FORWARD-FORWARD ALGORITHM REVISITED

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INTRODUCTION

- FFA is trying to be more biologically plausible and as a side effect more efficient for certain hardware configurations such as analog hardware.
- The algorithm revolves around local update rules based on a goodness score calculated as the **p(positive) = σ(Sum(yl^2) – θ)** where **θ** is the hyper-parameter threshold and **yl** are the activations of the **layer l** thus localizing the loss calculation and update on each individual layer thus parallelizing the training process.

APPROACH

- We are building our neural networks in Pytorch, testing the performance of both a Forward-Forward trained model and two traditionally trained models for each task.
- Hardware configurations:
    - i3-10100F + gtx 1050ti
    - i7 14650-hx + rtx 4060M
    - i7-10750H + gtx 1650ti

  (we will specify the hardware used for each experiment as to not confuse them)

APPROACH

We will test and compare FFA results to the other models by looking at the following metrics:

- Train time
- Number of epochs
- Accuracy
- Memory usage on similar performance
- Overfit and underfit tendencies

The Predictive Forward-Forward Algorithm

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Abstract

We propose the predictive forward-forward (PFF) algorithm for conducting credit assignment in neural systems. Specifically, we design a novel, dynamic recurrent neural system that learns a directed generative circuit jointly and simultaneously with a representation circuit. Notably, the system integrates learnable lateral competition, noise injection, and elements of predictive coding, an emerging and viable neurobiological process theory of cortical function, with the forward-forward (FF) adaptation scheme. Furthermore, PFF efficiently learns to propagate learning signals and updates synapses with forward passes only, eliminating key structural and computational constraints imposed by backpropagation-based schemes. Besides computational advantages, the PFF process could prove useful for understanding the learning mechanisms behind biological neurons that use local signals despite missing feedback connections. We run experiments on image data and demonstrate that the PFF procedure works as well as backpropagation, offering a promising brain-inspired algorithm for classifying, reconstructing,

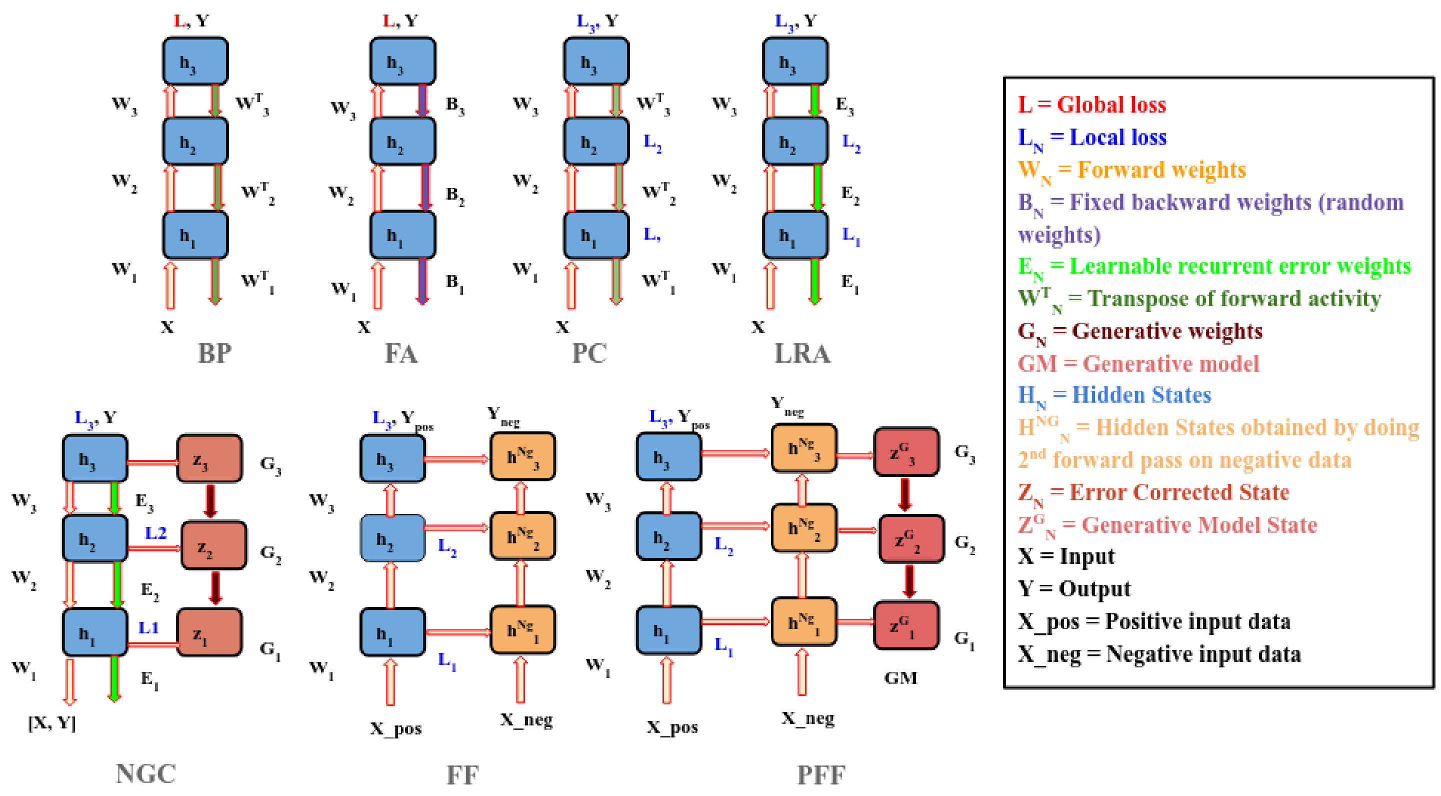

Figure 1: Comparison of credit assignment algorithms that relax constraints imposed by backpropagation of errors (BP). Algorithms visually depicted include feedback alignment (FA) [31], predictive coding (PC) [48, 52], local representation alignment (LRA) [45], neural generative coding (NGC) [43, 41], the forward-forward procedure (FF) [19], and the predictive forward-forward algorithm (PFF).

Extending the Forward Forward Algorithm

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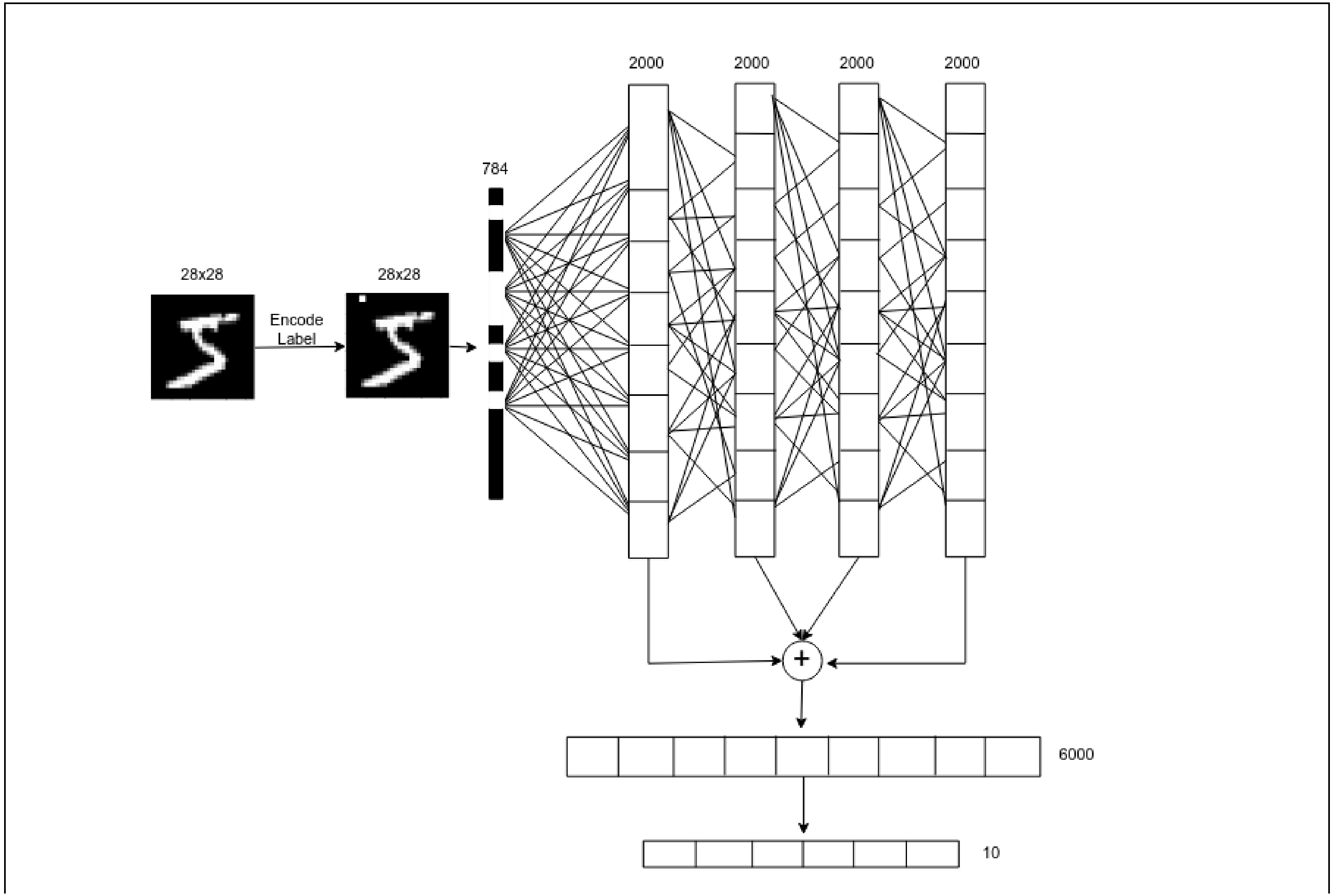
Abstract

The Forward Forward algorithm, proposed by Geoffrey Hinton in November 2022, is a novel method for training neural networks as an alternative to backpropagation. In this project, we replicate Hinton's experiments on the MNIST dataset, and subsequently extend the scope of the method with two significant contributions. First, we establish a baseline performance for the Forward Forward network on the IMDb movie reviews dataset. As far as we know, our results on this sentiment analysis task marks the first instance of the algorithm's extension beyond computer vision. Second, we introduce a novel pyramidal optimization strategy for the loss threshold - a hyperparameter specific to the Forward Forward method. Our pyramidal approach shows that a good thresholding strategy causes a difference of upto 8% in test error. [1] Lastly, we perform visualizations of the trained parameters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Training convolutional neural networks with the Forward–Forward Algorithm

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Recent successes in image analysis with deep neural networks are achieved almost exclusively with Convolutional Neural Networks (CNNs), typically trained using the backpropagation (BP) algorithm. In a 2022 preprint, Geoffrey Hinton proposed the Forward–Forward (FF) algorithm as a biologically inspired alternative, where positive and negative examples are jointly presented to the network and training is guided by a locally defined goodness function. Here, we extend the FF paradigm to CNNs. We introduce two spatially extended labeling strategies, based on Fourier patterns and morphological transformations, that enable convolutional layers to access label information across all spatial positions. On CIFAR10, we show that deeper FF-trained CNNs can be optimized successfully and that morphology-based labels prevent shortcut solutions on dataset with more complex and fine features. On CIFAR100, carefully designed label sets scale effectively to 100 classes. Class Activation Maps reveal that FF-trained CNNs learn meaningful and complementary features across layers. Together, these results demonstrate that FF training is feasible beyond fully connected networks, provide new insights into its learning dynamics and stability, and highlight its potential for neuromorphic computing and biologically inspired learning.

Keywords Forward–forward, CNN, Explainable AI, Class activation maps

Machine learning using deep neural networks (DNN) continues to transform human life in areas as different as art (DALL-E, stable diffusion), medicine (Alpha-Fold), transport, or natural language models (ChatGPT, Gemini). Here, the adjective "deep" refers to the number of layers of artificial neurons, which can reach hundreds. Training these networks means shifting the weights that connect the layers from their initial random

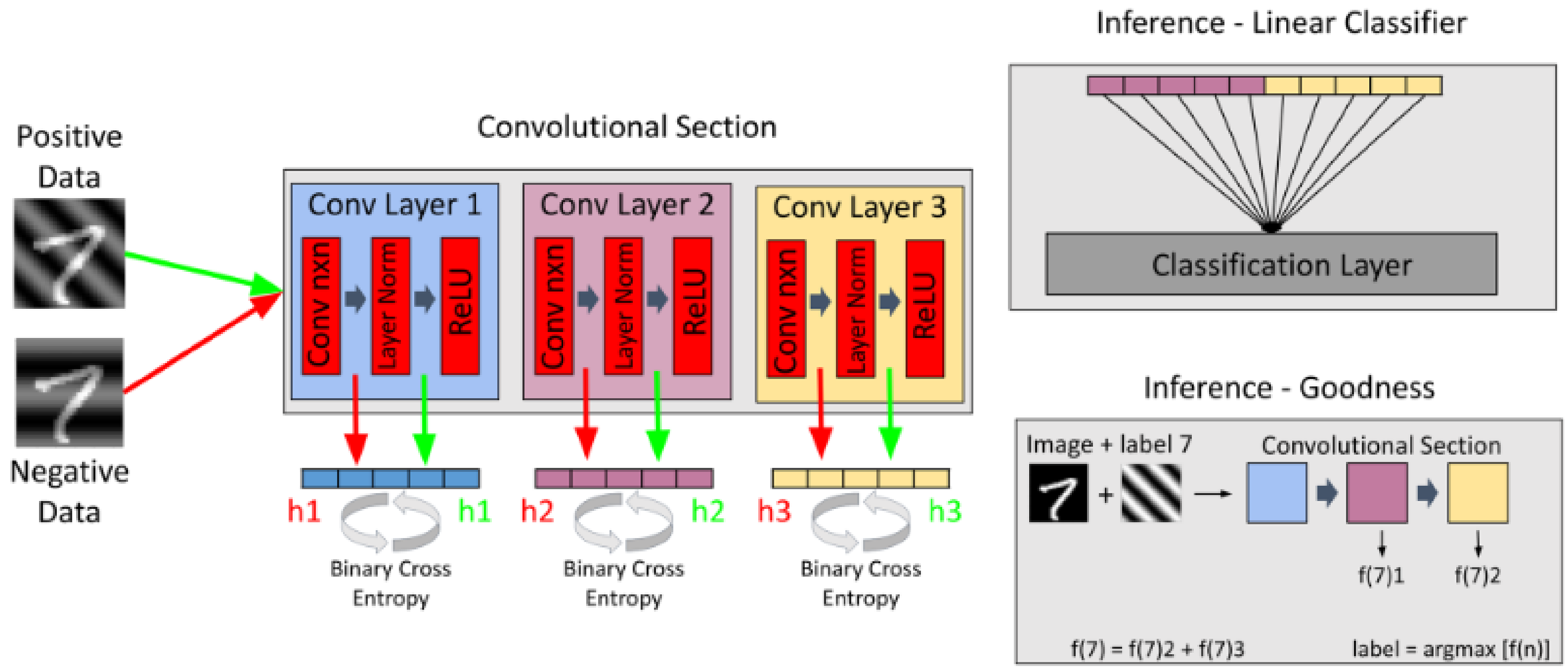

Fig. 2. Schematic overview of the FF-trained CNN applied to the MNIST dataset. Positive and negative samples are processed through three convolutional layers, each followed by layer normalization and ReLU activation. At every layer, the goodness function is computed using binary cross-entropy for both positive and negative samples. Final classification can then be performed either through a linear classifier or by evaluating the goodness scores across all labels.

12/12/2025

TASK 1: XOR

- This is just a validation problem proving that FFA can solve this problem as well as showing difference in the ration of neurons necessary to solve it.

TASK 2: MNIST

The MNIST dataset is composed of 70,000, label 28x28 images of grayscale handwritten digits that is used to benchmark image classification algorithms.

For this test we are going to write a FFA MLP network as well as the 2 corresponding MLP backprop networks, and try our hands at a FFA CNN and it's comparison networks .

TASK 3: IMDB REVIEWS

The IMDB Reviews dataset consists of 50K tagged movie reviews, the tag can be positive or negative. In this case we are to preprocess the text and using the model word2vec to get the embeddings for the model.

Now as for the architecture of the model we are going to use a MLP and it's corresponding backprop models. Here we have the chance to compare the results of this model with a basic RNN or LSTM, these being architectures that are normally impossible to train using FFA.

TASK 4: SHERLOCK HOLMES NEXT-WORD PREDICTION CORPUS

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LIMITATIONS

- The main limitations to Forward-Forward Algorithm:

  - difficult to create Deep Neural Networks

  - fails on large datasets or complex tasks

  - highly dependent on negative data

ARTICOLE

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https://www.cs.toronto.edu/~hinton/FFA13.pdf

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