tinyML® Research Symposium

Enabling Ultra-low Power Machine Learning at the Edge

April 22, 2024

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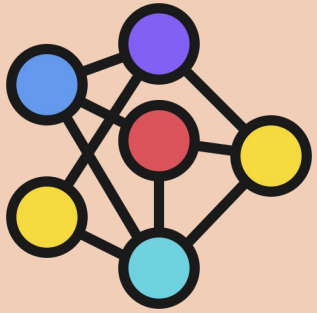
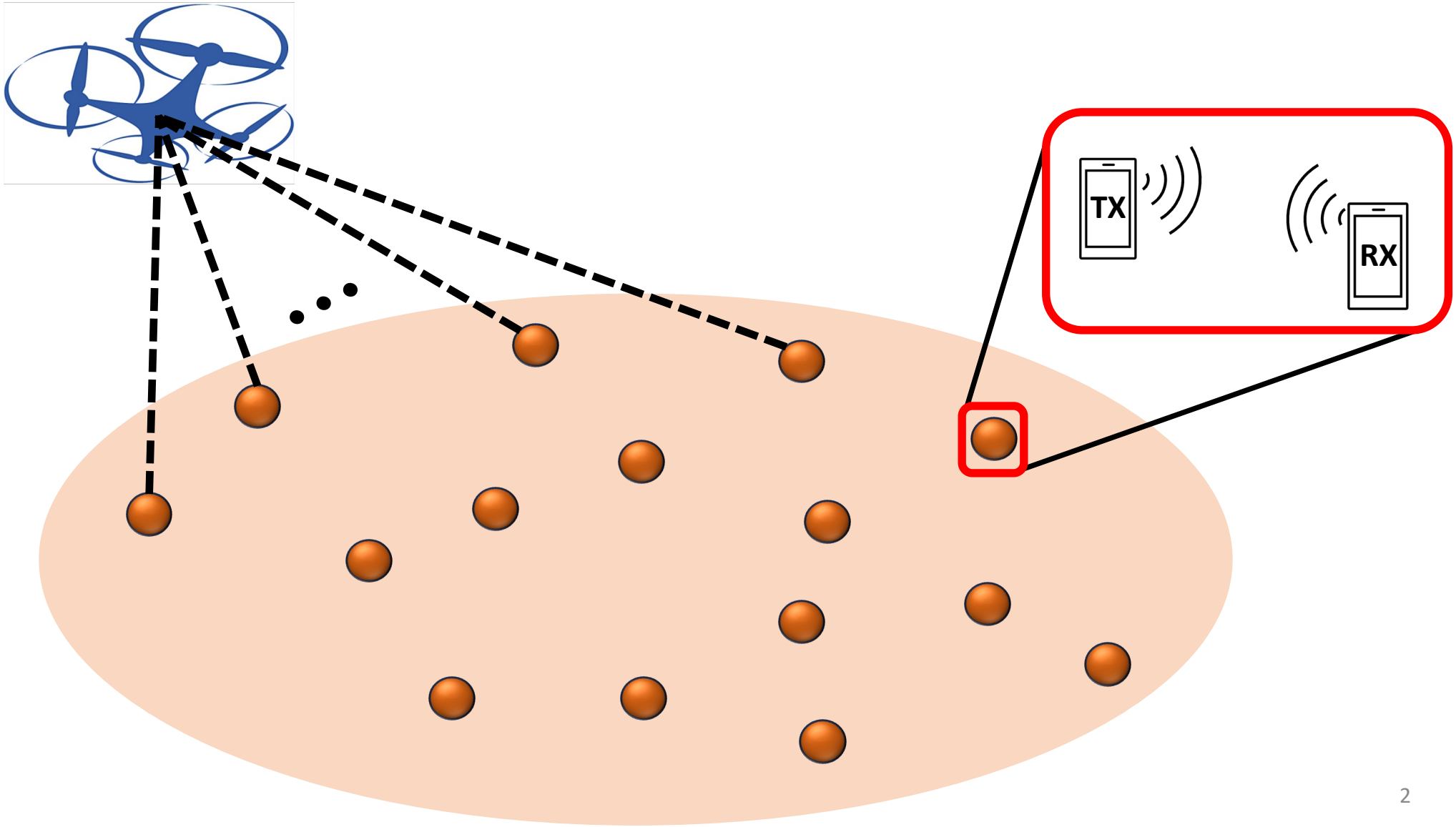
Tiny Graph Neural Networks for Radio Resource Management

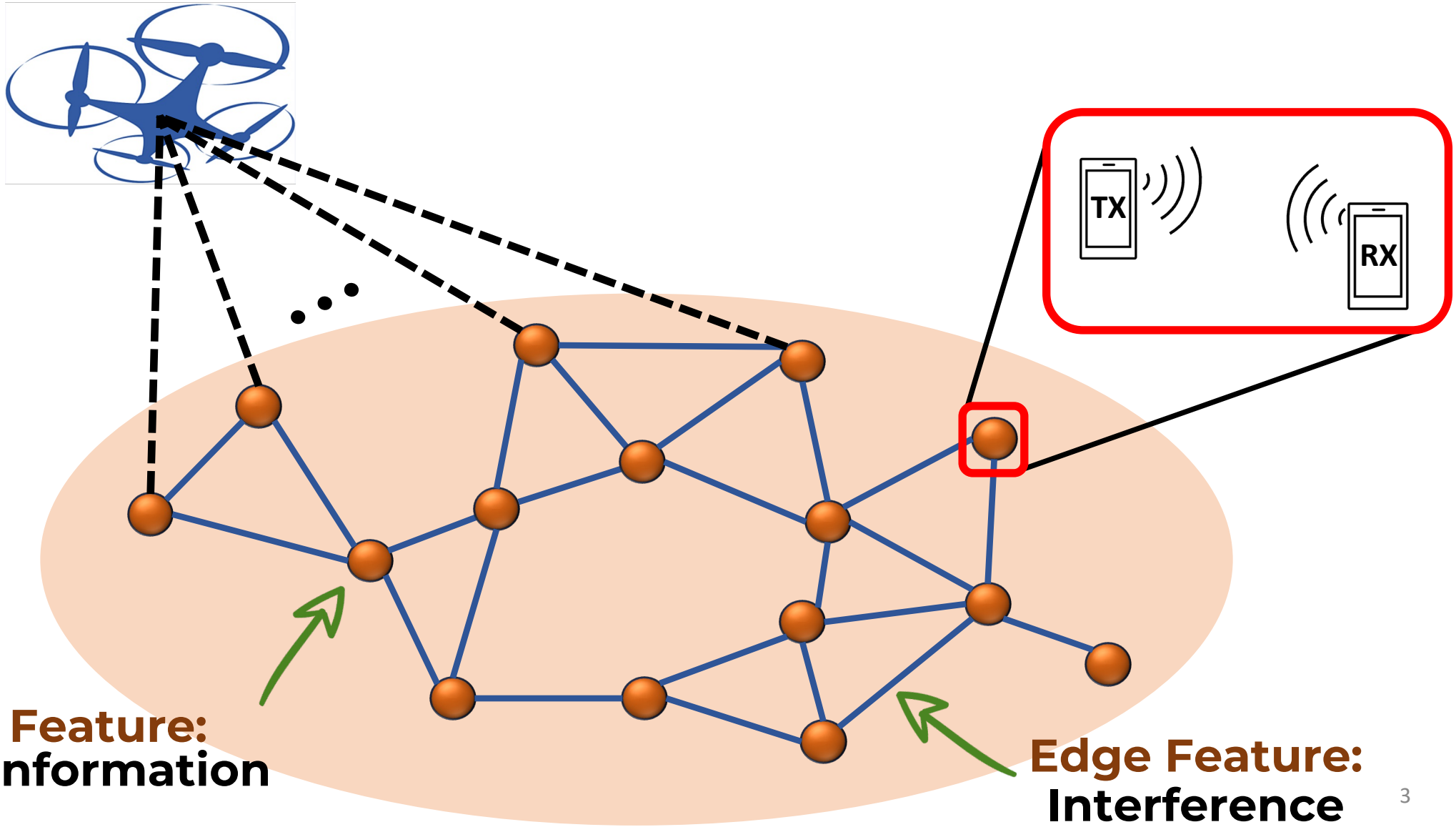
Ahmad Ghasemi and Hossein Pishro-Nik



Radio Resource Management (RRM)



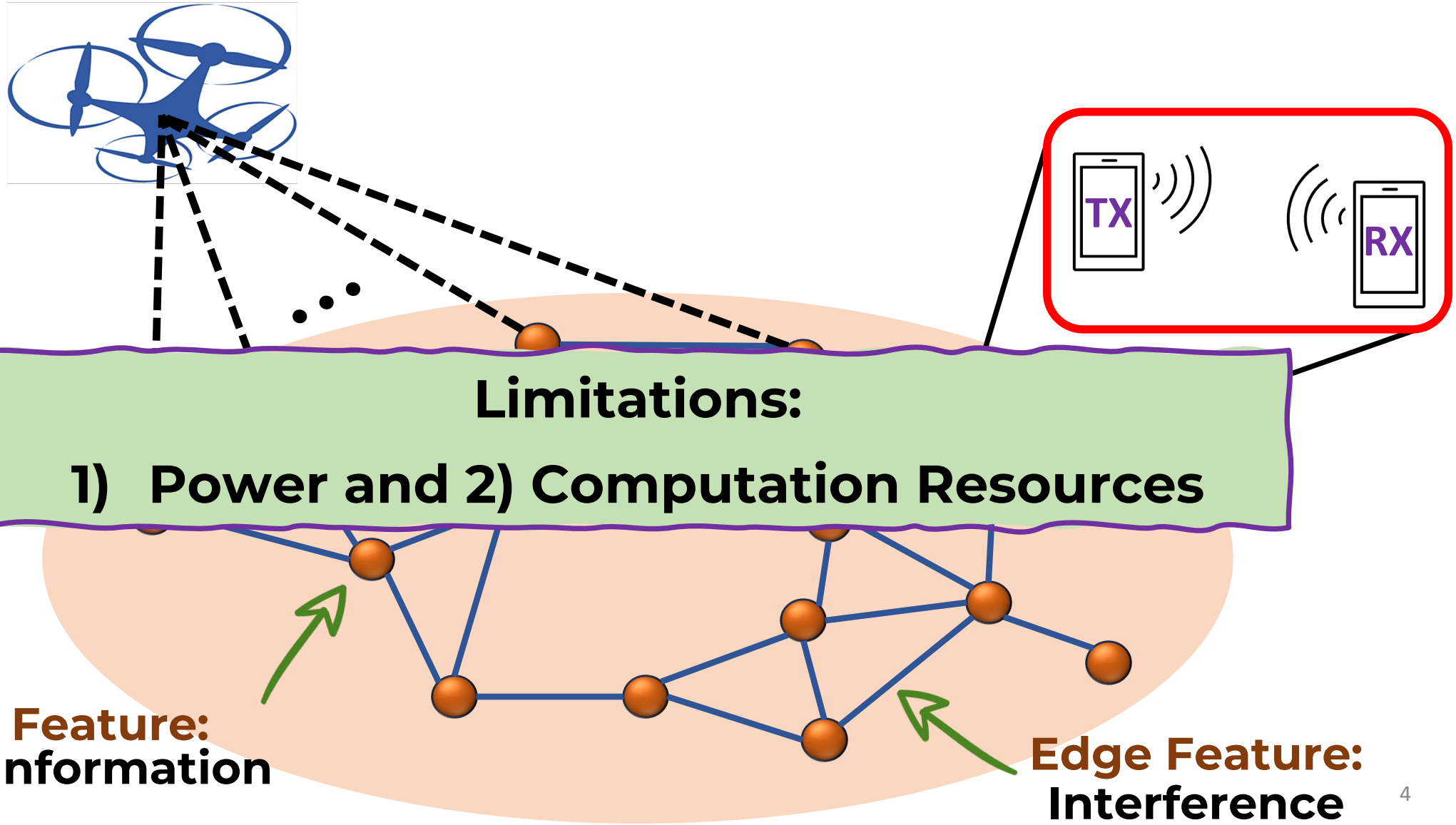
GNN based RRM



Vertex Feature:
Channel Information

Edge Feature:
Interference

GNN based RRM



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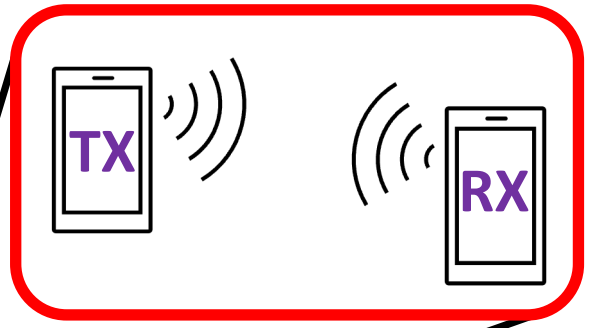


Limitations:

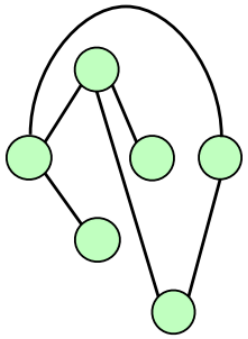
1) Power and 2) Computation Resources

➔ Smaller Models

Vertex Feature:
Channel Information

Edge Feature:
Interference

Message Passing GNN



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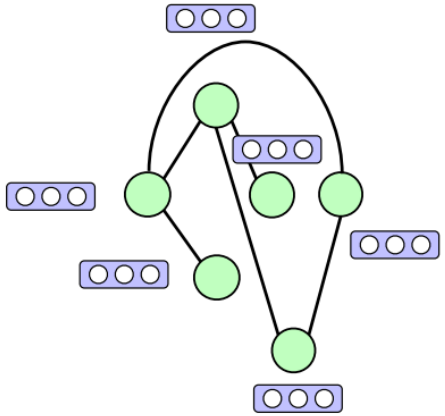

Input Encoding

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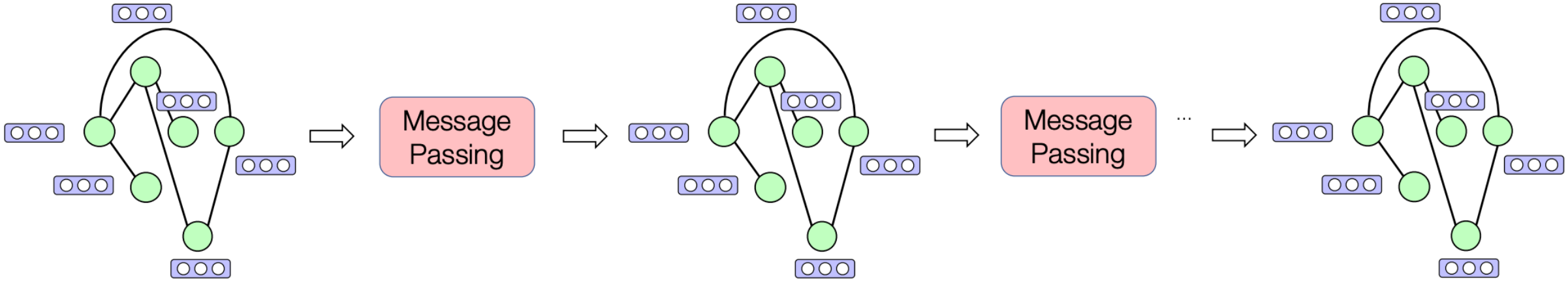
Message Passing GNN



Input Encoding

Message Passing Layers/Steps

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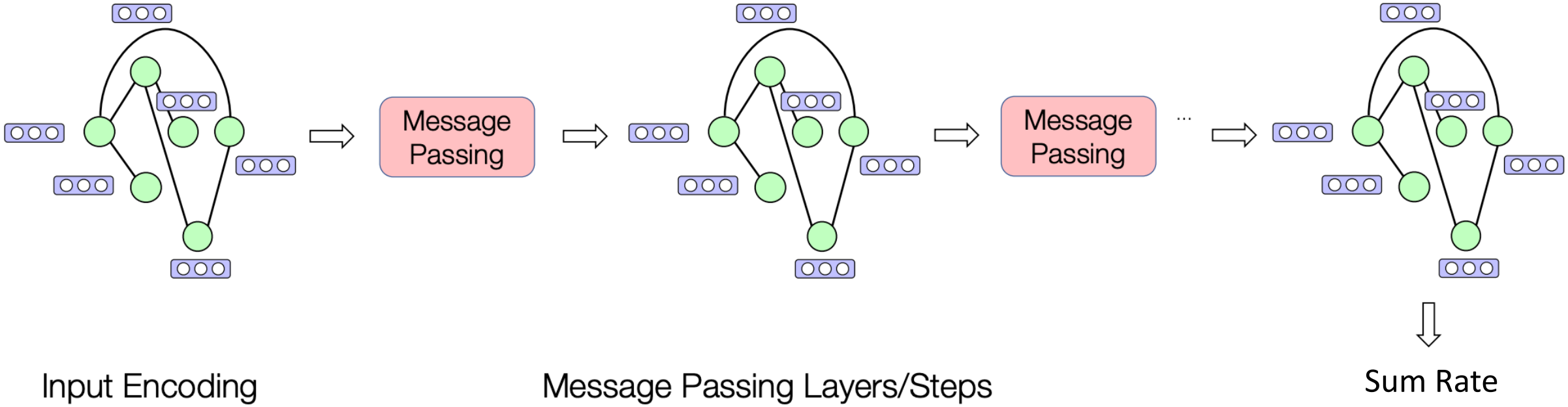
Message Passing GNN



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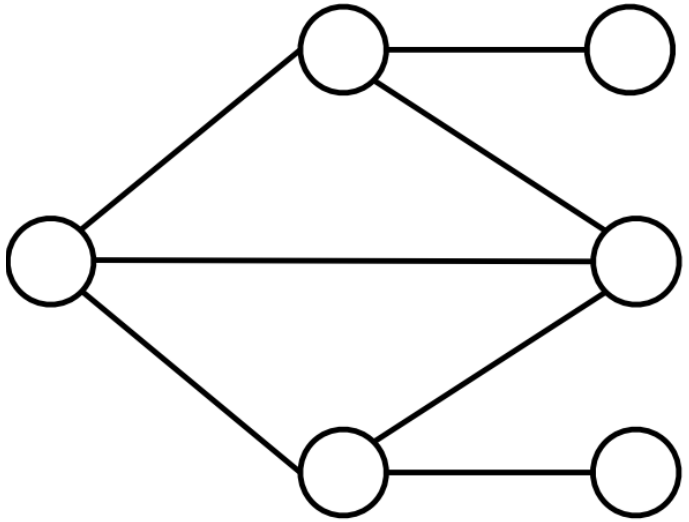
Massage Passing in MPGNN

(t+1)-th message passing step/layer



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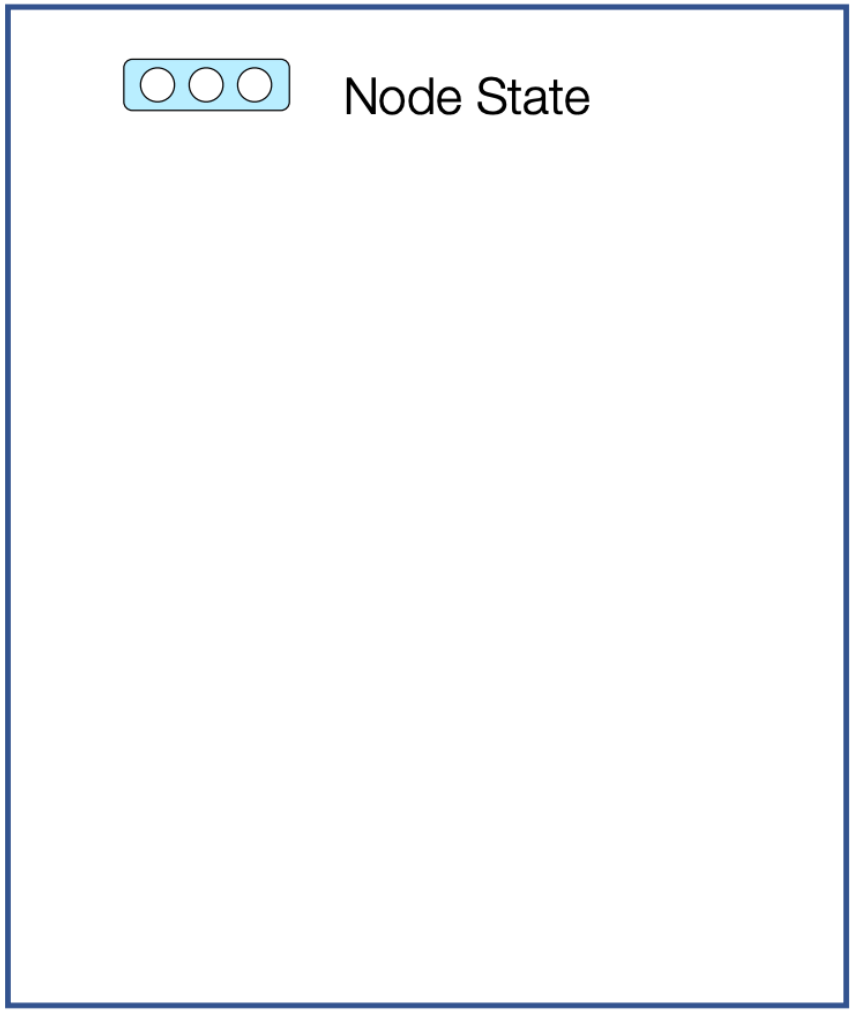
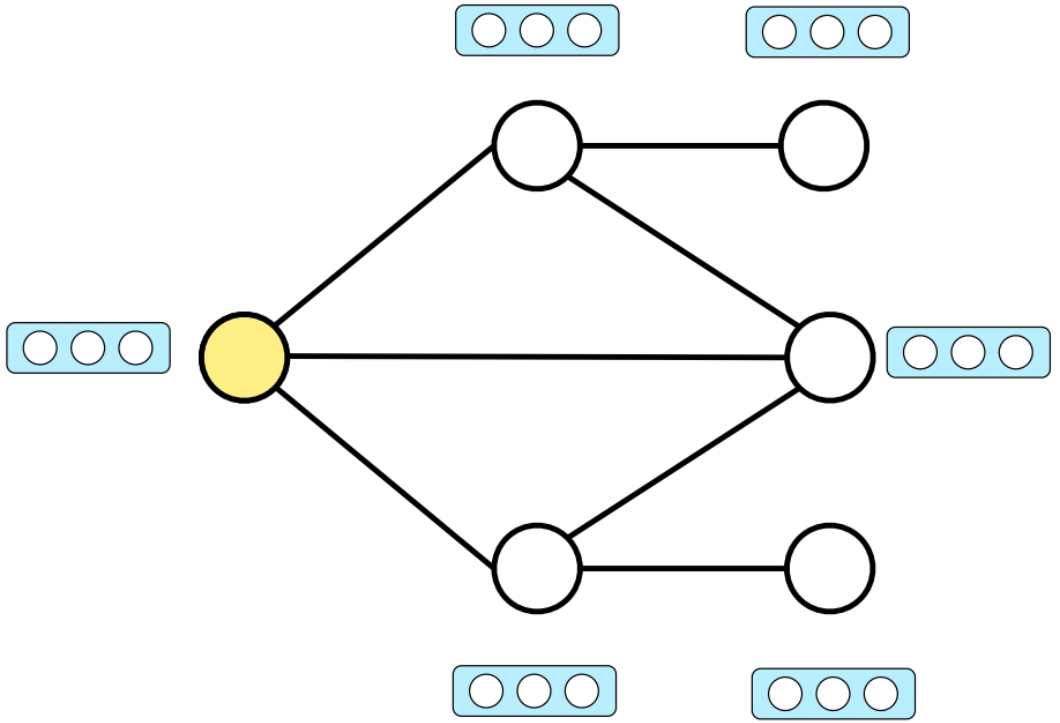
Massage Passing in MPGNN

(t+1)-th message passing step/layer

$\mathbf{h}_i^t$





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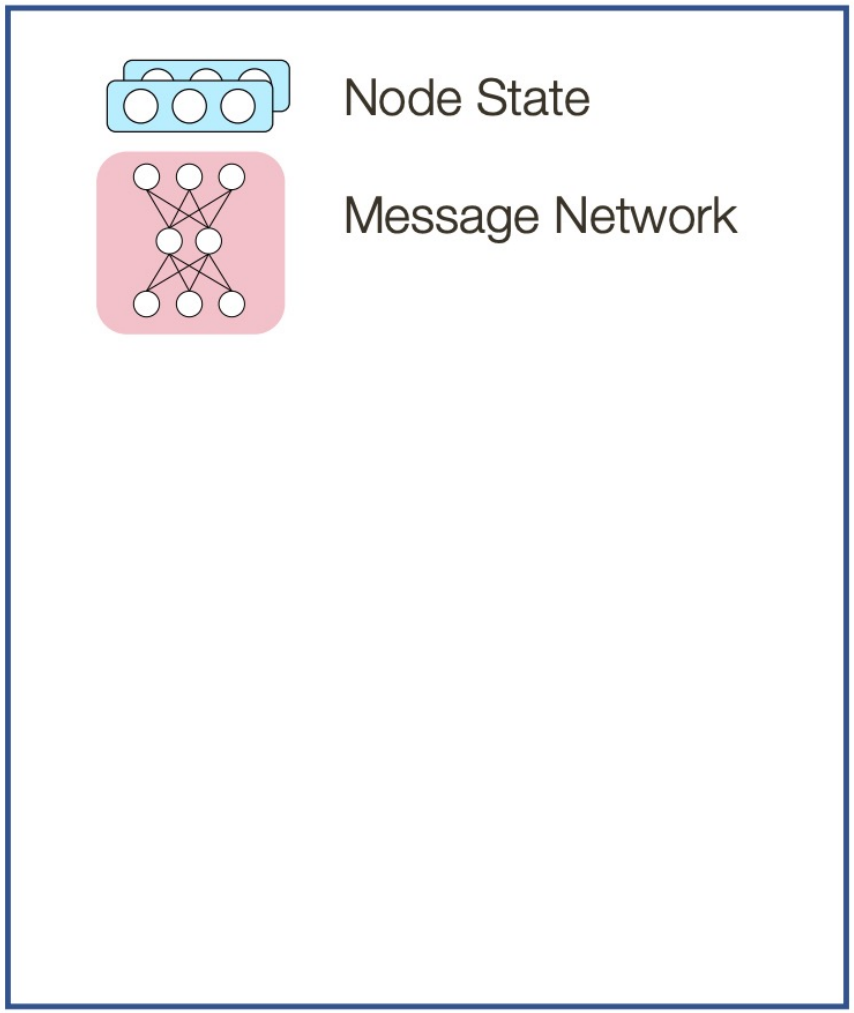
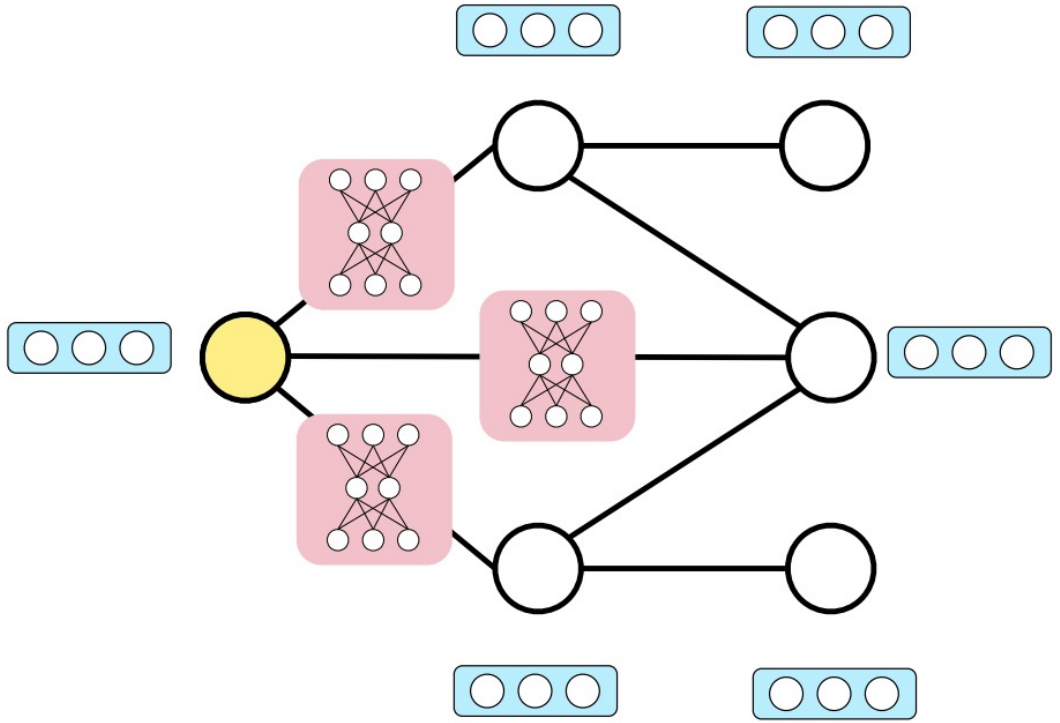
$\mathbf{h}_i^t \quad \mathbf{h}_j^t$





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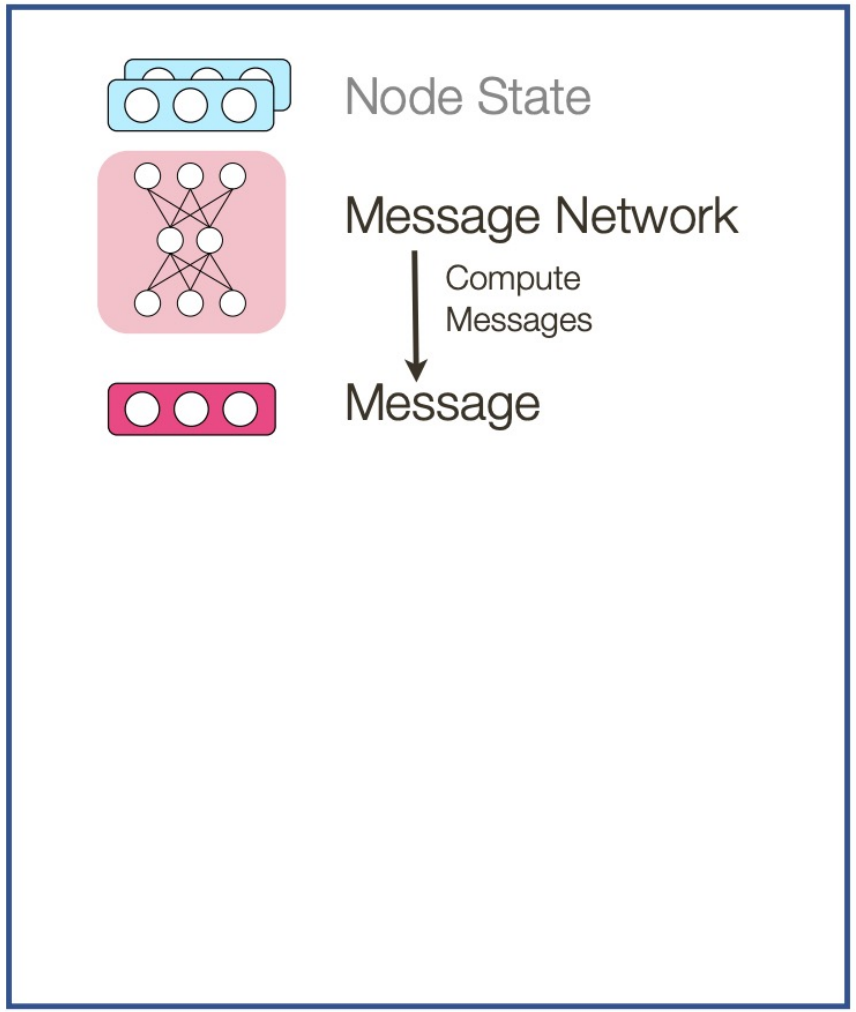
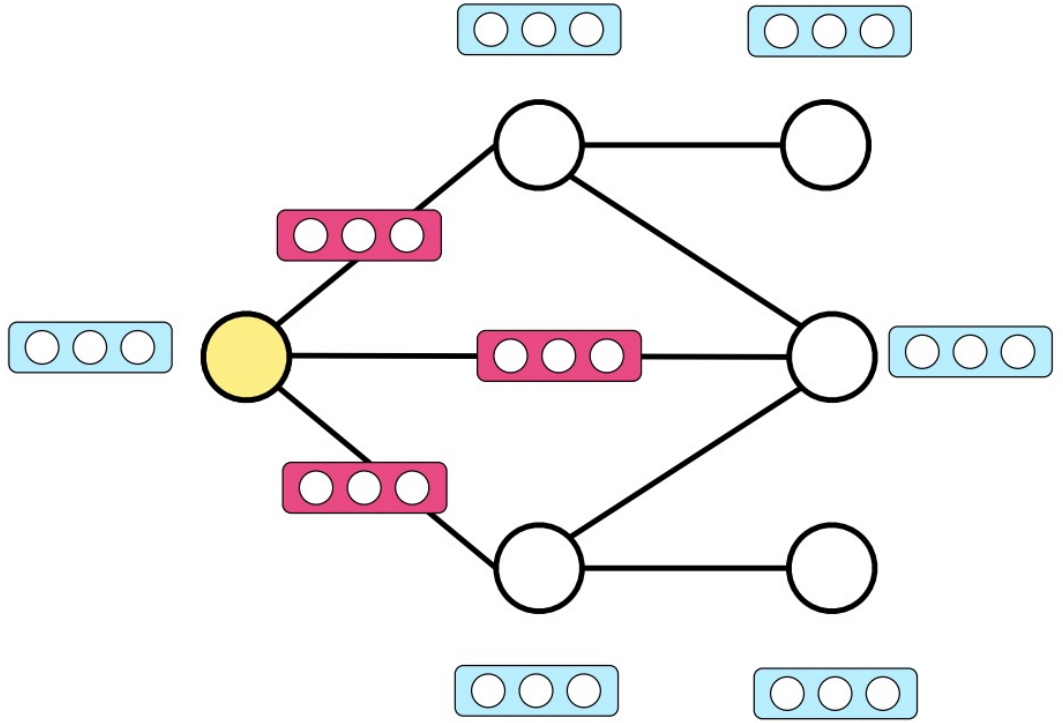
Massage Passing in MPGNN

(t+1)-th message passing step/layer

$\mathbf{h}_i^t \quad \mathbf{h}_j^t$

$\mathbf{m}_{ji}^t = f_{\text{msg}}(\mathbf{h}_j^t, \mathbf{h}_i^t)$





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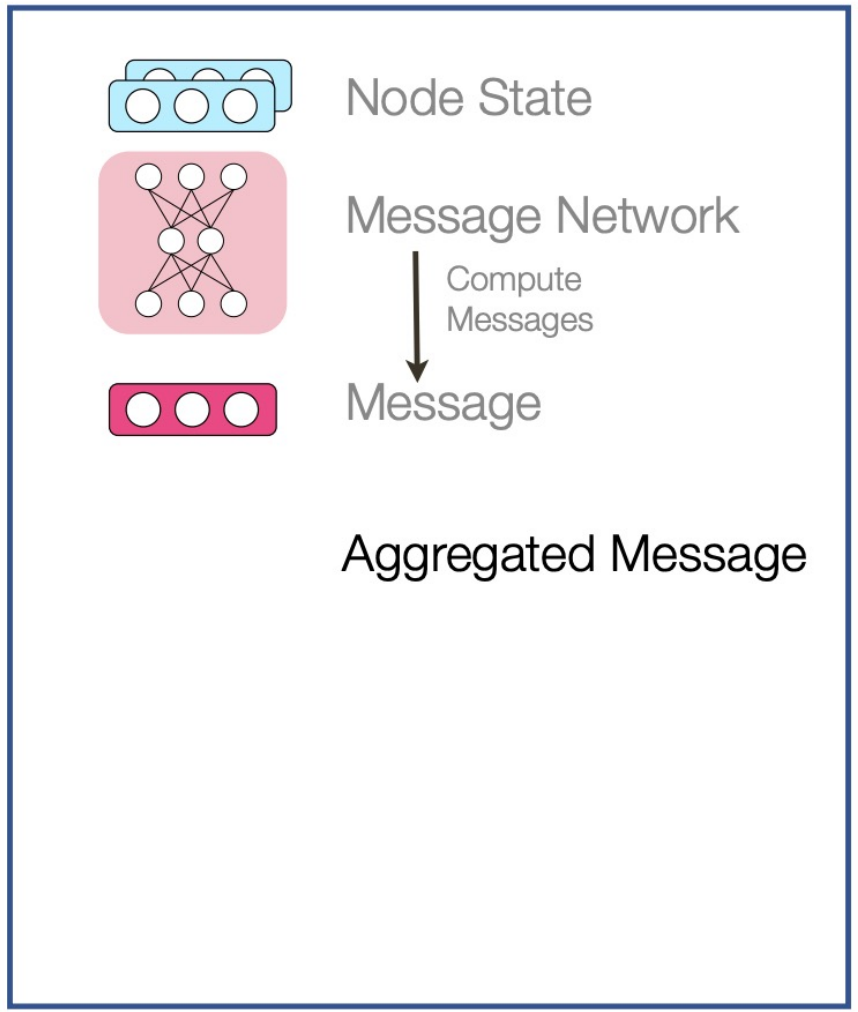

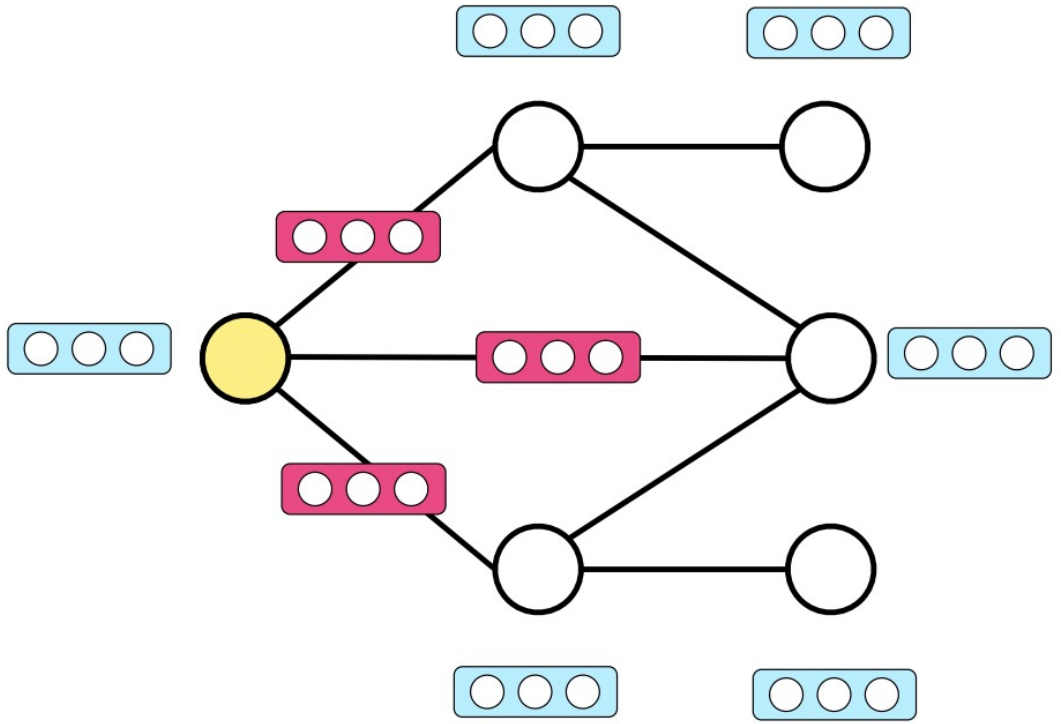

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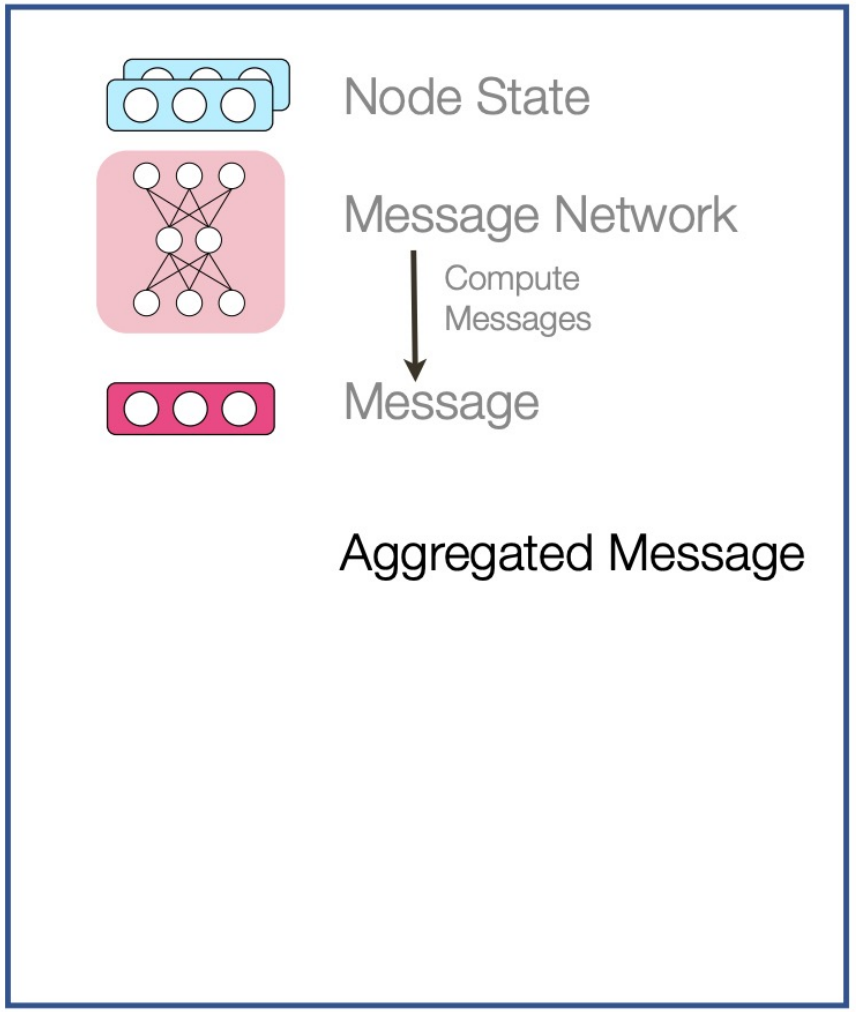

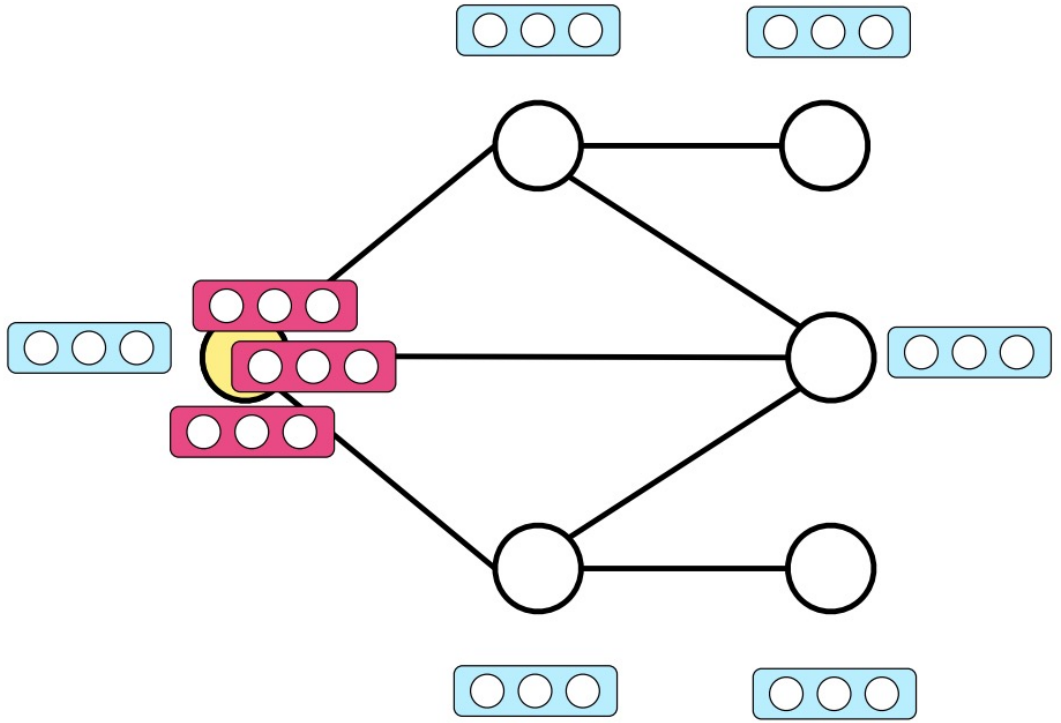

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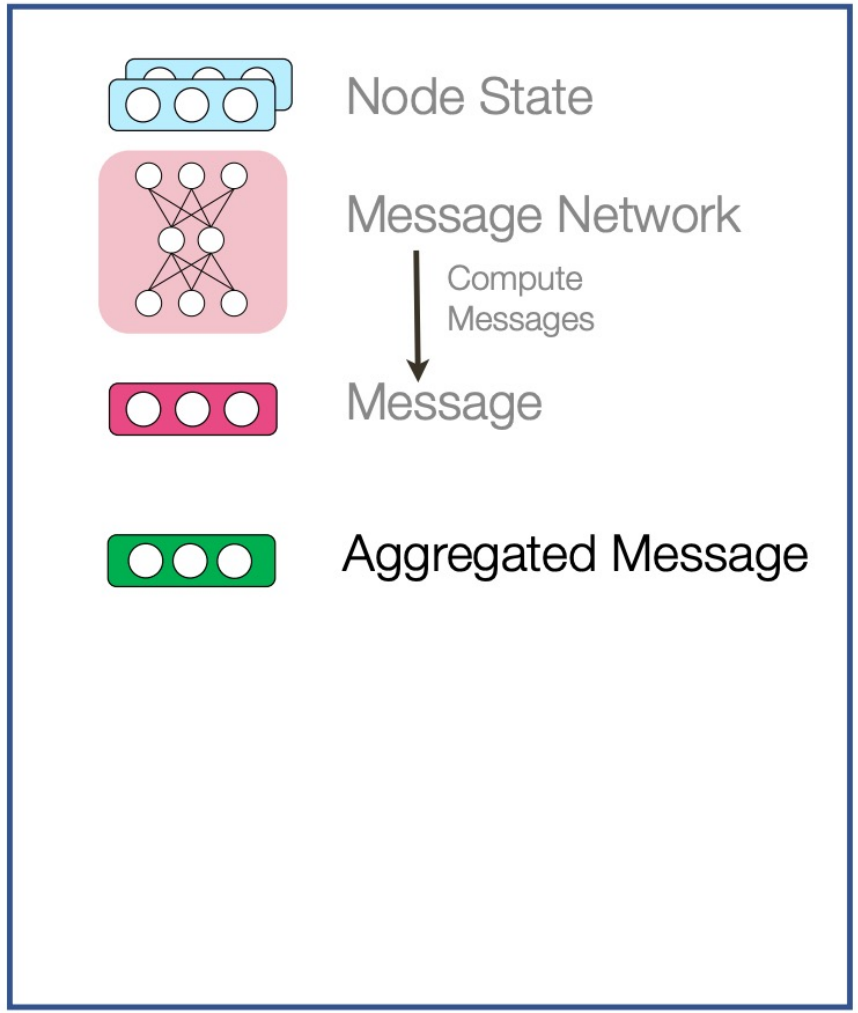

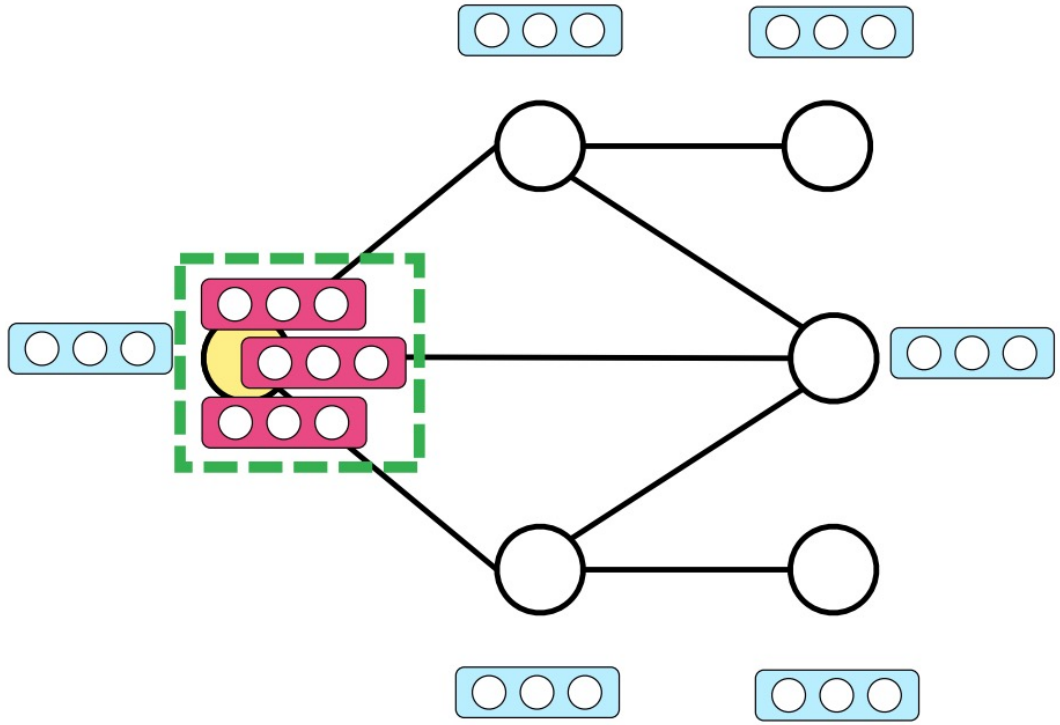

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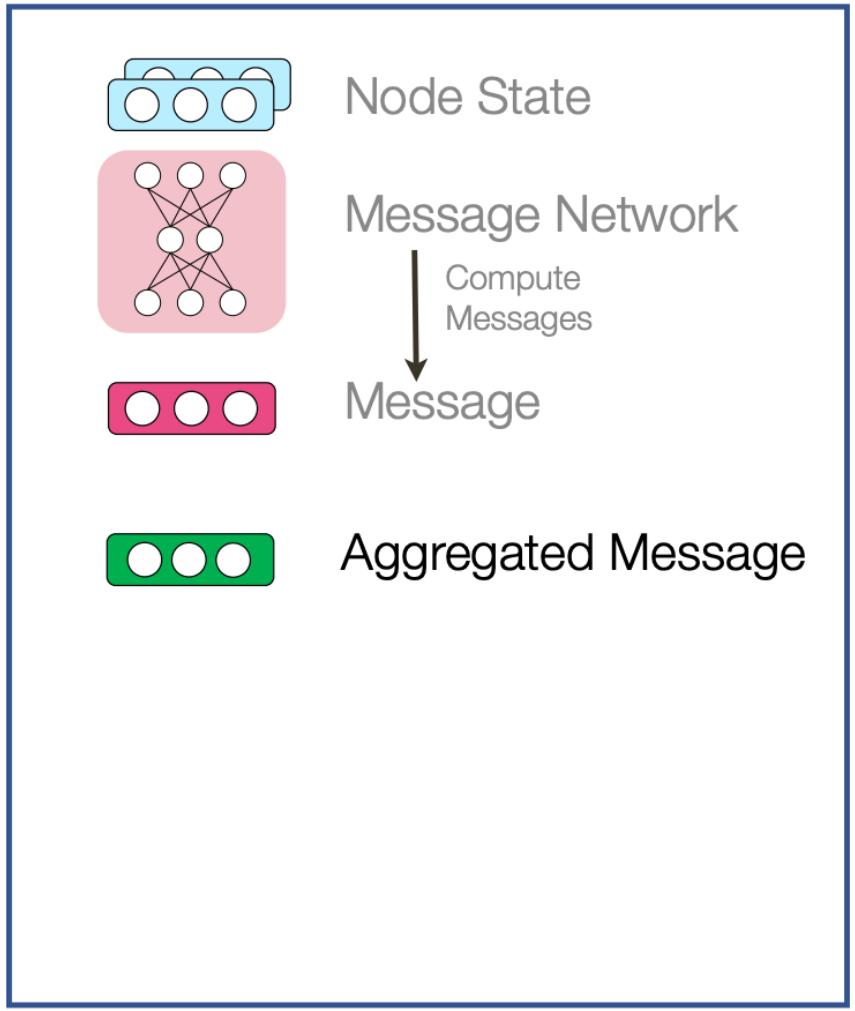

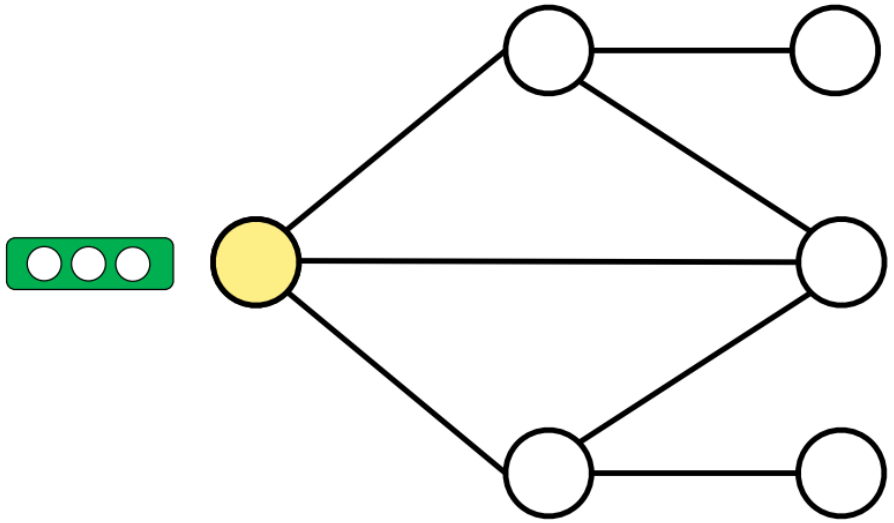

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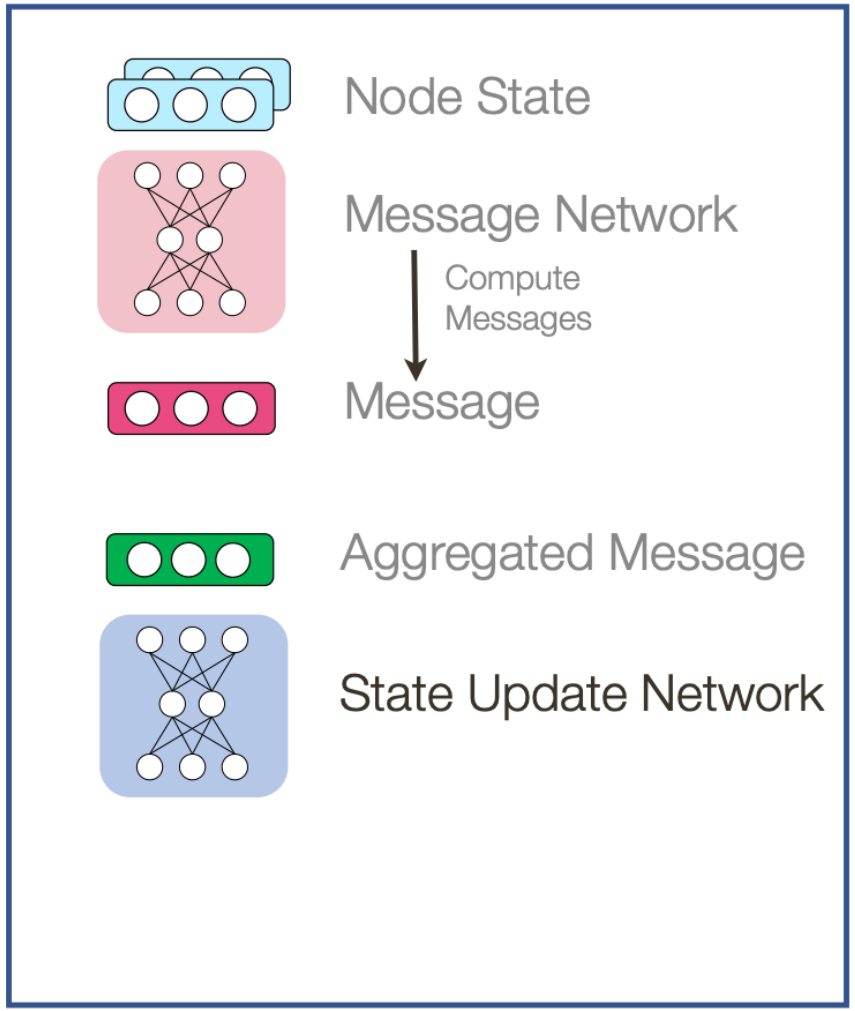

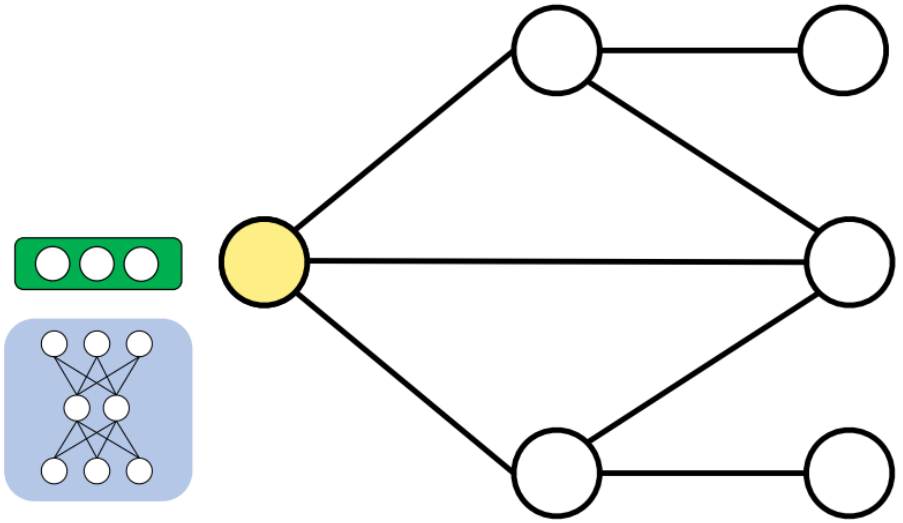

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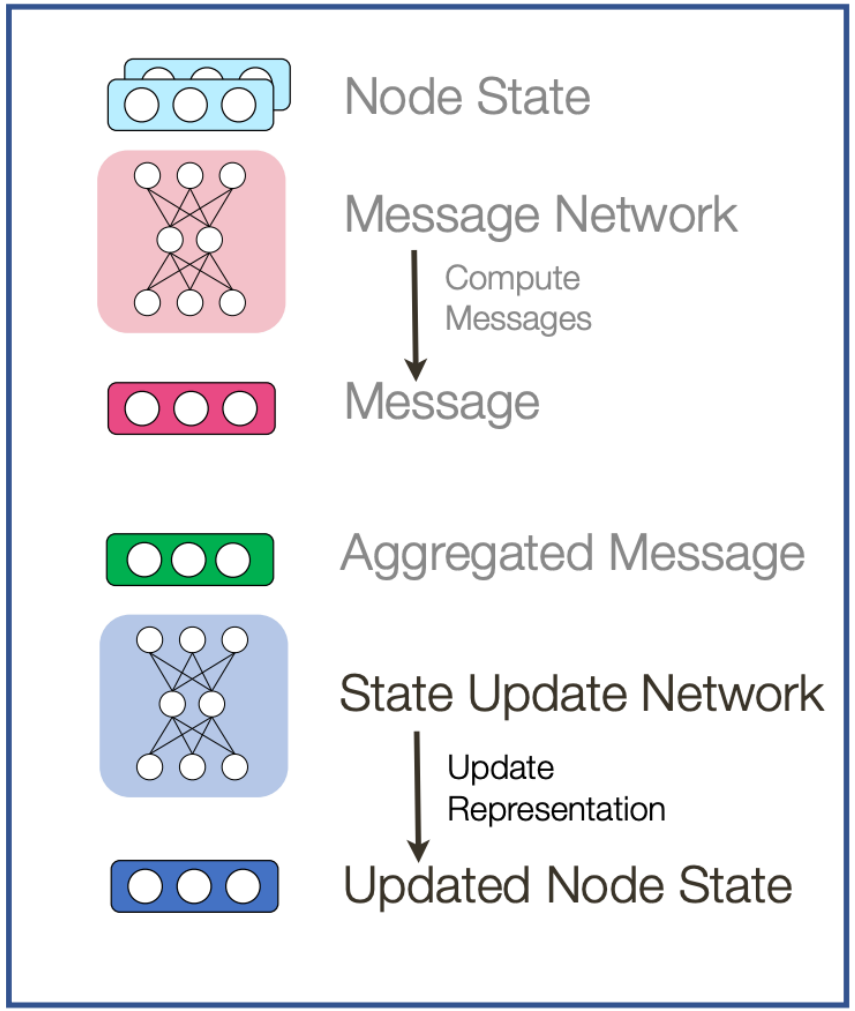

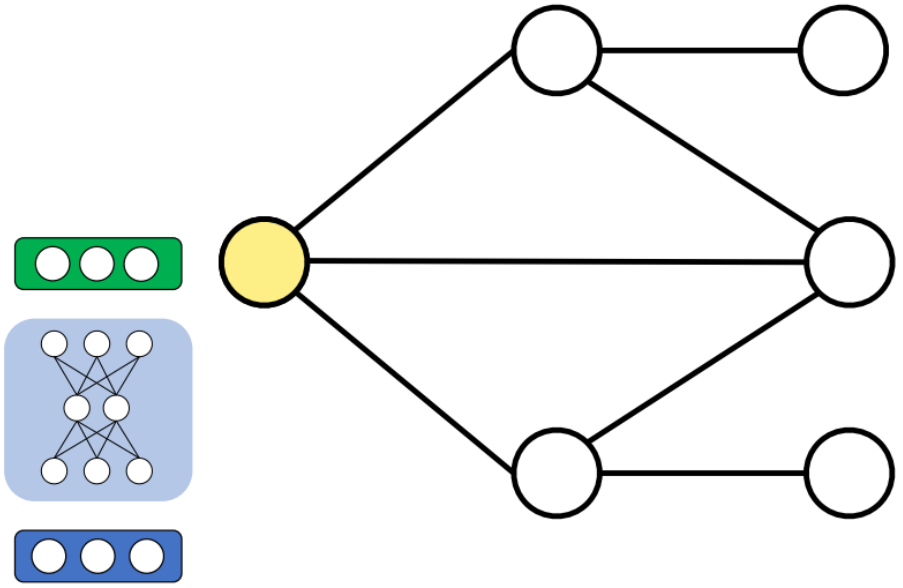

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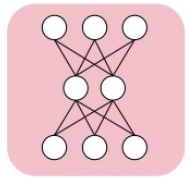
Massage Passing in MPGNN

1. Compute Messages

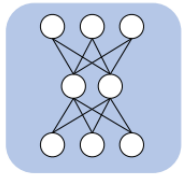
$$\mathbf{m}_{ji}^t = f_{\text{msg}}(\mathbf{h}_j^t, \mathbf{e}_{ji})$$

$$f_{\text{msg}}(\mathbf{h}_j^t, \mathbf{e}_{ji}) = \text{MLP}([\mathbf{h}_j^t, \mathbf{e}_{ji}])$$

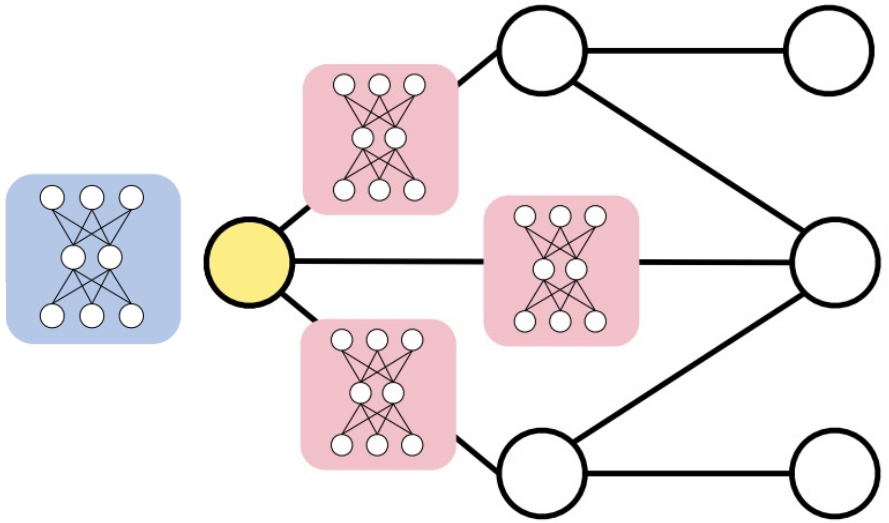
Edge Feature



Message Network



State Update Network



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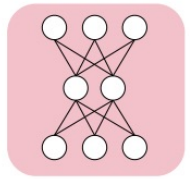

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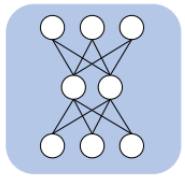

State Update Network

2. Aggregate Messages

$$\bar{\mathbf{m}}_i^t = f_{\text{agg}}\left(\{\mathbf{m}_{ji}^t | j \in \mathcal{N}_i\}\right)$$

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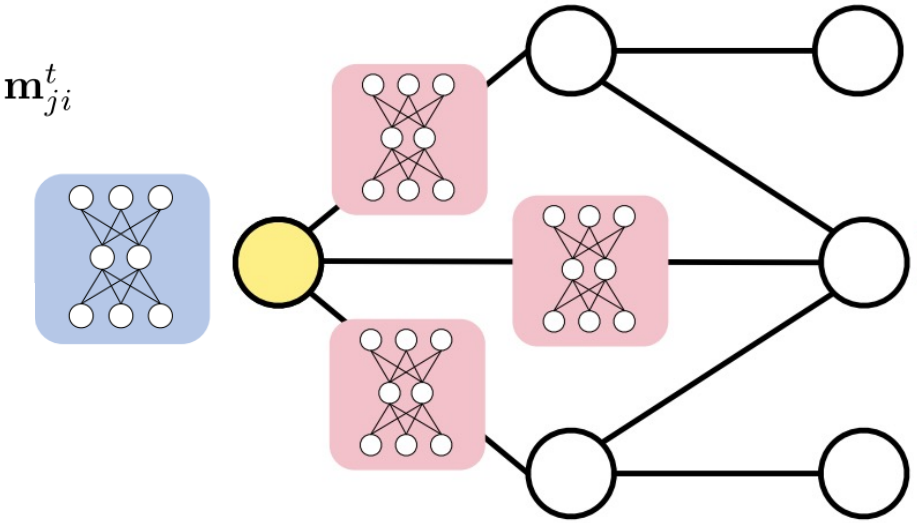

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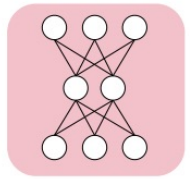

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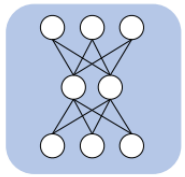

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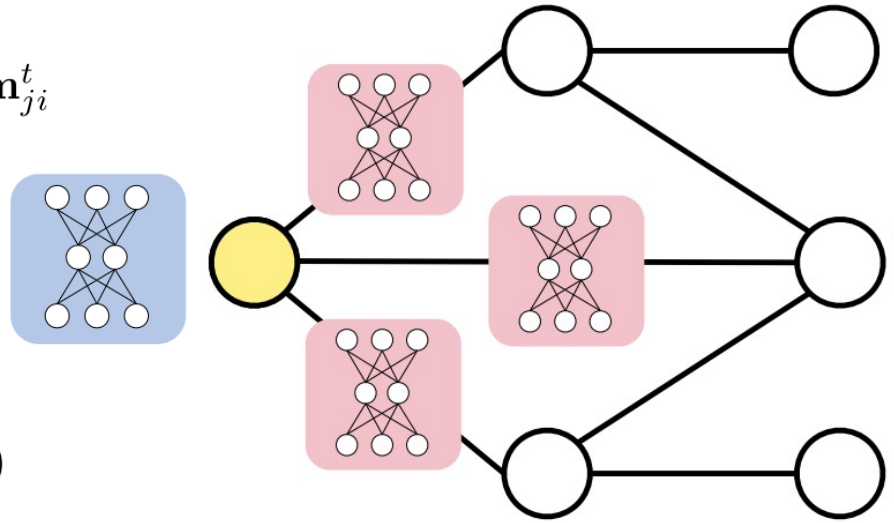

3. Update Node Representations

$$\mathbf{h}_i^{t+1} = f_{\text{update}}(\mathbf{h}_i^t, \bar{\mathbf{m}}_i^t) \qquad f_{\text{update}}(\mathbf{h}_i^t, \bar{\mathbf{m}}_i^t) = \text{MLP}([\mathbf{h}_i^t, \bar{\mathbf{m}}_i^t])$$

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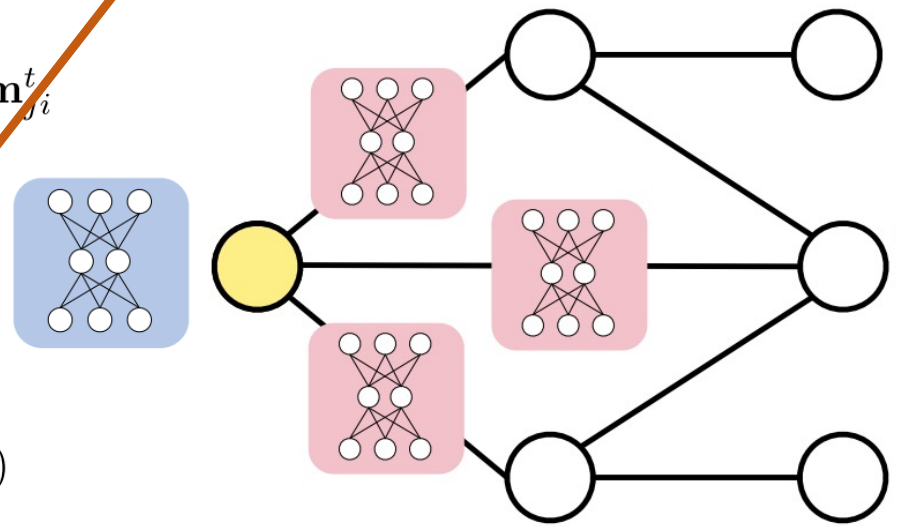

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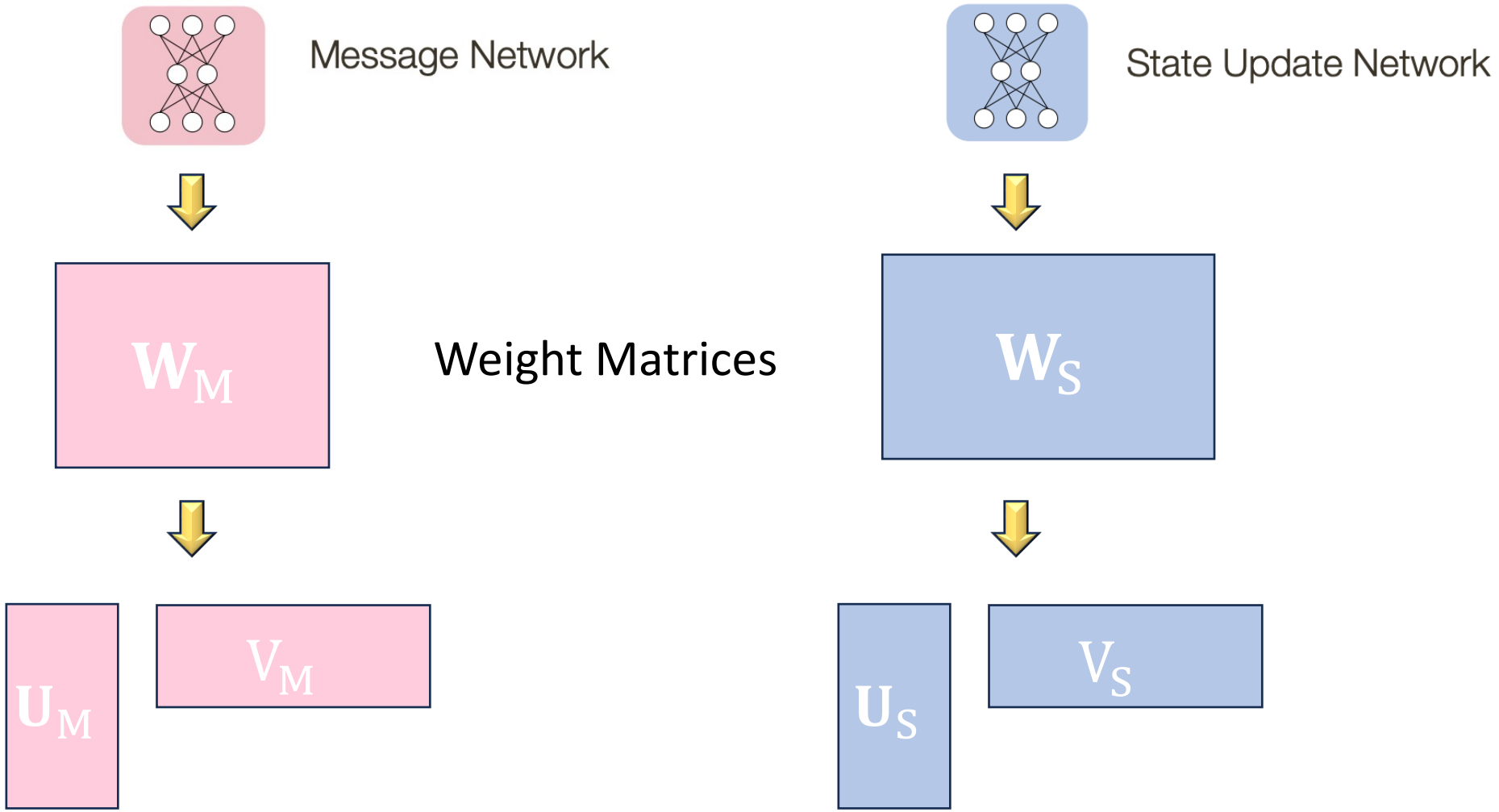
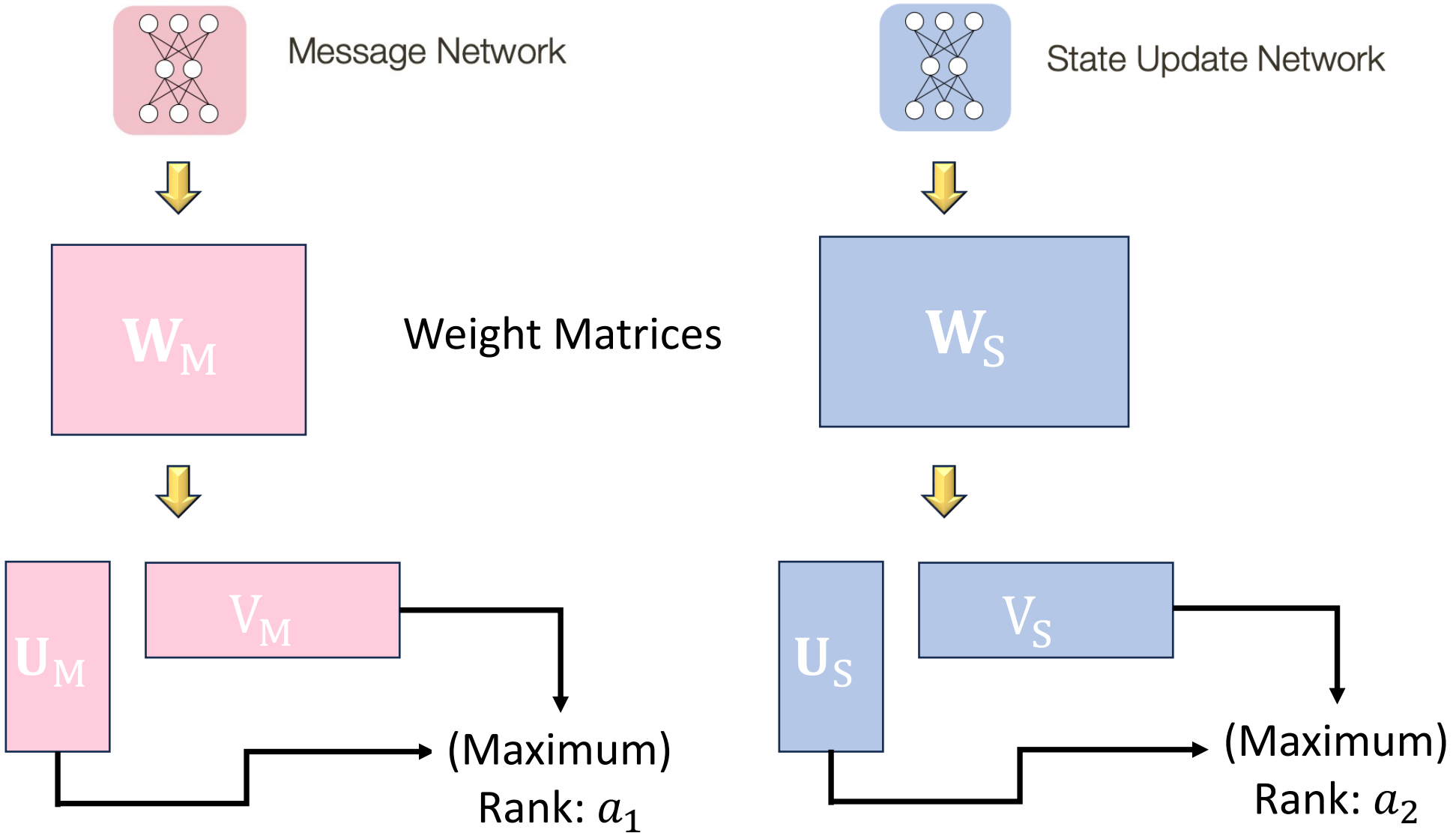
Proposed Approach: Low-Rank Linear Layer



Proposed Approach: Low-Rank Linear Layer



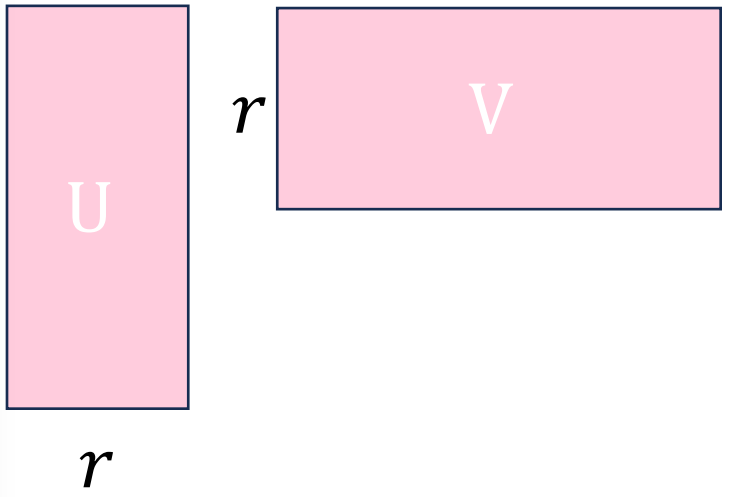
Proposed Approach: Low-Rank Linear Layer

Algorithm 1 Low-Rank Linear Layer in MPGNN

Require: Input features $\mathbf{X} \in \mathbb{R}^{N \times d_{\text{in}}}$, rank r

Ensure: Output features $\mathbf{Y} \in \mathbb{R}^{N \times d_{\text{out}}}$

1: Initialize $\mathbf{U} \in \mathbb{R}^{d_{\text{in}} \times r}$, $\mathbf{V} \in \mathbb{R}^{r \times d_{\text{out}}}$
2: **for** each layer in the MPGNN **do**
3: Compute $\mathbf{Y} \leftarrow \mathbf{X}(\mathbf{UV}) + \mathbf{b}$
4: Apply activation function (e.g., ReLU) to Y
5: $\mathbf{X} \leftarrow \mathbf{Y}$ ▷ Feed to next layer
6: **end for**
7: **return** Y



Proposed Approach: Low-Rank Linear Layer

Algorithm 1 Low-Rank Linear Layer in MPGNN

Require: Input features $\mathbf{X} \in \mathbb{R}^{N \times d_{\text{in}}}$, rank r

Ensure: Output features $\mathbf{Y} \in \mathbb{R}^{N \times d_{\text{out}}}$

1: Initialize $\mathbf{U} \in \mathbb{R}$

2: **for** each layer

3: Compute $\mathbf{Y} \leftarrow \mathbf{X}(\mathbf{UV}) + \mathbf{b}$

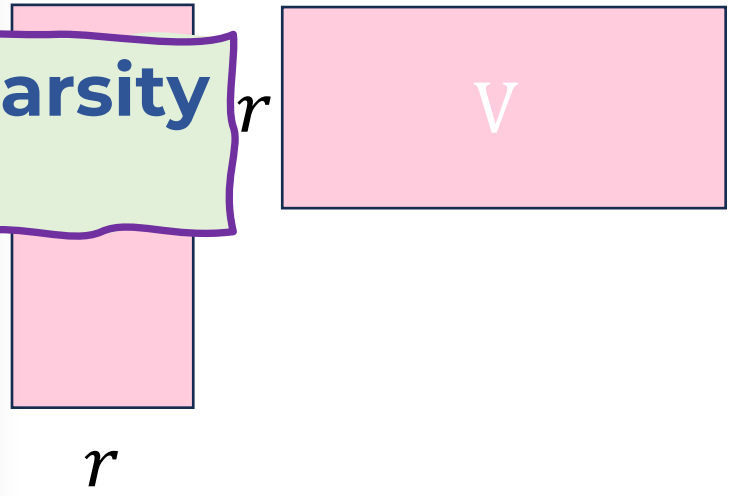
4: Apply activation function (e.g., ReLU) to $\mathbf{Y}$

5: $\mathbf{X} \leftarrow \mathbf{Y}$ ▷ Feed to next layer

6: **end for**

7: **return** $\mathbf{Y}$

We can do this because of the Sparsity of the Weight Matrices.



Proposed Approach: Low-Rank Linear Layer

Advantages

- No fine-tuning/retraining required.

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Advantages

- No fine-tuning/retraining required.
- Prevent overfitting by regularizing the model
- Reduce computational complexity ➔ faster training and inference.

Results

Message and Update State Nets: two fully-connected

 # Transceiver pairs = 50

 # Training samples = 2000

 # Testing samples = 500

Evaluation metric = Sum Rate

Results

Model Size Ratio: $\frac{\text{Original size}}{\text{Low rank size}}$

a1 \ a2	4	16	32	64	128	256
4	58.82	22.42	12.29	6.45	3.31	1.68
16	25.87	15.10	9.71	5.66	3.09	1.62
32	14.81	10.51	7.58	4.87	2.84	1.55
64	7.98	6.54	5.27	3.80	2.44	1.42

a_1: (Maximum) rank for Message Network

a_2: new rank for State Update Network.

Results

Sum Rate Ratio: $\frac{\text{Low rank sum rate}}{\text{Original sum rate}}$

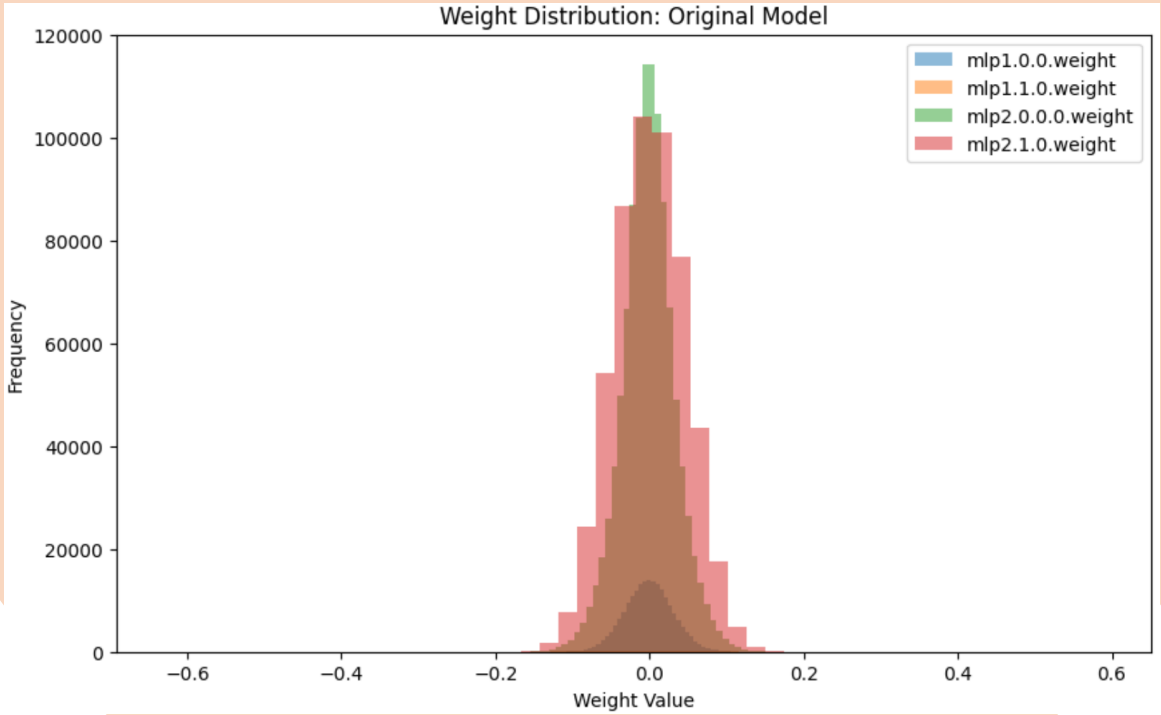
a1 \ a2	4	16	32	64	128	256	512
4	0.762	0.819	0.596	0.739	0.723	0.57	0.765
16	0.971	0.603	0.896	0.99	0.99	0.838	0.819
32	0.743	0.603	0.652	0.714	0.67	0.64	0.99
64	0.80	0.71	0.904	0.790	0.844	0.884	0.853

a_1: (Maximum) rank for Message Network

a_2: new rank for State Update Network.

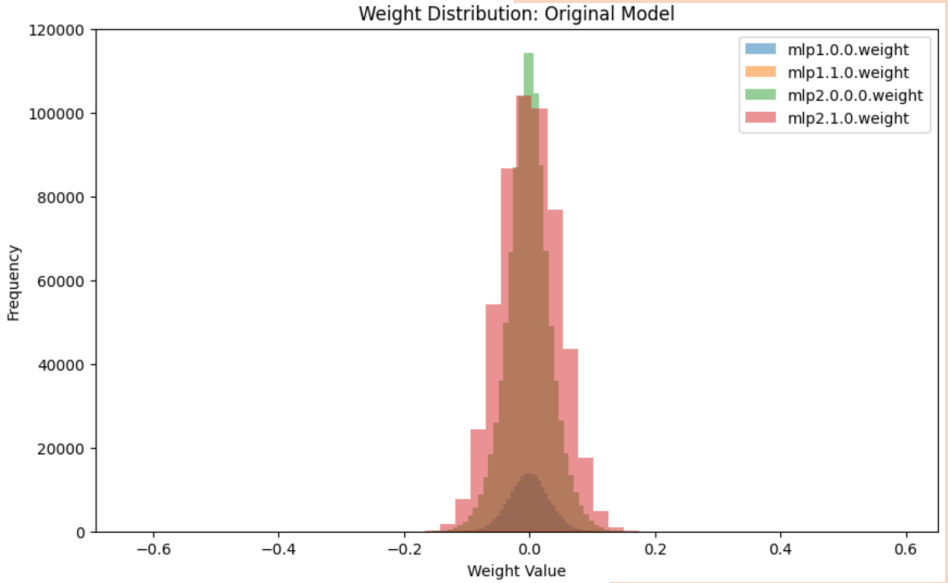
Results

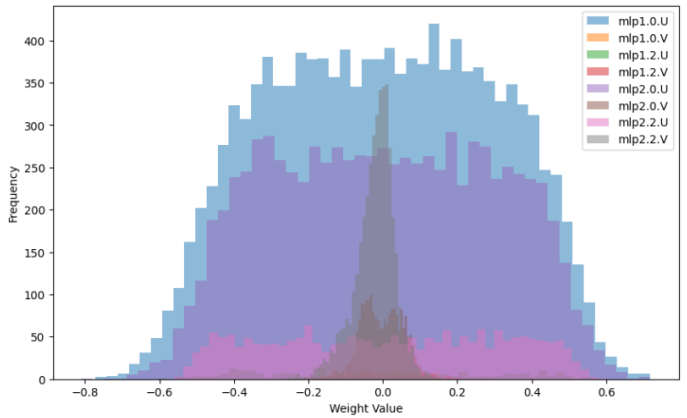
Weight Distribution



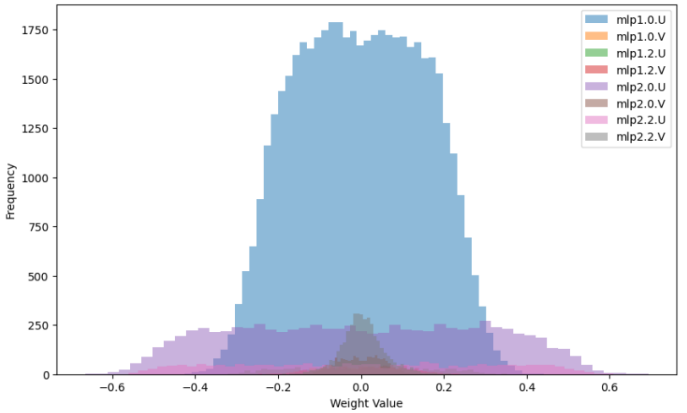
Results

Weight Distribution

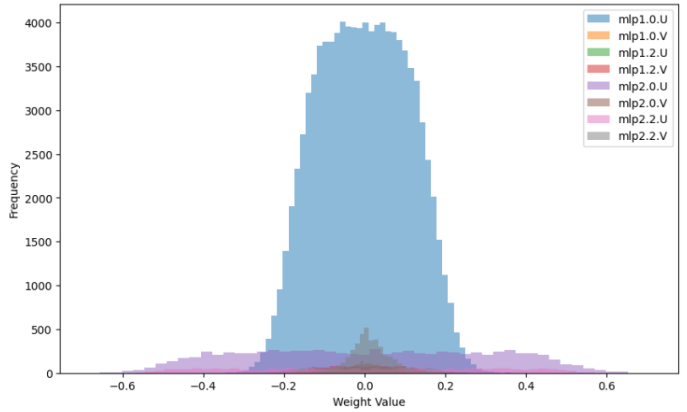




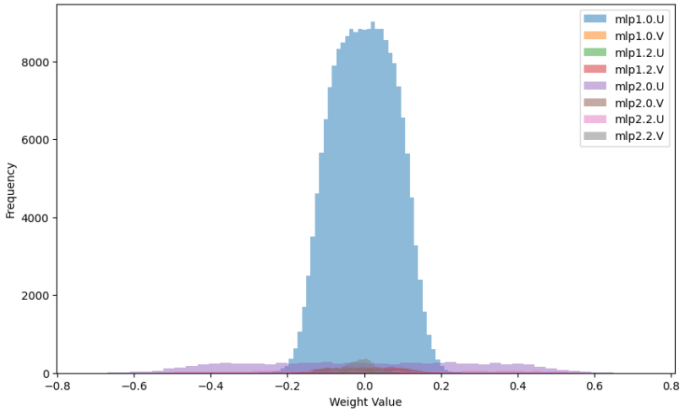
(a) $a_1 = 4$ and $a_2 = 4$



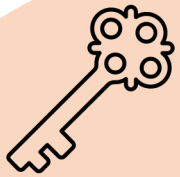
(b) $a_1 = 16$ and $a_2 = 4$



(c) $a_1 = 32$ and $a_2 = 4$



(d) $a_1 = 64$ and $a_2 = 4$



Key Takeaways

✓ GNN-based RRM

✓ Proposed Low-Rank GNN

✓ Reduces the model size 60X

✓ Keep the performance (At best $\leq 1\%$ loss)

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Acknowledgement

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