Spiking Forward-Forward

Independent Research Project

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Spiking Forward-Forward

- Definition
  - Purpose
  - Composition
- Implementation
  - Design
  - Optimization
- Experiment
  - Poisson datasets
  - Non-Poisson datasets

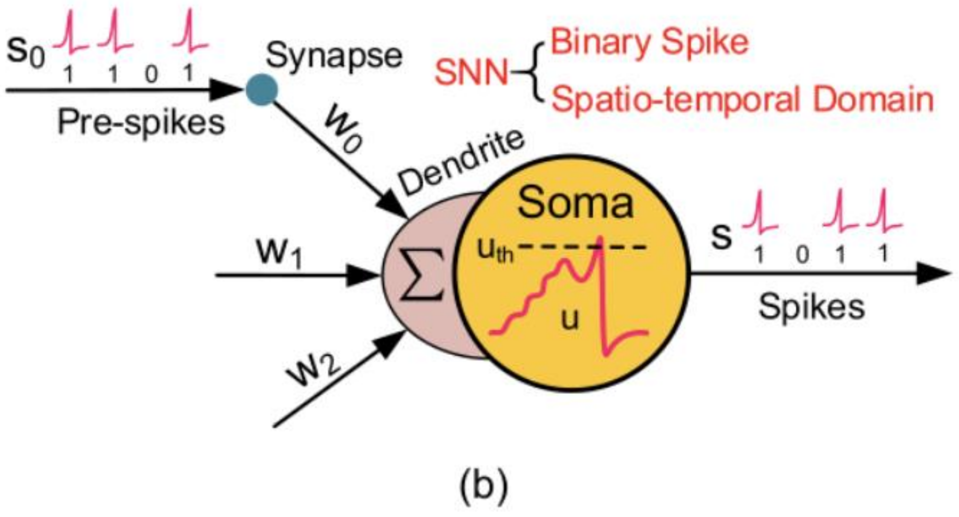
Definition: Purpose

- What is Spiking Forward-Forward?
  - A machine learning algorithm based on spiking neural networks that does not require backpropagation.
- Two key features:
  - The low power consumption advantage from SNN
  - The flexibility from backpropagation-free
- Purposes and potential:
  - Deployed on neuromorphic edge hardware for training and inference
  - Further alleviating the difficulty of training spiking neural networks

Definition: Composition

- As a combination, Spiking Forward-Forward consists of two key parts:

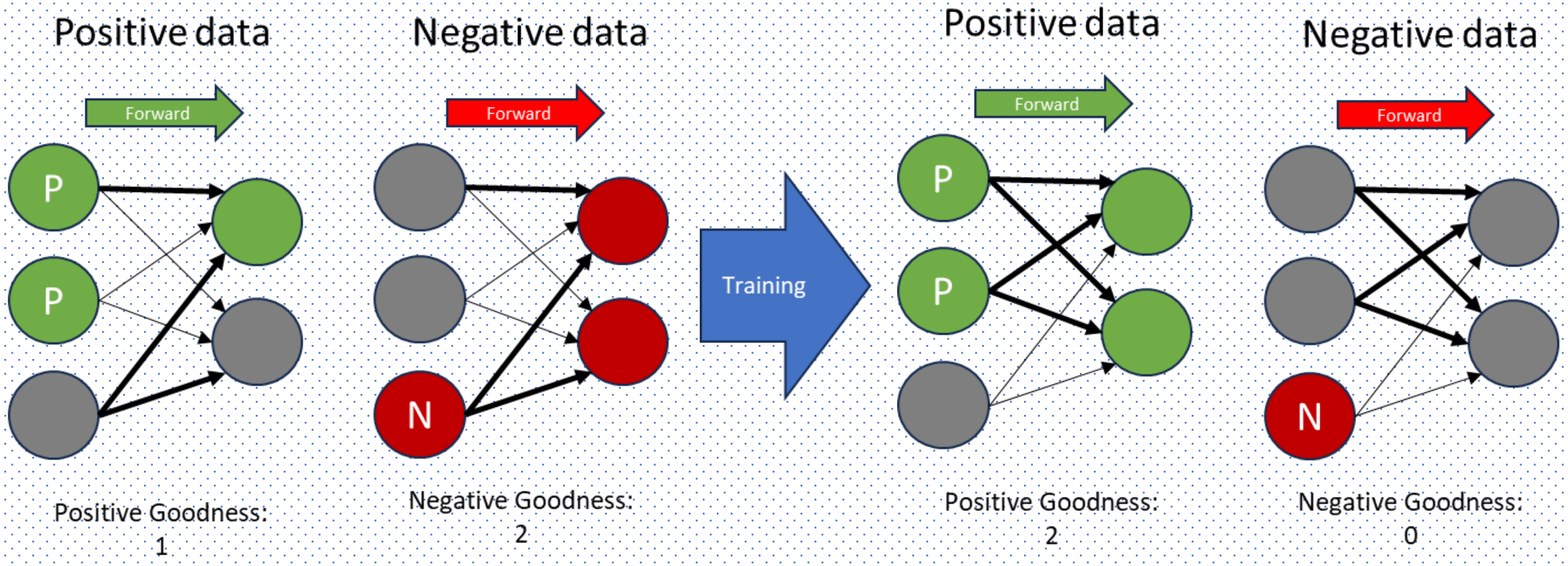
- Spiking neural network



Definition: Composition

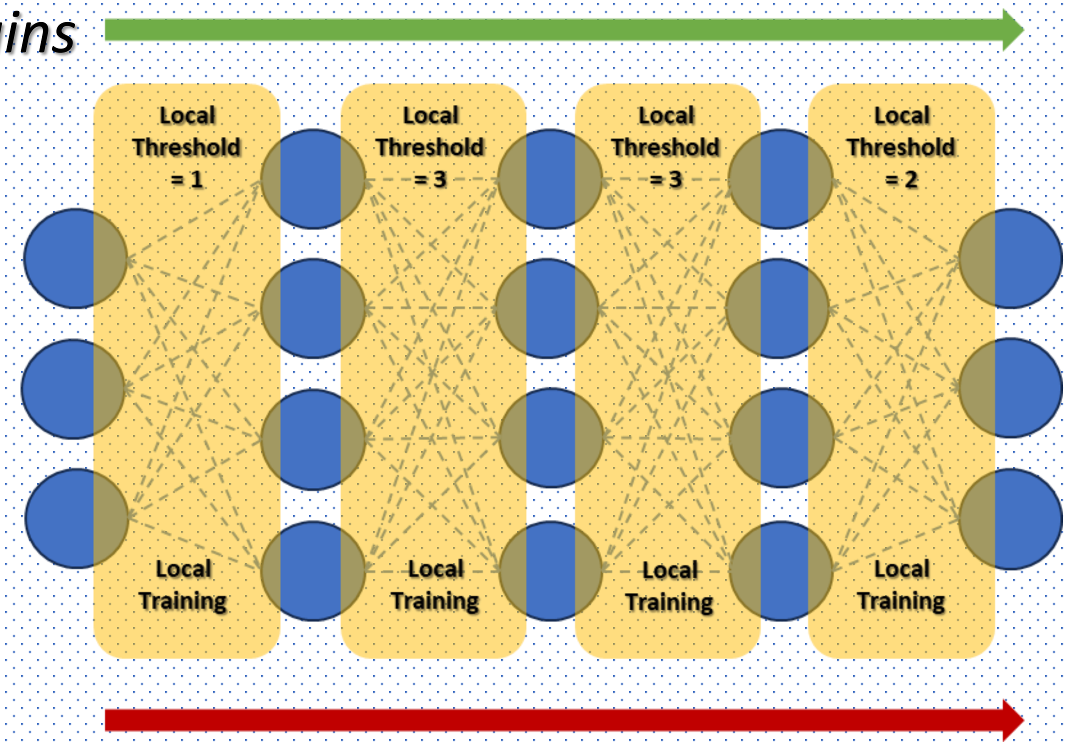
- As a combination, Spiking Forward-Forward consists of two key parts:

- **Forward-Forward** algorithm



Main technical problems

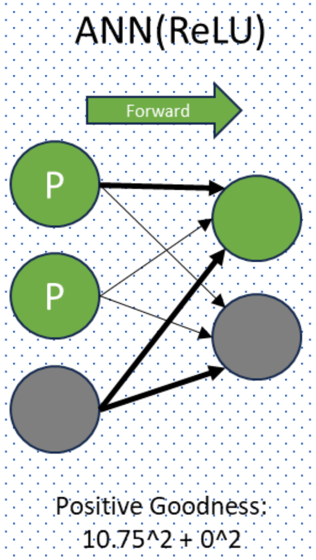
- How to redesign the FF algorithm
  - To adapt to *binary data*
  - To gain the ability to process *spike trains*

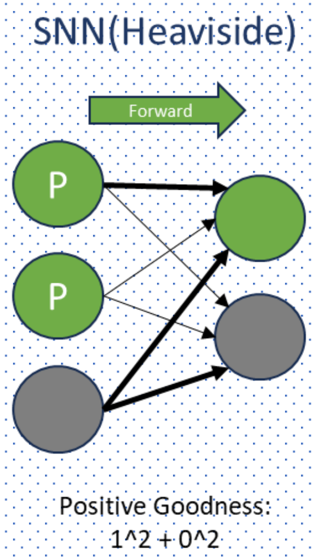


- How to reconstruct the SNN
  - To allow the FF algorithm to be trained locally on the level of layer.

Implementation: Design

- Output vector normalization
  - To force the hidden layers of the neural network to learn high-level features
  - Binary spike signals break the integrity of vector length information



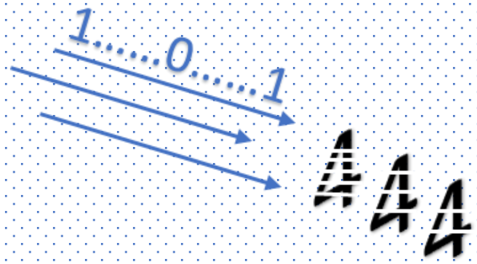


$$\gamma_i = \left(\max\left(0, \left(\mathbf{W}\frac{\mathbf{x}}{||\mathbf{x}||_2} + \mathbf{b}\right)_i\right)\right)^2$$

$$\gamma_i = \left(H\left((\mathbf{W}\mathbf{x} + \mathbf{b})_i\right)\right)^2$$

Implementation: Design

- Signal processing

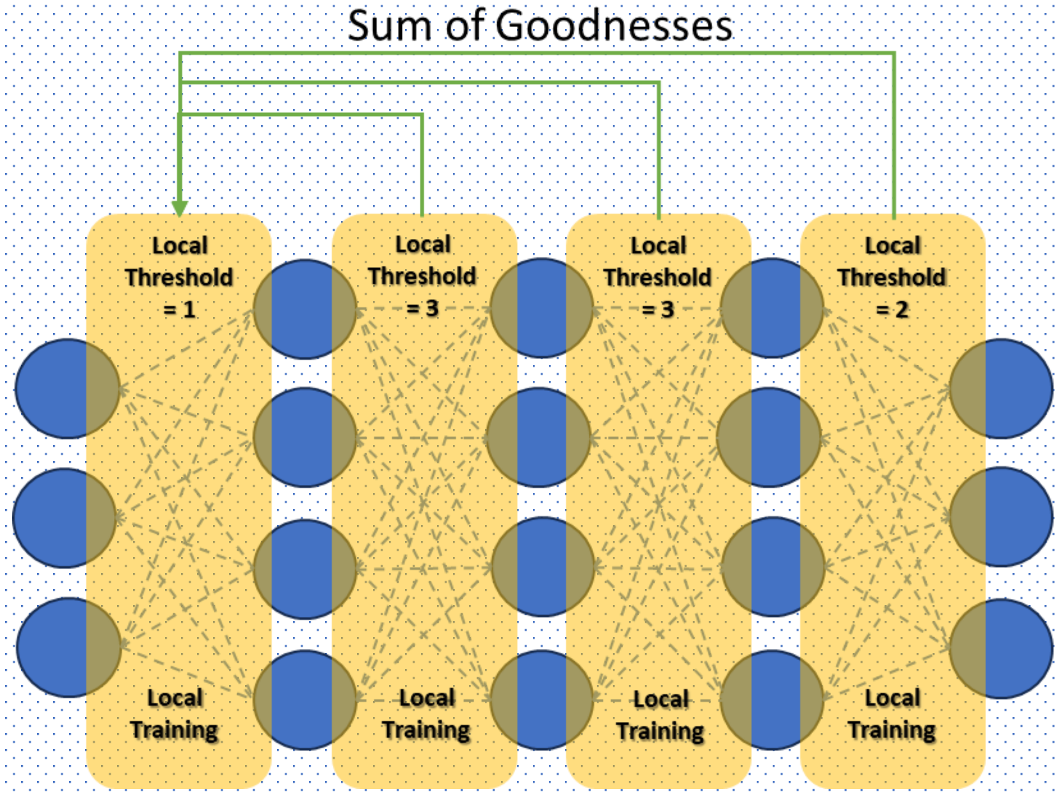


  - Integrate the spike signal in the form of frames.
  - Use the average of the goodness of all frames of a sample to update the weight
- Weight update
  - Spiking timing-dependent plasticity
  - Surrogate gradient

Implementation: Optimization

- Combine two weight updates into one.

- Layer collaboration in training



Experiment

- MNIST and FashionMNIST data sets processed by Poisson encoder,
- N-MNIST dataset processed by neuromorphic cameras,
- Auditory dataset - Spiking Heidelberg Digits.

N-MNIST-R-STDP Experiment

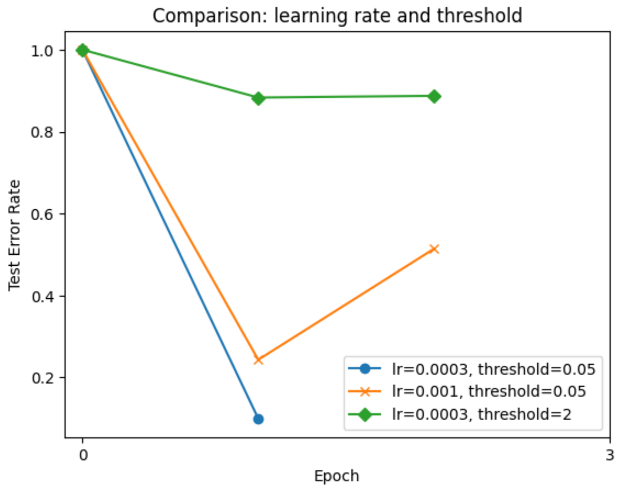
- Result:
  - Error rate of 87%

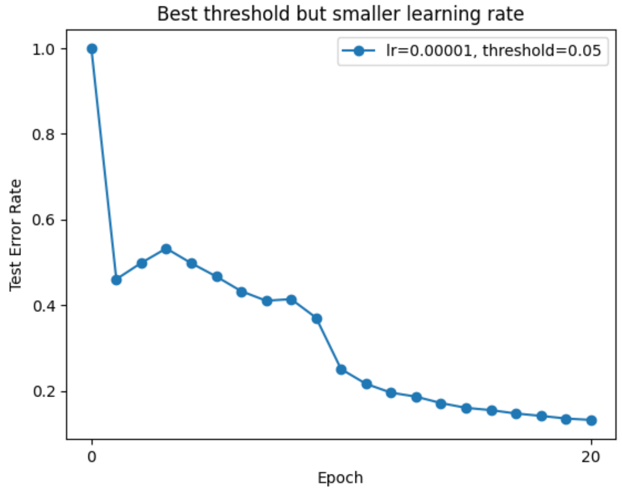
- Conclusions:
  - 1. SFF algorithm is sensitive to threshold(Order of magnitude).
  - 2. Although STDP has limited capabilities, it is possible to combine it with gradient calculation schemes.

Poisson-Spike-MNIST experiment

- Result:

Dataset	Spiking Forward-Forward in SNN	Forward-Forward in ANN	BP in SNN
MNIST	11.03% (± 2% in 5 runs)	8.67% (± 2%)	7.45% (± 1%)





- Conclusions:
  - 1. Spiking Forward-Forward does have learning and generalization capabilities when using surrogate gradient calculations.
  - 2. Update the weight of STDP before gradient calculation, which will bring small but positive changes to the final result.

Poisson-Spike-FashionMNIST experiment

- Result:

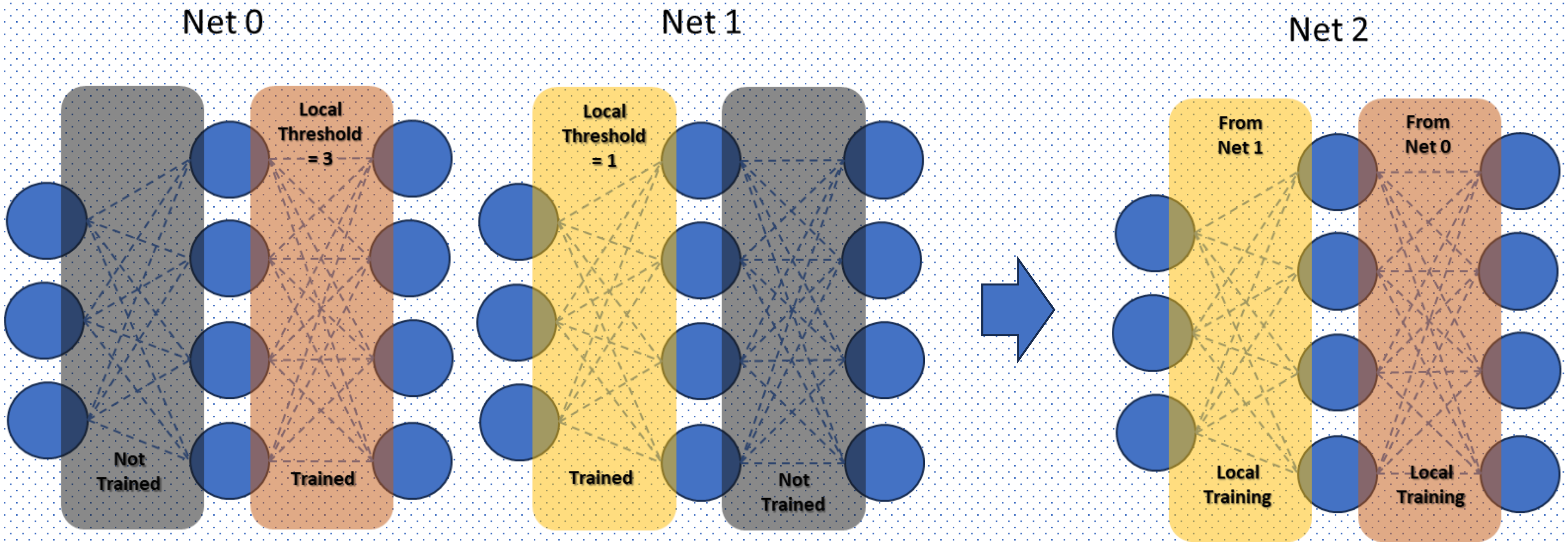
Dataset	Collaborative SFF error rate	SFF error rate
MNIST	11.03% (± 2% in 5 runs)	17.22% (± 2%)
FashionMNIST	24.15% (± 2%)	39.89% (± 2%)

- Conclusions:
  - 1. Learning and generalization capabilities in multiple Poisson datasets.
  - 2. Layer collaboration improved Spiking Forward-Forward

N-MNIST & SHD Surrogate Gradient Experiment

- Result in N-MNIST:
  - Error rate of 41.5%
- Phenomenon:
  - The spiking neurons of the hidden layer are barely activated on non-Poisson dataset. It greatly affects the learning capability of hidden layers.
- Result in SHD:
  - Error rate of 57.1% (hidden layer: from 90% to 70%)(traditional SNN: 51.9%)
- Conclusions:
  - Although the generalization ability has been demonstrated on a series of data sets,
  - There is a gap between it and the standard algorithm,
  - Room for further exploration and improvement.

Decentralized Training Experiment



Conclusion

- Despite the gap between the back-propagation-based algorithms and Spiking Forward-Forward,

- The Spiking Forward-Forward algorithm is able to train and generalize spiking neural networks on multiple spike morphology datasets.

Reference

- Deng, L., Wu, Y., Hu, X., Liang, L., Ding, Y., Li, G., . . . Xie, Y. (2020). Rethinking the performance comparison between SNNS and ANNS. *Neural networks*, *121*, 294–307.