AI CLUB PROJECT:

OPTIWING

PAPER IMPLEMENTATION

REPORT

LEARNING RESOURCES

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INVERSE DESIGN OF AIRFOILS USING CONVOLUTIONAL NEURAL NETWORK AND DEEP NEURAL NETWORK

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ABSTRACT

In this paper, we compare the efficacy of two neural network based models: Convolutional Neural Network (CNN) and Deep Neural Networks (DNN) to inverse design the airfoil shapes. Given the pressure distribution over the airfoil in pictorial (for CNN) or numerical form (for DNN), the trained neural networks predict the airfoil shapes. During the training phase, the critical hyper-parameters of both the models, namely – learning rate, number of epochs and batch size, are tuned to reduce the mean squared error (MSE) and increase the prediction accuracy. The training parameters in DNN are an order of magnitude lower than that of CNN and hence the DNN model is found to be $\approx 7\times$ faster than the CNN. In addition, the accuracy of DNN is also observed to be superior to that of CNN. After processing the raw airfoil shapes, the smoothed airfoils are shown to yield the target pressure distribution thereby validating the framework.

over the aerodynamic surfaces. Designing efficient aerodynamic control surfaces, both external (wings/flaps/slats/ailerons,etc) and internal (compressor/turbine/propeller blades), is crucial to minimize the total pressure losses due to drag forces. During the design process, the component shape evolves iteratively. The designer solves an optimization problem with a single/multi-objective function of reducing the total pressure loss and/or increasing the efficiency satisfying certain design constraints like mass flow rate/rotational speed, etc. One of the techniques which accelerates this process is the Inverse Design method. In this method, the designer sets the required target; say the pressure distribution over the airfoil; and generates an optimized airfoil shape or blade [1]. As noted by [2], the optimization processes are broadly classified into gradient-based and gradient-free algorithms. Gradient-free algorithms can reach a globally optimal solution but require longer convergence times and are much more complex. On the other hand, as noted by [3], gradient-based algorithms are suitable for designing the shapes that are

INVERSE DESIGN OF AIRFOILS USING CNN AND DNN

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Year : 2021

TASK:

Implementing the Model

LEARNING OBJECTIVES

Objective 1 Learn the basics of a CNN/DNN and How to implement them in PyTorch

Objective 2 Get accustomed with using XFoil to generate training Airfoil Data

Objective 3 Implement the Model in the paper to get a baseline model to improve upon

LEARNING OUTCOMES

Outcome 1

Created an automated workflow for generating training data using XFoil from UIUC Database.

Outcome 2

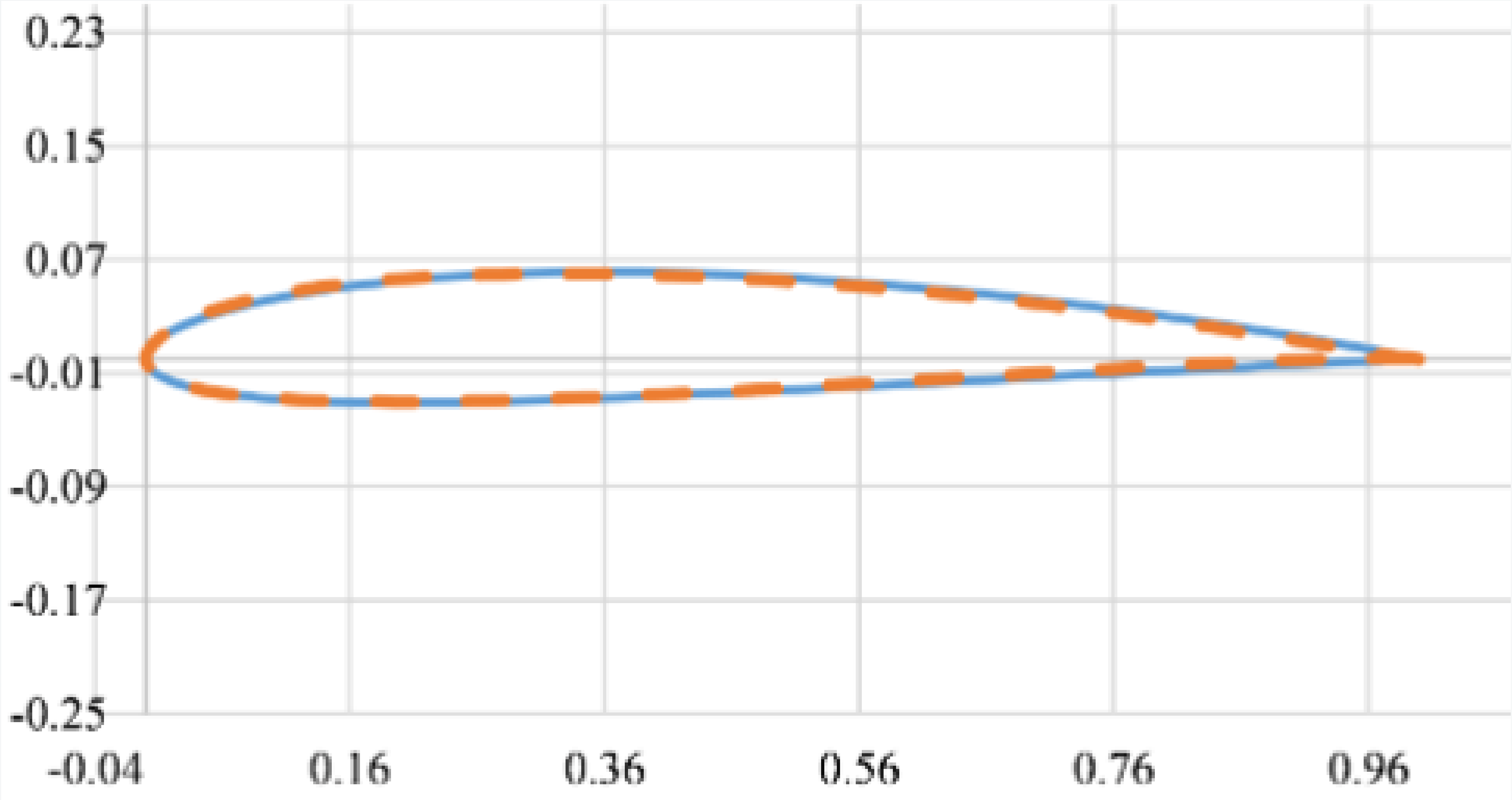
Implemented the model mentioned in the paper and trained it using preprocessed training data generated from automated workflow

Outcome 3

Generated comparison data for improving the model in the future

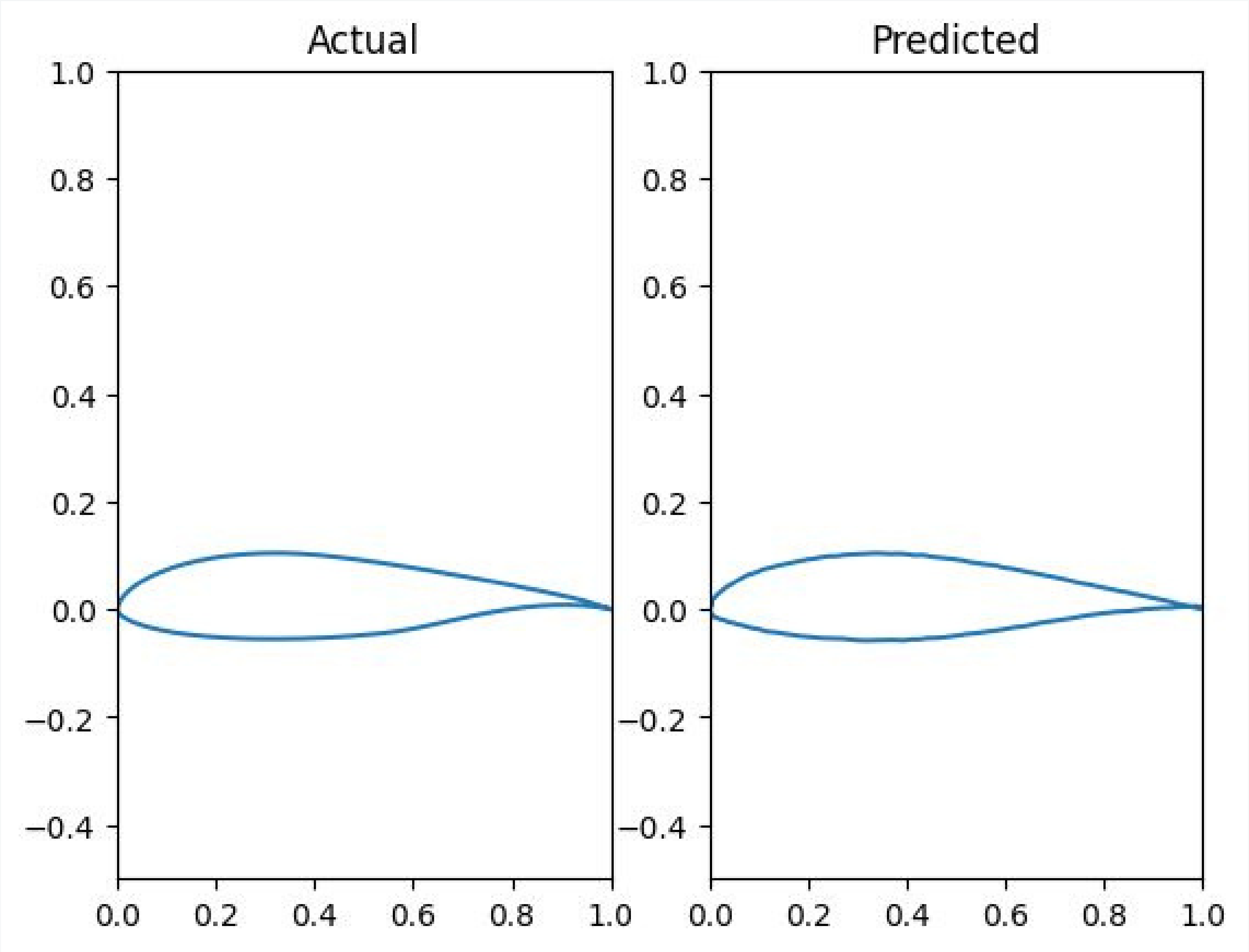
Plots

Predicted vs actual (as per paper)

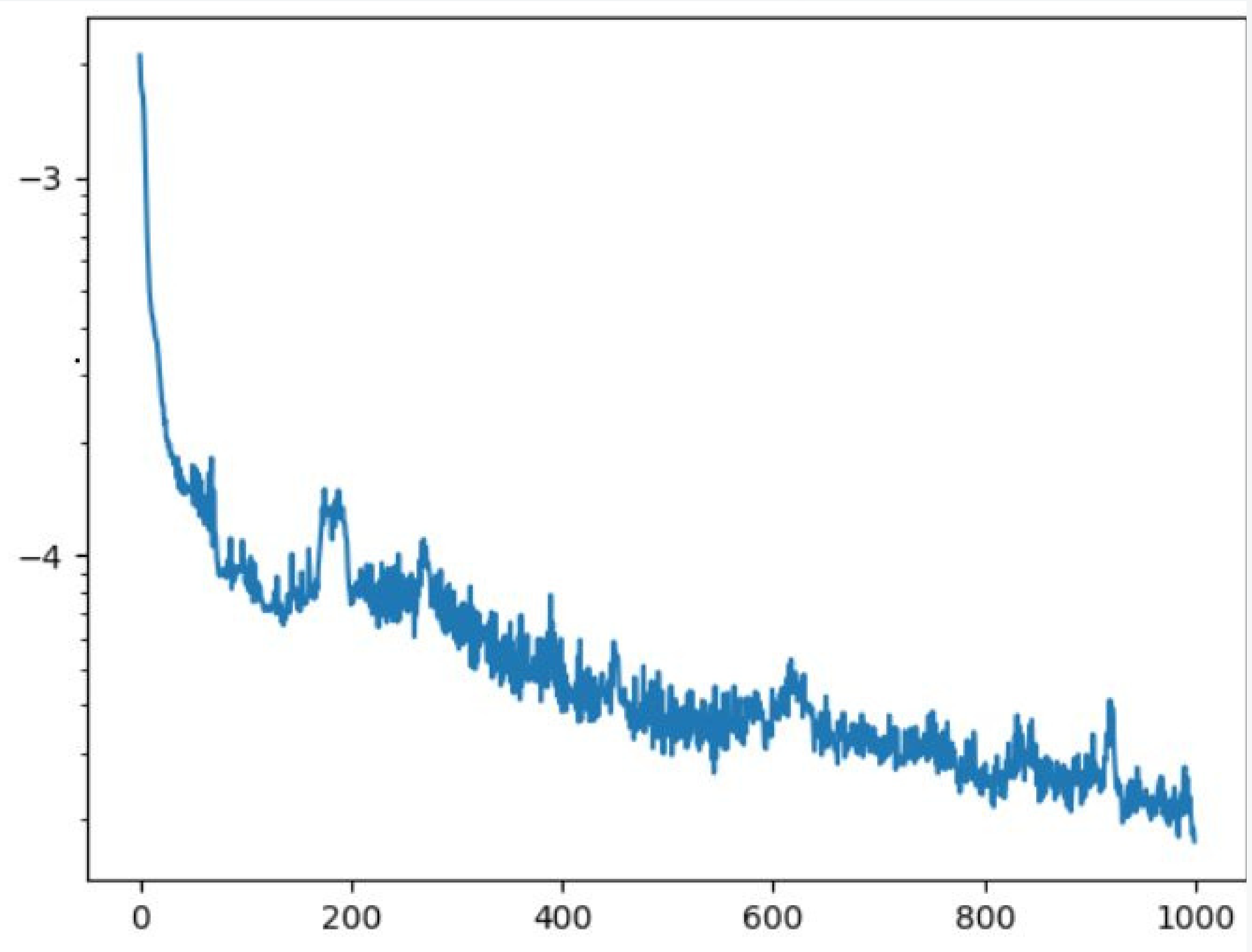


Learning Rate : 0.001

Predicted vs actual airfoil

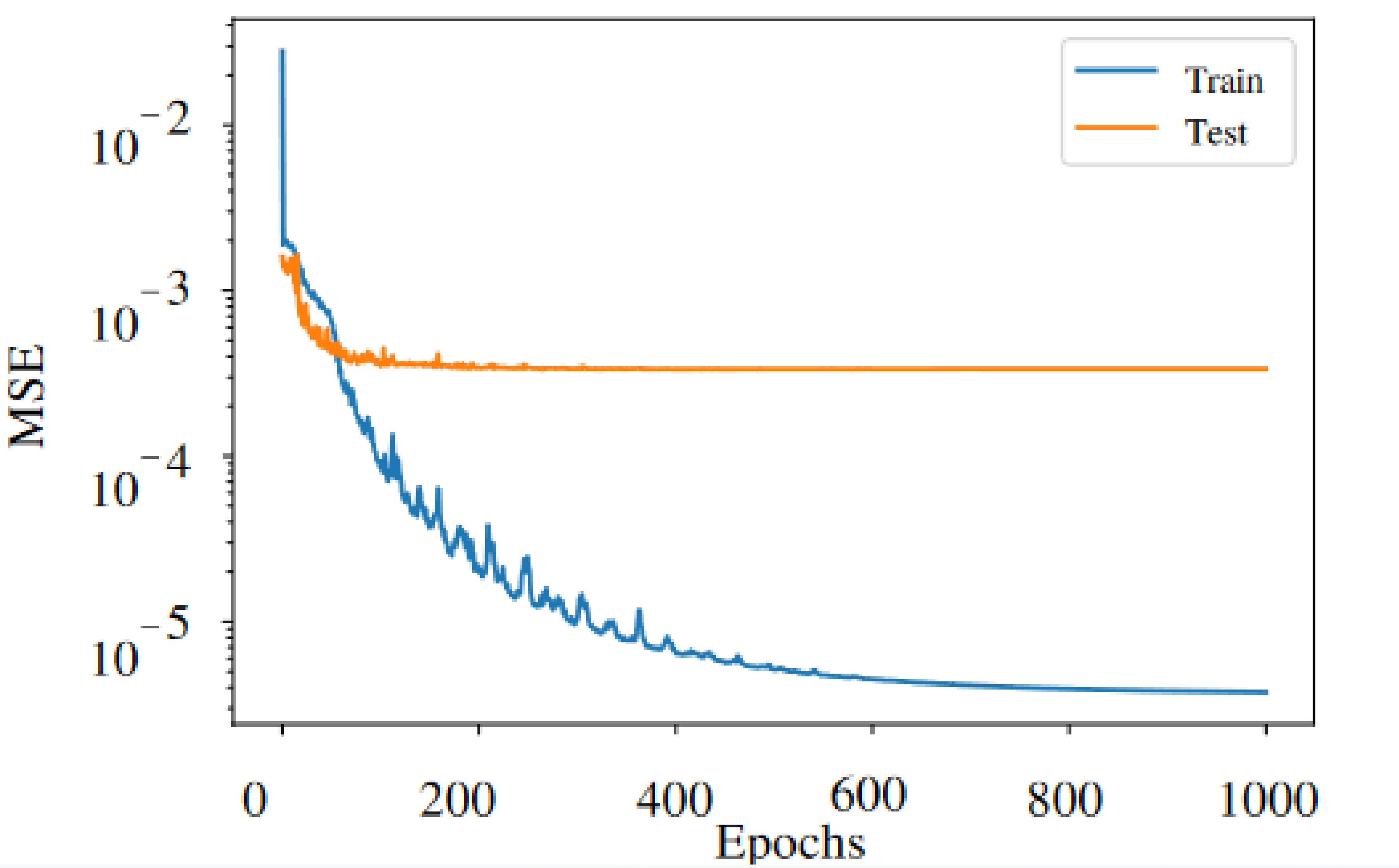


Epochs vs log(MSE loss)



Learning Rate : 0.001

Epoch vs MSE loss in paper



Other Plots

Insights from the picture:

- Optimal Learning rate is around 0.001
- Optimal Epochs is around 400
- Higher Learning rate results in missing the minima
- Higher Epoch might result in over-fit