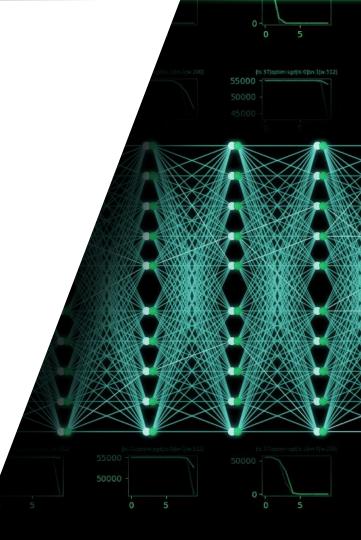


Pre-interpolation Loss Behavior in Neural Networks

Venter, Theunissen & Davel

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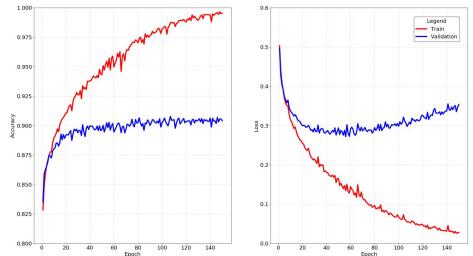
Overview

- Paradoxical relationship between validation loss and accuracy:
 - Limits of a point estimator
 - Overfitting on selected validation samples
- Empirical evidence
- Implications on generalization



Introduction

- Witnessed phenomenon:
 - Increase in both validation loss and accuracy
- Shallow local optima and borderline cases



- Evaluating using individual validation loss distributions:
 - Validation samples with large loss contributions



Approach

- Fully-connected feedforward networks using MLP architecture
- Omitted any regularization
- Trained till convergence
- First step
 - Determine whether phenomenon occurs in general scenarios
- Second step
 - Select best models for further analysis



Architecture

- Cross-entropy loss function
- Equal number of nodes per hidden layers
- Varied hyperparameters values:
 - Training and validation set sizes
 - Number of hidden layers
 - Number of nodes
 - Mini-batch sizes
 - Datasets (MNIST or FMNIST)
 - Optimizers (Adam or SGD)

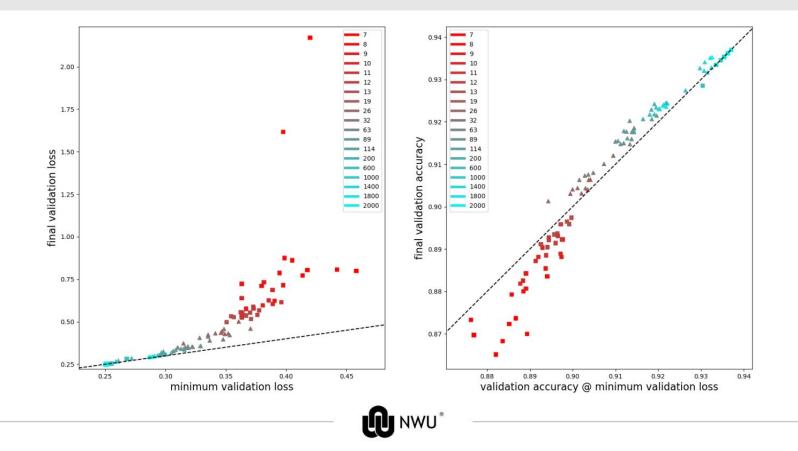


Experimental Setups

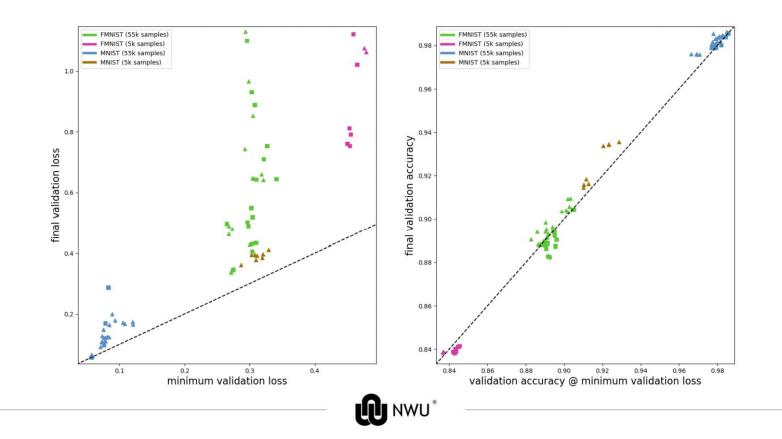
- First Experiment (MNIST):
 - \circ 95 two-layer MLPs with 7 2000 nodes per layer
 - 5000 training samples
 - Mini-batch size of 64
 - Adam (57) and SGD (38) optimizers
- Second Experiment (MNIST, FMNIST):
 - 80 MLPs with varying depth (1 /3 /10 layers) and width (100/ 1000 nodes)
 - 5000 /55000 training samples
 - Mini batch sizes of 16/ 64/ 256
 - Adam and SGD optimizers



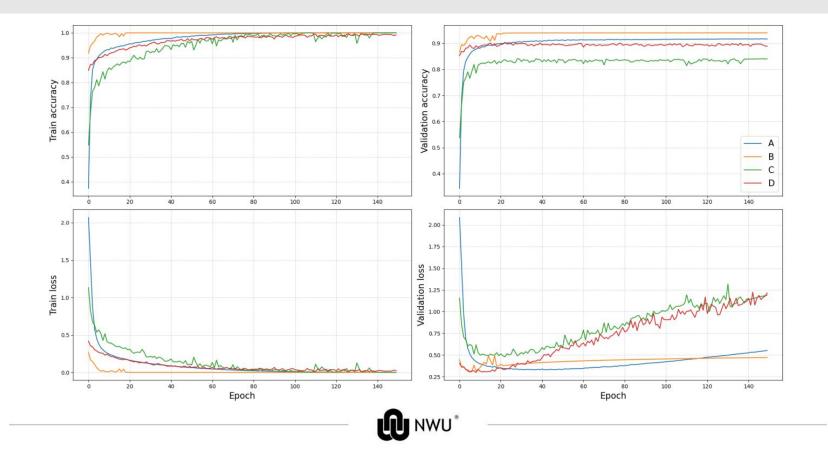
Results – First Experiment



Results – Second Experiment



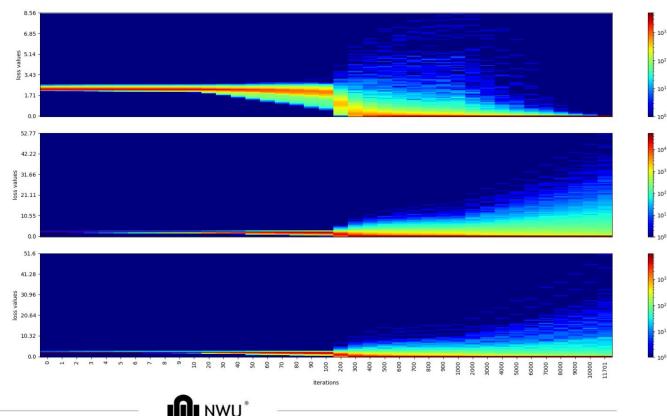
Results – Distribution analysis



Results – Distribution analysis

Model A:

- 3x100 MLP
- 5000 MNIST samples •
- Adam optimizer ٠
- Mini-batch of 64 ٠

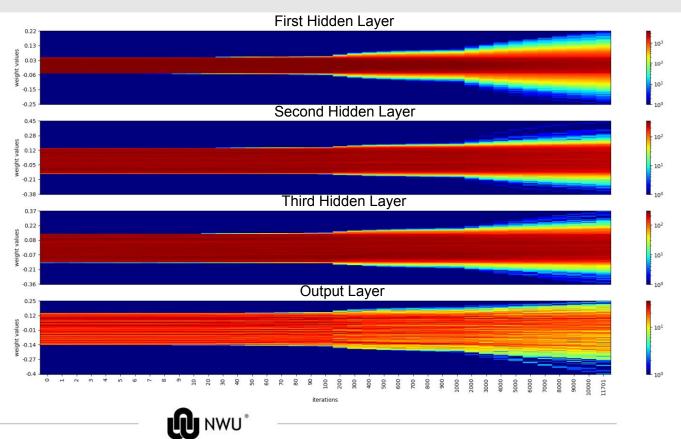


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Results – Distribution analysis

Model A:

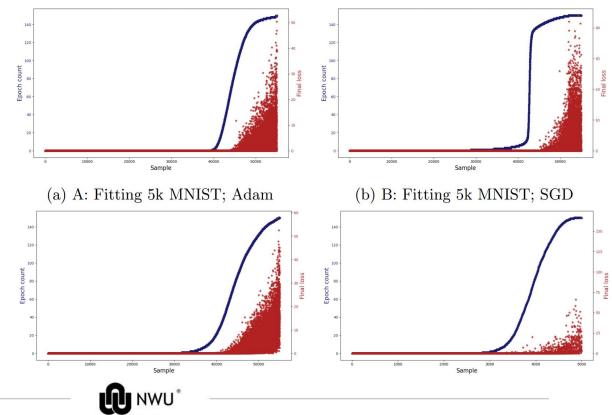
- 3x100 MLP
- 5000 MNIST samples
- Adam optimizer
- Mini-batch of 64



Results - Outliers

 $Q_3 + 1.5 \times (Q_3 - Q_1)$

Q₃ - Third quartile of loss values Q₁ - First Quartile of loss values



In summary

- Discrepancies between validation loss and accuracy can exist where both will show increases their respective metrics
- This is due to the large loss contributions of a minority of validation loss samples
- Point estimators are a poor estimate of generality because loss values aren't necessarily close to a mean value
- Weight values are increased to minimize training loss but sacrifices generality in the process
- DNNs seem to be distributed and heterogenous and should be considered when focussing on generalization



Thank you!

