

Problem

ReLU networks express continuous piece-wise affine functions of their input **x**. To **quantify their expressivity**, the number of linear "pieces", i.e. the **density of linear regions**, has been studied as a proxy for model **nonlinearity**. Intuitively, high nonlinear behaviour requires expressing many regions.

Research Question

Linear region density heavily assumes that all regions **mean**ingfully contribute nonlinearity relevant to learning. Is it the case for **overparameterized** models?

Existing Methods

Prior empirical approaches have been limited to MLPs (Hanin & Rolnick, 2019; Novak et al., 2018) or small ConvNets (Zhang & Wu, 2020). Analytic methods don't scale to modern networks, while numerical ones assume *uniform* density in the input space.

Adaptive Linear Region Discovery



Our fast numerical method finds the smallest $\lambda > 0$ to cross the nearest region boundary, in directions tangent to the "data" ", with a single forward pass. We use it to compute manifold our novel measure of nonlinearity, *absolute deviation*.

Are All Linear Regions Created Equal?

Matteo Gamba, Adrian Chmielewski-Anders, Josephine Sullivan, Hossein Azizpour, Mårten Björkman

KTH Royal Institute of Technology



(1) **Density is** a **noisy** estimator of nonlinearity of large networks. (2) In **model-wise double descent** (Nakkiran et al., 2019), past the noise interpolation threshold, local linearity increases, connecting reduced test error to reduced model nonlinearity.

Ranking Nonlinearity

Capturing Effective Nonlinearity

2019. *ICLR*, 2018.

Density & Variation

Table: Spearman rank correlation between density and absolute deviation.

	CIFAR-10		CIFAR-100
	VGG8	ResNet18	VGG8
vanilla	-0.15 ± 0.00	0.05 ± 0.03	0.00 ± 0.02
augment.	-0.08 ± 0.02	0.17 ± 0.06	0.11 ± 0.08
noise 0.2	0.04 ± 0.02	0.21 ± 0.02	
noise 0.4	0.11 ± 0.02	0.21 ± 0.04	
noise 0.6	0.18 ± 0.07	0.25 ± 0.03	
noise 0.8	0.26 ± 0.04	0.22 ± 0.02	
noise 1.0	0.14 ± 0.04	0.27 ± 0.04	

References

B. Hanin and D. Rolnick. Complexity of linear regions in deep networks. In *ICML*, pp. 2596–2604, 2019.

G. Montufar, R. Pascanu, K. Cho, and Y. Bengio. On the number of linear regions of deep neural networks. In Advances in NeurIPS, 2014.

P. Nakkiran, G. Kaplun, Y. Bansal, T. Yang, B. Barak, and I. Sutskever. Deep double descent: Where bigger models and more data hurt. In *ICLR*,

R. Novak, Y. Bahri, D.Ã. Abolafia, J. Pennington, and J. Sohl-Dickstein. Sensitivity and generalization in neural networks: an empirical study. In

X. Zhang and D. Wu. Empirical studies on the properties of linear regions in deep neural networks. In *ICLR*, 2020.

