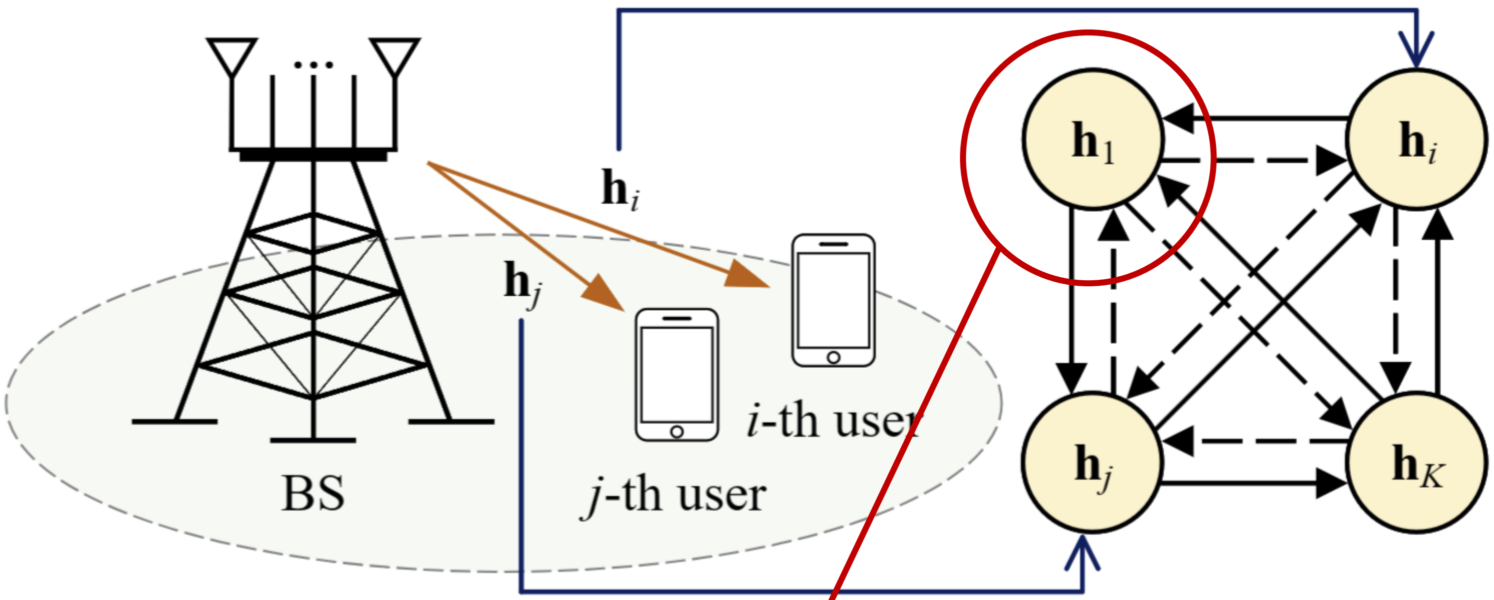
$$\mathbf{w}_i \in \mathbb{C}^{N_\mathrm{T}}, \forall i \in \mathcal{K}.$$

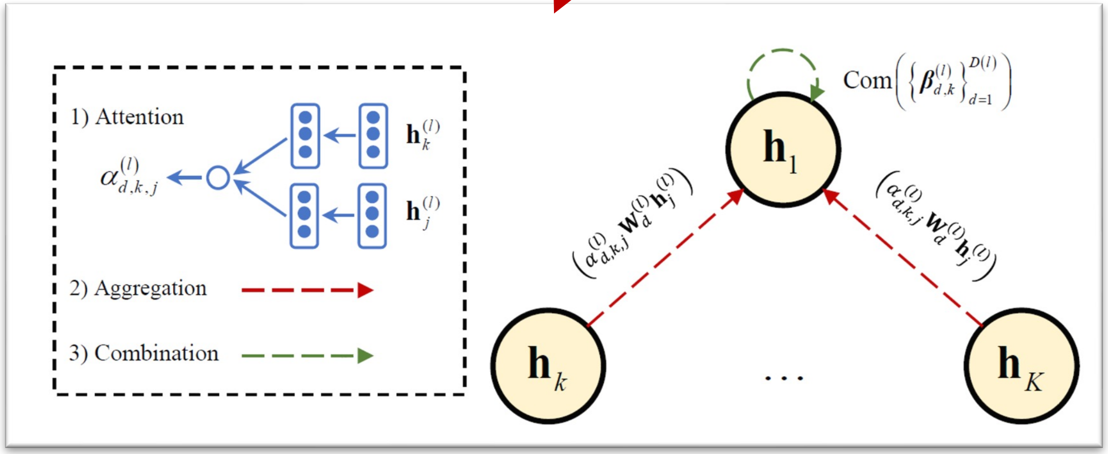
$$\mathrm{EE}(\{\mathbf{w}_i\}) = \frac{\sum_{k=1}^{K} R_k(\{\mathbf{w}_i\})}{\sum_{k=1}^{K} \|\mathbf{w}_k\|_2^2 + P_\mathrm{C}}$$

$$R_k(\{\mathbf{w}_i\}) = \log_2\left(1 + \frac{\left|\mathbf{h}_k^H \mathbf{w}_k\right|^2}{\sum_{i\neq k}^{K} \left|\mathbf{h}_k^H \mathbf{w}_i\right|^2 + \sigma_k^2}\right)$$

1. Y. Li, **Y. Lu***, R. Zhang, B. Ai, Z. Zhong. Deep learning for energy efficient beamforming in MU-MISO networks: A GAT-based approach [J]. IEEE Wireless Communications Letters, 2023, 12(7): 1264-1268.

5/ Case Study I：图神经网络与传统优化算法对比





基于注意力机制的聚合方法：

1）注意力系数计算

$$\alpha_{d,k,j}^{(l)} = \frac{\exp\left(f_2\left(f_1\left(\mathbf{W}_{d,\mathrm{dir}}^{(l)}\mathbf{h}_k^{(l)} + \mathbf{W}_{d,\mathrm{ner}}^{(l)}\mathbf{h}_j^{(l)}\right)^T \mathbf{a}_d^{(l)}\right)\right)}{\sum_{i\in\mathcal{N}(k)}\exp\left(f_2\left(f_1\left(\mathbf{W}_{d,\mathrm{dir}}^{(l)}\mathbf{h}_k^{(l)} + \mathbf{W}_{d,\mathrm{ner}}^{(l)}\mathbf{h}_i^{(l)}\right)^T \mathbf{a}_d^{(l)}\right)\right)}$$

2）聚合

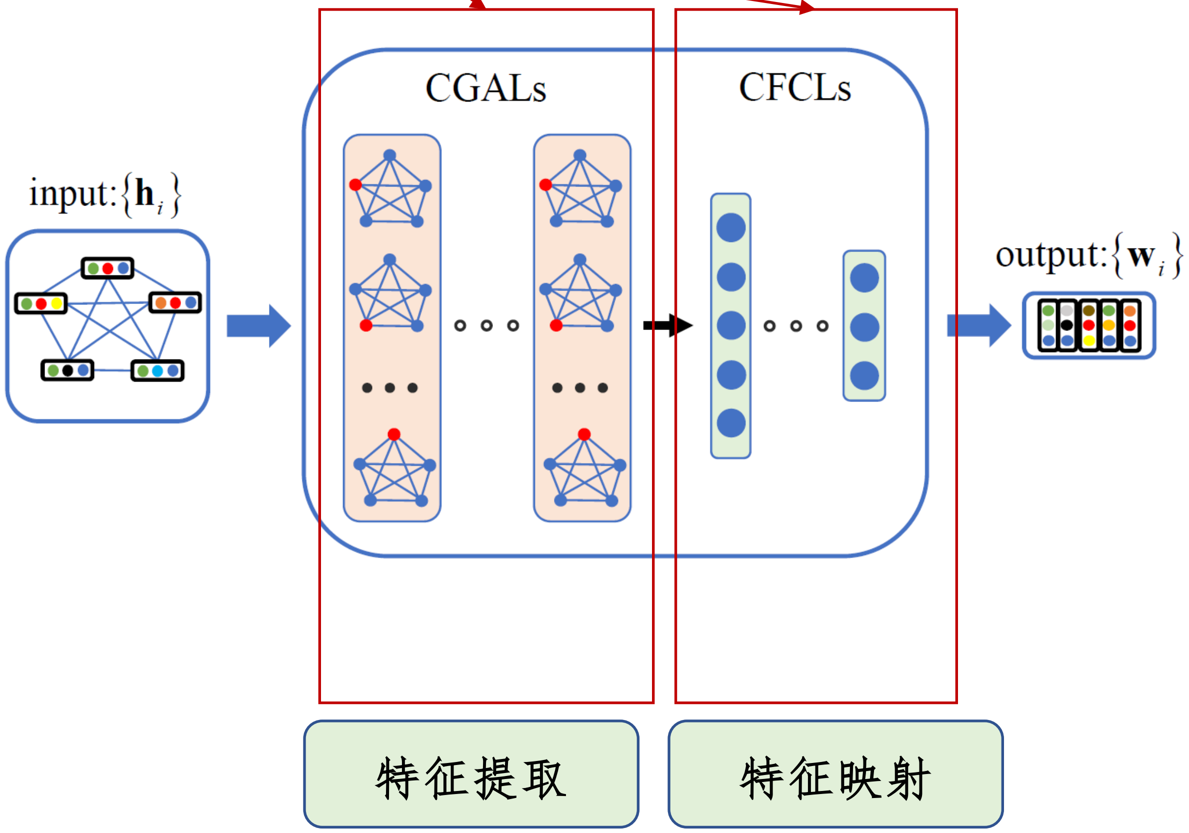
$$\boldsymbol{\beta}_{d,k}^{(l)} = f_3\left(\alpha_{d,k,j}^{(l)}\mathbf{W}_{d,\mathrm{ner}}^{(l)}\mathbf{h}_j^{(l)} \,|j\in\mathcal{N}(k)\right)$$

3）点特征更新

$$\tilde{\mathbf{h}}_k^{(l)} = \mathrm{Com}\left(\left\{\boldsymbol{\beta}_{d,k}^{(l)}\right\}_{d=1}^{D(l)}\right)$$

5/ Case Study I：图神经网络与传统优化算法对比

CGAL: Complex Graph Attention Layer
CFCL: Complex Fully Connected Layer



输出激活函数

$$\phi\left(\mathbf{w}_k^{(C)}\right) = \begin{cases} \sqrt{P_k}\mathbf{w}_k^{(C)}, & \left\|\mathbf{w}_k^{(C)}\right\|_2 \le 1, \\ \dfrac{\sqrt{P_k}\mathbf{w}_k^{(C)}}{\left\|\mathbf{w}_k^{(C)}\right\|_2}, & \left\|\mathbf{w}_k^{(C)}\right\|_2 > 1. \end{cases}$$

Loss function

$$L_N(\boldsymbol{\theta}) = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{\mathrm{EE}\left(\left\{\phi\left(\mathbf{w}_k^{(C)}\right)\right\}^{(n)}|_{\boldsymbol{\theta}}\right) - \mathrm{EE}_n^{\mathrm{BSUM}}}{\mathrm{EE}_n^{\mathrm{BSUM}}}\right|$$

No.	Layer type	IFs	OFs	AMs	CReLU	BN
1	CGAL	N_{T}	64	20	✓	×
2	CGAL	1280	512	20	✓	×
3	CFCL	10240	512	-	✓	✓
4	CFCL	512	256	-	✓	✓
5	CFCL	256	N_{T}	-	×	×

IFs: The dimension of the input feature.
OCs: The dimension of the output feature.
AMs: Number of attention mechanisms.
For each CGAL, a residual connection is added [13].

训练集中用户数量 测试集中用户数量

传统优化方法 深度学习优化方法

N_T	K_{tr}	K_{te}	BSUM	MLP	GCN	GAT
4	2	2	100%	95.8%	95.5%	97.2%
Running time			55.6s	1.6ms	3.2ms	4.2ms
8						
Ru						
16		9	×	×	65.2%	90.9%
Running time			223.3s	3.3ms	3.4ms	4.3ms

N_T	K_{tr}	K_{te}	BSUM	MLP	MLP*	GCN	GCN*	GAT	GAT*
16	8	7	×	×	×	67.1%	67.1%	91.1%	90.7%
		8	100%	47.9%	47.9%	65.5%	65.5%	93.0%	92.8%
		9	×	×	×	65.2%	65.1%	90.9%	90.4%

Models that use unsupervised learning are marked with *.

每个场景：
- ➢ 训练集 100,000
- ➢ 测试集 2,000

数量

练。

全连接神经网络 普通图神经网络

5/ Case Study II：基于先验知识的大规模网络传输

Beamforming vector

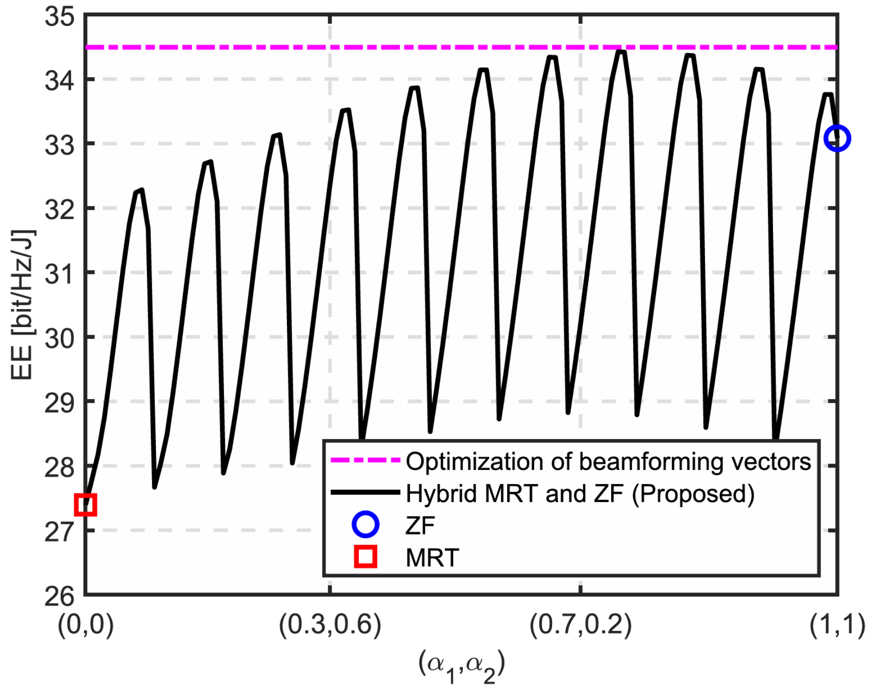
$$\mathbf{w}_k = \sqrt{p_k}\overline{\mathbf{w}}_k, \quad \|\overline{\mathbf{w}}_k\|^2 = 1$$

Hybrid zero-forcing and maximum ratio transmission

$$\overline{\mathbf{w}}_k^{(\mathrm{HZM})}(\alpha_k) = \frac{\alpha_k \frac{\mathbf{u}_k}{\|\mathbf{u}_k\|} + (1-\alpha_k)\frac{\mathbf{g}_k}{\|\mathbf{g}_k\|}}{\left\|\alpha_k \frac{\mathbf{u}_k}{\|\mathbf{u}_k\|} + (1-\alpha_k)\frac{\mathbf{g}_k}{\|\mathbf{g}_k\|}\right\|}$$

$\alpha_k \in [0,1]$

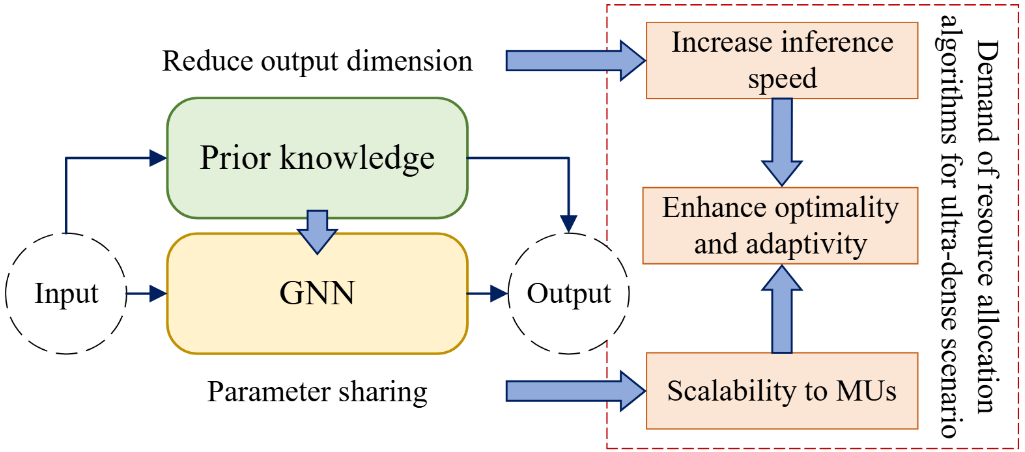
ZF方向 **MRT方向**



It is observed that the **output dimension** is reduced from **complex-valued *KN*** to **real-valued *2K***.

1. R. Zhang, **Y. Lu***, W. Chen, B. Ai, Z. Ding. Model-based GNN enabled energy-efficient beamforming for ultra-dense wireless networks [J]. IEEE Transactions on Wireless Communications, 2025.

5/ Case Study II：基于先验知识的大规模网络传输



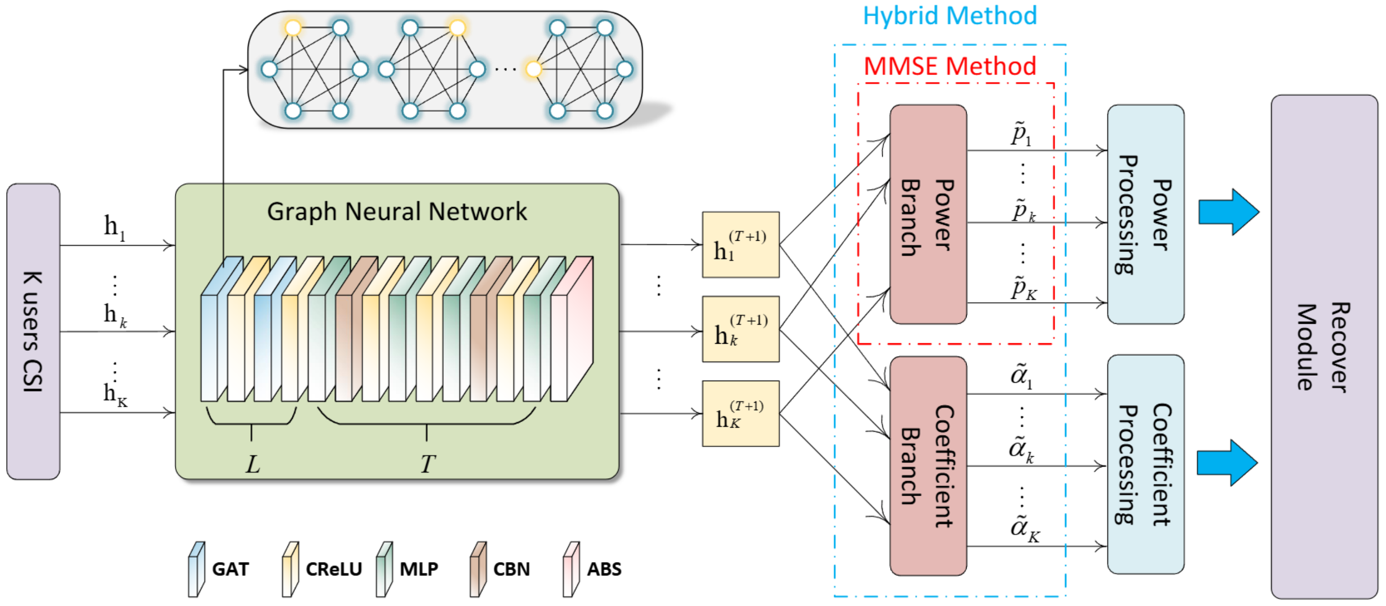
先验知识降维

参数共享

混合输入训练

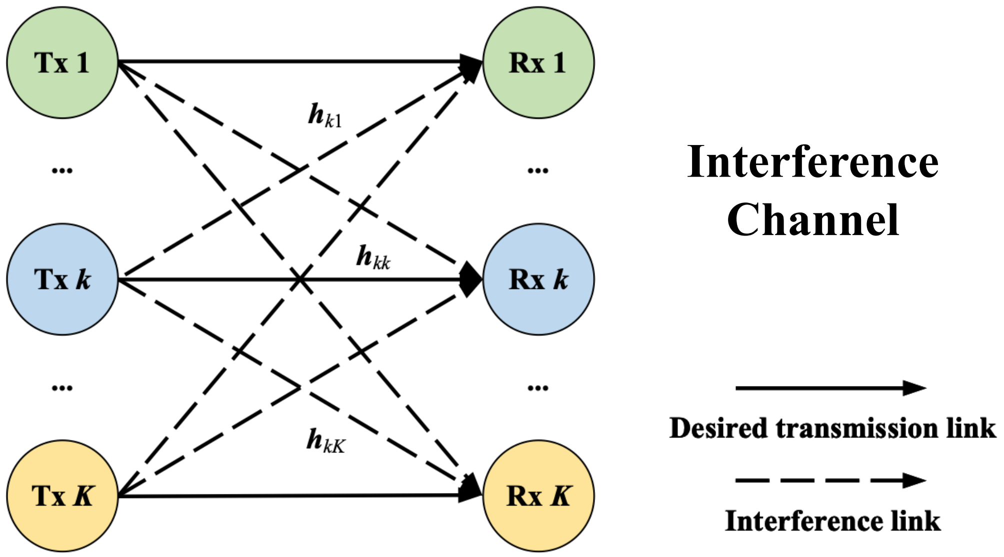
Method	K_{Tr}	MLP		CNN		GNN	
		OP	FR	OP	FR	OP	FR
MMSE	30	94.09%	100%	95.12%	100%	95.14%	100%
HZM	30	94.56%	100%	94.62%	100%	98.48%	100%

Method	K_{Te}	MLP		CNN		GNN	
		SP	FR	SP	FR	SP	FR
MMSE	15	85.54%	100%	86.57%	100%	85.62%	100%
	20	89.09%	100%	89.98%	100%	89.06%	100%
	35	×	×	×	×	96.98%	100%
	40	×	×	×	×	98.44%	98.2%
	45	×	×	×	×	98.53%	75.3%
	50	×	×	×	×	0%	0%
HZM	15	86.05%	100%	86.46%	100%	86.28%	100%
	20	89.92%	100%	89.82%	100%	90.53%	100%
	35	×	×	×	×	97.59%	100%
	40	×	×	×	×	93.65%	100%
	45	×	×	×	×	89.94%	100%
	50	×	×	×	×	86.18%	57.6%



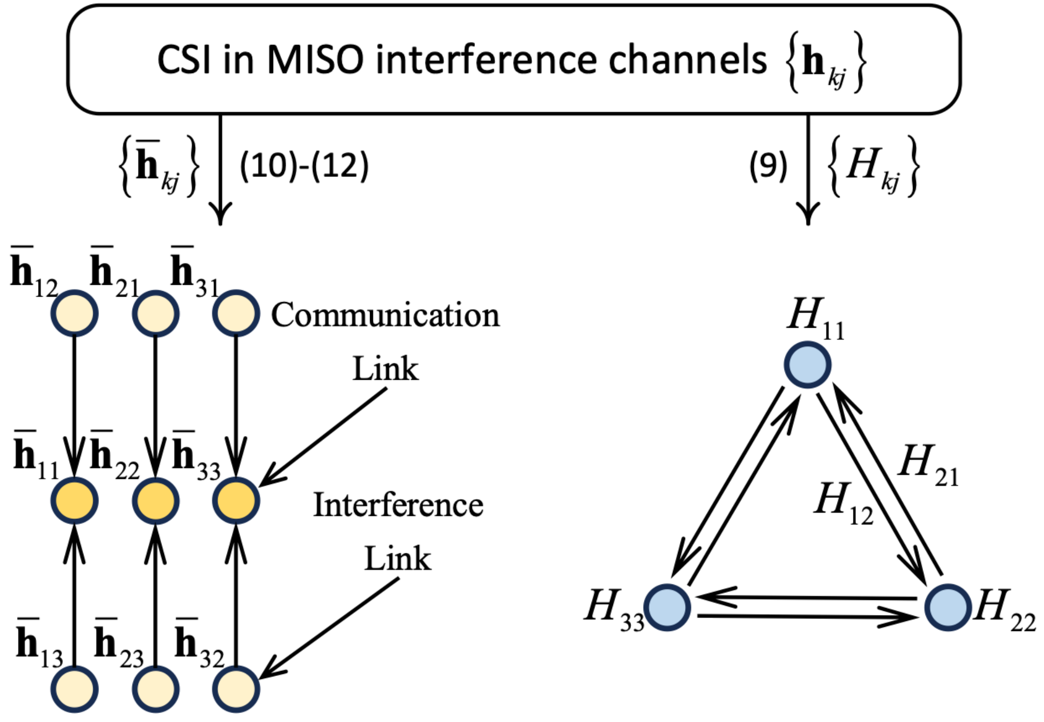
由于GNN算法具有快速推理能力，针对大规模复杂场景，并行运行多个具有不同先验知识的模型，择优选取功率分配方案

5/ Case Study III：基于OTA的分布式图神经网络方法



$$\max_{\{\mathbf{w}_i\}} \frac{\sum_{k=1}^{K} R_k(\{\mathbf{w}_i\})}{\sum_{k=1}^{K} \|\mathbf{w}_k\|^2 + P_c}$$

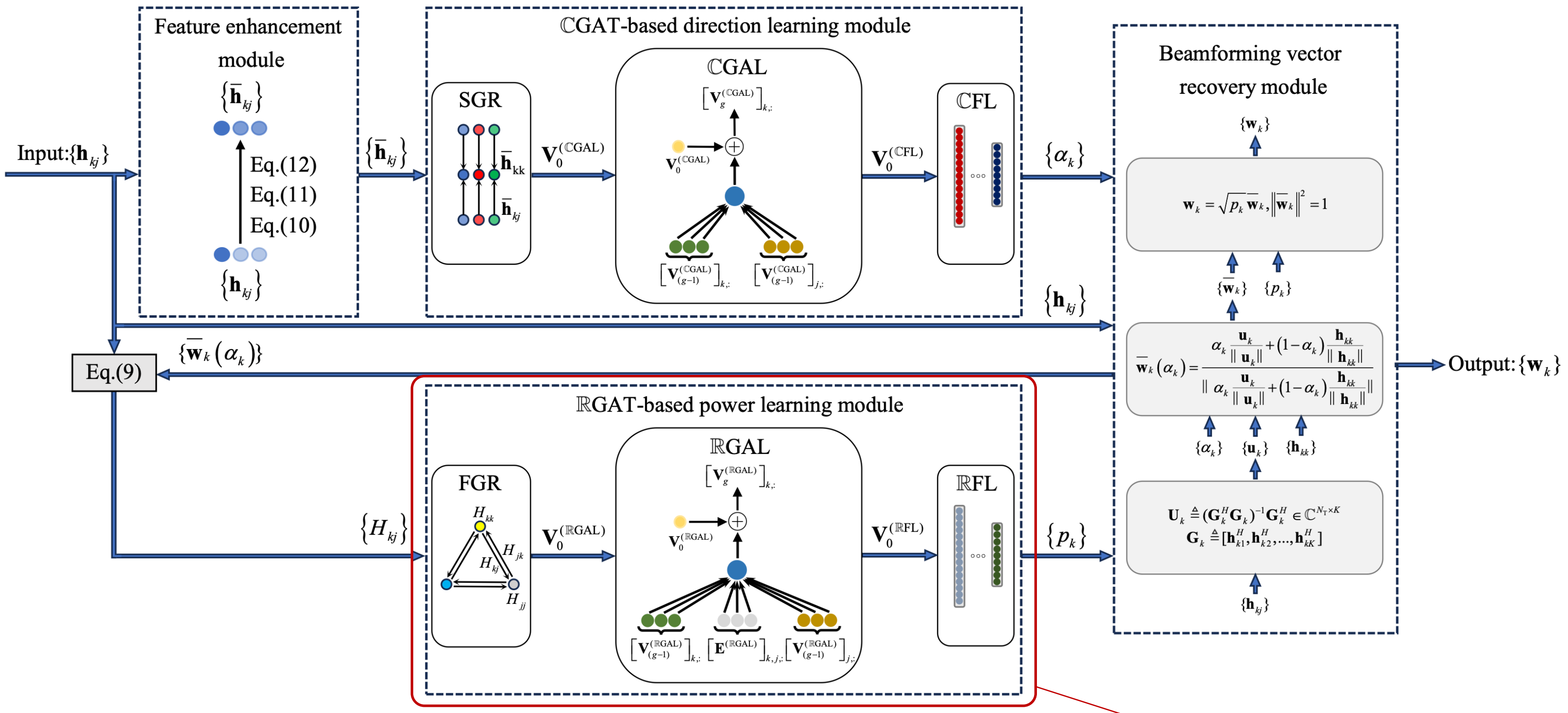
$$\begin{aligned} \text{s.t.}\ & R_k(\{\mathbf{w}_i\}) \geq R_{\text{req}}, \\ & \|\mathbf{w}_k\|^2 \leq P_{\max}, \\ & \mathbf{w}_i \in \mathbb{C}^{N_T}, \forall i, k \in \mathcal{K}, \end{aligned}$$



(a) Subgraph representation for direction learning.
(b) Fully-connected graph representation for power learning.

1. C. He, **Y. Lu***, B. Ai, O. Dobre, Z. Ding, D. Niyato. ICGNN: Graph neural network enabled scalable beamforming for MISO interference channels [J]. IEEE Transactions on Mobile Computing, 2025.

5/ Case Study III：基于OTA的分布式图神经网络方法



Signaling overhead

$$\delta_{\text{Total}}^{(\text{OTA})} = K \sum_{g=1}^{G_2} \delta_g^{(\text{OTA})} + K(K-1)$$

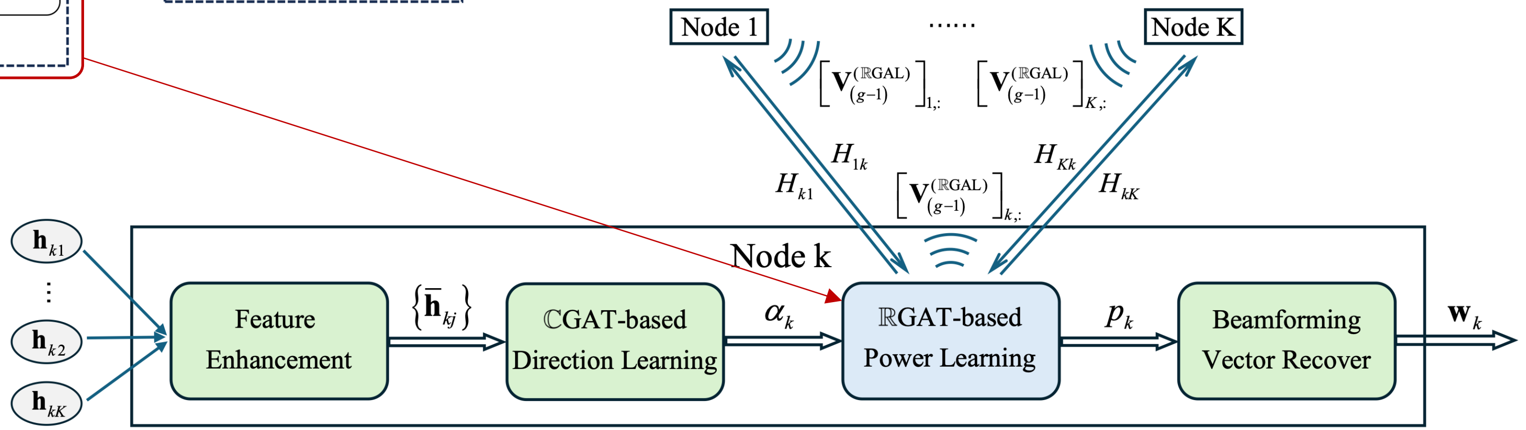
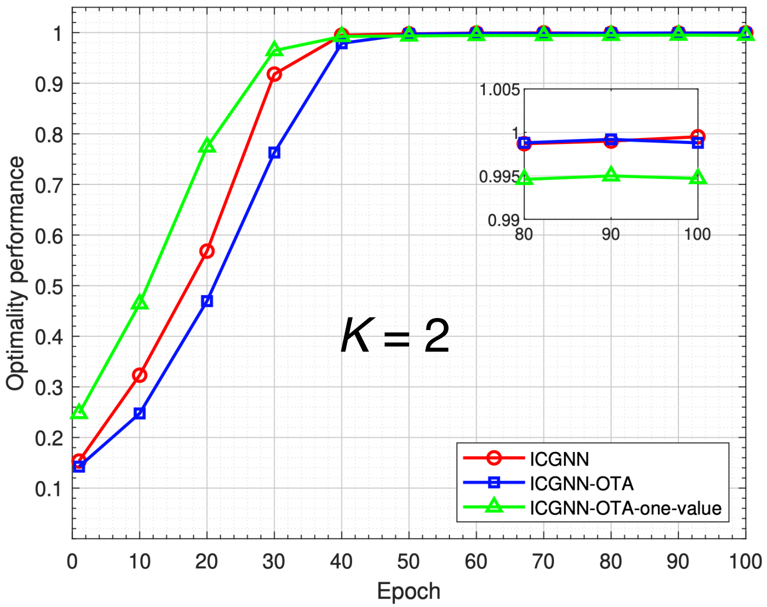


Illustration of the ICGNN via OTA distributed implementation.

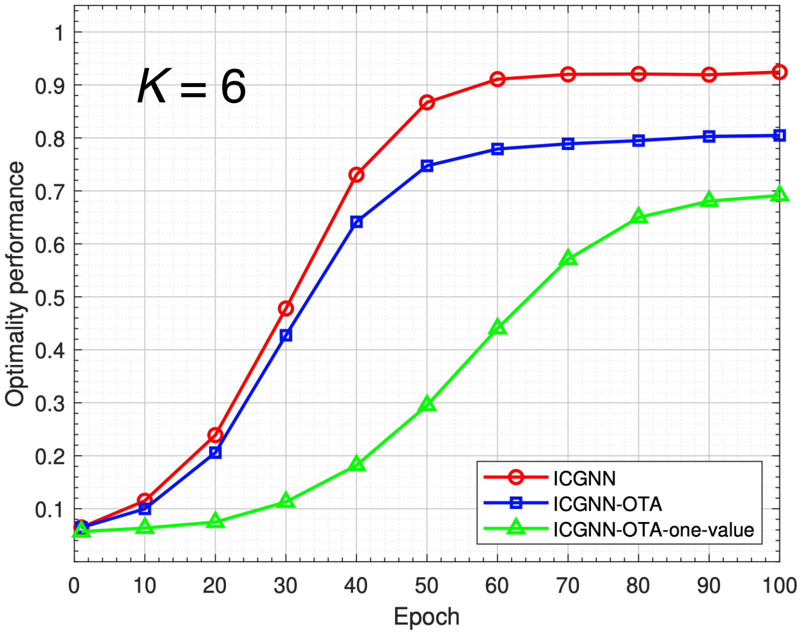
5/ Case Study III：基于OTA的分布式图神经网络方法

MP	RD	SR	FE	OP (Gain)	FR (Gain)	Inference time
×	×	×	×	84.93% (-)	89.35% (-)	0.0501 ms
✓	×	×	×	85.75% (1.82%)	95.10% (5.75%)	0.0674 ms
✓	✓	×	×	86.70% (0.95%)	95.85% (0.75%)	0.0684 ms
✓	✓	✓	×	93.25% (6.55%)	100% (4.15%)	0.0804 ms
✓	✓	✓	✓	94.10% (0.85%)	100% (0.00%)	0.0804 ms

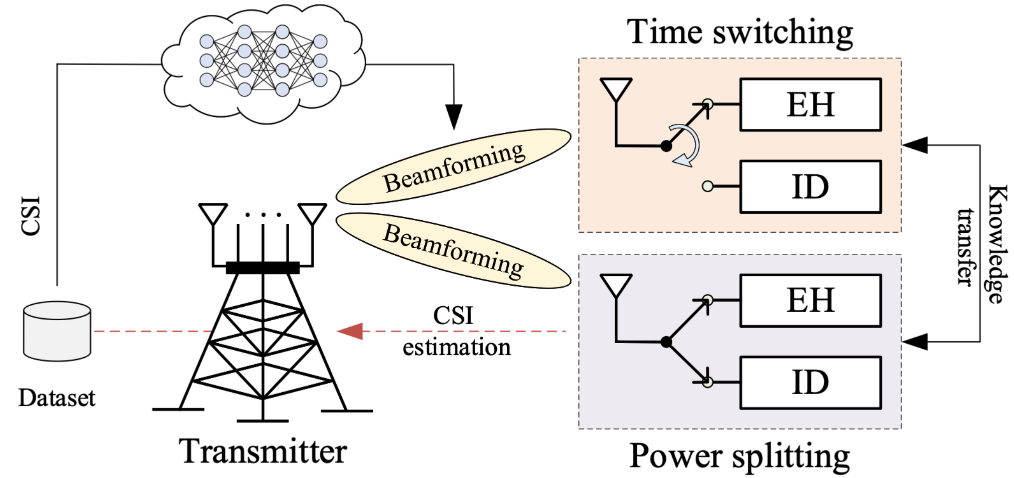
MP/RD/SR/FE: message passing/residual/subgraph representation/feature enhancement.
OP/FR: Optimality performance/feasibility rate.



	$K_{\mathrm{Tr}} = 2$		$K_{\mathrm{Tr}} = 4$		$K_{\mathrm{Tr}} = 6$	
	SC/OP	FR	SC/OP	FR	SC/OP	FR
$K_{\mathrm{Te}} = 2$	99.92%†	100%	90.50%	100%	83.28%	100%
$K_{\mathrm{Te}} = 3$	94.91%	99.70%	93.25%	99.95%	86.99%	100%
$K_{\mathrm{Te}} = 4$	80.33%	81.80%	89.02%†	99.51%	80.02%	99.75%
$K_{\mathrm{Te}} = 5$	79.83%	82.00%	91.61%	58.90%	90.45%	100%
$K_{\mathrm{Te}} = 6$	73.02%	75.55%	89.66%	36.70%	94.10%†	100%
$K_{\mathrm{Te}} = 7$	66.48%	65.30%	86.84%	23.95%	93.14%	98.90%
$K_{\mathrm{Te}} = 8$	61.24%	48.75%	83.32%	12.50%	92.42%	51.00%



5/ Case Study IV：图神经网络与迁移学习

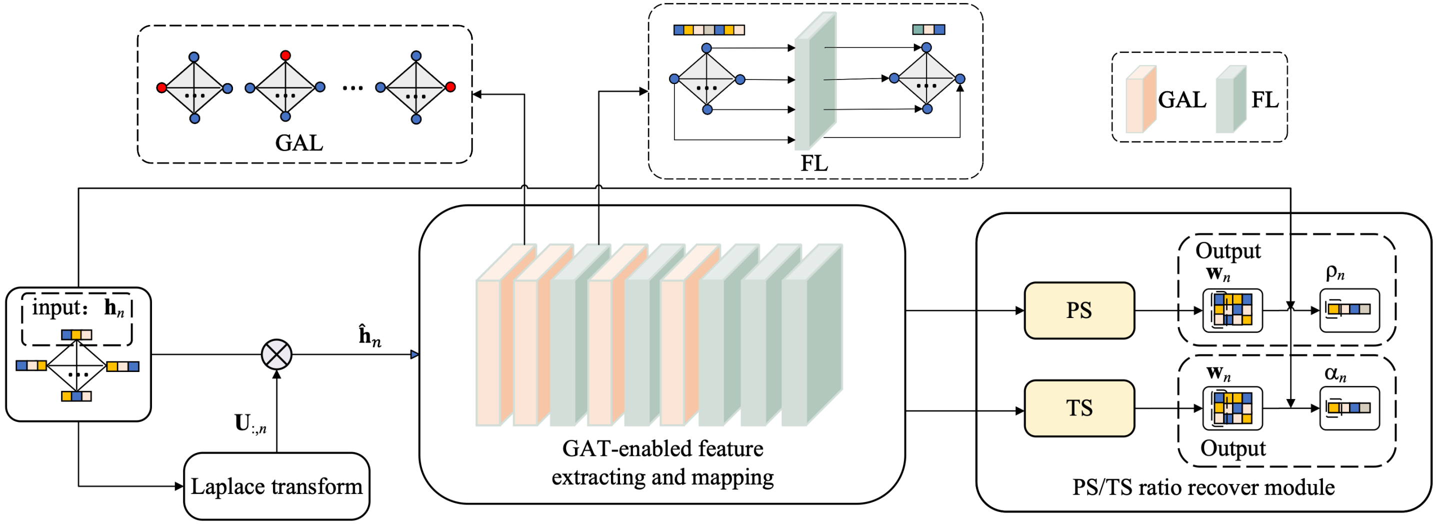


Power splitting

$$\max_{\{\mathbf{w}_i,\rho_i\}} \sum_{n=1}^{N} R_n^{\mathrm{PS}}\left(\{\mathbf{w}_i\},\rho_n\right)$$
$$\text{s.t. } R_n^{\mathrm{PS}}\left(\{\mathbf{w}_i\},\rho_n\right) \ge R_{\mathrm{req}},$$
$$\gamma_n^{\mathrm{PS}}\left(\{\mathbf{w}_i\},\rho_n\right) \ge \gamma_{\mathrm{req}},$$
$$\sum_{n=1}^{N} \|\mathbf{w}_n\|_2^2 \le P_{\max},$$
$$0 \le \rho_n \le 1, \forall n \in \mathcal{N},$$

Time switching

$$\max_{\{\mathbf{w}_i,\alpha_i\}} \sum_{n=1}^{N} \alpha_n R_n^{\mathrm{TS}}\left(\{\mathbf{w}_i\}\right)$$
$$\text{s.t. } R_n^{\mathrm{TS}}\left(\{\mathbf{w}_i\}\right) \ge R_{\mathrm{req}}/\alpha_n,$$
$$\gamma_n^{\mathrm{TS}}\left(\{\mathbf{w}_i\}\right) \ge \gamma_{\mathrm{req}}/\left(1-\alpha_n\right),$$
$$\sum_{n=1}^{N} \|\mathbf{w}_n\|_2^2 \le P_{\max},$$
$$0 \le \alpha_n \le 1, \forall n \in \mathcal{N}.$$



$$\rho_n = 1 - \frac{\gamma_{\mathrm{req}}}{\sum_{i=1}^{N} \left|\mathbf{h}_n^H \mathbf{w}_i\right|^2}$$

$$\alpha_i = 1 - \frac{\gamma_{\mathrm{req}}}{\sum_{i=1}^{N} \left|\mathbf{h}_n^H \mathbf{w}_i\right|^2}$$

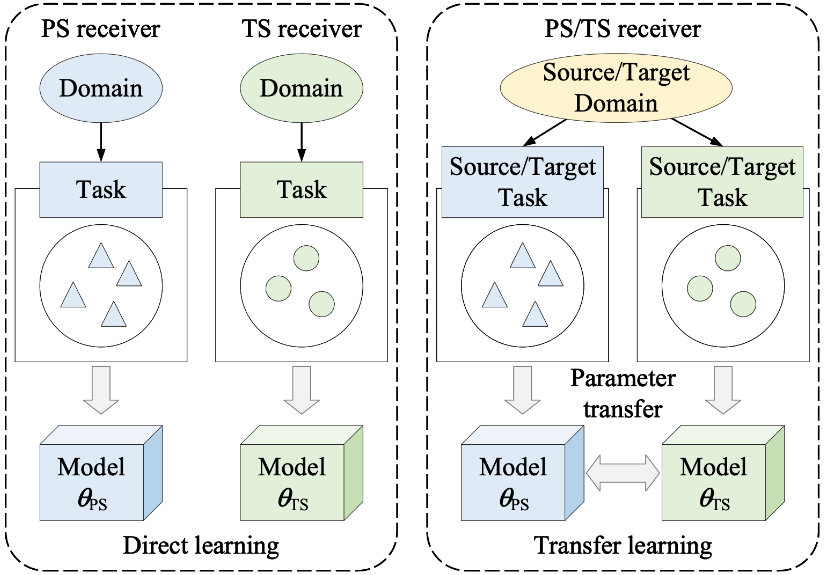
1. H. Han, **Y. Lu***, Z. Song, R. Zhang, W. Chen, B. Ai, D. Niyato, D. I. Kim. SWIPTNet: A unified deep learning framework for SWIPT based on GNN and transfer learning [J]. IEEE Transactions on Mobile Computing, 2025.

5/ Case Study IV：图神经网络与迁移学习

PS；训练集上K=12

LM	SO	LC	N_{Te} 12 OP	12 FR	13 SC	13 FR	14 SC	14 FR	15 SC	15 FR
×	✓	✓	82.97%	99.20%	76.97%	89.88%	75.63%	85.13%	71.69%	78.10%
✓	×	✓	91.96%	99.14%	89.92%	98.14%	88.35%	97.13%	87.27%	94.16%
✓	✓	×	85.16%	99.29%	83.36%	95.01%	82.03%	89.80%	78.95%	87.92%
✓	✓	✓	**93.27%**	99.48%	**91.03%**	99.34%	**90.00%**	99.32%	**88.79%**	98.17%

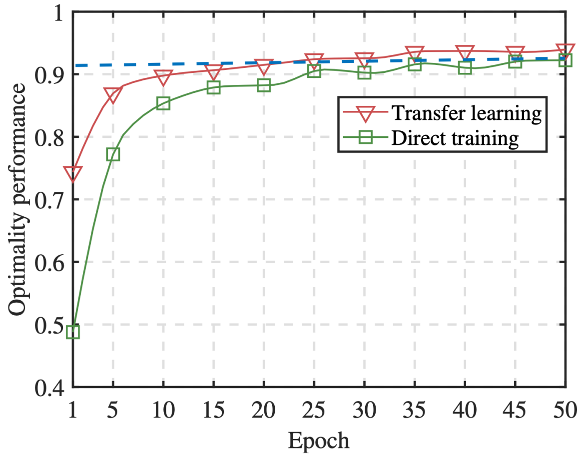
LT/SO/SL: Laplace transform/ Single-type output/ layer connection.
OP/SC/FR: Optimality performance/ scalability performance/ feasibility rate.



TS；训练集上K=12

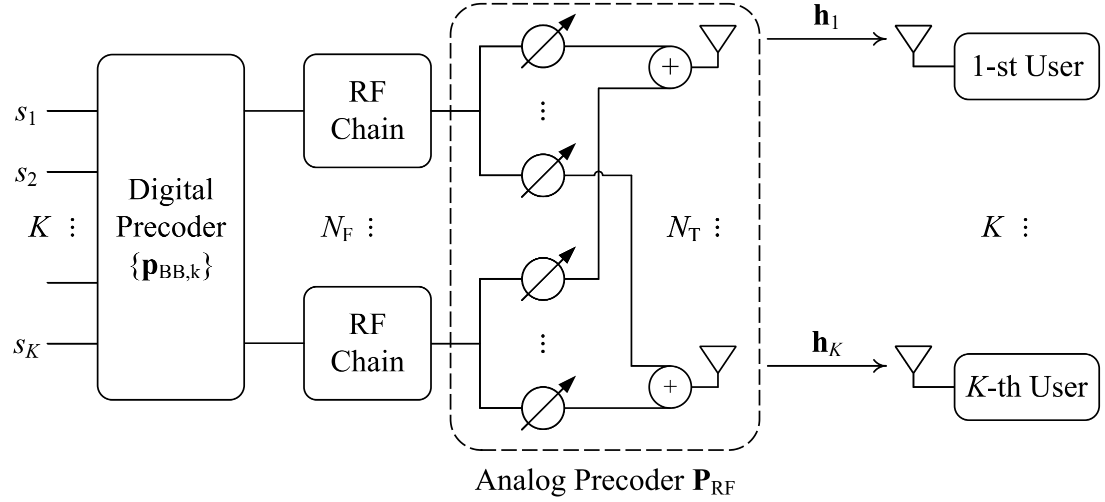
N_{Te}	CVX OP/SC	CVX FR	MLP OP/SC	MLP FR	GCN OP/SC	GCN FR	GAT OP/SC	GAT FR	SWIPTNet OP/SC	SWIPTNet FR
12	100%†	100%	27.84%†	99.49%	67.58%†	98.19%	84.12%†	99.17%	**93.79%**†	99.50%
13	100%	100%	×	×	64.37%	93.31%	81.98%	99.24%	**91.98%**	99.15%
14	100%	100%	×	×	62.17%	88.62%	81.49%	92.16%	**90.73%**	98.89%
15	100%	100%	×	×	59.31%	86.76%	75.51%	86.11%	**88.16%**	97.17%
IT	3.306s		1.514ms		2.633ms		3.033ms		2.962ms	

PS→TS

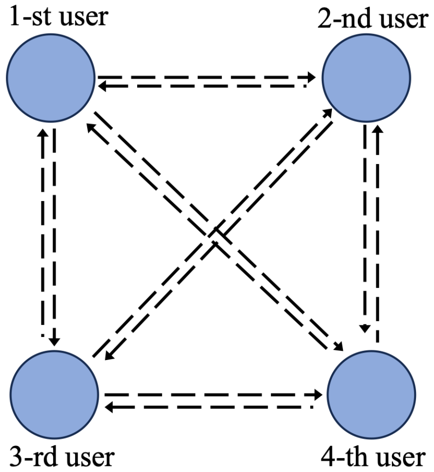


1. H. Han, **Y. Lu***, Z. Song, R. Zhang, W. Chen, B. Ai, D. Niyato, D. I. Kim. SWIPTNet: A unified deep learning framework for SWIPT based on GNN and transfer learning [J]. IEEE Transactions on Mobile Computing, 2025.

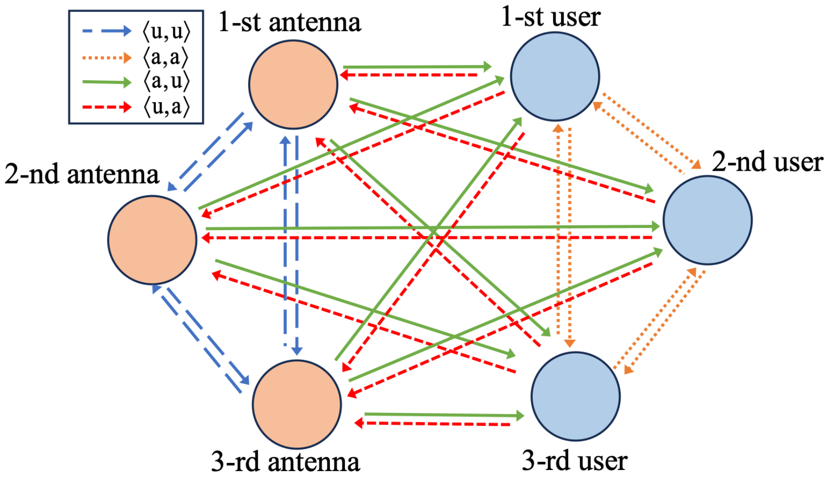
5/ Case Study V：同构图与异构图学习



混合波束赋形（HBF）



同构图表示



异构图表示

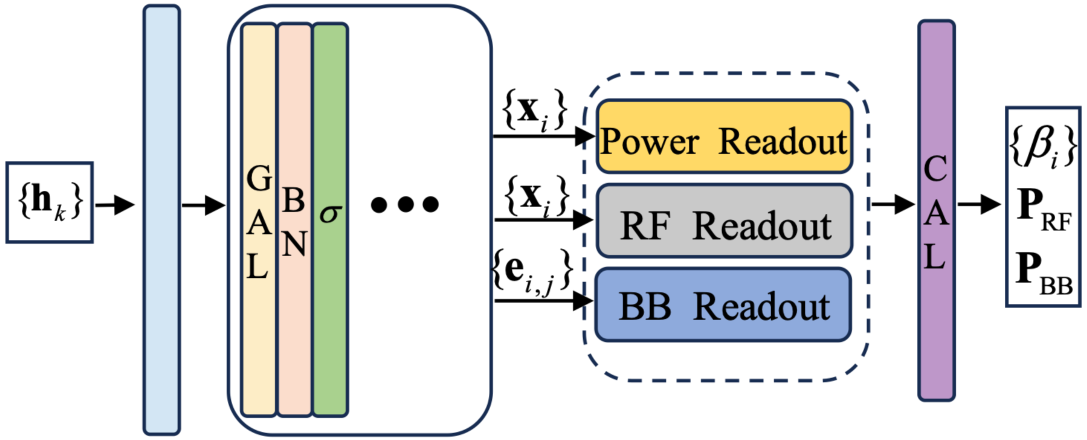
$$
\begin{aligned}
&\{\mathbf{P}_{\mathrm{RF}}^{\star}, \{\mathbf{p}_{\mathrm{BB},i}^{\star}, \beta_i^{\star}\}\} = \\
&\arg\max \sum\nolimits_{k=1}^{K} R_k\left(\mathbf{P}_{\mathrm{RF}}, \{\mathbf{p}_{\mathrm{BB},i}, \beta_i\}\right) \\
\text{s.t. } & \mathbf{P}_{\mathrm{RF}_{(:,k)}} \in \mathfrak{F}, \ \forall k, \\
& \left\|\mathbf{P}_{\mathrm{RF}}\left[\sqrt{\beta_1}\mathbf{p}_{\mathrm{BB},1}, \ldots, \sqrt{\beta_K}\mathbf{p}_{\mathrm{BB},K}\right]\right\|_{\mathrm{F}}^{2} \leq P_{\max},
\end{aligned}
$$

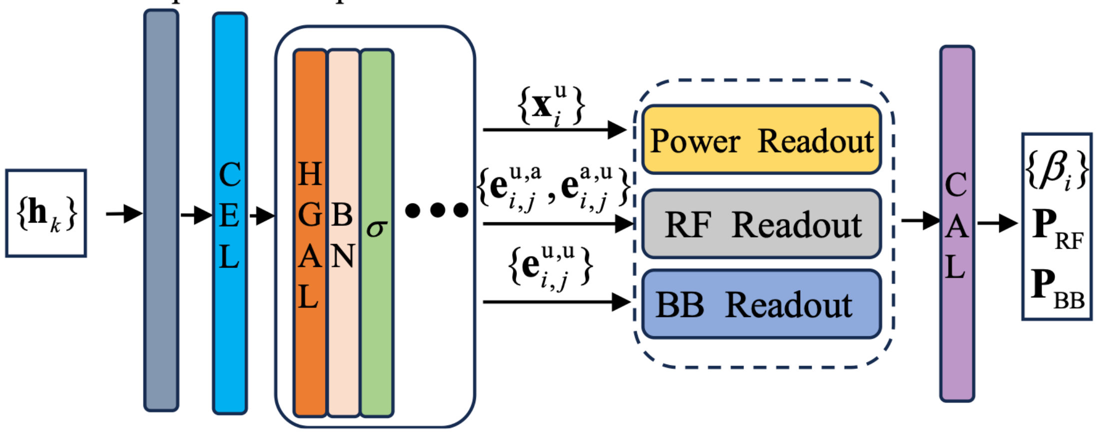
图表示方法

1）图建立；2）特征设置；3）图任务分配

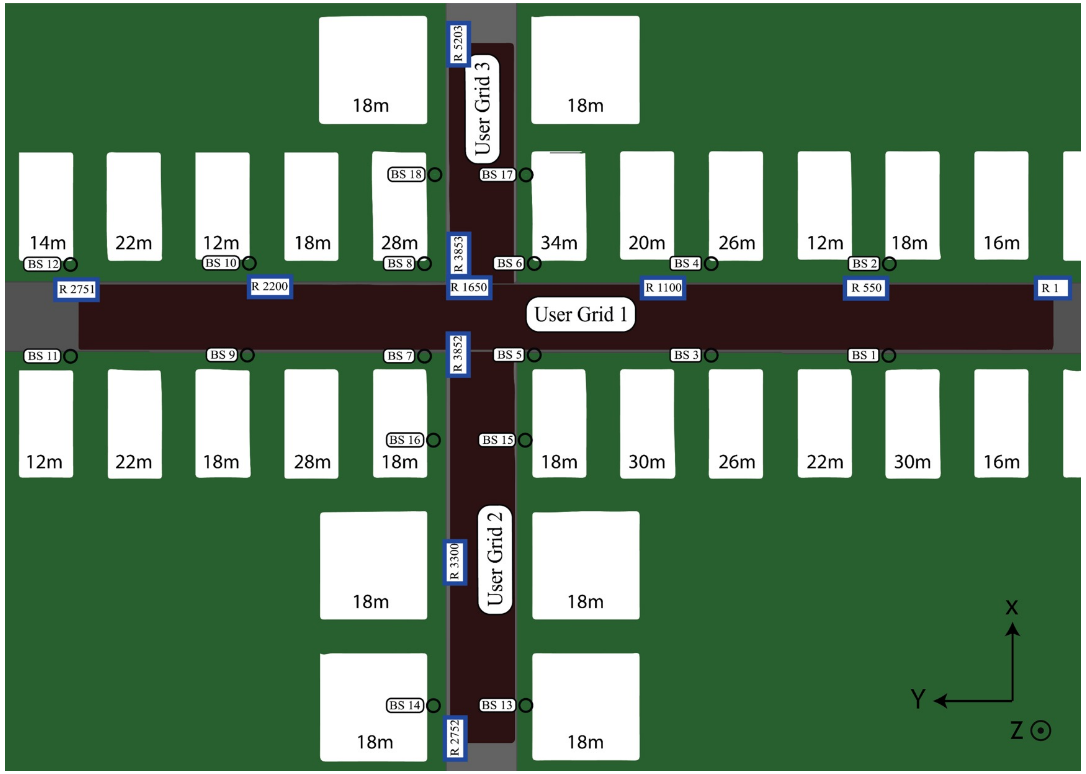
1. Y. Li, **Y. Lu***, G. Zhang, B. Ai, D. Niyato, S. Cui. Homogeneous and heterogeneous graph learning for hybrid beamforming in mmWave systems [J]. IEEE Transactions on Wireless Communications, 2025.

5/ Case Study V：同构图与异构图学习

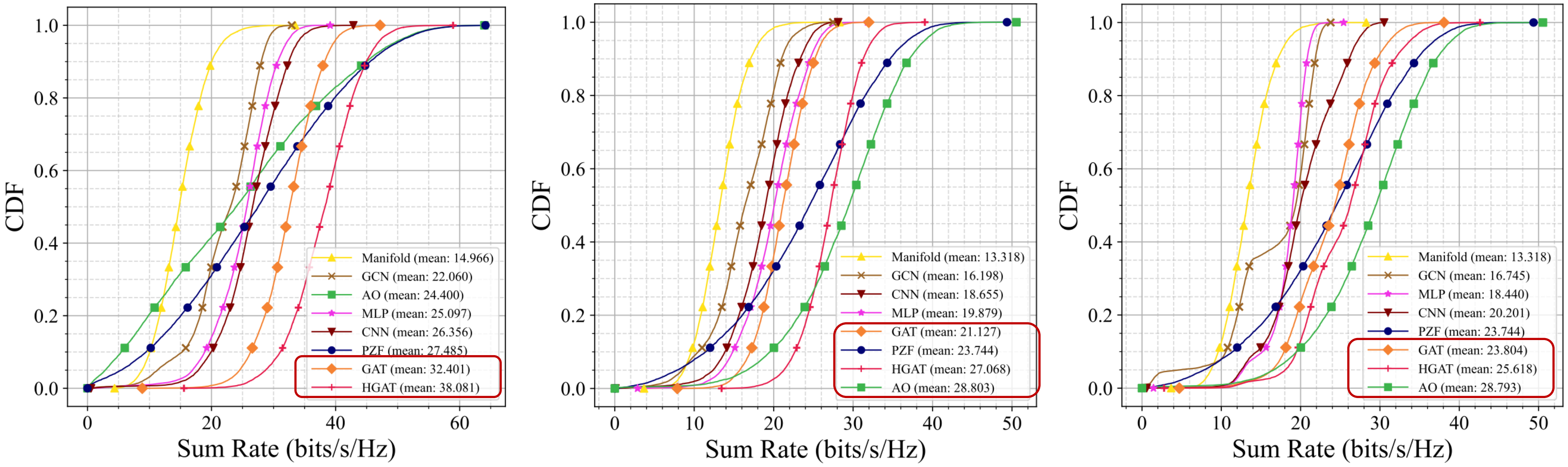




DeepMIMO



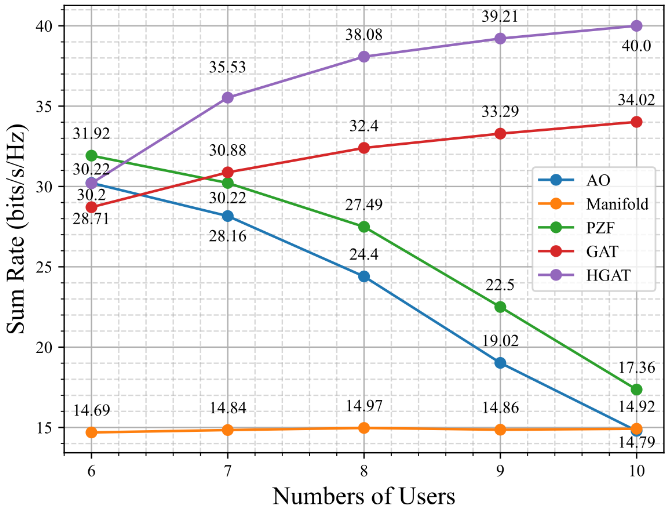
5/ Case Study V：同构图与异构图学习

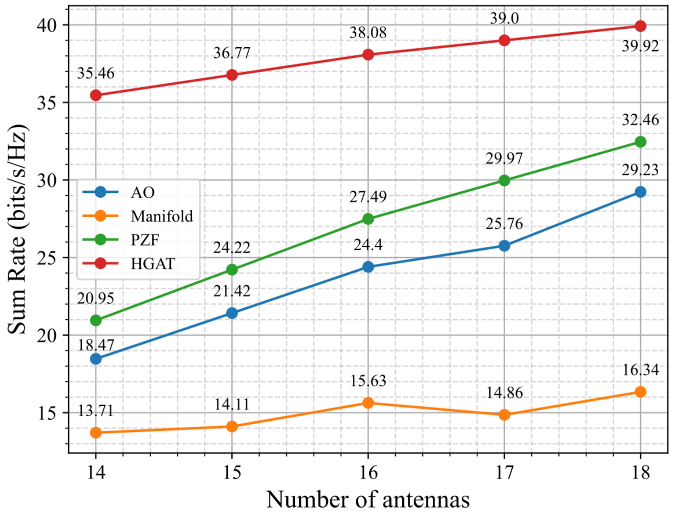


(a) BS 1 (b) BS 5 (c) BS 15

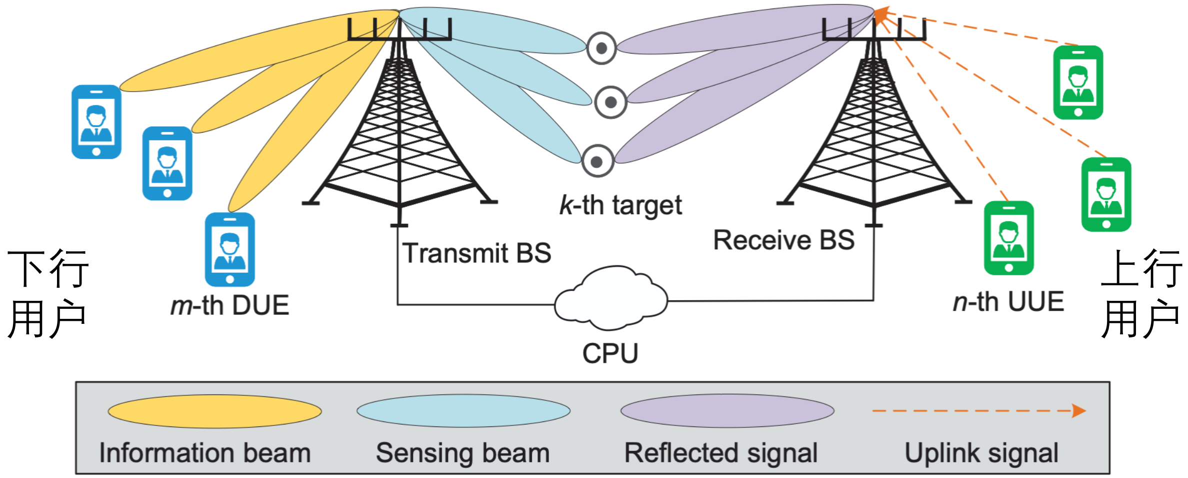
同构图方法：
对用户数量泛化

异构图方法
对用户、天线数量泛化





5/ Case Study VI：图神经网络与通感一体化



$$\mathbf{P}_1: \min_{\{\mathbf{w}_m\},\{\mathbf{v}_n\},\mathbf{R}_s} \operatorname{Tr}\left(\mathbf{F}^{-1}\right)$$

$$\text{s.t.} \sum_{m\in\mathcal{M}} \log_2\left(1+\Gamma_m^{\mathrm{d}}\right) \geq R_{\mathrm{d}},$$

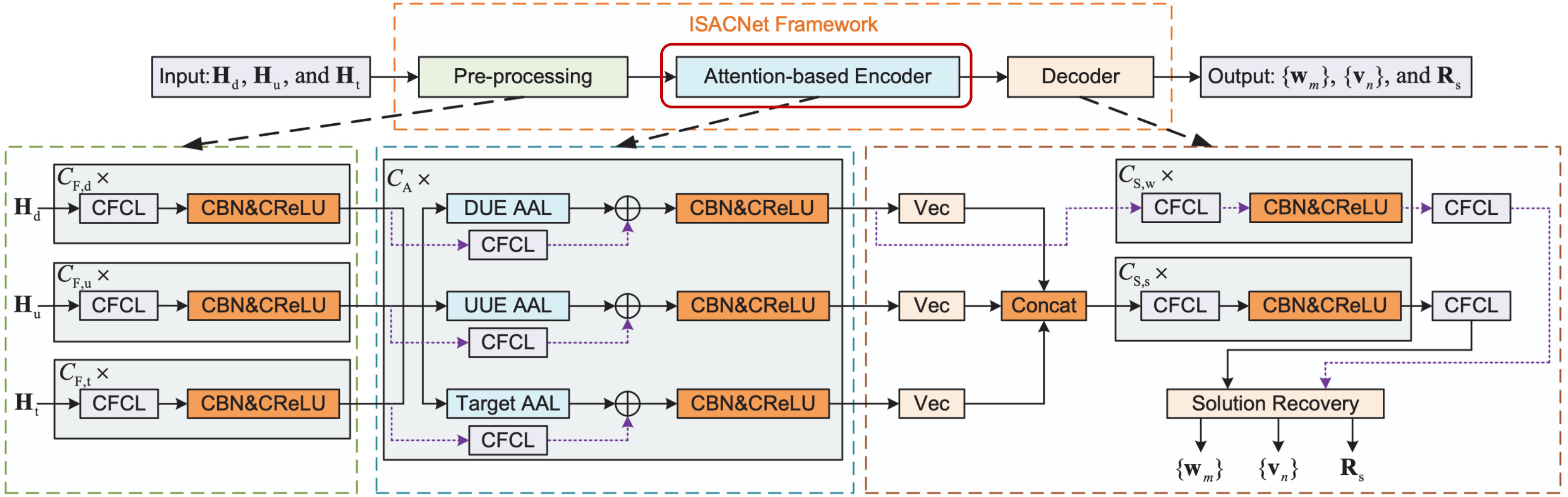
$$\sum_{n\in\mathcal{N}} \log_2\left(1+\Gamma_n^{\mathrm{u}}\right) \geq R_{\mathrm{u}},$$

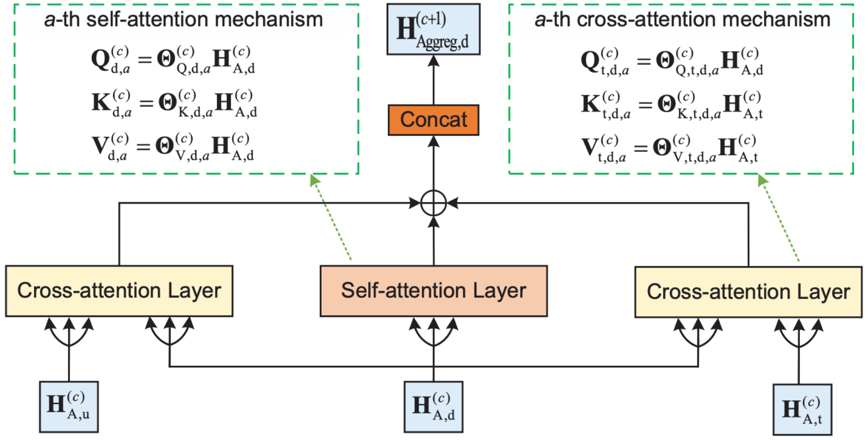
$$\sum_{m\in\mathcal{M}} \mathbf{w}_m^H \mathbf{w}_m + \operatorname{Tr}\left(\mathbf{R}_{\mathrm{s}}\right) \leq P_{\max},$$

$$\mathbf{v}_n^H \mathbf{v}_n = 1,\ \forall n \in \mathcal{N},$$

$$\mathbf{R}_{\mathrm{s}} \succeq \mathbf{0}.$$

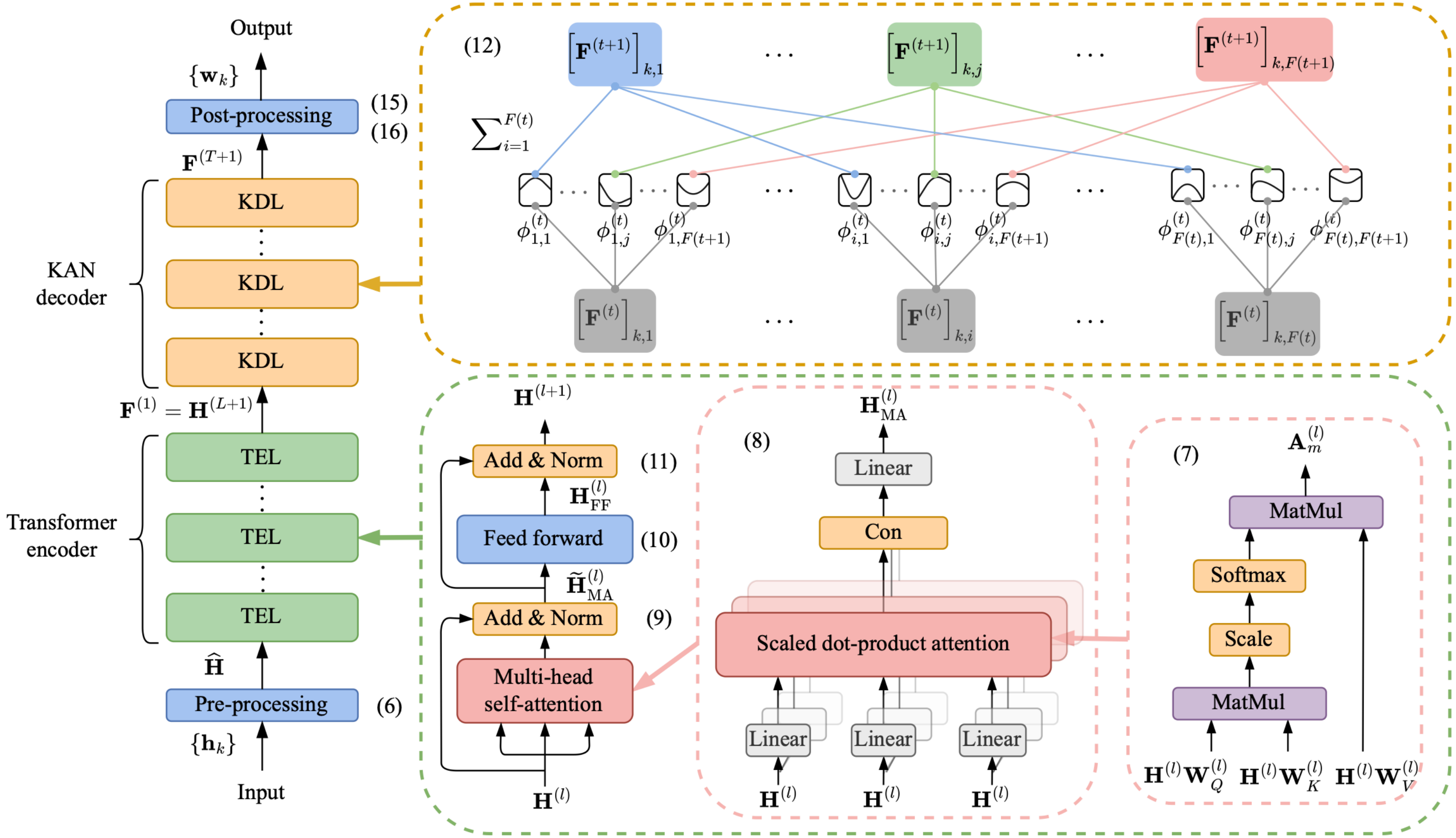
CRB for target positions and reflection coefficients





1. W. Mao, **Y. Lu***, G. Pan, J. An, B. Ai, D. W. K. Ng, "Cramer-Rao bound optimization for bistatic ISAC: Transceiver design and attention-based ISACNet," submit to IEEE Journal on Selected Areas in Communications, 2025. (Available on arXiv)

5/ Case Study VI：图神经网络与通感一体化



Encoder		Decoder		K_{Te}		
GAT	TF†	MLP	KAN	7	8	9
✓	×	✓	×	84.0%	85.6%	82.8%
✓	×	×	✓	89.5%	91.2%	88.1%
×	✓	✓	×	82.5%	85.8%	83.2%
×	✓	×	✓	**91.1%**	**92.9%**	**90.8%**
Avg. gain		-		0.1%	1.9%	3.1%
-		Avg. gain		14.1%	7.3%	12.9%

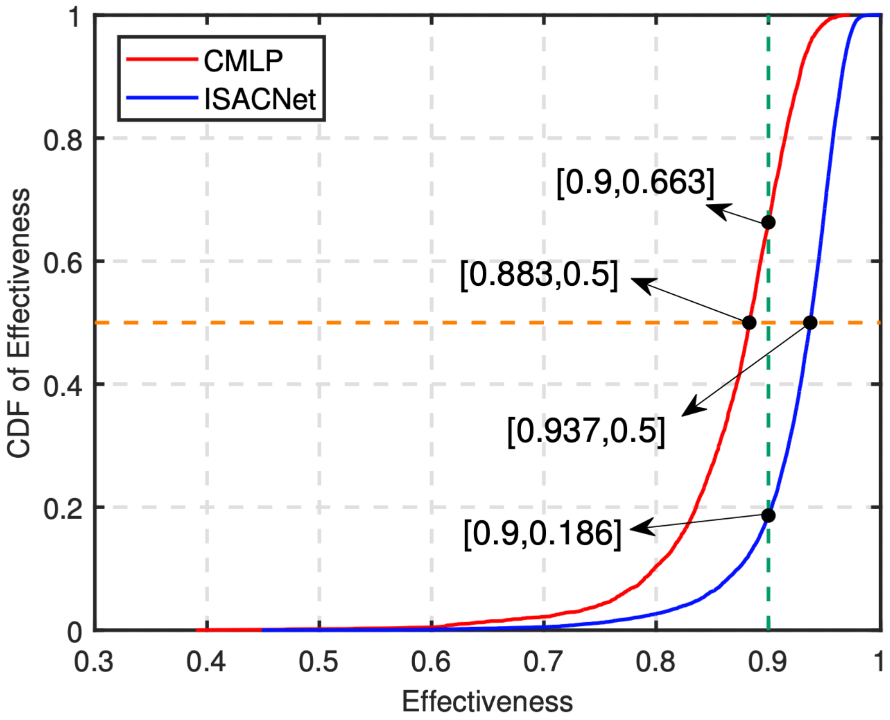
†TF is short for Transformer.

1. X. Xie, **Y. Lu***, C.-Y. Chi, W. Chen, B. Ai, D. Niyato. KANsformer for scalable beamforming [J]. IEEE Transactions on Vehicular Technology, 2025.

5/ Case Study VI：图神经网络与通感一体化

PP†	AE†	MR†	Effectiveness	FR‡
×	✓	✓	89.4%	56.7%
✓	×	✓	59.3%	0.56%
✓	✓	×	91.8%	96.3%
✓	✓	✓	92.0%	98.2%

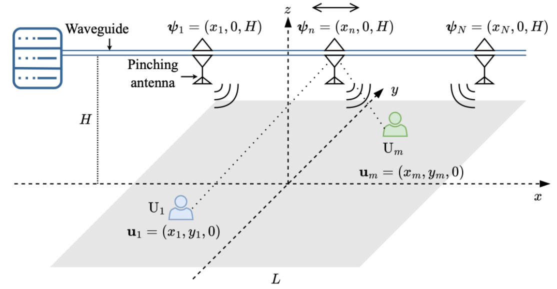
†PP/ AE/ MR/ FR: Pre-processing/ attention-based encoder/ model-based readout.
‡FR: Feasibility rate.

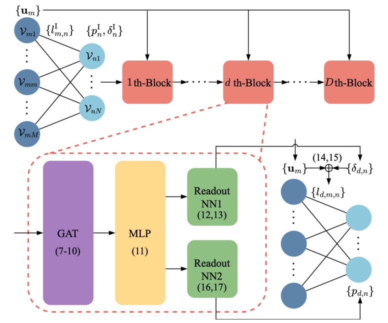


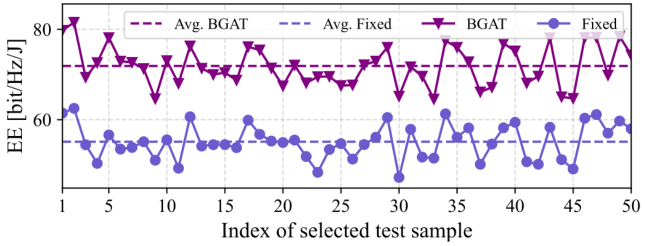
Approach	Effectiveness	FR†	IT†
SCA	100%	100%	13.97 s
ISACNet	92.0%	98.2%	3.71 ms
CMLP	86.3%	38.4%	3.23 ms
Vanilla CNN [23]	86.9%	57.3%	3.76 ms
SA CNN [28]	86.7%	54.6%	3.94 ms

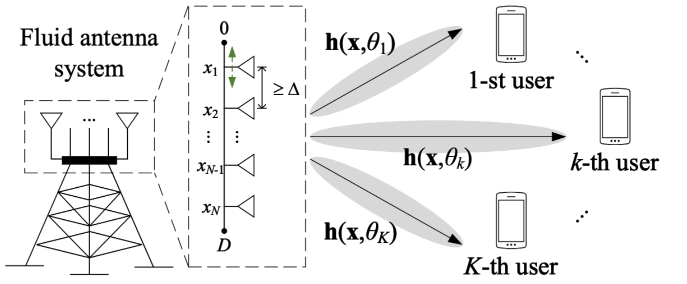
†FR/ IT: Feasibility rate/ inference time.

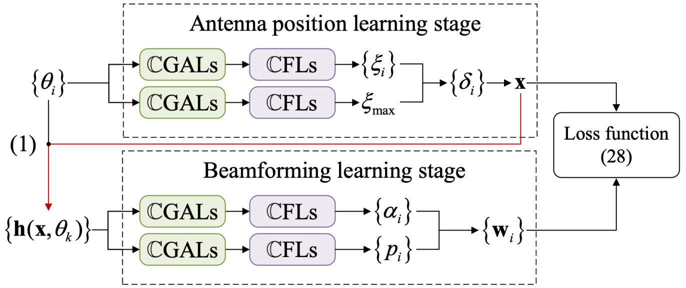
5/ Case Study VII：图神经网络与可重构天线





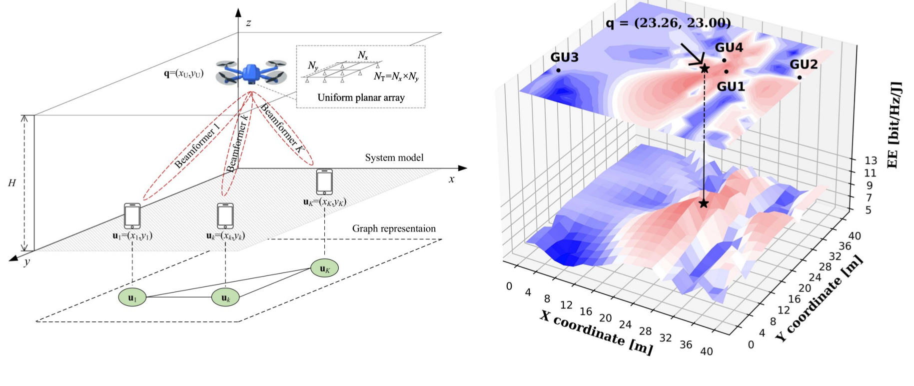


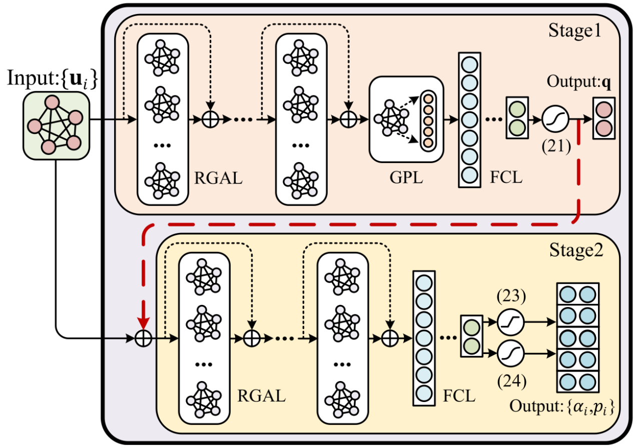




Beamforming \ Antenna	Equidistant SR	Equidistant EE	First stage SR	First stage EE
CVX	25.99	25.80	27.21	26.82
Second stage	25.03	24.78	26.58	26.17

SR stands for sum rate.





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6/ IEEE TNES Call For Paper

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Advanced Application of Graph Representation Learning in Communication Networks

Advanced Application of Graph Representation Learning in Communication Networks

Publication Date	Manuscript Submission Deadline
Second Quarter 2026	**1 January 2026**

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Thanks.

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