



Muon is Gauge Fixing

deriving the “Muon” orthogonalization

in terms of the renormalization group

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What is Muon ? : Momentum Update Orthogonalization

- For each layer, form the momentum the standard \mathbf{W} update
- Orthogonalized, all eigenvalues are one

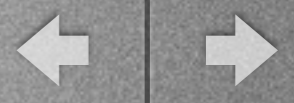
$$\mathbf{M}_t = \beta \mathbf{M}_{t-1} - \eta \nabla_{\mathbf{W}} L$$

$$\Delta \mathbf{W}_t = \mathbf{M}_t$$

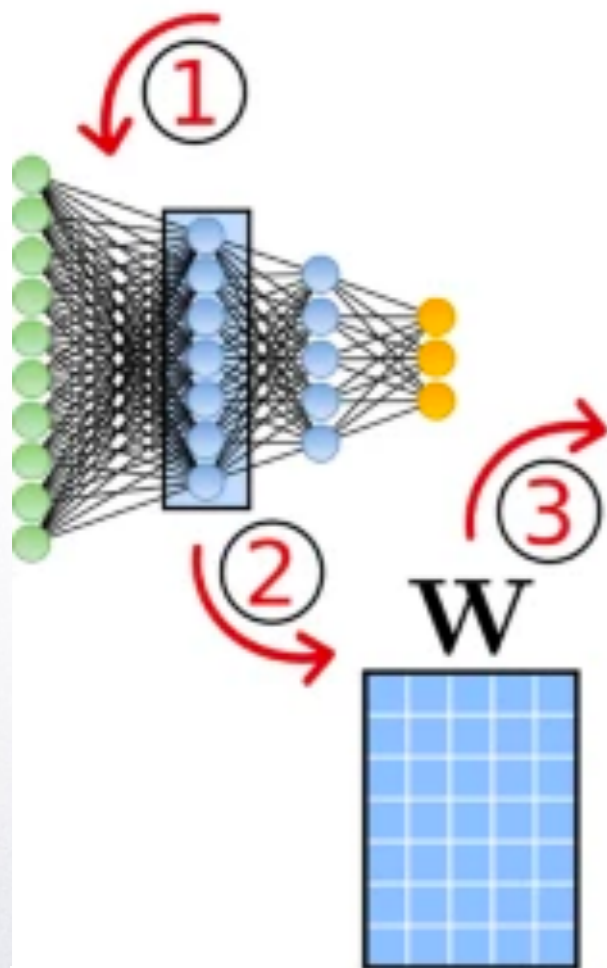
$$\Delta \mathbf{W}_t \longrightarrow \widetilde{\Delta \mathbf{W}}_t = \text{Orth}(\Delta \mathbf{W}_t)$$

$$\widetilde{\Delta \mathbf{W}}_t^\top \widetilde{\Delta \mathbf{W}}_t = \mathbf{I}$$

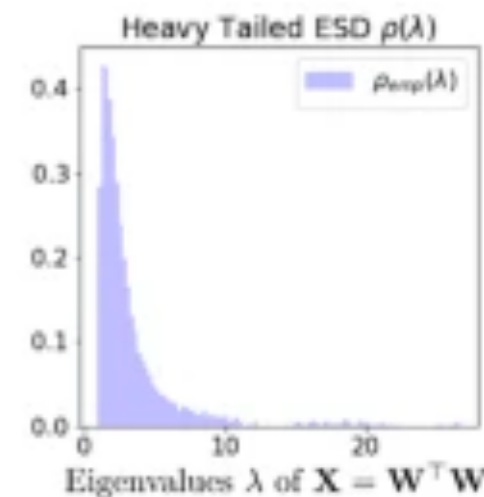
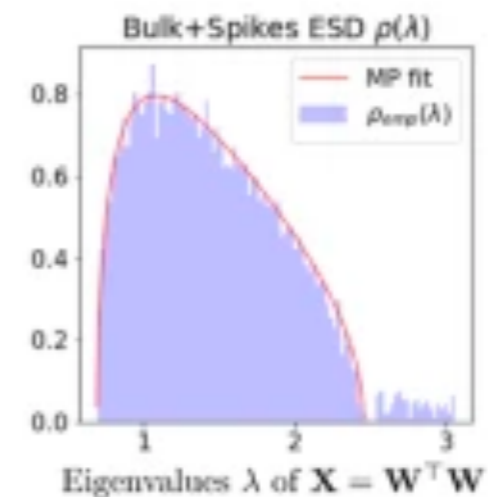
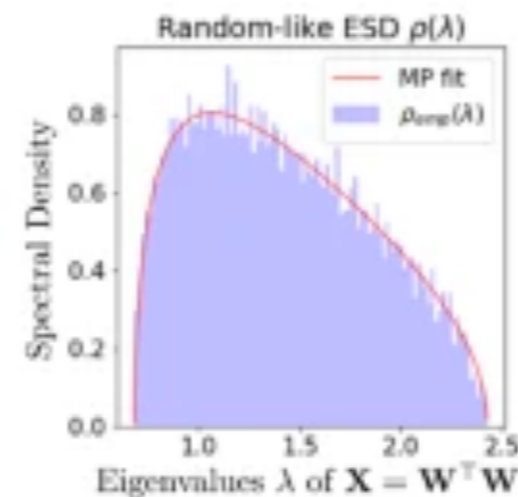
$$\lambda_i = 1$$



Analyzing DNN Weight matrices with **WeightWatcher**



1. Take a model
2. Take a weight matrix
3. Do Spectral analysis
4. Histogram of eigenvalues



$$\rho_{emp}(\lambda) \sim \lambda^{-\alpha}.$$



Theory-based: Layer Quality metrics

HTSR (2021)

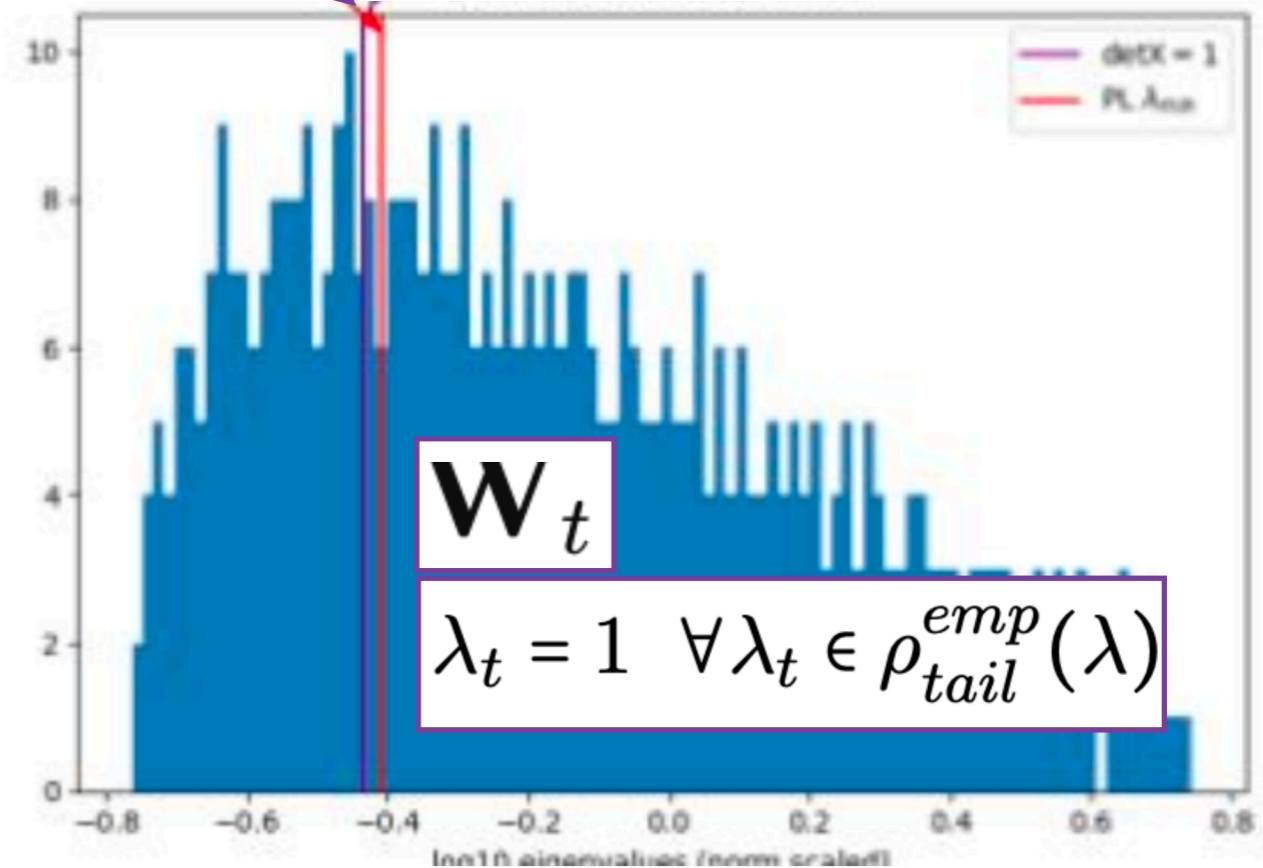
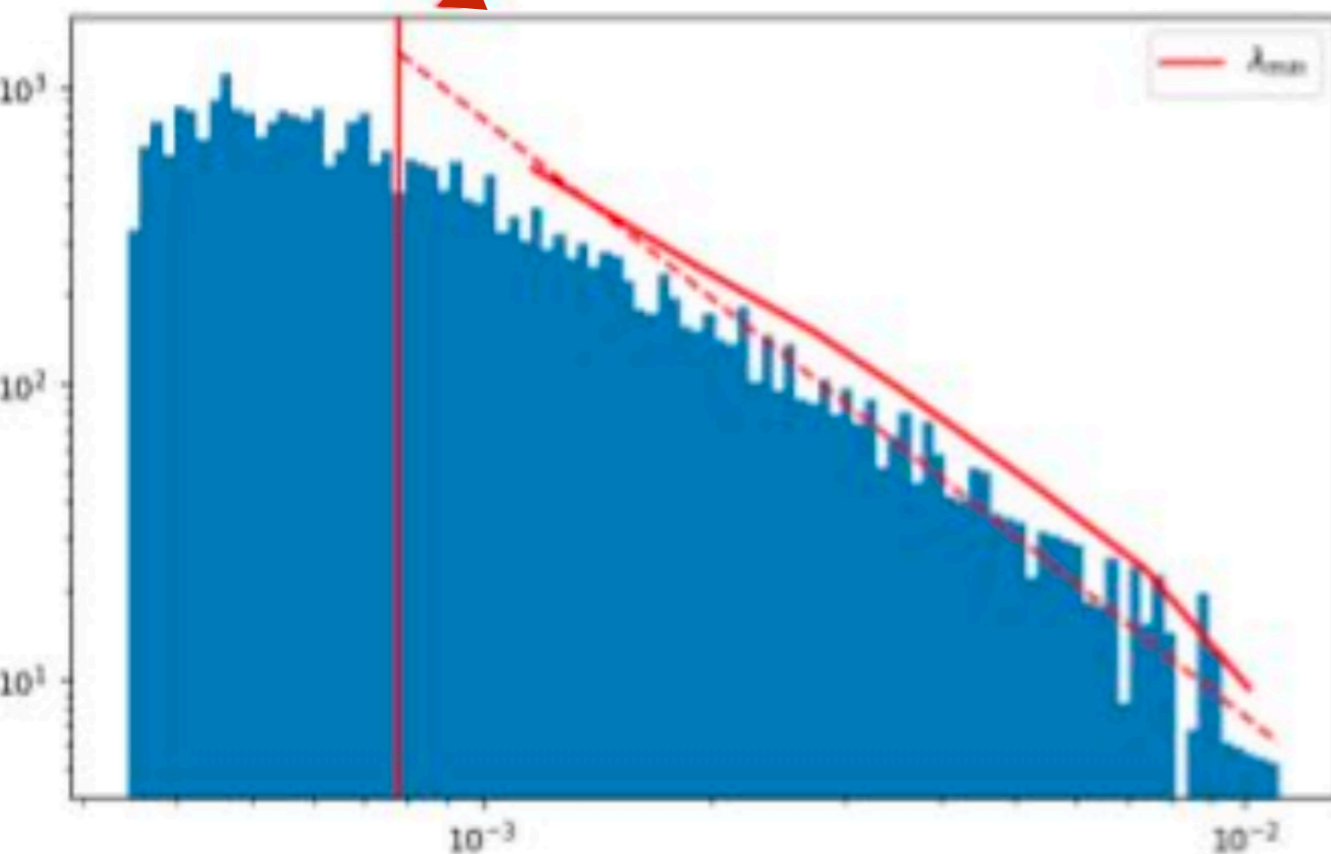
$$\rho_{tail}(\lambda) \sim \lambda^{-2}$$

$$\sum_{\lambda_i \in \text{tail}} \log \lambda_i = 0$$

SETOL (2025)

Start of Power Law Tail
(alpha=2.0)

Start of tail giving
Volume Preserving Transformation





How is Muon related: to Renormalization Group ?

non-Trivial: the RG fixed point

$$\lambda_t = 1 \quad \forall \lambda_t \in \rho_{tail}^{emp}(\lambda)$$

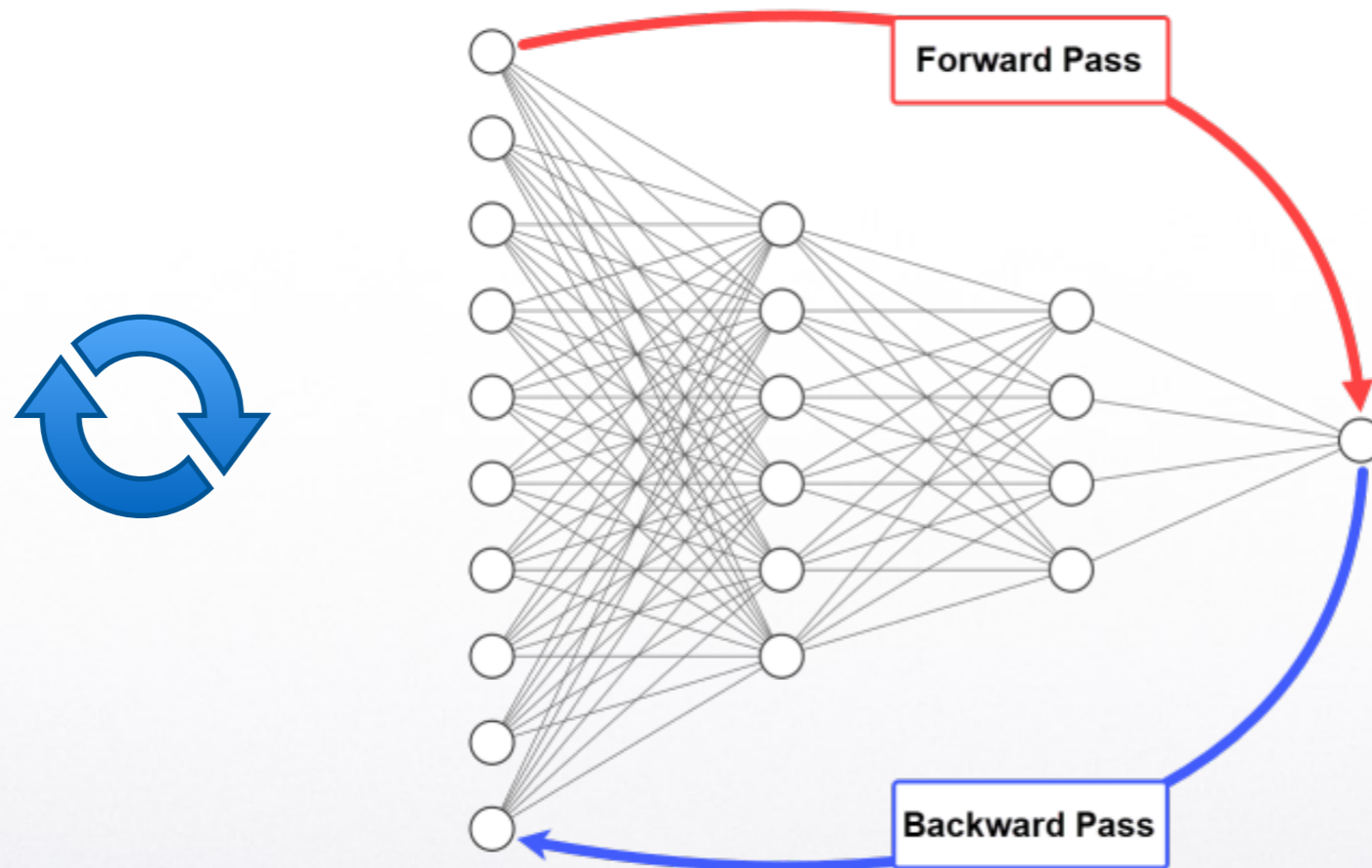
Trivial: fixes the gauge of the RG flow

$$\lambda_t = 1 \quad \forall \lambda_t \in \rho^{emp}(\lambda)$$

What does this mean ?



Why w|w works ? Fix Point Equation



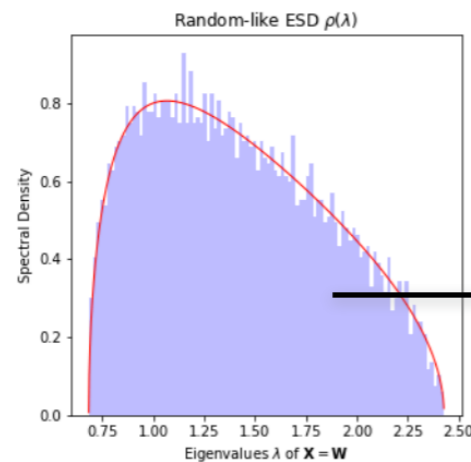
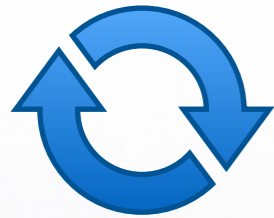
$W \rightarrow W \rightarrow W \rightarrow w \rightarrow w$



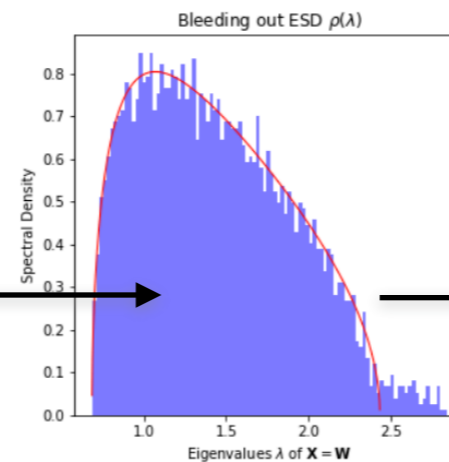
(TM)



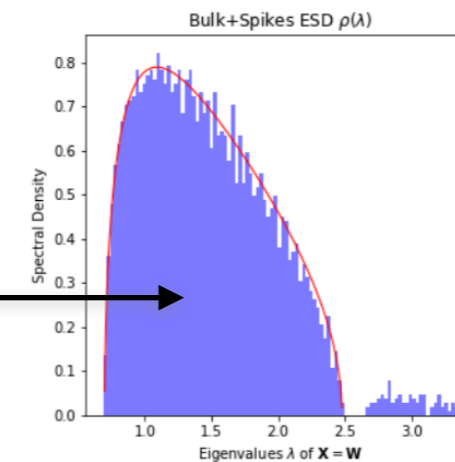
HTSR Theory: 5+1 Phases of Training



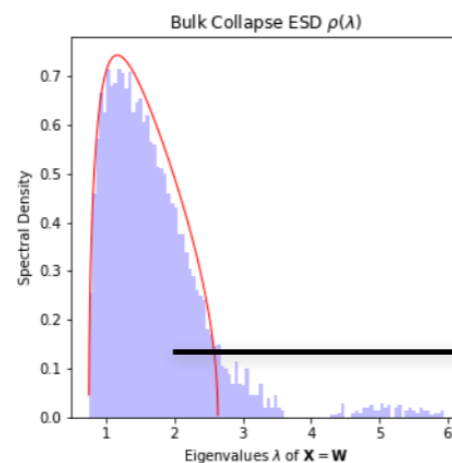
(a) Random-like.



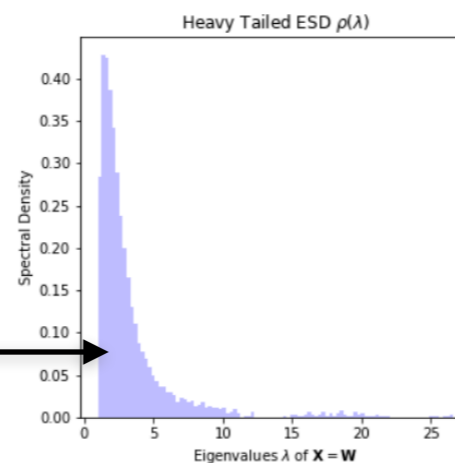
(b) Bleeding-out.



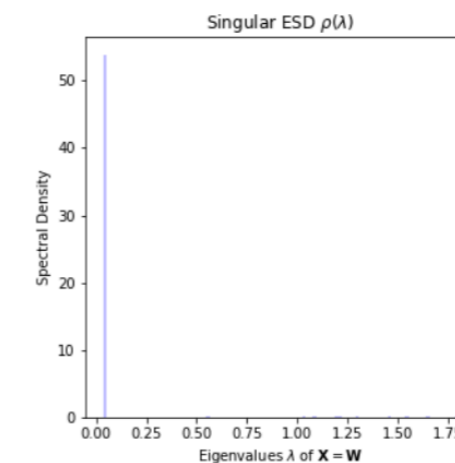
(c) Bulk+Spikes.



(d) Bulk-decay.



(e) Heavy-tailed.



(f) Singularity.

Implicit Self-Regularization in Deep Neural Networks: Evidence from Random Matrix Theory and Implications for Learning

Charles H. Martin, Michael W. Mahoney; JMLR 22(165):1–73, 2021.



Why $w|w$ works ? Renormalization Group (RG) theory

$$\ln \int d\mu(\mathbf{S}) e^{N\beta \text{Tr}[\mathbf{H}_{\bar{Q}^2}]} \xrightarrow{RG} \lim_{N \gg 1} \ln \int d\mu(\tilde{\mathbf{A}}) e^{N\beta \text{Tr}[\mathbf{H}_{\bar{Q}^2}^{ECS}]}$$

Diagram illustrating the Renormalization Group (RG) transformation. The left side shows the initial partition function $\ln \int d\mu(\mathbf{S}) e^{N\beta \text{Tr}[\mathbf{H}_{\bar{Q}^2}]}$ with a weight W indicated above it. The right side shows the transformed partition function $\lim_{N \gg 1} \ln \int d\mu(\tilde{\mathbf{A}}) e^{N\beta \text{Tr}[\mathbf{H}_{\bar{Q}^2}^{ECS}]}$ with a weight X indicated above it. A blue circular arrow labeled RG connects the two expressions. A blue line connects the \mathbf{S} and $\tilde{\mathbf{A}}$ variables, indicating a transformation. A small inset image shows a blue square with a red line and a purple dashed box.

Volume Preserving or Scale-Invariant Transformation

$$\det(\tilde{\mathbf{A}}) = 1 \quad \text{or} \quad \text{Tr}[\ln \tilde{\mathbf{A}}] = 0,$$

$$\prod_t \lambda_t = 1 \quad \forall \lambda_t \in \rho_{tail}^{emp}(\lambda),$$

SETOL: SemiEmpirical Theory of (Deep) Learning
Charles H. Martin & Christopher Hinrichs (arxiv, 2025).



ERG Condition: non-Trivial & Trivial solutions

non-Trivial: the RG fixed point

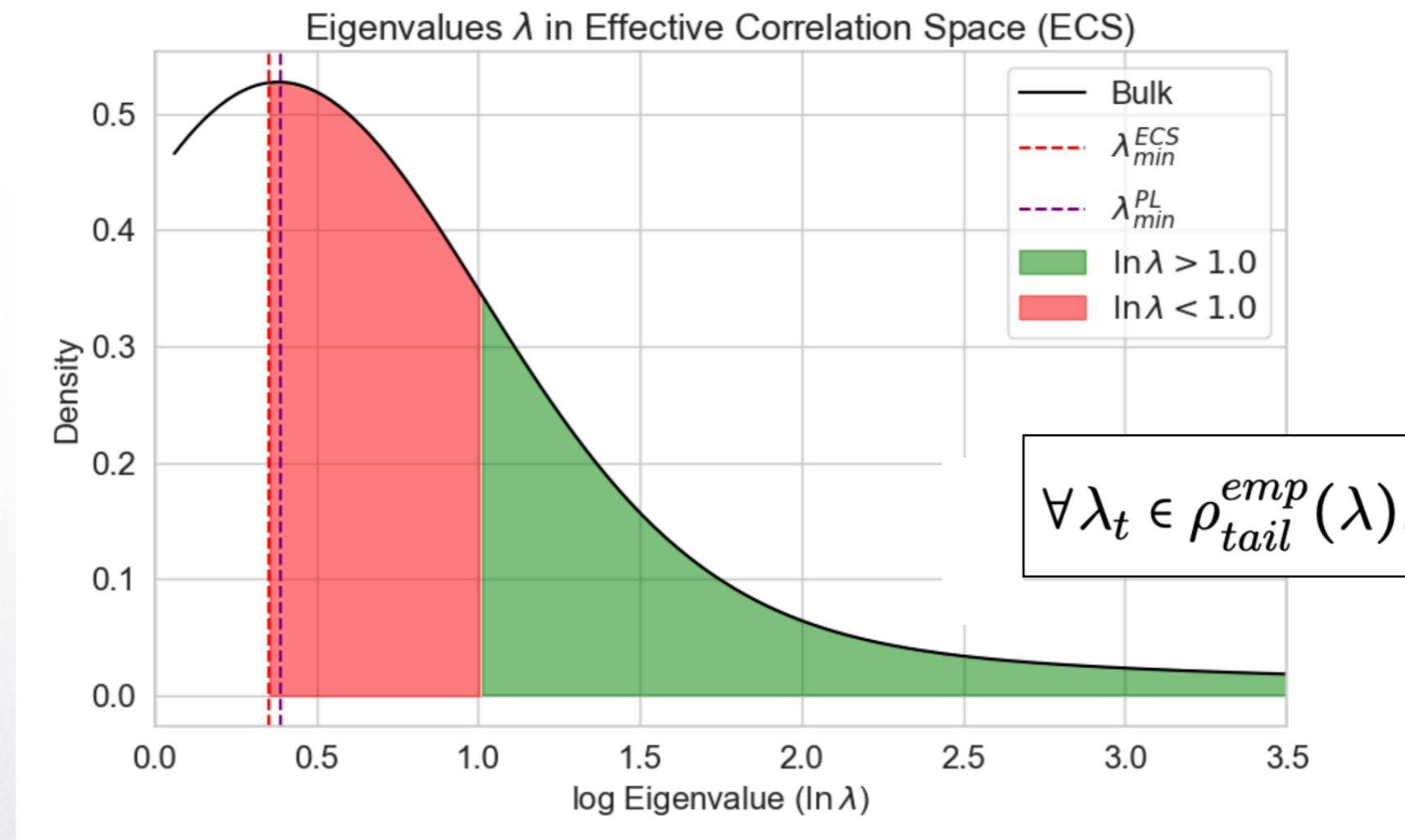
$$\lambda_t = 1 \quad \forall \lambda_t \in \rho_{tail}^{emp}(\lambda)$$

Trivial: fixes the gauge of the RG flow

$$\lambda_t = 1 \quad \forall \lambda_t \in \rho^{emp}(\lambda)$$



New Principle of **Ideal** Learning: Wilson Exact Renormalization Group (ERG) Condition



Non-Trivial Solution to ERG Trace-Log Condition $\alpha=2$



Muon: Removes Redundant RG Directions

Unrestricted flow allows dilations $\mathbf{W}_{t+1} = \mathbf{W}_t + \Delta \mathbf{W}_t$

$$\mathbf{W} \rightarrow \mathbf{W}e^{\mathbf{S}} \quad \text{GL}(n) = O(n) \times \text{SPD}(n)$$

The update lives in the tangent space of the flow

$$\Delta \mathbf{W}_t \approx \eta \dot{\mathbf{W}} \in T_{\mathbf{W}_t} \text{GL}(n)$$

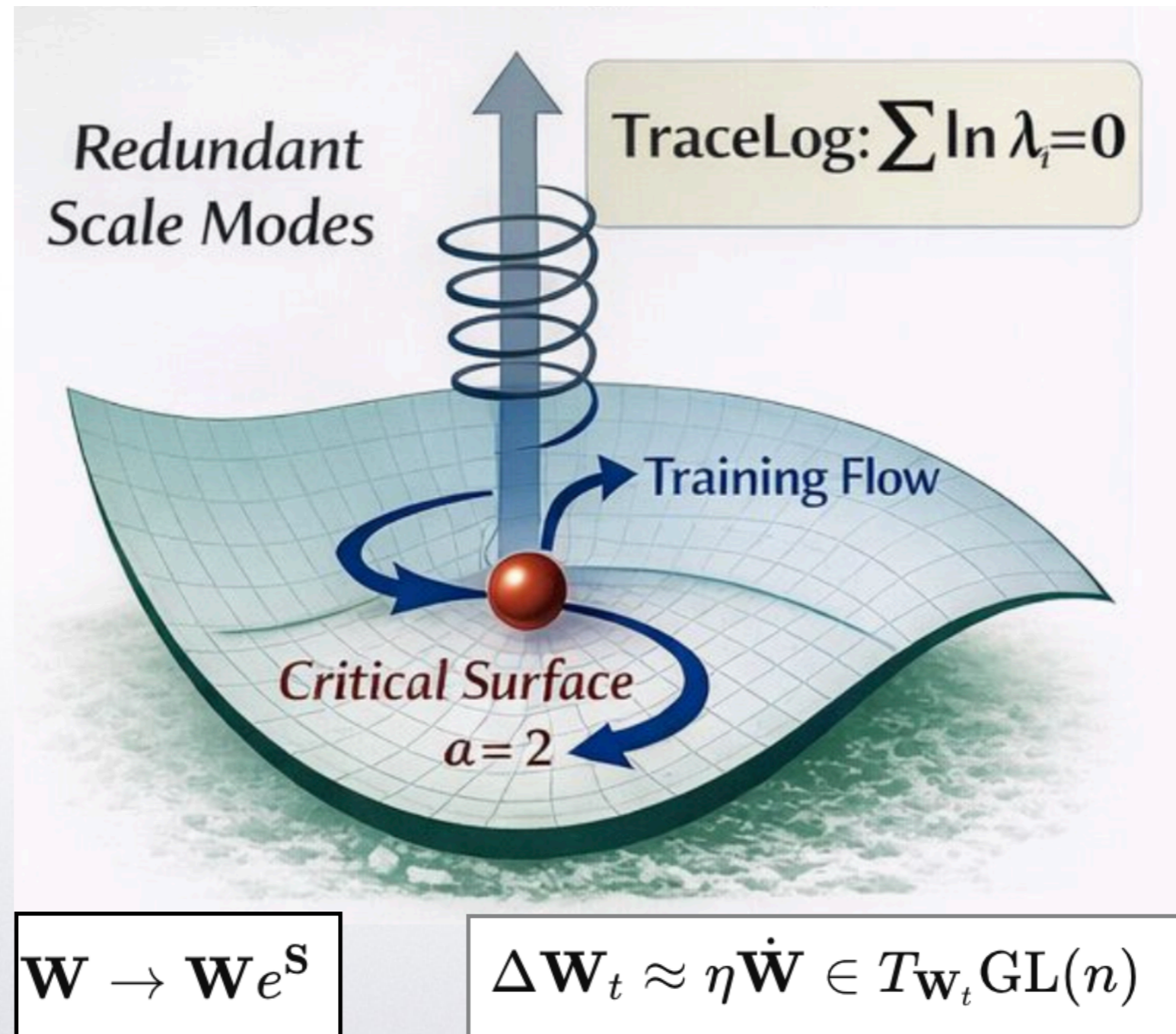
$$\Delta \mathbf{W}_t \longrightarrow \Delta \mathbf{W}_t + (\text{redundant direction})$$

Muon removes the dilation subgroup in the RG flow

$$\text{GL}(n) \longrightarrow O(n)$$



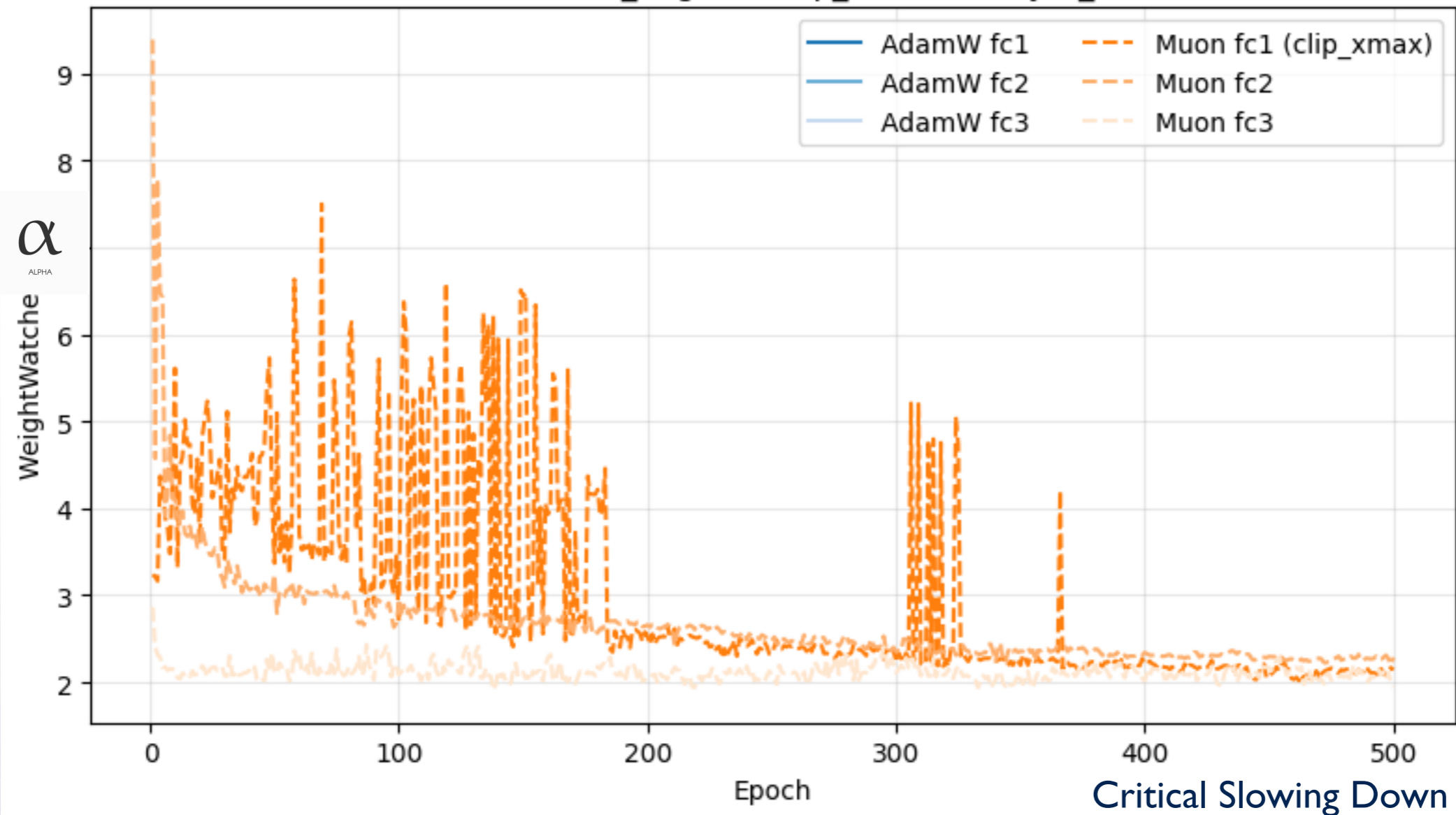
Muon: Removes Redundant RG Directions





Muon: Removes Redundant Directions

Layer-wise Spectral Exponents (α) vs Epoch
(Muon fc1 uses `fix_fingers='clip_xmax'` on `layer_id==1`)



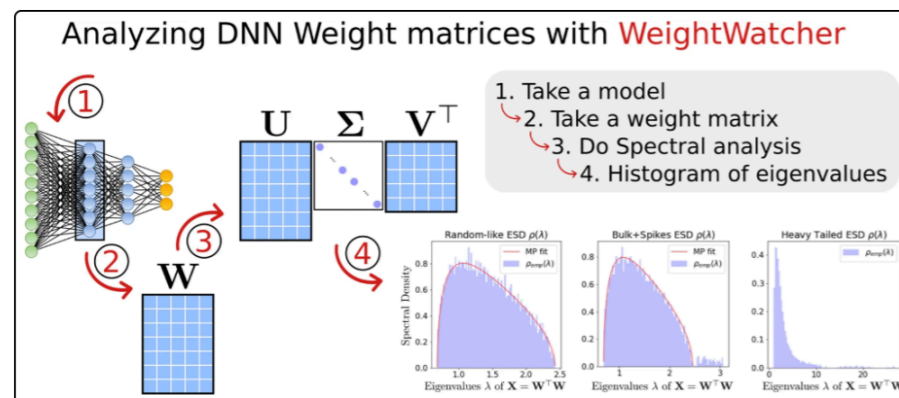


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Data-Free Diagnostics for Deep Learning

WeightWatcher (w|w) is an open-source, diagnostic tool for analyzing Deep Neural Networks (DNN), without needing access to training or even test data. It is based on theoretical research into Why Deep Learning Works, using the new Theory of Heavy-Tailed Self-Regularization (HT-SR), [published in JMLR and Nature Communications](#).

WeightWatcher is a one-of-a-kind must-have tool for anyone training, deploying, or monitoring Deep Neural Networks (DNNs).

`pip install weightwatcher`

[and check out our latest LLM Leaderboard!](#)

<https://weightwatcher.ai>

175K+ downloads; 17K+ stars

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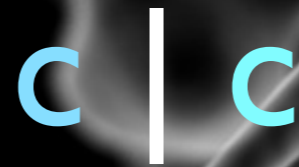
We are looking for early adopters and collaborators

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