DspGNN

Bringing **Spectral Design** to Discrete Time **Dynamic Graph Neural Networks** for **Edge Regression**

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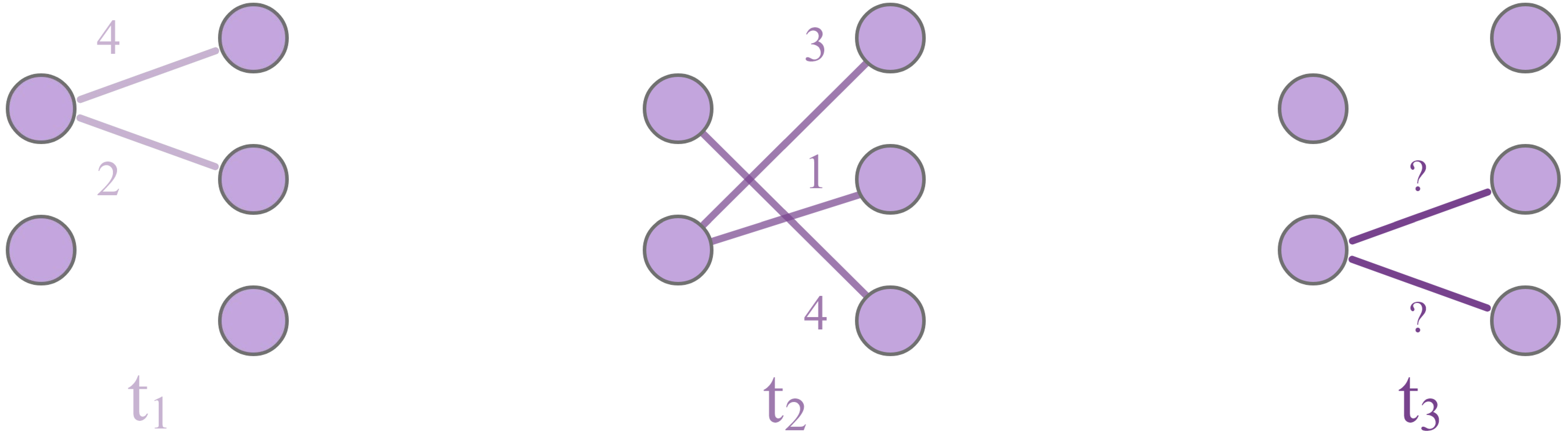
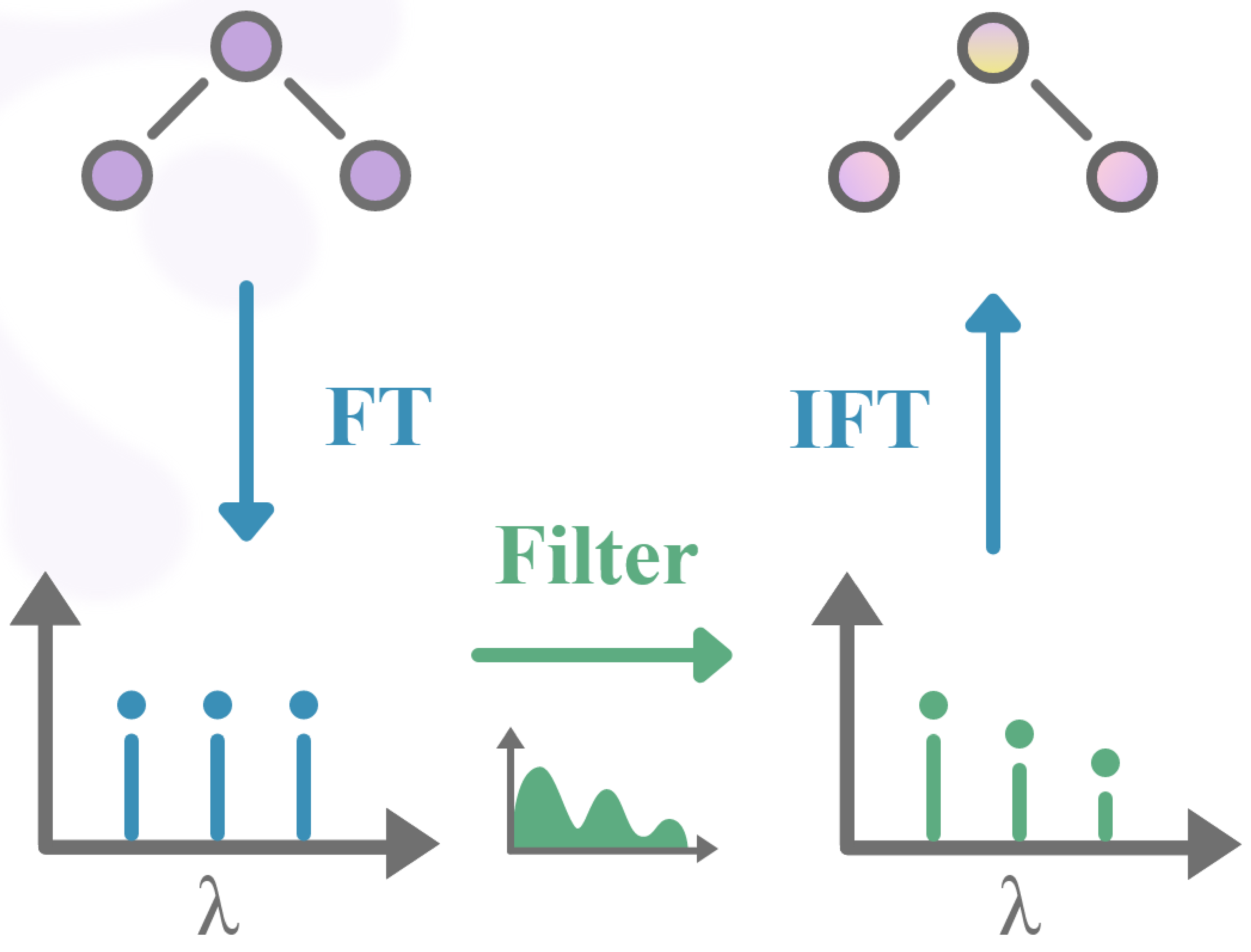
Discrete Time Dynamic Graph Edge Regression



Given

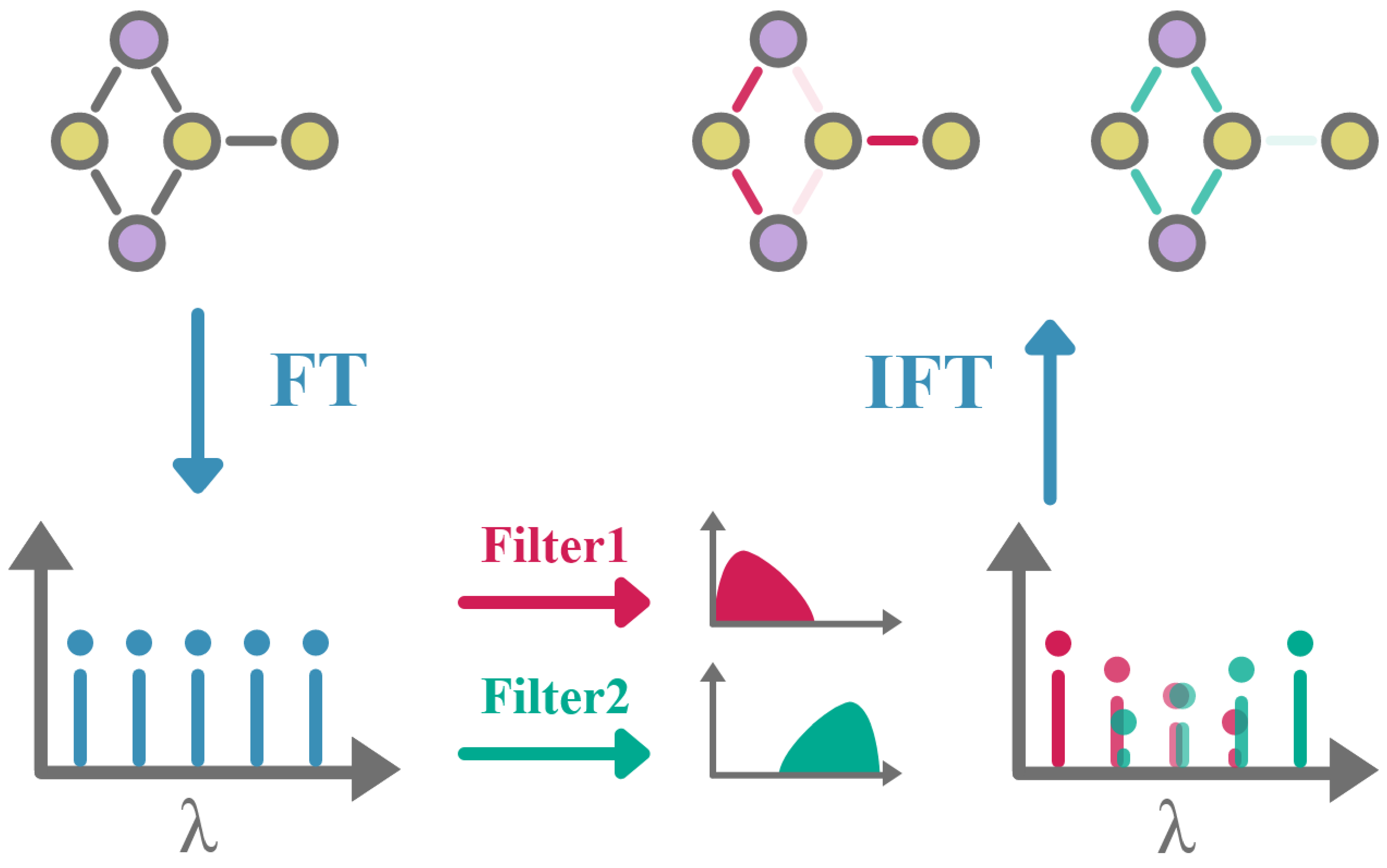
Predict

Spectral-Designed Graph Convolution



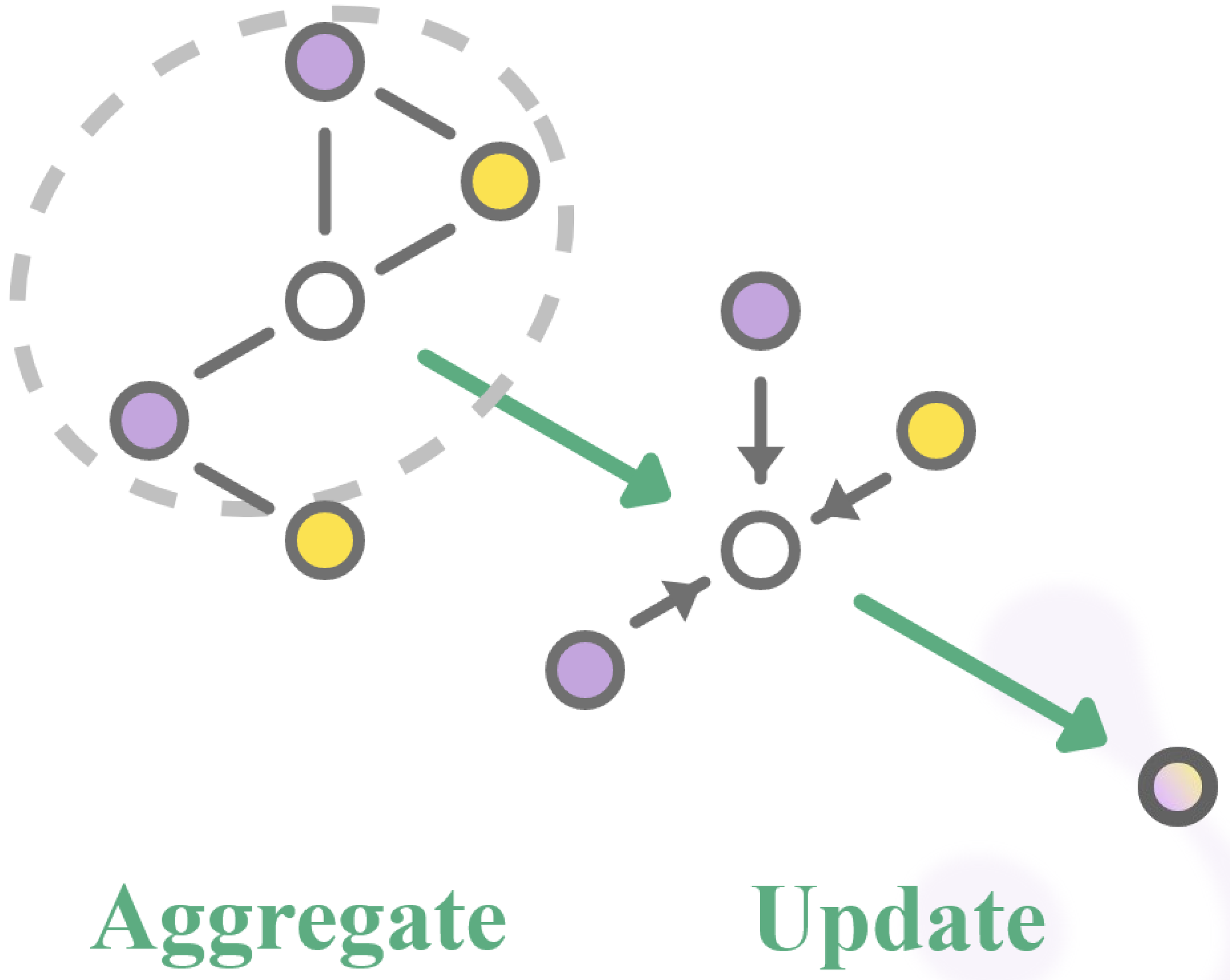
Spectral Convolution

$$\mathbf{H}' = \mathbf{U}\mathbf{g}(\boldsymbol{\Lambda})\mathbf{U}^{\mathbf{T}}\mathbf{H}$$



Spectral-Designed Convolution

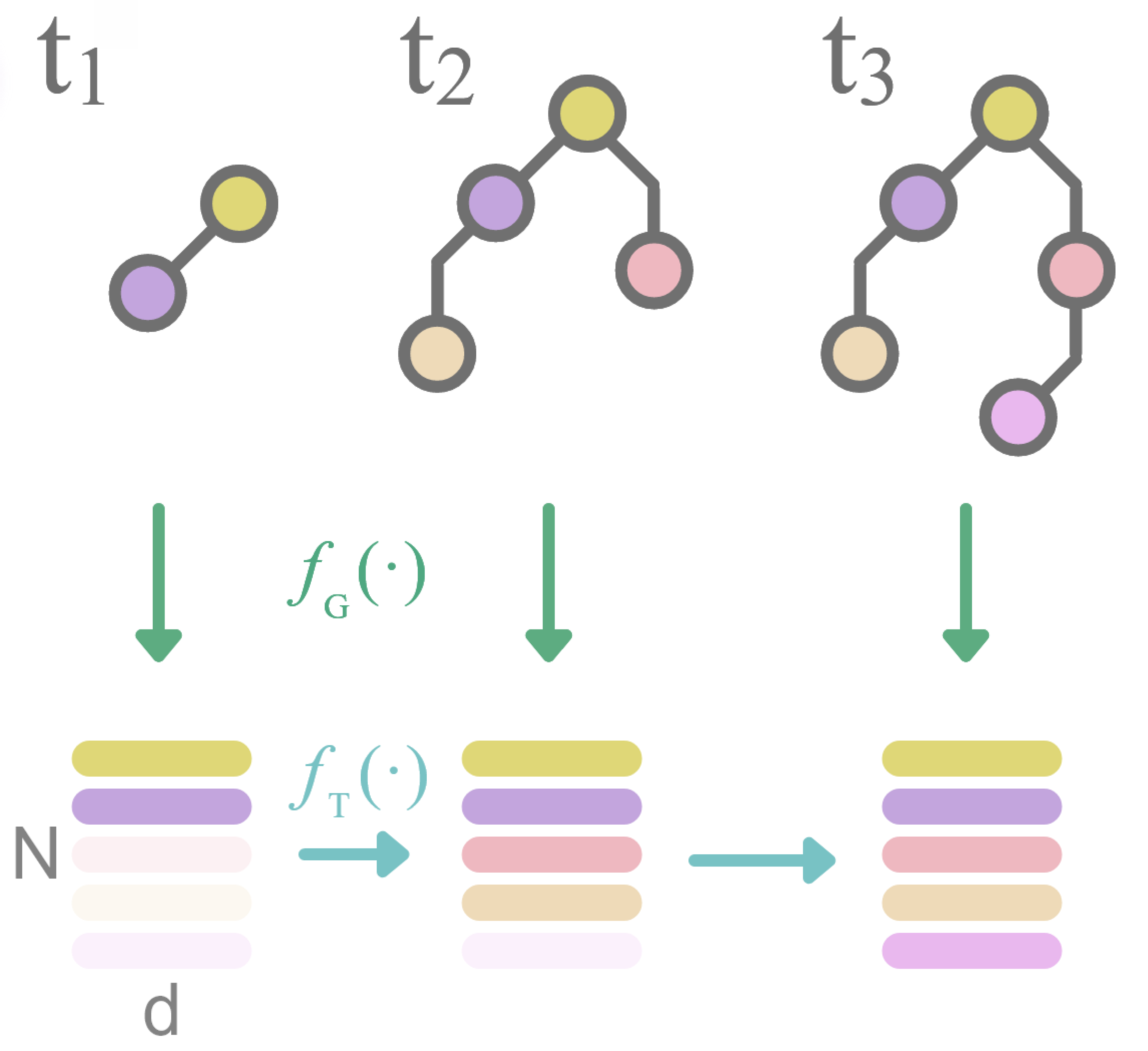
$$\mathbf{H}' = \sigma\left(\sum_{\mathbf{s}} \mathbf{C}^{(\mathbf{s})}\mathbf{H}\mathbf{W}^{(\mathbf{s})}\right), \quad \mathbf{C}^{\mathbf{s}} = \mathbf{U}\boldsymbol{\Phi}^{\mathbf{s}}(\boldsymbol{\Lambda})\mathbf{U}^{\mathbf{T}}$$



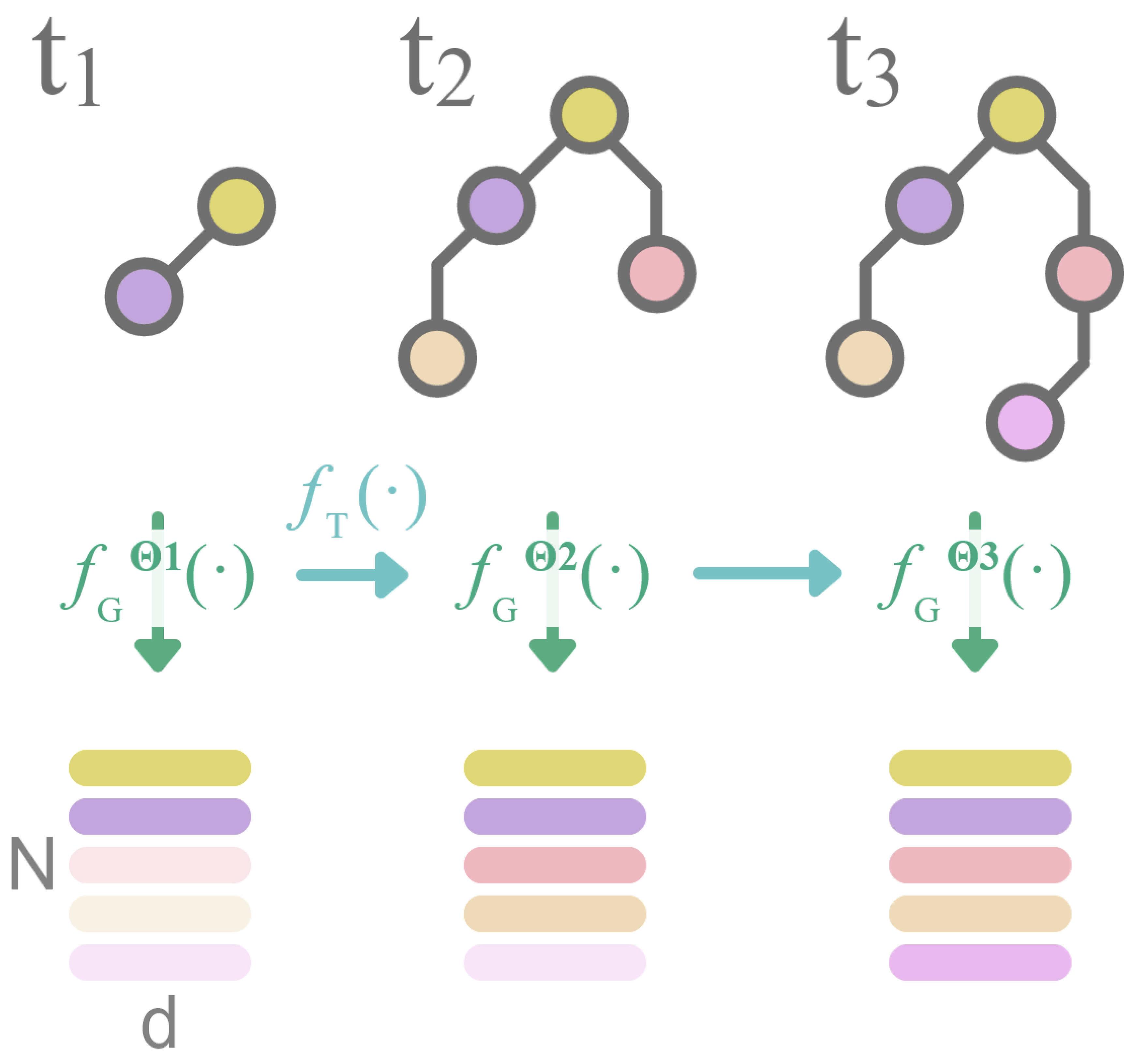
Spatial Convolution

$$\mathbf{H}' = \sigma\left(\sum_{\mathbf{s}} \mathbf{C}^{(\mathbf{s})}\mathbf{H}\mathbf{W}^{(\mathbf{s})}\right)$$

Discrete Time Dynamic Graph Neural Networks

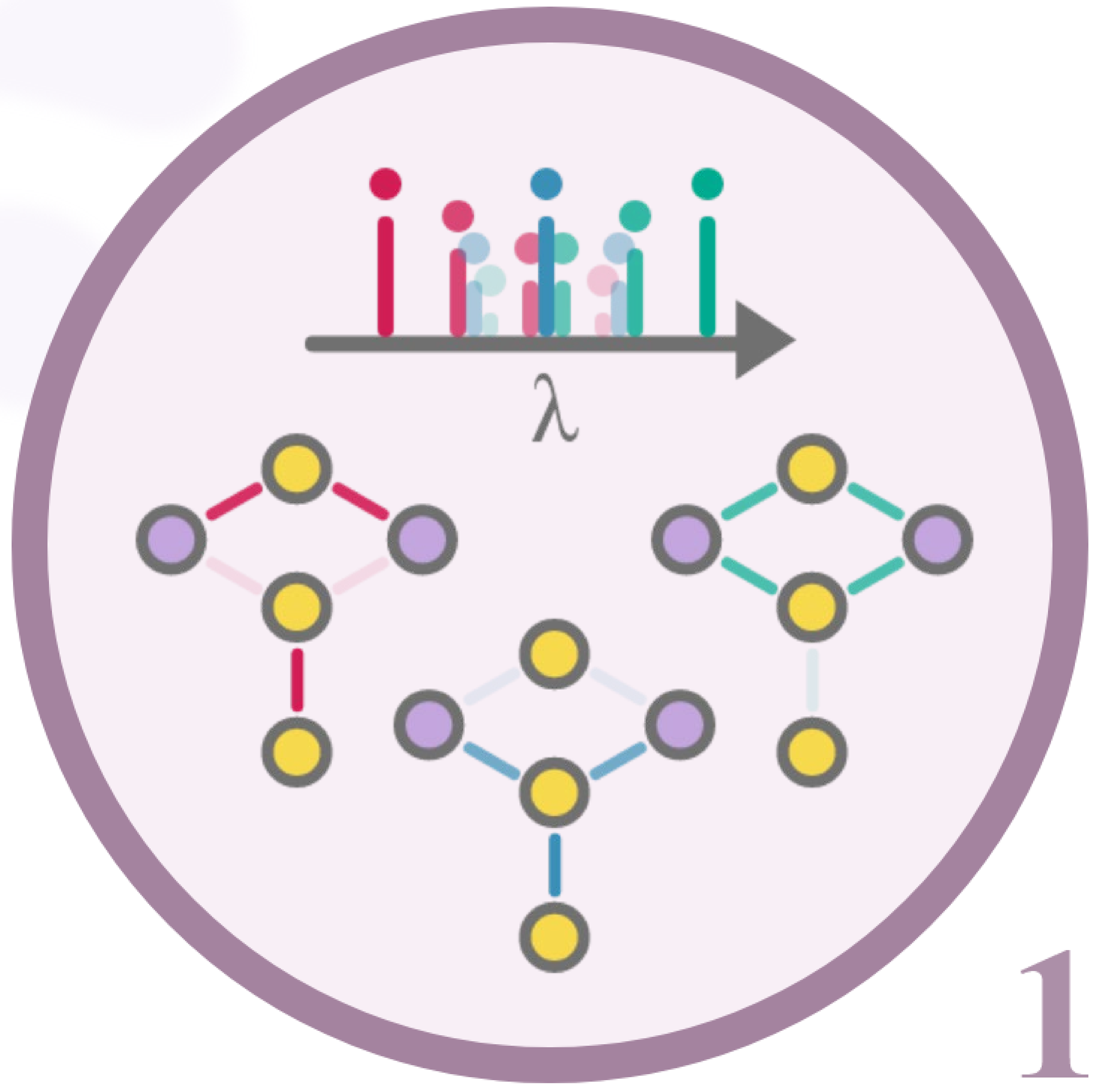


Sequentially Enc(H)

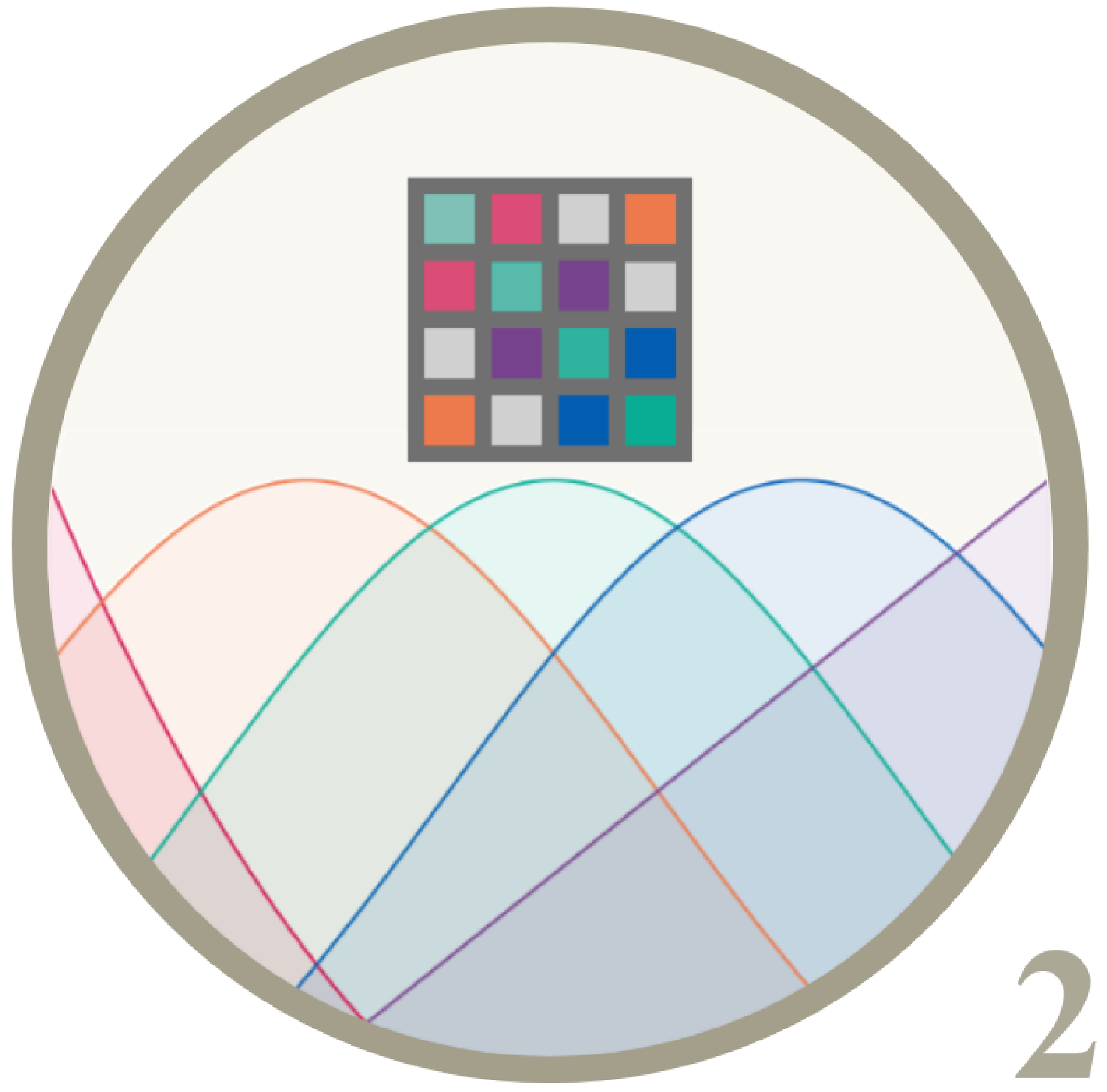


Sequentially Enc(Θ)

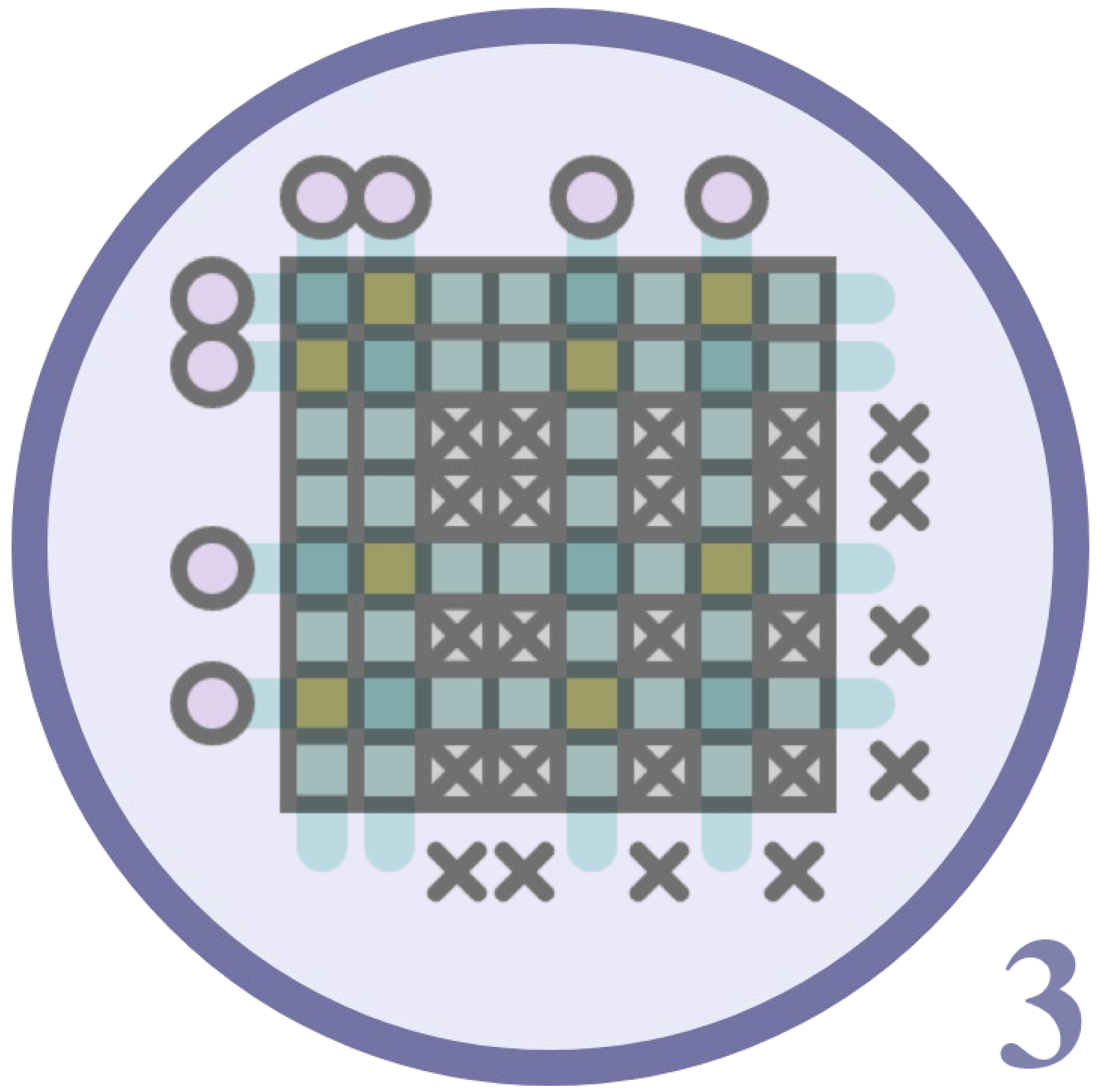
Motivation



DSGCN in DTDGNNs

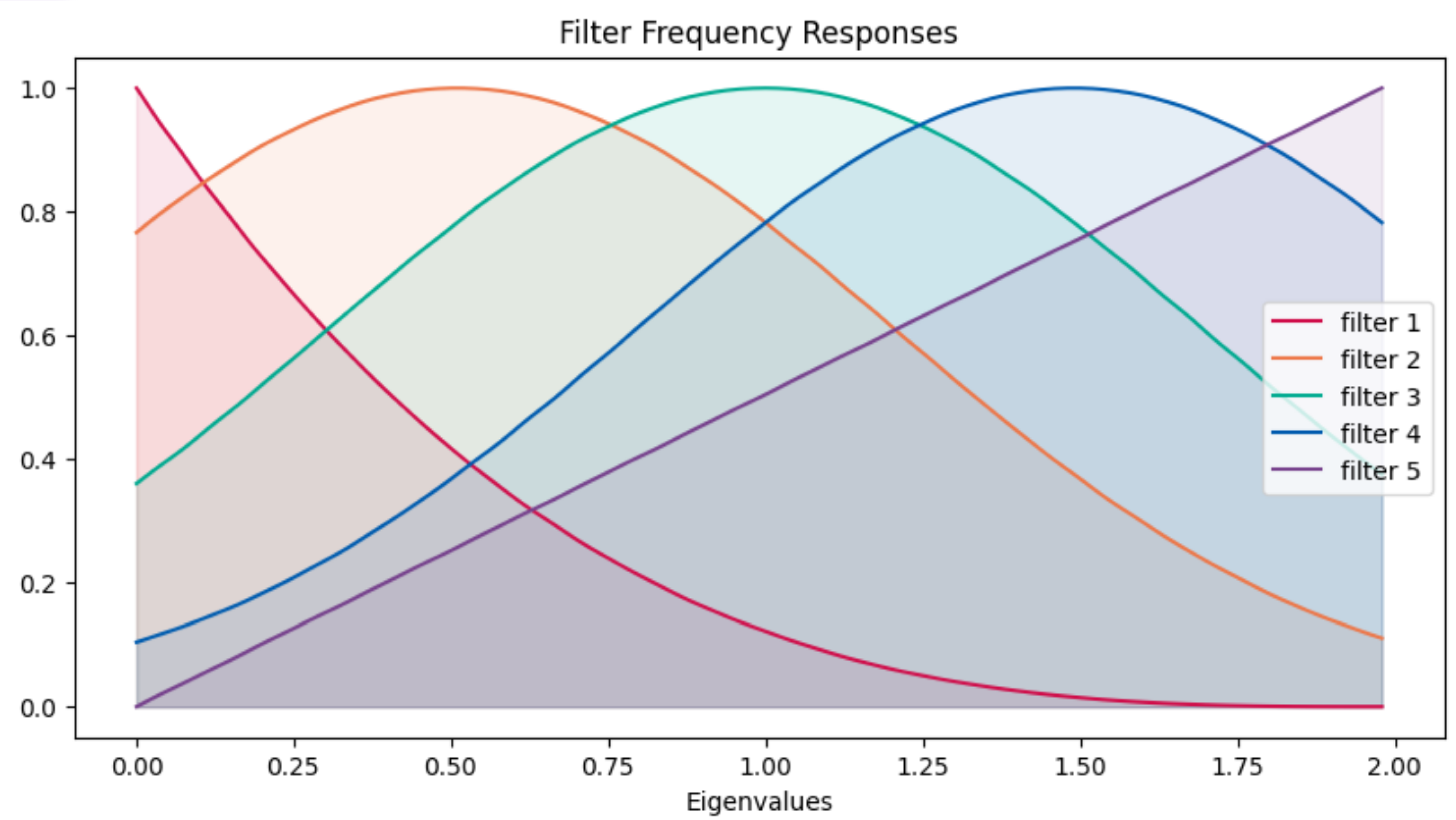


Combine filter outputs



Faster eigendecomposition

Spectral-Designed Filters



$$F_1(\lambda) = \left(1 - \frac{\lambda}{\lambda_{\text{max}}}\right)^3, \qquad \text{(Low-pass)}$$

$$F_2(\lambda) = e^{-((\lambda - \lambda_{c1})^2) \cdot \gamma}, \qquad \text{(Band-pass 1)}$$

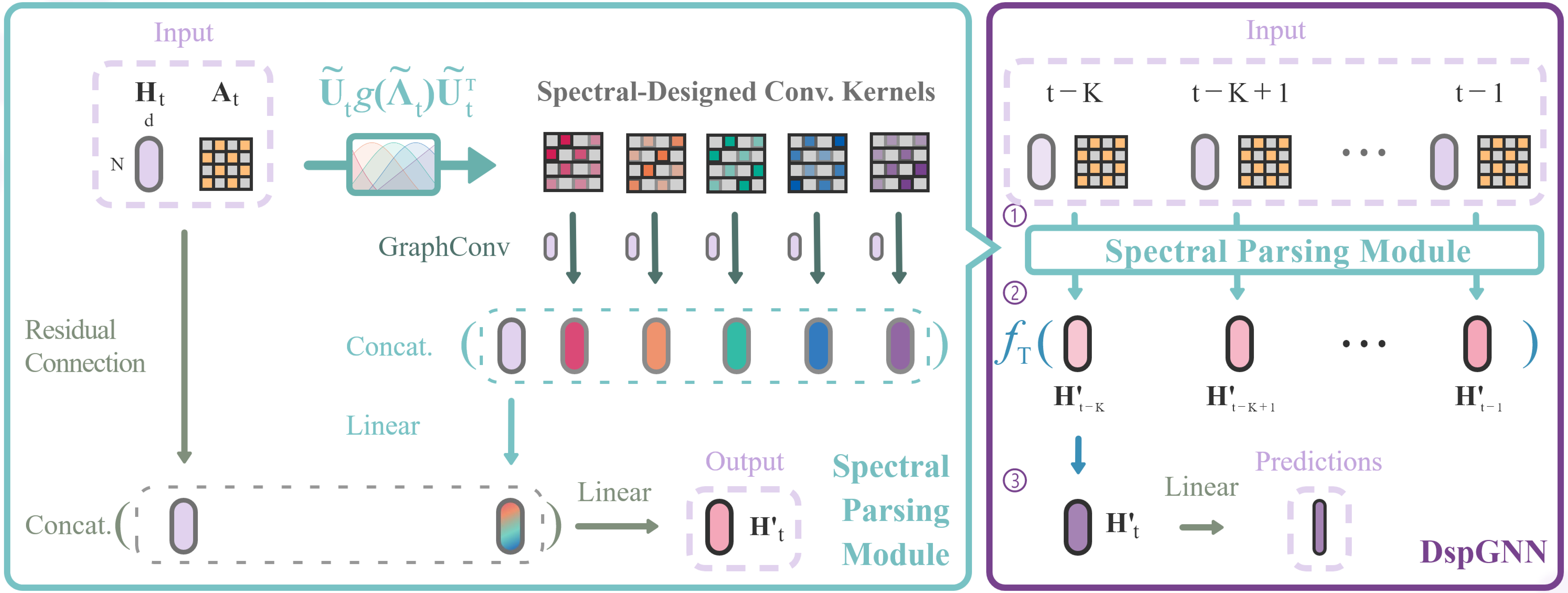
$$F_3(\lambda) = e^{-((\lambda - \lambda_{c2})^2) \cdot \gamma}, \qquad \text{(Band-pass 2)}$$

$$F_4(\lambda) = e^{-((\lambda - \lambda_{c3})^2) \cdot \gamma}, \qquad \text{(Band-pass 3)}$$

$$F_5(\lambda) = \frac{\lambda}{\lambda_{\text{max}}}, \qquad \text{(High-pass)}$$

DspGNN (Spectral Parsing Module)

DspGNN (Overall Architecture)



① Encode snapshots SP Module ② Encode with a temporal encoder ③ Compute the predictions

Active Node Mapping

Without Active Node Mapping $O(N^3)$

With Active Node Mapping $O(N_t^3)$

Experiments

Name	# Nodes	# Average active nodes per snapshot	# Edges	# Time steps	Time step split Train / Valid / Test
Bitcoin-Alpha	3,783	106	24,173	137	95 / 14 / 28
Bitcoin-OTC	5,881	148	35,588	136	95 / 13 / 28
MovieLens-100K	9,811	740	100,836	90	63 / 9 / 18

Bitcoin: level of trust, -10~+10 MovieLens-100K: movie rating, 0.5~5.0

	Bitcoin-Alpha		Bitcoin-OTC		MovieLens-100K	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
CoEvoGNN*	*0.1171* (0.0097)	*0.0879* (0.0100)	0.1638 (0.0066)	0.1145 (0.0106)	0.2381 (0.0058)	*0.1834* (0.0048)
CoEvoGNN	0.1231 (0.0033)	0.0928 (0.0030)	0.1671 (0.0073)	0.1176 (0.0064)	*0.2372* (0.0059)	0.1894 (0.0067)
EvolveGCN	0.1173 (0.0187)	0.0903 (0.0216)	*0.1556* (0.0049)	*0.1025* (0.0067)	0.2404 (0.0134)	0.1944 (0.0160)
DspGNN(Ours)	**0.0968** (0.0002)	**0.0637** (0.0006)	**0.1471** (0.0009)	**0.0831** (0.0019)	**0.2293** (0.0000)	**0.1812** (0.0000)

Edge regression performance: MEAN and STD of the normalized scores for the five seeds

Computing cost comparison

		W/O Active Node Mapping		With Active Node Mapping
Max space complexity (Theo.)	Bitcoin-Alpha		1×10^7	3×10^5
	Bitcoin-OTC		3×10^7	3×10^5
	MovieLens-100K		1×10^8	6×10^6
Time complexity (Theo.)	Bitcoin-Alpha		7×10^{12}	6×10^8
	Bitcoin-OTC		3×10^{13}	1×10^9
	MovieLens-100K		9×10^{13}	1×10^{11}
Real time consumed (seconds)	Library	Numpy	Scipy	Numpy
	Bitcoin-Alpha	1826.31	225.69	0.31
	Bitcoin-OTC	7203.62	592.23	0.55
	MovieLens-100K	11150.19	1159.91	12.83

Acknowledgments

NEURAL INFORMATION PROCESSING SYSTEMS

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