

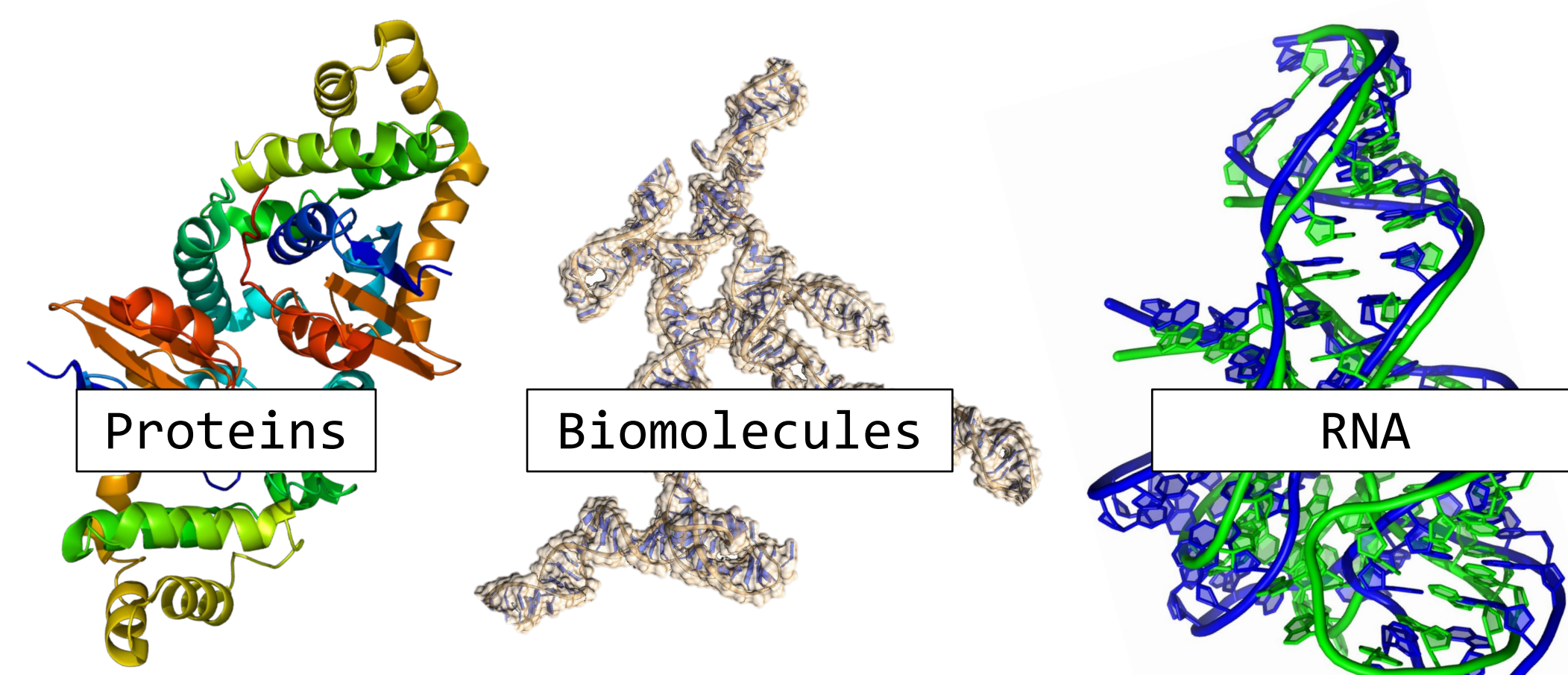
Geometric Hyena Networks for Large-scale Equivariant Learning

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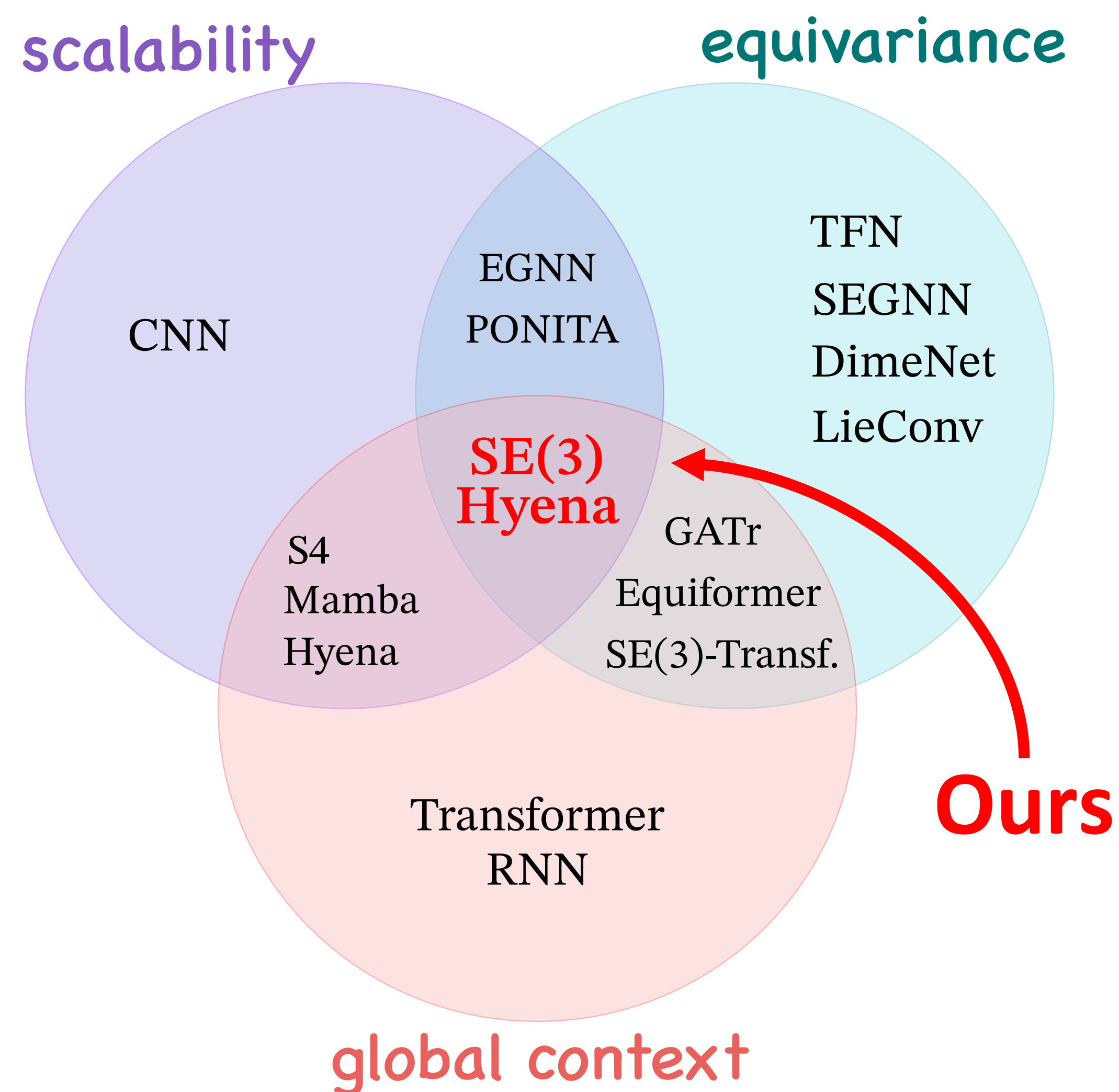
Large-scale systems



number of atoms: $\sim 10^3 - 10^8$

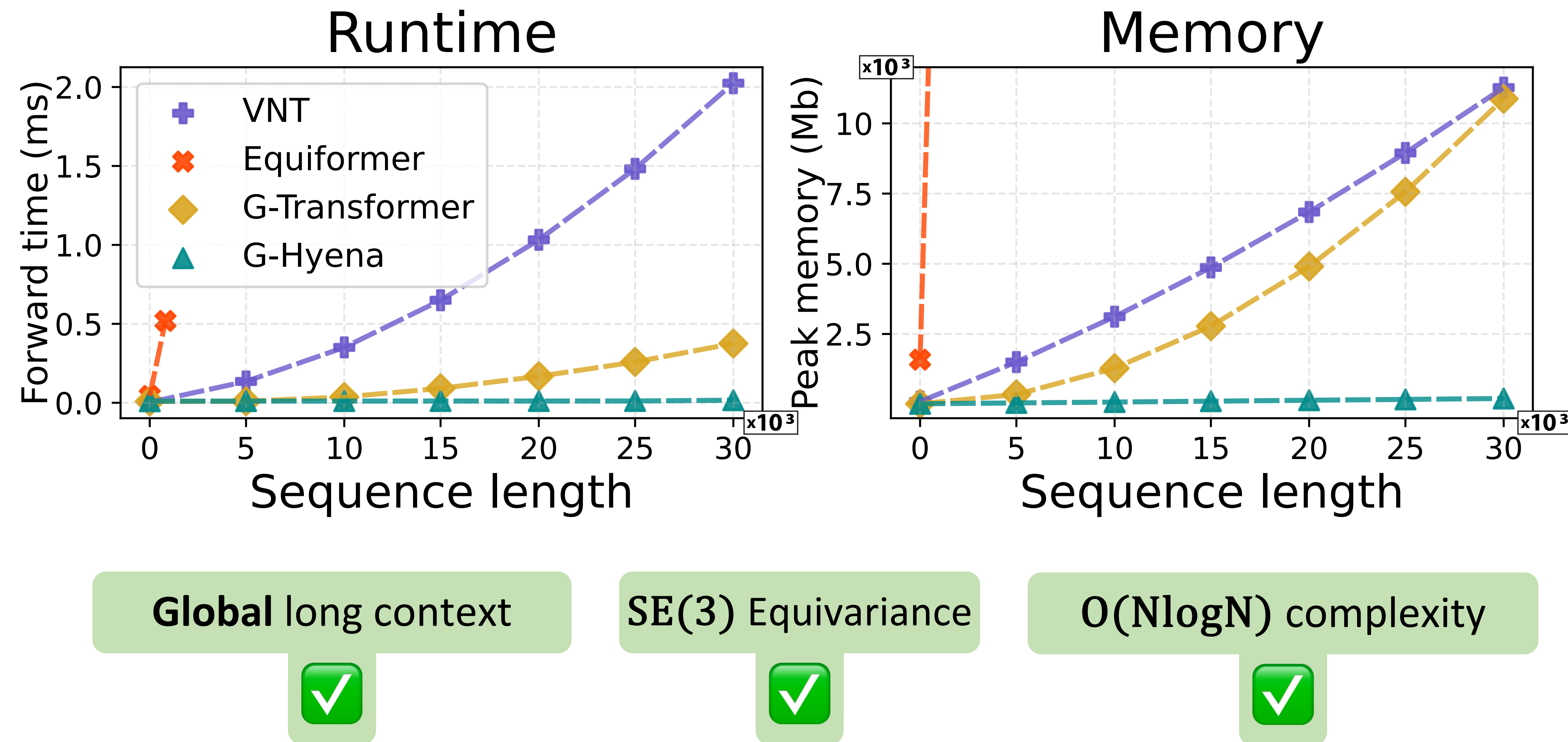
Quadratic complexity of global context with equivariance limits model scalability for large systems

Other models

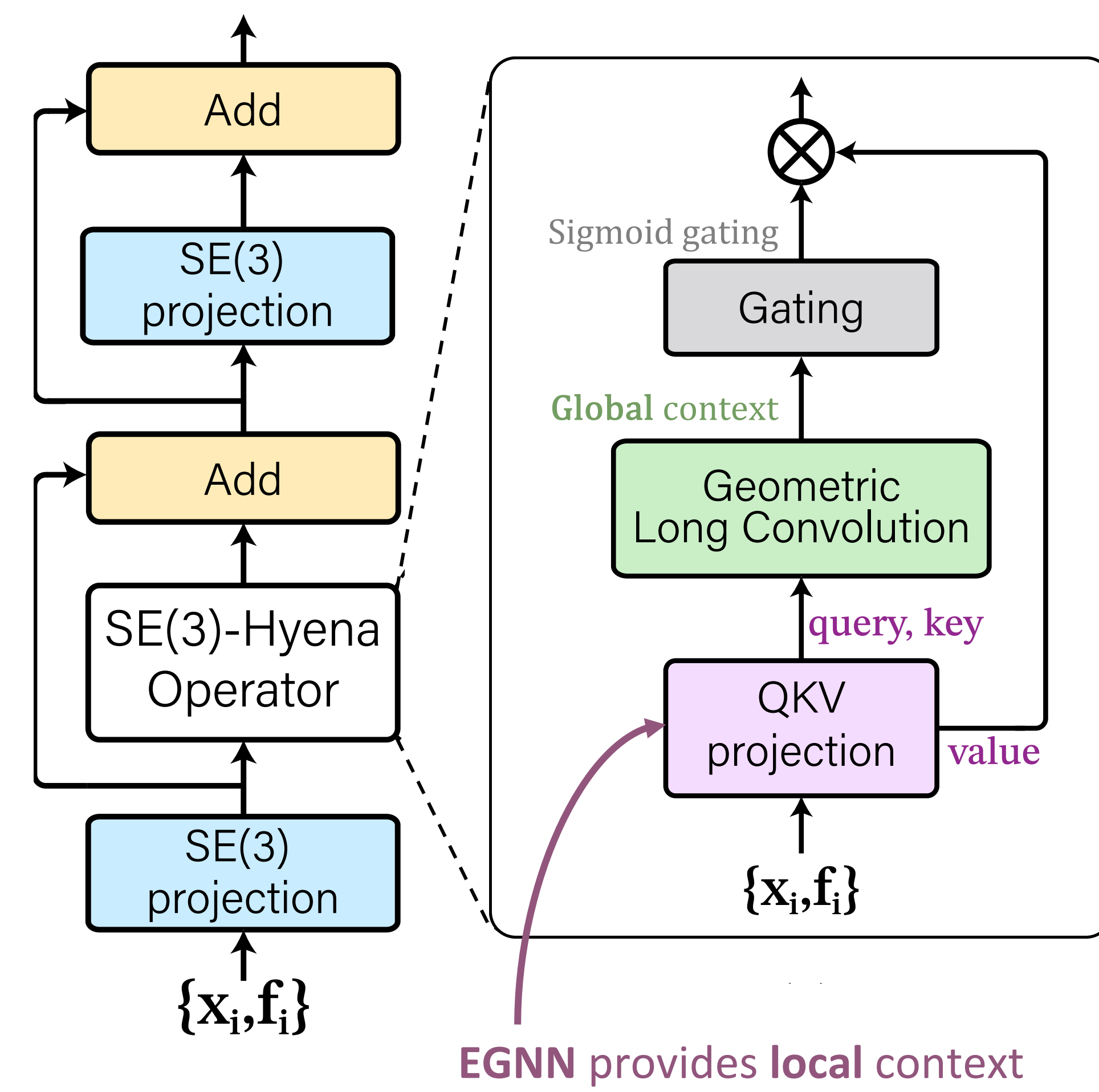


The first long-convolutional equivariant model

2.7 million tokens on a single GPU (A10G)



Architecture



!! Assumption: canonical ordering

Geometric long-convolution replaces equivariant self-attention

Vector-convolution:

$$\mathbf{a}_i = (\mathbf{b} \otimes \times \mathbf{c})_i = \sum_{j=1}^N \mathbf{b}_i \times \mathbf{c}_{j-i}$$

Scalar-decomposition:

$$\begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} \times \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix} = \begin{bmatrix} b_y c_z - c_y b_z \\ c_x b_z - b_x c_z \\ b_x c_y - c_x b_y \end{bmatrix}$$

$$(\mathbf{b} \otimes \times \mathbf{c})_i[x] = \sum_{y,z} \varepsilon_{xyz} \sum_{j=1}^N b_i[y] c_{j-i}[z]$$

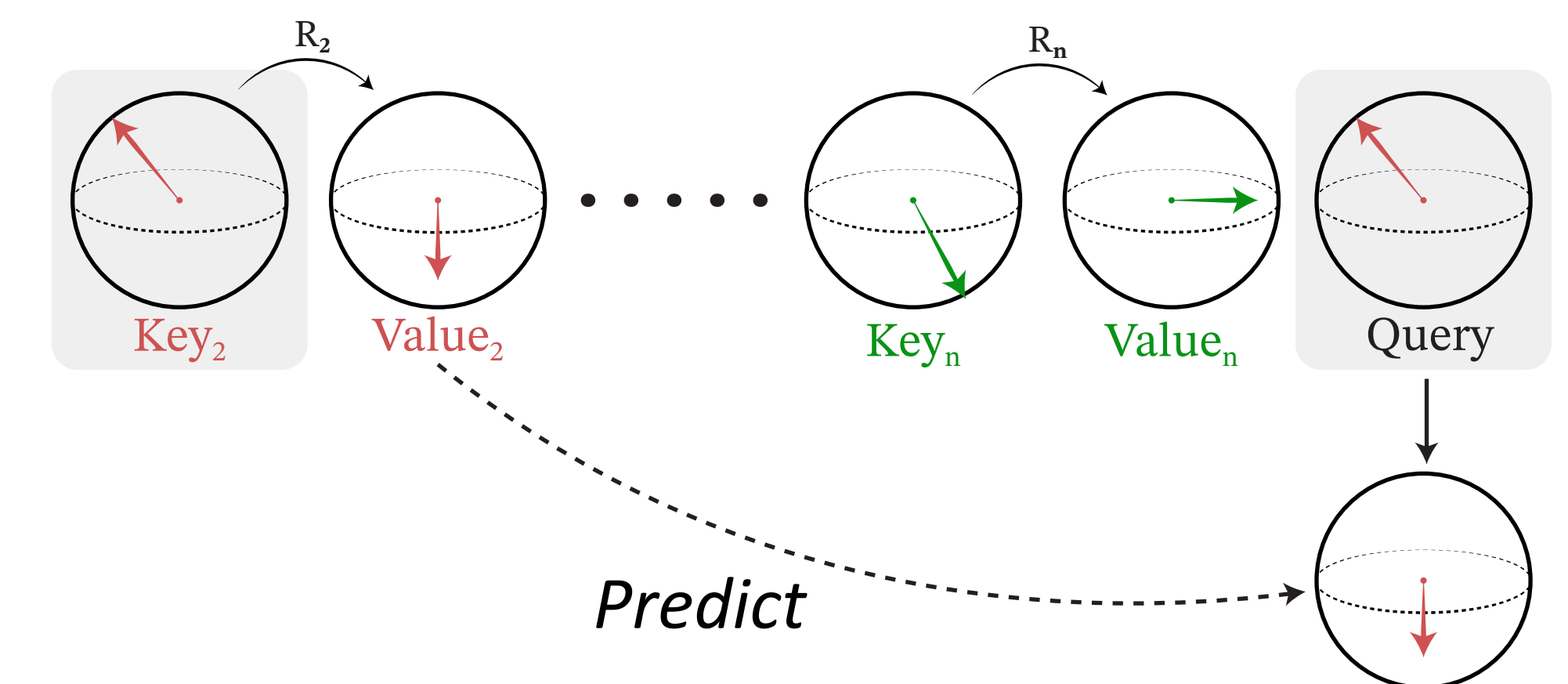
FFT-conv.: $O(N \log N)$

Higher-order steerable form:

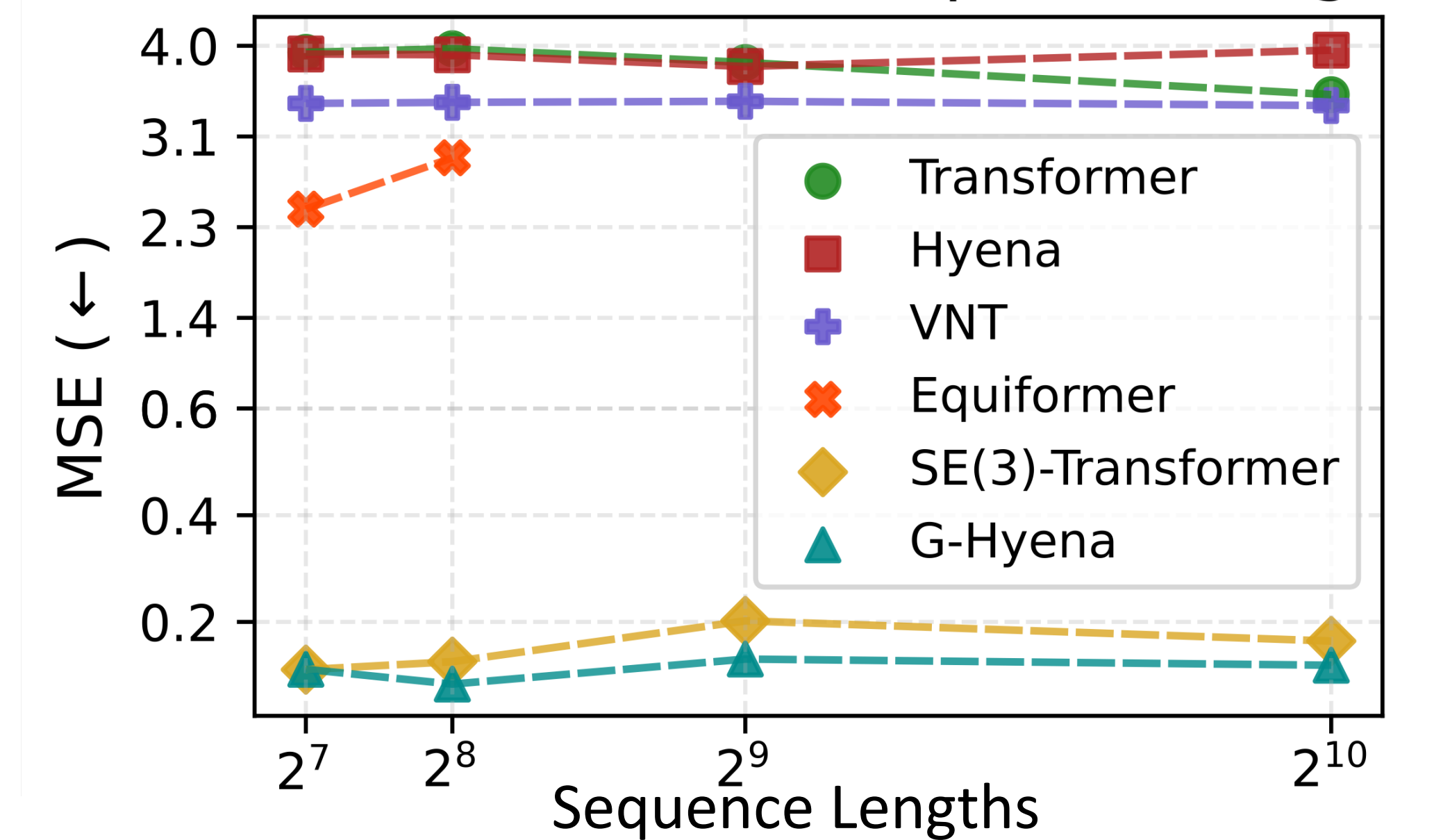
$$(\mathbf{b}^{(l_1)} \otimes_{CG} \mathbf{c}^{(l_2)})_{i,m}^{(l)} = \sum_{j=1}^N \sum_{m_1=-l_1}^{l_1} \sum_{m_2=-l_2}^{l_2} C_{(l_1 m_1)(l_2 m_2)}^{(lm)} \mathbf{b}_{i,m_1}^{(l_1)} \mathbf{c}_{j-i,m_2}^{(l_2)}$$

$$\mathbf{u}_{i,m}^{(l)} = \sum_{m_1=-l_1}^{l_1} \sum_{m_2=-l_2}^{l_2} C_{(l_1 m_1)(l_2 m_2)}^{(lm)} (\mathbf{b}_{m_1}^{(l_1)} \otimes \mathbf{c}_{m_2}^{(l_2)})_i$$

Equivariant Associative Recall (EAR)



EAR over various sequence length



Alternating global-local context is crucial

RNA degradation prediction

Data: Large RNA biomolecules up to 11k atoms.			Label: Degradation rate and Thermostability parameters per nucleotide		Eval.: RMSE (\downarrow)
Model	Open Vaccine Covid-19 (Das et al., 2020)	Ribonanza-2k (He et al., 2024)	Model	Open Vaccine Covid-19 (Das et al., 2020)	Ribonanza-2k (He et al., 2024)
<i>Backbone representation</i>			<i>All-atom representation</i>		
SchNet	0.515 \pm 0.005	0.911 \pm 0.008	SchNet	0.512 \pm 0.005	0.891 \pm 0.008
TFN	0.522 \pm 0.006	0.927 \pm 0.006	TFN	0.510 \pm 0.004	0.910 \pm 0.011
EGNN	0.529 \pm 0.006	0.943 \pm 0.008	EGNN	0.511 \pm 0.005	0.928 \pm 0.022
FastEGNN	0.519 \pm 0.012	0.912 \pm 0.032	FastEGNN	0.498 \pm 0.004	0.873 \pm 0.010
LEFTNet	0.502 \pm 0.004	0.889 \pm 0.008	LEFTNet	0.501 \pm 0.005	0.880 \pm 0.008
TMD-ET	0.500 \pm 0.006	0.781 \pm 0.006	TMD-ET	0.494 \pm 0.009	0.855 \pm 0.002
Transformer	0.400 \pm 0.004	0.637 \pm 0.006	Transformer	0.399 \pm 0.004	0.633 \pm 0.007
Hyena	0.447 \pm 0.007	0.810 \pm 0.124	Hyena	0.393 \pm 0.013	0.605 \pm 0.017
VNT	0.401 \pm 0.005	0.659 \pm 0.005	VNT	0.391 \pm 0.013	0.638 \pm 0.008
G-Transformer	0.412 \pm 0.008	0.537 \pm 0.007	G-Transformer	0.391 \pm 0.071	0.592 \pm 0.043
Equiformer	0.409 \pm 0.008	0.649 \pm 0.004	Equiformer	OOM	OOM
G-Hyena	0.363 \pm 0.045	0.529 \pm 0.005	G-Hyena	0.339 \pm 0.004	0.546 \pm 0.006

RNA switching factor prediction

Data: Large RNA biomolecules up to few thousand atoms.		
Label: RNA switching factor		
Eval.: RMSE (\downarrow)		
Model	Tc-Ribo (Groher et al., 2018)	
	Backbone repr.	All-atom repr.
SchNet	0.737 \pm 0.002	0.691 \pm 0.018
TFN	0.733 \pm 0.003	0.710 \pm 0.009
EGNN	0.728 \pm 0.001	0.729 \pm 0.002
FastEGNN	0.704 \pm 0.005	0.727 \pm 0.011
LeftNet	0.749 \pm 0.006	0.750 \pm 0.004
TMD-ET	0.750 \pm 0.004	0.751 \pm 0.003
Transformer	0.556 \pm 0.001	0.553 \pm 0.002
Hyena	0.560 \pm 0.002	0.569 \pm 0.001
G-Transformer	0.554 \pm 0.003	0.553 \pm 0.001
Equiformer	0.550 \pm 0.009	OOM
G-Hyena	0.548 \pm 0.008	0.548 \pm 0.001

Protein Molecular Dynamics

G-Hyena outperforms other local and global* methods

*at a fraction of their computational cost