Understanding Deep Learning Requires Rethinking Generalization

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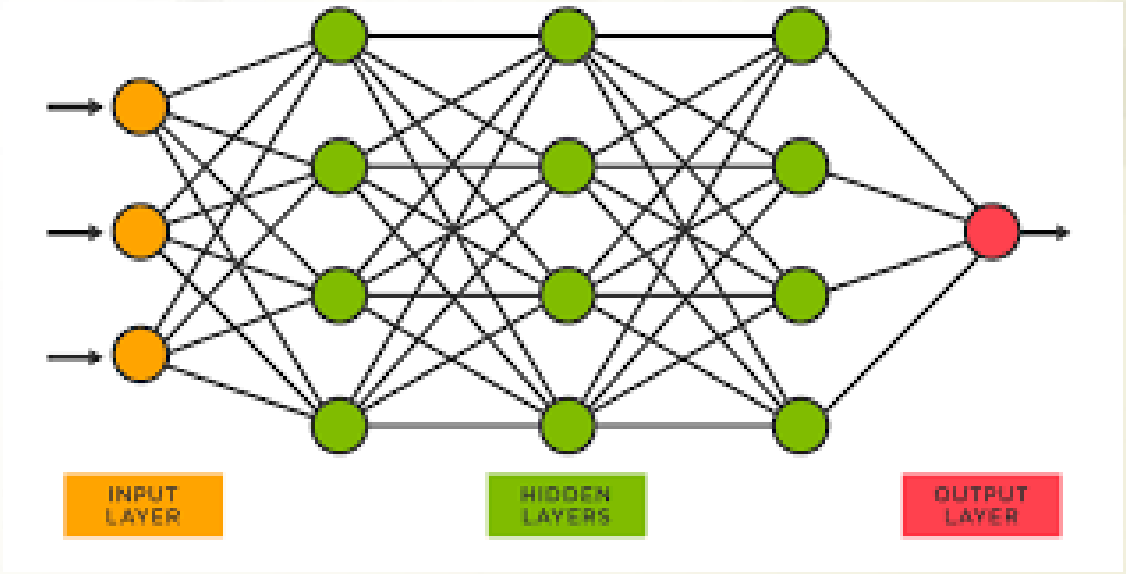


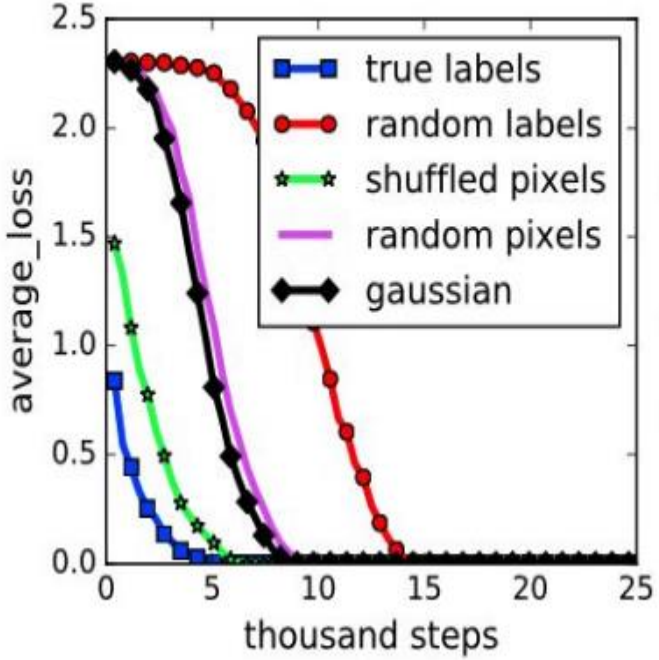
INTRODUCTION

- Deep Neural Networks have the ability to generalise well on the given dataset.
- They show very small difference in the training and test performance.
- But the questions to consider here are:
  - What gives them the ability to generalize well?
  - Are they learning the 'actual' association?
  - Can we train the network to learn random associations?
  - Does regularization play a significant role while training a deep network?
- Due to the way in which neural networks are formulated, we cannot use traditional methods (VC dimension, uniform stability, etc.) to understand the generalization ability.

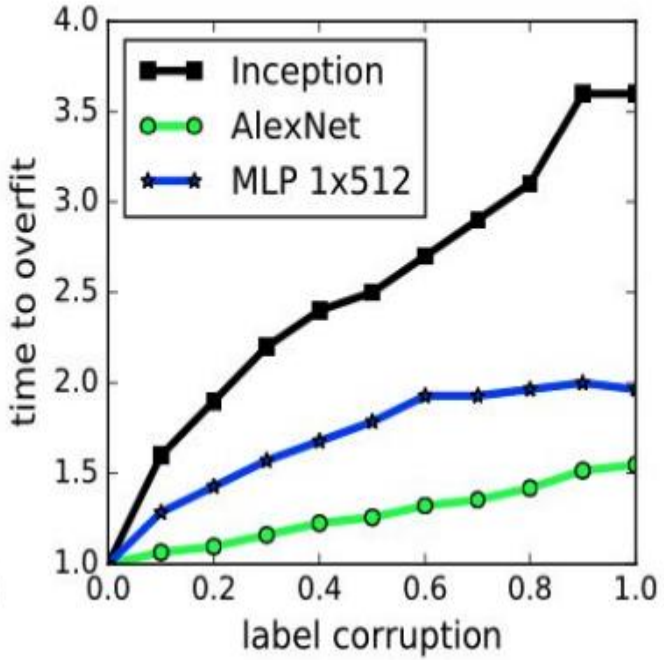
INTRODUCTION

- This following experiments shows that the traditional view of generalization is incapable of distinguishing between different neural networks that have different generalization performance.
- For that purpose we do the following experiments:
  - Randomized testing
    - As the name suggests, here the neural networks are provided a different set of inputs and outputs and the performance is checked.
  - Role played by explicit regularization
    - Here we try to understand how well various regularization techniques like, weight decay, dropout, and data augmentation, are playing role in generalization.
  - Role played by implicit regularization
    - Implicit regularization techniques such as batch norm, SGD and early stopping are applied to check the performance of neural network

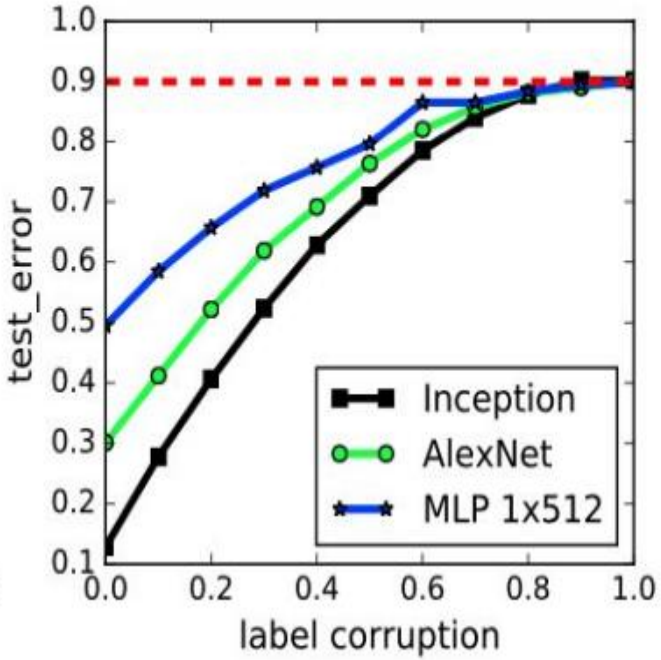
Randomized Testing



(a) learning curves



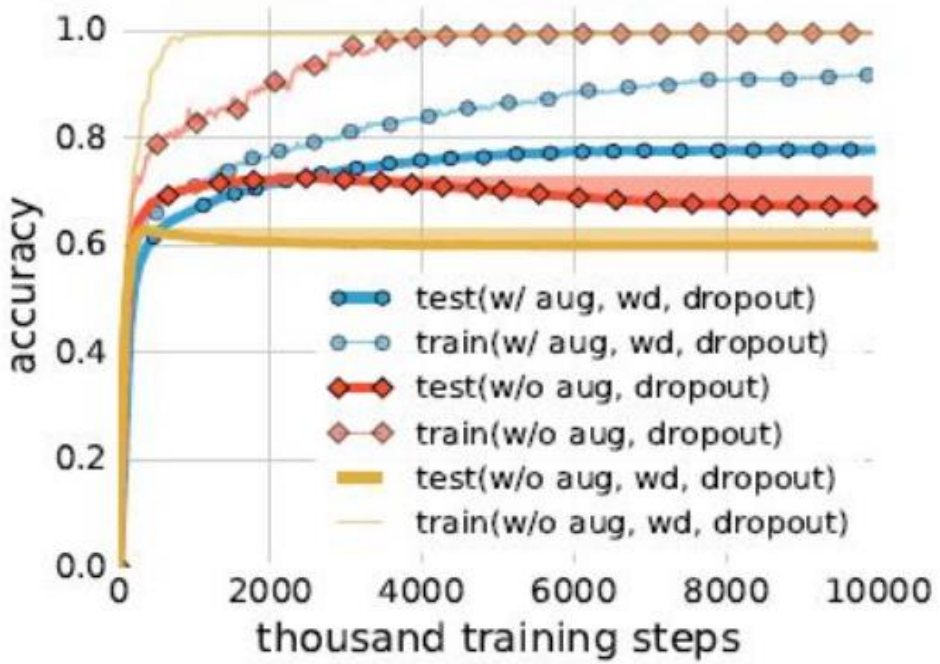
(b) convergence slowdown



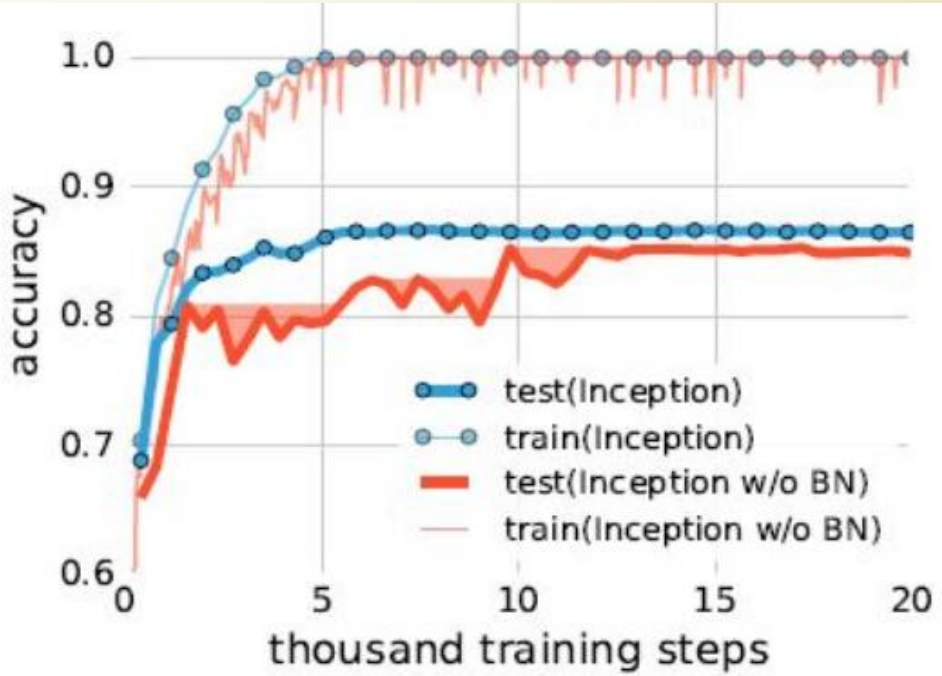
(c) generalization error growth

Figure 1: Fitting random labels and random pixels on CIFAR10. (a) shows the training loss of various experiment settings decaying with the training steps. (b) shows the relative convergence time with different label corruption ratio. (c) shows the test error (also the generalization error since training error is 0) under different label corruptions.

Role Played by Regularization



(a) Inception on ImageNet



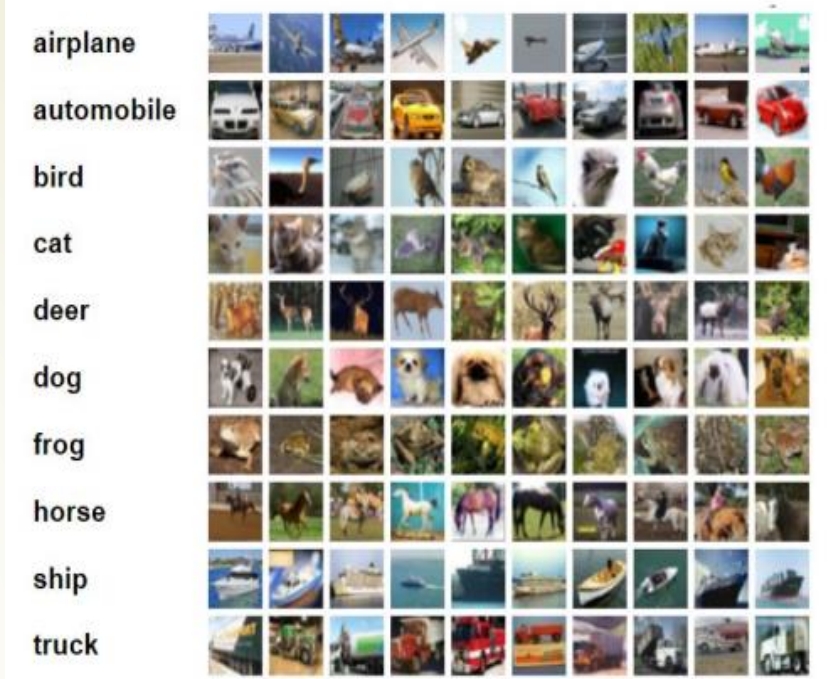
(b) Inception on CIFAR10

Figure 2: Effects of implicit regularizers on generalization performance. aug is data augmentation, wd is weight decay, BN is batch normalization. The shaded areas are the cumulative best test accuracy, as an indicator of potential performance gain of early stopping. (a) early stopping could potentially improve generalization when other regularizers are absent. (b) early stopping is not necessarily helpful on CIFAR10, but batch normalization stablize the training process and improves generalization.

Datasets

CIFAR-10 :

- Dataset contains 50,000 training and 10,000 validation
- images
- Total Number of classes: 10
- Image size is 32x32 with 3 channels (cropped to 28x28)



ImageNet :

- Dataset contains 1,281,167 training and 50,000
- validation images
- Total Number of classes: 1000
- Image resized to 299x299 with 3 channels

Randomized Testing

- Here the goal is to see how well the neural networks generalize to data which is not 'logical' for us humans.
- To make sure that the results are what is being observed, we perform these set of experiments:
  - Using true labels as a baseline.
  - Corrupting the labels by replacing a label with a random class's label.
  - Shuffling pixels of the input image.
  - Randomizing the pixels of the input image.
  - Creating noisy images using Gaussian noise while using the variance & mean of the dataset.
- Logically, it feels like apart from the first case, the models should not converge but, as we will see in the slides ahead, the results are surprising.

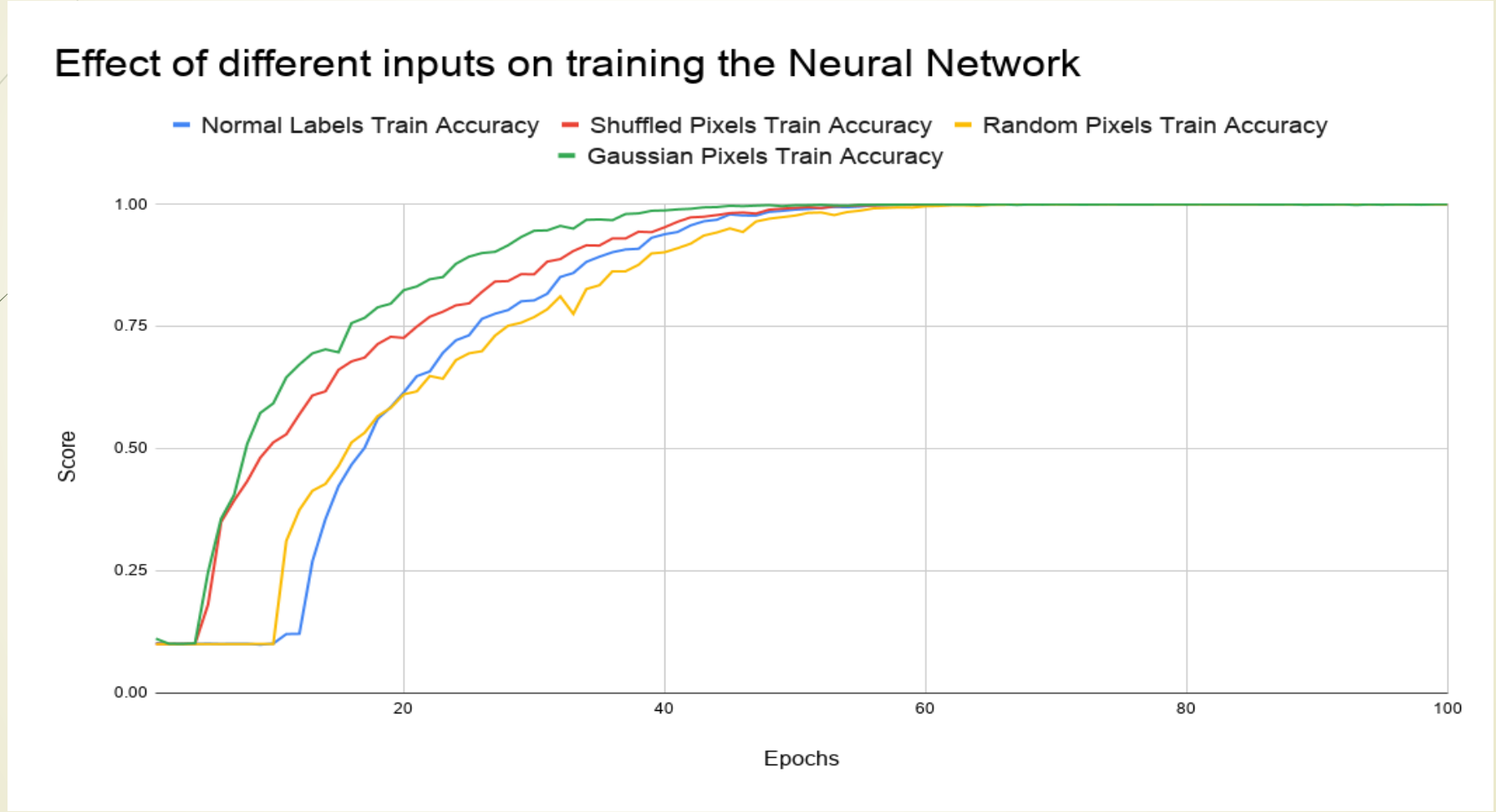
Randomized Testing

- The following trends are observed in the graphs in the original paper
  - With zero input and zero output corruption, the training converges in very few number of iterations
  - The time to converge for different corruption scenarios has the order:

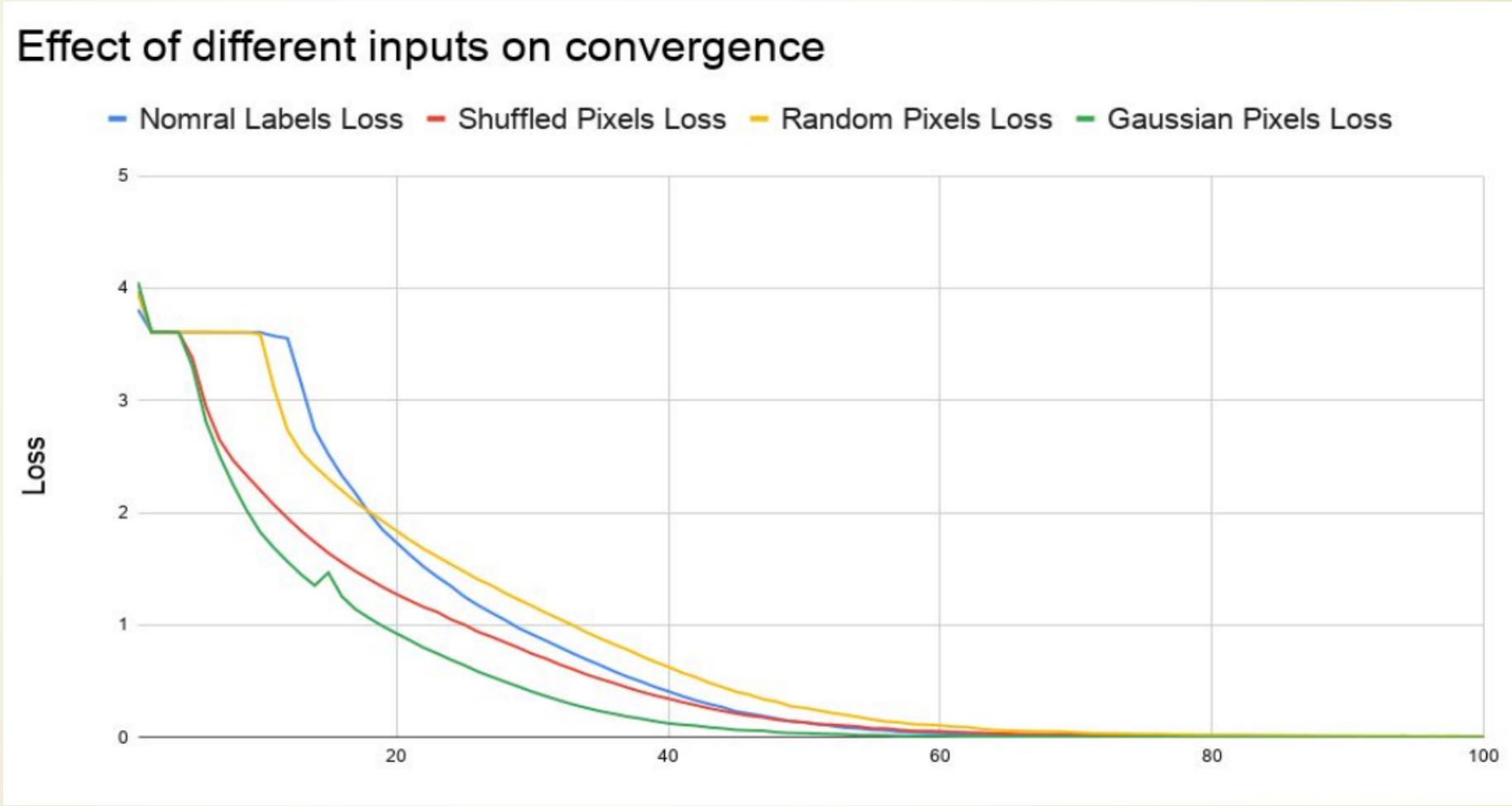
No corruption < Pixel shuffling < Gaussian pixels < Random pixels < Random labels

  - For label corruption experiment, the time to converge increases with increase in the percentage of corrupted labels
  - For label corruption experiment, the generalization error increases with increase in the percentage of corrupted label
- In all randomization experiments, the model is able to "shatter" the training data ie achieve 100% accuracy with sufficient number of iterations.

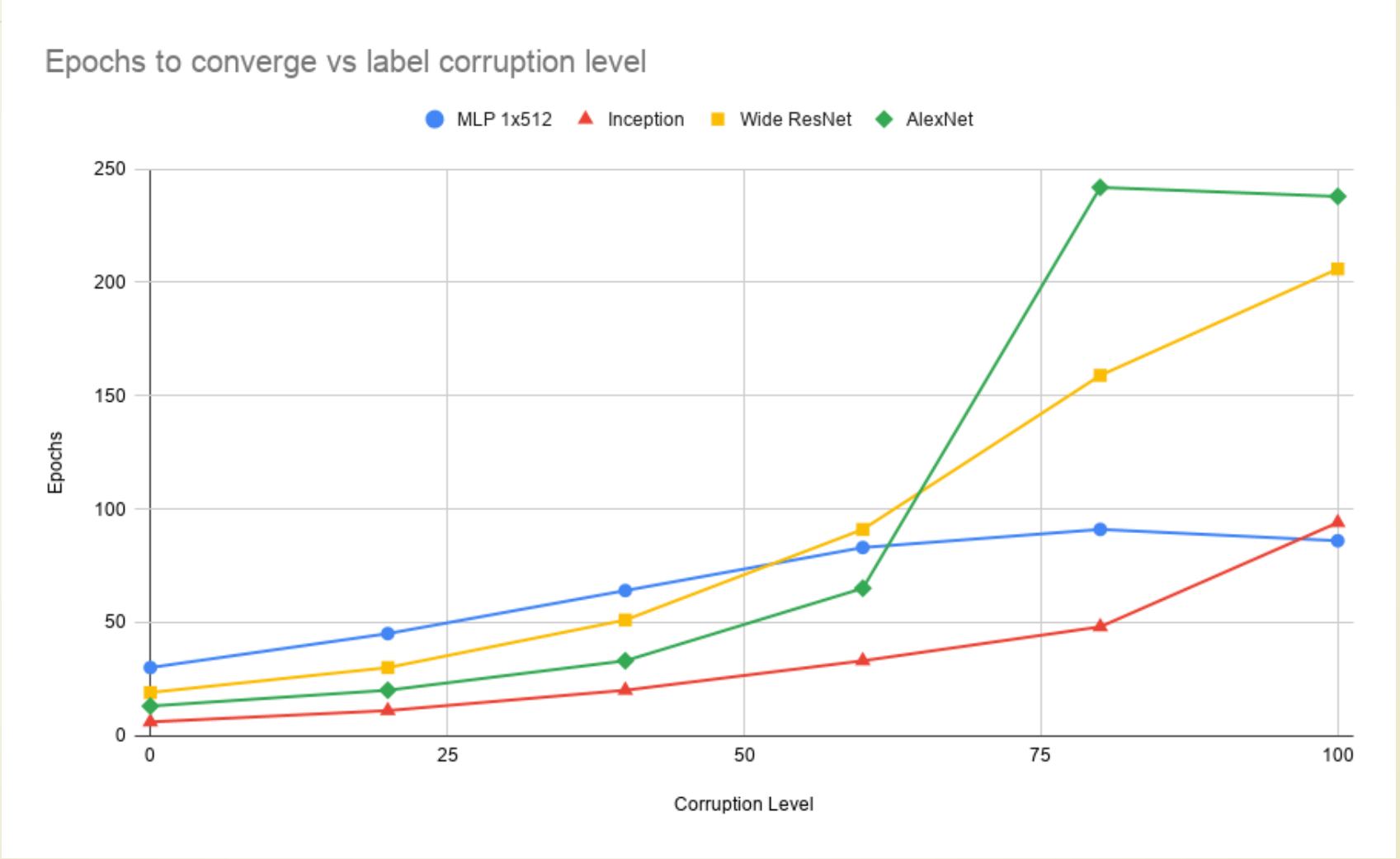
Effect of different inputs



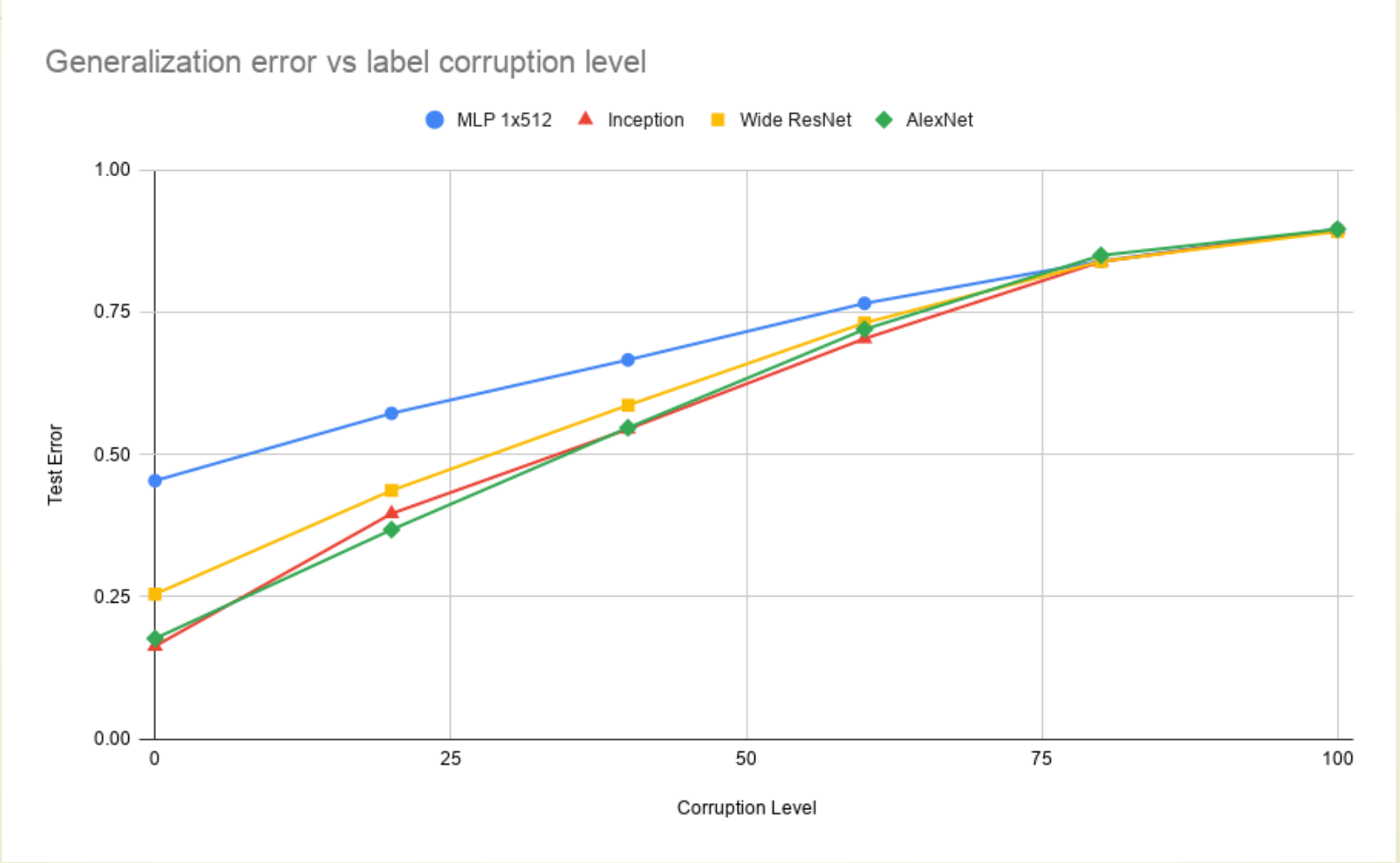
Effect of different inputs



Label corruption: convergence



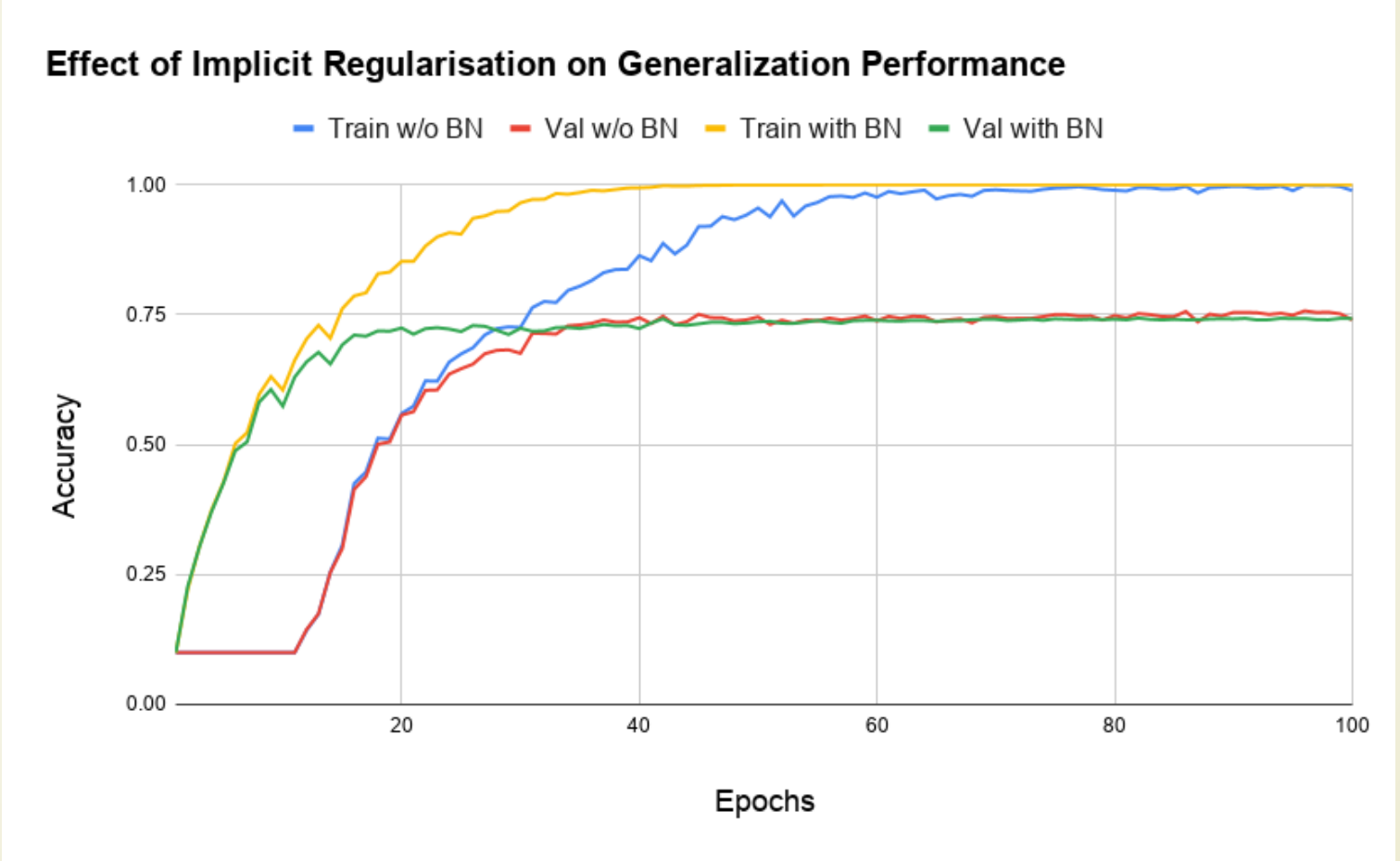
Label corruption: Generalization Error



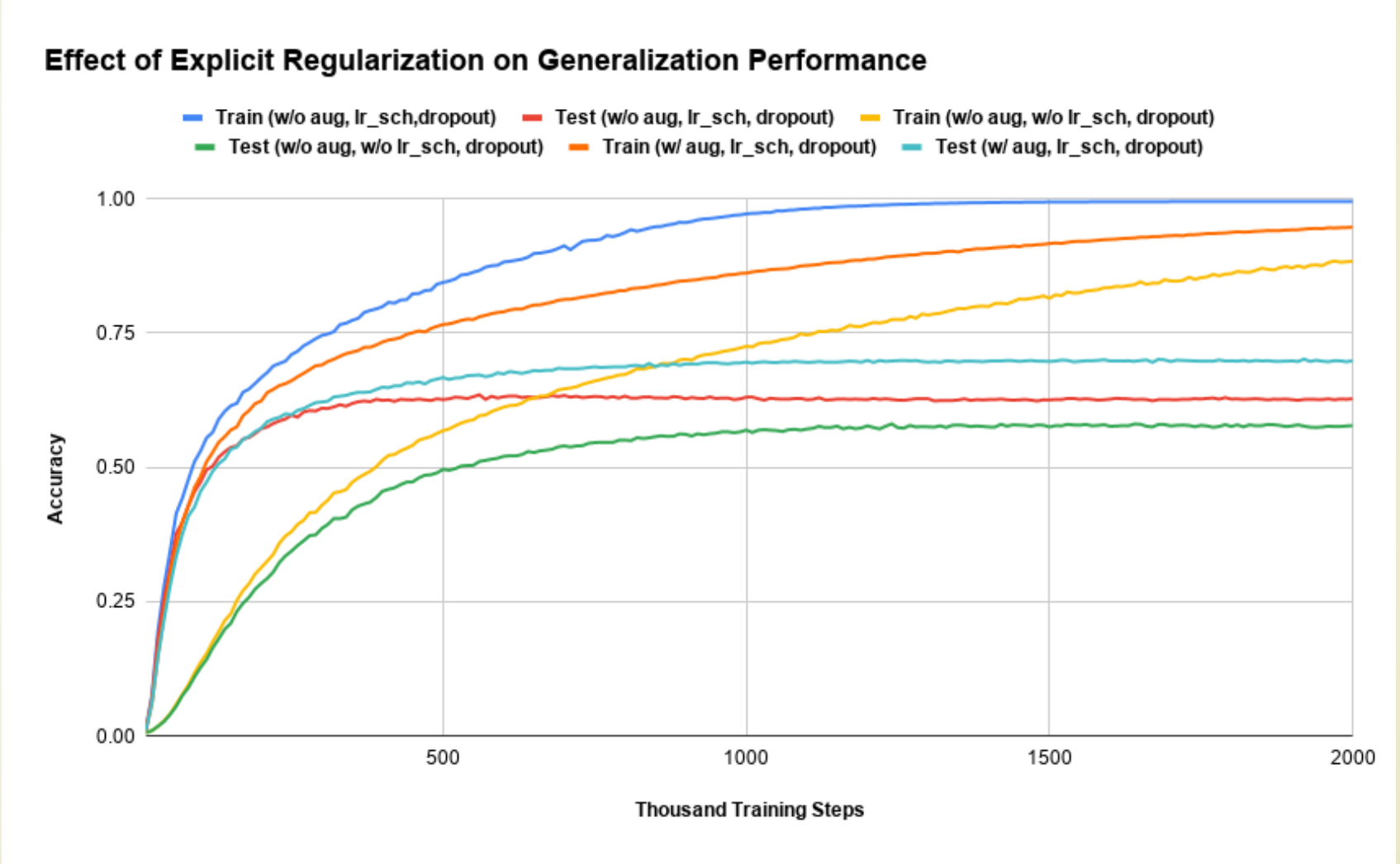
Role played by regularization

- We study the role of applying regularization on model training and its ability to generalize.
- There are some techniques like Batch Normalization which are not meant for regularization but indeed they gave regularization effect (Implicit Regularization).
- Other commonly used regularization techniques like weight deacy, dropout and data augmentation are explicitly used to induce regularization (Explicit Regularization).
- The author argues that "Explicit regularization may improve generalization performance, but is neither necessary nor by itself sufficient for controlling generalization error."
- The experiments suggests that tuning parameters help in improving generalization.
- **The effect of regularization is minimal on generalization.**

Our experiments on Regularization



Our experiments on Regularization



Project Summary

- **Aim**: To understand what differentiates neural networks that generalize well from those that do not
- **Datasets**: CIFAR10, ImageNet
- **Models**: MLP-512, Inception (tiny), Wide ResNet, AlexNet, Inception_v3
- Experiments done:
  - Effect of explicit regularization like augmentation, weight decay, dropout
  - Effect of implicit regularization like BatchNorm
  - Input data corruption: Pixel shuffle, Gaussian pixels, Random pixels
  - Label corruption with different corruption levels from 1 to 100 %

Conclusion

- Neural networks have the capacity to memorize massive training datasets and achieve

  near 100% training accuracy with enough training iterations. This is irrespective of both corruption in input data and corruption in output labels
- With input or output corruption, the convergence time goes up only by a small factor
- The progressive label corruption experiment shows that NNs capture remaining signal in

  the uncorrupted portion of training data and overfit on the corrupted portion
- Explicit regularization may improve generalization performance, but is neither necessary

  nor by itself sufficient for controlling generalization error
- Implicit regularization like SGD and BatchNorm are also not the primary reasons for

  generalization capability. They only helps in making training process smooth.
- We have yet to discover a precise formal measure which we can use to construct small

  models with good generalization capacity. As of now it is based on experimentation

THANK YOU