



# Efficient On-Device Machine Learning with a Biologically-Plausible Forward-Only Algorithm

Baichuan Huang, Amir Aminifar

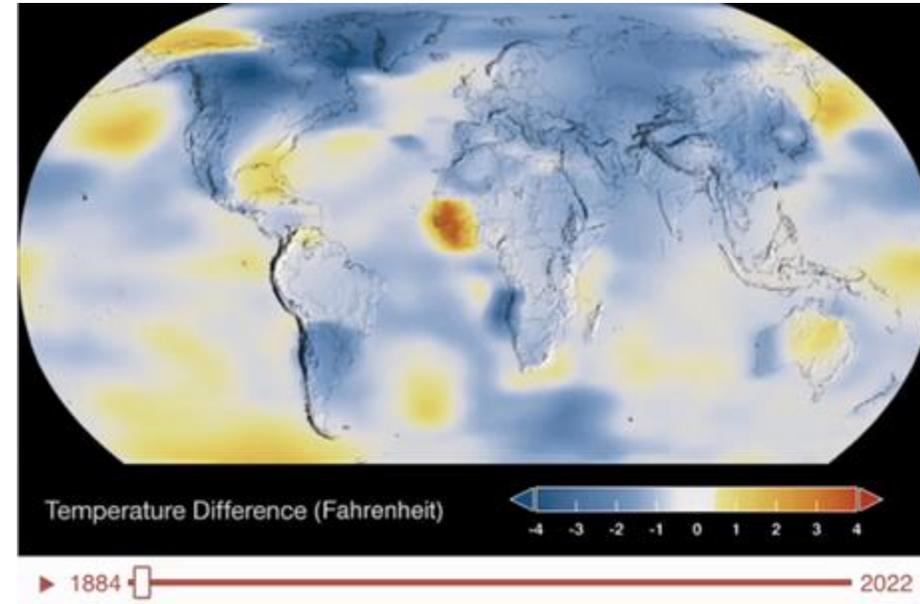
Department of Electrical and Information Technology, Lund University, Sweden

*This research has been partially supported by the Swedish Wallenberg AI, Autonomous Systems and Software Program (WASP), the Swedish Research Council (VR), Swedish Foundation for Strategic Research (SSF), the ELLIIT Strategic Research Environment, and the European Union (EU).*

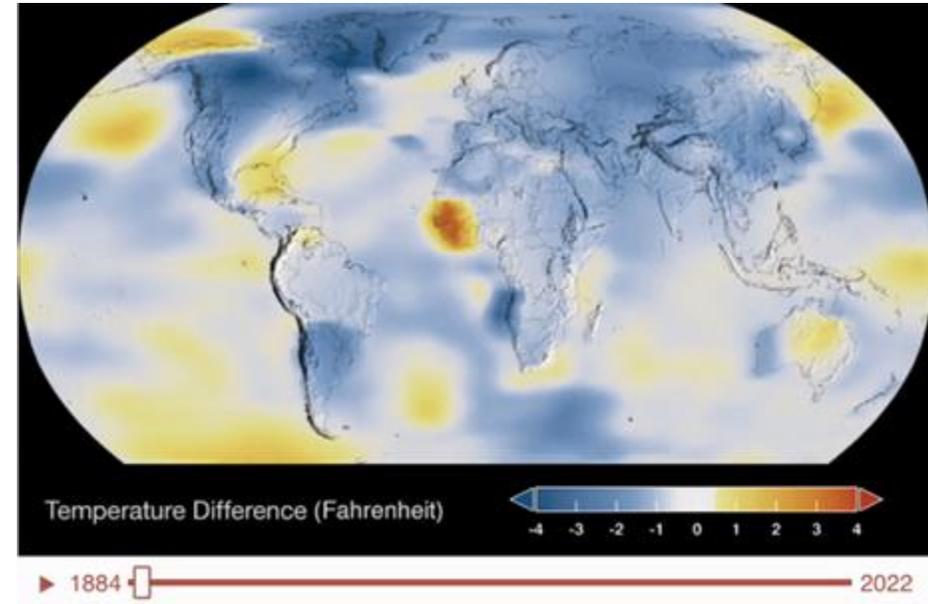


# Introduction and Background

# Global Warming



# Global Warming



Europe: an average rise of  $2.3^{\circ}\text{C}$  compared to pre-industrial levels  
 $1^{\circ}\text{C}$  **higher than** the global average.

# Energy Consumption of Training LLMs



**GPT-3**



**GPT-4**

D. Patterson, et al. Carbon emissions and large neural network training, 2021.

<https://tinymml.substack.com/p/the-carbon-impact-of-large-language>

Data sources: U.S. Energy Information Administration, Electric Power Research Institute (EPRI)

# Energy Consumption of Training LLMs



GPT-3



GPT-4



1,216,950 lbs

×13

15,238,333 lbs

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# Energy Consumption of Training LLMs



GPT-3



GPT-4



1,216,950 lbs

×13

15,238,333 lbs



1,287 Megawatt-Hour

×48

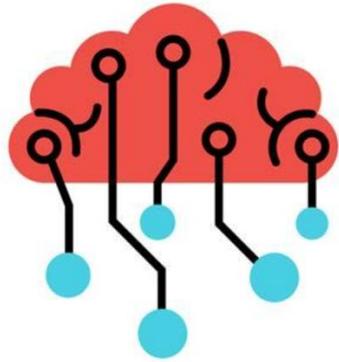
62,318 Megawatt-Hour

D. Patterson, et al. Carbon emissions and large neural network training, 2021.

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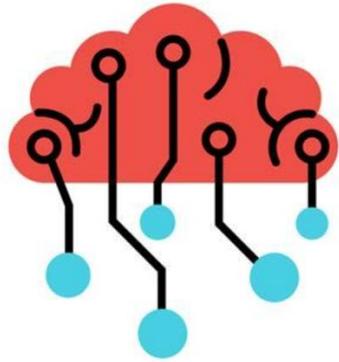
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# Biologically Plausible Alternatives

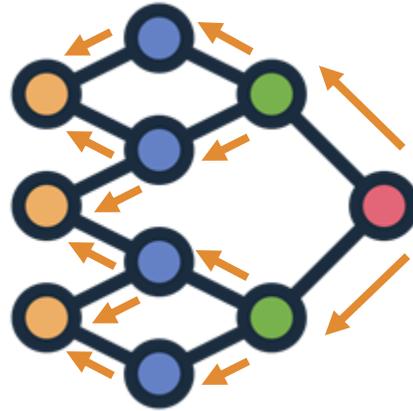


Human Brain  
(~20 Watts)

# Biologically Plausible Alternatives

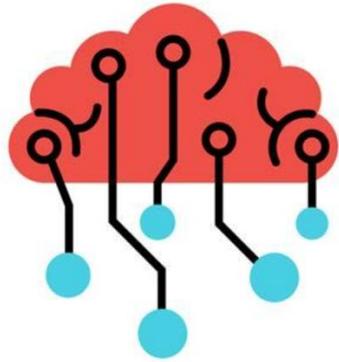


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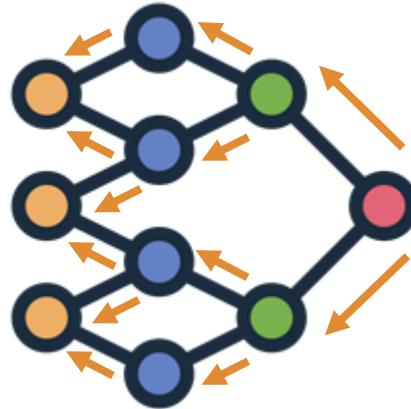


Back-Propagation  
(Bio-**Implausible**)

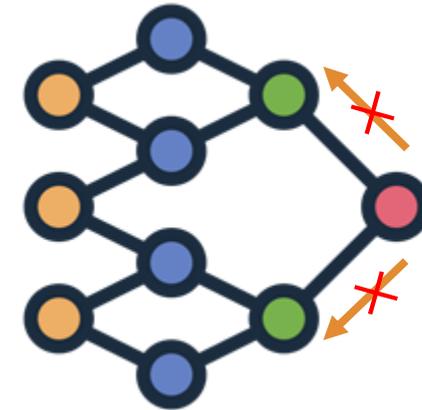
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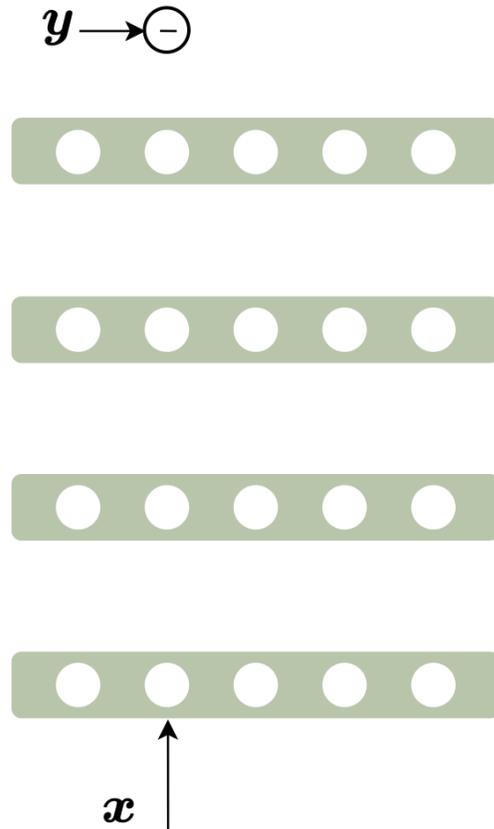


Back-Propagation  
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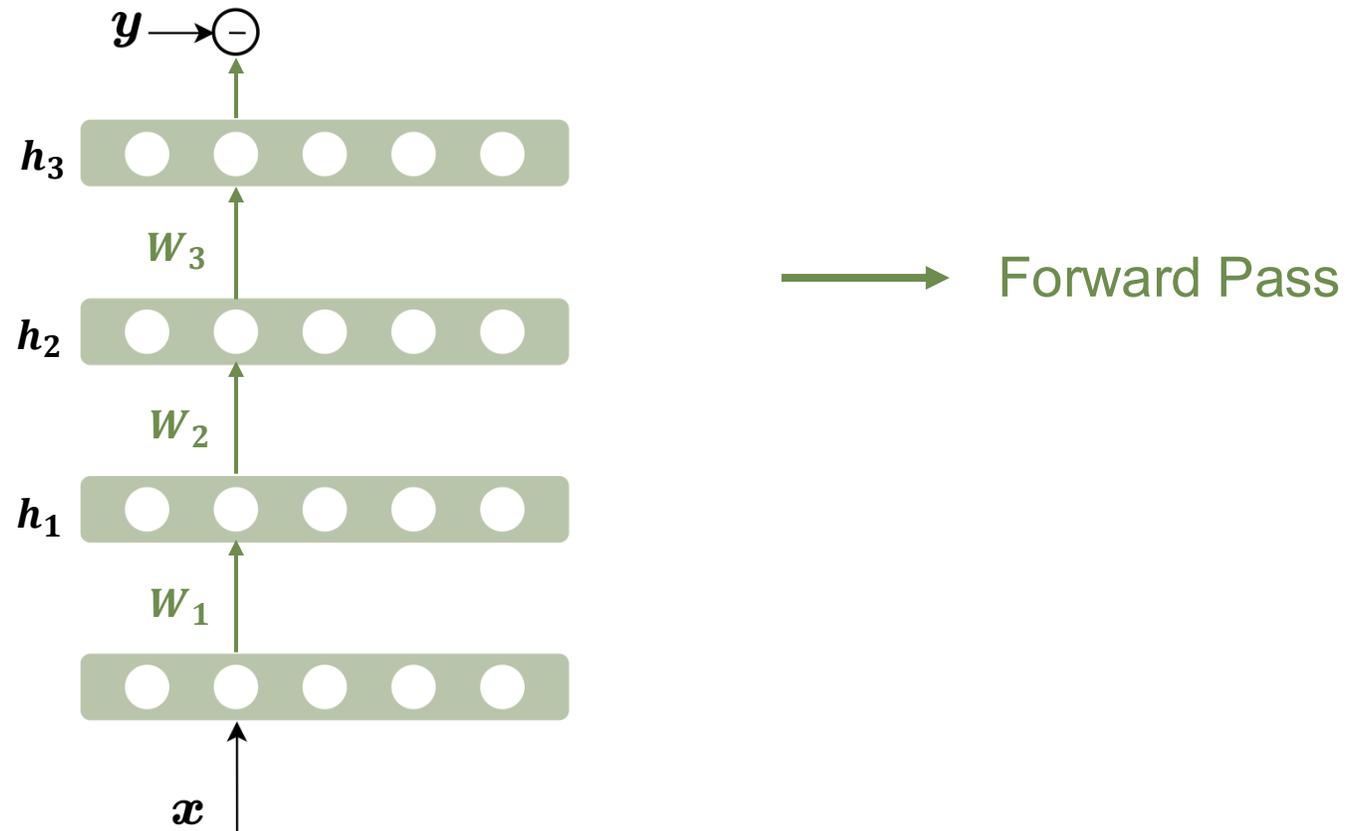


Forward-Only Algorithm  
(Bio-**Plausible**)

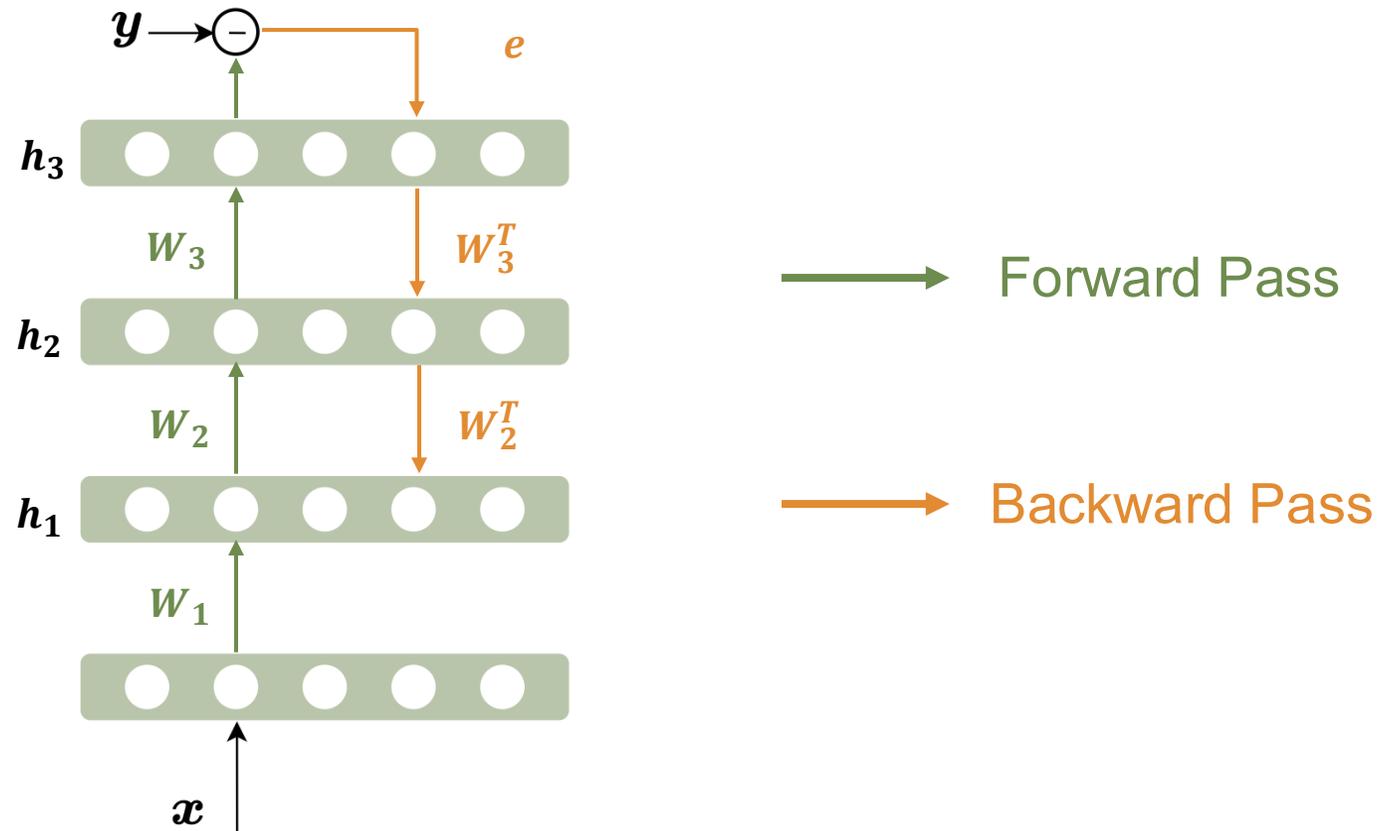
# The Process of Backpropagation



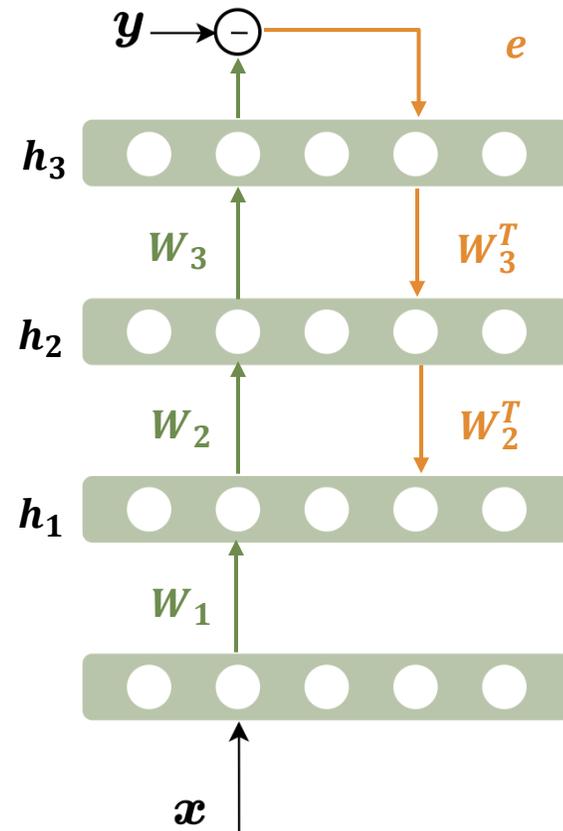
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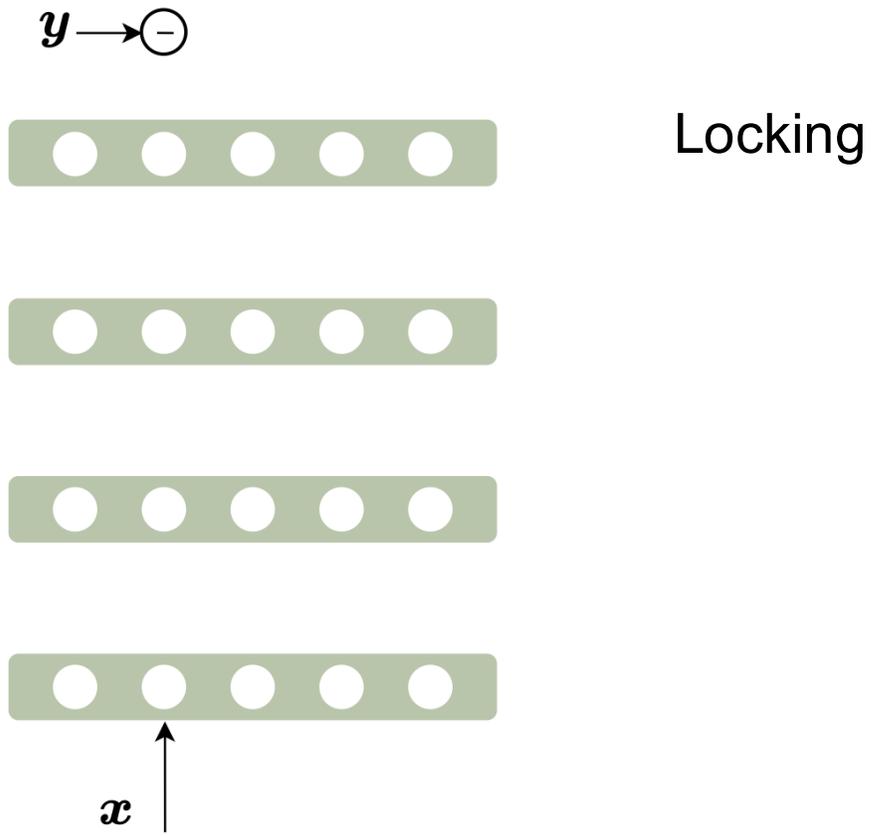
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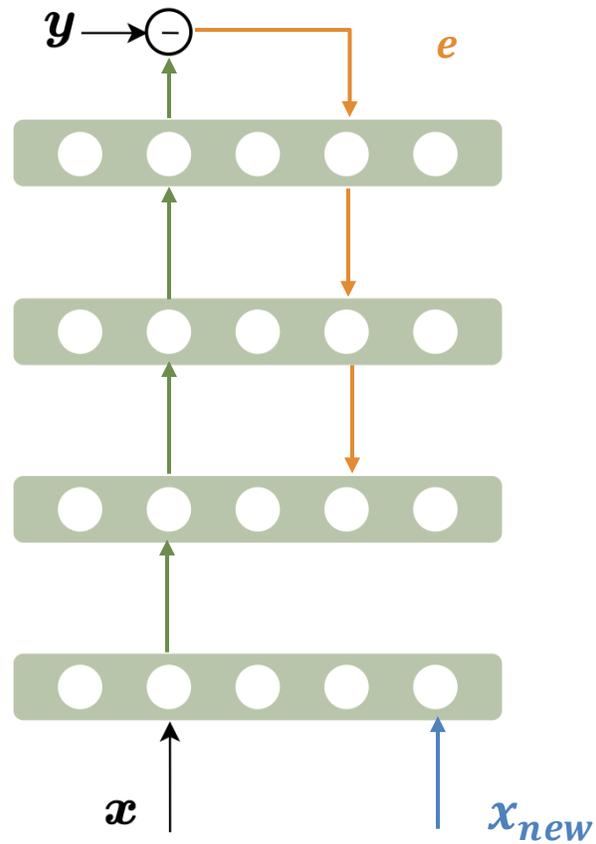
# The Biological Implausibility of BP



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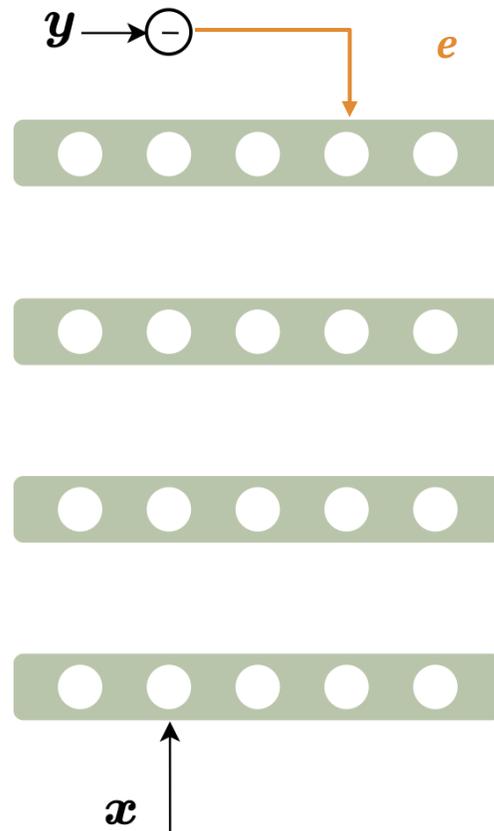


# The Biological Implausibility of BP



Locking

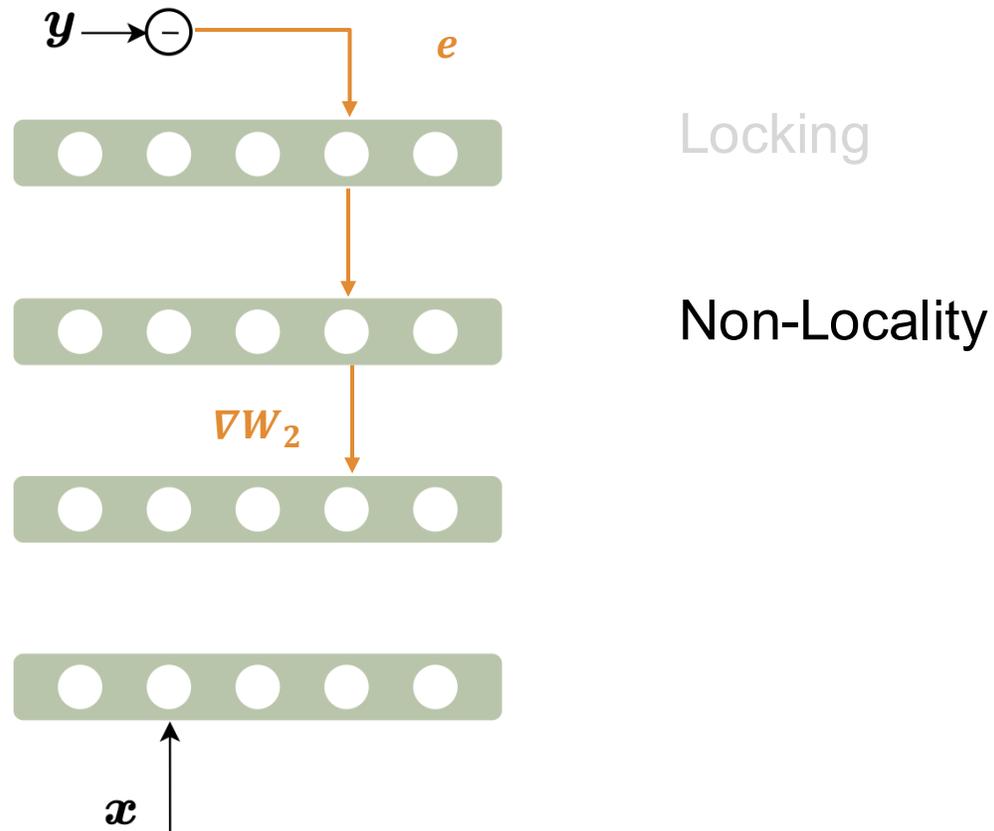
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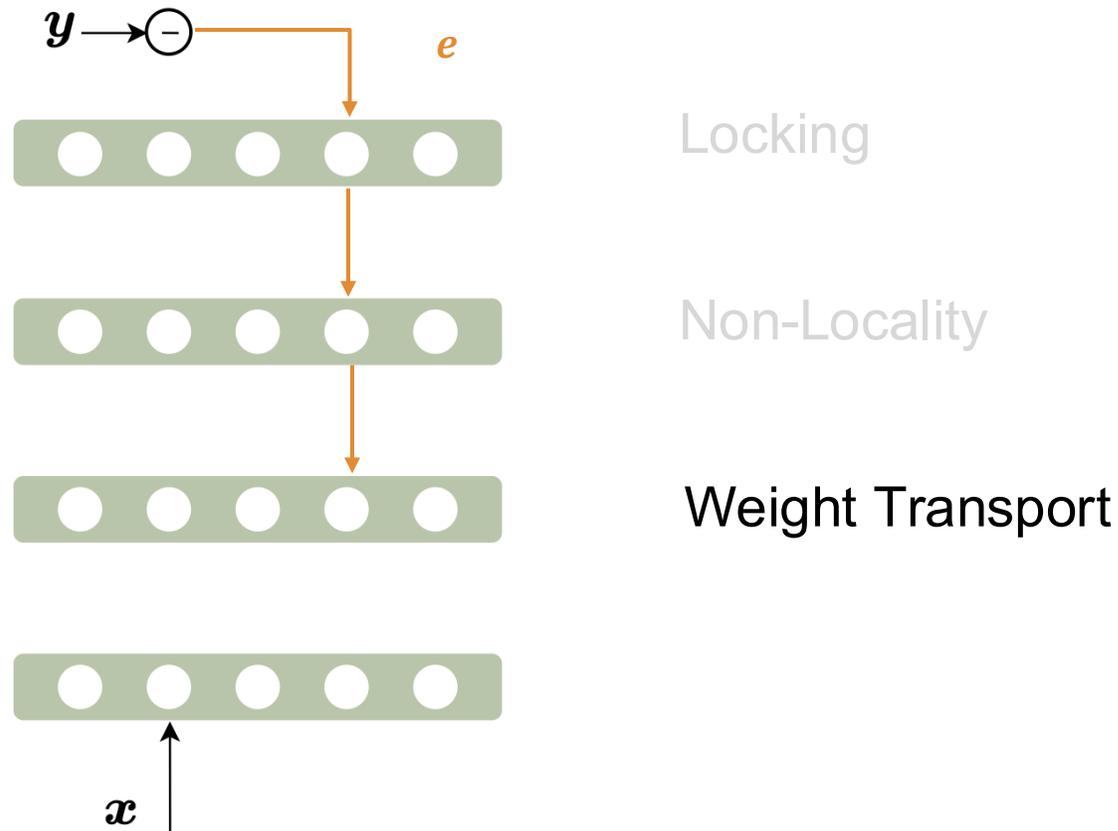
Locking

Non-Locality

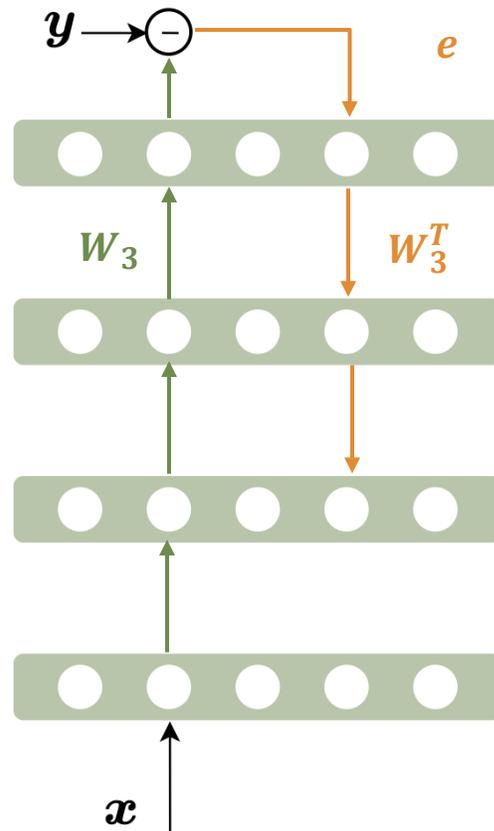
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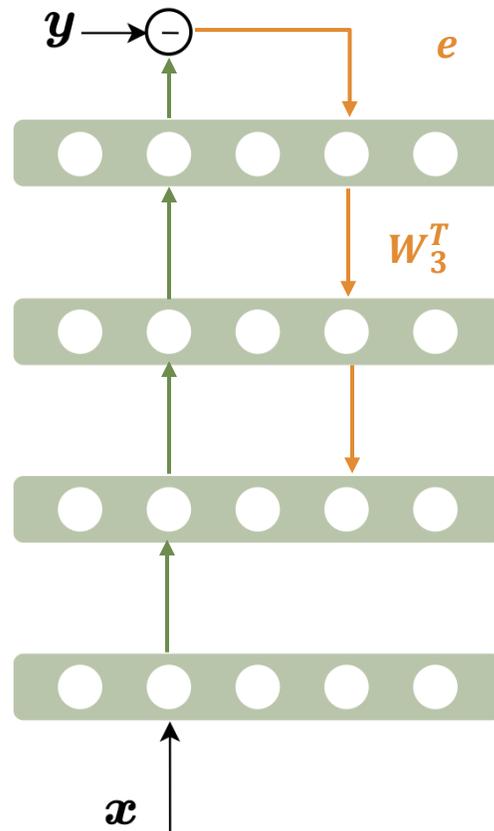


Locking

Non-Locality

Weight Transport

# The Biological Implausibility of BP



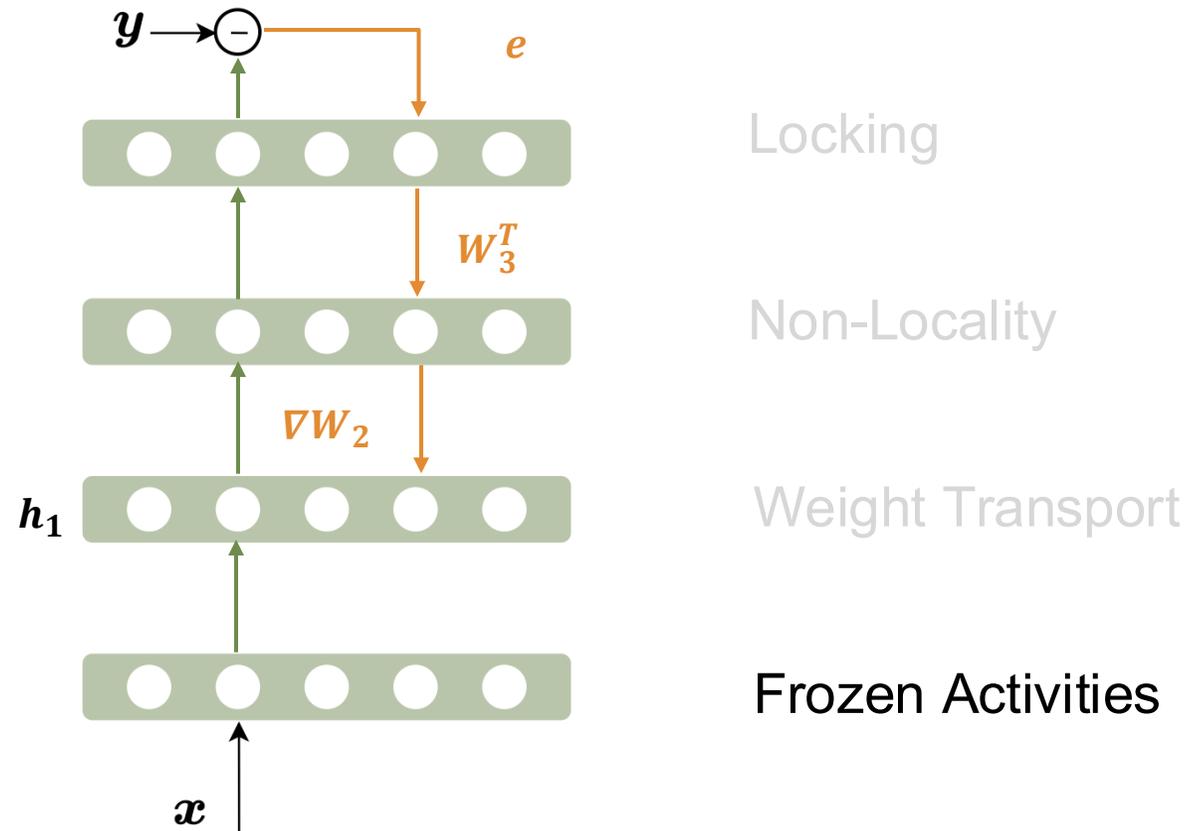
Locking

Non-Locality

Weight Transport

Frozen Activities

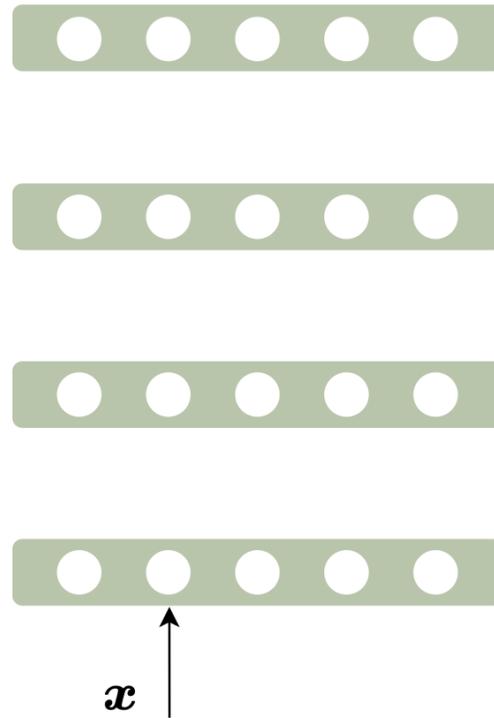
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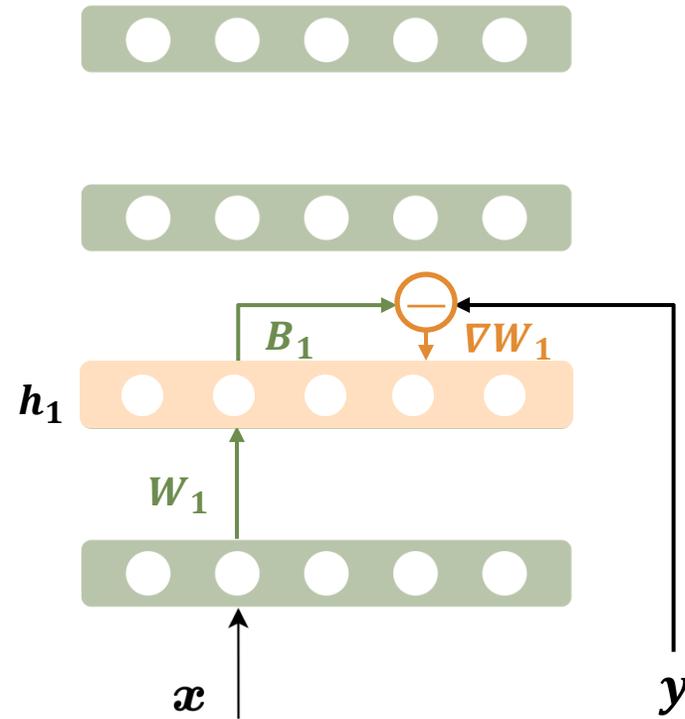


# Bio-FO: a Biologically-Plausible Forward-Only Algorithm

# Our Proposed Bio-F0

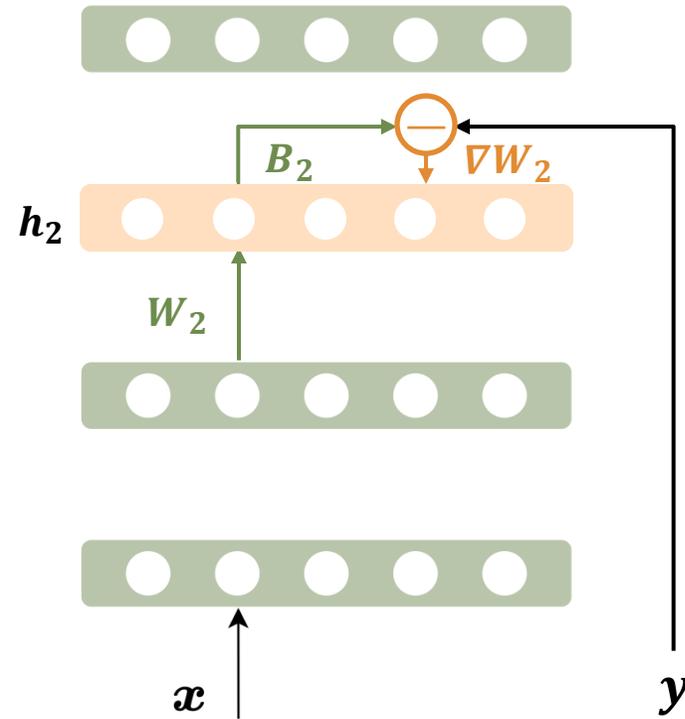


# Our Proposed Bio-F0



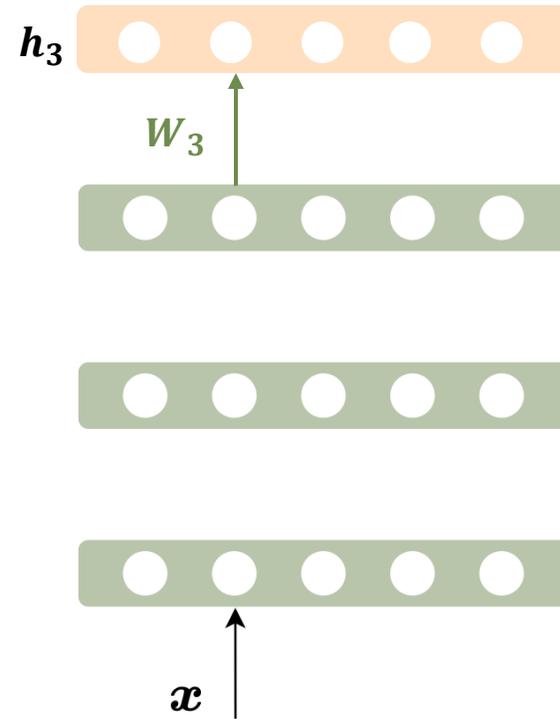
**$B$ : Fixed Random Projection**

# Our Proposed Bio-F0

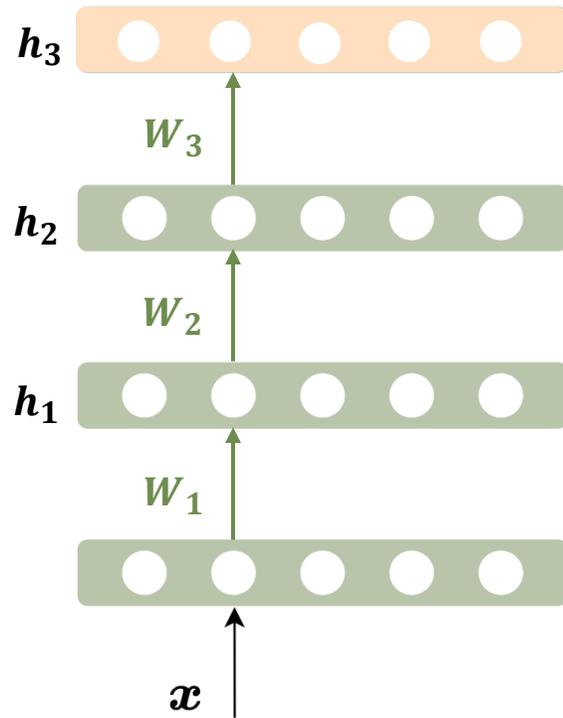


$B$ : Fixed Random Projection

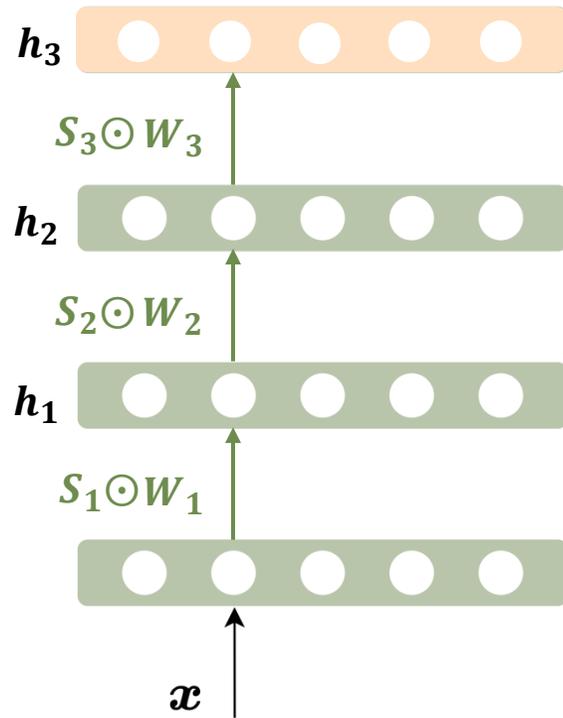
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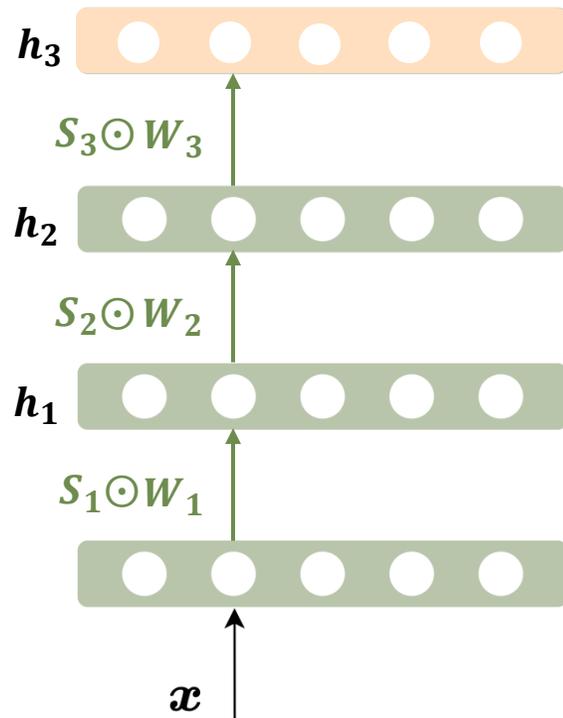


# Our Proposed Bio-F0

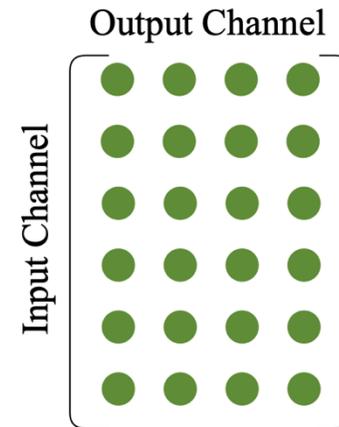


$S$ : Sparsity Mask

# Our Proposed Bio-F0

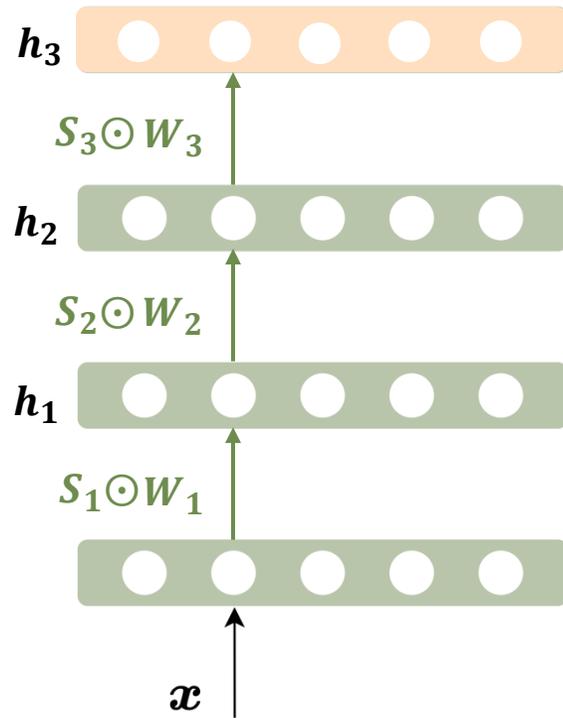


$S$ : Sparsity Mask

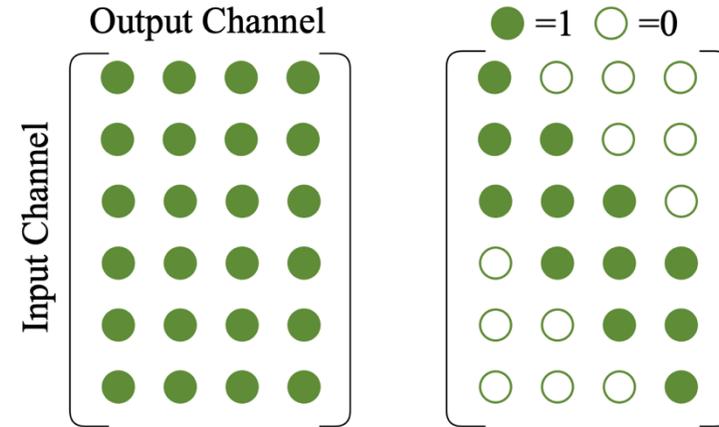


Fully Connected

# Our Proposed Bio-F0



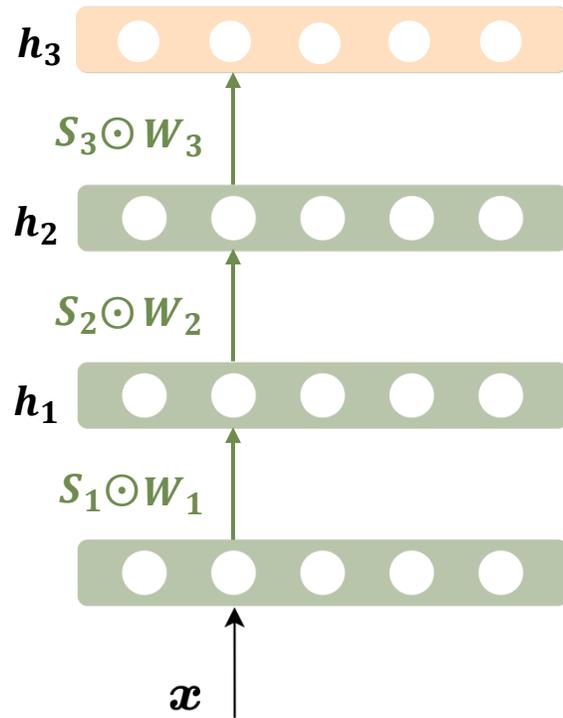
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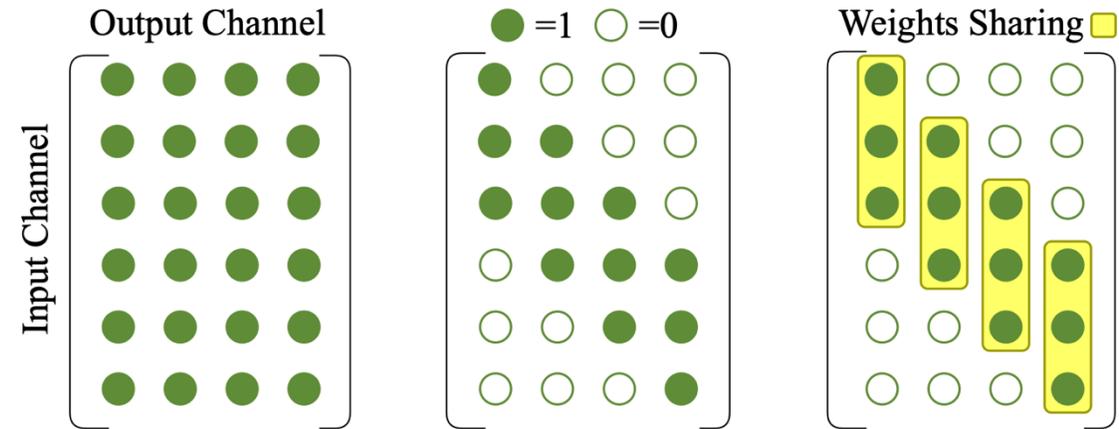
Fully Connected

Local Connected

# Our Proposed Bio-FO



$S$ : Sparsity Mask



Fully Connected

Local Connected

CNN



# Evaluation and Results

# Dataset and Application



MNIST  
Grayscale  
Image



CIFAR-10(100)  
RGB  
Images



Mini-ImageNet  
Subset of  
ImageNet

# Dataset and Application



MNIST  
Grayscale  
Image



CIFAR-10(100)  
RGB  
Images



Mini-ImageNet  
Subset of  
ImageNet



CHB-MIT  
Electroencephalogram  
(EEG)



MIT-BIH  
Electrocardiogram  
(ECG)

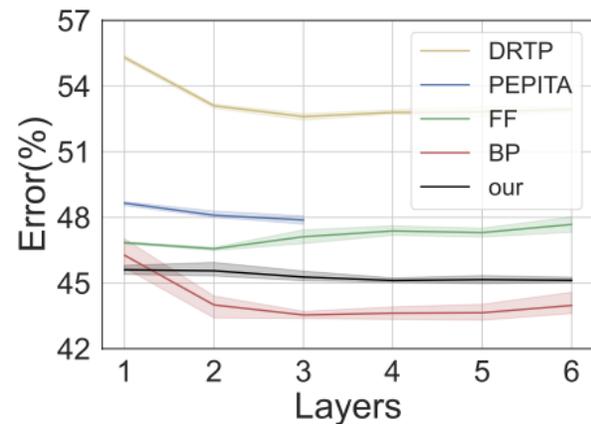
**Real-world wearable applications:  
Complexity overhead/energy consumption is a major constraint.**

Vinyals, O., et al. Matching networks for one shot learning. Advances in neural information processing systems, 2016.

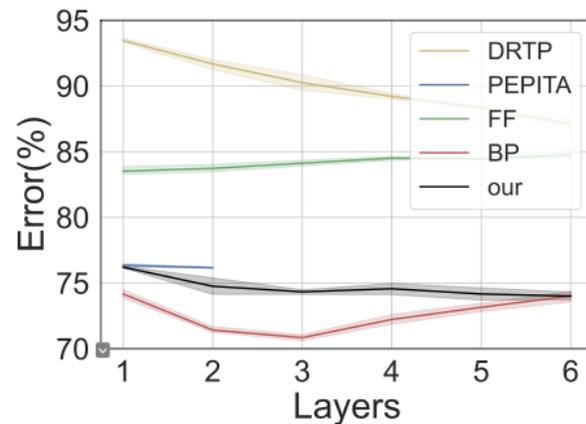
A. H. Shoeb. Application of machine learning to epileptic seizure onset detection and treatment. PhD thesis, MIT, 2009.

R. Mark, et al. An annotated ecg database for evaluating arrhythmia detectors. IEEE Transactions on Biomedical Engineering, 1982.

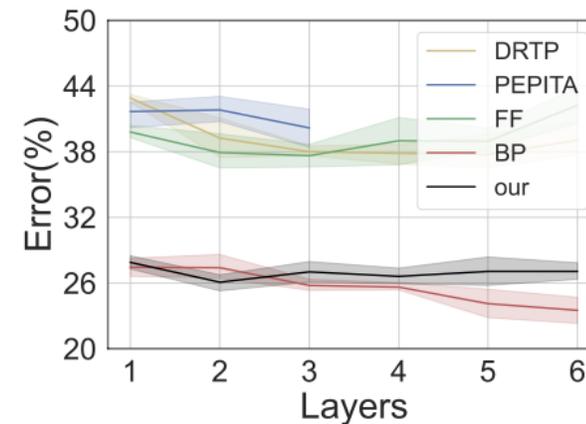
# Classification Performance



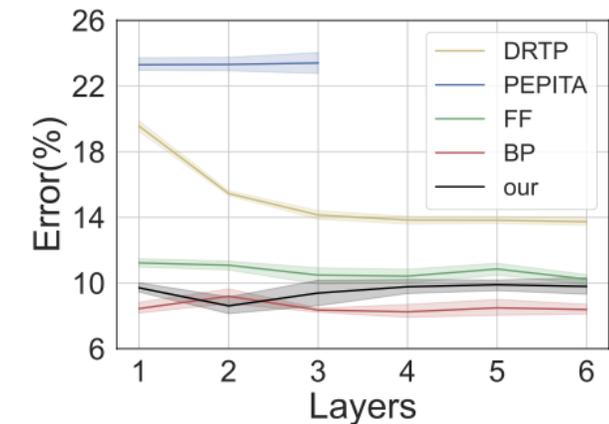
CIFAR-10



CIFAR-100



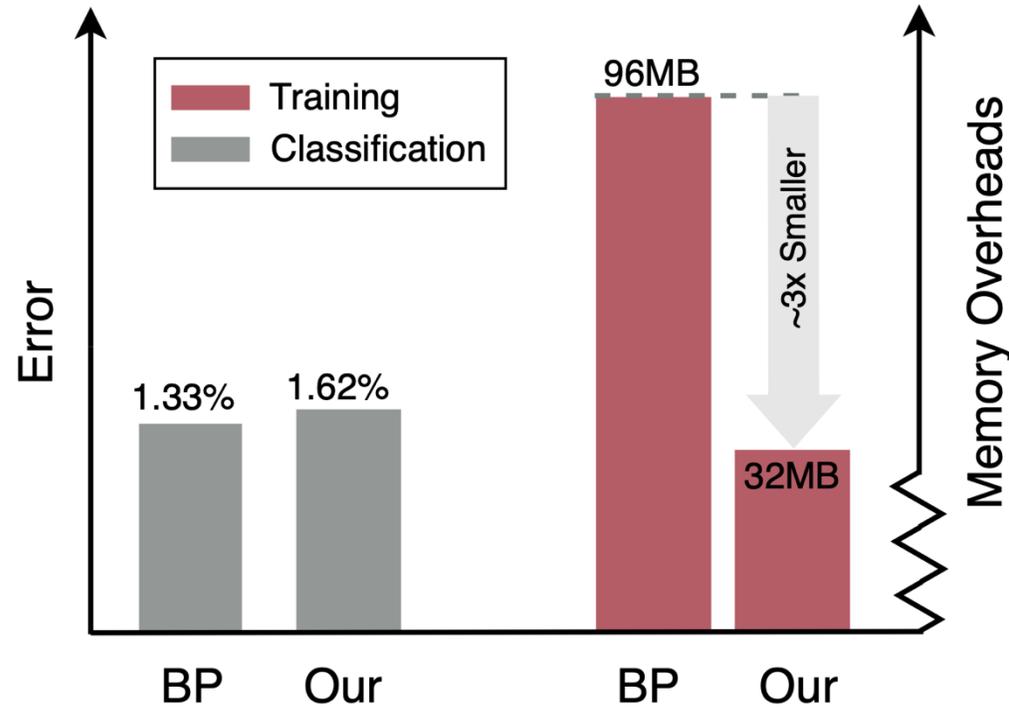
CHB-MIT



MIT-BIH

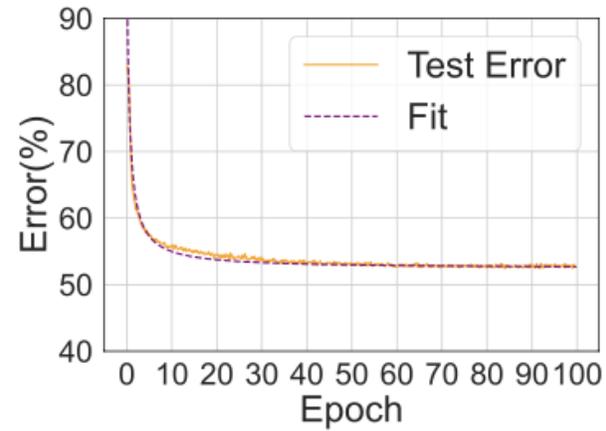
**Bio-FO outperforms** the state-of-the-art forward-only algorithms, with the potential to achieve **comparable performance** to BP.

# Memory Efficiency

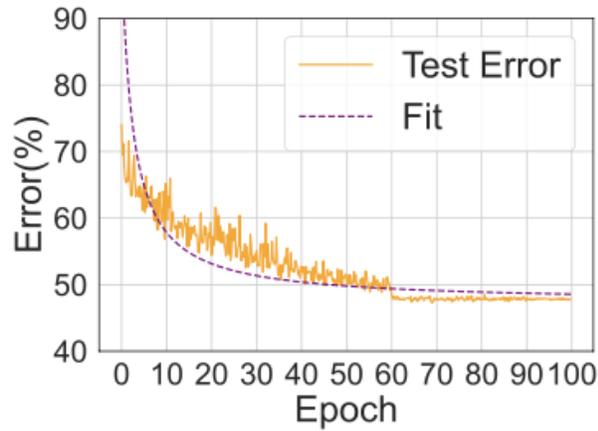


Bio-FO improves the memory efficiency and has approximately **3 times less memory overheads** when compared to BP.

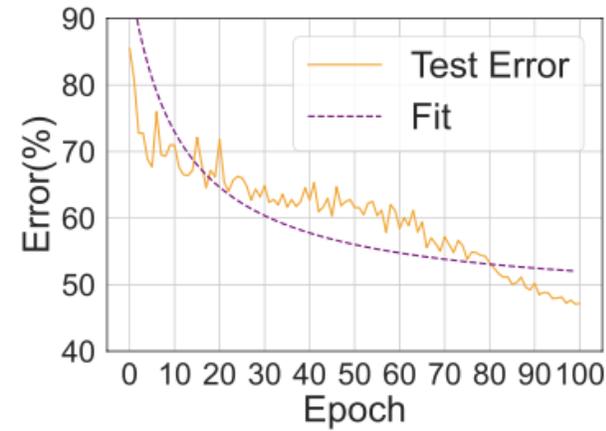
# Convergence Rate (CIFAR-10)



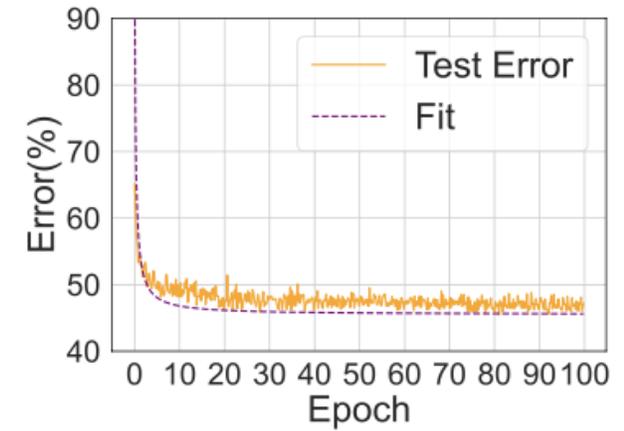
DRTP



PEPITA



FF



Our

Bio-FO enjoys **faster convergence** than PEPITA, and FF.

Algorithms	Energy Overheads (Wh)		
	CIFAR-100	CHB-MIT	MIT-BIH
DRTP	131.9	6.4	317.7
PEPITA	<u>123.9</u>	5.9	<u>191.0</u>
FF	753.5	<u>4.8</u>	221.9
Our	<b>37.9</b>	<b>3.5</b>	<b>121.1</b>

Bio-FO **outperforms** the state-of-the-art forward-only algorithms in terms of energy consumption.

# Scalability (Architectures)

Datasets	Error (%)		
	Our-FC	Our-LC	Our-CNN
MNIST	1.62	<u>1.36</u>	<b>0.57</b>
CIFAR-10	45.12	<u>35.13</u>	<b>26.08</b>
CIFAR-100	74.57	<u>64.06</u>	<b>64.06</b>

The relevance of Bio-FO with LC and CNN shows **the importance of architectures** for improving classification performance.

# Scalability (mini-ImageNet)

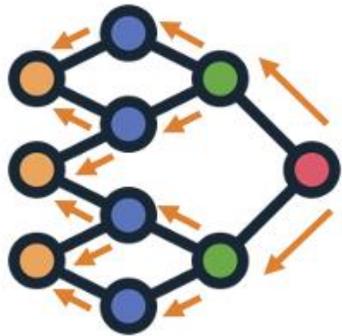
Datasets	Error (%)				
	DRTP	PEPITA	FF	Our	BP
mini-ImageNet	94.20 $\pm$ 0.49	91.23 $\pm$ 0.18	93.64 $\pm$ 0.26	67.39 $\pm$ 0.25	53.49 $\pm$ 0.40

Bio-FO achieves the **closest classification performance** to BP, on relatively large-scale datasets such as mini-ImageNet.

## Challenge

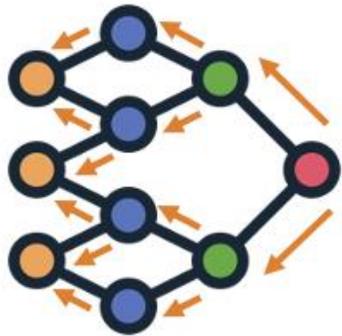
### Bio-Implausibility

Incurs  
Inefficiency



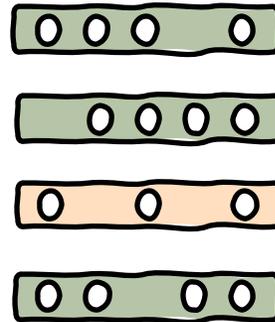
## Challenge

**Bio-Implausibility**  
Incurs  
Inefficiency



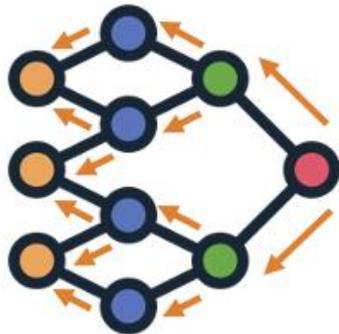
## Approach

A Biologically Plausible  
**Forward-Only**  
Algorithm



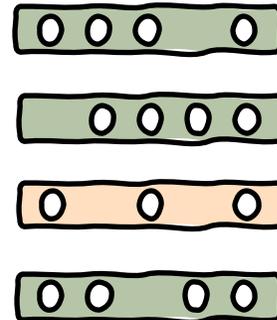
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Inefficiency



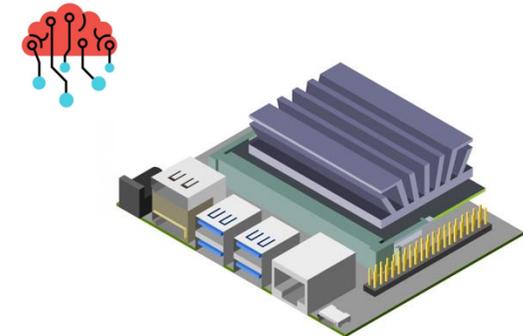
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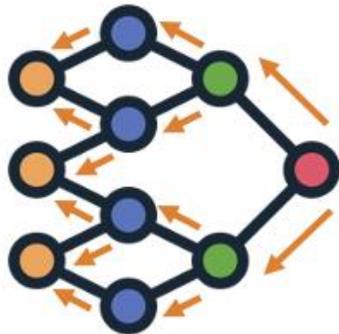
## Performance

Memory & Energy  
**Efficiency**  
Maintain Performance



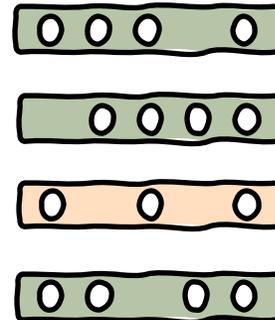
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**Bio-Implausibility**  
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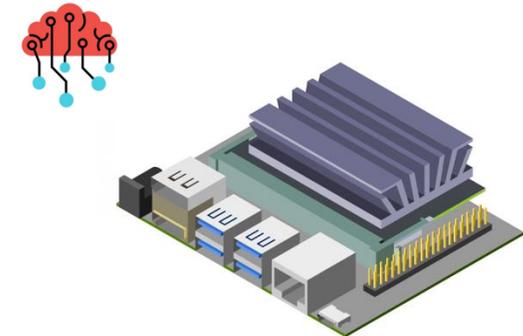
## Approach

A Biologically Plausible  
**Forward-Only**  
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## Performance

Memory & Energy  
**Efficiency**  
Maintain Performance



Welcome to Our Poster Session

**Thank you!**