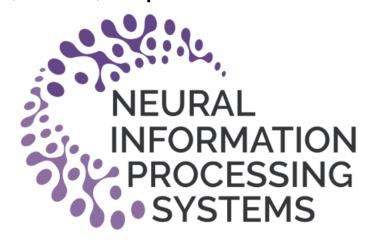
Recurrent Self-Attention Dynamics: An Energy-Agnostic Perspective from Jacobians

Akiyoshi Tomihari & Ryo Karakida Artificial Intelligence Research Center, AIST, Japan



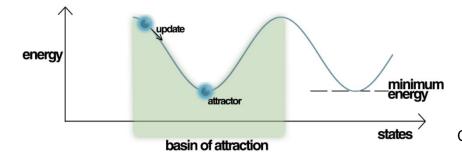


Theoretical Analysis of Self-attention

- Self-attention (SA) is a core mechanism in Transformers
 - Transformers are the backbone of modern language models

$$\mathrm{SA}_h(\boldsymbol{X}) \coloneqq \mathrm{softmax}(\beta \boldsymbol{X} \boldsymbol{W}_h^Q \boldsymbol{W}_h^{K\top} \boldsymbol{X}^\top) \boldsymbol{X} \boldsymbol{W}_h^V$$

- Theoretical analysis of SA is challenging
 - Mainly due to the Softmax function
- A major approach involves energy-based analysis
 - SA can be viewed as minimizing an implicit or explicit energy function



Energy-based analysis of SA

- SA can be viewed as minimizing an energy function [Geshkovski et al., 2023, 2024, Bruno et al., 2025]
- Often formulated using continuous equations and a particlebased interpretation of tokens

$$\dot{\boldsymbol{X}} = \operatorname{Proj}_{\boldsymbol{X}} \left(\operatorname{softmax}(\beta \boldsymbol{X} \boldsymbol{W}^Q \boldsymbol{W}^{K\top} \boldsymbol{X}^\top) \boldsymbol{X} \boldsymbol{W}^V \right)$$

- To define an energy function, constraints are typically assumed
 - Weight constraints and single-head constraint

$$\boldsymbol{W}^{Q}\boldsymbol{W}^{K\top} = \boldsymbol{W}^{V} = \boldsymbol{W}^{V\top} \text{ or } \boldsymbol{W}^{Q} = \boldsymbol{W}^{K} = \boldsymbol{W}^{V} = \boldsymbol{I}_{D}$$

However, these constraints deviate from practical scenarios

Our approach

- 1. Relax constraints in energy-based formulations
 - remove symmetry constraints on weights
 - extend beyond single-head SA
- 2. Apply Jacobian-based analysis to SA
 - Captures linear stability without requiring an energy function
 - Compute Lyapunov exponents from Jacobians
- → Our study reveals Jacobians and Lyapunov exponents as fundamental tools for realistic SA.

Revisit Energy-based analysis

What is a more realistic setting for energy guarantees?

• Remove symmetry constraints on weights (W^Q, W^K)

Proposition 4.1. Consider the continuous-time dynamics for single-head SA equipped with projection (3). The energy function

$$E_{single}(\boldsymbol{X}) = -\sum_{i,j} \exp\left(\beta \boldsymbol{X}_{[i,:]}^{\top} \boldsymbol{W}^{Q} \boldsymbol{W}^{K\top} \boldsymbol{X}_{[j,:]}\right)$$
(10)

is monotonically decreasing as $dE_{single}(\mathbf{X})/dt \leq 0$ under the condition:

$$\boldsymbol{W}^{V} = (\boldsymbol{W}^{Q\top} \boldsymbol{W}^{K} + \boldsymbol{W}^{Q} \boldsymbol{W}^{K\top})/2. \tag{11}$$

Extend beyond single-head self-attention

Proposition 4.2. Consider the continuous-time dynamics for multi-head SA without projection: $d\mathbf{X}/dt = \sum_{h=1}^{H} SA_h(\mathbf{X})$. An energy function

$$E_{multi}(\boldsymbol{X}) = -\sum_{h} \sum_{i,j} \exp\left(\beta \boldsymbol{X}_{[i,:]}^{\top} \boldsymbol{W}_{h}^{Q} \boldsymbol{W}_{h}^{K\top} \boldsymbol{X}_{[j,:]}\right)$$
(12)

is monotonically decreasing as $dE_{multi}(\mathbf{X})/dt \leq 0$ under the condition

$$W_h^V = (W_h^{Q\top} W_h^K + W_h^Q W_h^{K\top})/2, \ W_h^Q W_h^{K\top} = U_{1,h} U_{2,h}^{\top},$$
 (13)

where $U_{1(2),h} \in \mathbb{R}^{D \times D/(2H)}$ ($h \in [1,H]$) satisfies the orthogonality condition $U_{k,h}^{\top} U_{k',h'} = \delta_{hh'} \delta_{kk'} I_{D/(2H)}$.

Apply Jacobian-based analysis to SA

- More general than energy-based analysis:
 - captures linear stability
 - detects non-stationary dynamics more easily
- Normalization plays a crucial role in discrete systems
 - no counterpart in continuous-time dynamics

Proposition 5.1. Suppose that, in the update of ItrSA (9), the input to the normalization layer satisfies $\|X_{[i,:]} + \eta \Delta X_{[i,:]}\| \ge R$ for all $i \in [1, S]$. Then, the spectral norm of the Jacobian satisfies

$$\left\| \frac{\partial \operatorname{RMSNorm}(\boldsymbol{X} + \eta \Delta \boldsymbol{X})}{\partial \boldsymbol{X}} \right\|_{2} \leq \frac{\max_{j}(|\gamma_{j}|)}{R} \left(1 + |\eta| \|\boldsymbol{J}_{MSA}(\boldsymbol{X})\|_{2} \right), \tag{14}$$

where $J_{MSA}(X) := \partial MSA(X)/\partial X$ denotes the Jacobian of MSA.

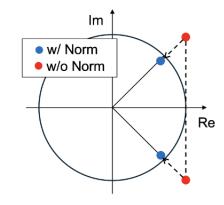
Normalization operators suppress the Jacobian eigenvalues

Example: oscillatory components

$$\dot{m{x}} = m{\Omega} m{x}, \qquad m{J}(m{x}) = m{\Omega} \qquad \qquad ext{(continuous)}$$
 $m{x}^{(t+1)} = (m{I}_D + \eta m{\Omega}) m{x}^{(t)}, \qquad m{J}(m{x}^{(t)}) = m{I}_D + \eta m{\Omega} \qquad \qquad ext{(discrete w/o Norm)}$ $m{x}^{(t+1)} = \Pi ig((m{I}_D + \eta m{\Omega}) m{x}^{(t)} ig), \quad m{J}(m{x}^{(t)}) = ig(m{I}_D - rac{m{y} m{y}^\top}{\|m{y}\|^2} ig) rac{m{I}_D + \eta m{\Omega}}{\|m{y}\|} \qquad ext{(discrete w/ Norm)}$

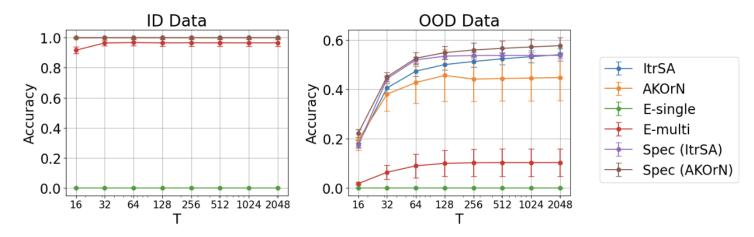
 Ω : anti-symmetric matrix

- The continuous systems can exhibit stability
- Discrete counterparts require normalization for stability



(b) Effect of normalization on eigenvalues in oscillatory case

Application: Regularization



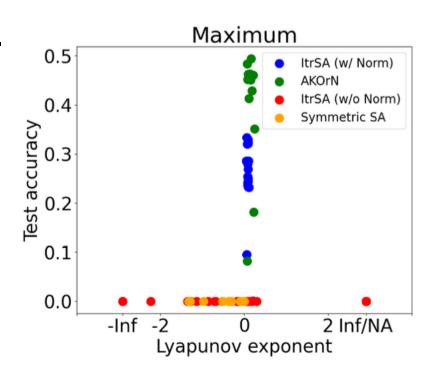
- Apply energy-based and Jacobian spectral regularization
 - Regularization based on each approach
- Energy-based regularization performs worse than the original
- Jacobian spectral regularization outperforms both

Lyapunov Exponent and Criticality

- Measures local divergence/convergence rate in dynamics
 - Positive → instability, Negative → convergence, Zero → criticality

Normalization

- → exponents toward zero & higher acc.
- Successful models: max exponent ≈ +0.1
 - → near-critical, from the chaotic side



Conclusion

- Relax constraints in energy-based formulations
- Extend Jacobian-based analysis to SA
- Empirically, strong SA models have Lyapunov exponent ≈ 0
- Jacobians and Lyapunov exponent emerge as fundamental tools for realistic SA architectures

Paper link:

