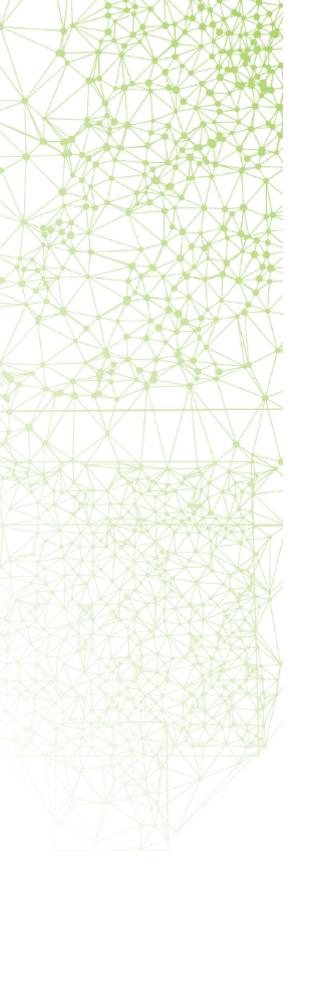
TRAIN DEEP LEARNING MODELS DATA PARALLELISM: HOW TO ON MULTIPLE GPUS

-AB 1, PART 2: MORE REALISTIC NETWORKS



DEEP LEARNING INSTITUTE



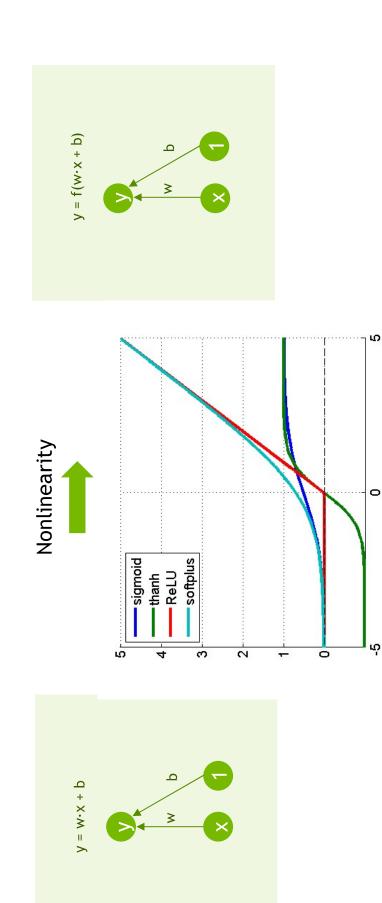


MODERN NEURAL NETWORKS

How do they differ from our trivial example?

Not significantly!

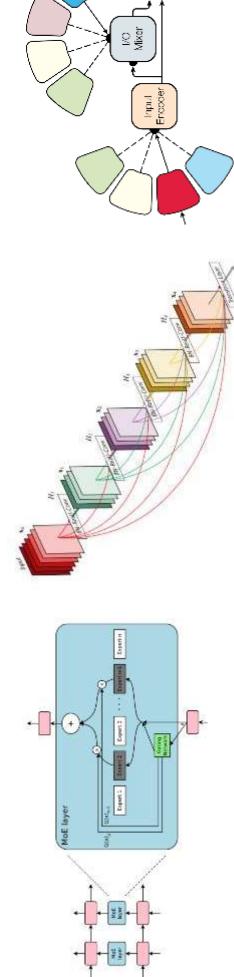
MODERN NEURAL NETWORKS How do they differ from our trivial example?

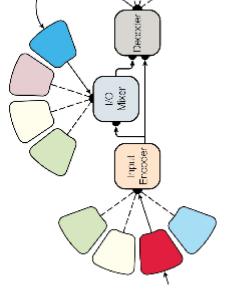


MODERN NEURAL NETWORKS

How do they differ from our trivial example?

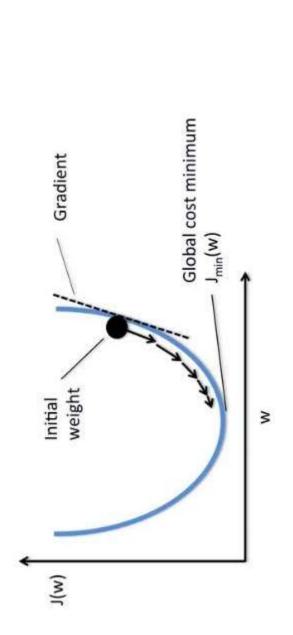
More complex interconnection and many more parameters

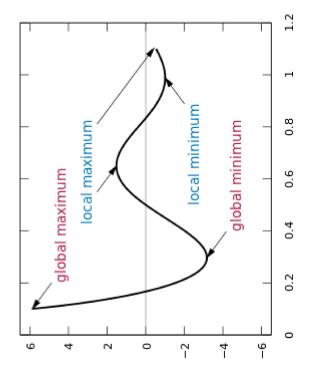




Kaiser, L., Gomez, A. N., Shazeer, N., Vaswani, A., Parmar, N., Jones, L., & Uszkoreit, J. (2017). One model to learn them all. arXiv preprint arXiv. 1706.05137. landola, F., Moskewicz, M., Karayev, S., Girshick, R., Darrell, T., & Keutzer, K. (2014). Densenet: Implementing efficient convnet descriptor pyramids. arXiv preprint arXiv. 1404. 1869. Shazeer, N., Mirhoseini, A., Maziarz, K., Davis, A., Le, Q., Hinton, G., & Dean, J. (2017). Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. arXiv preprint arXiv:1701.

Those differences make the optimization problem much more difficu

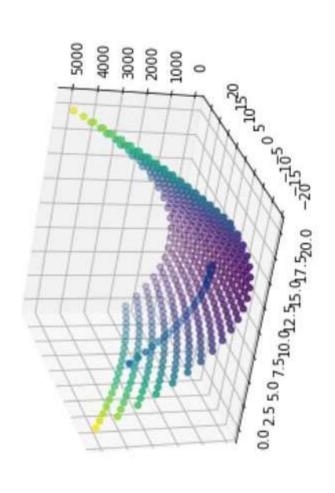


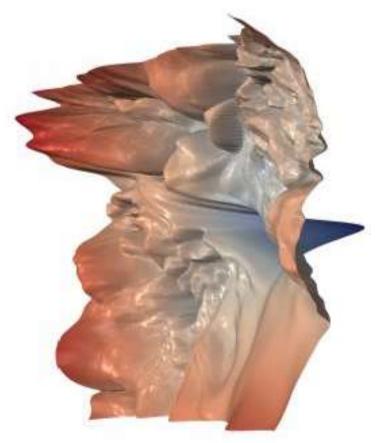


Those differences make the optimization problem much more difficu

Linear model loss function

ResNet-56 loss function projection to 3D - no sl connections



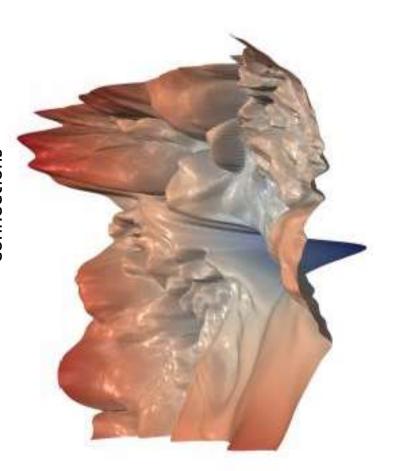


Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. <u>arXiv:1712.09913</u>.

Those differences make the optimization problem much more difficu

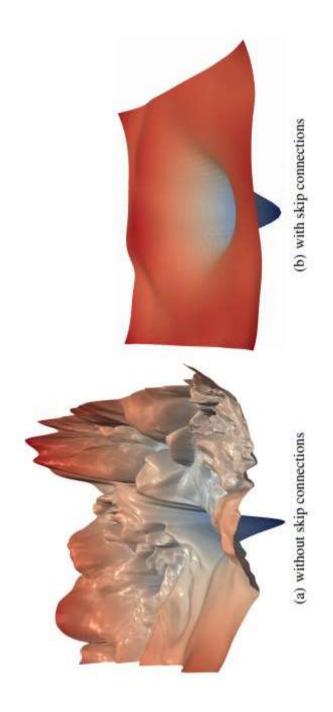
ResNet-56 loss function projection to 3D - no sl connections

Why do we succeed in finding good local minima?



Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. *arXiv:1712.09913*.

Recent advances such as residual connections simplify optimizatior



Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. <u>arXiv:1712.09913</u>.

