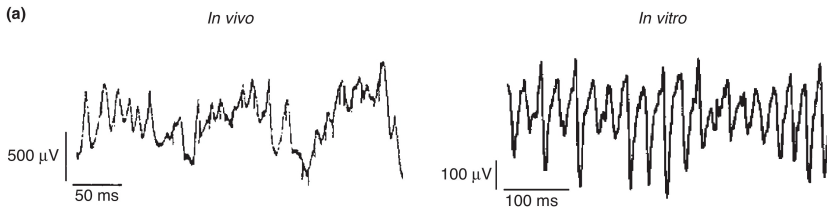


# Graph-Coupled Oscillator Networks

T. Konstantin Rusch, Benjamin P. Chamberlain, James Rowbottom, Siddhartha Mishra, Michael M. Bronstein

# Oscillators (for GNNs?)

Oscillators are ubiquitous in nature and engineering systems



Why oscillators for GNNs:

- **Neurobiological motivation** for networks of oscillatory neurons
- **Expressivity** of oscillators (Fourier series approximation)
- Well-behaved gradients of oscillators  $\rightarrow$  **Exploding/vanishing gradients problem mitigated?**
- Desirable stability properties: **A solution for the oversmoothing problem?**

# Oscillatory inductive bias for GNNs

## Set-up:

- Undirected Graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E} \subseteq \mathcal{V} \times \mathcal{V})$
  - Edges  $\mathcal{E}$ : pairs of nodes  $\{i, j\}$  (denoted  $i \sim j$ )
  - Node features  $\mathbf{X}$
- 

GraphCON based on graph dynamical system:

$$\mathbf{X}'' = \sigma(\mathbf{F}_\theta(\mathbf{X}, t)) - \gamma\mathbf{X} - \alpha\mathbf{X}' \iff \begin{cases} \mathbf{Y}' = \sigma(\mathbf{F}_\theta(\mathbf{X}, t)) - \gamma\mathbf{X} - \alpha\mathbf{Y}, \\ \mathbf{X}' = \mathbf{Y} \end{cases}$$

- General learnable 1-neighborhood coupling  $\mathbf{F}_\theta$  (e.g. GCN, GAT, ...):

$$(\mathbf{F}_\theta(\mathbf{X}, t))_{ij} = \mathbf{F}_\theta(\mathbf{X}_i(t), \mathbf{X}_j(t), t) \quad \forall i \sim j,$$

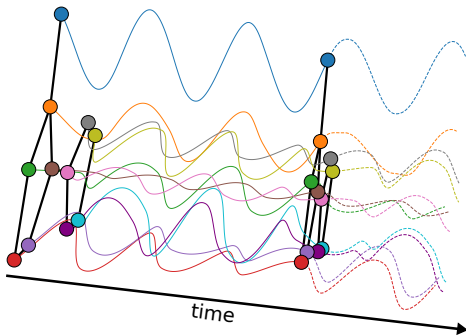
- Activation function  $\sigma$
- Control parameters  $\gamma, \alpha > 0$

IMEX discretization yields GraphCON:

$$\begin{aligned}\mathbf{Y}^n &= \mathbf{Y}^{n-1} + \Delta t [\sigma(\mathbf{F}_\theta(\mathbf{X}^{n-1}, t^{n-1})) - \gamma \mathbf{X}^{n-1} - \alpha \mathbf{Y}^{n-1}], \\ \mathbf{X}^n &= \mathbf{X}^{n-1} + \Delta t \mathbf{Y}^n,\end{aligned}$$

for  $n = 1, \dots, N$ , and

- $\Delta t > 0$  time-step
- $\mathbf{X}^n, \mathbf{Y}^n$  hidden node features at time  $t^n = n\Delta t$



# Properties of GraphCON

We provide mathematical definition of oversmoothing:  
exponential convergence to zero of layer-wise Dirichlet  
energy

**Main result:**

GraphCON mitigates the oversmoothing problem

We further show:

- GraphCON mitigates the exploding gradients problem
- GraphCON mitigates the vanishing gradients problem
- Naive multi-layer stacking of GNNs corresponds to fixed-point iteration of GraphCON → higher expressive power of GraphCON

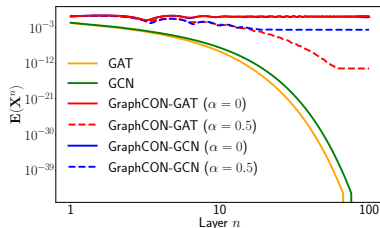


Table: Transductive node classification test accuracy (MAP in %) on heterophilic datasets.

<i>Homophily level</i>	<b>Texas 0.11</b>	<b>Wisconsin 0.21</b>	<b>Cornell 0.30</b>
GPRGNN	78.4 $\pm$ 4.4	82.9 $\pm$ 4.2	80.3 $\pm$ 8.1
H2GCN	<b>84.9 <math>\pm</math> 7.2</b>	<b>87.7 <math>\pm</math> 5.0</b>	<b>82.7 <math>\pm</math> 5.3</b>
GCNII	77.6 $\pm$ 3.8	80.4 $\pm$ 3.4	77.9 $\pm$ 3.8
Geom-GCN	66.8 $\pm$ 2.7	64.5 $\pm$ 3.7	60.5 $\pm$ 3.7
PairNorm	60.3 $\pm$ 4.3	48.4 $\pm$ 6.1	58.9 $\pm$ 3.2
GraphSAGE	<b>82.4 <math>\pm</math> 6.1</b>	81.2 $\pm$ 5.6	76.0 $\pm$ 5.0
MLP	80.8 $\pm$ 4.8	85.3 $\pm$ 3.3	81.9 $\pm$ 6.4
GAT	52.2 $\pm$ 6.6	49.4 $\pm$ 4.1	61.9 $\pm$ 5.1
<b>GraphCON-GAT</b>	82.2 $\pm$ 4.7	<b>85.7 <math>\pm</math> 3.6</b>	<b>83.2 <math>\pm</math> 7.0</b>
GCN	55.1 $\pm$ 5.2	51.8 $\pm$ 3.1	60.5 $\pm$ 5.3
<b>GraphCON-GCN</b>	<b>85.4 <math>\pm</math> 4.2</b>	<b>87.8 <math>\pm</math> 3.3</b>	<b>84.3 <math>\pm</math> 4.8</b>

**Table:** Test accuracy in % on MNIST Superpixel 75.

Model	Test accuracy
ChebNet	75.62
MoNet	91.11
PNCNN	<b>98.76</b>
SplineCNN	95.22
GIN	97.23
<b>GraphCON-GIN</b>	98.53
GatedGCN	97.95
<b>GraphCON-GatedGCN</b>	98.27
GCN	88.89
<b>GraphCON-GCN</b>	<b>98.68</b>
GAT	96.19
<b>GraphCON-GAT</b>	<b>98.91</b>

**Table:** Test mean absolute error on ZINC (**without edge features, small 12k version**) restricted to small network sizes of  $\sim 100k$  parameters.

Model	Test MAE
GIN	$0.41 \pm 0.008$
GatedGCN	$0.42 \pm 0.006$
GraphSAGE	$0.41 \pm 0.005$
MoNet	$0.41 \pm 0.007$
PNA	<b><math>0.32 \pm 0.032</math></b>
DGN	<b><math>0.22 \pm 0.010</math></b>
GCN	$0.47 \pm 0.002$
<b>GraphCON-GCN</b>	<b><math>0.22 \pm 0.004</math></b>
GAT	$0.46 \pm 0.002$
<b>GraphCON-GAT</b>	<b><math>0.23 \pm 0.004</math></b>

## Conclusion / Outlook

- GraphCON: physics-inspired framework to construct very deep GNNs
- GraphCON provably overcomes the oversmoothing problem as well as exploding/vanishing gradient problem
- GraphCON reaches SOTA on a variety of different graph learning tasks

**Main message: "Don't stack GNNs naively – use GraphCON!"**

### **Future projects:**

- Physics-inspired methods work – GraphCON is only the start