Towards Robust ResNet

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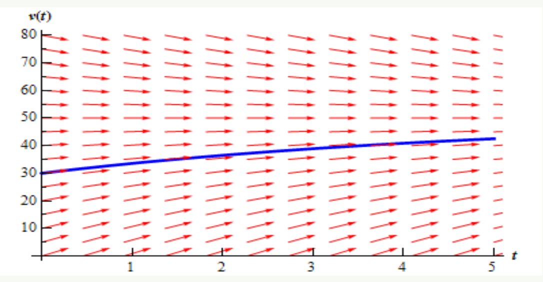
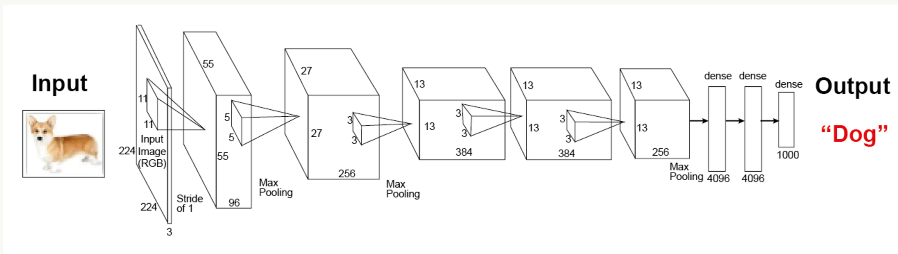
http://www.comp.nus.edu.sg/~lowkh/research.html

Motivation & Idea

Partial Differential Equation



Deep Neural Network



Object trajectory over time

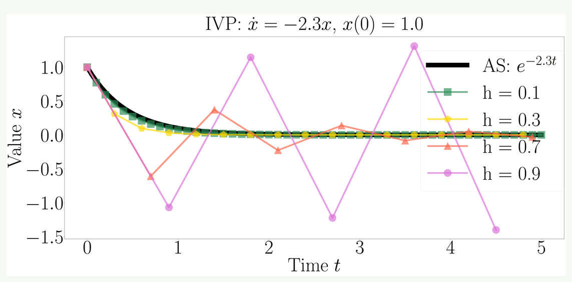
Feature transformation over depth of layers

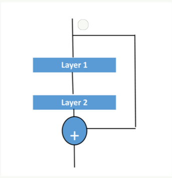
Explicit Euler Method

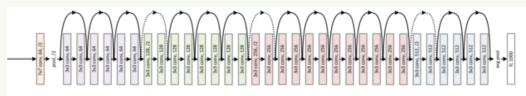
$x_{n+1} = x_n + hf(t_n + x_n)$

Residual Neural Network (ResNet)

$y_n = x_n + F(x_n); \quad x_{n+1} = I(y_n)$

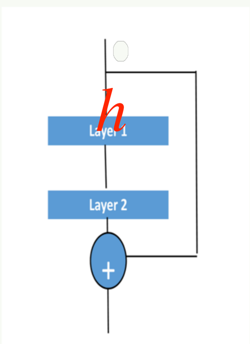






Euler-viewed ResNet

$y_n = x_n + h F(x_n); \quad x_{n+1} = I(y_n)$

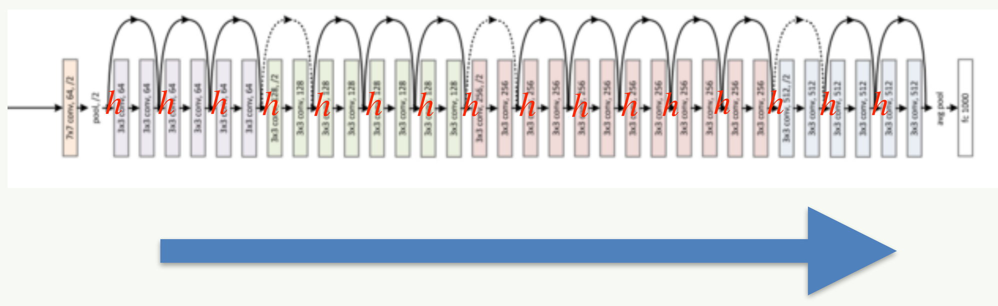


How step factor h helps ResNet?

Our Contribution:
We introduce a hyperparameter step factor h into Residual Neural Network (ResNet), theoretically and empirically confirming its efficacy in ResNet in term of **training robustness** and **generalization robustness**.

Training robustness refers to the stability of model training with an increasing depth, a larger learning rate, and different types of optimizer.
Generalization robustness refers to how well a trained model generalizes to classify test data whose distribution may not match that of the training data.

Small h on Generalization Robustness

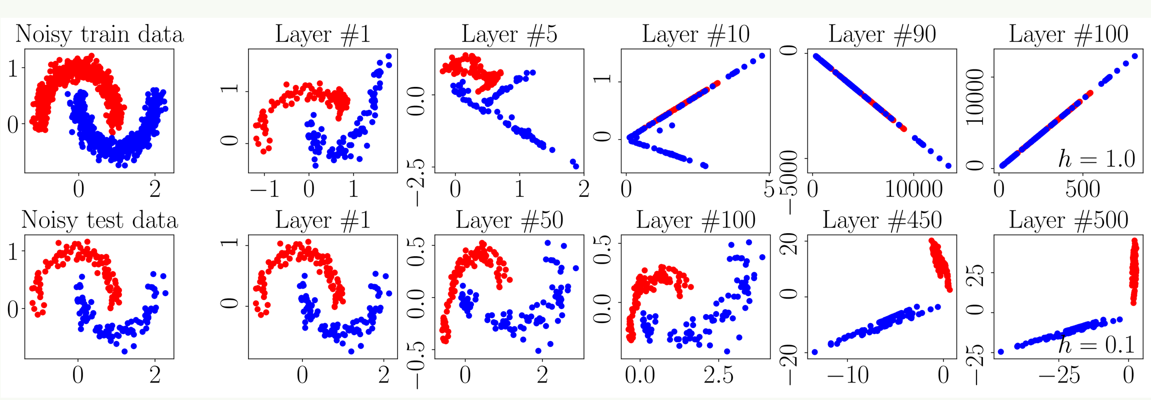


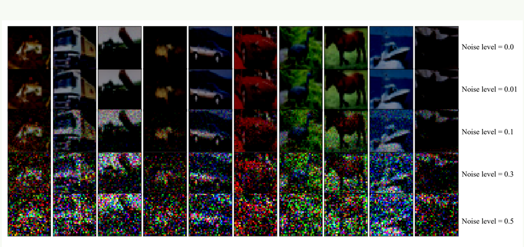
x_0 x_D

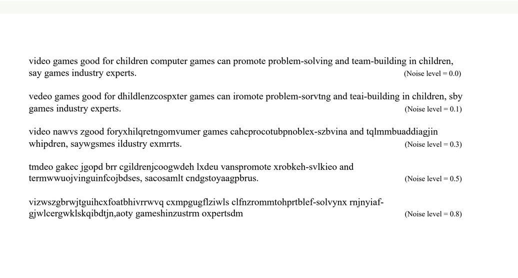
x_0^ϵ x_D^ϵ

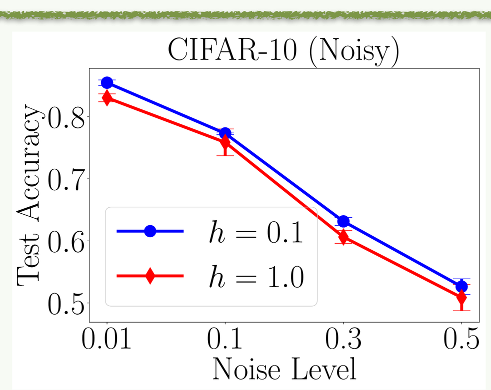
$$\epsilon_D = \|x_D^\epsilon - x_D\| \le \epsilon + hDW$$

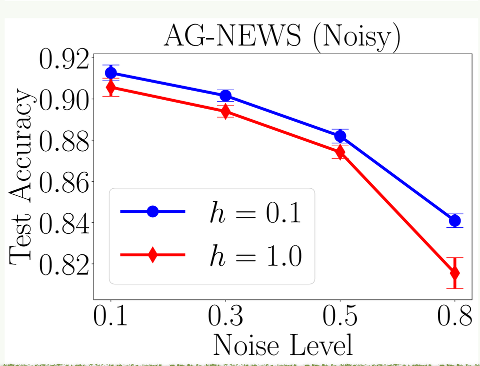
Small h can limit the noise amplification and provide the extra capacity for filtering out the input noise.







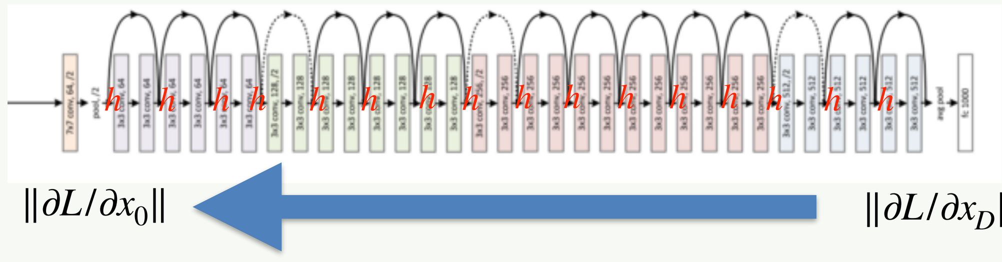




To verify the effectiveness of small h on generalization robustness of ResNet, we train on noisy input data with various noise level, and compare ResNet with reduced step factor (h = 0.1) and original ResNet (h = 1) on the clean test data.

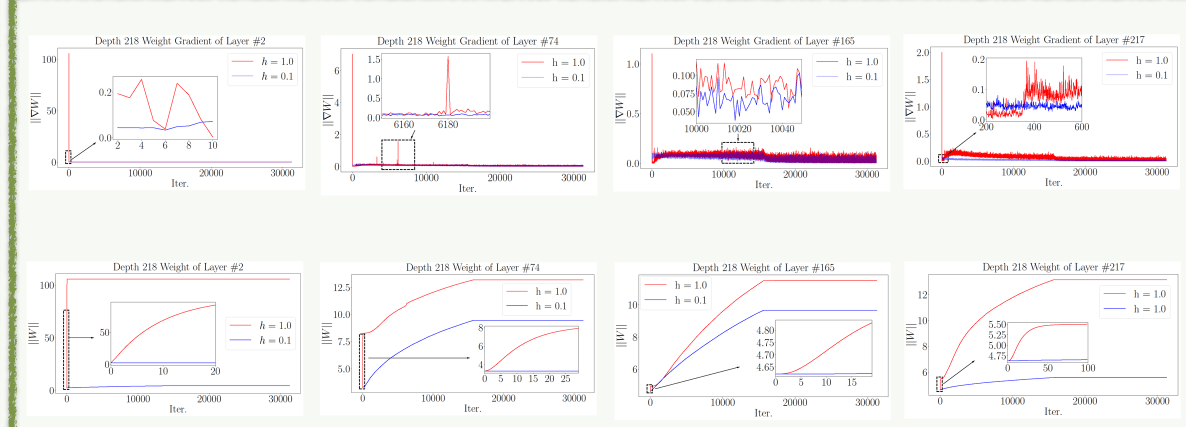
*Small h can ameliorate the input noise.

Small h on Training Robustness



$\|\partial L/\partial x_0\|$ $\|\partial L/\partial x_D\|$

$$\|\partial L/\partial x_0\| \le \|\partial L/\partial x_n\|(\sqrt{d} + hW)^D$$

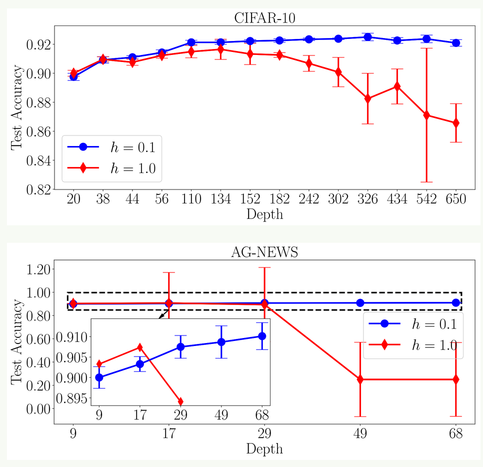


For existing method (h = 1.0, red line), ResNet has (a) exploding gradients problem (unstable training) and (b) large weight problem (input noise amplification over depth).

How the existing tricks handle above problems?
1 Warming up the training with a small LR
2 Gradient clipping
3 Weight decay (regularization)

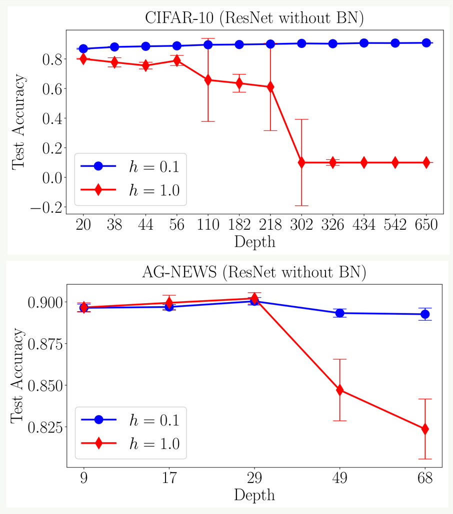
•By comparison, our method (h = 0.1) naturally has stable gradients and smaller weights!!!
•*Our method is compatible with existing techniques.

Small h helps training deeper ResNet



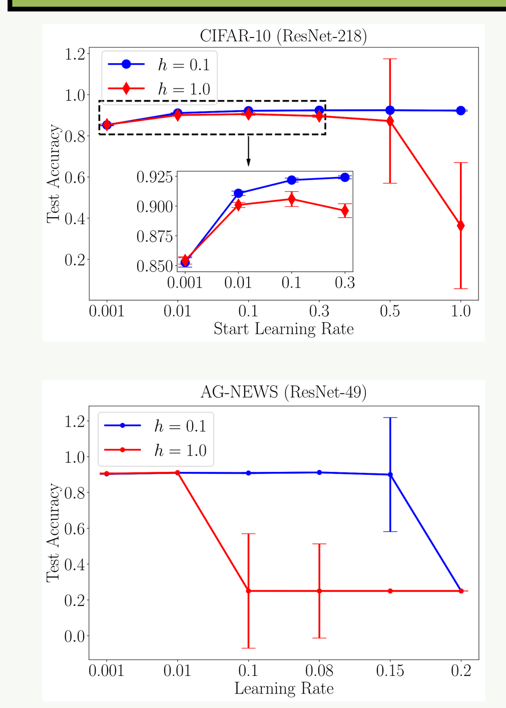
Our method (smaller h, .e.g. h = 0.1) makes the training procedure of ResNet more robust to increasing depth.

Small h helps without applying Batch Normalization



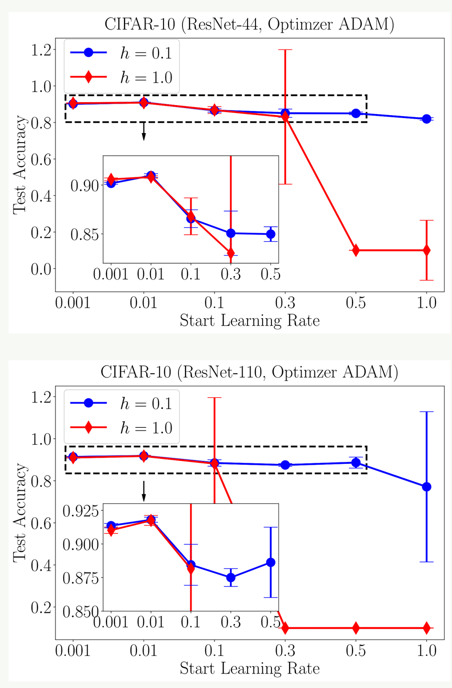
BN can help to stabilize the training procedure of DNN. Without applying BN, our small h can still stabilize the training by preventing the explosion of back-propagated information.
*Our small h is compatible with BN.

Small h can enable larger learning rate (SGD with momentum)



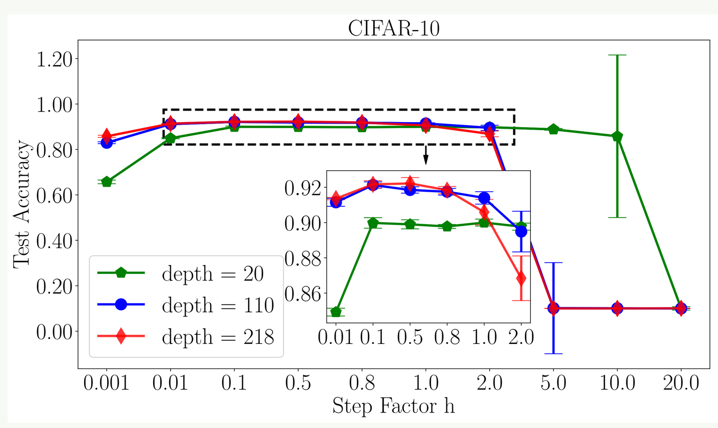
Training with smaller h (h = 0.1) is robust to larger LR with little chance of performance degradation.
For h = 1.0, gradient is unstable and bumpy over training iterations so that it requires careful adaptation of LR. By contrast, for h =0.1, gradient are small and stable, which enable larger LR.

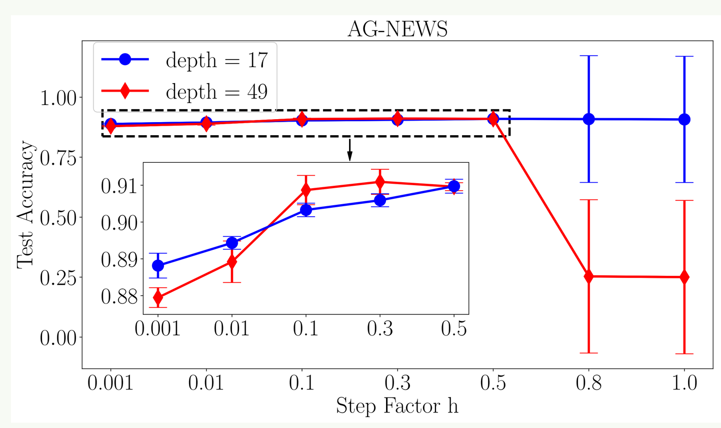
Small h even works on different optimizer - ADAM



We train ResNet using another popular optimizer - ADAM. Our small h still exhibits the competitive training robustness.

How to Select Step Factor h





Too large h will lead to unstable training.
Too small h will smooth out the useful transformations.

The take-away guidance is "smaller but not too small".

Acknowledgements

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