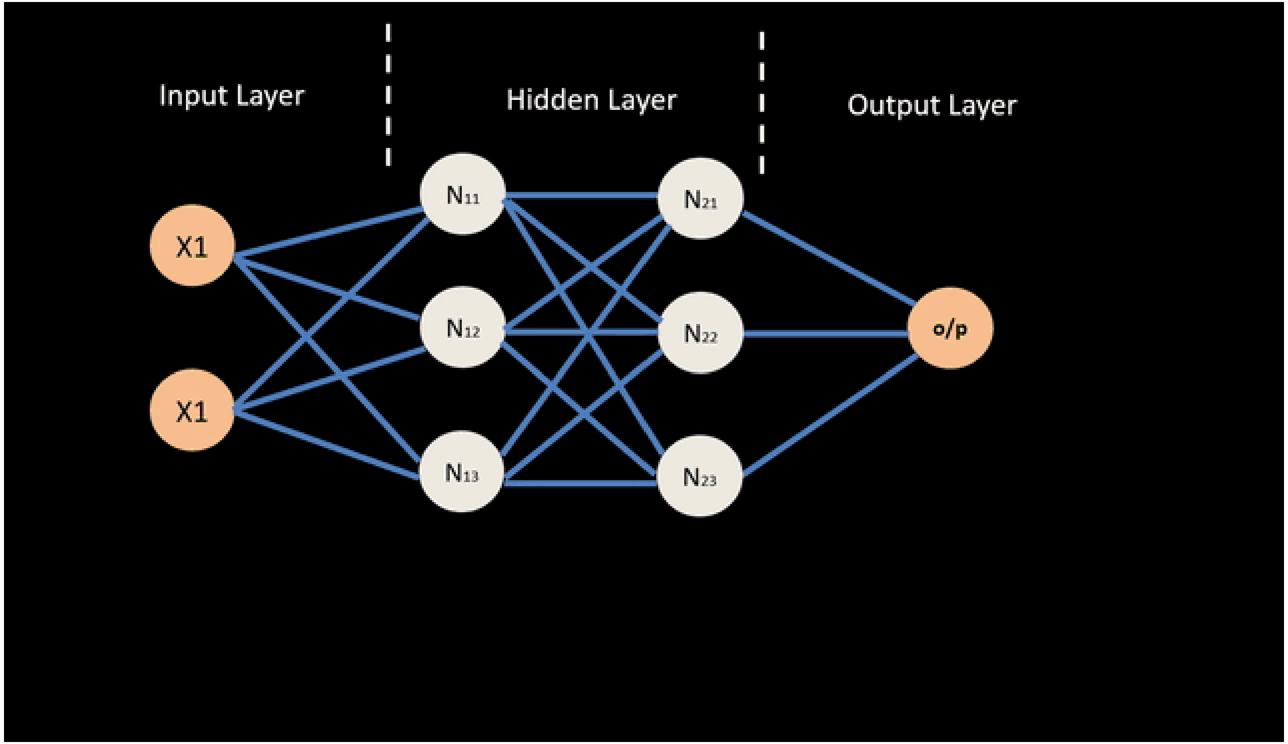
Lecture 11-a

Unconventional Algorithms and Hardware for Neural Networks

Artificial Neural Networks



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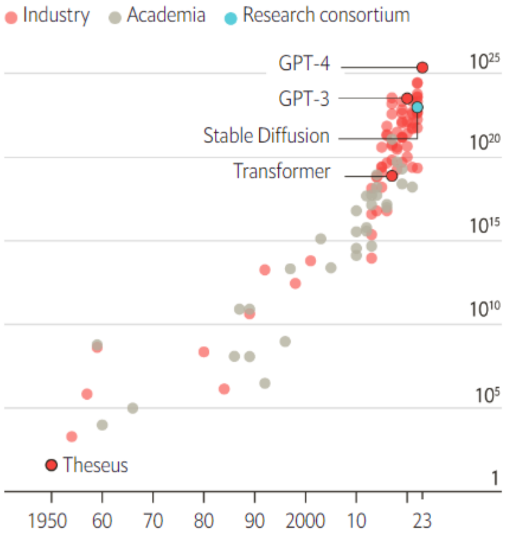
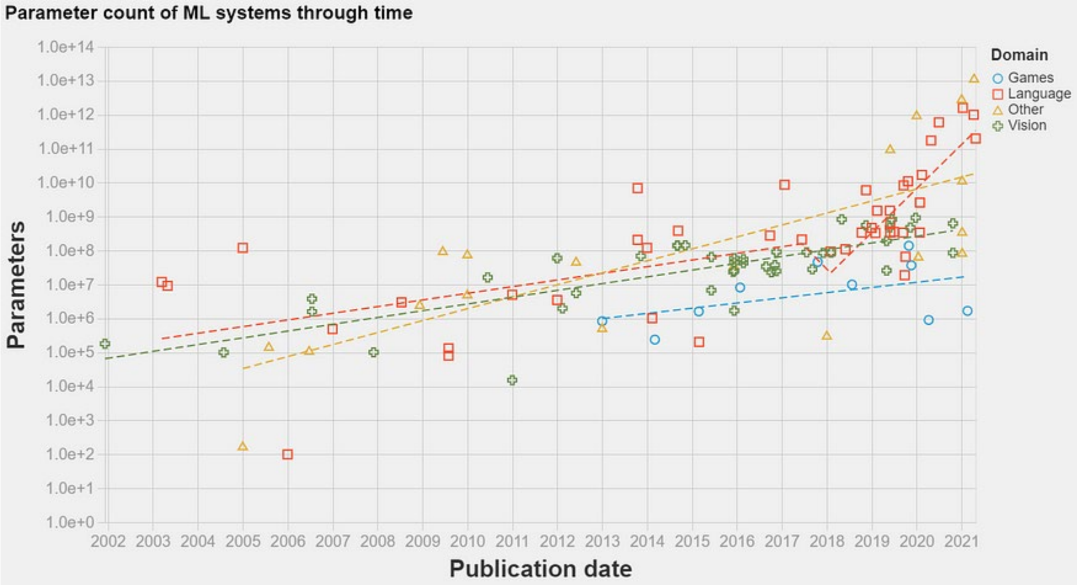
Artificial Neural Networks

Computing power used in training AI systems
Selected systems, floating-point operations, log scale



Sources: Sevilla et al., 2023; Our World in Data



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Reservoir Computing

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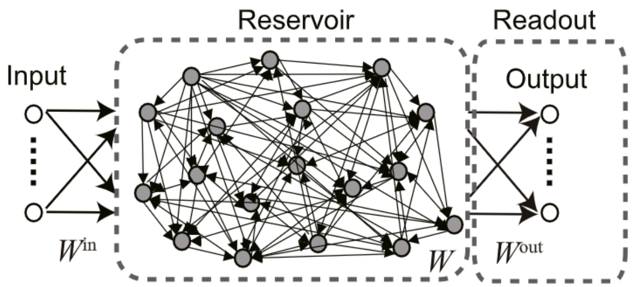
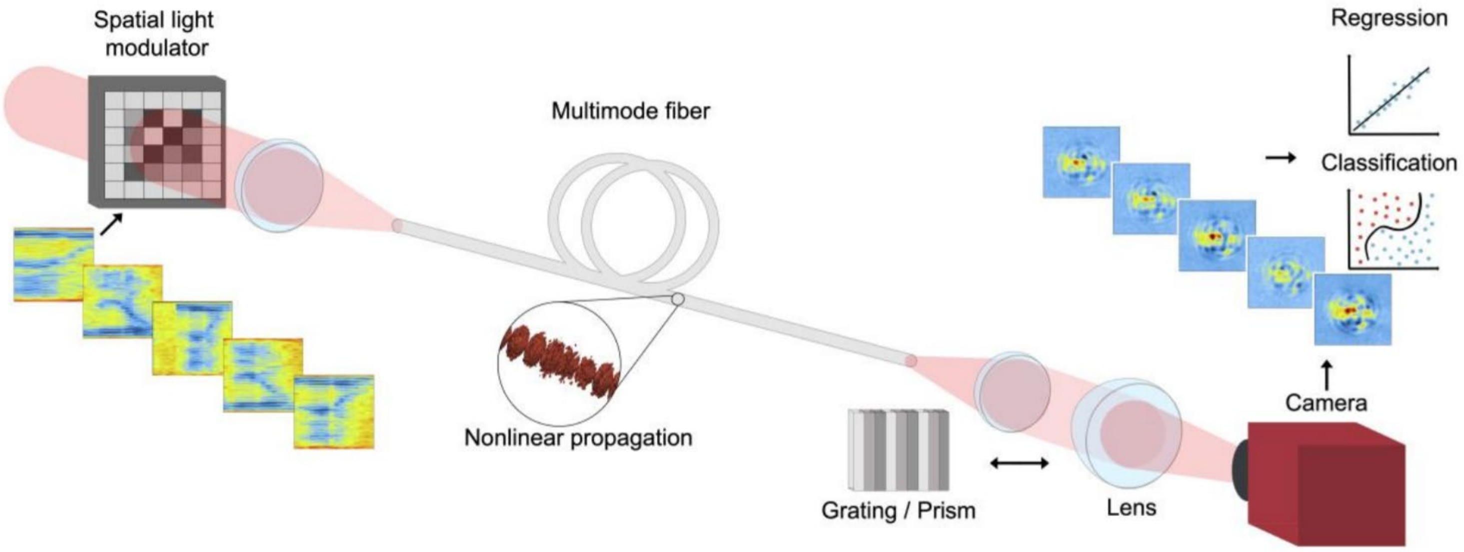
- Consists of high-dimensional, fixed, non-linear connections for transforming data, only output weights are optimized.
- Especially useful for fast operation and low training cost
- Can be realized by **high dimensional** and **nonlinear** physical systems.



(a) Conventional RC

Computing with Spatiotemporal Nonlinearities of MMFs

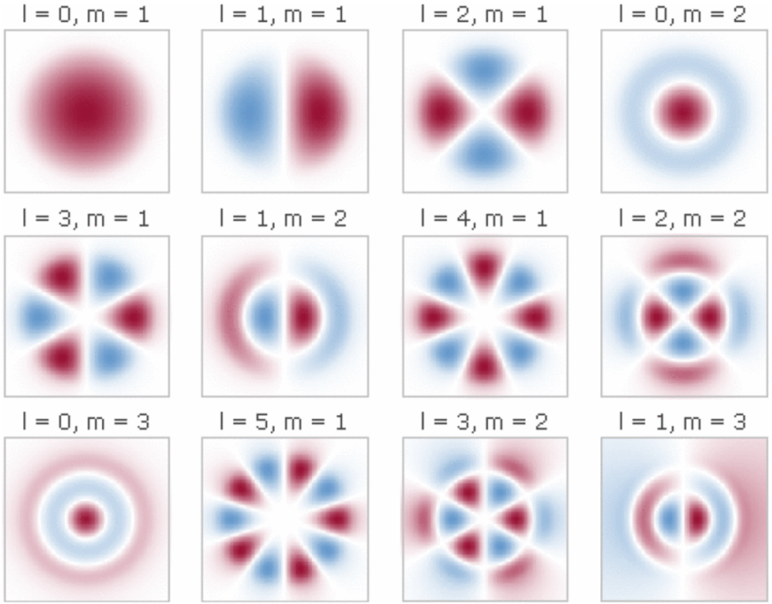


Teğin, U., Yıldırım, M., Oğuz, İ., Moser, C. & Psaltis, D. Scalable optical learning operator. *Nat. Comput. Sci. 2021 18* **1**, 542–549 (2021).

Computing with Spatiotemporal Nonlinearities of MMFs

- In multimode fibers light propagate in discrete channels, depending on their properties MMFs can support up to millions of channels:
  $E\,(\mathrm{x}, \mathrm{y}, \omega) = \sum_{n}^{N} \mathrm{A}_n F_n(\mathrm{x}, \mathrm{y}, \omega)$

- At high intensities modes start to couple each other due to light-matter interactions.



Computing with Spatiotemporal Nonlinearities of MMFs

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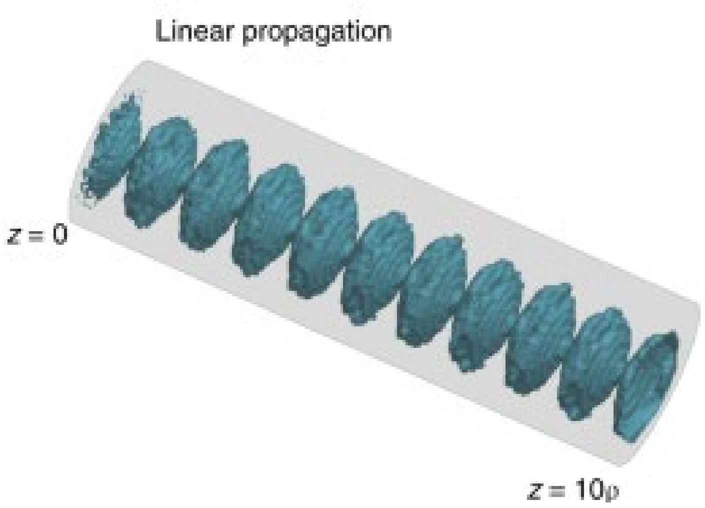
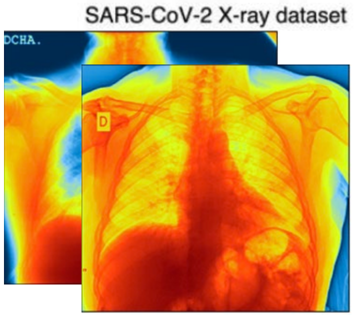
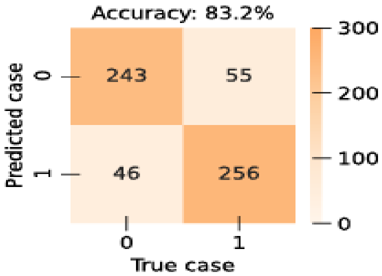
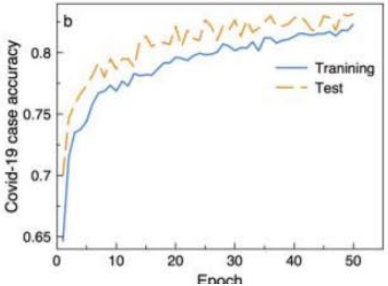
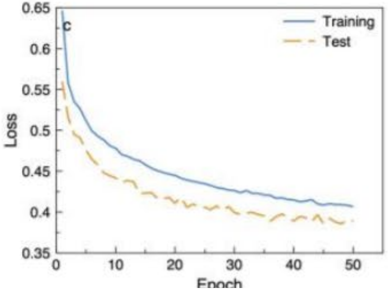


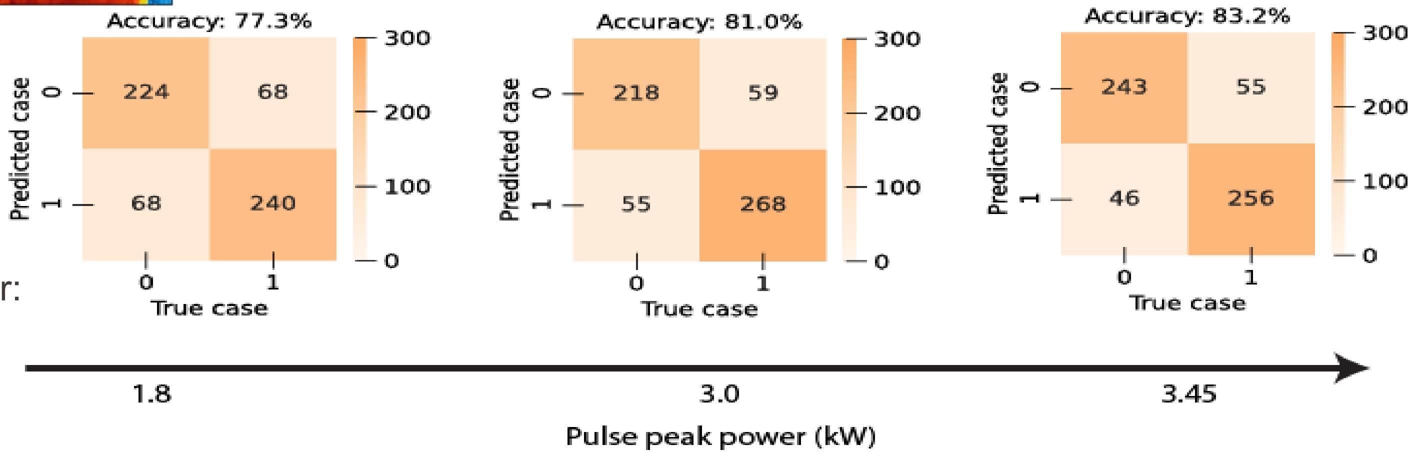
Computing with Spatiotemporal Nonlinearities of MMFs











W/out fiber: 77%

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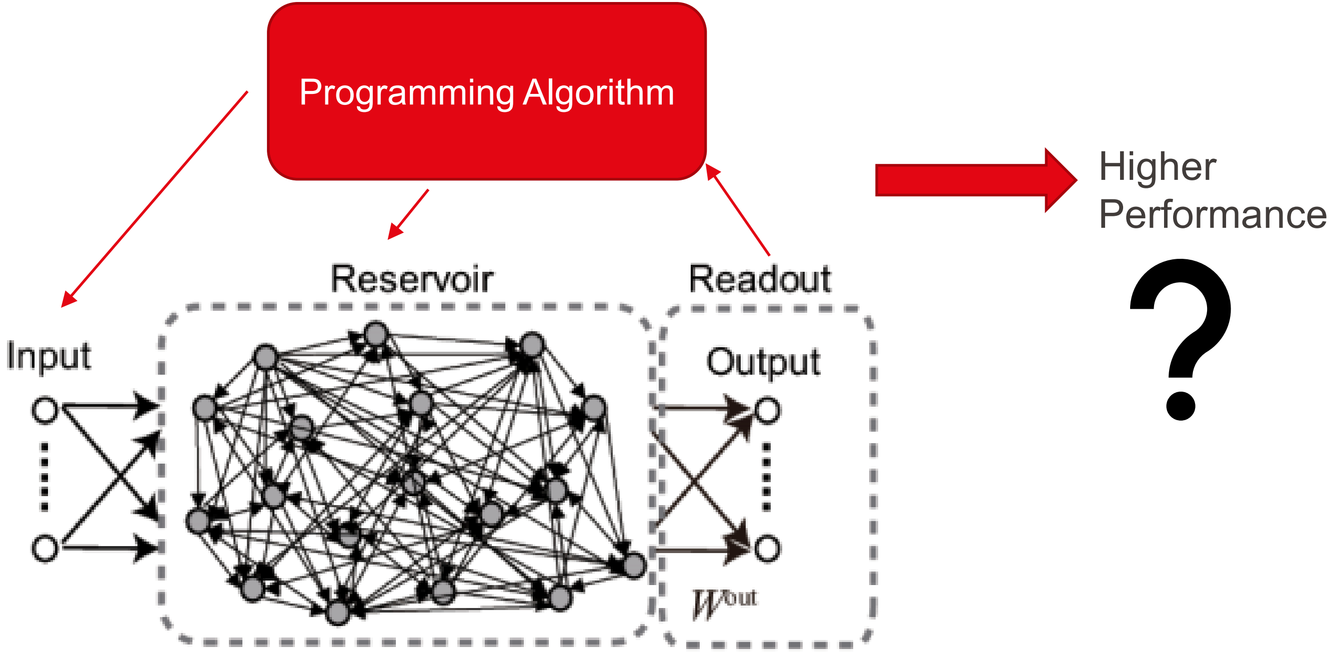
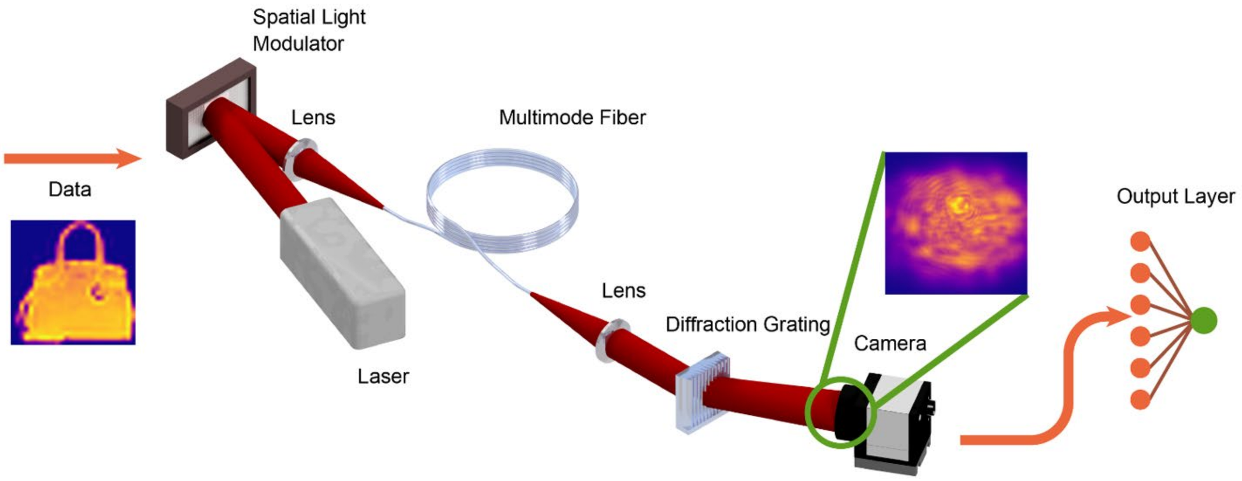
Programming Propagation inside MMFs



Programming Propagation inside MMFs



Programming Propagation inside MMFs

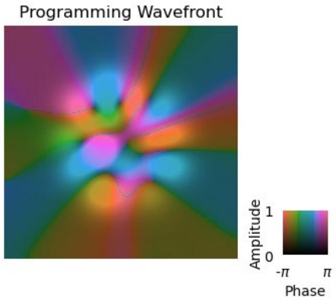
Programming Parameters

Mode Shape Coefficients

Experimental Parameters

- Intensity
- Diffraction Angle of Blazed Grating
- Pattern Displacement
- Defocus

$$WF(x,y) = \sum_{n=1}^{N} (a_{2n-1} + i * a_{2n}) * F_n(x,y)$$



Optimization of Programming Parameters

$f^{\sim}(x, w') \rightarrow y$

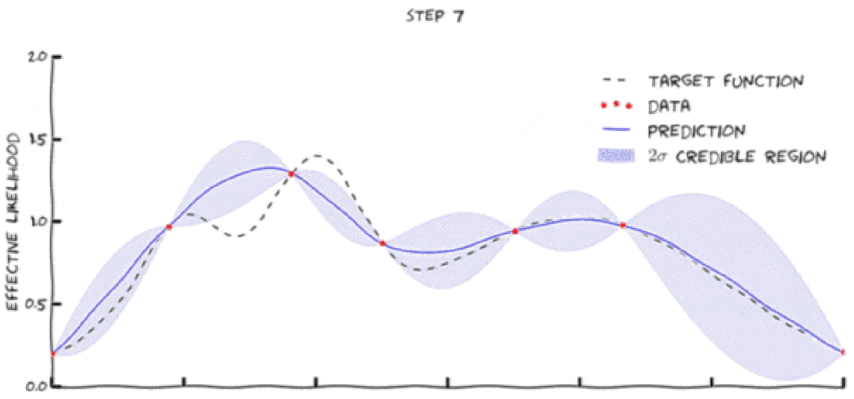
Surrogate Model: Simple function(RBFs) to fit to experimental results

New Sampling Points for Exploring/ Exploiting a Solution

Outputs from Experiment for Refining the Surrogate Model

Experiment: Unknown function, costly to evaluate, tens of parameters

$f(x, w) \rightarrow y$



Forward-Forward Algorithm

The Forward-Forward Algorithm: Some Preliminary Investigations

Geoffrey Hinton
Google Brain
geoffhinton@google.com

Training with FF:
for i in layerCount:

1- optimize W_{ij} such that goodness is high for positive samples and low for negative samples:

$p(\,positive\,) = \sigma\left(\sum_j y_j^2 - \theta\right)$, where $y_j = f(\sum_i^N W_{ij} x_i)$

2- Normalize $\sum_j y_j^2$'s for each sample before passing it to the next layer

EPFL

Forward-Forward Algorithm

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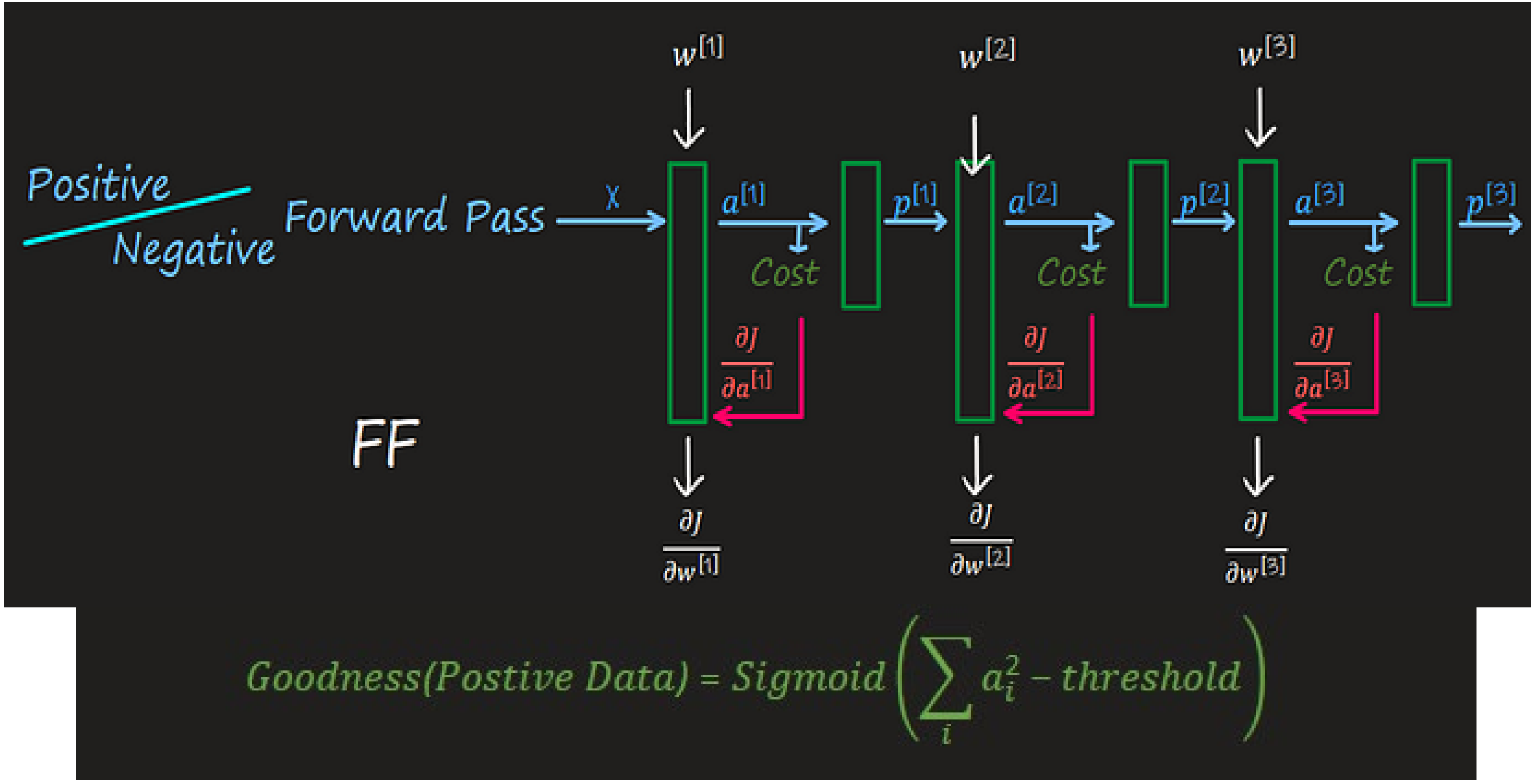
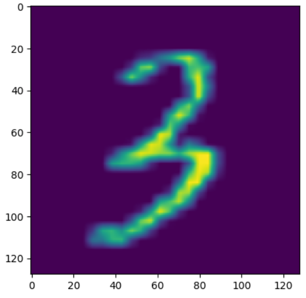


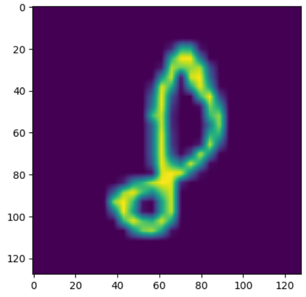
Forward-Forward Algorithm

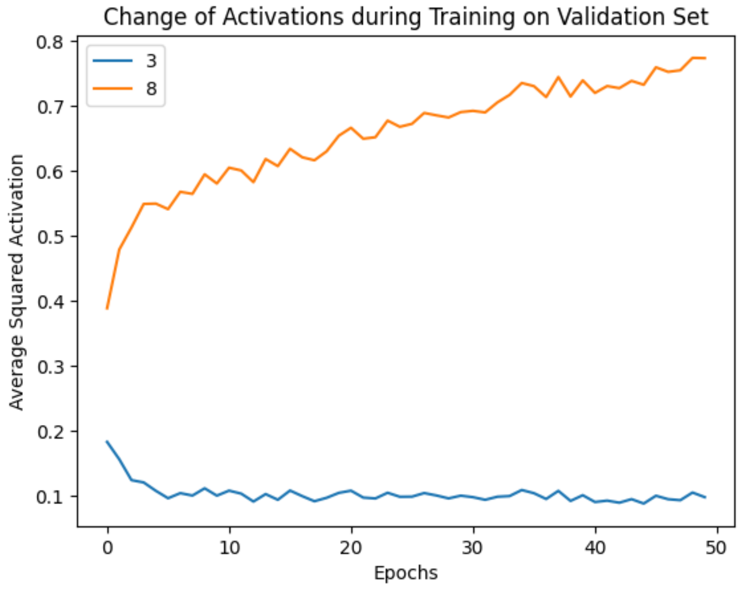
- The connections between layers can be unknown transforms ➔ Can be used by very-low power analog computing devices
- Each layer is updated at a time ➔ No need to save all activations ➔ Less memory consumption
- Biologically plausible
- Can be used by very-low power analog computing devices

Forward-Forward Algorithm on MNIST

- 8’s are labelled as positive and 3’s are labelled as negative data
- Fully connected layer with 1024 neurons are trained FFA
- Thresholding activations: 92.7 %
- Backprop training: 96.5 %







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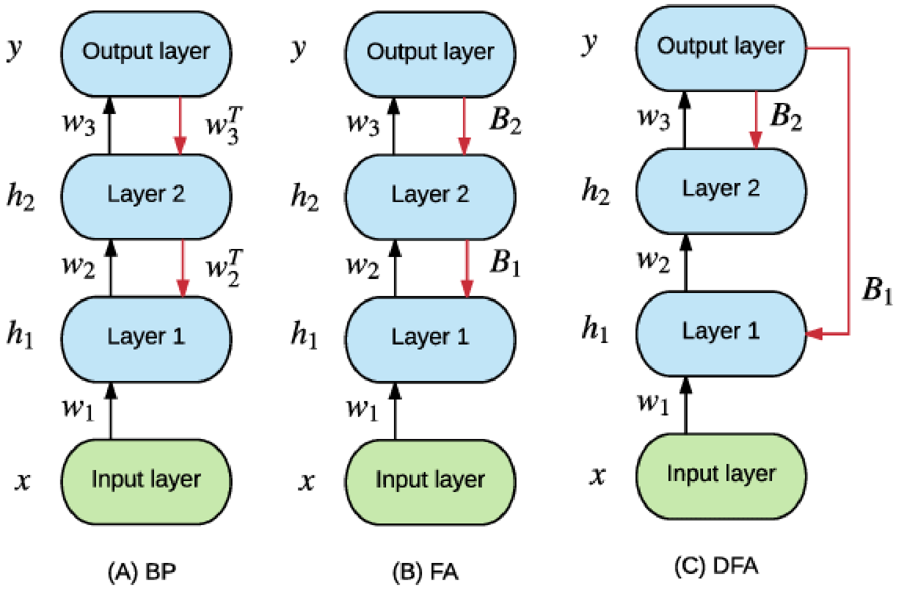
Feedback Alignment

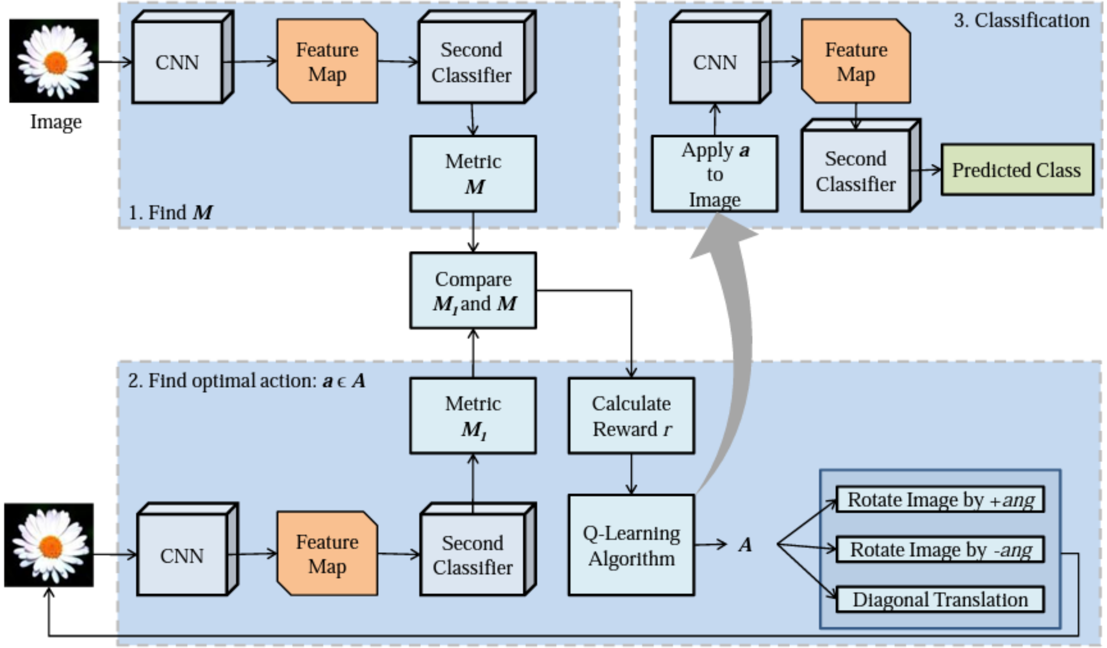
- Instead of backpropagating errors with same weights as the forward pass, feedback alignment uses random backward connection.
- When w and B matrices are from similar distribution, convergence is observed.



Error Rate

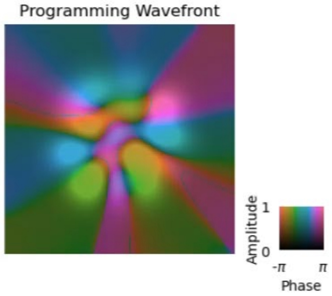
	Dataset	
	MNIST	Fashion MNIST
BP	0.91	9.20
FA	1.7	13.06
DFA	1.61	12.81

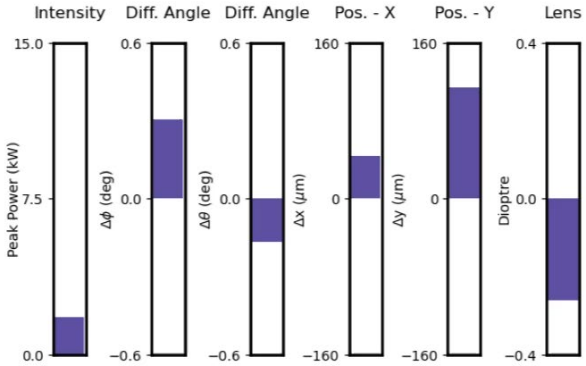
An Alternative: Reinforcement Learning

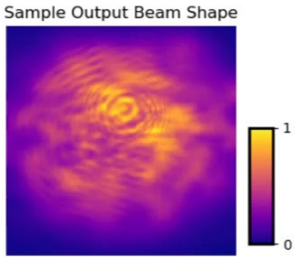


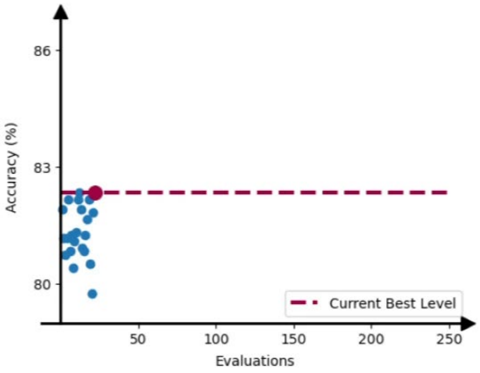
Hafiz, Abdul Mueed. "Image Classification by Reinforcement Learning With Two-State Q-Learning." *Handbook of Intelligent Computing and Optimization for Sustainable Development* (2022): 171-181.

Programming Propagation for MNIST-Fashion









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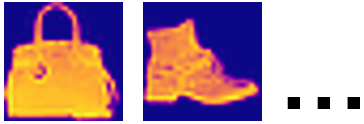
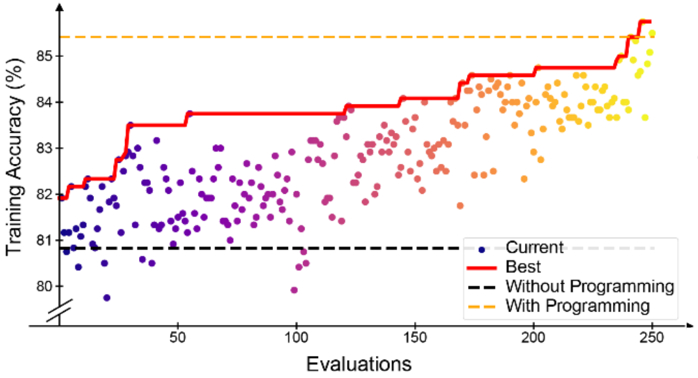
Programming Propagation for MNIST-Fashion

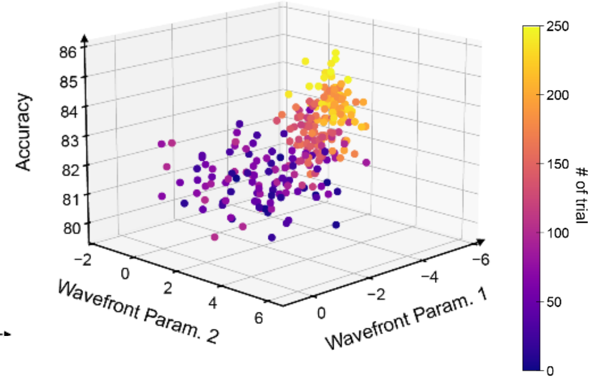
1200 training and 300 test samples

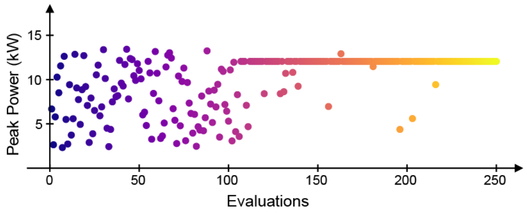


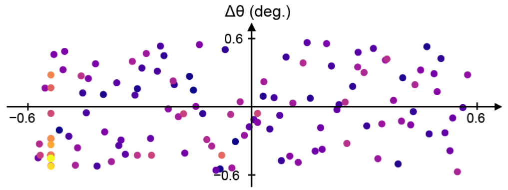
Bag Boot

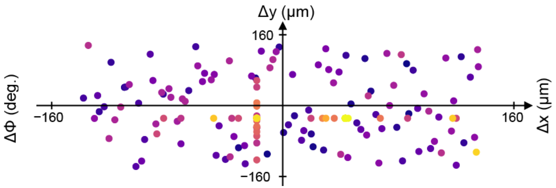
$\Delta Acc = \ +5.0\%$











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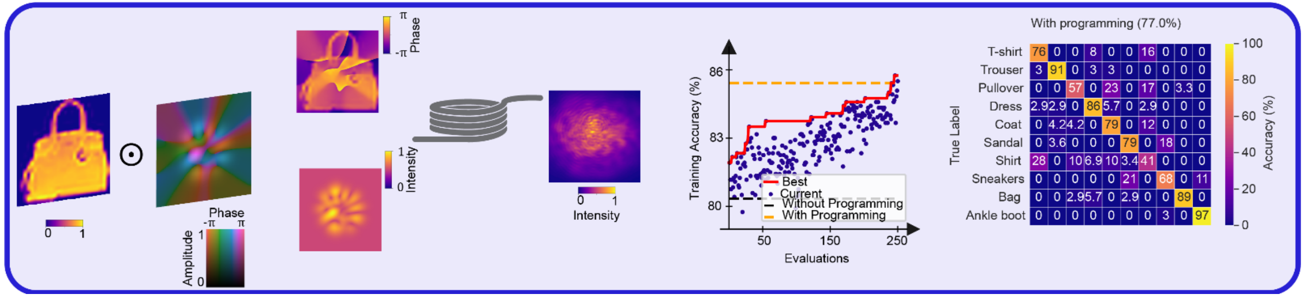
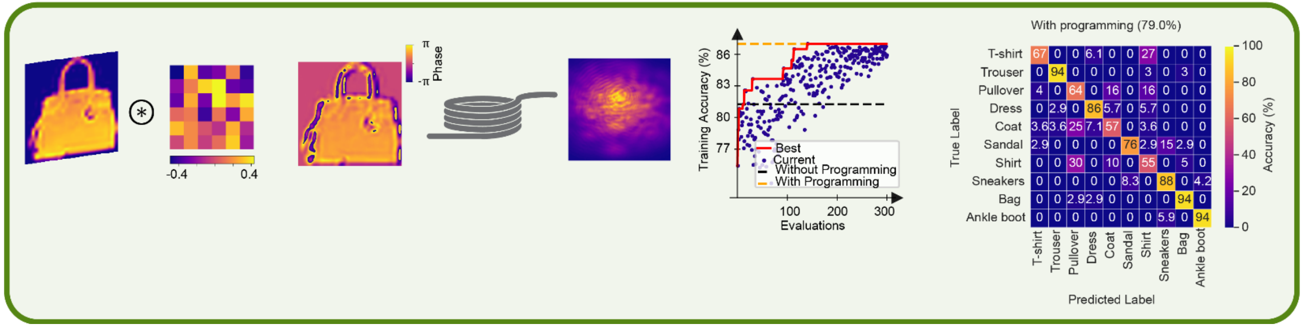
EPFL

Programming Propagation for MNIST-Fashion

Complex Field Control



Convolution with Kernel



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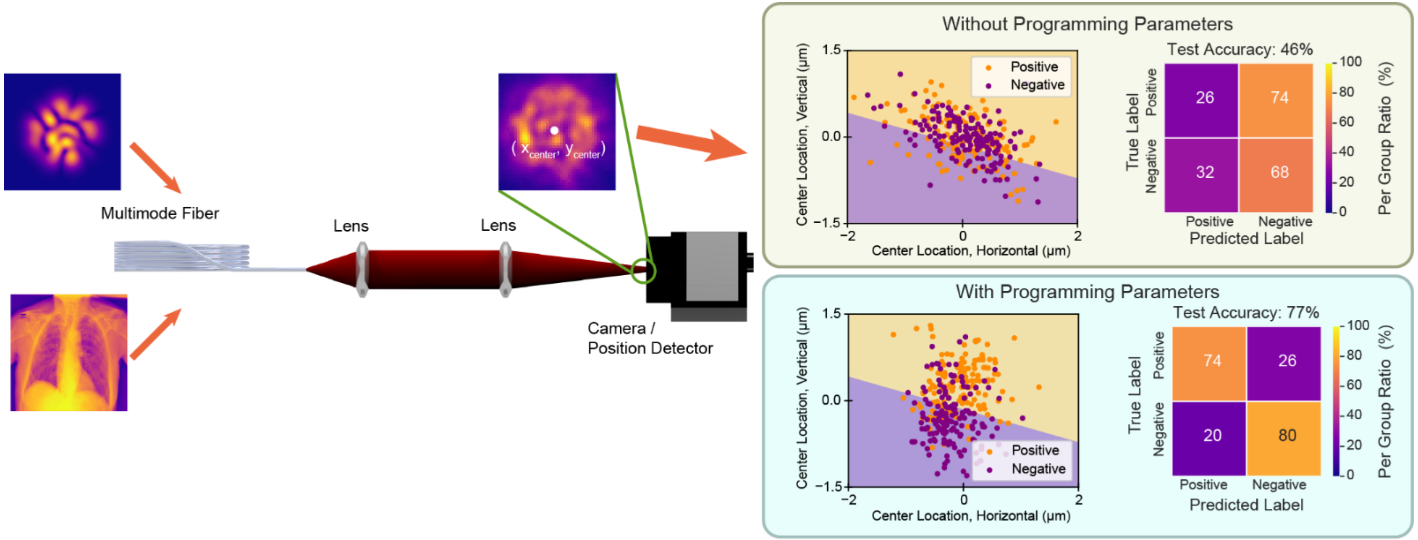
Programming Propagation for All-Optical Classification



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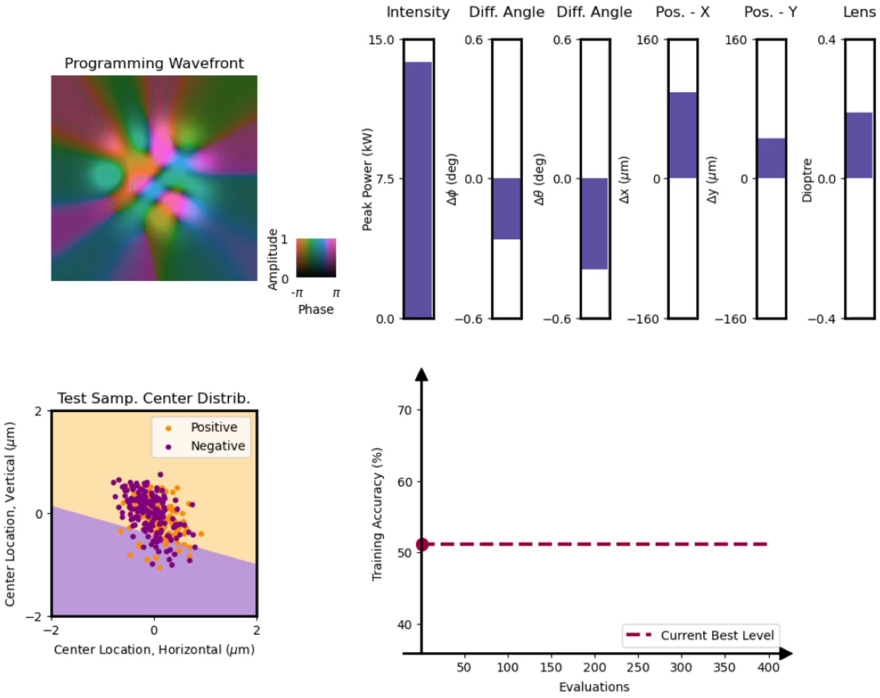
Programming Propagation for All-Optical Classification



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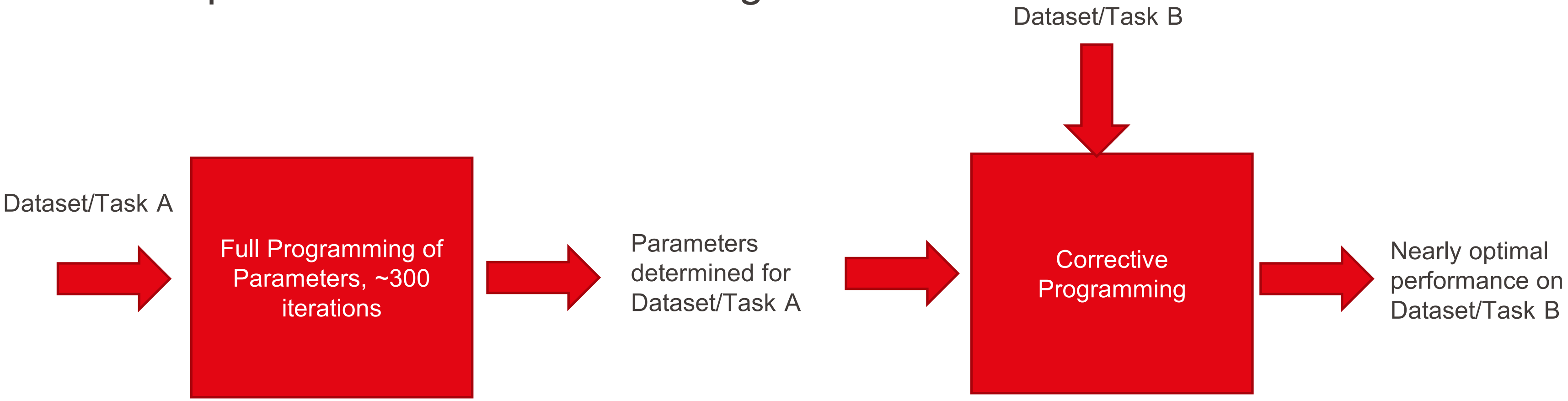
Programming Propagation for All-Optical Classification

Network Structure	Total Number of Parameters	Operations per Sample on Digital Computer (FLOP)	Accuracy on Melanoma dataset (%)	Accuracy on COVID-19 dataset (%)
LeNet-5	82826	1175640	64.9	74.6
MMF + classification with output location (with programming)	55	2029	61.3	77.0

Transferring Programming Parameters between Different Tasks

- Current method requires ~300 iterations over the dataset for programming to converge.
- For 1500 samples at 50 images per second, full programming corresponds to ~3 hours of training.



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Transferring Programming Parameters between Different Tasks

CelebA - Gender

CelebA – Young/ Not Young

Full P
Para

Test Acc

readout
ngle
l pass,
version

Test Acc:
69.0% ⇒ 76.0%

- Training from scratch : 76.3%

Comparison with GPU-based NNs

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Digital

Network Structure	Total Number of Parameters	Operations per Sample on Digital Computer (FLOP)	Test Accuracy on Age Task	Test Accuracy on Gender Task
LeNet-5	~82k	~1.2M	63.0	75.2
7-layer Convolutional NN	~410k	~65M	65.3	80.1
MMF + linear output layer	2026	4050	59.0	69.0
Programmed MMF for Age Task + linear output layer	2078	6075	67.0	76.0
Programmed MMF for Gender Task + linear output	2078	6075	64.7	76.3

Optical + Digital

Published as a conference paper at ICLR 2019

THE LOTTERY TICKET HYPOTHESIS: FINDING SPARSE, TRAINABLE NEURAL NETWORKS

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Michael Carbin
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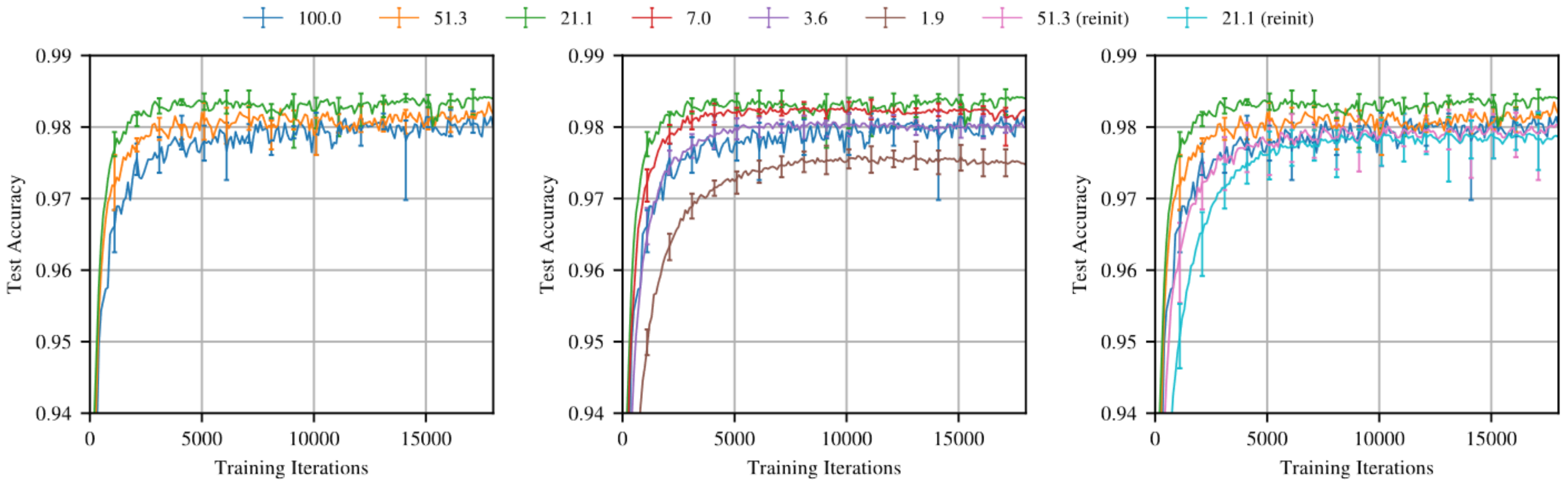

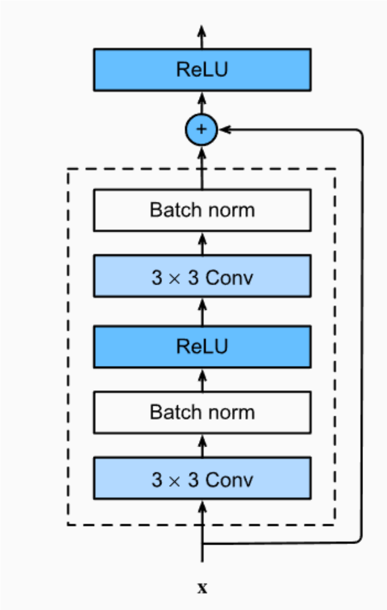

Published as a conference paper at ICLR 2021

TRAINING BATCHNORM AND ONLY BATCHNORM: ON THE EXPRESSIVE POWER OF RANDOM FEATURES IN CNNS

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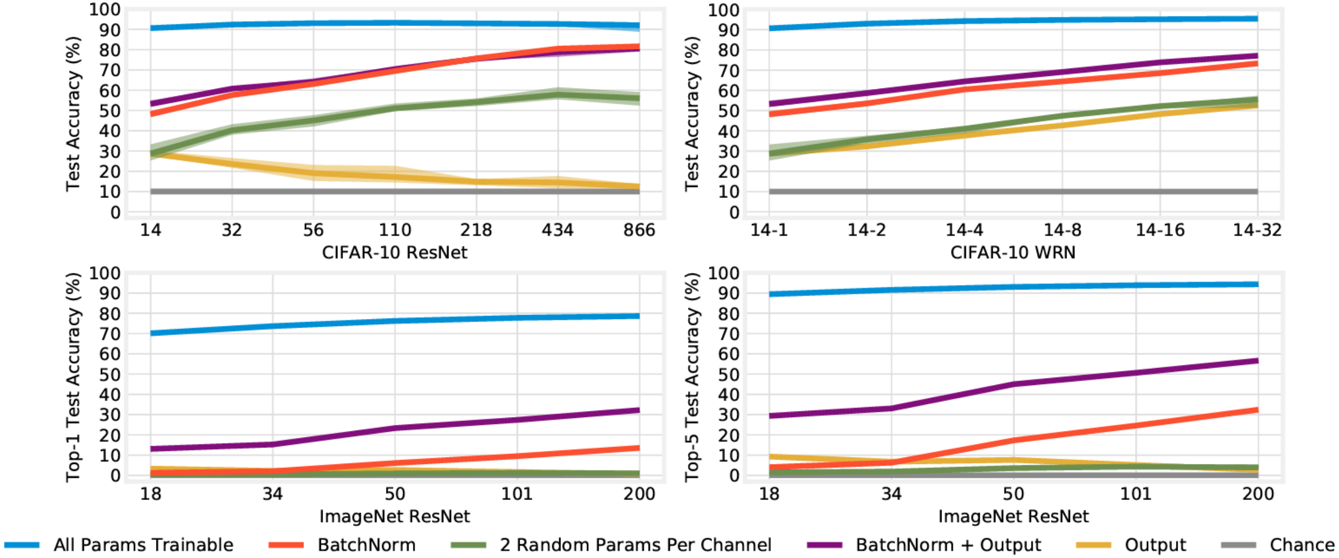

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