



Approximation Theory for Graph Machine Learning

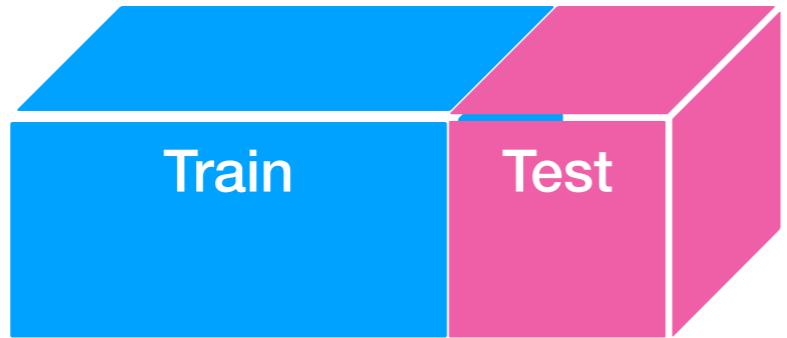
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Computer Science and Engineering

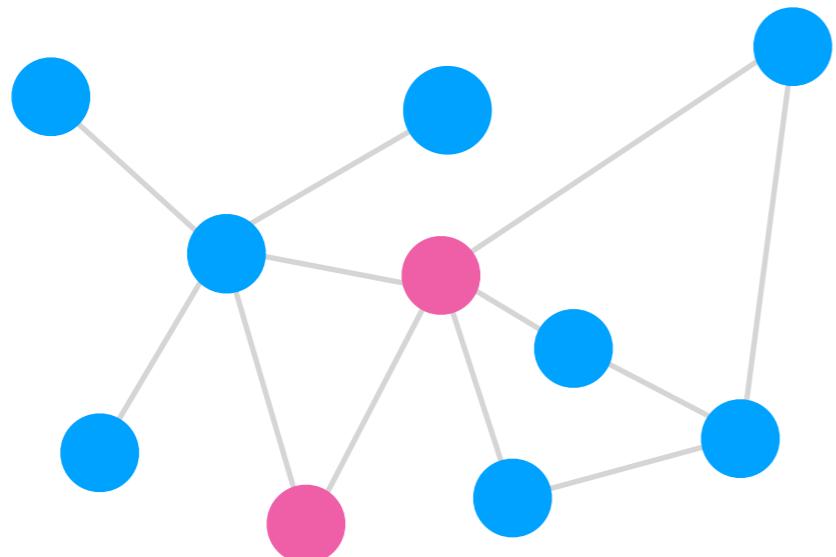


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Graph Machine Learning

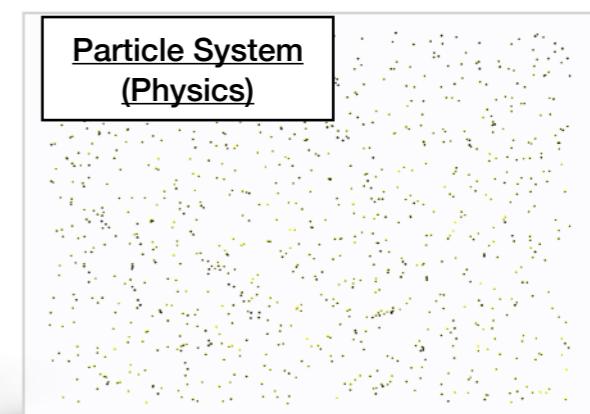
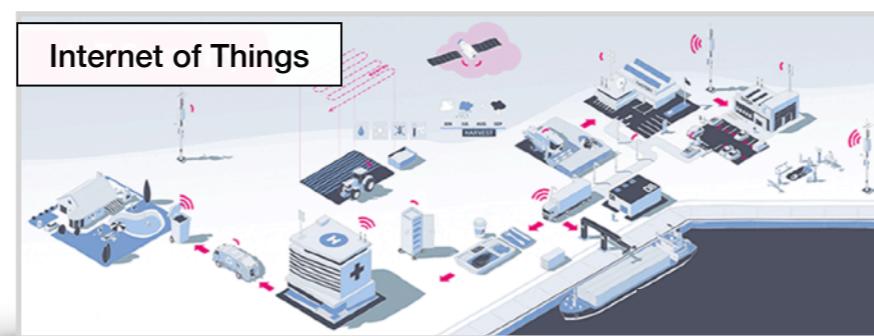
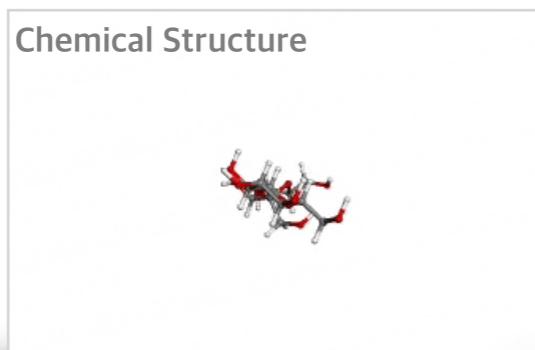
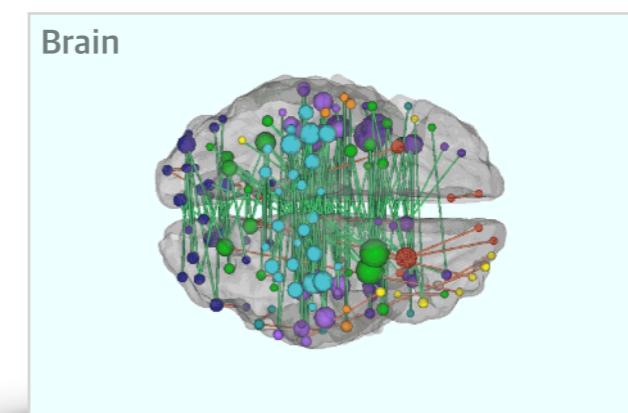
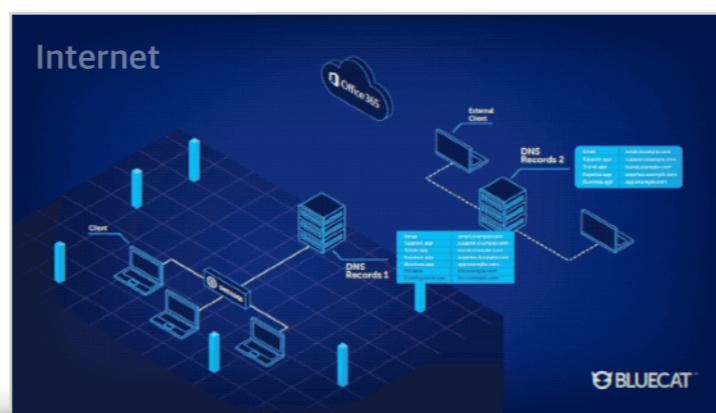


Machine Learning
Block Split

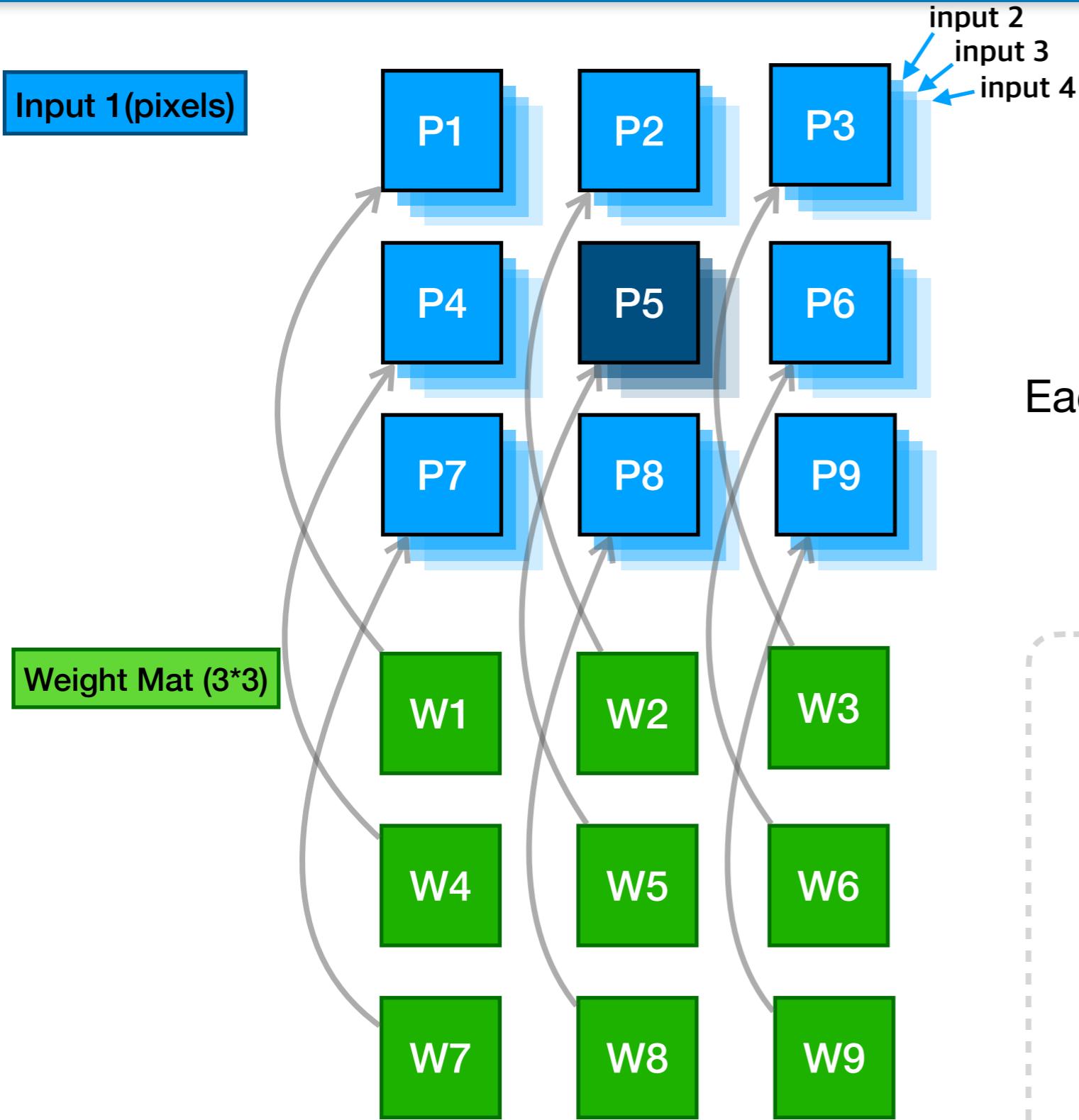


Graph Machine Learning
Geometric Split

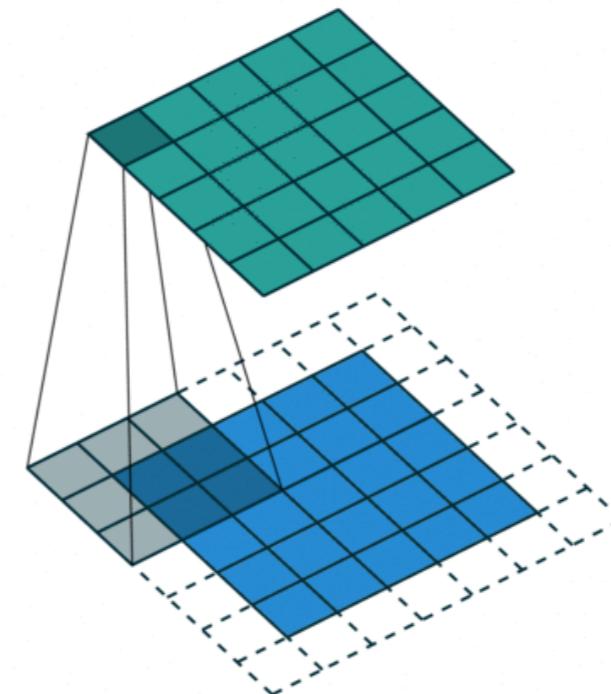
Graph is Pervasive



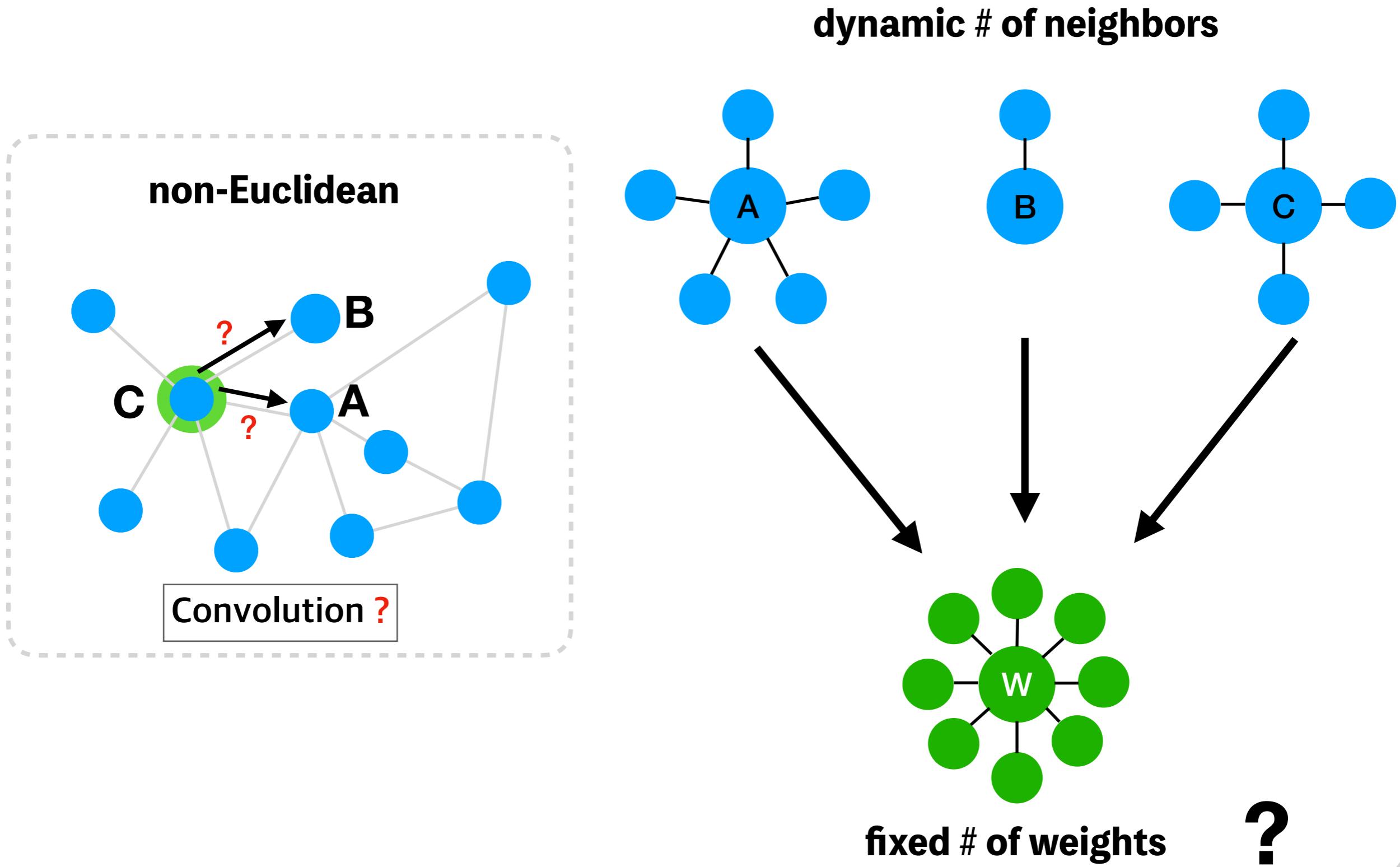
Convolutional Neural Networks



Convolution

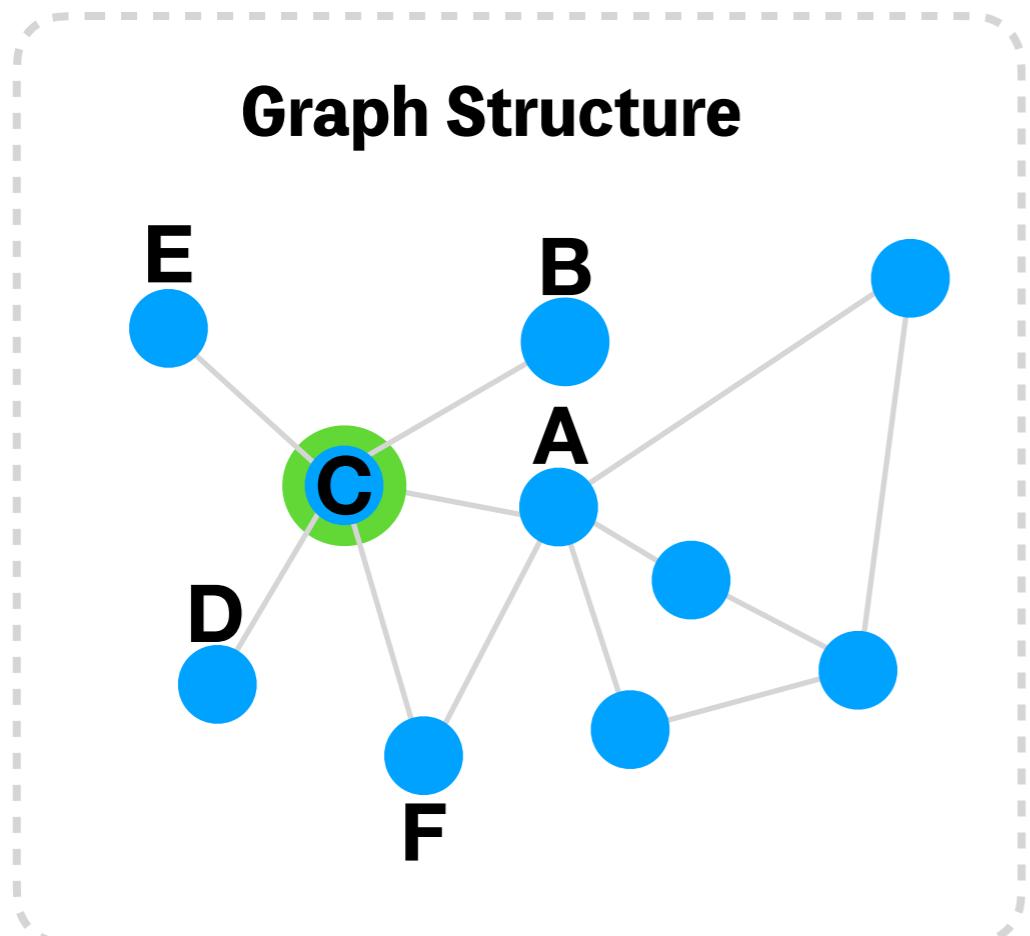


Challenge for non-Euclidean

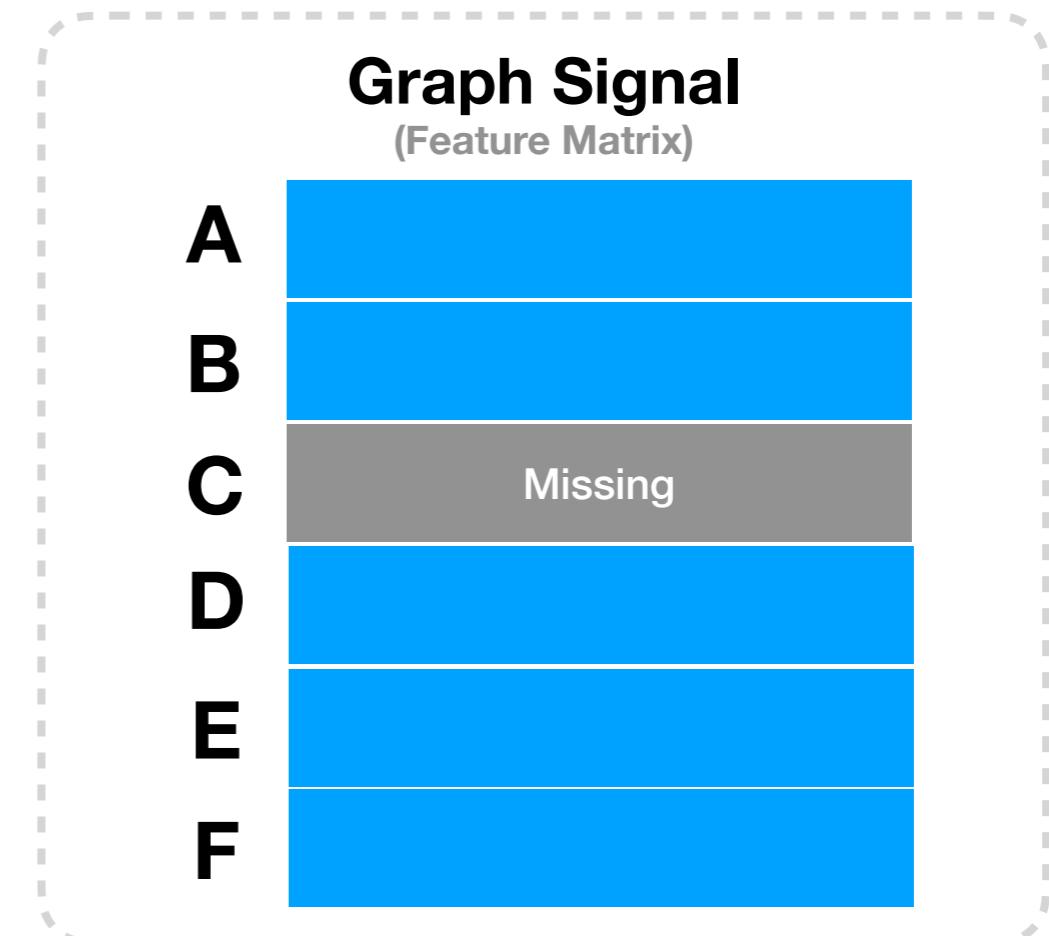


Challenge for non-Euclidean

Task: Infer the value of C



+



$$C = \frac{A + B + D + E + F}{5}$$

Simple

$$C = f(A, B, D, E, F | Graph)$$

Real-World

Overview of Graph Research

Graph Neural Networks



Theory

Theoretical understanding is limited

- **White-box: Graph Theory**
- Black-box: XAI for Graph

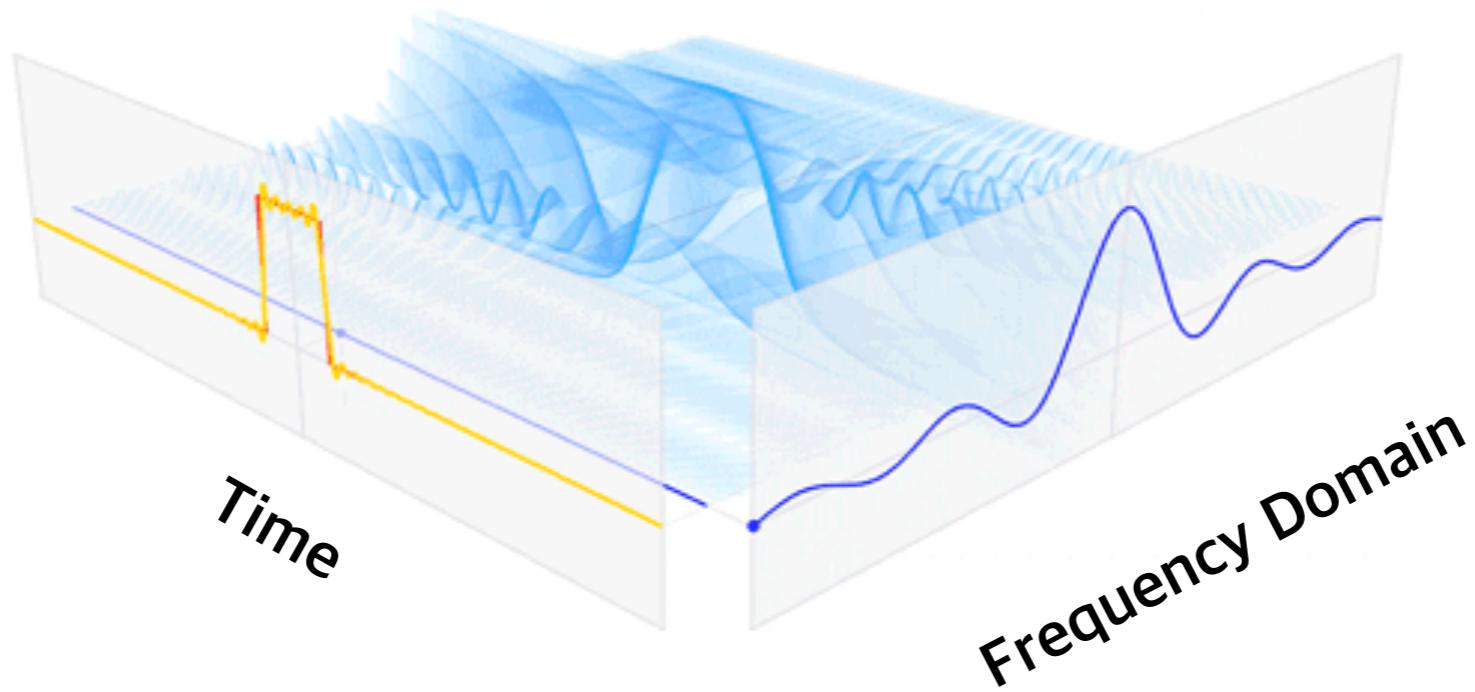
Application

Limited in social networks

- Transportation Network
- Circuit Modeling
- Brain Network
- Disease Spreading

Spectral Analysis

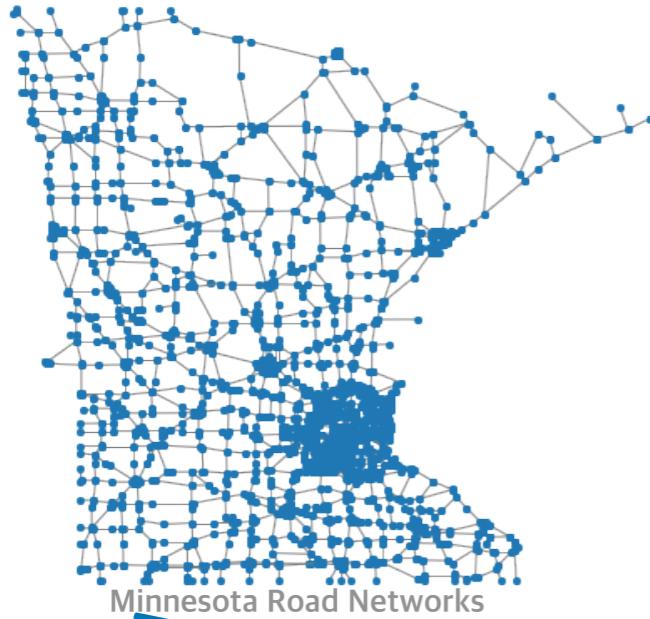
credit: [giphy](#)



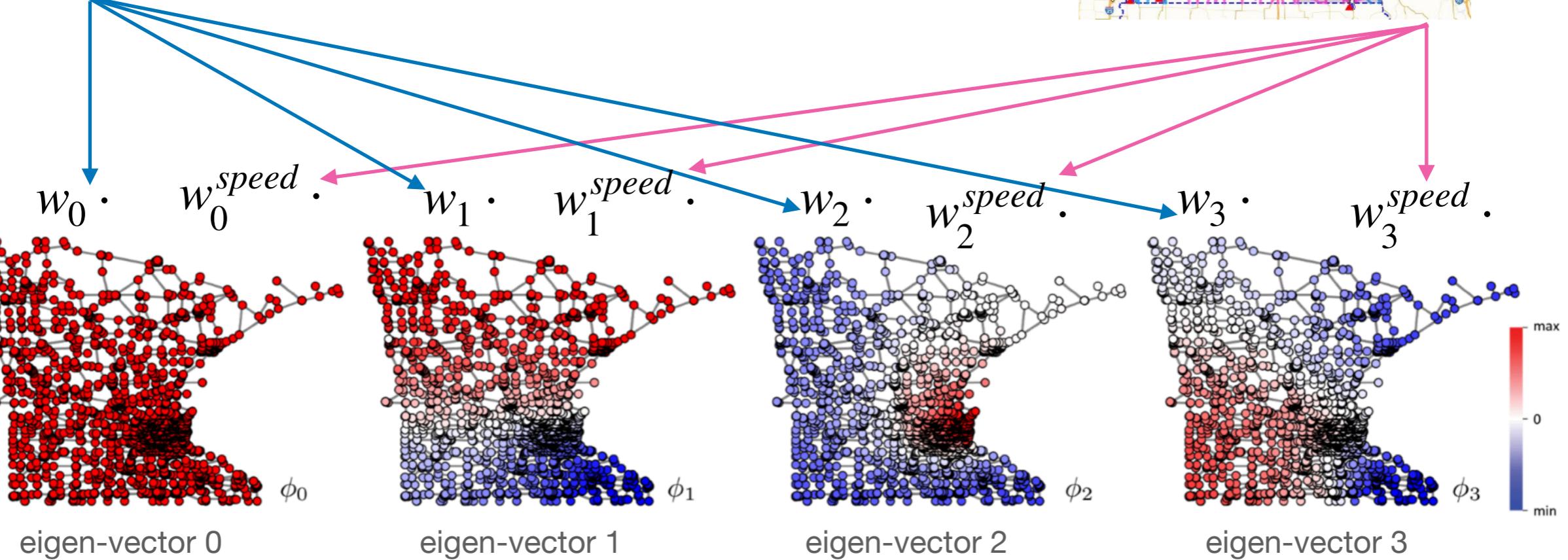
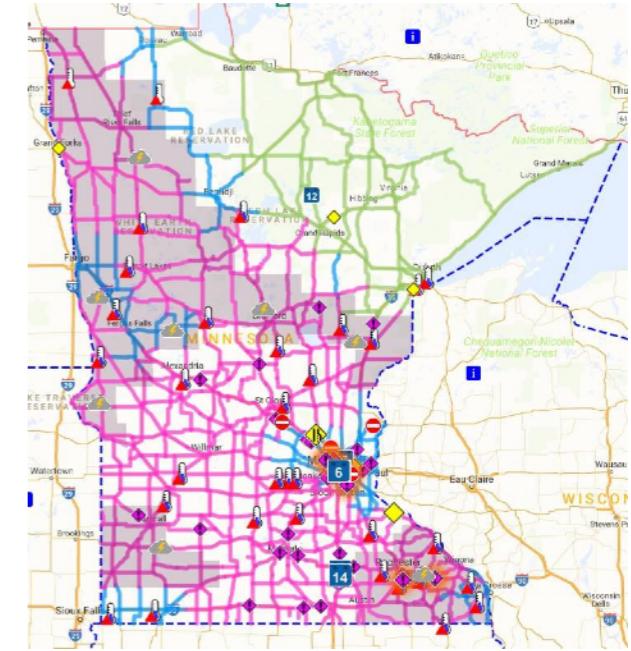
$$\text{Square Wave} = w_0 \cdot \text{DC} + w_1 \cdot \text{Sine Wave}_1 + w_2 \cdot \text{Sine Wave}_2 + w_3 \cdot \text{Sine Wave}_3 + \dots$$

Spectral Analysis for Graph

Graph Structure

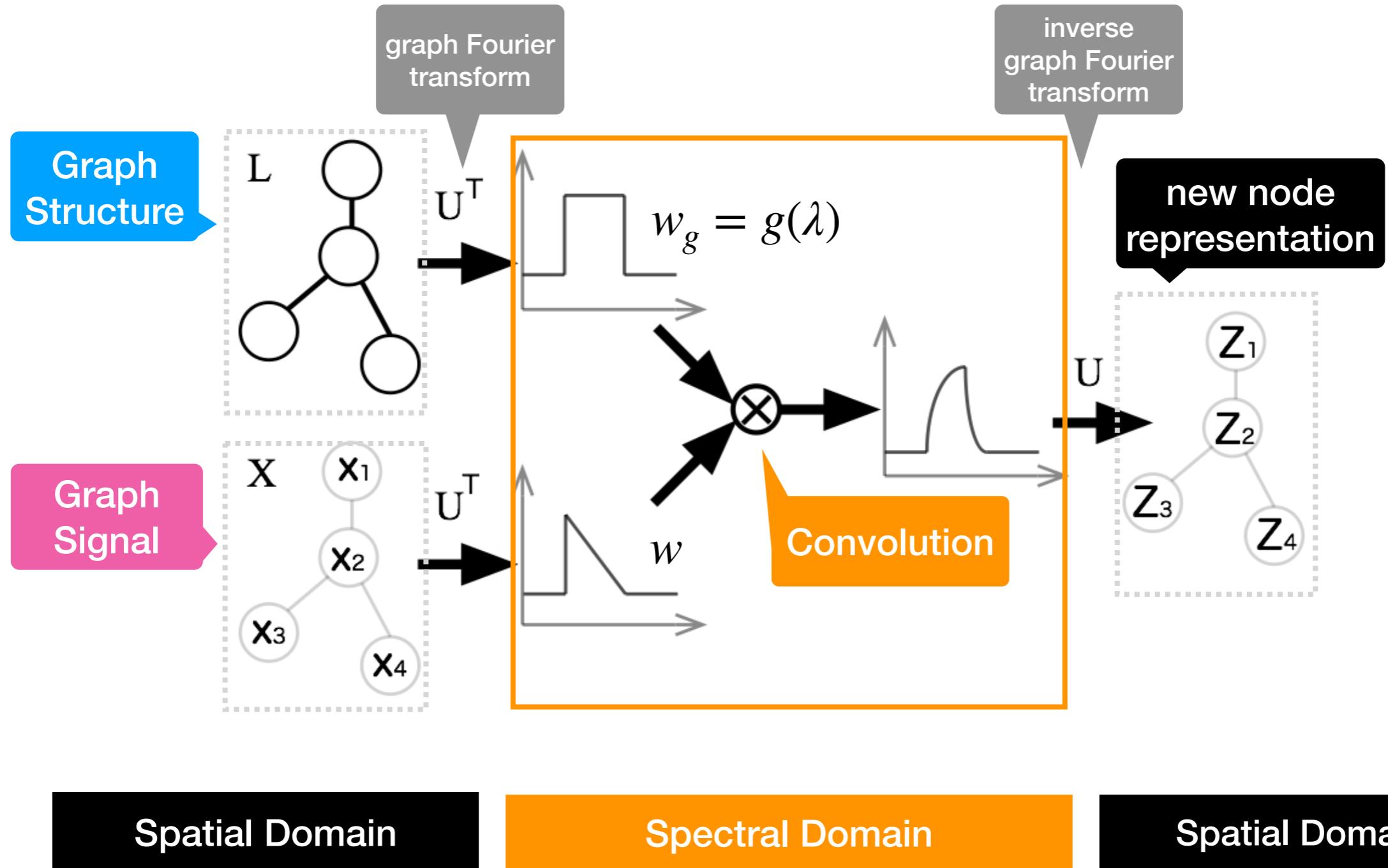


Graph Signal (e.g., Traffic Speed)

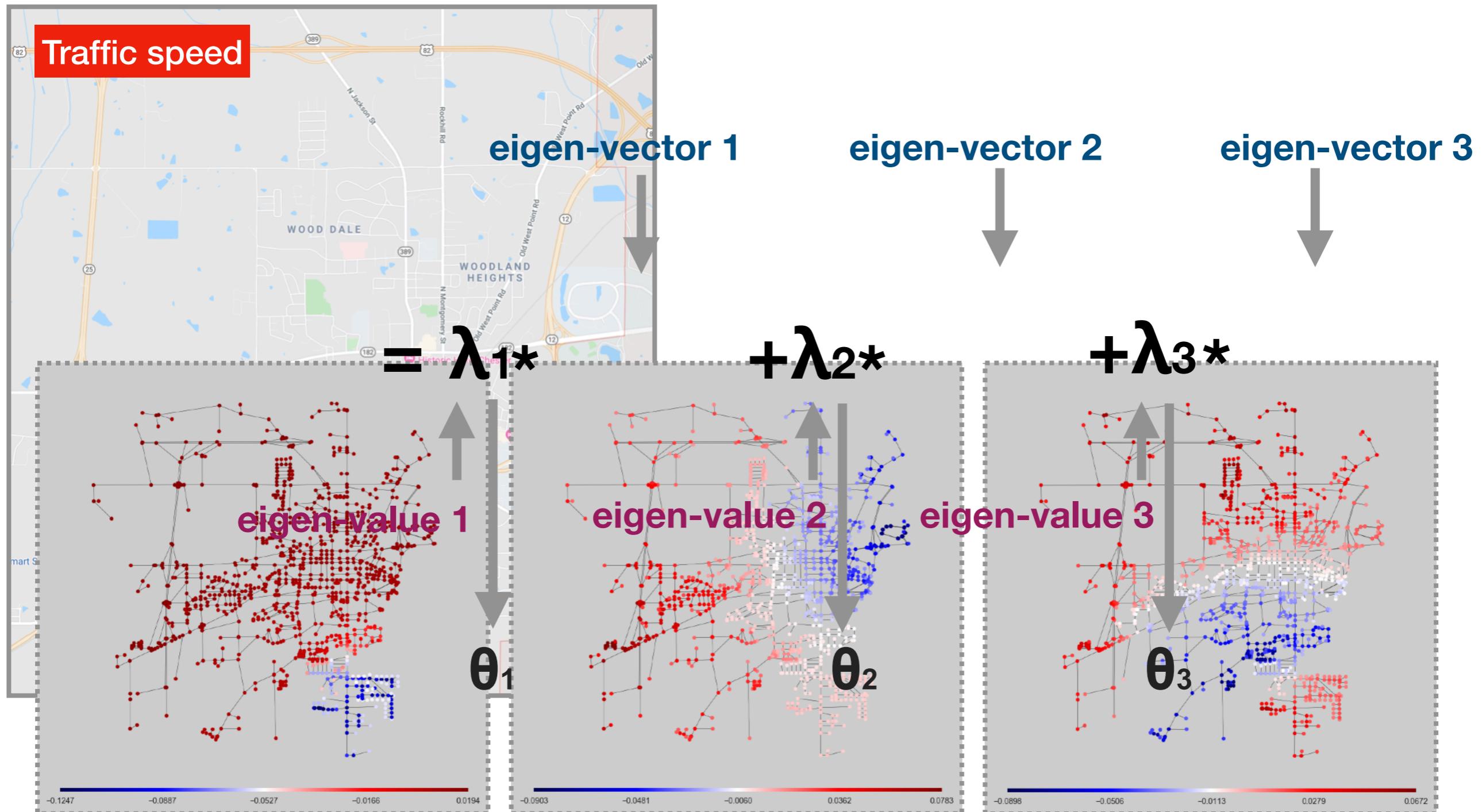


Graph Fourier Transform (Spectral Decomposition)

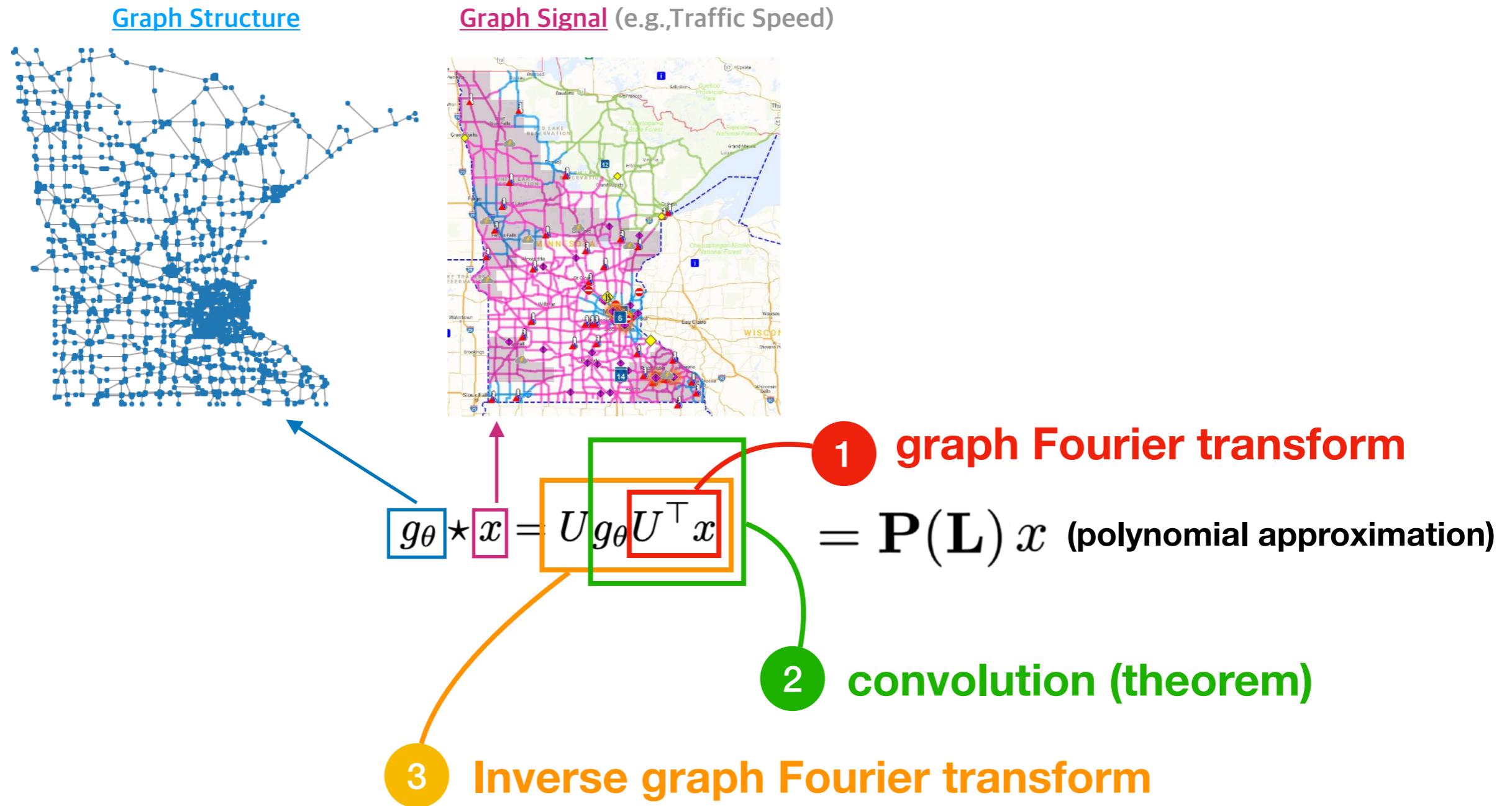
What is Graph Convolution



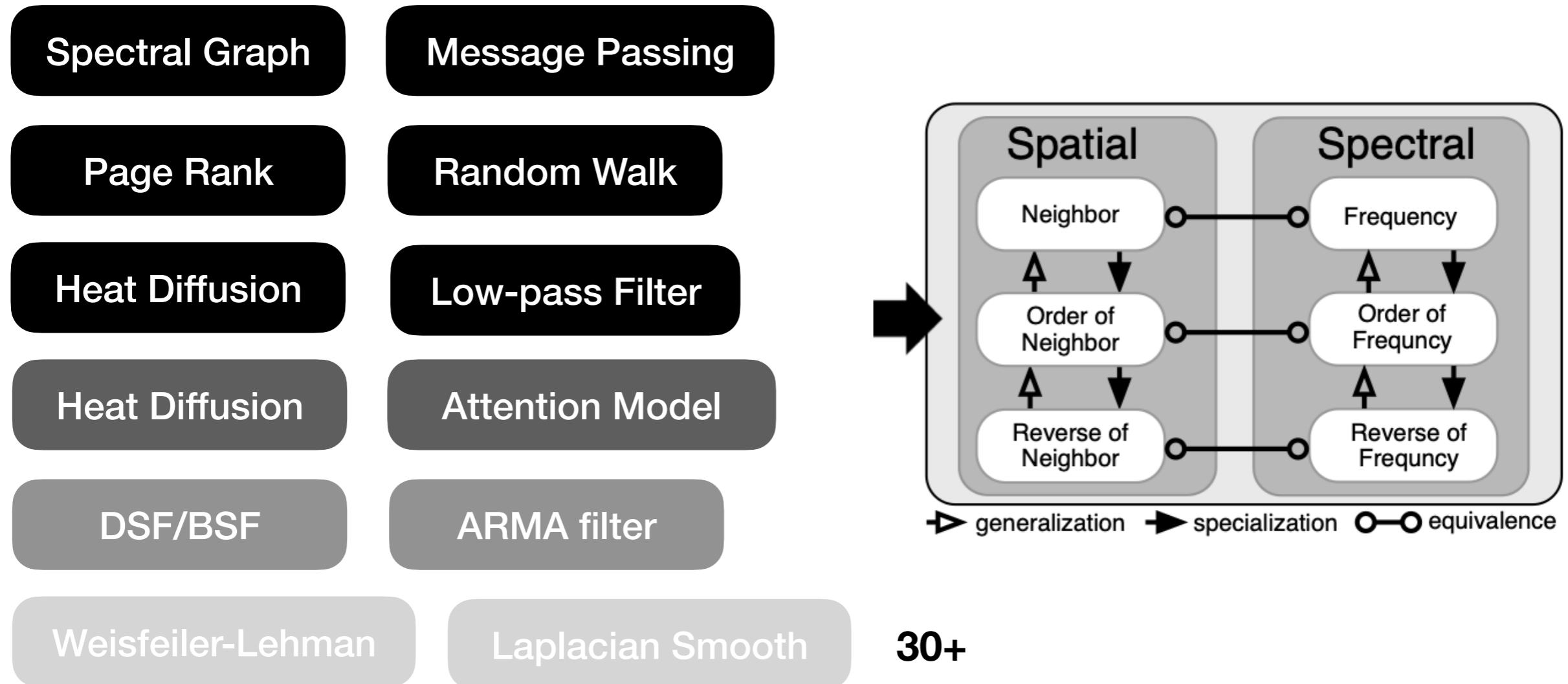
What is Spectral Graph



What is Graph Convolution



GNN, What else?

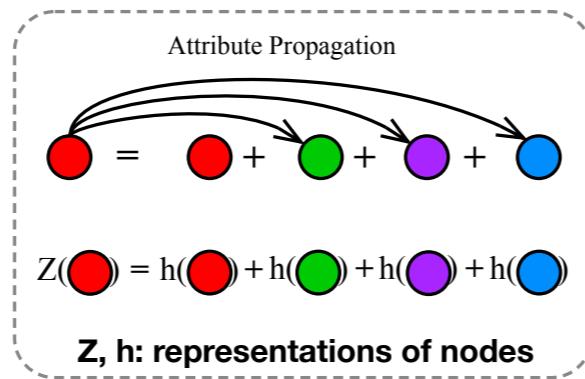
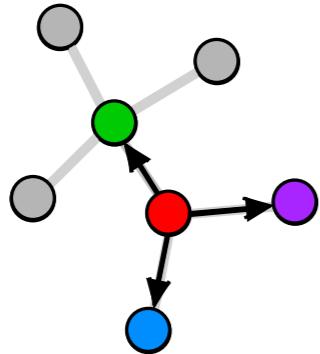


- A large number of graph neural networks, with different mechanisms
- **Challenge for research:** no uniform framework to compare them

Analysis 1: Spatial-based GNN

function of Adjacency

Linear



GCN Thomas N. Kipf et al. (2016)

$$\mathbf{Z} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{A}} \hat{\mathbf{D}}^{-\frac{1}{2}} \mathbf{X} = \hat{\mathbf{D}}^{-\frac{1}{2}} (\mathbf{I} + \mathbf{A}) \hat{\mathbf{D}}^{-\frac{1}{2}} \mathbf{X} = (\mathbf{I} + \tilde{\mathbf{A}}) \mathbf{X}$$

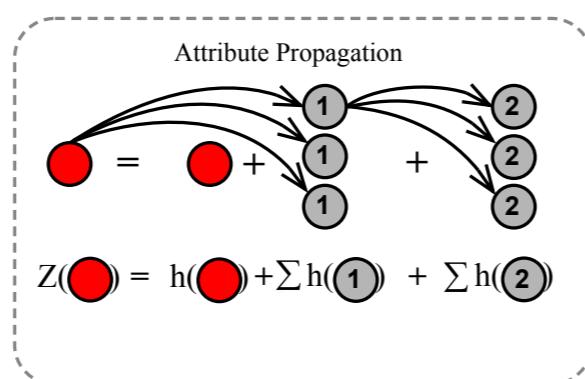
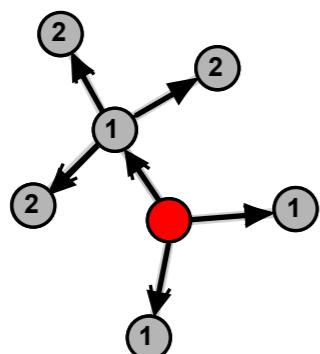
GraphSAGE Will Hamilton et al. (2017)

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

GIN Xukeyu Lu et al. (2019)

$$\mathbf{Z} = (1 + \epsilon) \cdot \mathbf{h}(v) + \sum_{u_j \in \mathcal{N}(v_i)} \mathbf{h}_{(u_j)} = [(1 + \epsilon)\mathbf{I} + \mathbf{A}] \mathbf{X}$$

Polynomial



DeepWalk Bryan Perozzi et al. (2014)

$$\mathbf{Z} = \frac{1}{t+1} (\mathbf{I} + \tilde{\mathbf{A}} + \tilde{\mathbf{A}}^2 + \dots + \tilde{\mathbf{A}}^t) \mathbf{X} = \frac{1}{t+1} \mathbf{P}(\tilde{\mathbf{A}}) \mathbf{X}$$

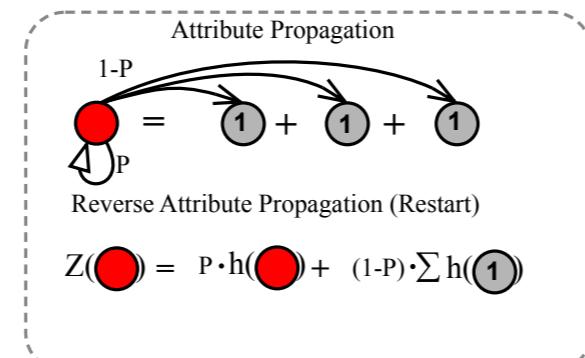
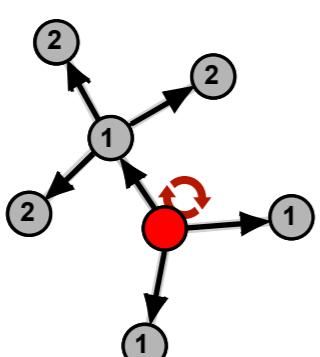
ChebyNet Defferrard, Michael et al. (2016)

$$\mathbf{Z} = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{\mathbf{L}}) \mathbf{X} = \left[\tilde{\theta}_0 \mathbf{I} + \tilde{\theta}_1 (\mathbf{I} - \tilde{\mathbf{A}}) + \tilde{\theta}_2 (\mathbf{I} - \tilde{\mathbf{A}})^2 + \dots \right] \mathbf{X} = \left(\phi \mathbf{I} + \sum_{i=1}^k \psi_i \tilde{\mathbf{A}}^i \right) \mathbf{X} = \mathbf{P}(\tilde{\mathbf{A}}) \mathbf{X}$$

Node2Vec Aditya Grover et al. (2016)

$$\mathbf{Z} = \left(\frac{1}{p} \cdot \mathbf{I} + \tilde{\mathbf{A}} + \frac{1}{q} (\tilde{\mathbf{A}}^2 - \tilde{\mathbf{A}}) \right) \mathbf{X} = \left[\frac{1}{p} \mathbf{I} + \left(1 - \frac{1}{q} \right) \tilde{\mathbf{A}} + \frac{1}{q} \tilde{\mathbf{A}}^2 \right] \mathbf{X} = \mathbf{P}(\tilde{\mathbf{A}}) \mathbf{X}$$

Rational



Personalized PageRank Johannes Klicpera et al. (2018)

$$\mathbf{Z} = \frac{\alpha}{\mathbf{I} - (1-\alpha)\tilde{\mathbf{A}}} \mathbf{X}$$

ARMA Filter Filippo Maria Bianchi et al. (2018)

$$\mathbf{Z} = \frac{b}{\mathbf{I} - a\tilde{\mathbf{A}}} \mathbf{X}$$

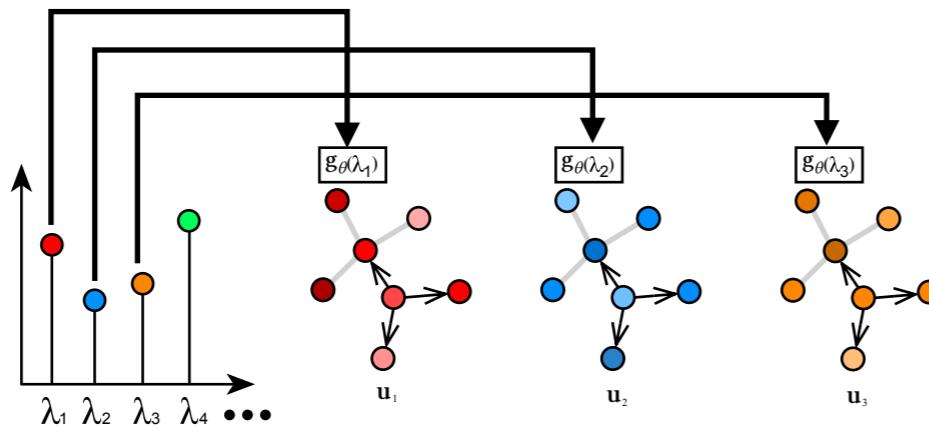
Auto Regressive Filter Qimai Li et al. (2019)

$$\mathbf{Z} = (\mathbf{I} + \alpha \tilde{\mathbf{L}})^{-1} \mathbf{X} = \frac{\mathbf{I}}{\mathbf{I} + \alpha(\mathbf{I} - \tilde{\mathbf{A}})} \mathbf{X}$$

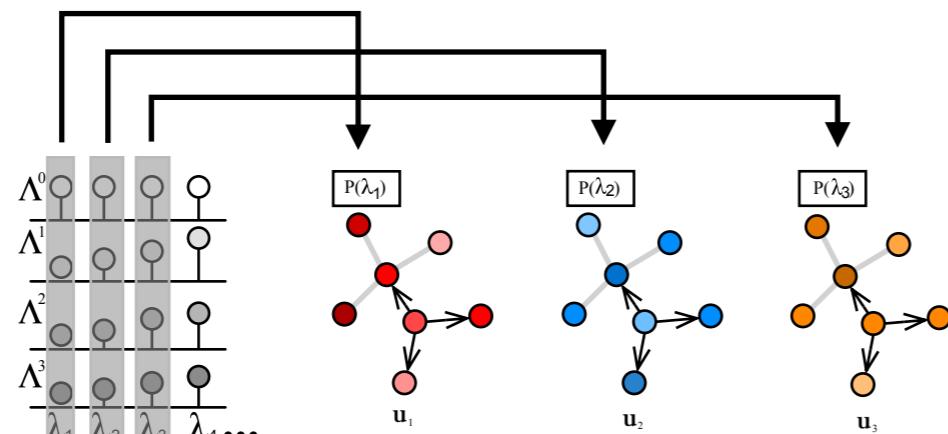
Analysis 2: Spectral-based GNN

function of Eigenvalues

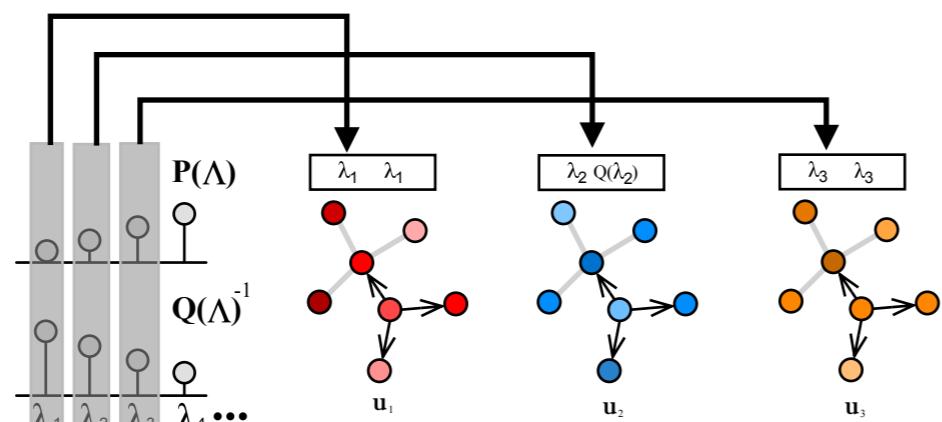
Linear



Polynomial



Rational



GCN Thomas N. Kipf et al. (2016)

$$Z = \tilde{A}X = D^{-\frac{1}{2}}(A + I)D^{-\frac{1}{2}}X = D^{-\frac{1}{2}}(D - L + I)D^{-\frac{1}{2}}X = (I - L + I)D^{-\frac{1}{2}}X = U(2 - \Lambda)U^T X$$

GraphSAGE Will Hamilton et al. (2017)

$$Z = D^{-\frac{1}{2}}(I + A)D^{-\frac{1}{2}}X = (I + \tilde{A})X = (2I - \tilde{L})X = U(2 - \Lambda)U^T X$$

GIN Xukeyu Lu et al. (2019)

$$Z = D^{-\frac{1}{2}}[(1 + \epsilon)I + A]D^{-\frac{1}{2}}X = D^{-\frac{1}{2}}[(2 + \epsilon)I - \tilde{L}]D^{-\frac{1}{2}}X = U(2 + \epsilon - \Lambda)U^T X$$

DeepWalk Bryan Perozzi et al. (2014)

$$Z = \frac{1}{t+1} (I + (I - \tilde{L}) + (I - \tilde{L})^2 + \dots + (I - \tilde{L})^t) X = U (\theta_0 + \theta_1 \Lambda + \theta_2 \Lambda^2 + \dots + \theta_t \Lambda^t) U^T X$$

ChebyNet Defferrard, Michael et al. (2016)

$$Z = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{L})X = U (\tilde{\theta}_0 \cdot 1 + \tilde{\theta}_1 \Lambda + \tilde{\theta}_2 \Lambda^2 + \dots) U^T X$$

Node2Vec Aditya Grover et al. (2016)

$$Z = \left[\left(1 + \frac{1}{p} \right) I - \left(1 + \frac{1}{q} \right) \tilde{L} + \frac{1}{q} \tilde{L}^2 \right] X = U \left[\left(1 + \frac{1}{p} \right) - \left(1 + \frac{1}{q} \right) \tilde{\Lambda} + \frac{1}{q} \tilde{\Lambda}^2 \right] U^T X$$

Personalized PageRank Johannes Klicpera et al. (2018)

$$Z = \frac{\alpha}{I - (1 - \alpha)(I - \tilde{L})} X = U \frac{\alpha}{\alpha I + (1 - \alpha)\Lambda} U^T X$$

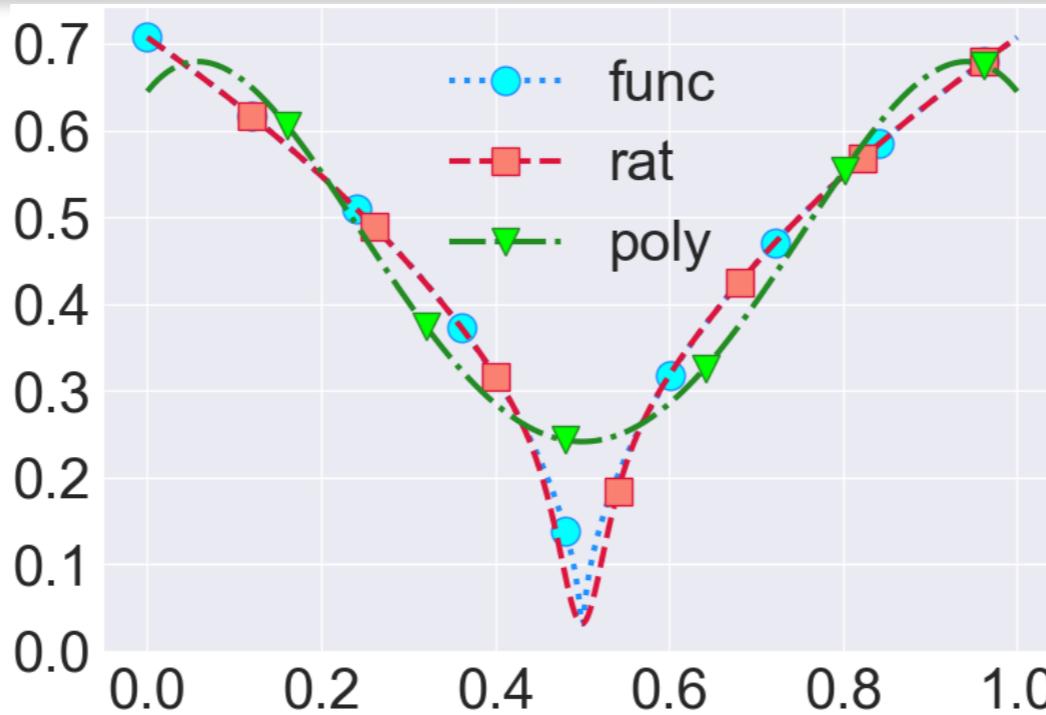
ARMA Filter Filippo Maria Bianchi et al. (2018)

$$Z = \frac{b}{I - a(I - \tilde{L})} X = U \frac{b}{(1 - a)I + a\Lambda} U^T X$$

Auto Regressive Filter Qimai Li et al. (2019)

$$Z = (I + \alpha \tilde{L})^{-1} X = U \frac{1}{1 + \alpha(1 - \Lambda)} U^T X$$

Theoretical Support



Polynomial approximation

$$f(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_2 x^2 + a_1 x + a_0$$

simple form, well known properties

computationally **easy** to use

notorious for oscillations between exact-fit value

only high degree can model **complicated** structure

poor interpolatory/extrapolatory/asymptotic properties



easy to compute
hard to be accurate

Rational approximation

$$f(x) = \frac{p(x)}{q(x)}$$

moderately **simple** form, not well-known properties

moderately **easy** to handle computationally



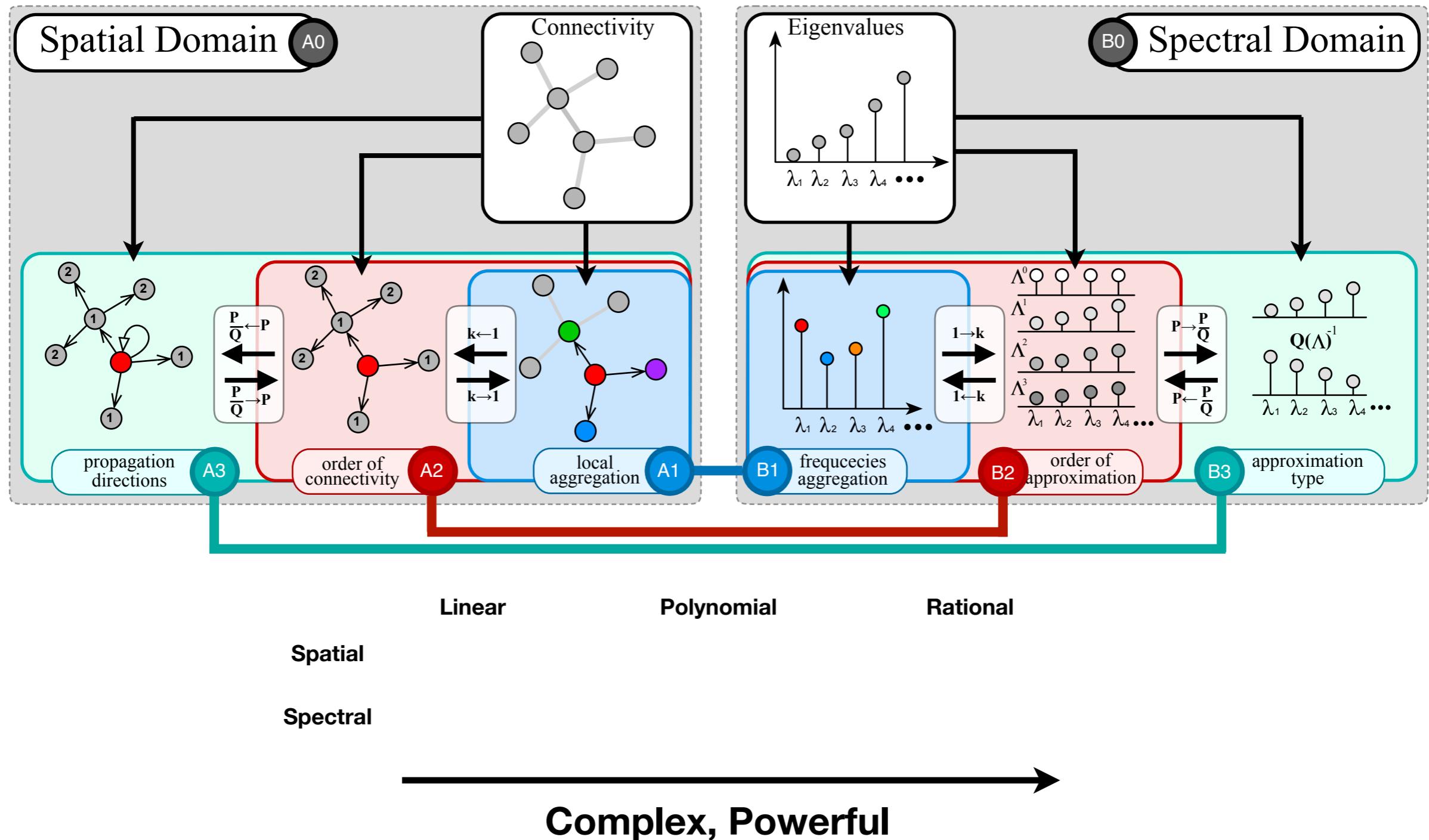
excellent for oscillations between exact-fit value

model **complicated** structure with a fairly low degree

excellent interpolatory/extrapolatory/asymptotic properties

moderately easy to compute
easy to be accurate

Analysis 3: The Framework



GNNs

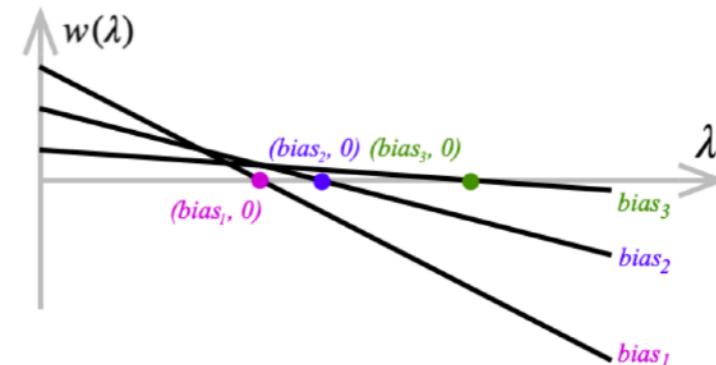
	Spatial-based (A0)	Spectral-based (B0)
	$f(\mathbf{A}) \text{ in } \mathbf{Z} = f(\mathbf{A}) \mathbf{X}$	$g(\Lambda) \text{ in } \mathbf{Z} = \mathbf{U} g(\Lambda) \mathbf{U}^T \mathbf{X}$
	linear function of \mathbf{A} (A1)	linear function of Λ (B1)
GCN	$\mathbf{I} + \tilde{\mathbf{A}}$	$2 - \Lambda$
GraphSAGE	$\hat{\mathbf{D}}^{-1} + \tilde{\mathbf{A}}$	$2 - \Lambda$
GIN	$(1 + \epsilon) \mathbf{I} + \mathbf{A}$	$2 + \epsilon - \Lambda$
	polynomial function of \mathbf{A} (A2)	polynomial function of Λ (B2)
ChebNet	$\phi \mathbf{I} + \sum_{i=1}^k \psi_i \tilde{\mathbf{A}}^i$	$\tilde{\theta}_0 \cdot \mathbf{1} + \tilde{\theta}_1 \Lambda + \tilde{\theta}_2 \Lambda^2 + \dots$
DeepWalk	$\frac{1}{t+1} (\mathbf{I} + \tilde{\mathbf{A}} + \tilde{\mathbf{A}}^2 + \dots + \tilde{\mathbf{A}}^t)$	$\frac{1}{t+1} [\dots + (-1)^{t-1} + \left(\begin{array}{c} 1 \\ t \end{array} \right) (-1)^{t-1}] + \dots$
DCNN	$\psi_1 \tilde{\mathbf{A}} + \psi_2 \tilde{\mathbf{A}}^2 + \psi_3 \tilde{\mathbf{A}}^3 + \dots$	$\theta_1 \Lambda + \theta_2 \Lambda^2 + \theta_3 \Lambda^3 + \dots$
Node2Vec	$\frac{1}{p} \mathbf{I} + \left(1 - \frac{1}{q}\right) \tilde{\mathbf{A}} + \frac{1}{q} \tilde{\mathbf{A}}^2$	$\left(1 + \frac{1}{p}\right) - \left(1 + \frac{1}{q}\right) \Lambda + \frac{1}{q} \Lambda^2$
SGC	$0 \cdot \mathbf{I} + 0 \cdot \tilde{\mathbf{A}} + 0 \cdot \tilde{\mathbf{A}}^2 + \dots + 1 \cdot \tilde{\mathbf{A}}^K$	$\left(\begin{array}{c} K \\ 0 \end{array} \right) + \left(\begin{array}{c} K \\ 1 \end{array} \right) \Lambda^1 + \left(\begin{array}{c} K \\ 2 \end{array} \right) \Lambda^2 + \dots + \Lambda^n$
	rational function of \mathbf{A} (A3)	rational function of Λ (B3)
Auto-Regress	$\mathbf{I} / [(1 + \alpha) \mathbf{I} - \alpha \tilde{\mathbf{A}}]$	$1 / [1 + \alpha(1 - \Lambda)]$
PPNP	$\alpha / [\mathbf{I} - (1 - \alpha) \tilde{\mathbf{A}}]$	$\alpha / [\alpha \mathbf{I} + (1 - \alpha) \Lambda]$
ARMA	$b / (\mathbf{I} - a \tilde{\mathbf{A}})$	$b / (1 - a + a\Lambda)$

Analysis 4: Bias of Linear Model

Bias: 2 for *GCN*, 2 for *GraphSAGE*, and $2 + \epsilon$ for *GIN*

GCN	$2 - \Lambda$
GraphSAGE	$2 - \Lambda$
GIN	$2 + \epsilon - \Lambda$

Why is 2?



Ratio of each spectral component using spectral filtering function

Ratio \rightarrow Adjusted Ratio

$$w(\lambda_i) = \frac{|bias - \lambda_i|}{\sum_j |bias - \lambda_j|}$$

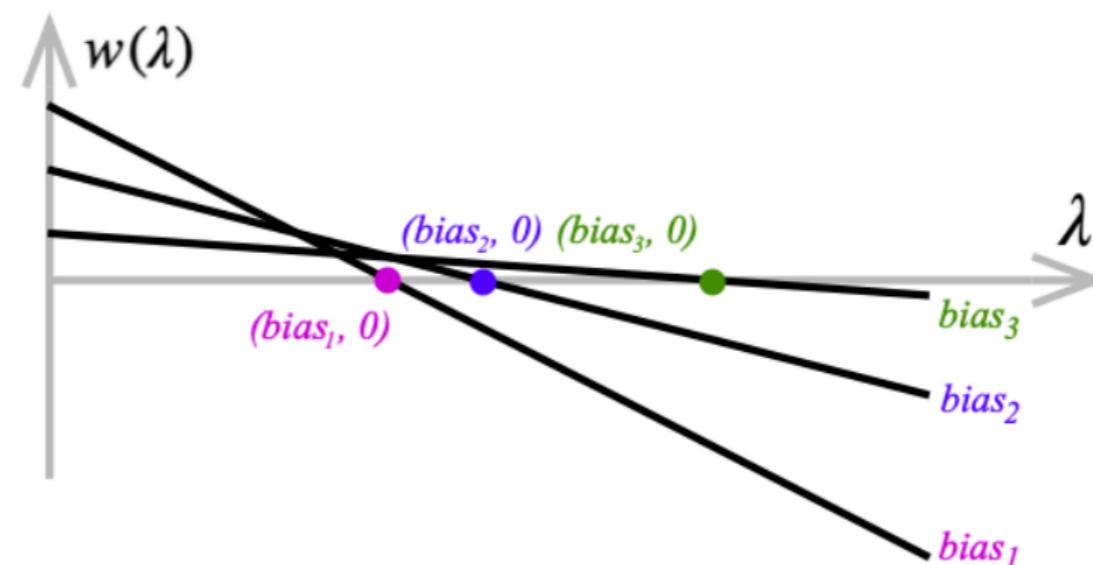
Analysis 4: Design of Linear Model

Eigenvalue is in $[0, 2)$ for the normalized graph Laplacian matrix:

$$\lim_{N \rightarrow \infty} \sup \lambda = 2$$

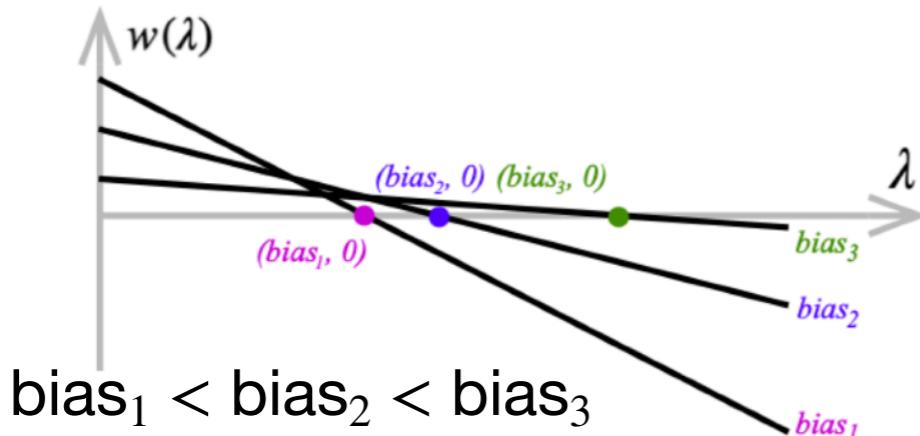
if bias>2, we have: $bias - \lambda > 0$

$$w(\lambda_i) = \frac{|bias - \lambda_i|}{\sum_j |bias - \lambda_j|} = \frac{bias - \lambda_i}{N \cdot bias - \sum_j \lambda_j} = \underbrace{\frac{-1}{N \cdot bias - \sum_j \lambda_j}}_{slope} \lambda_i + \underbrace{\frac{bias}{N \cdot bias - \sum_j \lambda_j}}_{intercept},$$

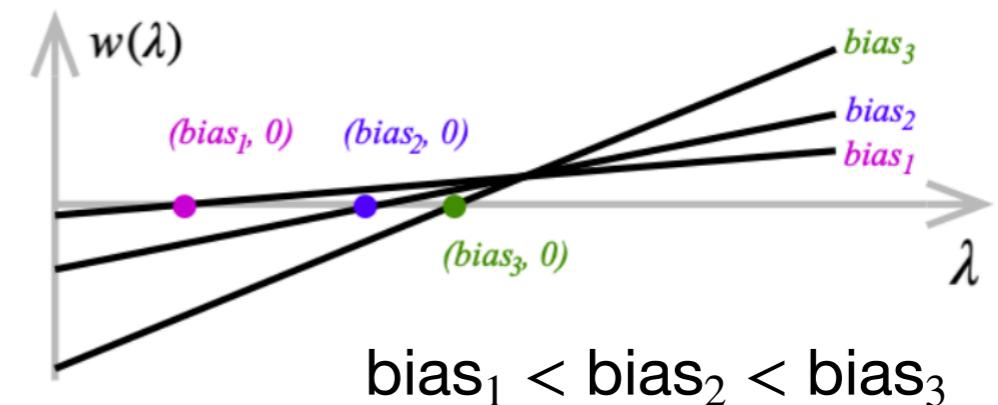


Analysis 4: Design of Linear Model

Low-pass
More weight on low-frequency
Neighbors are similar



High-pass
More weight on high-frequency
Neighbors are dissimilar



Conclusion: Magic number “**2**” ensure that

- Each adjusted weight is positive
- Filtering function is low-pass

Analysis 5: Effect of Rational Model

Polynomial

$$P(L) \quad x$$

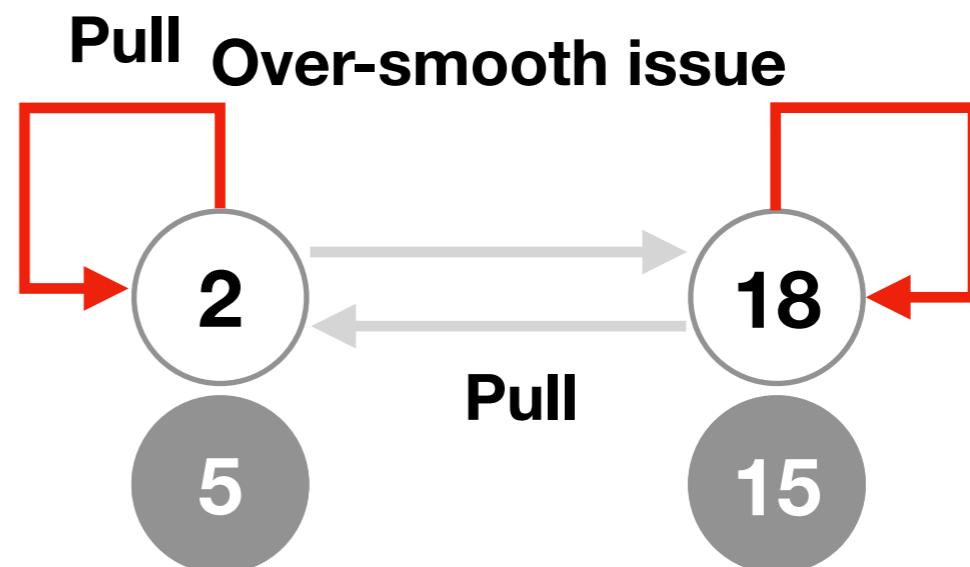
Label propagation

Rational

$$P(L) Q(L)^{-1} \quad x$$

Label propagation

Reverse Label propagation



Analysis 5: Effect of Rational Model

Johannes Klicpera et al. (2018)

**Personalized Page Rank
(information retrieval)**

$$\pi_{\text{ppr}}(i_x) = (1 - \alpha)\hat{A}\pi_{\text{ppr}}(i_x) + \alpha i_x$$

$(1 - \alpha)$

α

Filippo Maria Bianchi et al. (2018)

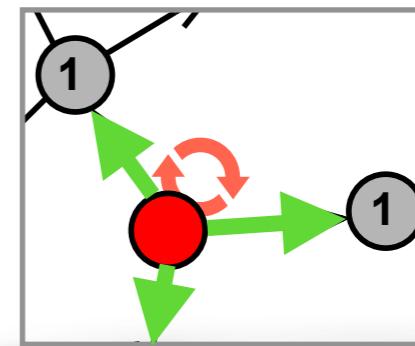
**ARMA
(time series)**

$$\bar{\mathbf{X}}^{(t+1)} = a\mathbf{M}\bar{\mathbf{X}}^{(t)} + b\mathbf{X}$$

a

b

$$\text{next} = \alpha \text{ current} + \beta \text{ original}$$



Summary

- **Analysis 1:** Spatial-based GNNs
 - Feature is a Function of Graph Adjacency
- **Analysis 2:** Spectral-based GNNs
 - Feature is a Function of Eigenvalues
- **Analysis 3:** A Unified Framework
 - Connect Spatial- and Spectral-based GNNs
- **Analysis 4:** Linear Model
 - Effect of Different Bias Design
- **Analysis 5:** Rational Model
 - Effect of Rational Model

Convergence rate

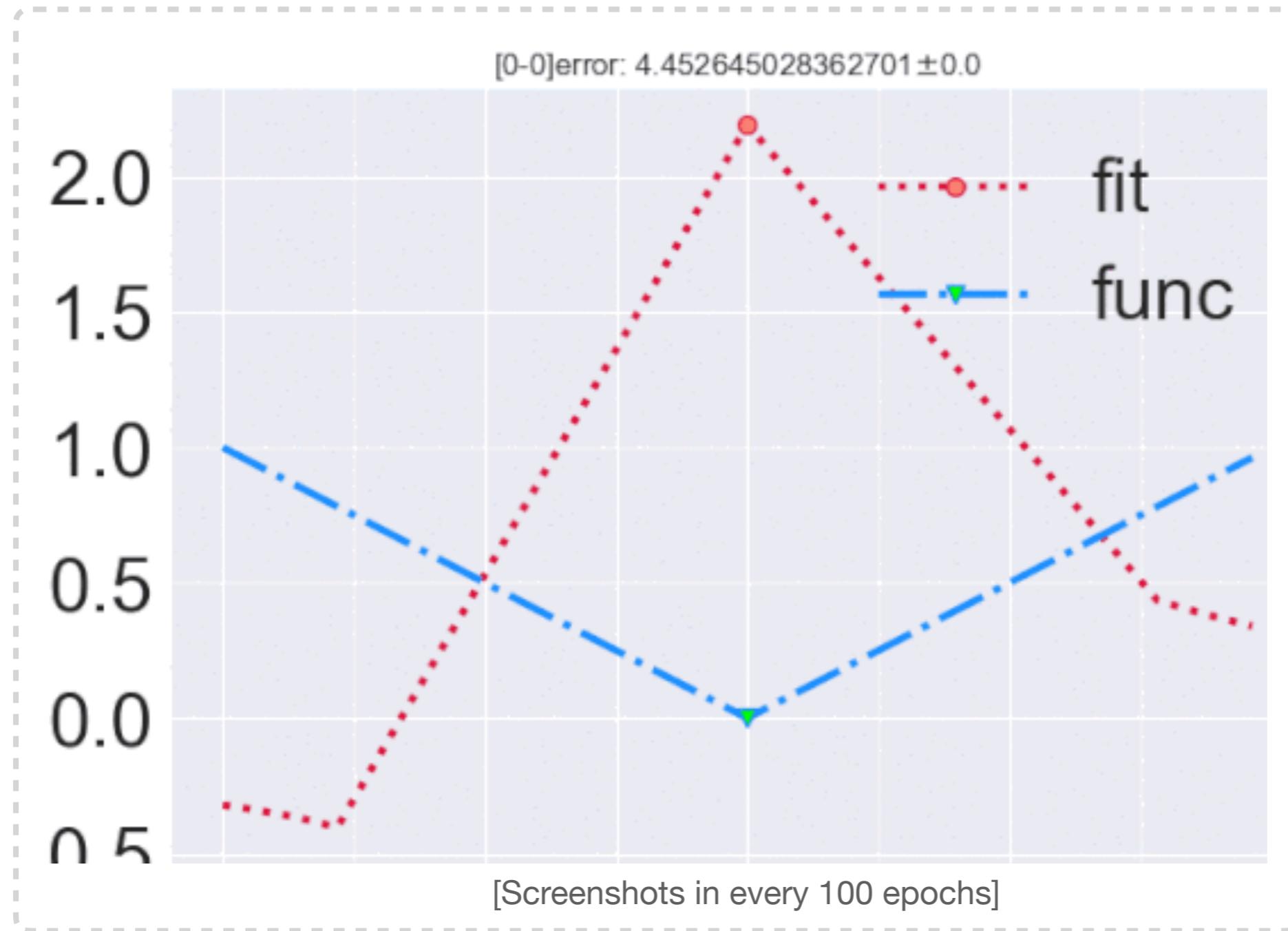
Theorem: Given $n > 5$, there exists a rational function of degree n that satisfies:

$$\sup_{x \in [-c, c]} |f_{1,2} - R_n(x)| \leq C e^{-\sqrt{n}}.$$

**When the order is greater than 5
RemezNet is more accurate than GCN/ChebNet**

$$\mathcal{O}(\text{poly log}(1/\epsilon)) < \Omega(\text{poly}(1/\epsilon))$$

Evaluation: Approximation Demo



RemezNet: iteratively close to the target



Questions or Comments?