EECE 571F: Deep Learning with Structures

Lecture 4: Graph Neural Networks
Graph Convolution Models

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Course Scope

- Brief Intro to Deep Learning

- Geometric Deep Learning

  - Deep Learning Models for Sets and Sequences: Deep Sets & Transformers
  - Deep Learning Models for Graphs: Message Passing & Graph Convolution GNNs
  - Group Equivariant Deep Learning

- Probabilistic Deep Learning

  - Auto-regressive models, Large Language Models (LLMs)
  - Variational Auto-Encoders (VAEs) and Generative Adversarial Networks (GANs)
  - Energy based models (EBMs)
  - Diffusion/Score based models

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Deep Learning for Graphs

Graph Neural Networks (GNNs)

- Neural networks that can process general graph structured data
- First proposed in 2008 [1] and dates back to Recursive Neural Networks (mainly processing trees) in 90s [2]
- In fact, Boltzmann Machines [3] (fully connected graphs with binary units) in 80s can be viewed as GNNs
- Most of GNNs (if not all) can be incorporated by the **Message Passing** paradigm
- GNNs have been independently studied in signal processing community under **Graph Signal Processing** [4,5]
- The study of GNNs and other related models are also called **Geometric Deep Learning** [6]

Convolution on Graphs?

- Let us review Fourier Transform and Convolution Theorem

Fourier Transform

Given signal $f(t)$, the classical Fourier transform is:

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We have $$\Delta(e^{-2\pi i \xi t}) = \frac{\partial^2}{\partial t^2} e^{-2\pi i \xi t} = -(2\pi\xi)^2 e^{-2\pi i \xi t}$$

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$e^{-2\pi i \xi t}$ **is the eigenfunction of Laplacian operator!**

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Inverse Fourier transform

$$\hat{f}(\xi) = \int_{\mathbb{R}} f(t) e^{-2\pi i \xi t} dt \qquad f(t) = \int_{\mathbb{R}} \hat{f}(\xi) e^{2\pi i \xi t} d\xi$$

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Laplacian operator is:

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where $\hat{f}(\xi) = \int_{\mathbb{R}} f(t)e^{-2\pi i\xi t}dt$ and $\hat{h}(\xi) = \int_{\mathbb{R}} h(t)e^{-2\pi i\xi t}dt$

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How can we generalize them to graphs?

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Convolution on Graphs?

- Let us review Fourier Transform and Convolution Theorem

1. Based on the *eigenfunction of Laplacian operator*, we define Fourier transform
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  1. Based on the *eigenfunction of Laplacian operator*, we define Fourier transform
  2. Based on the convolution theorem, we can define convolution in Fourier domain

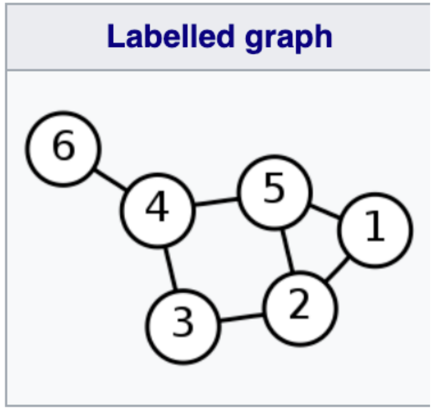
- How can we generalize convolution to graphs?

  1. What is the Laplacian operator on graph?
  2. How can we define convolution in (graph) Fourier domain?

Graph Signal

Graph G = (V, E), graph signal (node feature) X

G



A

Adjacency matrix

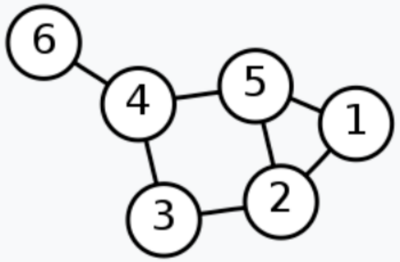
$$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

Image Credit: https://en.wikipedia.org/wiki/Laplacian_matrix

Graph Laplacian

Graph G = (V, E), graph signal (node feature) X

Degree matrix: $D_{ii} = \sum_{j=1}^{N} A_{ij}$

G	D	A
Labelled graph	**Degree matrix**	**Adjacency matrix**
	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$

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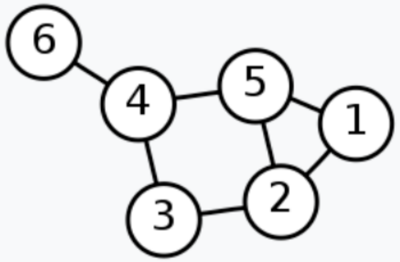
(Combinatorial) Graph Laplacian: $L = D - A$

G Labelled graph	D Degree matrix	A Adjacency matrix	$L = D - A$ Laplacian matrix
	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$

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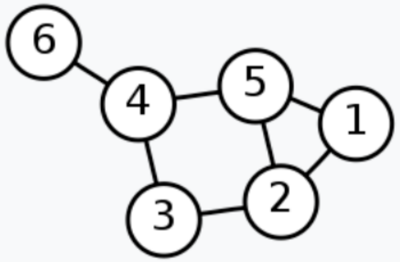
(Combinatorial) Graph Laplacian: $L = D - A$

Compute difference between current node and its neighbors!

G	D	A	$L = D - A$
Labelled graph	**Degree matrix**	**Adjacency matrix**	**Laplacian matrix**
	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$

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Graph Laplacian

For undirected graphs, (Combinatorial) Graph Laplacian:

- Symmetric
- Diagonally dominant
- Positive semi-definite (PSD)
- The number of connected components in the graph the algebraic multiplicity of the 0 eigenvalue.

G	D	A	$L = D - A$
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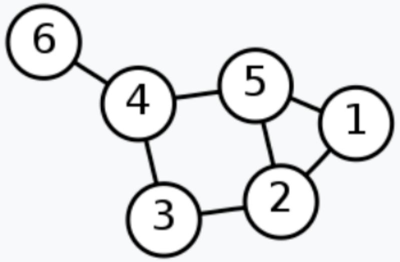	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$

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Graph Laplacian

Symmetrically Normalized Graph Laplacian:

$$L = D^{-\frac{1}{2}}(D - A)D^{-\frac{1}{2}} = I - D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$$

Eigenvalues lie in [0, 2], why? (Try to show it by yourself!)

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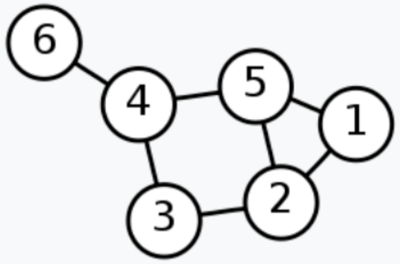	$\begin{pmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 2 & -1 & 0 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & -1 & 0 & -1 & 3 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 \end{pmatrix}$

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Spectral Theorem

If L is a symmetric matrix, we have

$$L = U\Lambda U^\top = \sum_{i=1}^N \lambda_i \mathbf{u}_i \mathbf{u}_i^\top$$

where $U = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_N]$ contains eigenvectors of L and is orthogonal $UU^\top = U^\top U = I$

$$\Lambda = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_N \end{bmatrix}$$

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Spectral Theorem

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Spectral Decomposition

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Graph Fourier Transform

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i.e., expansion in terms of complex exponentials (**eigenfunction of Laplacian operator**)

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Given graph signal $X \in \mathbb{R}^{N \times 1}$, the *Graph Fourier Transform* is:

$$\hat{X}[i] = \sum_{j=1}^{N} U[j, i] X[j]$$

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Eigenvalue corresponds to frequency!

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i.e., expansion in terms of **eigenvectors of Graph Laplacian operator**

Graph Convolution (Spectral Filtering)

Convolution:

$$(f * h)(t) = \int_{\mathbb{R}} f(\tau)h(t-\tau)d\tau = \int_{\mathbb{R}} \hat{f}(\xi)\hat{h}(\xi)e^{2\pi i\xi t}d\xi$$

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Graph Convolution in Fourier domain (Spectral Filtering):

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Can we find some efficient construction of h?

Spectral Filters

Graph Convolution in Fourier domain (Spectral Filtering):

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Can we find some efficient construction of h?

- Chebyshev polynomials [7]
- Graph wavelets [7]

Chebyshev Polynomials

Chebyshev polynomials of the first kind:

$$T_0(x) = 1$$
$$T_1(x) = x$$
$$T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$$

Image Credit: https://en.wikipedia.org/wiki/Chebyshev_polynomials

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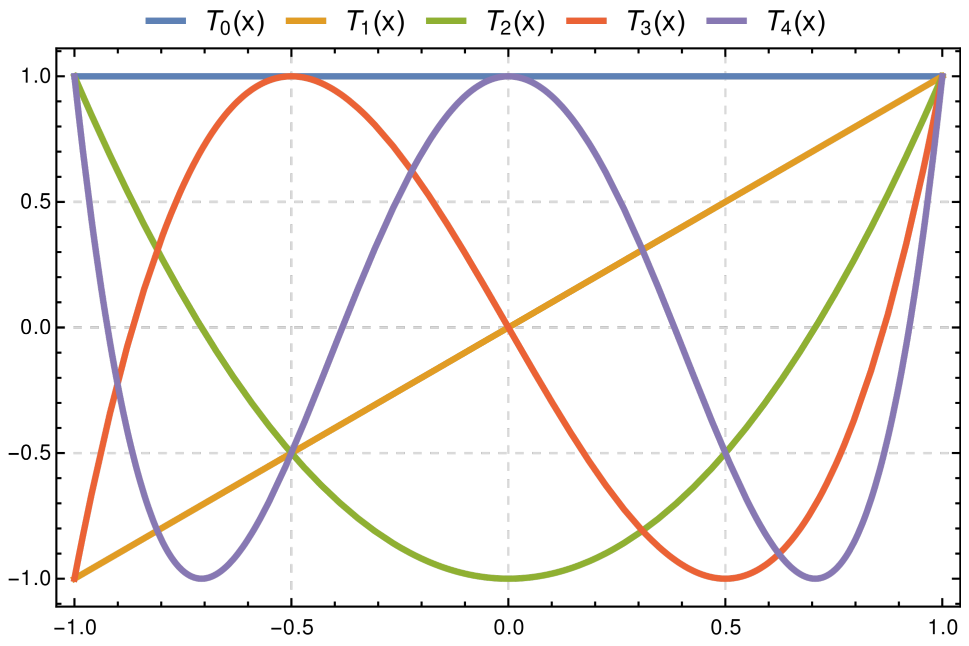

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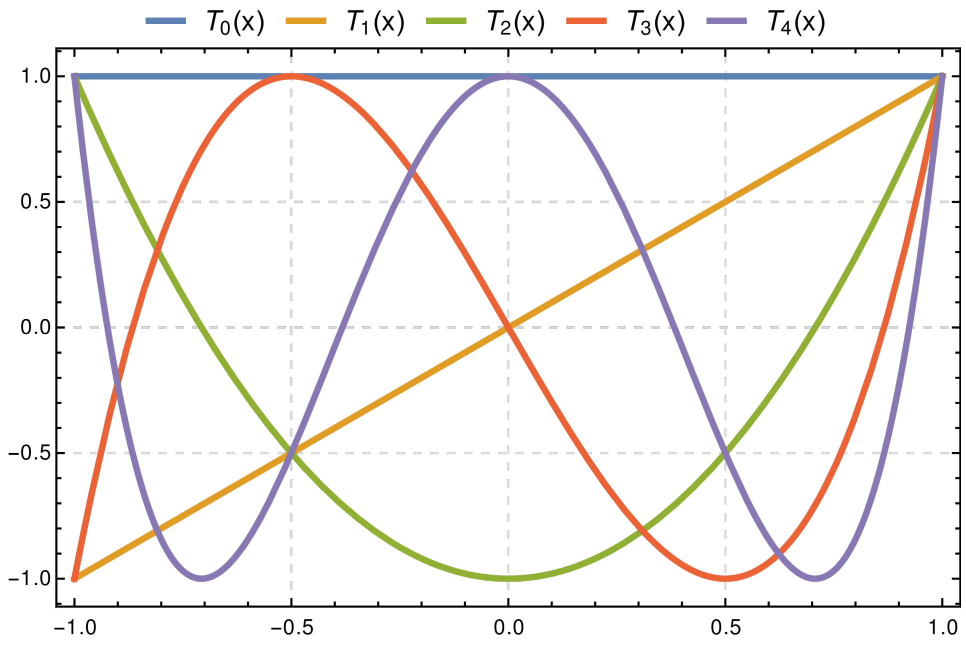

They provide orthonormal basis in some Sobolev space on [-1, 1]:

$$h(x) = \sum_{n=0}^{\infty} a_n T_n(x)$$

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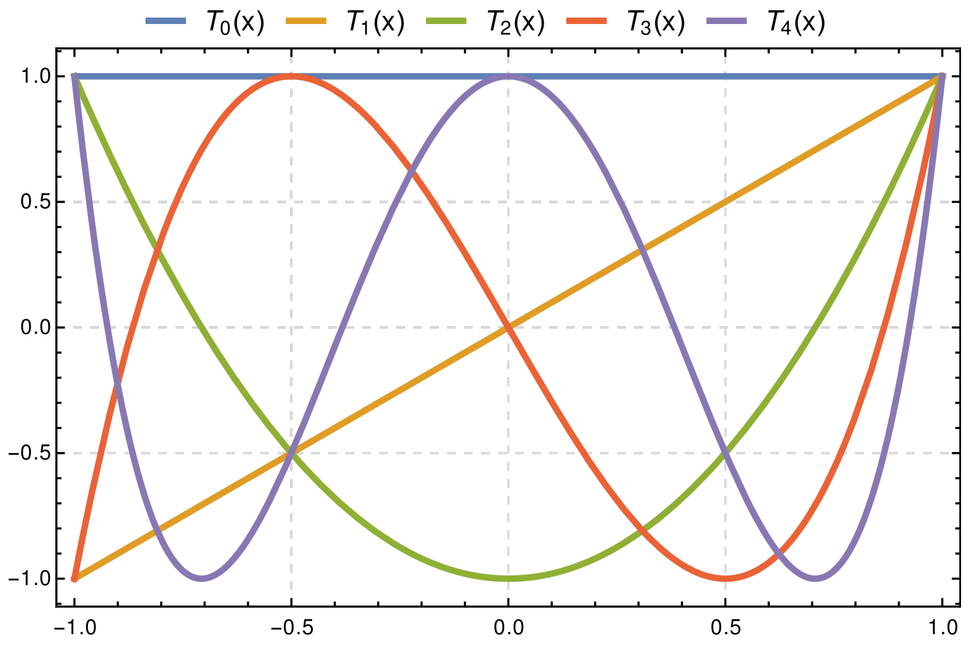

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$$h(x) = \sum_{n=0}^{\infty} a_n T_n(x)$$

$$\int_{-1}^{1} T_n(x)T_m(x)\frac{dx}{\sqrt{1-x^2}} = \begin{cases} 0 & \text{if } n \neq m \\ \pi & \text{if } n = m = 0 \\ \frac{\pi}{2} & \text{if } n = m \neq 0 \end{cases}$$

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Spectral Filters

Chebyshev expansion:

$$h(x) = \sum_{n=0}^{\infty} a_n T_n(x)$$

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Spectral Filters

Chebyshev expansion:

$$h(x) = \sum_{n=0}^{\infty} a_n T_n(x)$$

Spectral filtering:

$$h_\theta * X = U h_\theta(\Lambda) U^\top X$$

Truncated Chebyshev polynomials approximation:

$$h_\theta(\Lambda) \approx \sum_{n=0}^{K} \theta_n T_n(\tilde{\Lambda}) = \sum_{n=0}^{K} \theta_n T_n(\frac{2\Lambda}{\lambda_{\max}} - I)$$

Spectral Filters

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Graph Convolution:

$$h_\theta * X = U h_\theta(\Lambda) U^\top X$$

Truncated Chebyshev polynomials based Graph Convolution:

$$\begin{aligned} h_\theta * X &= U h_\theta(\Lambda) U^\top X \\ &\approx U \left(\sum_{n=0}^{K} \theta_n T_n(\frac{2\Lambda}{\lambda_{\max}} - I) \right) U^\top X \end{aligned}$$

Spectral Filters

Recall we do not want explicit spectral decomposition since it is expensive!

$$h_\theta * X \approx U \left(\sum_{n=0}^{K} \theta_n T_n(\frac{2\Lambda}{\lambda_{\max}} - I) \right) U^\top X$$

Spectral Filters

Recall we do not want explicit spectral decomposition since it is expensive!

$$h_\theta * X \approx U \left(\sum_{n=0}^{K} \theta_n T_n(\frac{2\Lambda}{\lambda_{\max}} - I) \right) U^\top X$$

Are Chebyshev polynomials efficient?

Spectral Filters

Recall

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Let

$$T_n(\tilde{L}) = UT_n\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top$$

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\end{aligned}
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$$T_n(\tilde{L}) = UT_n\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top$$

We have

$$
\begin{aligned}
T_0(\tilde{L}) &= I \\
T_1(\tilde{L}) &= U\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top = 2L/\lambda_{\max} - I \\
T_{n+1}(\tilde{L}) &= U\left(2\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)T_n\left(\frac{2\Lambda}{\lambda_{\max}} - I\right) - T_{n-1}\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)\right)U^\top \\
&= 2U\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top UT_n\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top - UT_{n-1}\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top \\
&= 2\left(\frac{2L}{\lambda_{\max}} - I\right)T_n(\tilde{L}) - T_{n-1}(\tilde{L})
\end{aligned}
$$

Spectral Filters

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We have

$$h_\theta * X \approx U\left(\sum_{n=0}^{K}\theta_n T_n(\frac{2\Lambda}{\lambda_{\max}} - I)\right)U^\top X$$

$$= \sum_{n=0}^{K}\theta_n T_n(\tilde{L})X$$

Spectral Filters

Recall

$$T_n(\tilde{L}) = UT_n\left(\frac{2\Lambda}{\lambda_{\max}} - I\right)U^\top$$

We have

$$\begin{aligned} h_\theta * X &\approx U\left(\sum_{n=0}^{K}\theta_n T_n(\frac{2\Lambda}{\lambda_{\max}} - I)\right)U^\top X \\ &= \sum_{n=0}^{K}\theta_n T_n(\tilde{L})X \end{aligned}$$

Let

$$T_0(\tilde{X}) = T_0(\tilde{L})X$$

Spectral Filters

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Let

$$T_0(\tilde{X}) = T_0(\tilde{L})X$$

We have

$$T_0(\tilde{X}) = X$$
$$T_1(\tilde{X}) = 2LX/\lambda_{\max} - X$$
$$T_{n+1}(\tilde{X}) = 2\left(\frac{2L}{\lambda_{\max}} - I\right)T_n(\tilde{X}) - T_{n-1}(\tilde{X})$$

Spectral Filters

Truncated Chebyshev polynomials based Graph Convolution:

$$h_\theta * X \approx \sum_{n=0}^{K} \theta_n T_n(\tilde{X})$$

where

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What if we truncate to 1st order?

Spectral Filters

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What if we truncate to 1st order?

That is Graph Convolutional Networks (GCNs) [8] !

Graph Convolutional Networks (GCNs)

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Graph Convolutional Networks (GCNs)

Truncated Chebyshev polynomials based Graph Convolution:

$$h_\theta * X \approx \sum_{n=0}^{K} \theta_n T_n(\tilde{X})$$

$$h_\theta * X \approx \theta_0 X + \theta_1 T_1(\tilde{X})$$

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We can use the normalize graph Laplacian so that its eigenvalues are in [0, 2]

$$L = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$$

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Assuming $\lambda_{\max} \approx 2$

$$h_\theta * X \approx \theta_0 X + \theta_1 T_1(\tilde{X})$$
$$\approx \theta_0 X - \theta_1 D^{-\frac{1}{2}} A D^{-\frac{1}{2}} X$$

Graph Convolutional Networks (GCNs)

Simplified Truncated Chebyshev polynomials based Graph Convolution:

$$
\begin{aligned}
h_\theta * X &\approx \theta_0 X + \theta_1 T_1(\tilde{X}) \\
&\approx \theta_0 X - \theta_1 D^{-\frac{1}{2}} A D^{-\frac{1}{2}} X \\
&= \theta \left(I + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \right) X
\end{aligned}
$$

Graph Convolutional Networks (GCNs)

Simplified Truncated Chebyshev polynomials based Graph Convolution:

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eigenvalues are in [0, 2]

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\end{aligned}
$$

$$I + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \quad \Longrightarrow \quad \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}$$

$$\tilde{D}_{ii} = \sum_j (A+I)_{ij}$$

eigenvalues are in [0, 2] ⟹ eigenvalues are in [-1, 1]

Graph Convolutional Networks (GCNs)

Simplified Truncated Chebyshev polynomials based Graph Convolution:

$$
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h_\theta * X &\approx \theta_0 X + \theta_1 T_1(\tilde{X}) \\
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&= \theta \left(I + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \right) X
\end{aligned}
$$

$$I + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$$

eigenvalues are in [0, 2]

$\Rightarrow$

$$\tilde{D}^{-\frac{1}{2}} (A + I) \tilde{D}^{-\frac{1}{2}}$$

$$\tilde{D}_{ii} = \sum_j (A + I)_{ij}$$

eigenvalues are in [-1, 1]

Final Form of Graph Convolution: $h_\theta * X \approx \theta \tilde{D}^{-\frac{1}{2}} (A + I) \tilde{D}^{-\frac{1}{2}} X$

Graph Convolutional Networks (GCNs)

Graph convolution in GCNs for 1D graph signal:

$$h_\theta * X \approx \theta \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}X$$

Graph Convolutional Networks (GCNs)

Graph convolution in GCNs for 1D graph signal:

$$h_\theta * X \approx \theta \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}X$$

Generalize to multi-input and multi-output convolution:

$$\begin{aligned} h_W * X &\approx \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}XW \\ &= \tilde{L}XW \end{aligned}$$

Graph Convolutional Networks (GCNs)

Graph convolution in GCNs for 1D graph signal:

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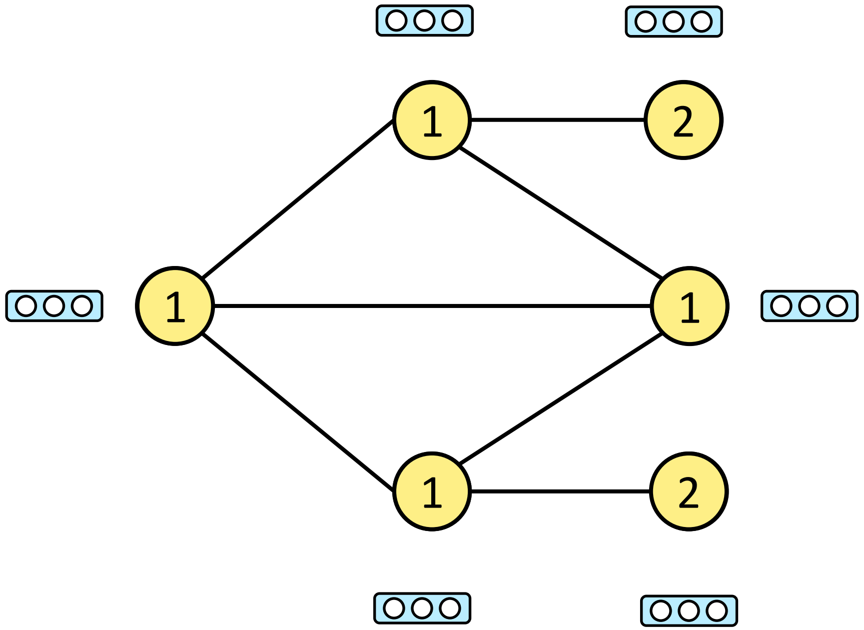
Add nonlinearity: $\sigma\left(h_W * X\right) \approx \sigma\left(\tilde{L}XW\right)$

Graph Convolutional Networks (GCNs)

Our Spectral Filters are Localized:



$$\tilde{L} = \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}$$

1-step Graph Convolution: $h_W * X \approx \tilde{L}XW$

2-step Graph Convolution: $h_{W_2} * h_{W_1} * X \approx \tilde{L}^2 X W_1 W_2$

⋮

Exponent of matrix power indicates how far the propagation is!

Graph Convolutional Networks (GCNs)

- We start with Chebyshev Polynomials which can represent any spectral filters (eigenvalues in [-1, 1])

$$h(x) = \sum_{n=0}^{\infty} a_n T_n(x)$$

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- Further simplification/approximation

$$h_\theta * X \approx \theta \tilde{D}^{-\frac{1}{2}} (A + I) \tilde{D}^{-\frac{1}{2}} X$$

$$h_W * X \approx \tilde{L} X W$$

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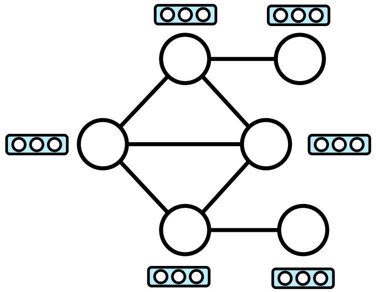
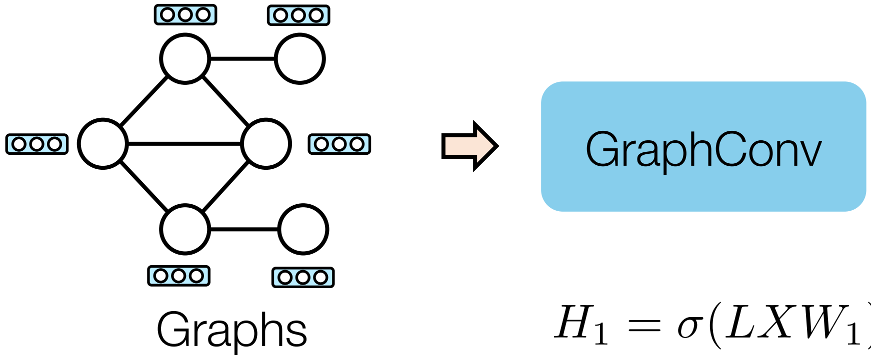
We can remedy the lost expressiveness by stacking multiple graph convolution layers!

Graph Convolutional Networks (GCNs)



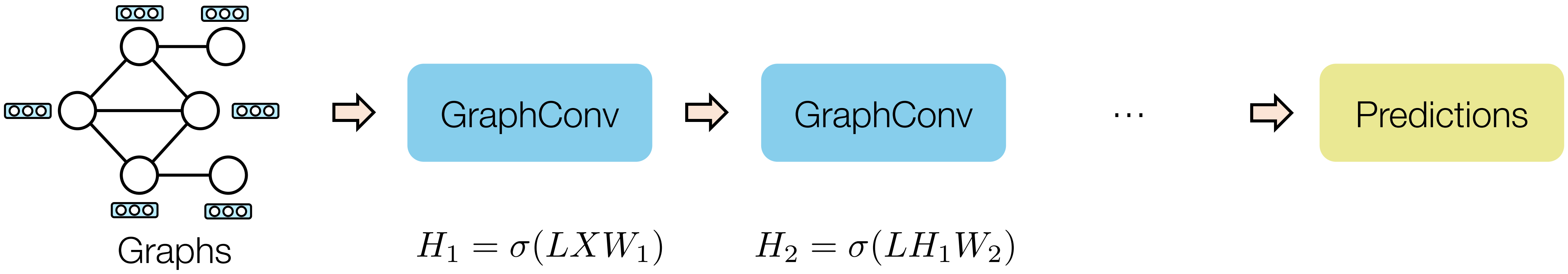
Graphs

Graph Convolutional Networks (GCNs)



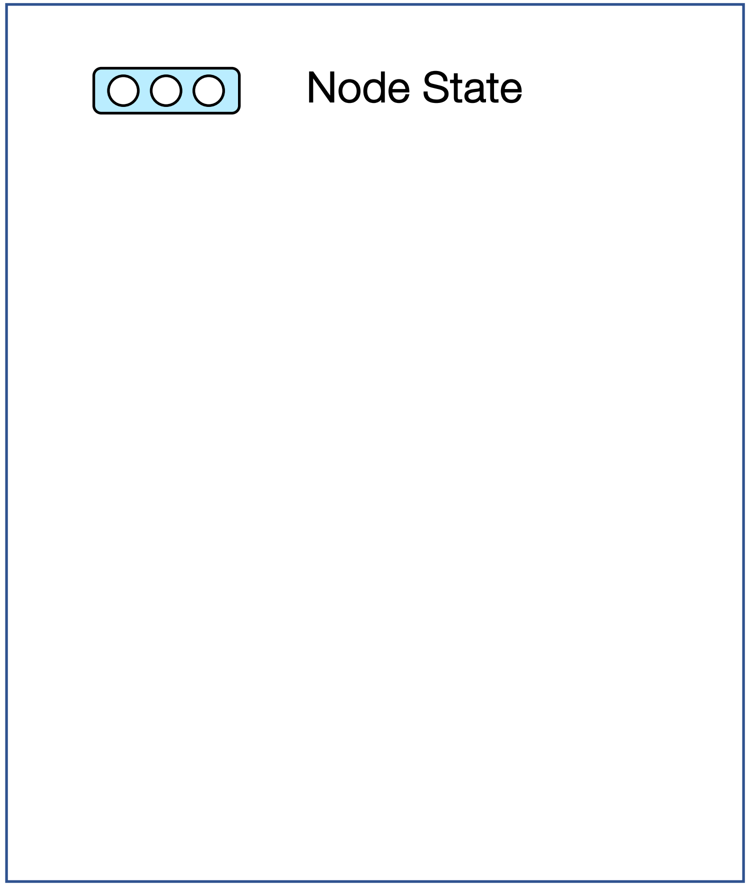
$$H_1 = \sigma(LXW_1)$$

Graph Convolutional Networks (GCNs)

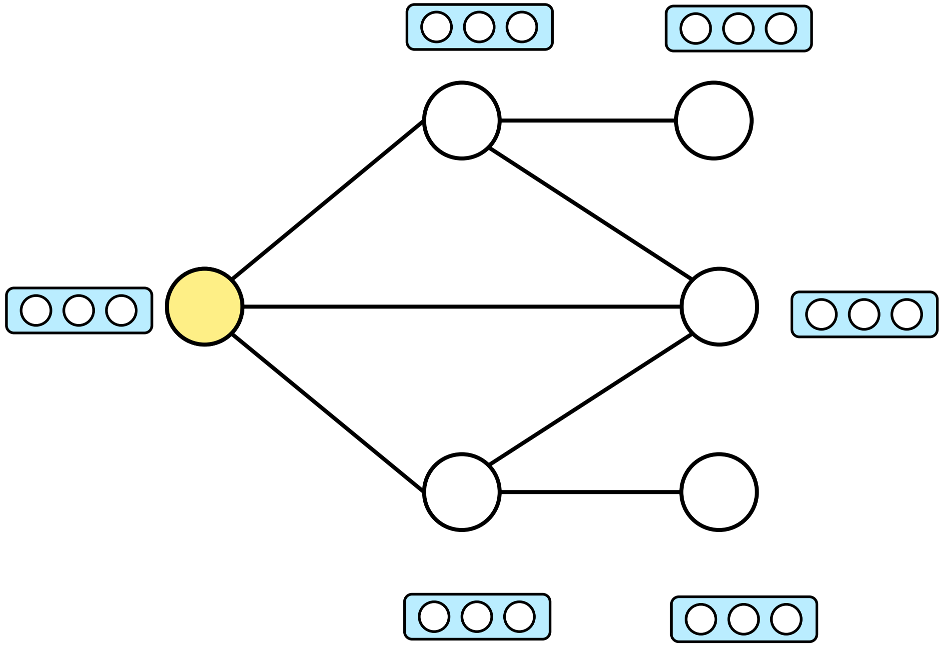


Message Passing GNNs

$\mathbf{h}_i^t$

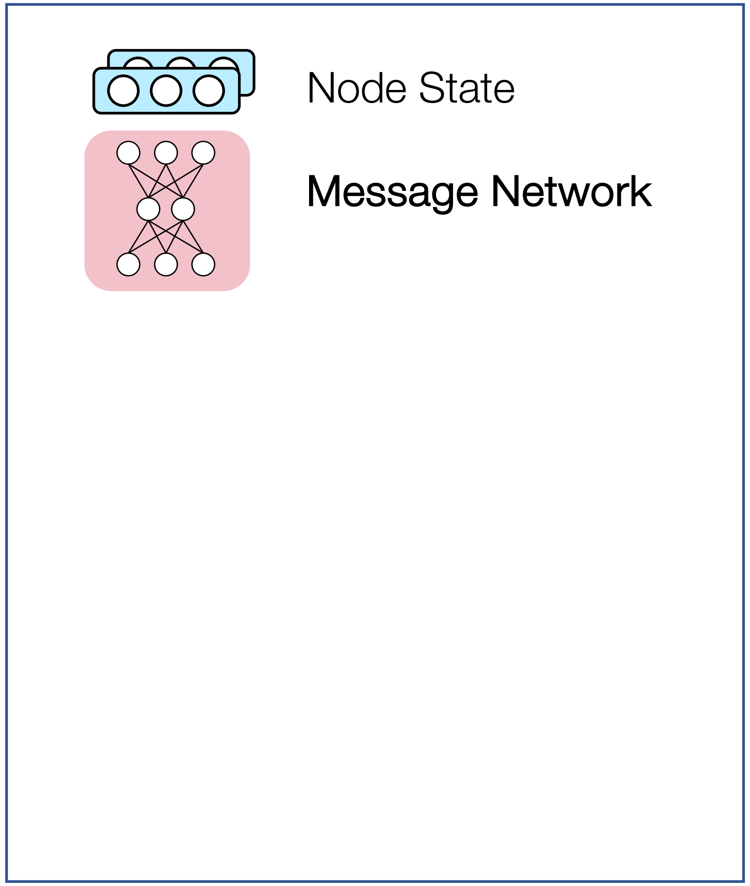


(t+1)-th message passing step/layer



Message Passing GNNs

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



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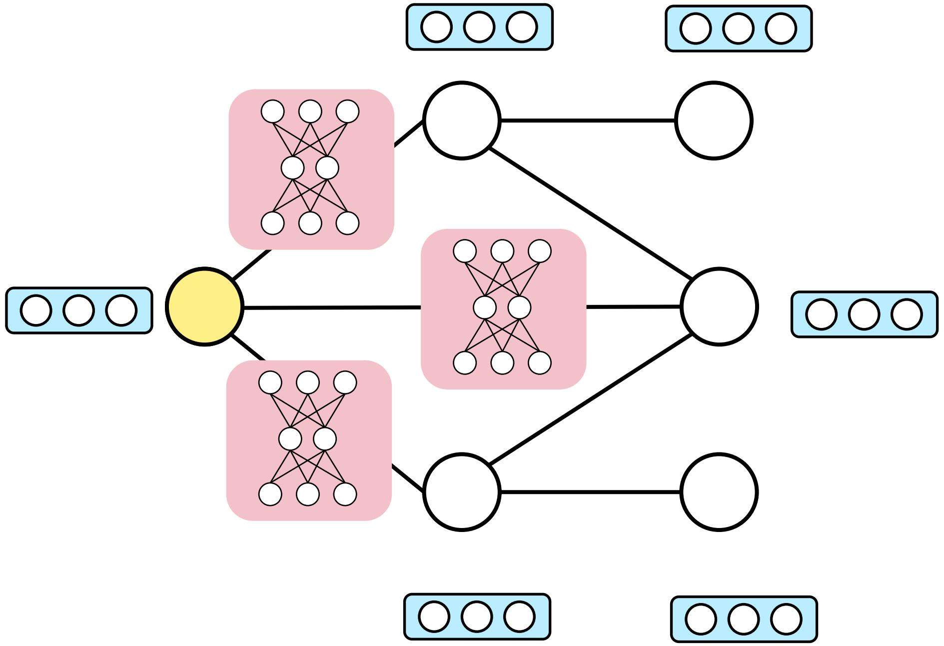
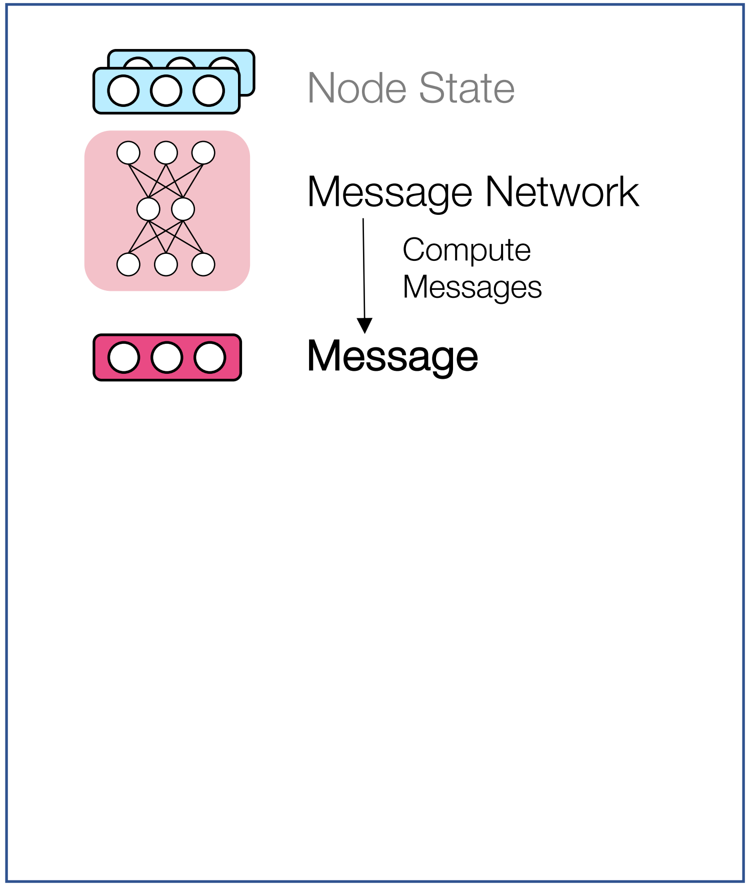


Message Passing GNNs

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

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



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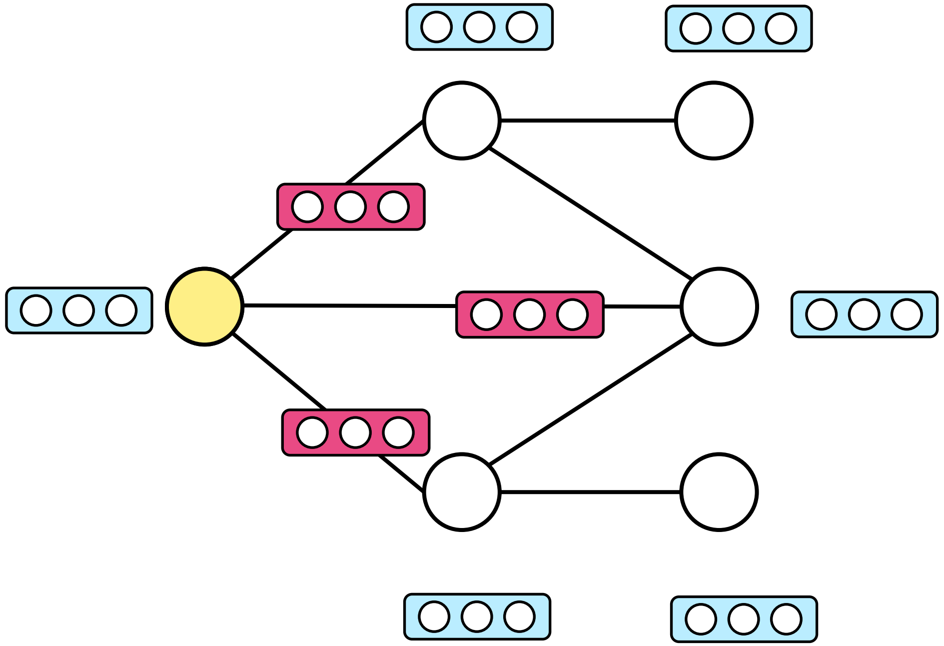

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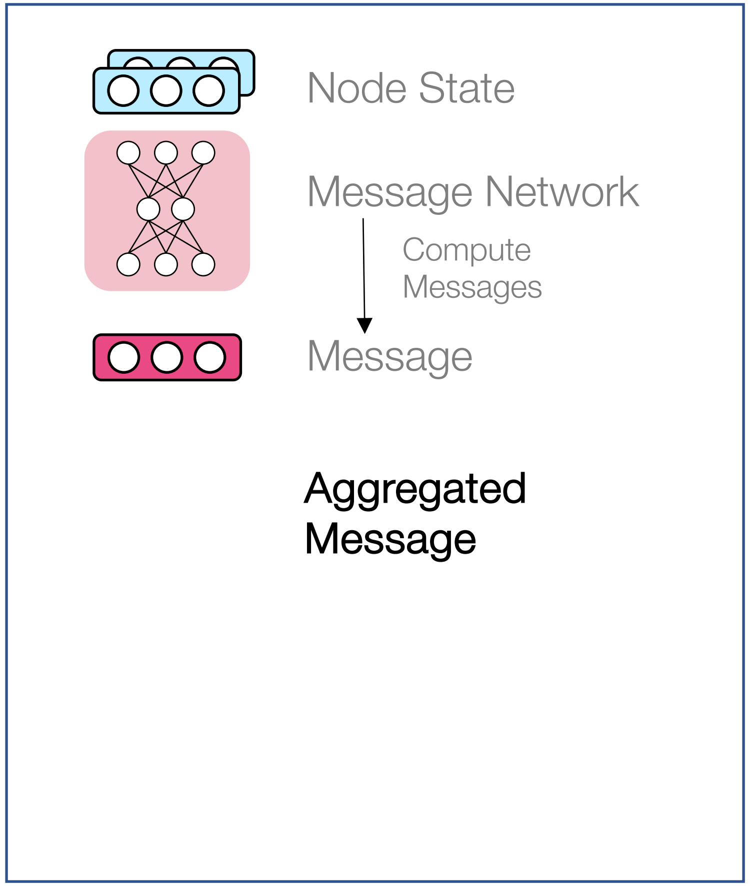

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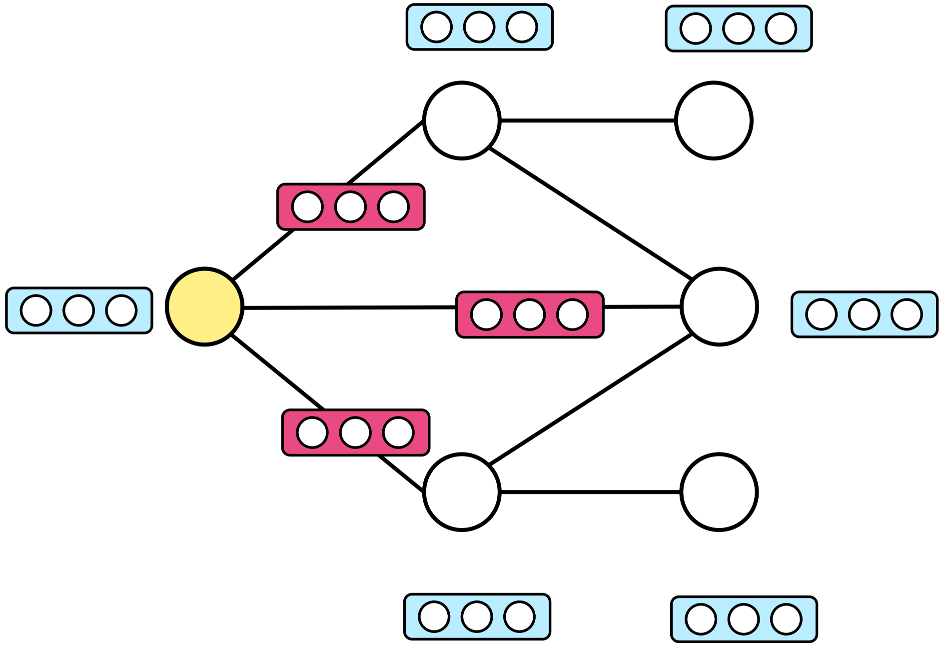
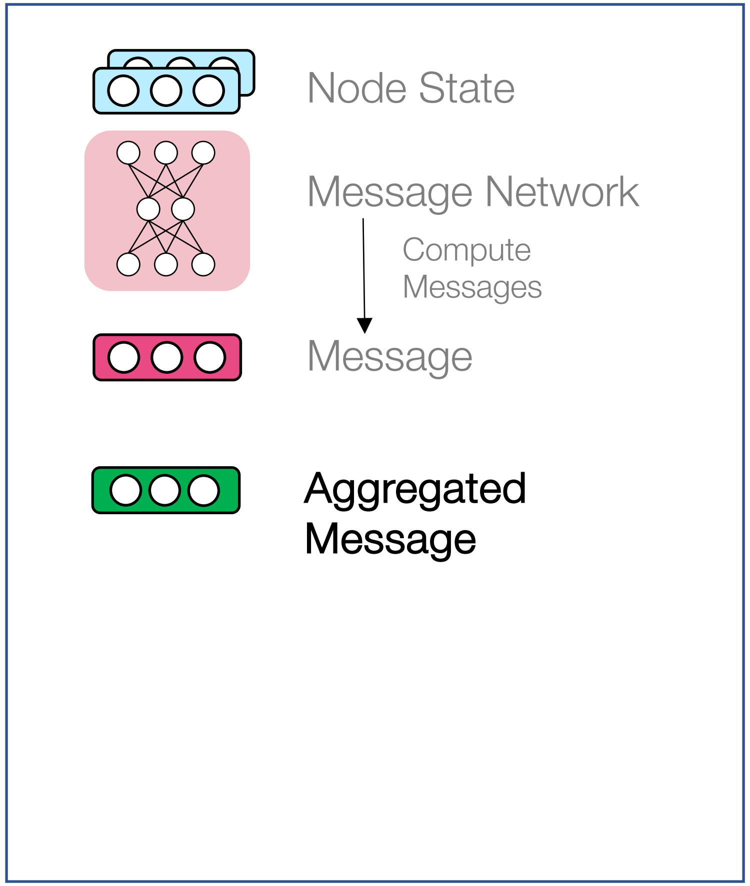


Message Passing GNNs

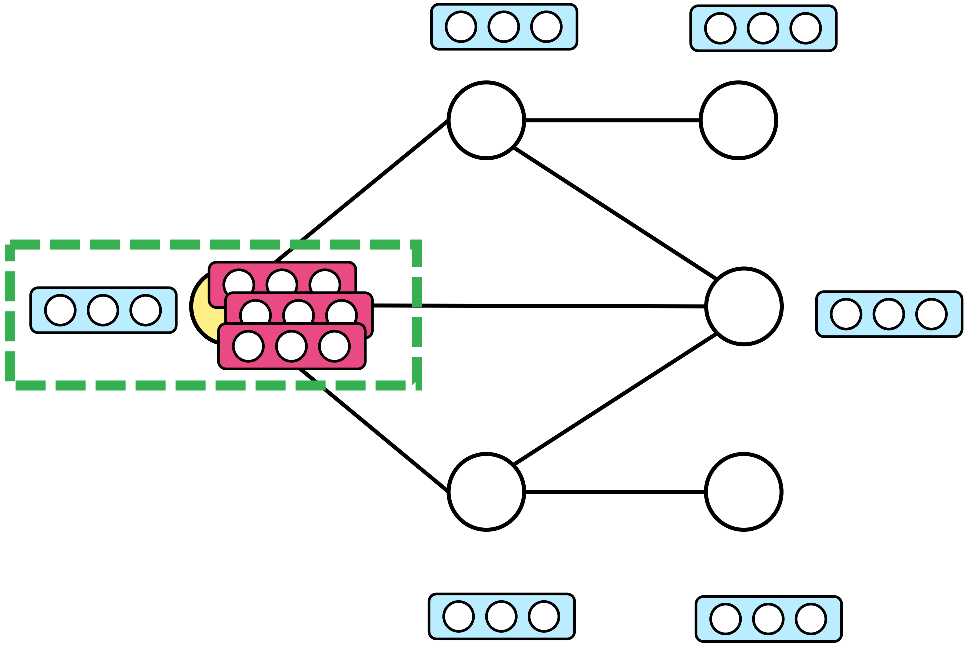
$\mathbf{h}_i^t \quad \mathbf{h}_j^t$

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

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



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



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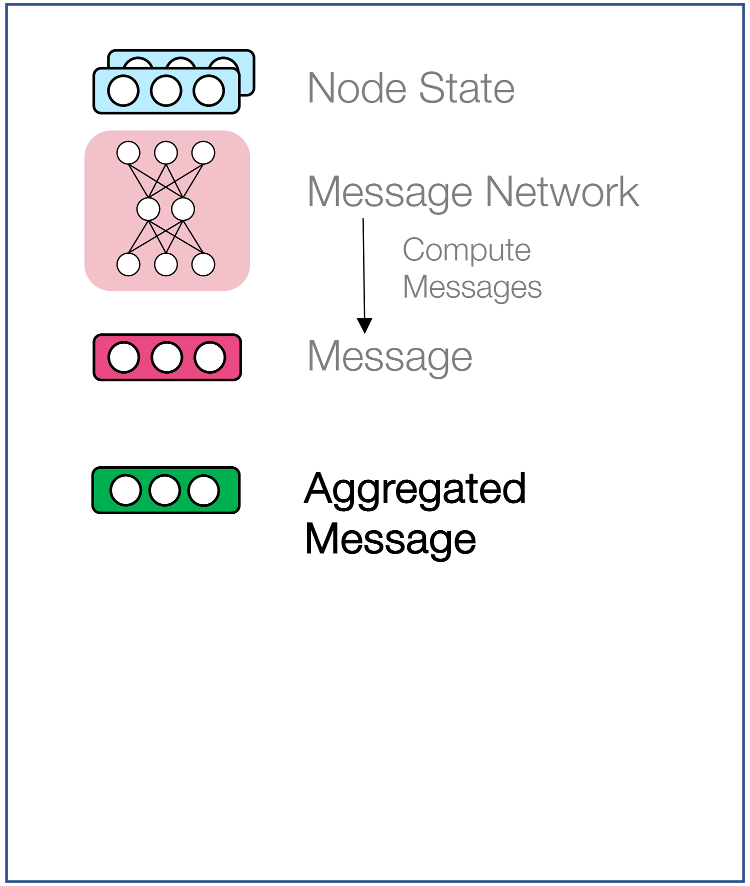

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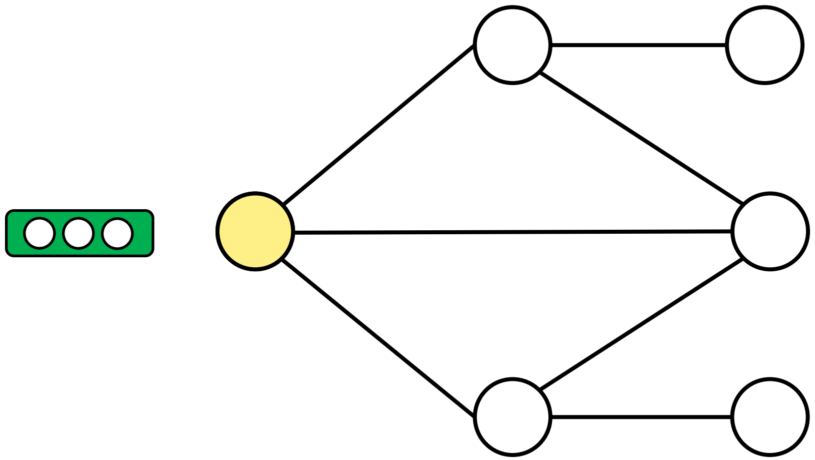

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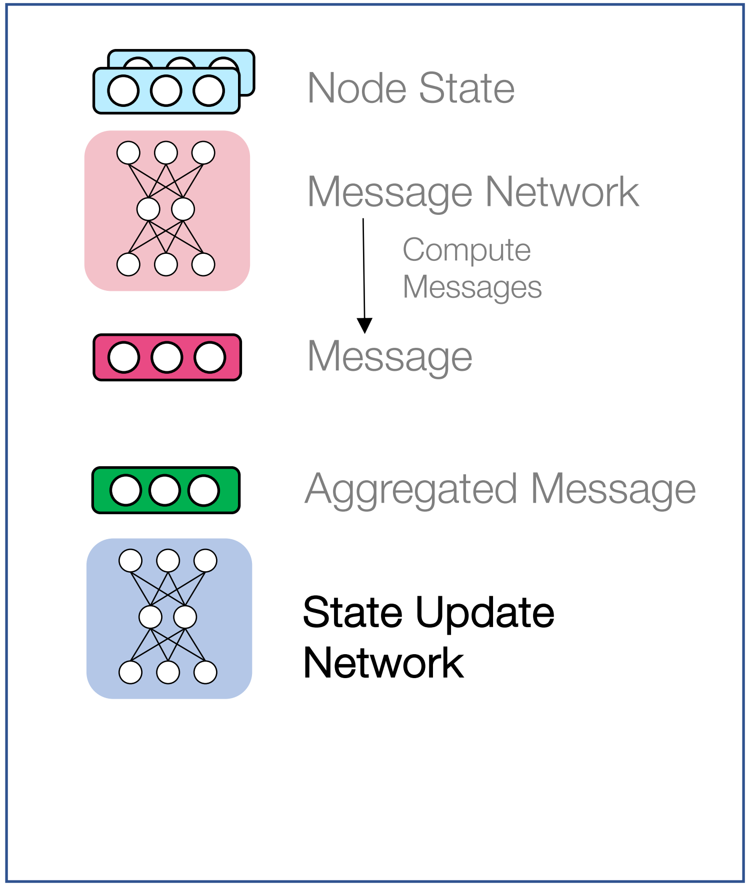

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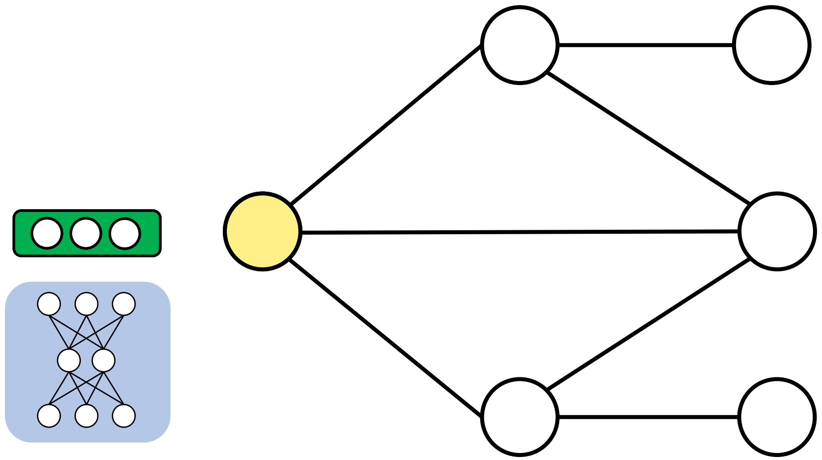

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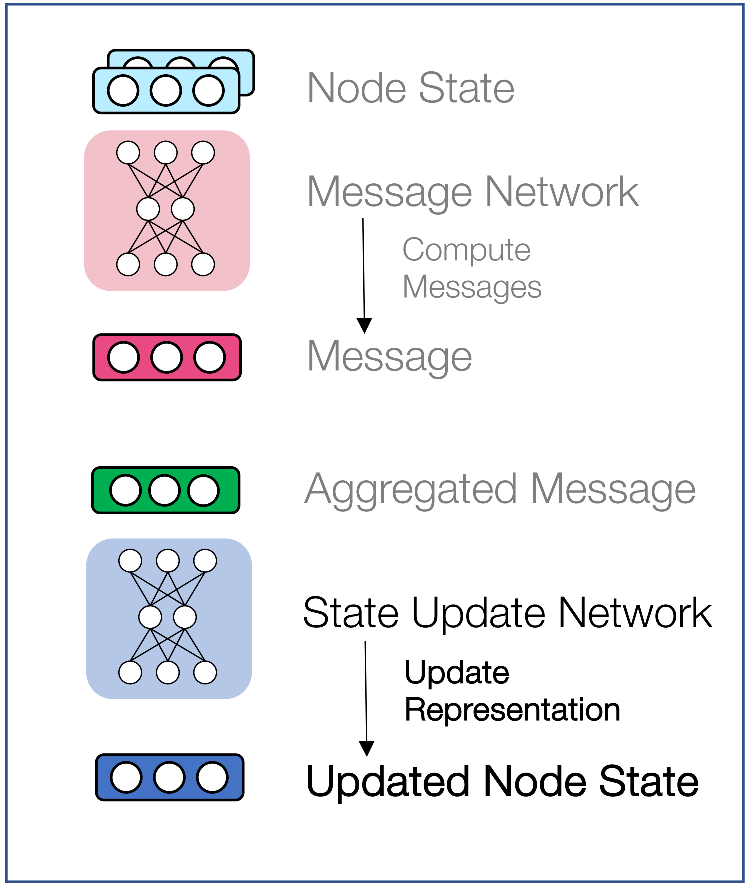
$$\mathbf{h}_i^{t+1} = f_{\text{update}}(\mathbf{h}_i^t, \bar{\mathbf{m}}_i^t)$$



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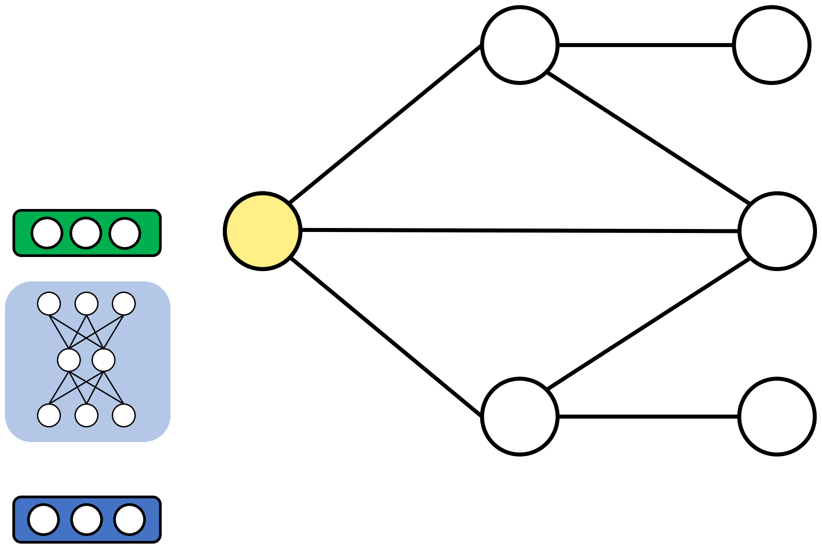

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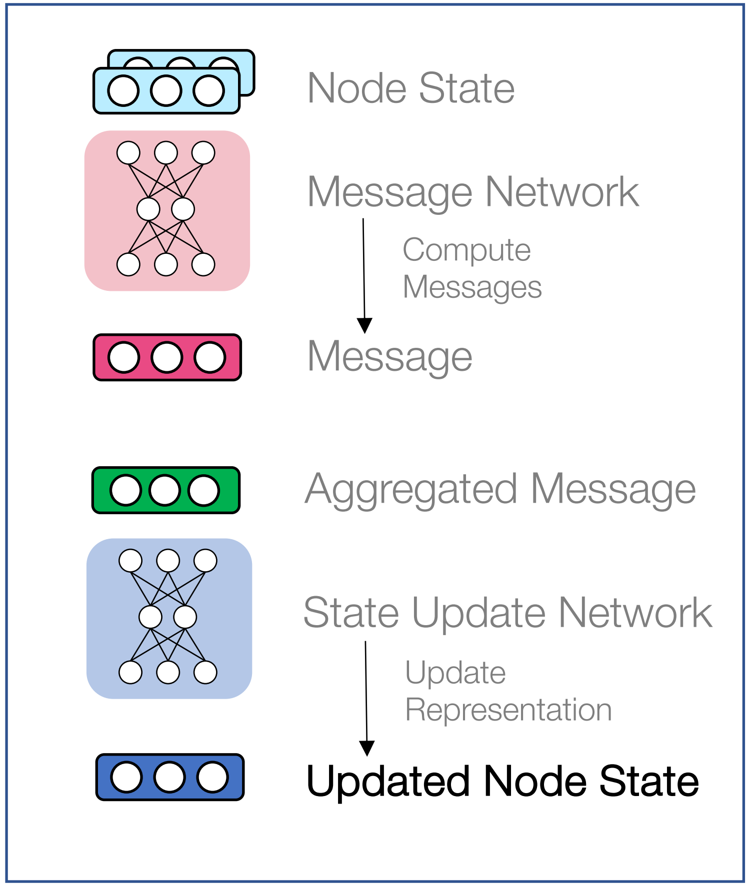

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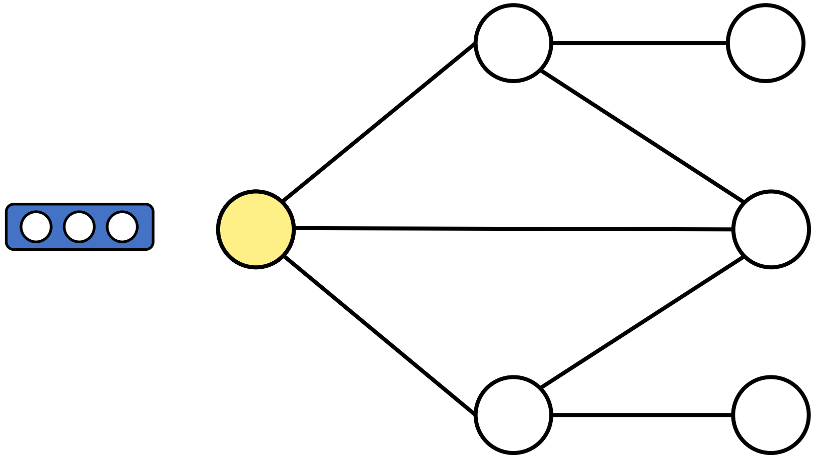
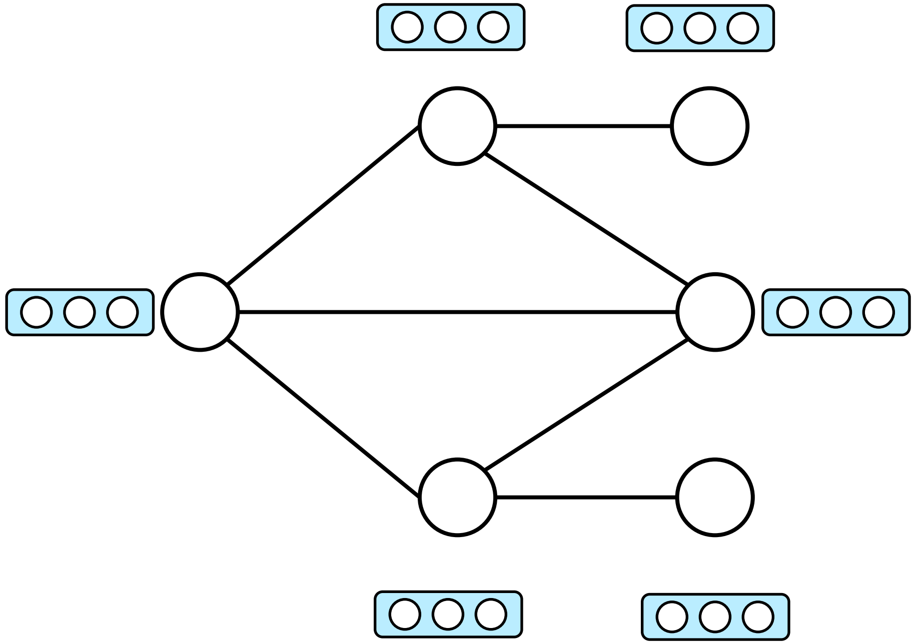
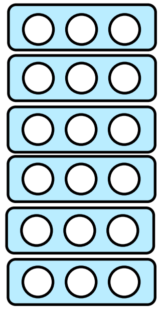


GCNs are Message Passing Networks

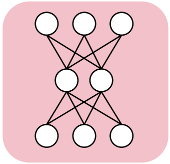


- Node State X



- Graph Laplacian

$$\tilde{L} = \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}$$



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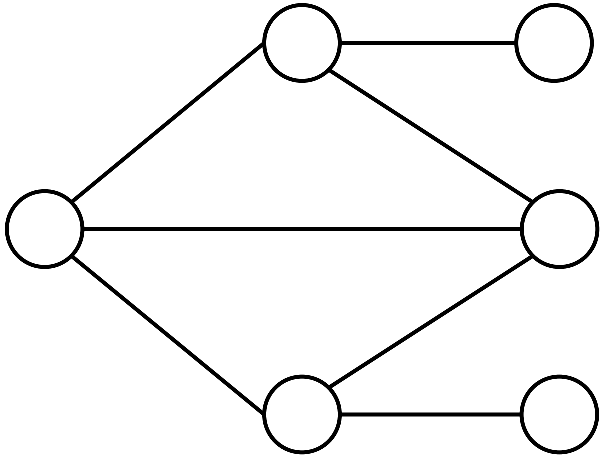

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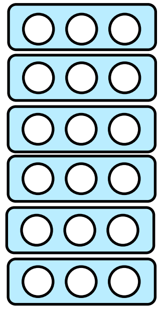

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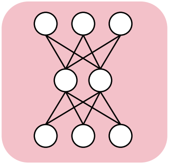
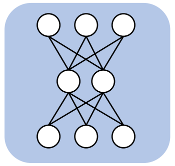


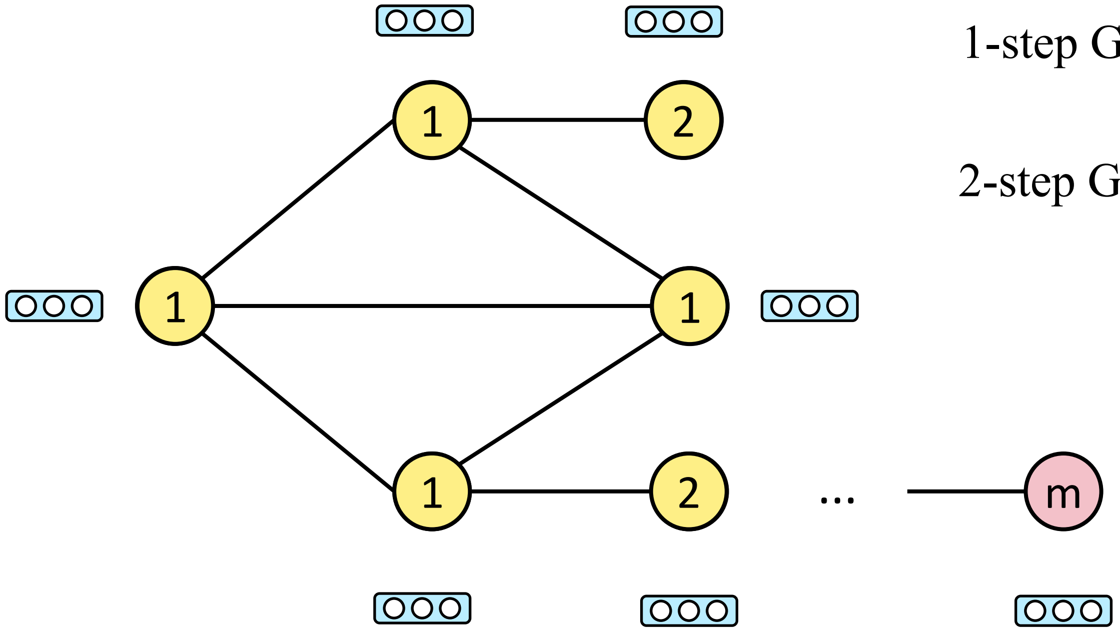
- Aggregated Message $\tilde{L}X$
- State Update Network W



Revisit Spectral Filtering

Our Spectral Filters are Localized:

$$\tilde{L} = \tilde{D}^{-\frac{1}{2}}(A+I)\tilde{D}^{-\frac{1}{2}}$$



1-step Graph Convolution: $h_W * X \approx \tilde{L}XW$

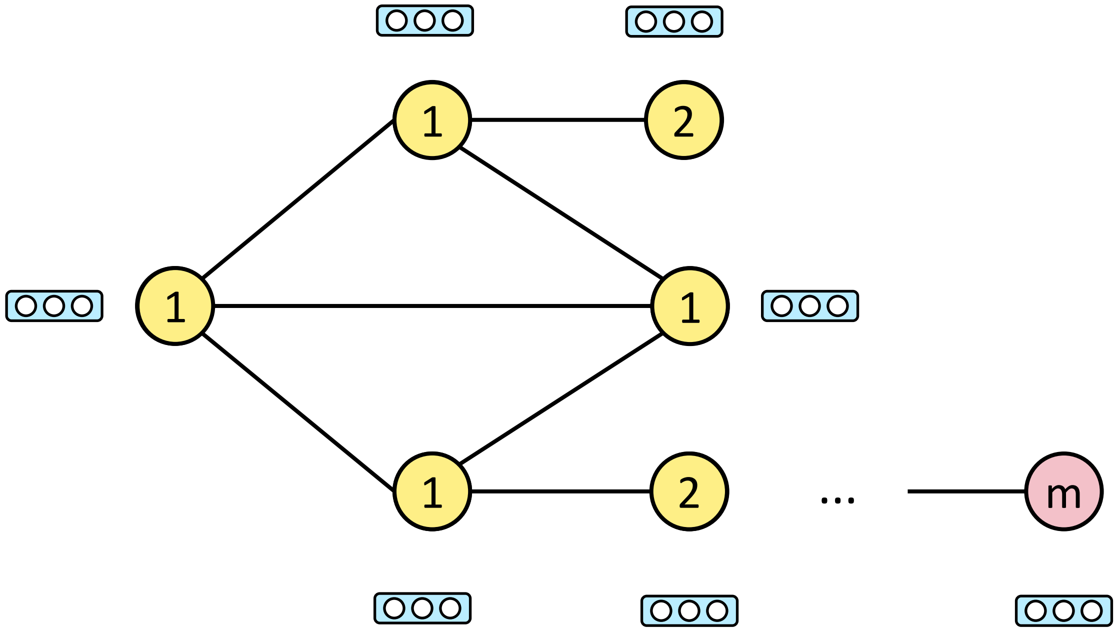
2-step Graph Convolution: $h_{W_2} * h_{W_1} * X \approx \tilde{L}^2 X W_1 W_2$

What if the graph diameter m is large?

Revisit Spectral Filtering

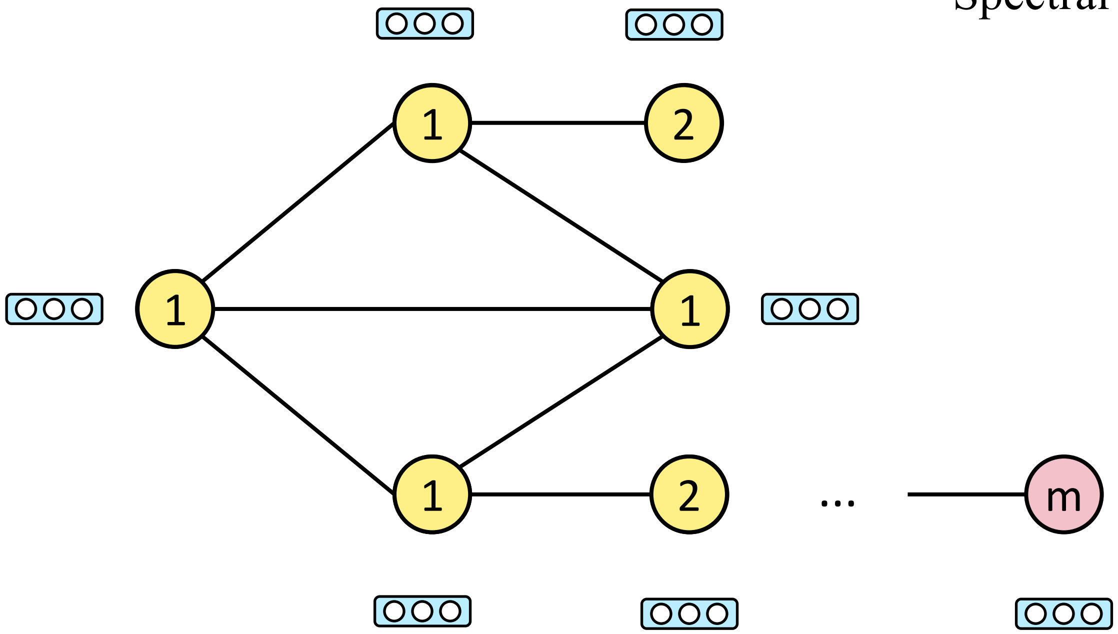
Our Spectral Filters are Localized:

m-step Graph Convolution: $h_W * X \approx \tilde{L}^m XW$



Revisit Spectral Filtering

Our Spectral Filters are Localized:



m-step Graph Convolution: $h_W * X \approx \tilde{L}^m XW$

Spectral Decomposition: $\tilde{L} = U\Lambda U^\top$

$$\tilde{L}^m = U\Lambda^m U^\top$$

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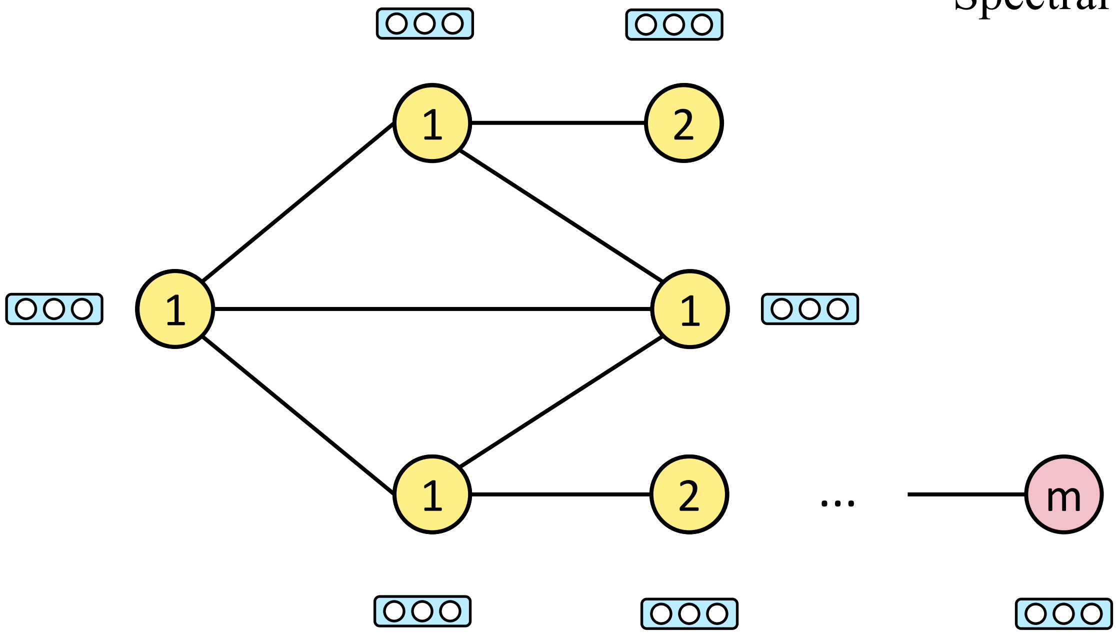

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Cubic complexity O(N^3) !

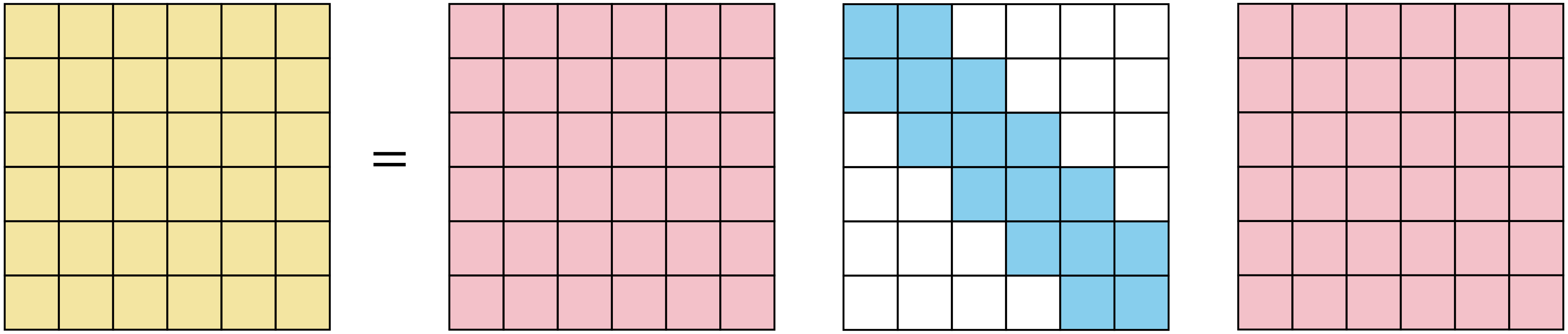
Lanczos Algorithm

Algorithm 1 : Lanczos Algorithm

Input: S, x, K, ϵ
Initialization: $\beta_0 = 0$, $q_0 = 0$, and $q_1 = x/\|x\|$
For $j = 1, 2, \ldots, K$:
    $z = Sq_j$
    $\gamma_j = q_j^\top z$
    $z = z - \gamma_j q_j - \beta_{j-1} q_{j-1}$
    $\beta_j = \|z\|_2$
    If $\beta_j < \epsilon$, quit
    $q_{j+1} = z/\beta_j$
$Q = [q_1, q_2, \cdots, q_K]$
Construct T following Eq. (2)
Eigen decomposition $T = BRB^\top$
Return $V = QB$ and R.

Lanczos Algorithm

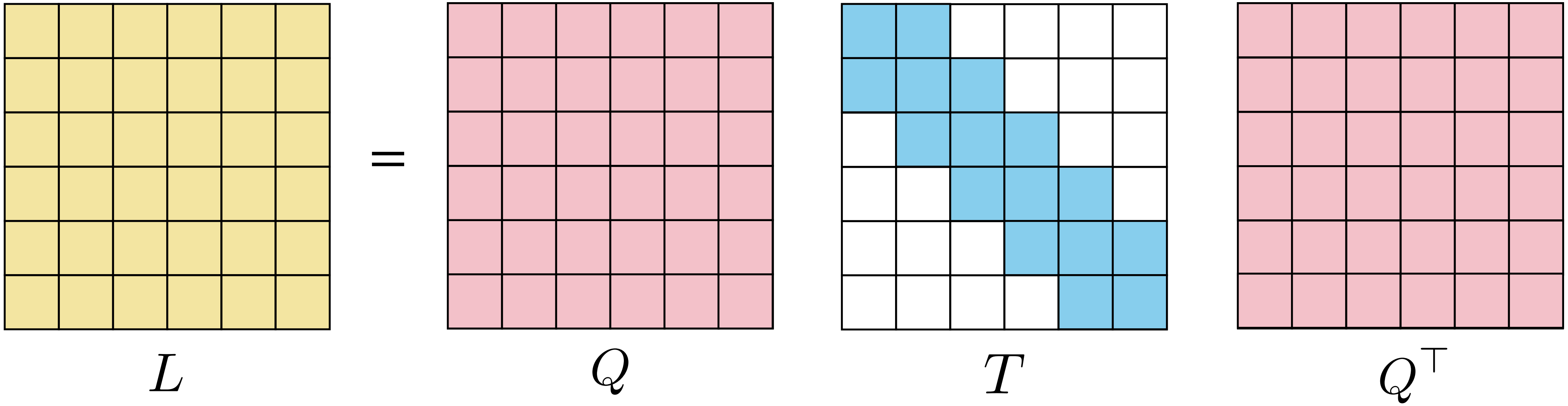
Tridiagonal Decomposition $L = QTQ^\top$



L Q T $Q^\top$

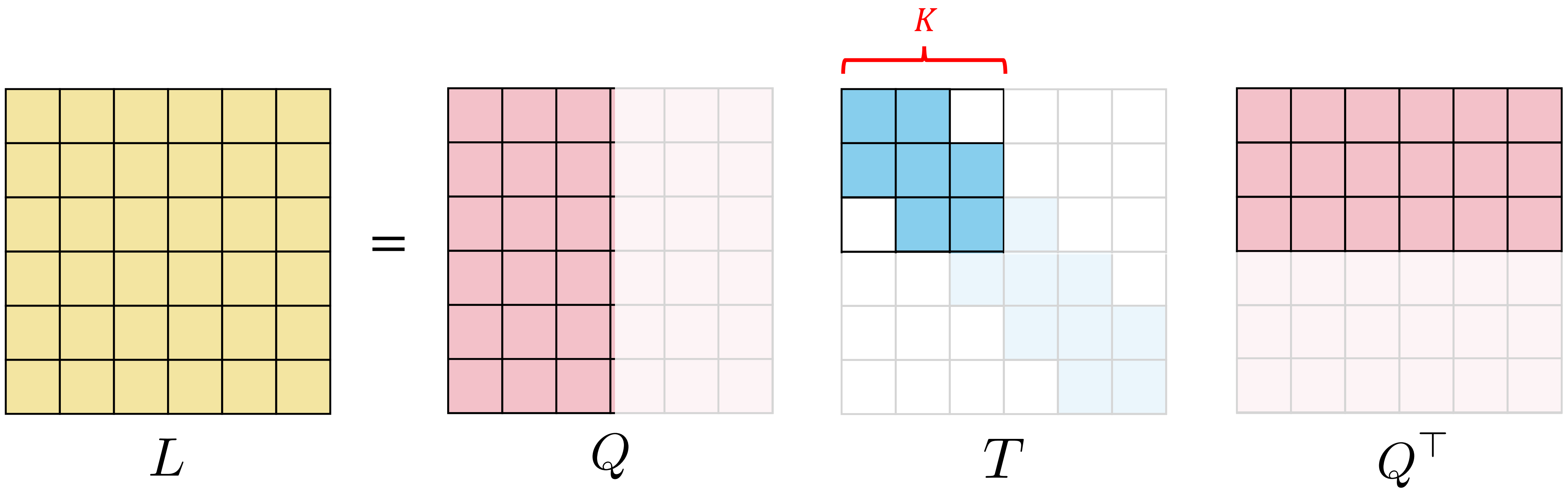
Lanczos Algorithm

Tridiagonal Decomposition $L = QTQ^\top$



Lanczos Algorithm

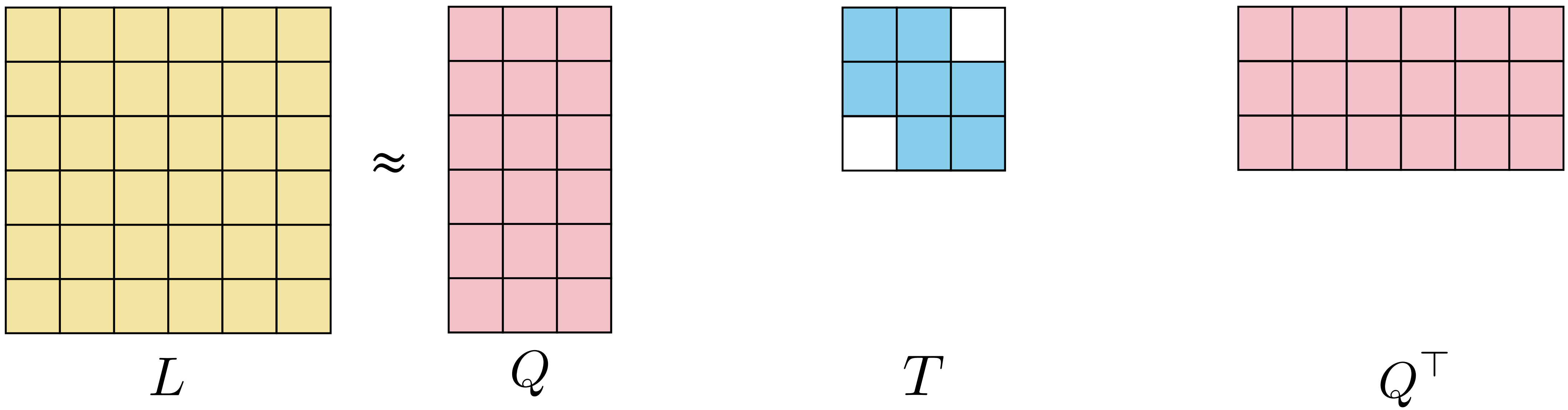
Tridiagonal Decomposition $L = QTQ^\top$



Lanczos Algorithm

Tridiagonal Decomposition $L = QTQ^\top$

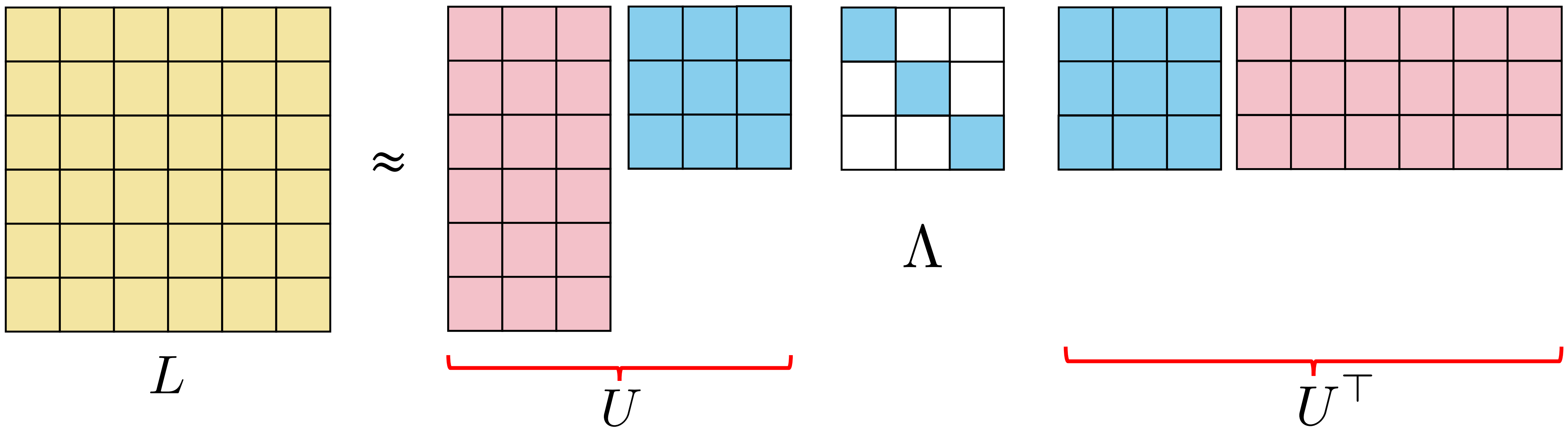
Low-rank approximation



Lanczos Algorithm

Tridiagonal Decomposition $L = QTQ^\top$

Low-rank approximation with **top K eigenpairs**



$O(N^3)$ → $O(KN^2)$

Multi-scale Graph Convolutional Networks

- m-step GraphConv (Prior Work) $H = L^m XW$

LanczosNet [9]:

- m-step GraphConv $H = U\Lambda^m U^\top XW$
- Learn Nonlinear Spectral Filter $H = U f_\theta(\Lambda^m) U^\top XW$
- Learning Graph Kernel / Metric $L_{ij} \propto \exp\left(-\|(X_i - X_j)M\|^2\right)$

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Questions?