The Effect of Network Width on Stochastic Gradient Descent and Generalization

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ICML 2019

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ICML 2019 1 / 9

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Work with Jascha Sohl-Dickstein, Quoc V. Le and Samuel L. Smith.

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Motivation

Let us assume that

- we found hyperparameters that maximize test set accuracy for a given network,
- but now we want to make the network bigger by widening all the channels by factor w.

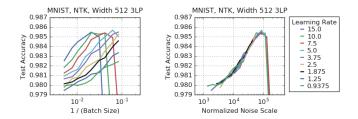
What do we do with the hyperparameters for the new network?

We find a rule that governs how hyperparameters that maximize test accuracy change when the network width is varied.

The rule is that the optimal value of the **normalized noise scale** (which is a function of the hyperparameters of SGD) scales proportionally to the width of the network.

The Normalized Noise Scale \bar{g}

- $\bar{g} = \frac{\epsilon}{B(1-m)} \cdot \frac{1}{\sigma_{init}^2}$ governs how noisy the SGD is.
- \bar{g} determines the generalization performance.*



*Mandt et al. (2017); Chaudhari & Soatto (2017); Jastrzebski et al. (2017); Smith & Le (2017).

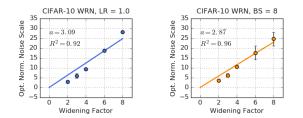
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Rule for Hyperparameter Selection

• There exists a simple rule for hyperparameter selection:

Increase \bar{g} proportionally with w.



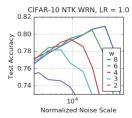
Wider networks require smaller batch sizes

• To maximize generalization performance, wide networks (eventually) need to be trained with small batch sizes:

$$B_{ ext{opt}} \leq rac{(ext{constant})}{w}$$

Bigger networks perform better due to noise resistance

• Bigger networks have better peak test set performance which is reached at higher noise scales.



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Thank you!

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ICML 2019 9 / 9

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