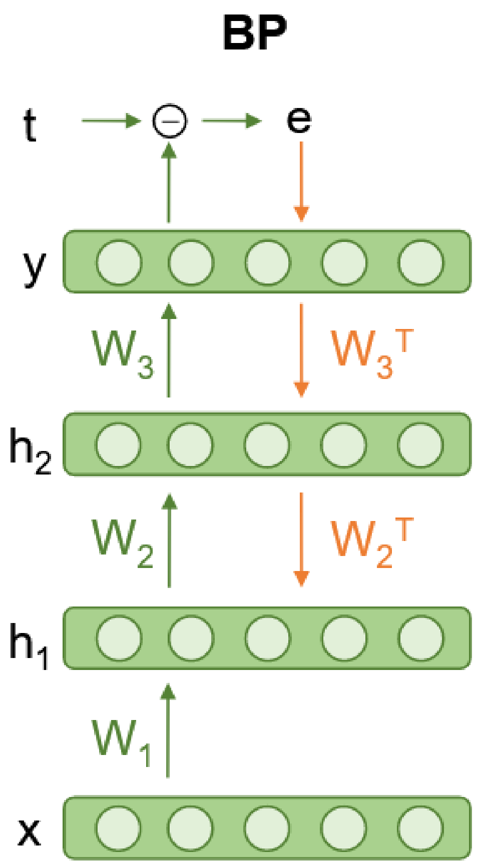
Error-driven Input Modulation: Solving the Credit Assignment Problem without a Backward Pass

Giorgia Dellaferrera & Gabriel Kreiman

ICML 2022

Backpropagation of the error is not biologically plausible



Rumelhart et al., 1995

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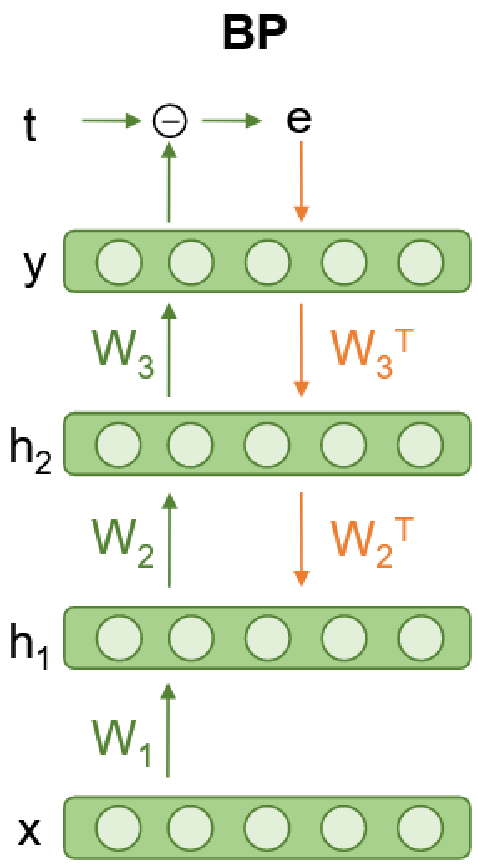

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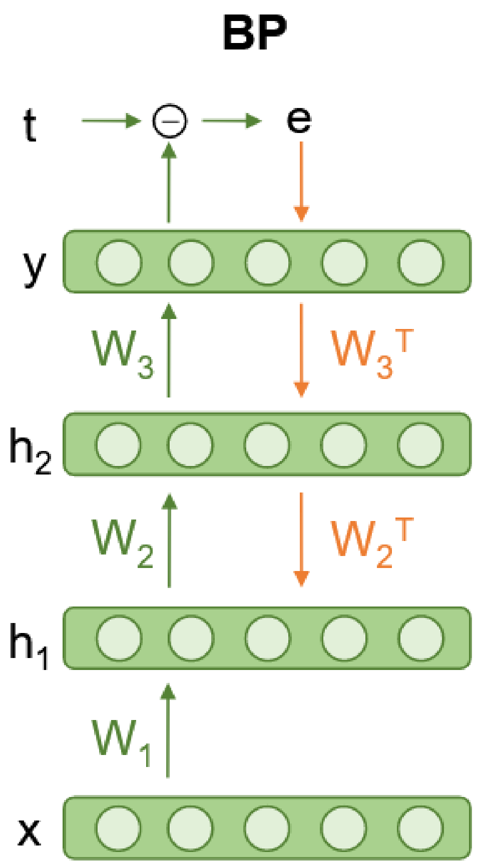

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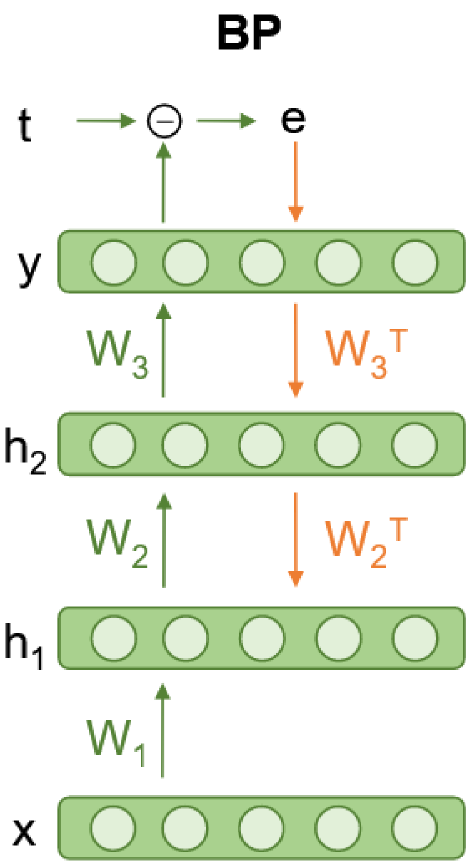

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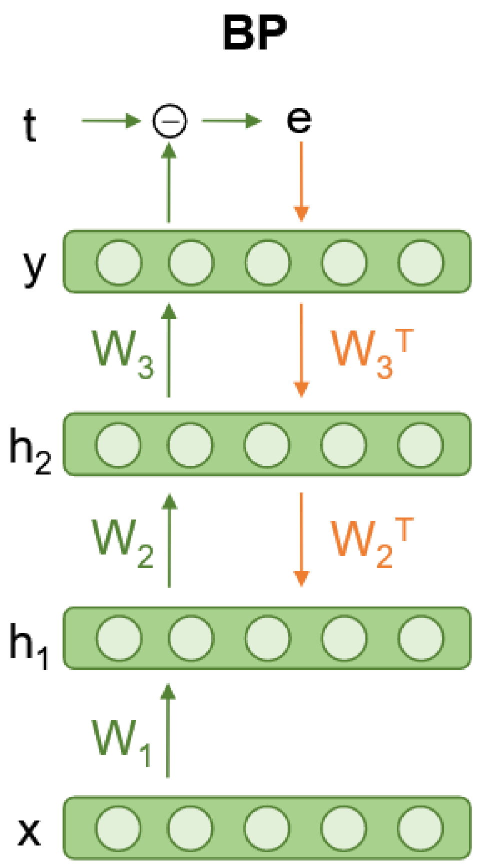

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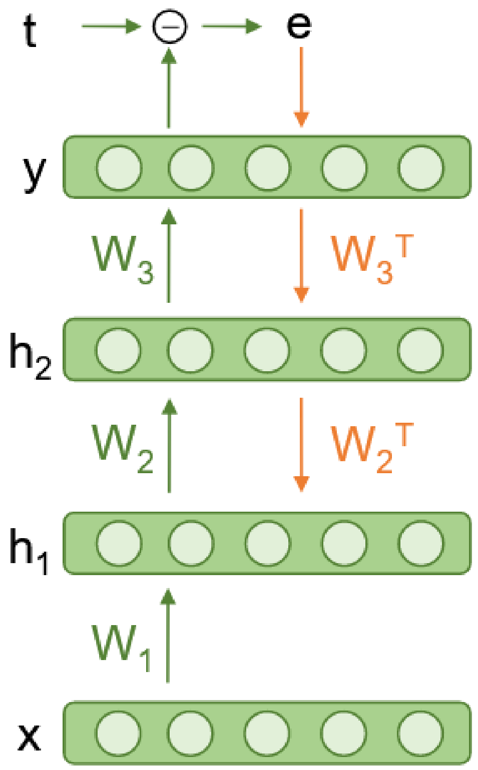

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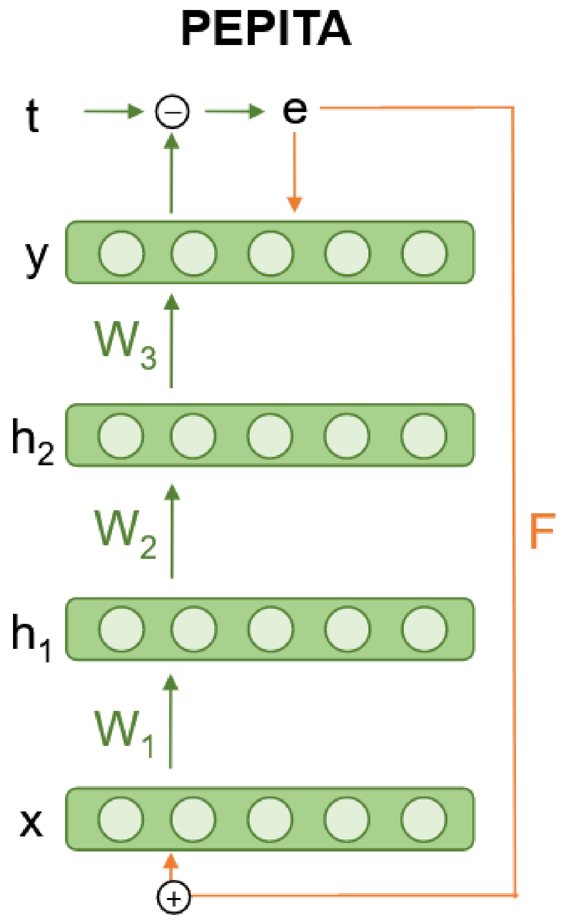
Alternative Training Schemes

Lillicrap et al., 2020

The PEPITA learning rule for Fully Connected Neural Networks

» **PEPITA** = Present the Error to Perturb the Input To modulate Activity

- Substitutes the standard Forward+Backward scheme with **two Forward Passes**



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Algorithm 1 Implementation of PEPITA

Given: Input (x) and label ($target$)
#standard forward pass
$h_0 = x$
for $\ell = 1, ..., L$
  $h_\ell = \sigma_\ell(W_\ell h_{\ell-1})$
$e = h_L - target$
#modulated forward pass
$h_0^{err} = x + Fe$
for $\ell = 1, ..., L$
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  if $\ell < L$:
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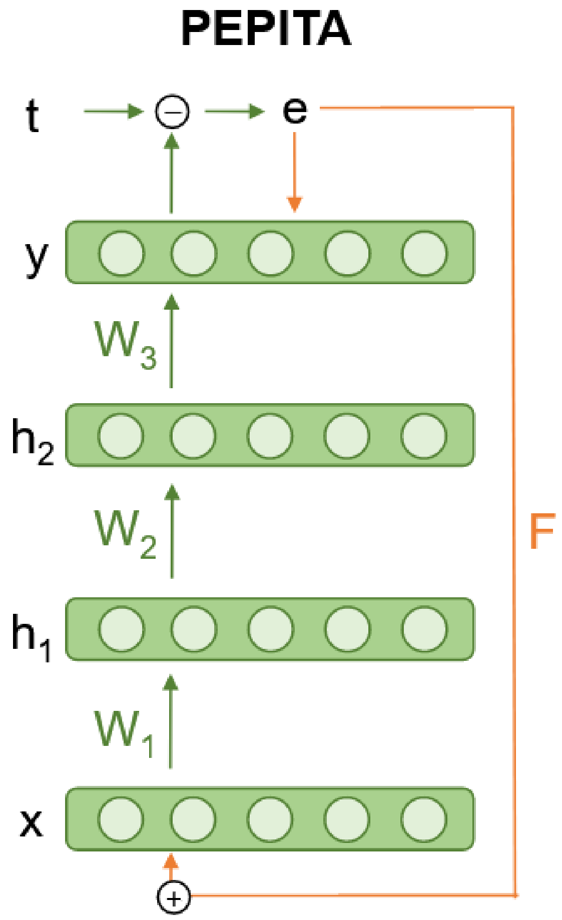

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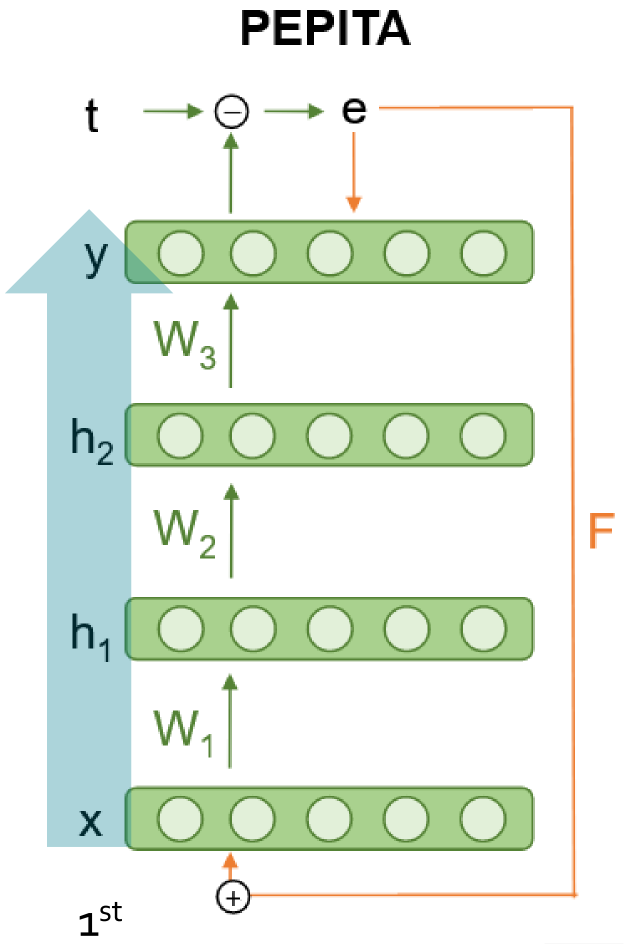

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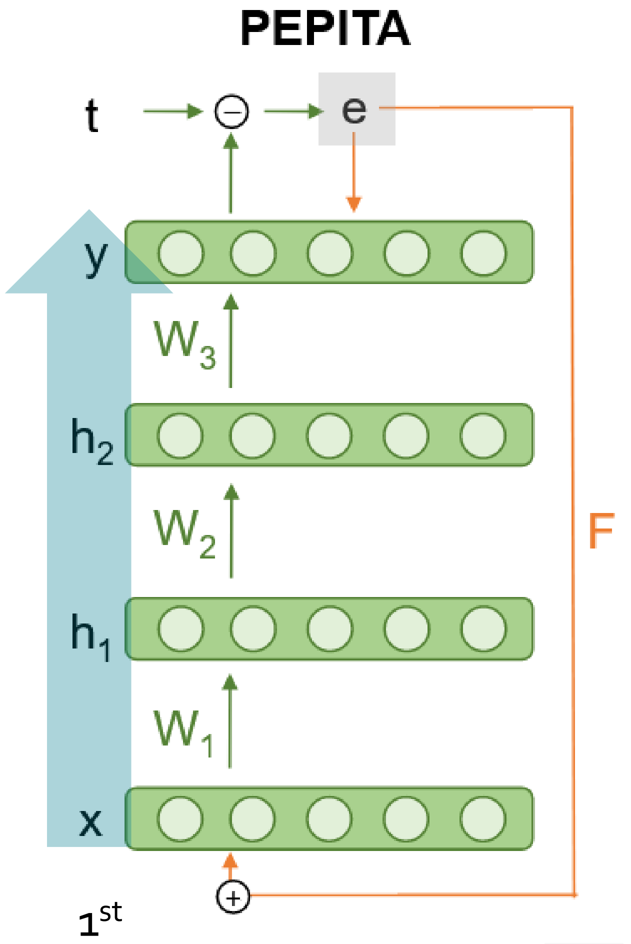

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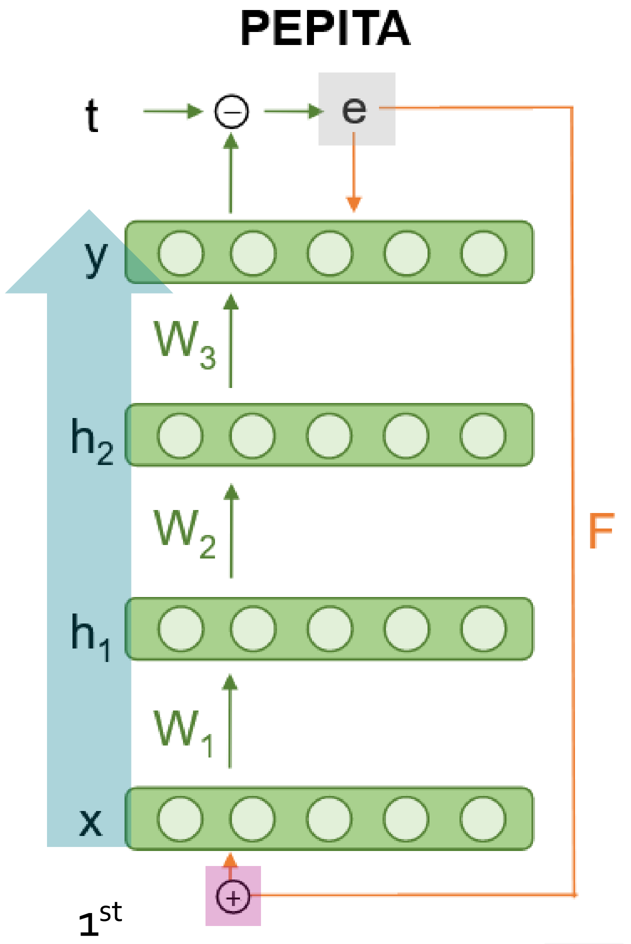

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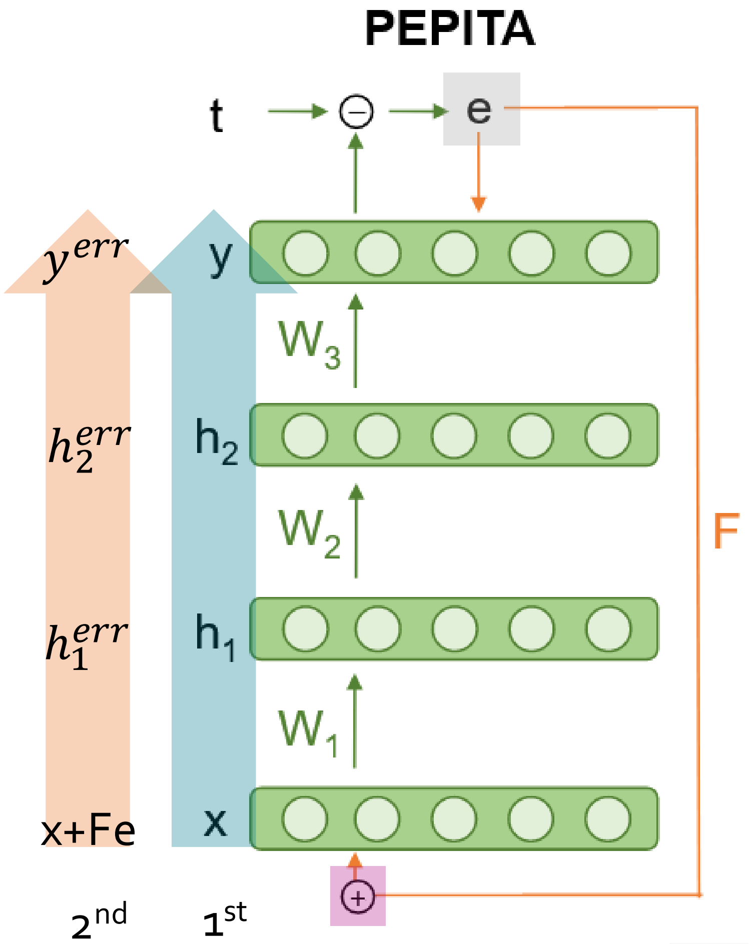

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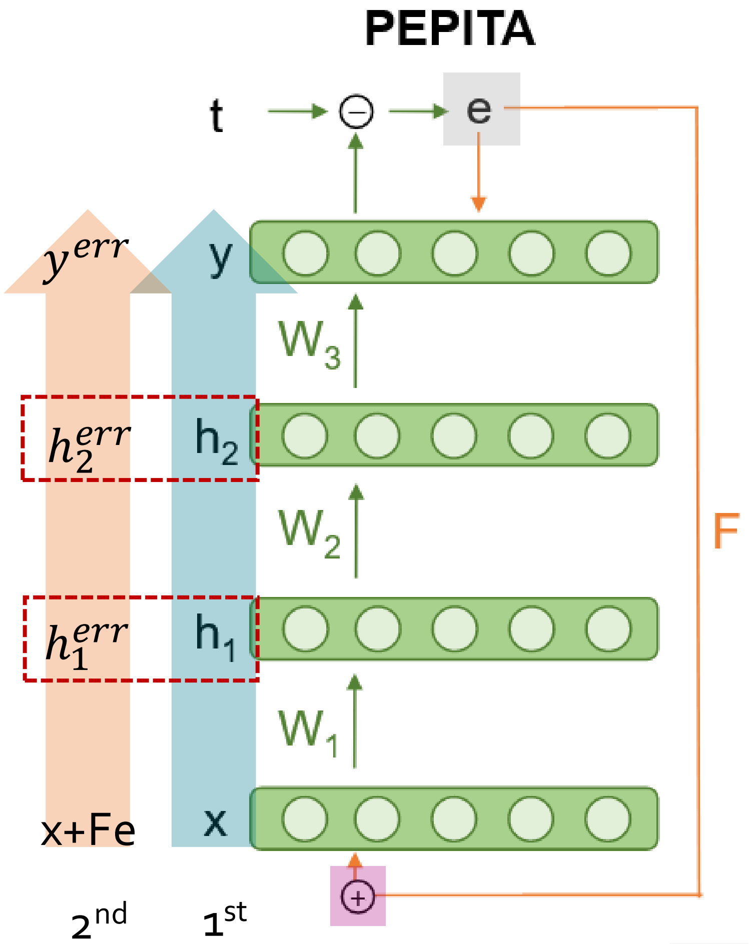
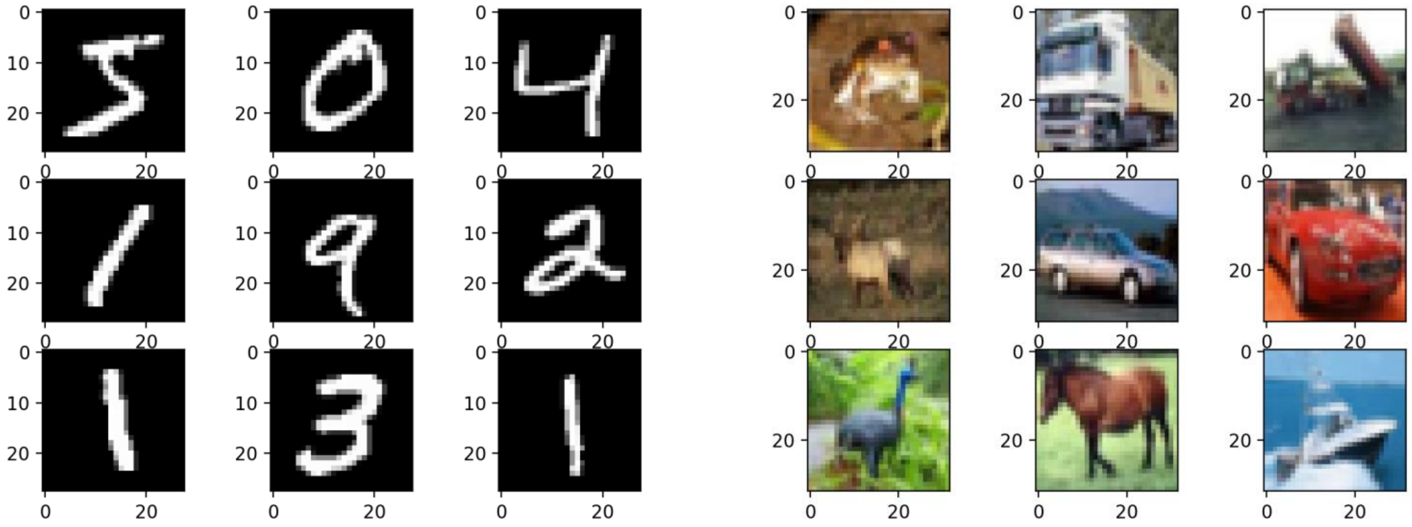


Testing PEPITA on image classification tasks - experimental results



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BP	98.63±0.03	55.27±0.32	27.58±0.09	98.86±0.04	64.99±0.32	34.20±0.20
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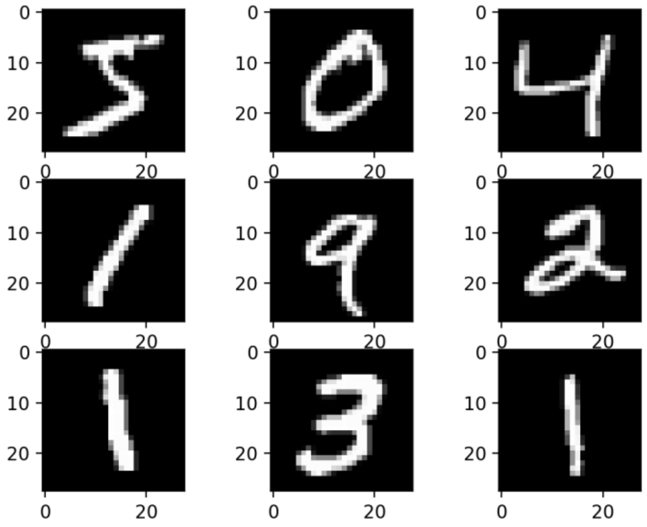

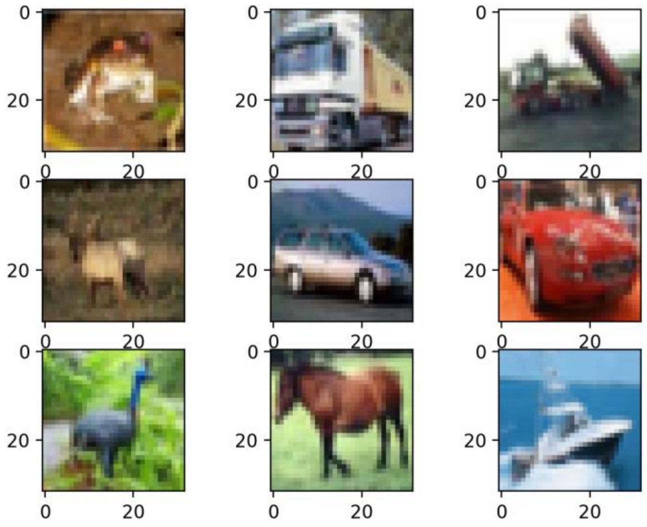

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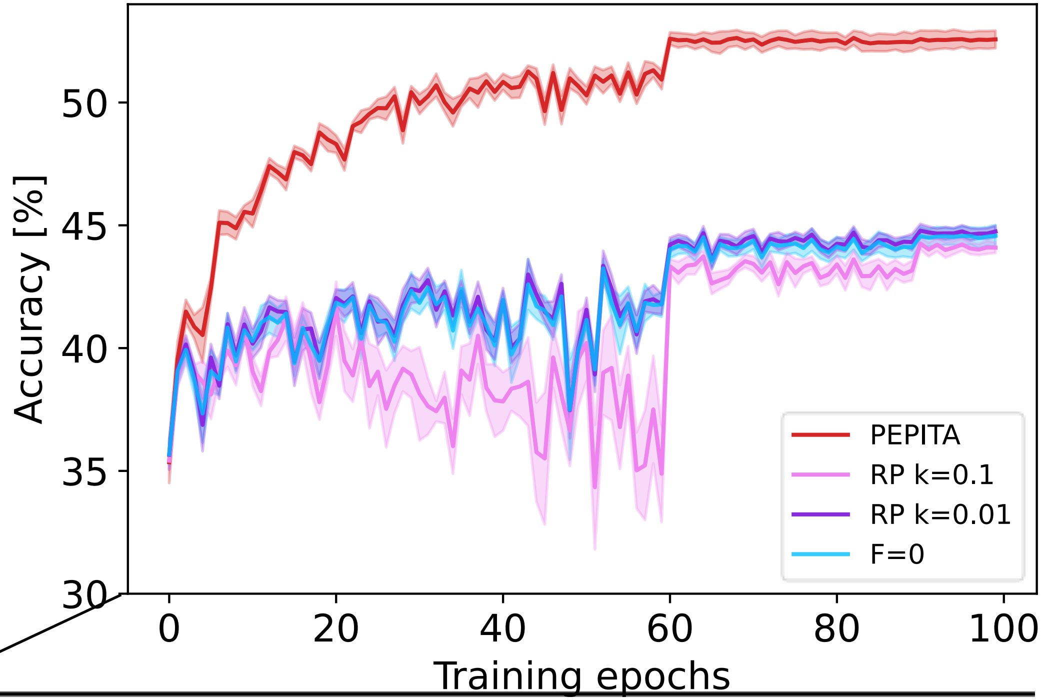

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Why it works: soft-antialignment

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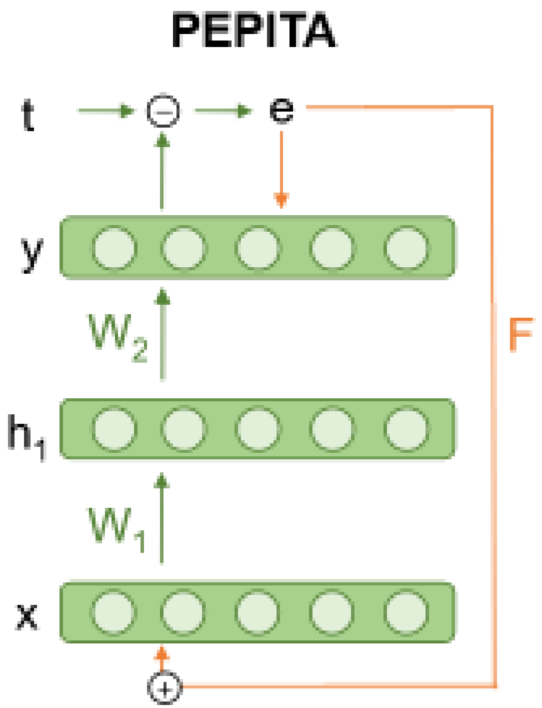

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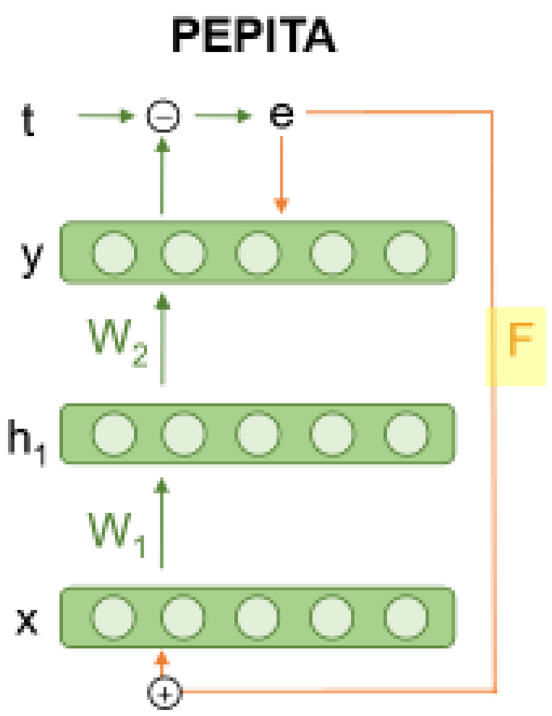

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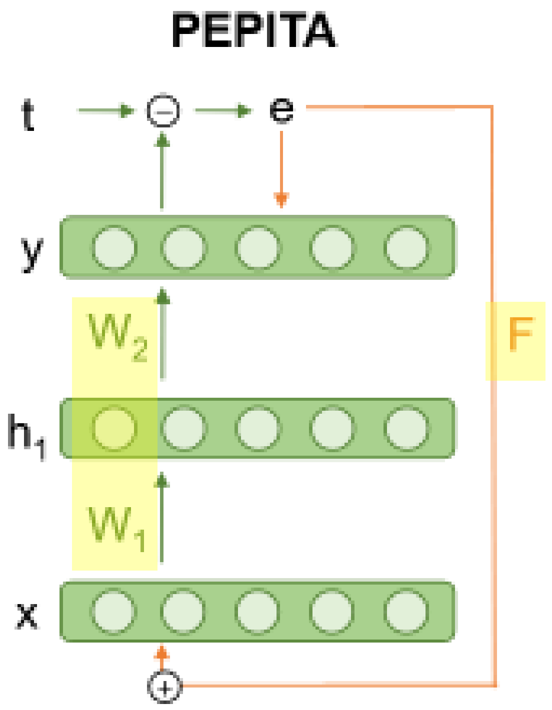

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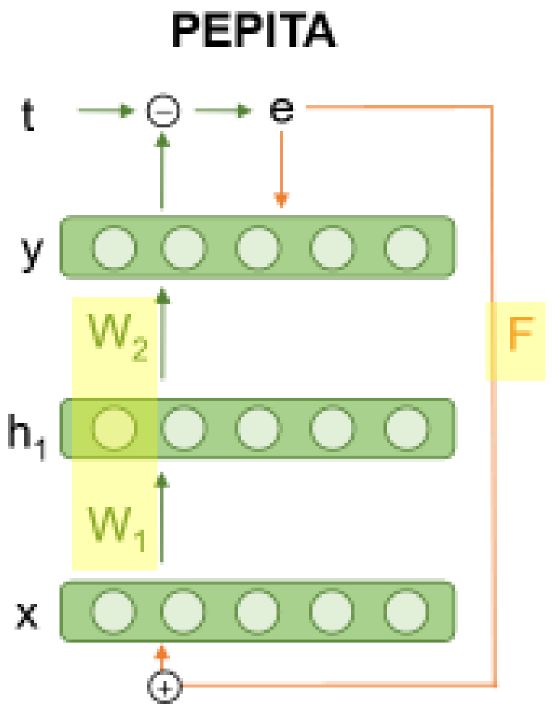

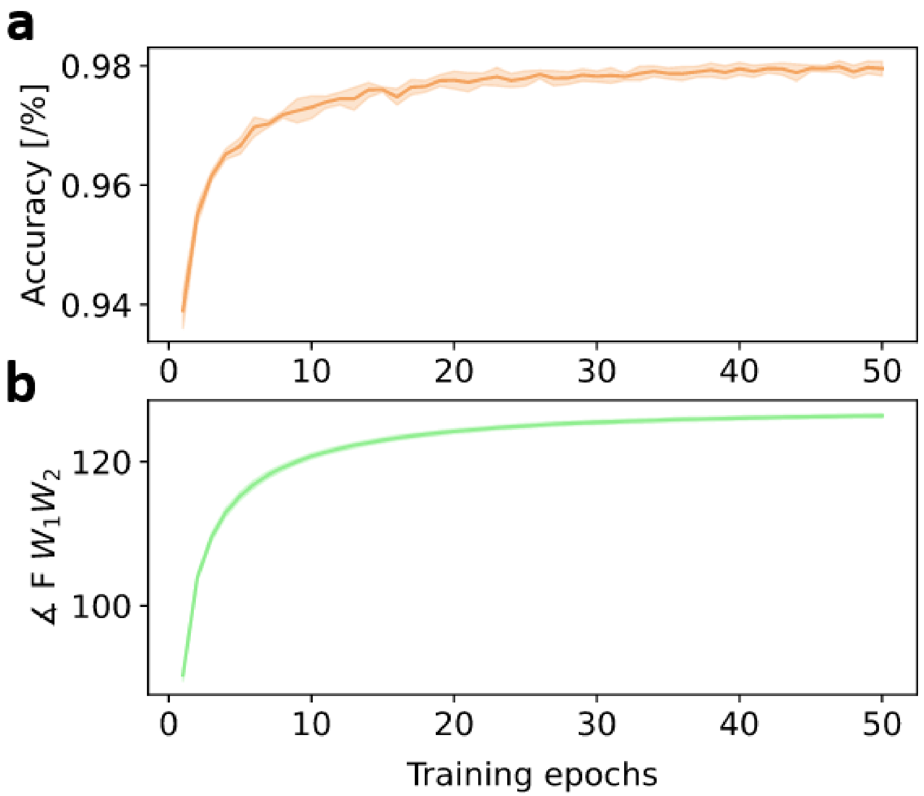

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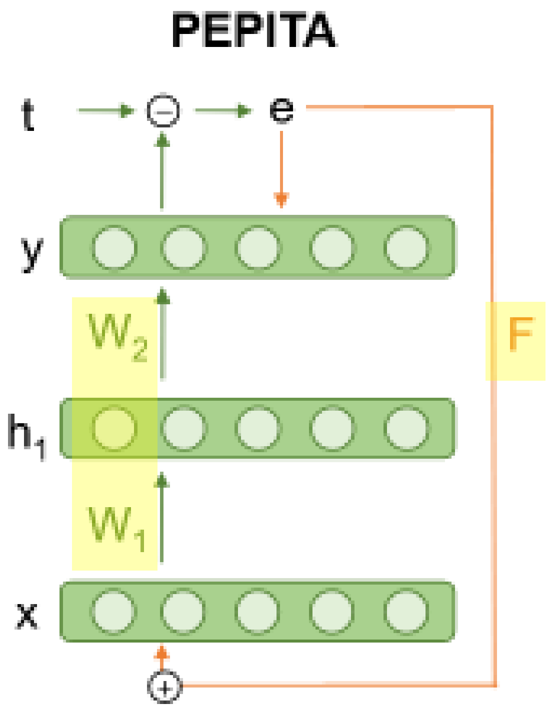
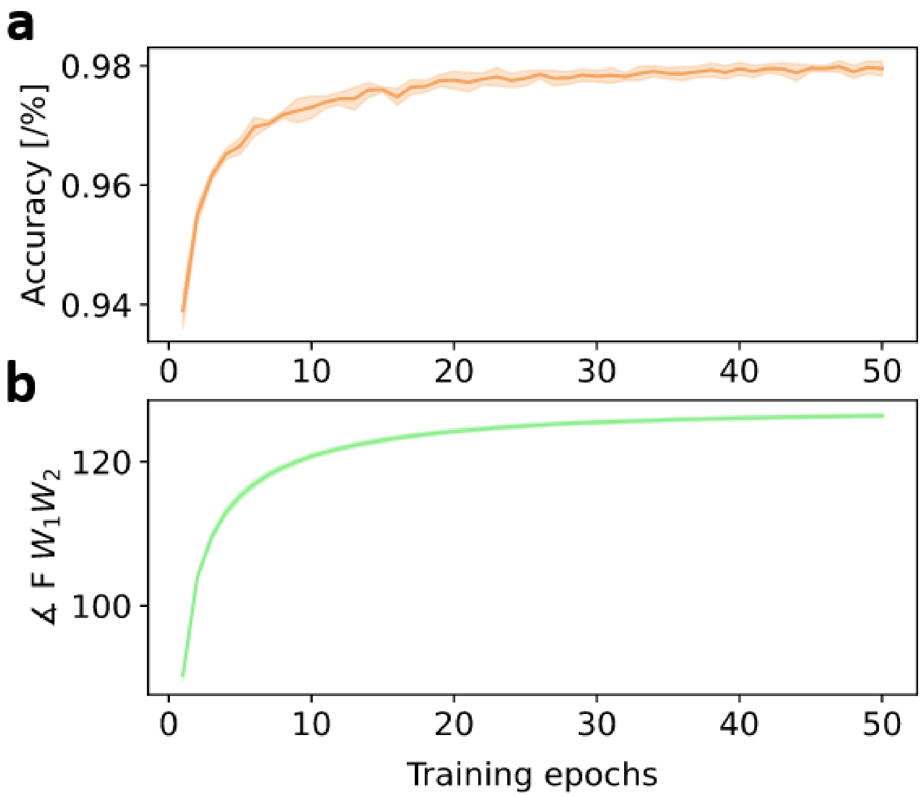
- <u>Analytically proven</u> for one-hidden layer linear network





Summary and Outlook

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» **Challenges**

- Performance **does not improve with depth**
- Different non-linearities
- Residual connection
- Training the F matrix

Thank you for your attention!

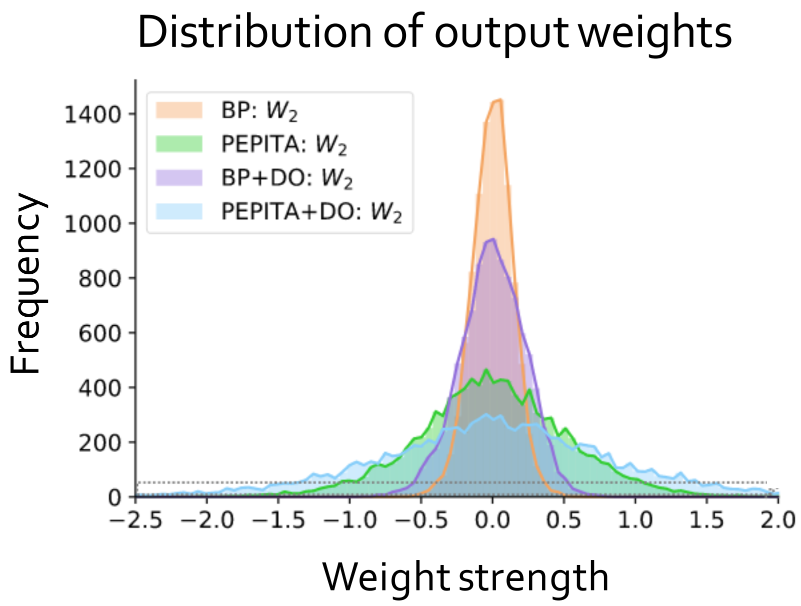
» Questions?
» Ideas?
» Suggestions?

✉ *gde@zurich.ibm.com*

Weight distribution after training

» **Wider weight distribution**

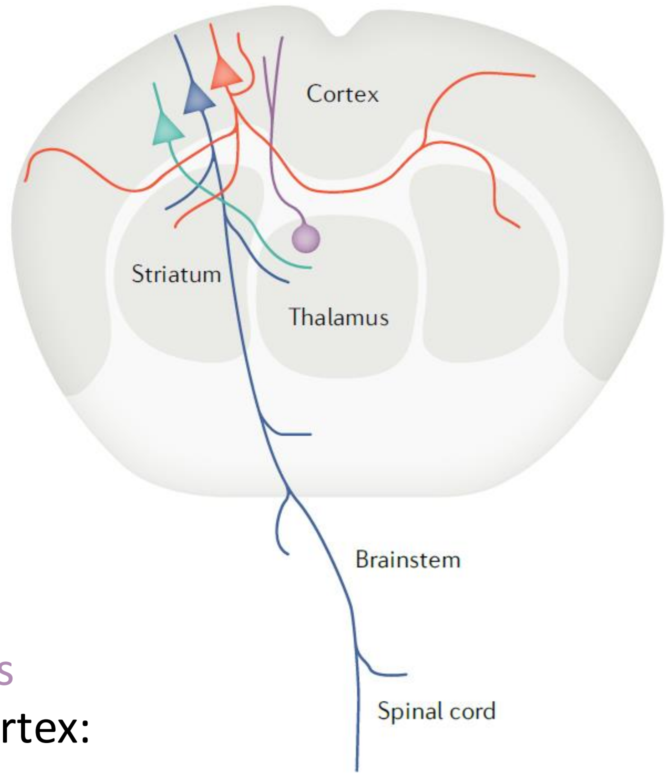
- PEPITA learns different solutions compared to BP



Analysis of PEPITA from a biological standpoint

PEPITA solves the BP's issues of biological plausibility, but it introduces additional elements:

» Projection of the error onto the input through a fixed random matrix
  - Reminiscent of cortico-thalamo-cortical loops



In the thalamus:
- Thalamocortical (TC) neurons

Excitatory neurons in the neocortex:
- Intratelencephalic (IT)
- Pyramidal tract (PT)
- Corticothalamic (CT) neurons

Shepherd & Yamawaki, 2021

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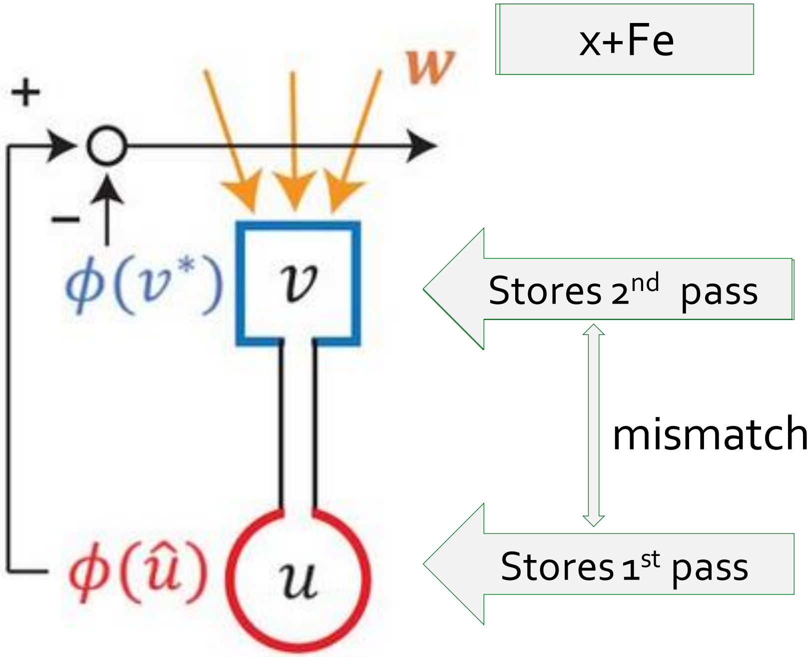
PEPITA solves the BP's issues of biological plausibility, but it introduces additional elements:

» Projection of the error onto the input through a fixed random matrix
  - Reminiscent of cortico-thalamo-cortical loops

» Storing of the activation of the *Standard pass* until the *Modulated pass*
  - Can be implemented in biological neurons through mismatch between dendritic and somatic activity



Asabuki & Fukai, 2020

The PEPITA learning rule

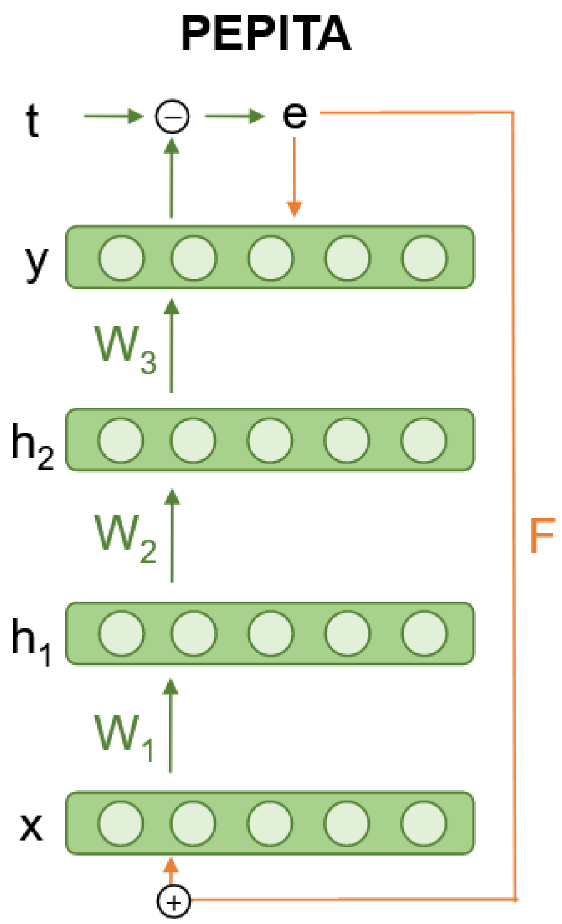
» **PEPITA** = Present the Error to Perturb the Input To modulate Activity

» Substitutes the standard Forward+Backward scheme with **two Forward Passes**

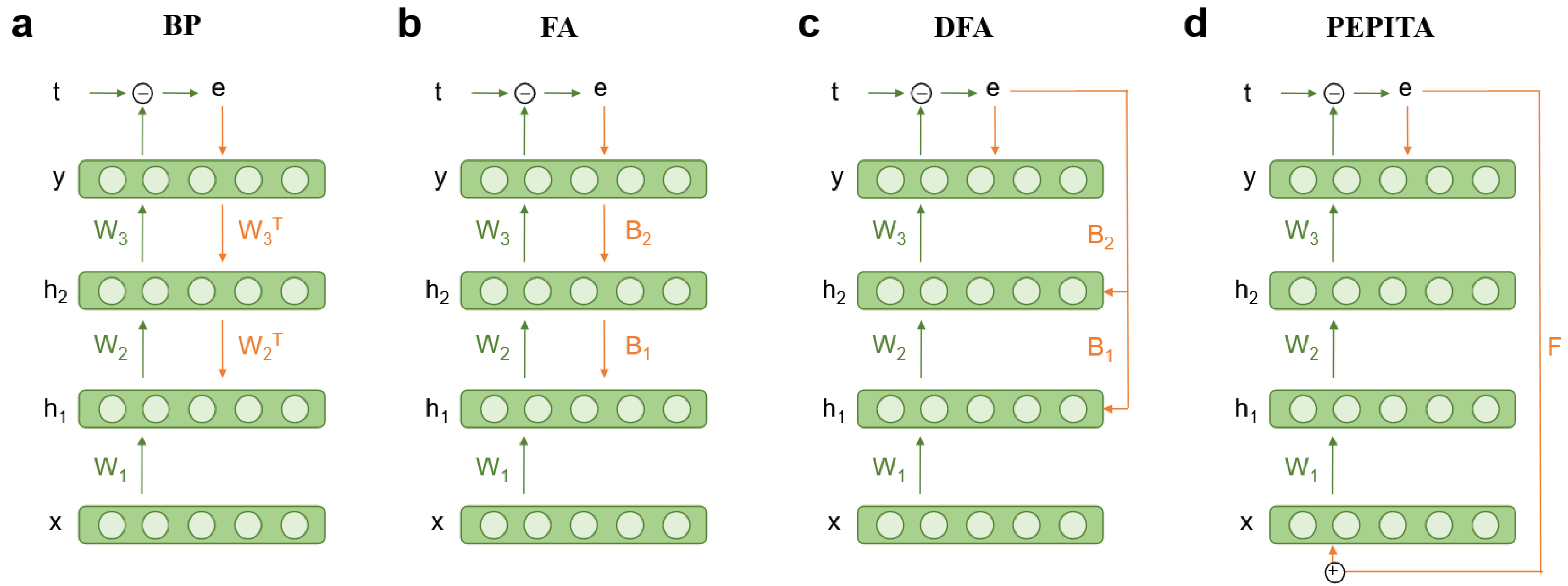
- *Standard Forward pass* → same as for standard algorithms
- *Modulated Forward pass* → input is modulated by the error

» F = **projection matrix** to add the error onto the input

» Update relies **on difference of activations** between *Standard* and *Modulated pass*

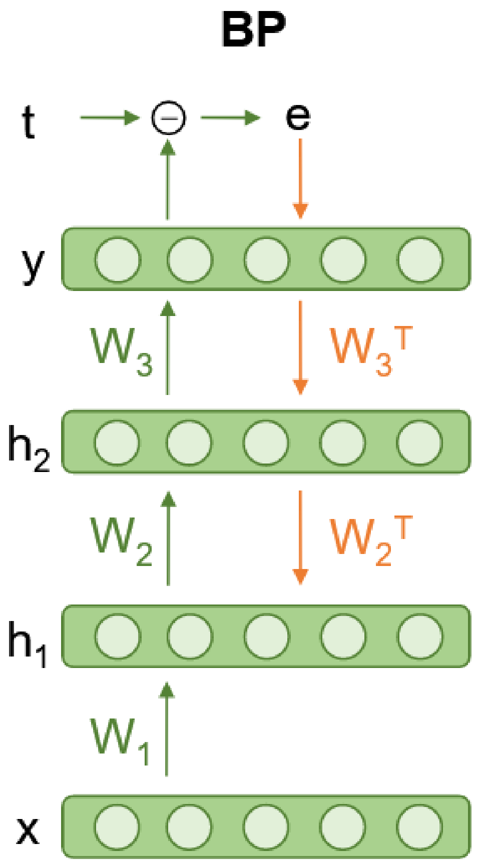


PEPITA solves the biologically implausible aspects of BP



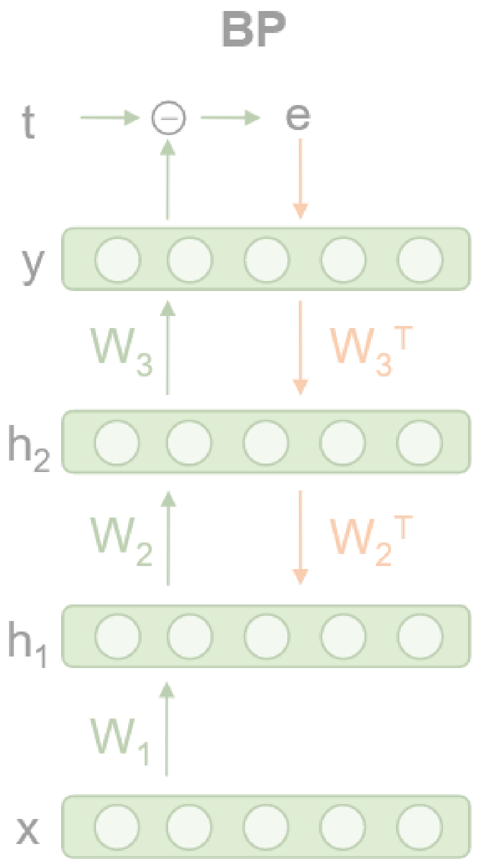
	BP	FA	DFA	PEPITA
$\Delta W_\ell =$	$-(W_{\ell+1}^T \delta a_{\ell+1}) \odot f'(a_\ell) h_{\ell-1}^T$	$-(B_\ell^T \delta a_{\ell+1}) \odot f'(a_\ell) h_{\ell-1}^T$	$-(B_\ell^T e) \odot f'(a_\ell) h_{\ell-1}^T$	$(h_\ell - h_\ell^{err}) \cdot (h_{\ell-1}^{err\,T})$
WEIGHT-TRANSPORT-FREE	✗	✓	✓	✓
LOCAL RULE	✗	✗	✗	✓
FREEZING OF ACTIVITY	✗	✗	✗	✓
UPDATE-UNLOCKED	✗	✗	PARTIALLY	PARTIALLY

Alternatives to BP: relaxing symmetry requirements

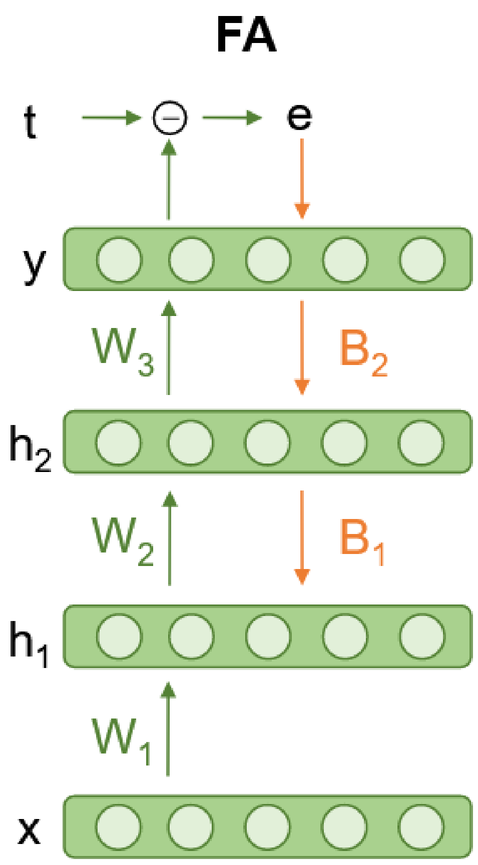


Rumelhart et al., 1995

Alternatives to BP: relaxing symmetry requirements

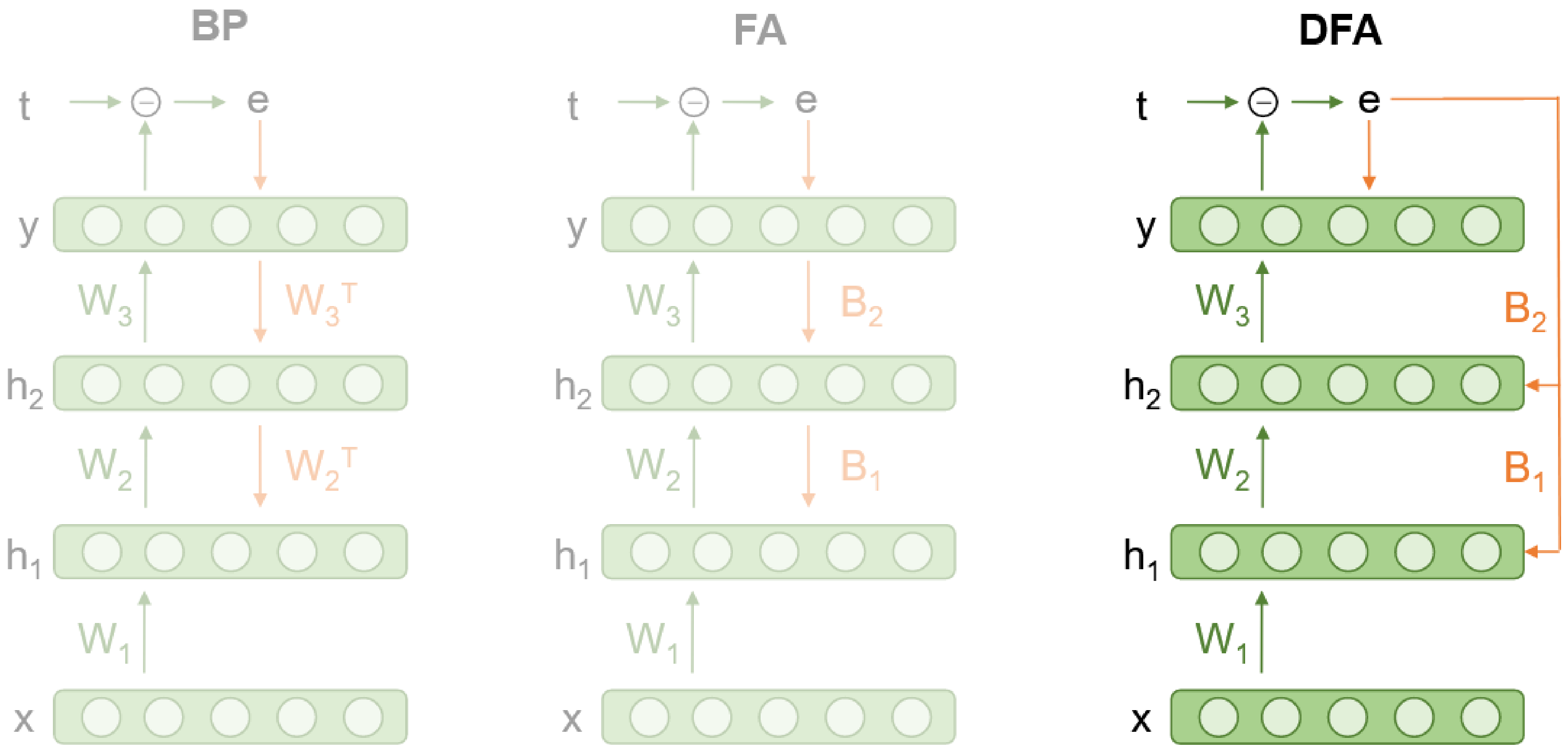


Rumelhart et al., 1995



Lillicrap et al., 2016

Alternatives to BP: relaxing symmetry requirements

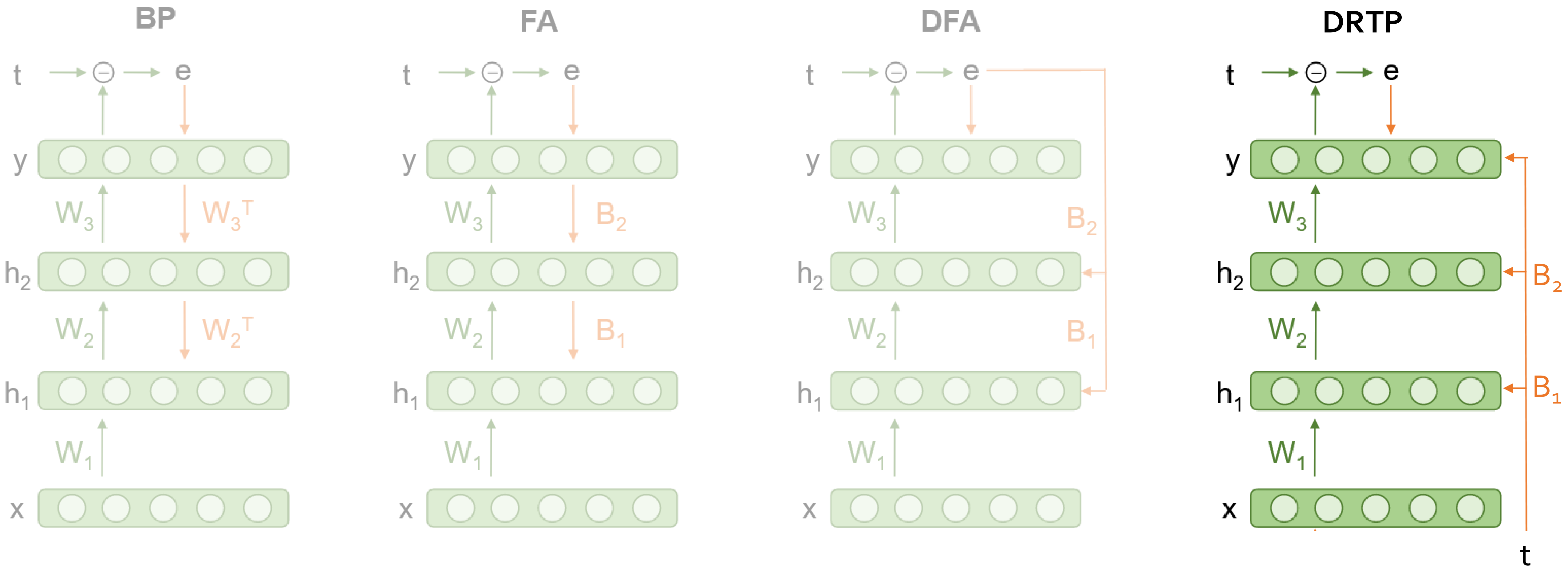


Rumelhart et al., 1995

Lillicrap et al., 2016

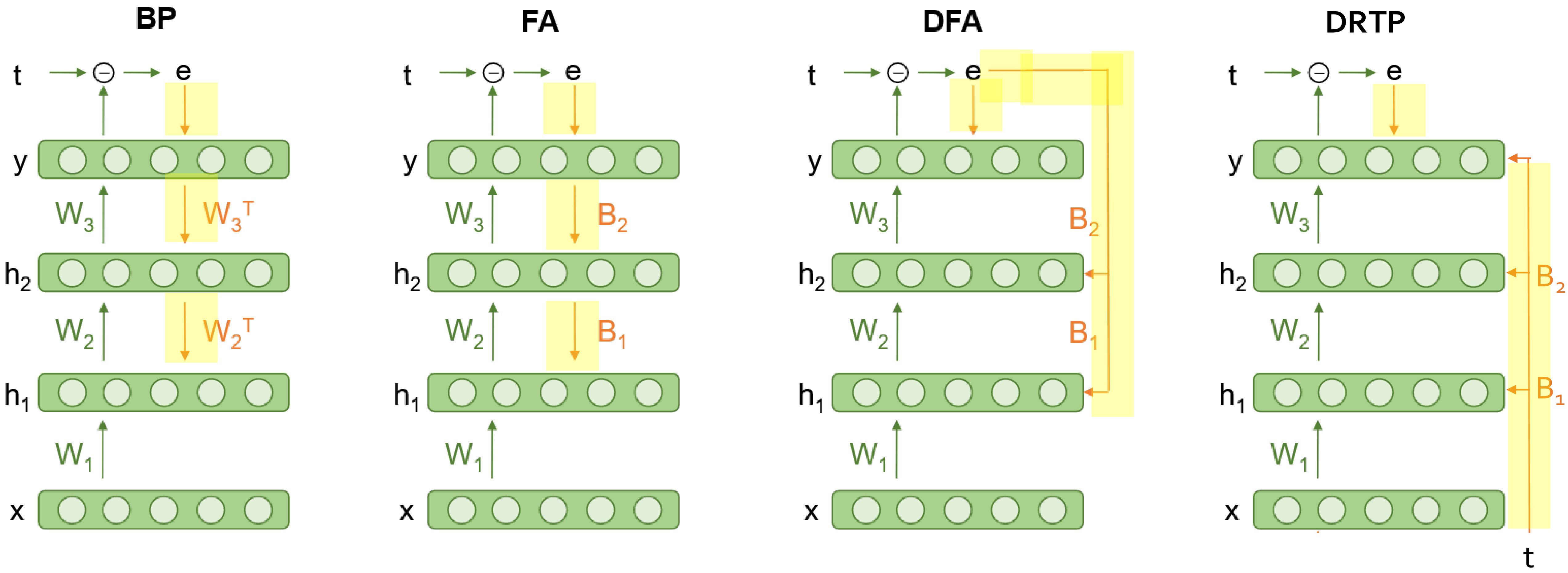
A. Nokland, 2016

Alternatives to BP: relaxing symmetry requirements



Rumelhart et al., 1995 | Lillicrap et al., 2016 | A. Nokland, 2016 | Frenkel et al., 2019

Alternatives to BP: relaxing symmetry requirements

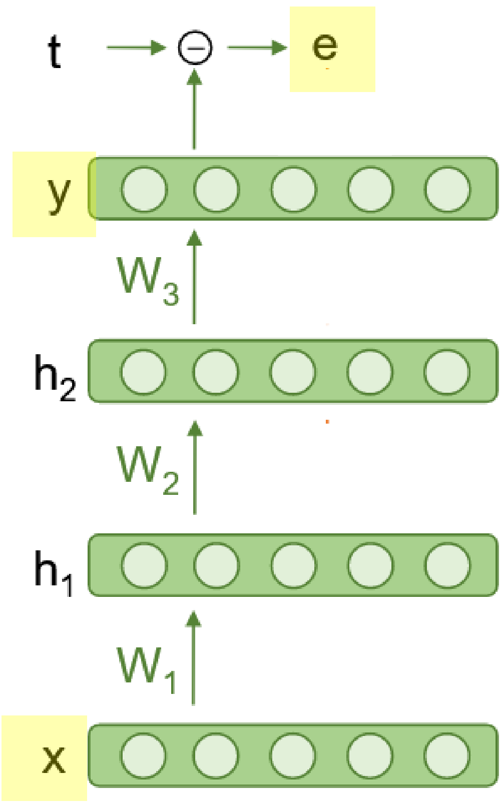


Rumelhart et al., 1995   Lillicrap et al., 2016   A. Nokland, 2016   Frenkel et al., 2019

The backpropagation algorithm

» **Forward pass**
- Network's response to input
- Error function $e = y - t$
- Weight updates proportional to its negative gradient

» **Backward pass**
- Error signal flows backward through the network
- Computed recursively via the chain rule
- Update phase



Lillicrap et al., 2020

The Backward Pass

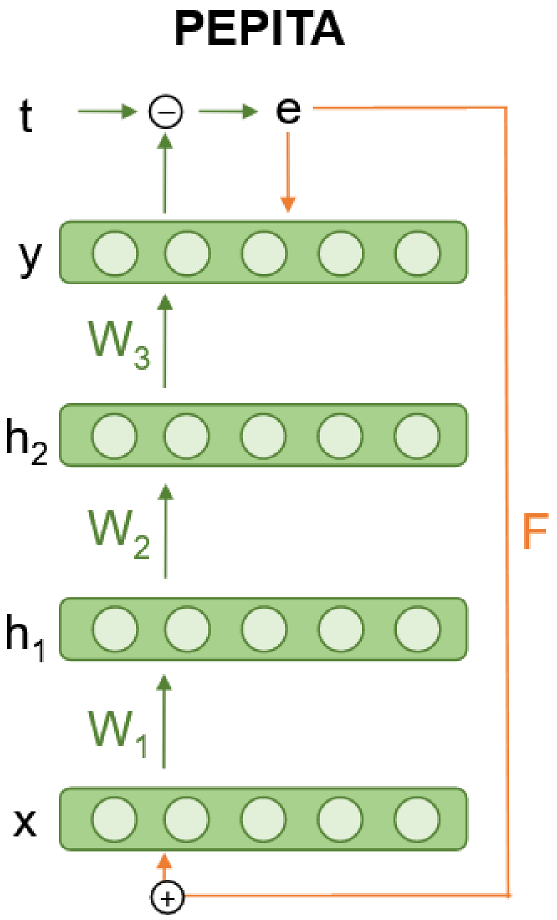
The backward pass implies:

» **Non-locality**

» **Frozen activity**

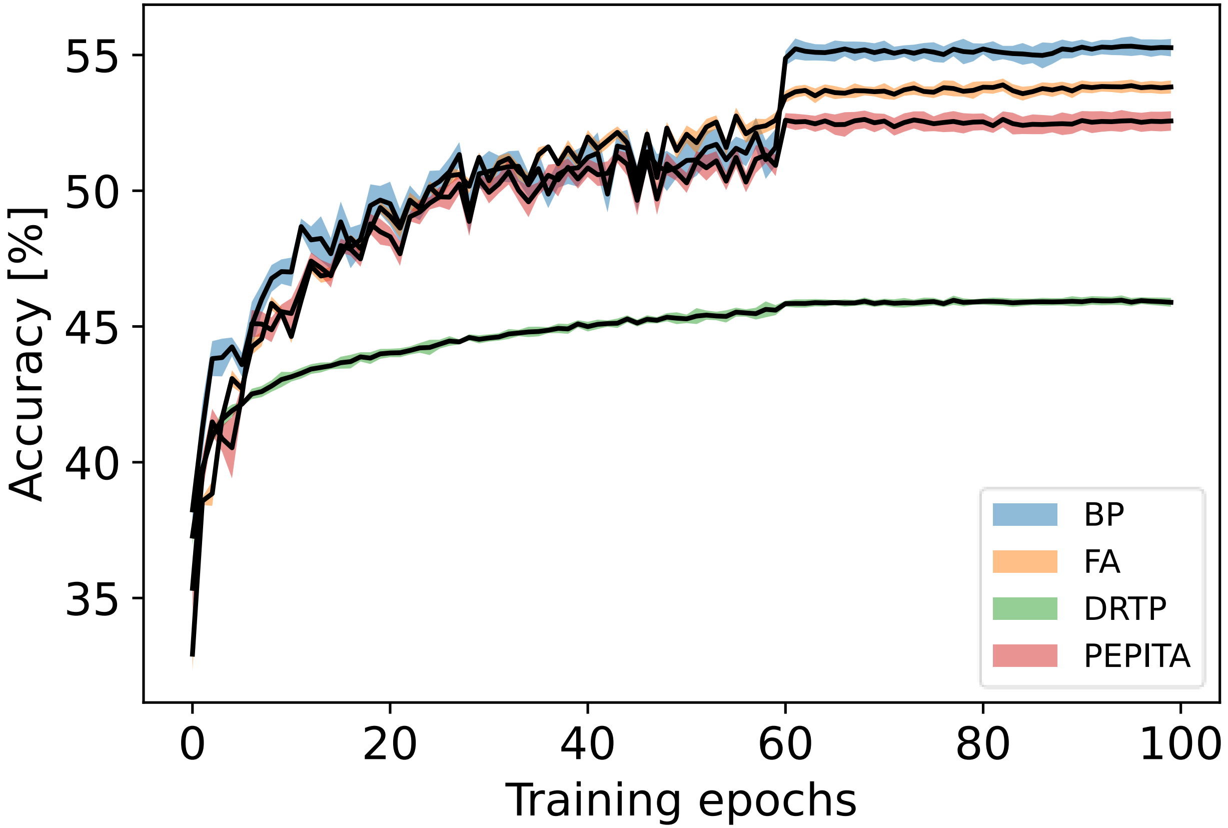
» At least **partial update locking**

Remove the backward pass

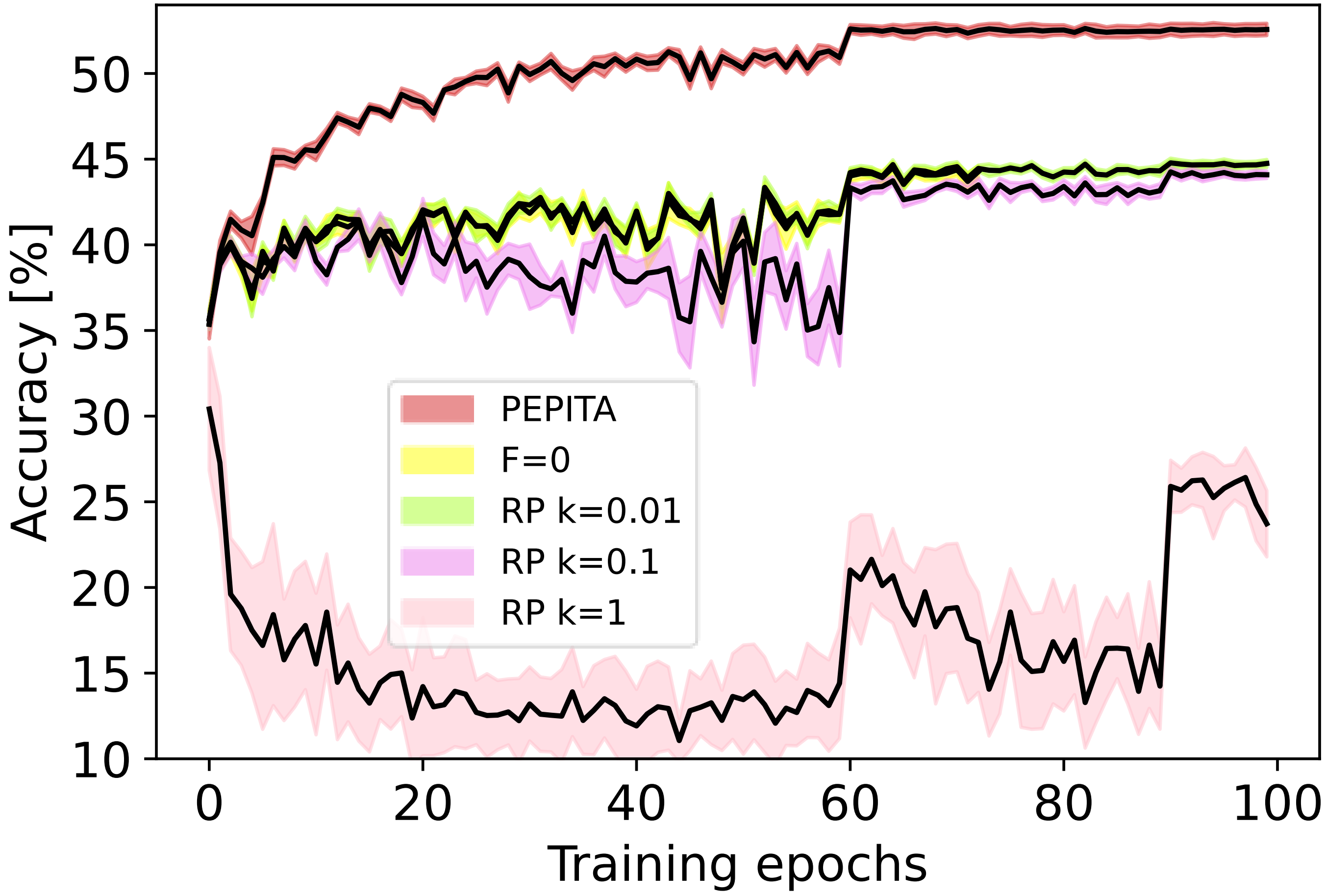


Dellaferrera & Kreiman, ICML 2022

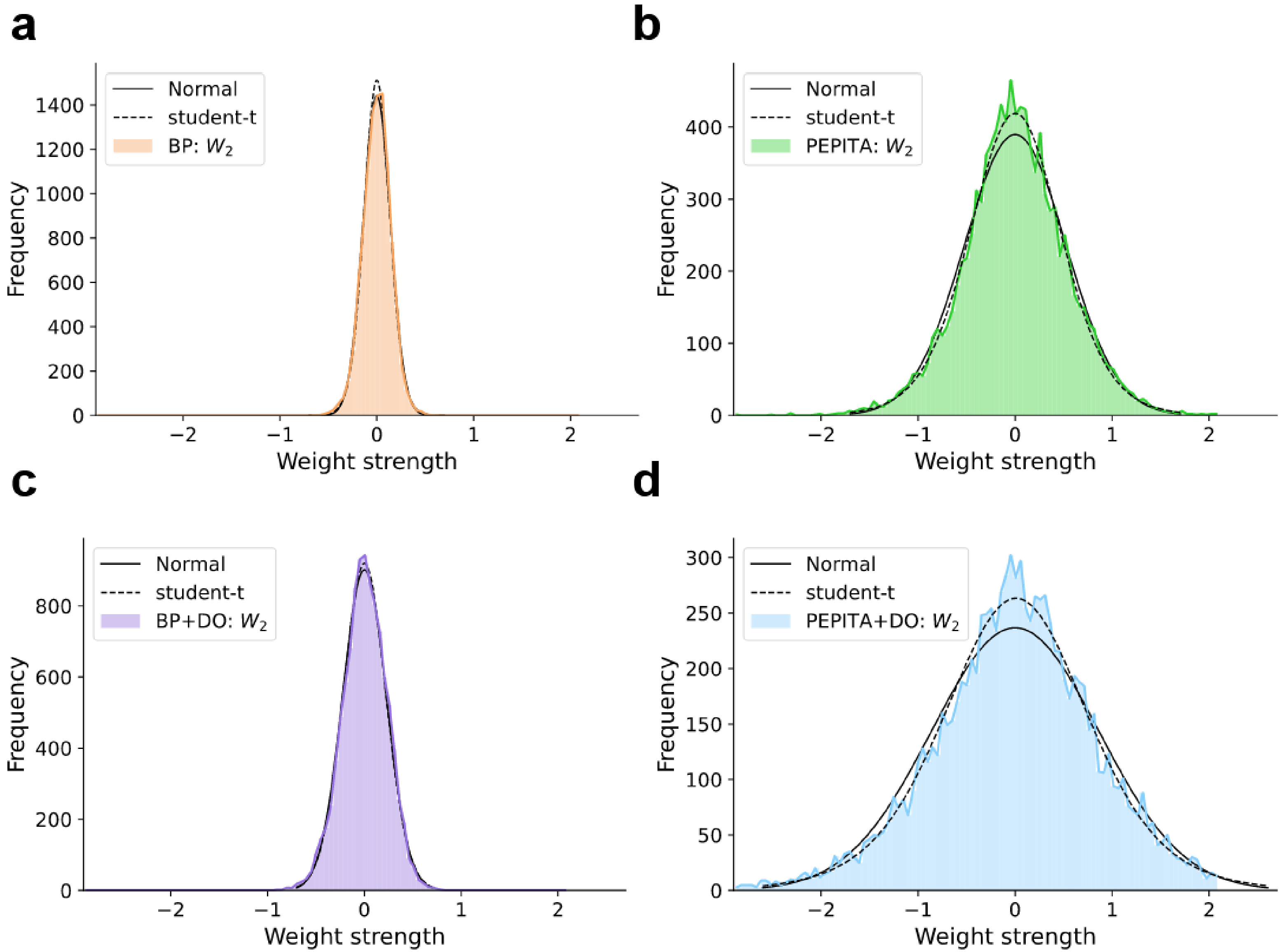
Test curves on CIFAR-10



Error-based modulation is key for good performance



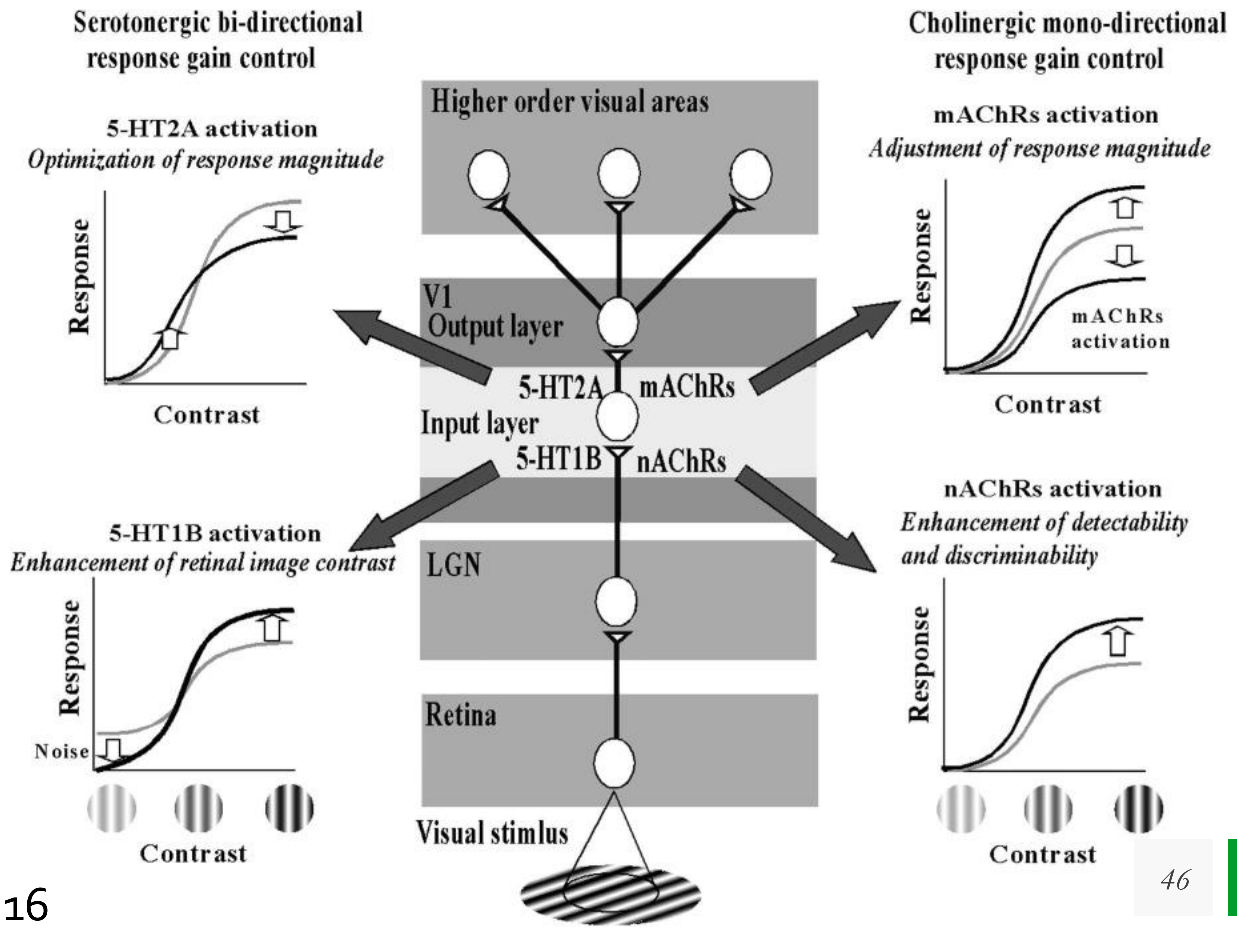
Weight distribution – heavy tailed



Analysis of PEPITA from a biological standpoint

PEPITA solves the BP's issues of biological plausibility, but it introduces additional elements:

» Projection of the error onto the input through a fixed random matrix
  - Global neuromodulatory signals modulate activity in V1

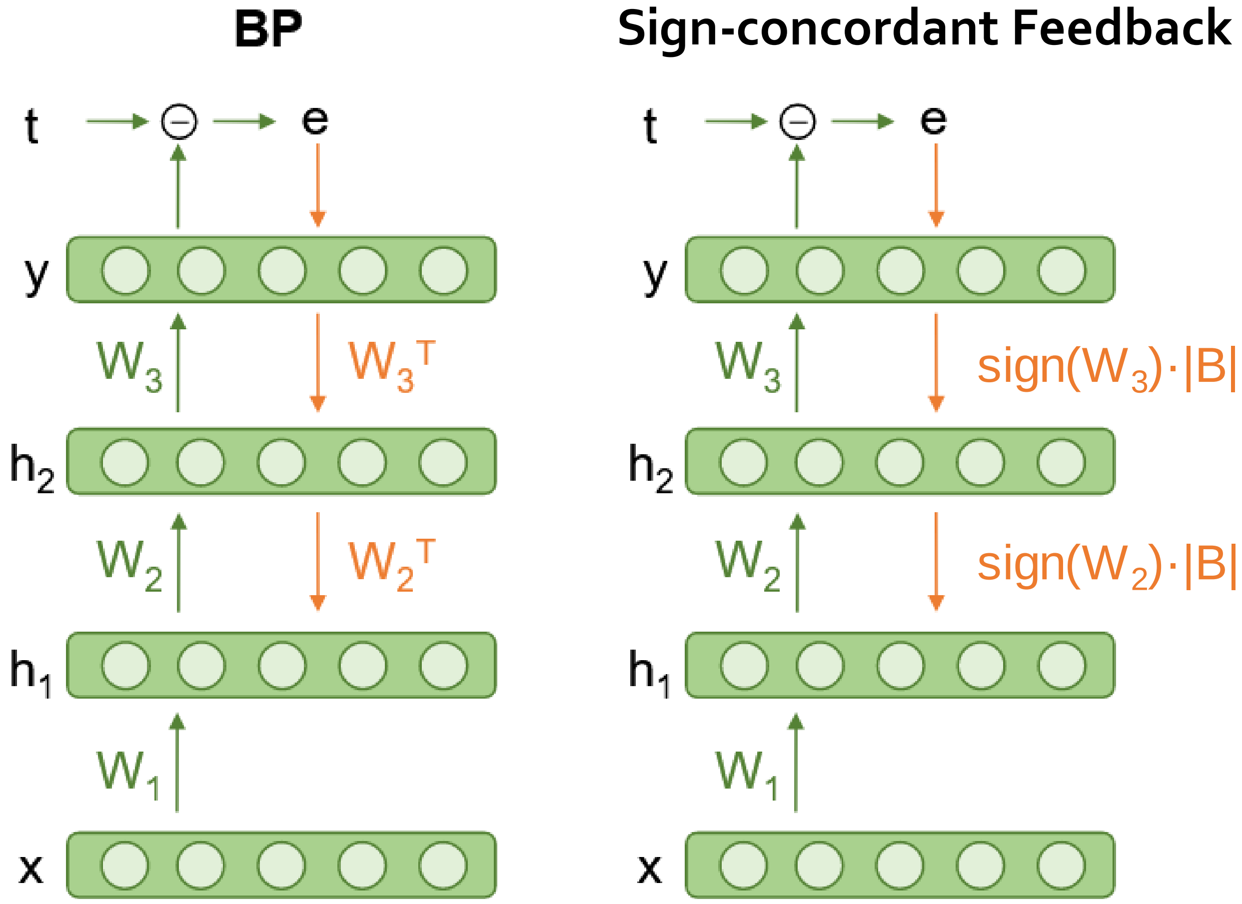


Shimegi et al., 2016

Alternatives to BP: Sign symmetry

» **Asymmetric backpropagation**
- Sign-concordant Feedback

» **Relax weight symmetry requirement**
- the magnitudes of feedback weights do not matter to performance
- the signs of feedback weights do matter — the more concordant signs between feedforward and their corresponding feedback connection



Liao et al., 2016
Xiao et al., 2019

Alternatives to BP: Feedback Alignment

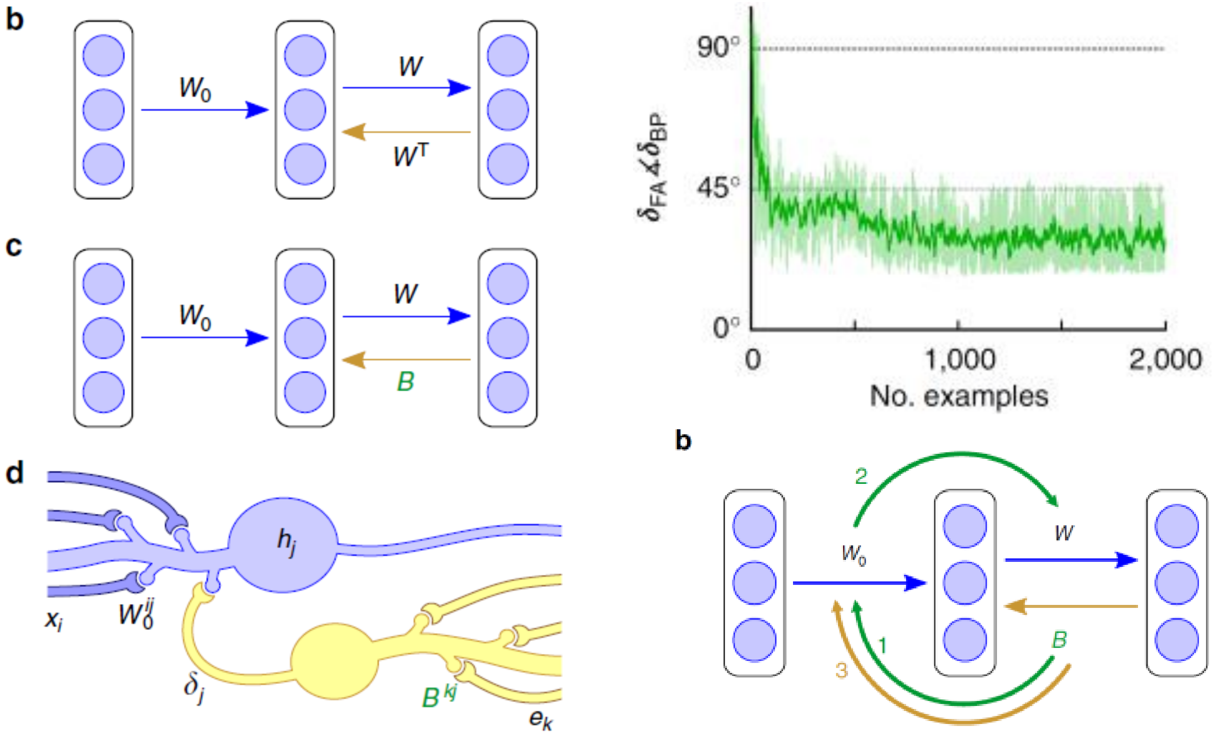
» Precise symmetric connectivity between connected layers is not required to obtain quick learning

» **Replaces W^T with a matrix of fixed random weights B**

- Each neuron in the hidden layer receives a random projection of the error vector
- Avoids all transport of synaptic weight information

» **The circuit learns by encouraging a soft alignment of W with B^T**

- The angle between modulator vectors prescribed by feedback alignment and backprop decreases
- As W aligns with B^T, B begins to act like W^T, sending useful teaching signals to the hidden units



Lillicrap et al., 2016

Alternatives to BP: Direct and Indirect Feedback Alignment

» The FA principle is used for training hidden layers more independently from the rest of the network

» **Feedback path disconnected from the forward path**

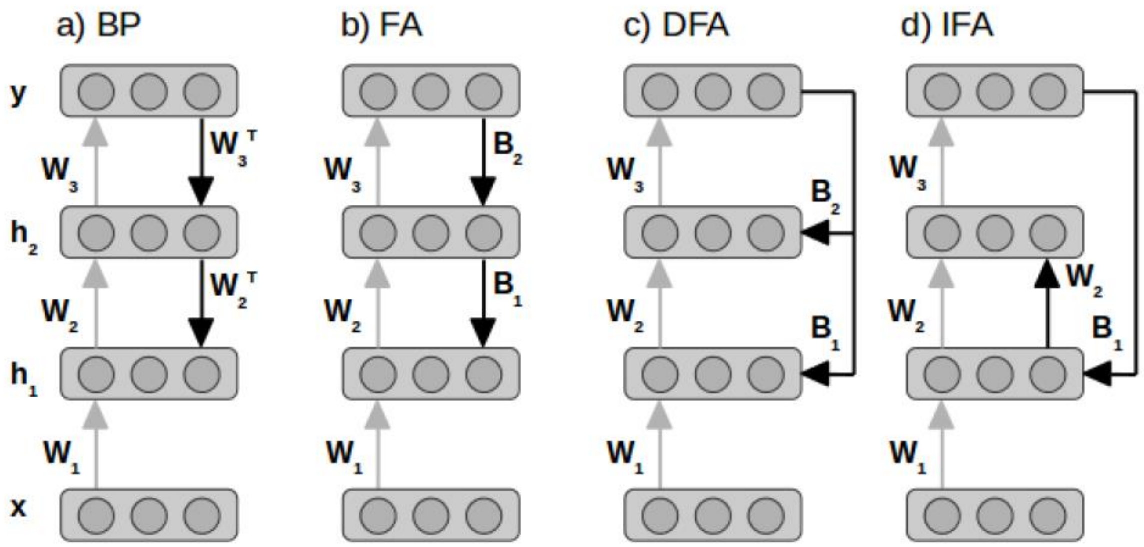
- Possibility that the error in the feedback layer is represented by neurons not participating in the forward pass
- layer is no longer reciprocally connected to the layer above

» **DFA**

- direct feedback path to each hidden layer

» **IFA**

- direct feedback path connecting to the first hidden layer
- then visiting every layer on its way forward



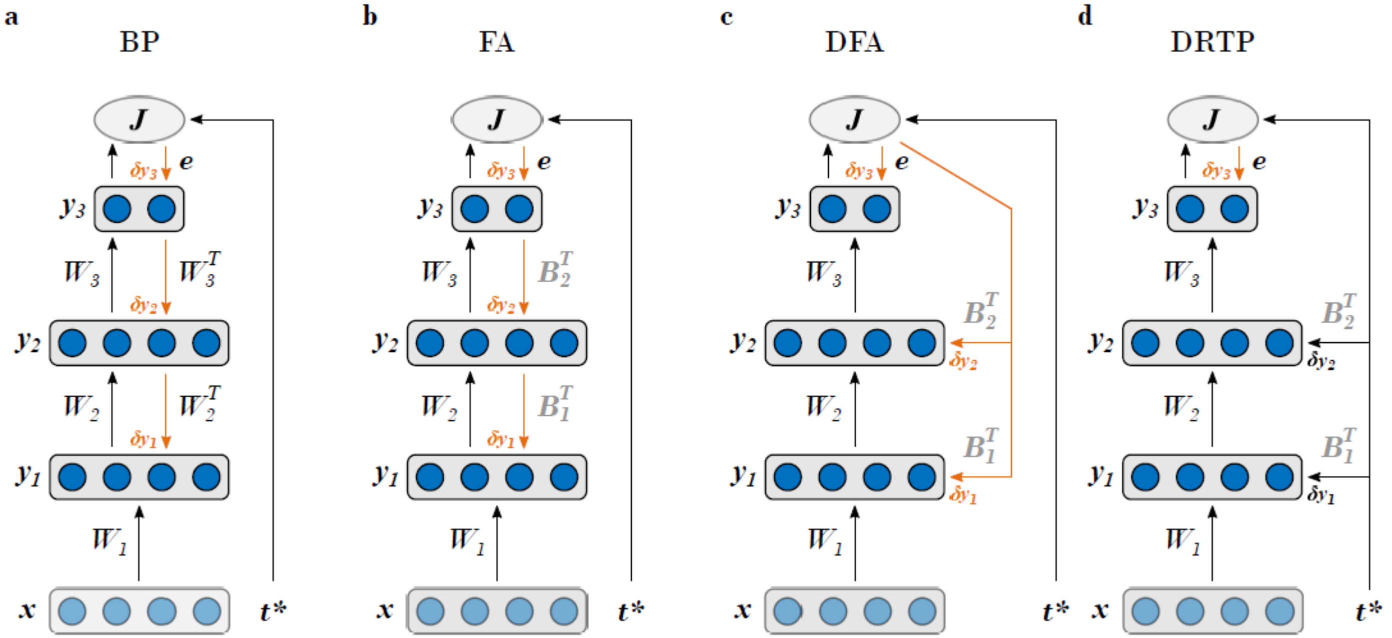
MODEL	BP	FA	DFA
7x240 Tanh	2.16 ± 0.13%	2.20 ± 0.13% (0.02%)	2.32 ± 0.15% (0.03%)
100x240 Tanh			3.92 ± 0.09% (0.12%)
1x800 Tanh	1.59 ± 0.04%	1.68 ± 0.05%	1.68 ± 0.05%
2x800 Tanh	1.60 ± 0.06%	1.64 ± 0.03%	1.74 ± 0.08%
3x800 Tanh	1.75 ± 0.05%	1.66 ± 0.09%	1.70 ± 0.04%
4x800 Tanh	1.92 ± 0.11%	1.70 ± 0.04%	1.83 ± 0.07% (0.02%)
2x800 Logistic	1.67 ± 0.03%	1.82 ± 0.10%	1.75 ± 0.04%
2x800 ReLU	1.48 ± 0.06%	1.74 ± 0.10%	1.70 ± 0.06%
2x800 Tanh + DO	1.26 ± 0.03% (0.18%)	1.53 ± 0.03% (0.18%)	1.45 ± 0.07% (0.24%)
2x800 Tanh + ADV	1.01 ± 0.08%	1.14 ± 0.03%	1.02 ± 0.05% (0.12%)

Test error on MNIST

A. Nokland, 2016

Alternatives to BP: Direct Random Target Propagation

- **The error sign provides useful modulatory signals to multi-layer networks**
  - Targets (i.e. one-hot-encoded labels) used in place of the output error
  - Targets are projected onto the hidden layers
- Fully solves both the weight transport and the update locking problems
- BUT: lower performance than BP, FA, DFA

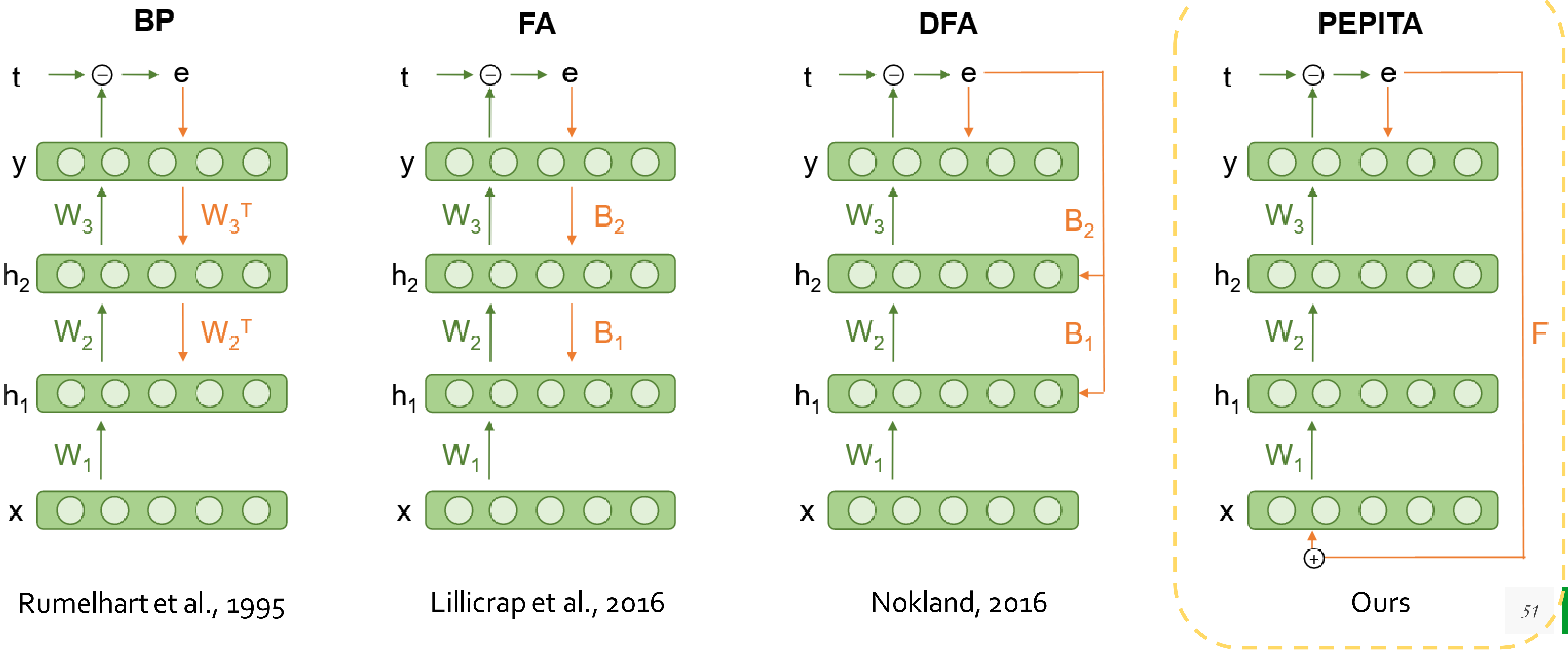


Network		BP	FA	DFA	DRTP
FC1-500	DO 0.0	1.72±0.08%	1.92±0.08%	2.59±0.11%	4.58±0.12%
	DO 0.1	1.55±0.03%	1.66±0.06%	2.17±0.10%	4.65±0.13%
	DO 0.25	1.64±0.06%	1.73±0.05%	2.32±0.08%	5.36±0.11%

Test error on MNIST

Frenkel et al., 2019

Training without a backward path: modulating the input through the error

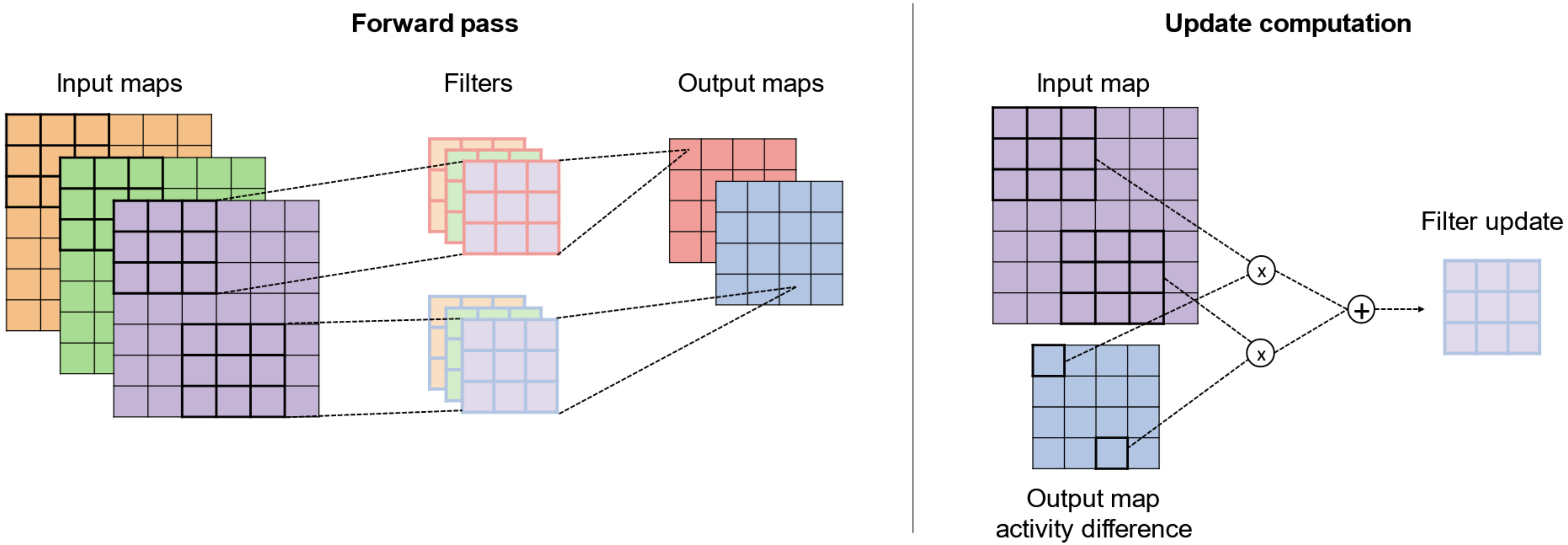


The PEPITA learning rule for Convolutional Neural Networks

» Same approach with *Standard* and *Modulated pass*

» Takes into account *weight sharing* of convolutional layers

» Each filter is updated based on the contributions of each *input-map-region – output-map-element* pair



Testing PEPITA on image classification tasks - experimental results

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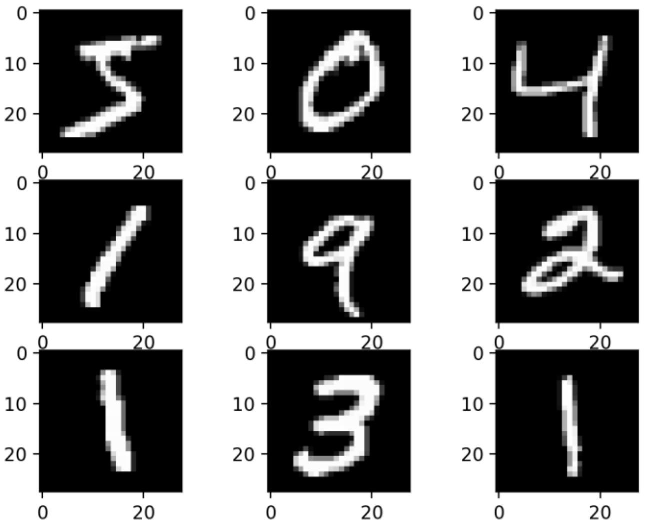

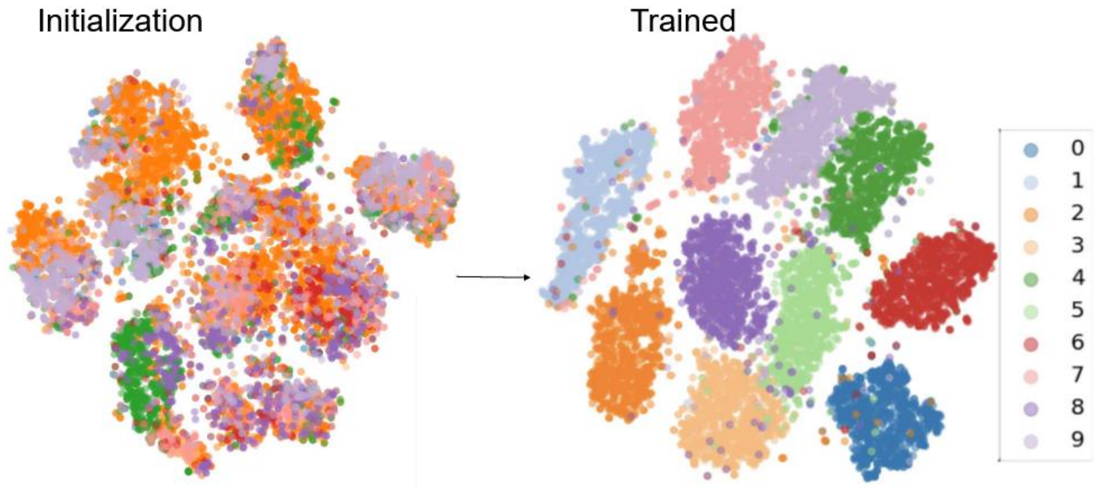

	Fully connected models			Convolutional models		
	MNIST	CIFAR10	CIFAR100	MNIST	CIFAR10	CIFAR100
BP	98.63±0.03	55.27±0.32	27.58±0.09	98.86±0.04	64.99±0.32	34.20±0.20
FA	98.42±0.07	53.82±0.24	24.61±0.28	98.50±0.06	57.51±0.57	27.15±0.53
DRTP	95.10±0.10	45.89±0.16	18.32±0.18	97.32±0.25	50.53±0.81	20.14±0.68
PEPITA	98.01±0.09	52.57±0.36	24.91±0.22	98.29±0.13	56.33±1.35	27.56±0.60

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