

Towards a Phenomenological Understanding of Neural Networks

Samuel Tovey, Sven Krippendorf, Michael Spannowsky
Konstantin Nikolaou, Christian Holm

Why is this Necessary?



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Parameters	175 billion
Training Time	Several months
Training Cost	~ \$4.6 million

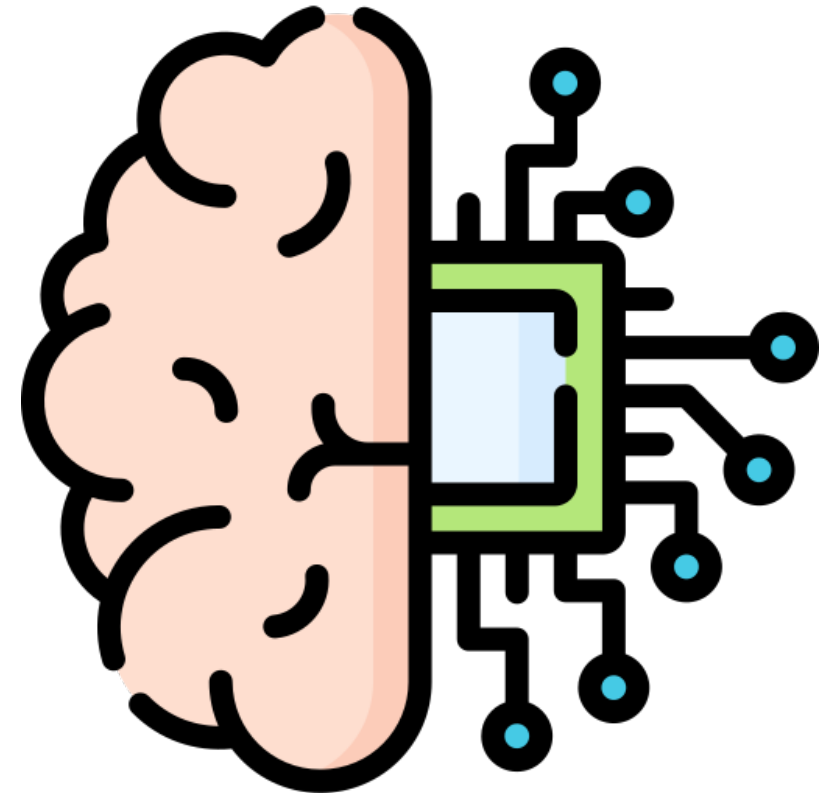
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We cannot afford to perform hyperparameter searches here.

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Why is this Necessary?

Parameters	175 billion	Neurons	86 billion
Training Time	Several months	Object recognition time^[2]	150 ms
Training Cost	~ \$4.6 million	Energy cost^[1]	< 20 W

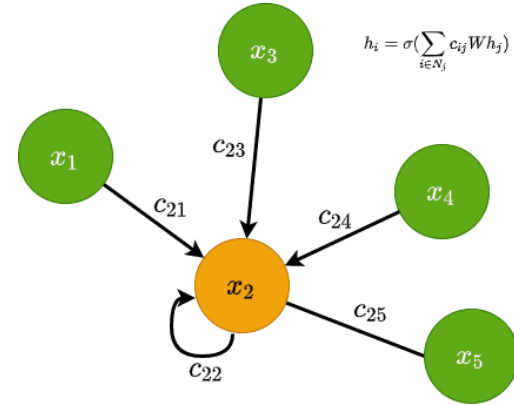
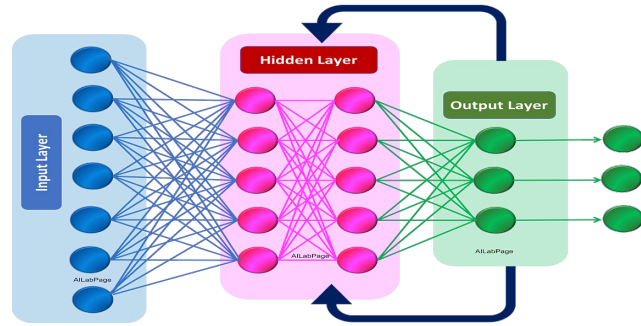
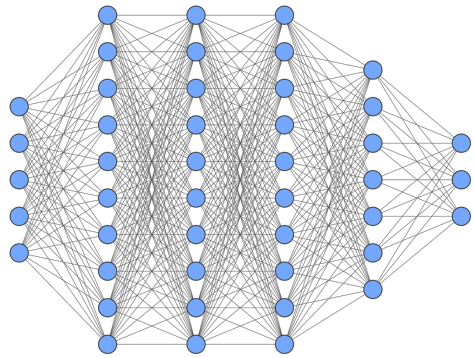
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Collective Variables for Neural Networks

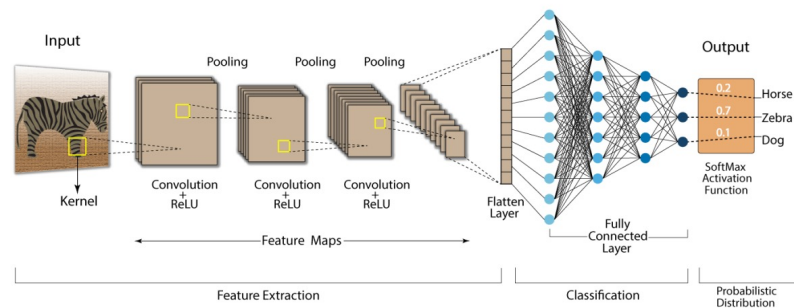
Entropy, trace, and more...

What is a Neural Network? (The NN Zoo)

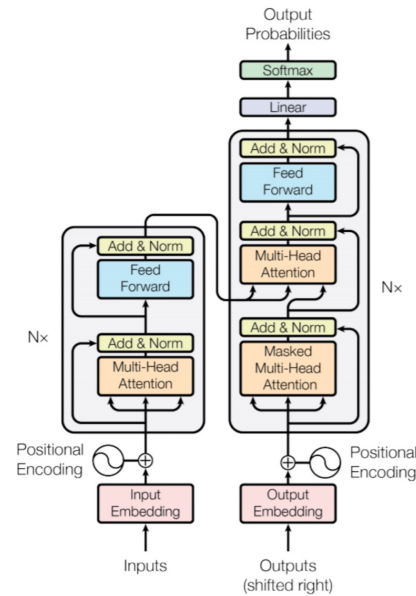
Function fitting in a very high dimensional space.



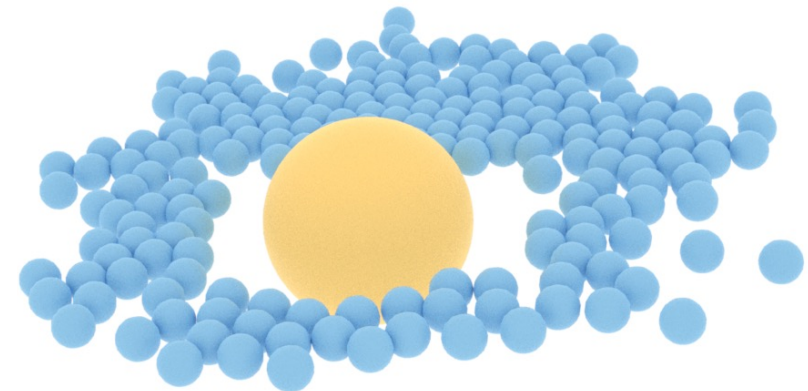
<https://medium.datadriveninvestor.com/recurrent-neural-network-58484977c445>



<https://developersbreach.com/convolution-neural-network-deep-learning/>

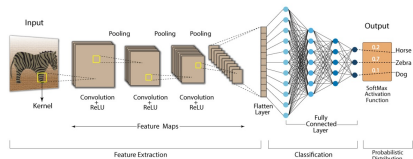
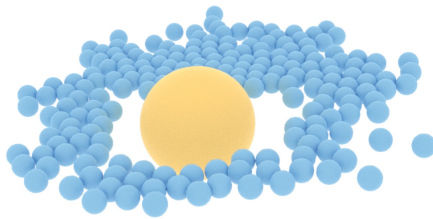
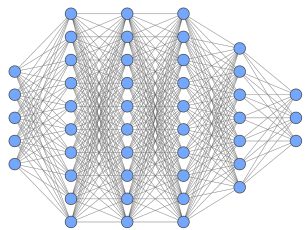


<https://builtin.com/artificial-intelligence/transformer-neural-network>

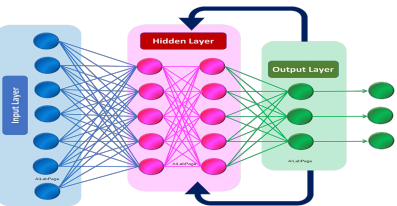


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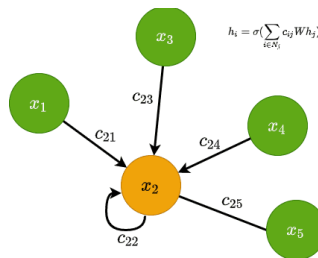
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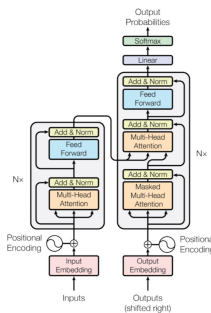
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$$h_i = \sigma \left(\sum_{j \in X_i} c_{ij} W h_j \right)$$



<https://builtin.com/artificial-intelligence/transformer-neural-network>

$$f_{\theta}: X \rightarrow Y$$

$$\theta = \{\theta_0, \dots, \theta_N\}$$

$$\theta'_i = \theta_i - \eta \cdot \partial_{\theta_i} \mathcal{L}(f(X), Y)$$

How do they evolve?

$$f'_\theta(X) = f_\theta(x) - \underbrace{\begin{pmatrix} \nabla_\theta f_\theta(x_0) \cdot \nabla_\theta f_\theta(x_0) & \cdots & \nabla_\theta f_\theta(x_0) \cdot \nabla_\theta f_\theta(x_N) \\ \vdots & \ddots & \vdots \\ \nabla_\theta f_\theta(x_N) \cdot \nabla_\theta f_\theta(x_0) & \cdots & \nabla_\theta f_\theta(x_N) \cdot \nabla_\theta f_\theta(x_N) \end{pmatrix}}_{\Theta} \cdot \nabla_{f_\theta} \mathcal{L}(X)$$

Architecture component

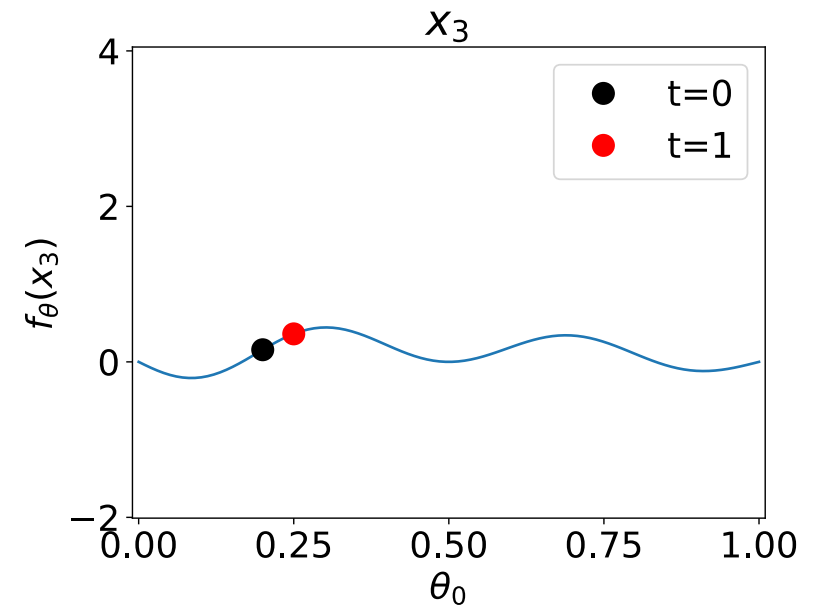
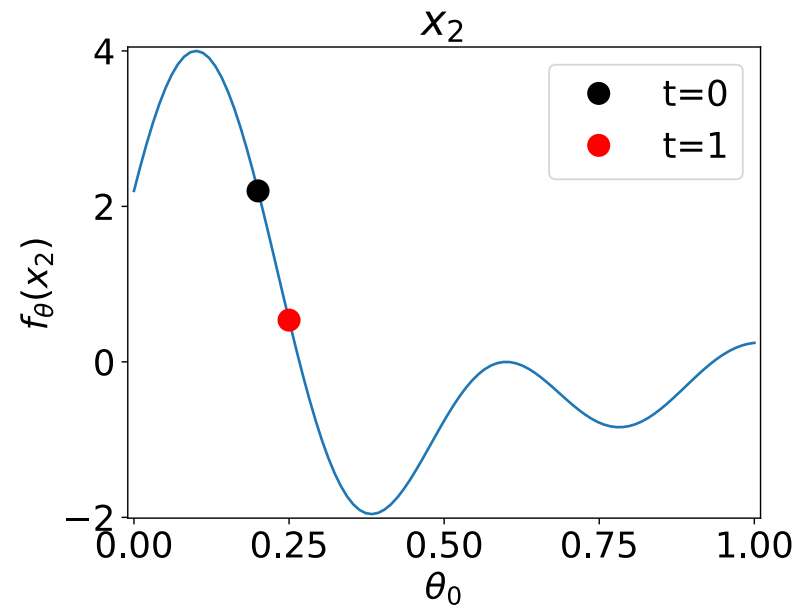
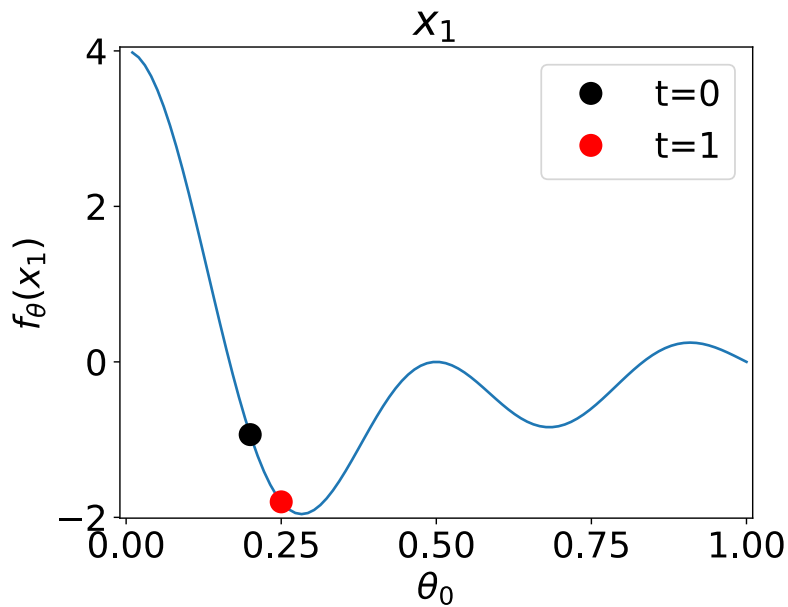
Loss component

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Architecture component

Loss component

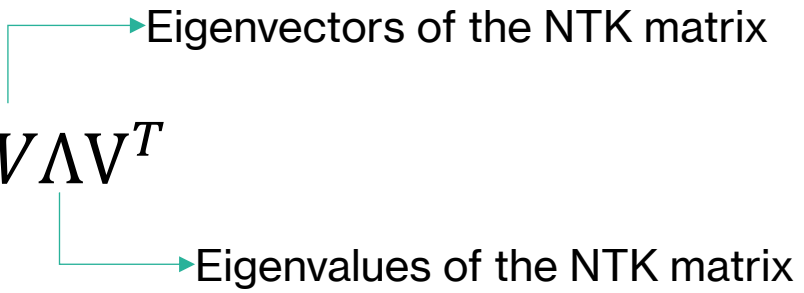


Collective Variables

$$\Theta = V\Lambda V^T$$

Eigenvectors of the NTK matrix

Eigenvalues of the NTK matrix



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Eigenvalues of the NTK matrix

$$S = - \sum_i \lambda_i \cdot \ln \lambda_i$$

Measure of correlation in data

$$Tr(\Theta) = \sum_i \Theta_{ii}$$

Weighting of largest step direction

Collective Variables

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Eigenvectors of the NTK matrix

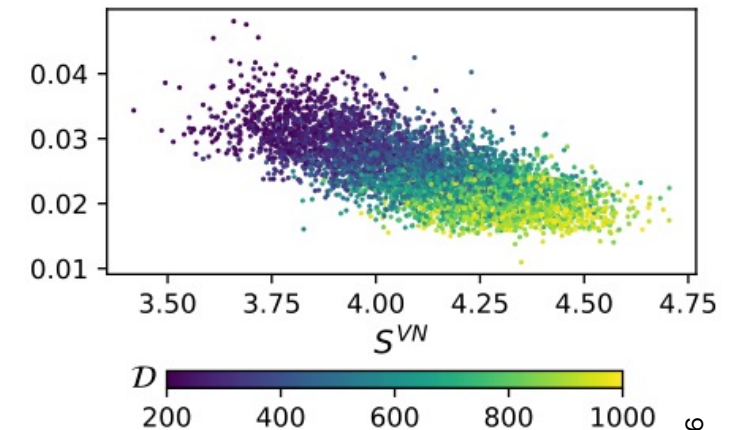
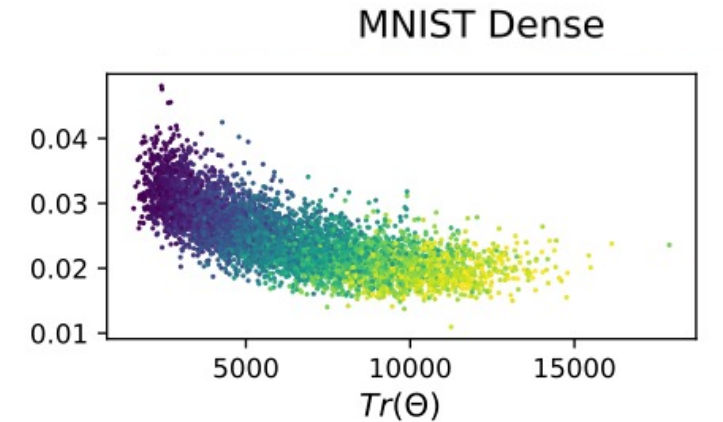
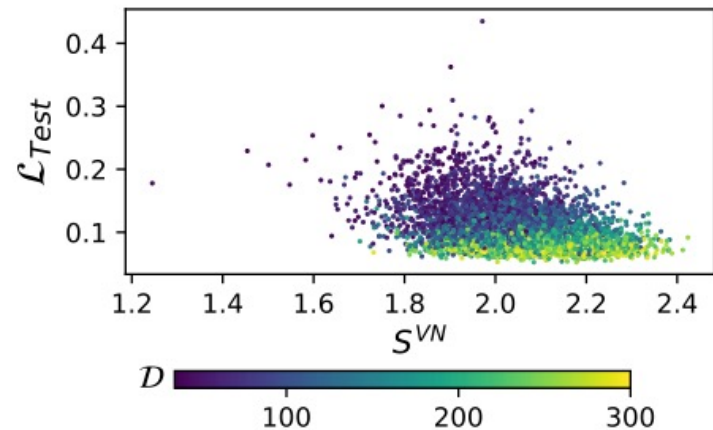
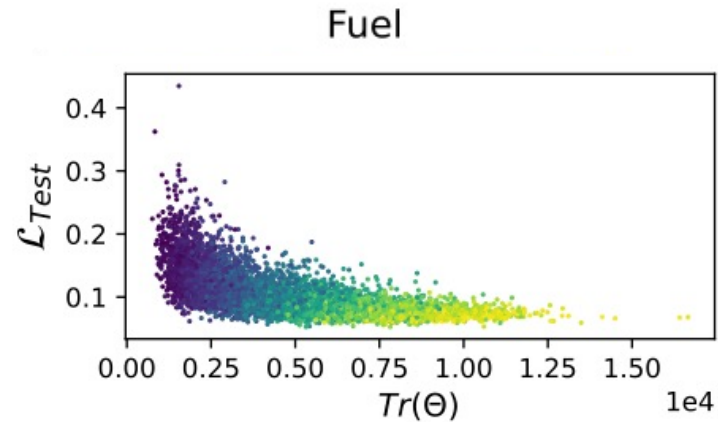
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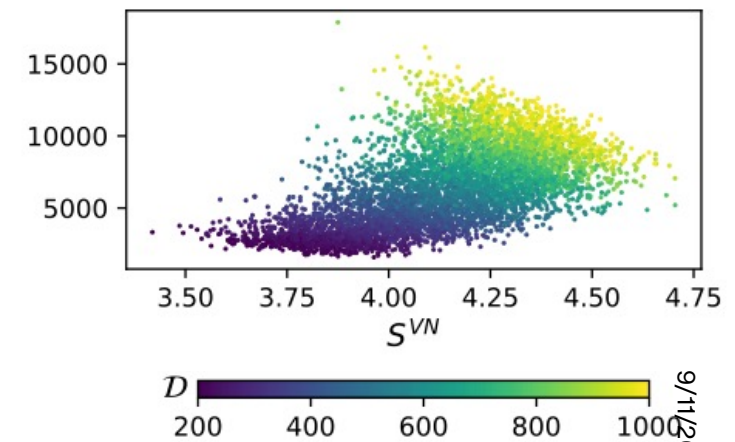
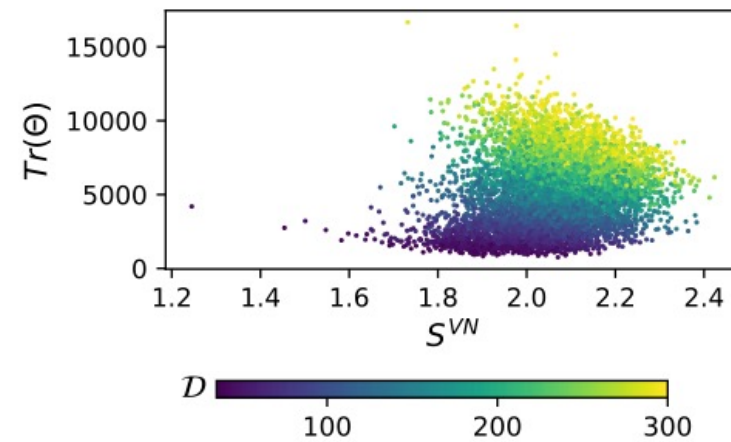
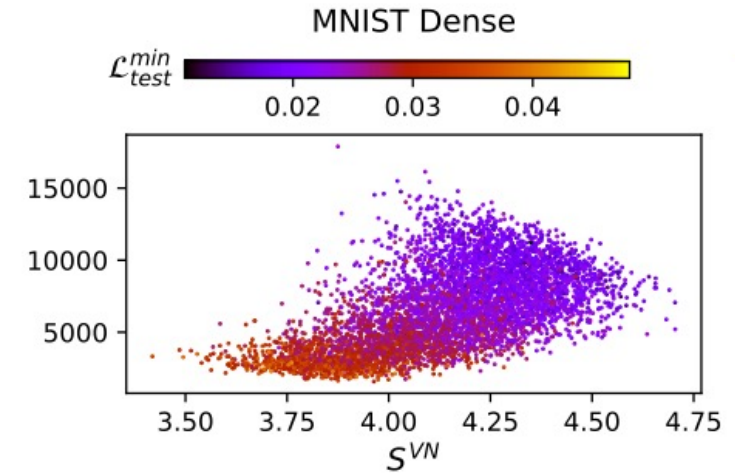
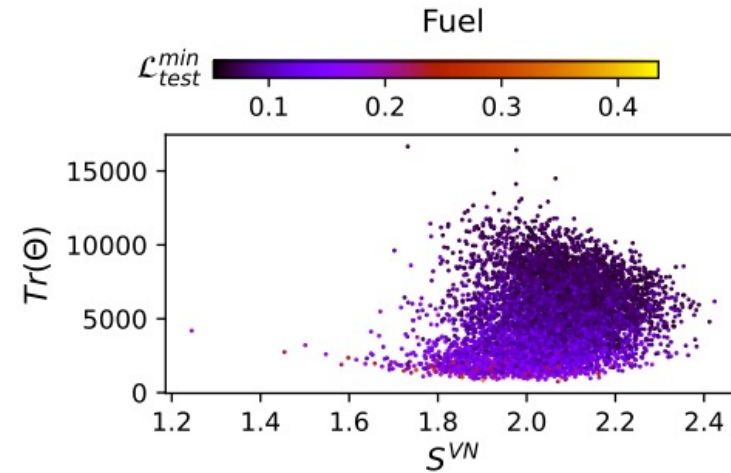
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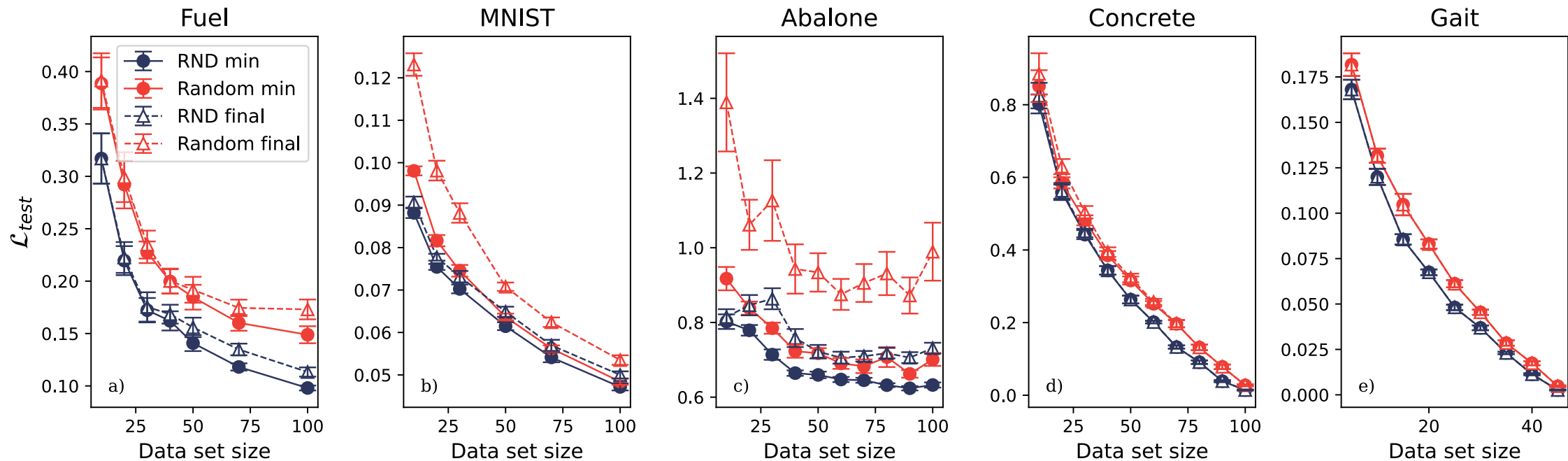
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Datasets	5
Optimizer	ADAM(0.001)
Loss Function	MSE or CE
Architectures	5
Epochs	200

Data

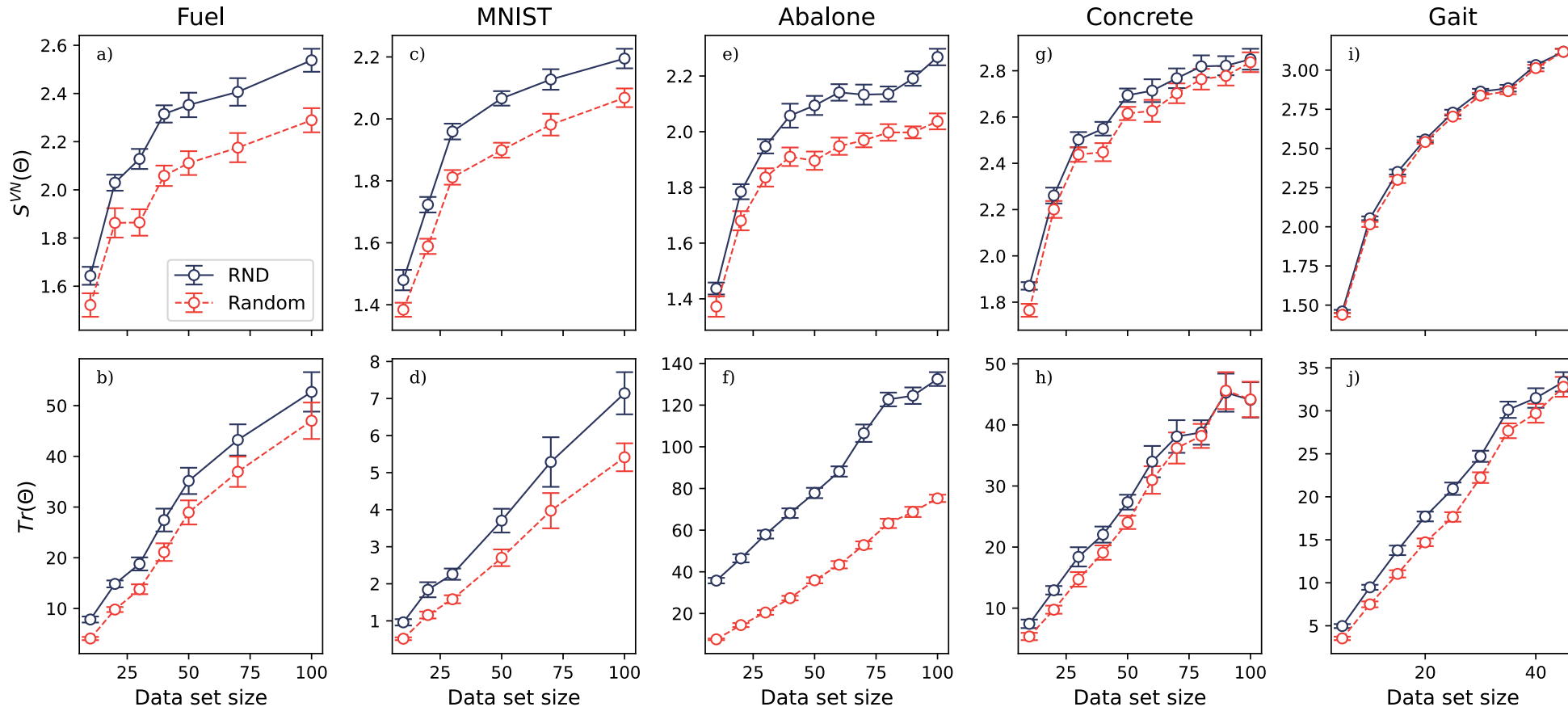
Levelling the playing field

Data Selection in Neural Networks



RND selected data-sets outperform random selection

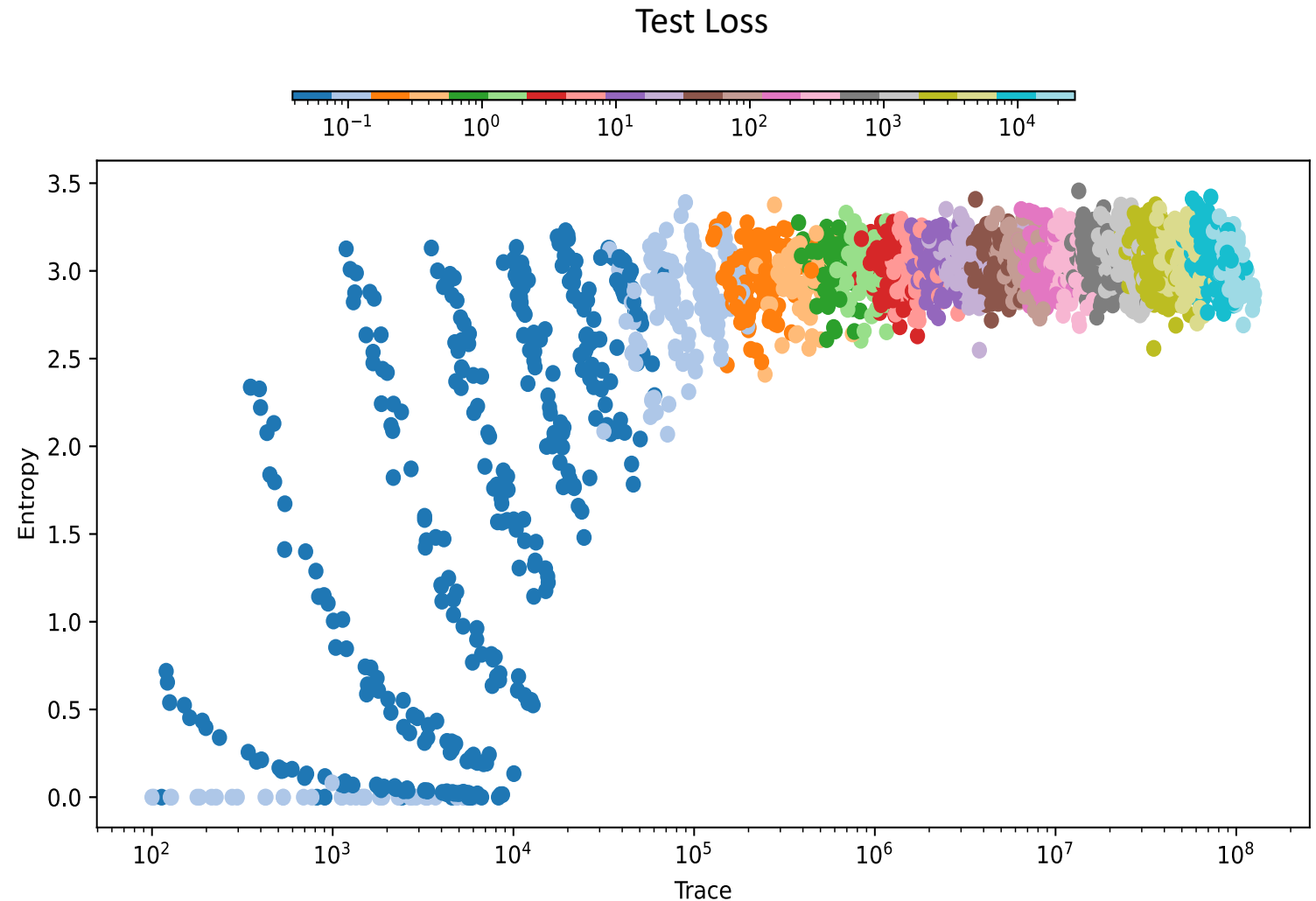
What do the collective variables say?



Datasets with larger trace / entropy perform better!

Next Steps: Initialization

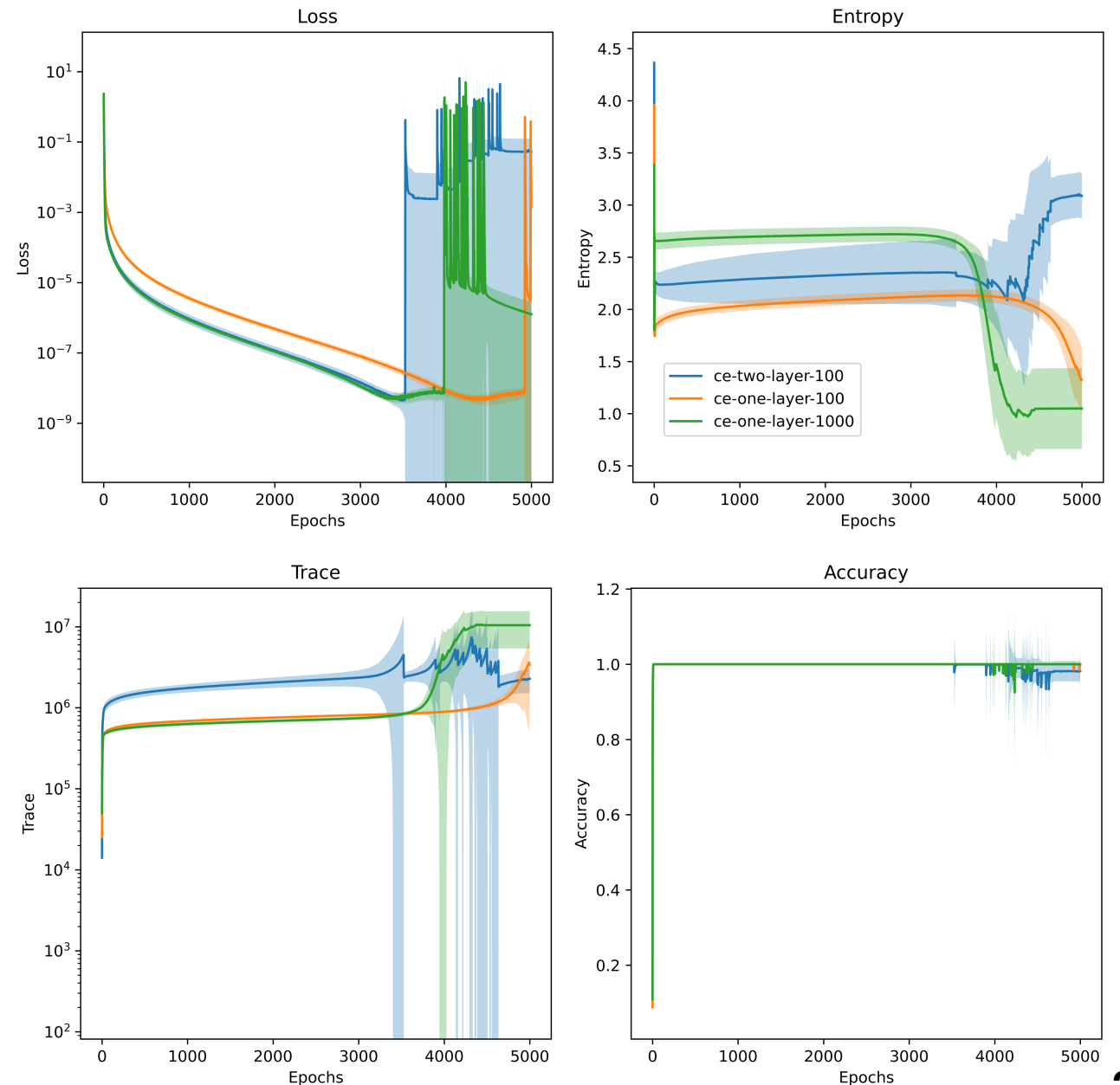
Dataset	MNIST (1000)
Optimizer	ADAM(0.001)
Architecture	$\mathcal{D}^{128}r\mathcal{D}^{128}r\mathcal{D}^{10}$
Weight std	0.0 – 1.0
Bias std	0.0 - 1.0



Next Steps: Dynamics

- Compute CVs at all epochs
- Search for universal behaviour
- Interesting long-time behaviour

Dataset	MNIST (1000)
Loss Function	Cross-entropy
Optimizer	SGD(0.01)
Architectures	3





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Towards a phenomenological understanding of neural networks: data

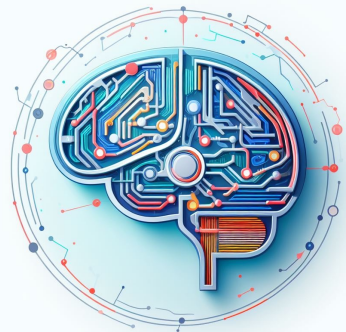
Samuel Tovey^{3,4,1} , Sven Krippendorf^{3,4,2} , Konstantin Nikolaou^{3,1}  and Christian Holm¹ 

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zincware/ZnNL

Python package to perform random network distillation.



 4
Contributors

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Issues

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Stars

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Forks



<https://github.com/zincware/ZnNL>

Wrapping Up: ZnNL

- Tools of physics can help us understand neural networks
 - Statistical Physics
 - Quantum Mechanics
- We can leverage this understanding
 - Data Selection
 - Initialization
 - Optimization and dynamics

9/11/2023