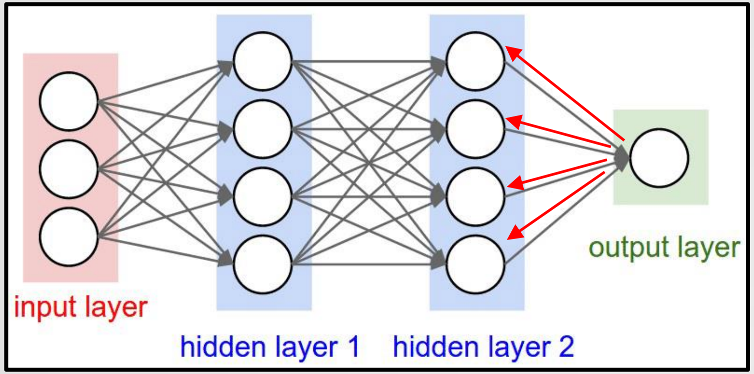
Biologically plausible deep learning

But how far can we go with shallow networks?

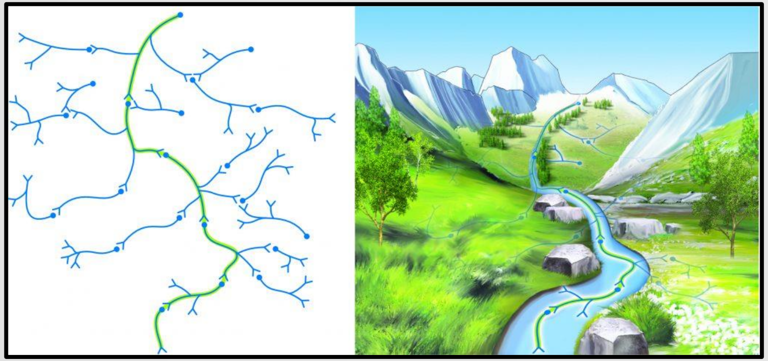
Bernd Illing, Wulfram Gerstner, Johanni Brea

Presentation by
Mohammad Amin Banayeean Zade

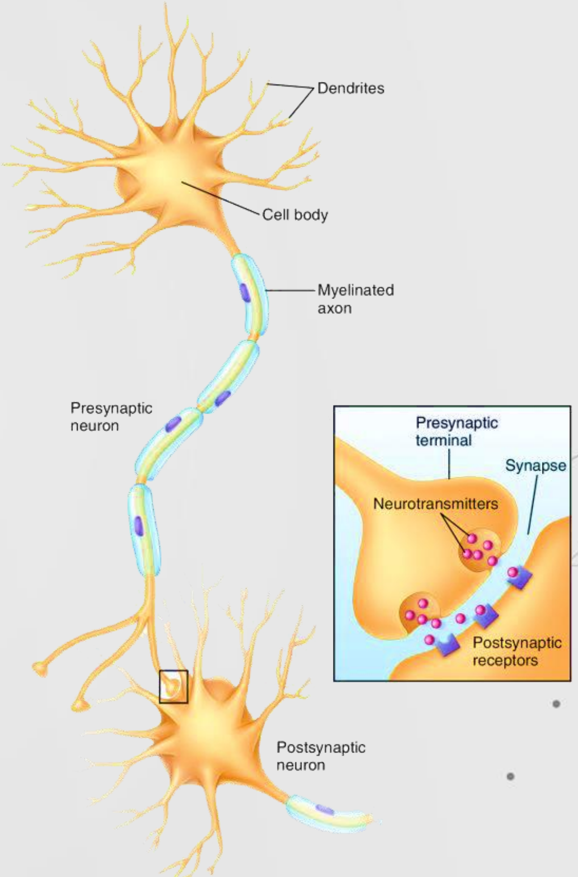
Introduction

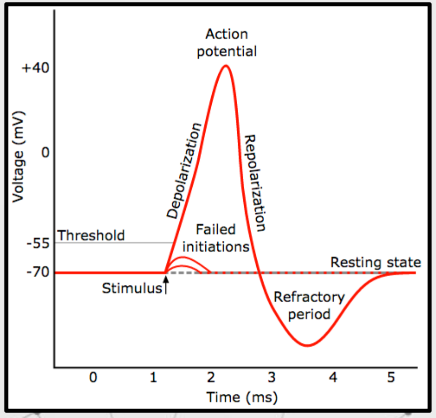


https://www.researchgate.net/figure/A-general-model-of-a-deep-neural-network-It-consists-of-an-input-layer-some-here-two_fig1_308414212



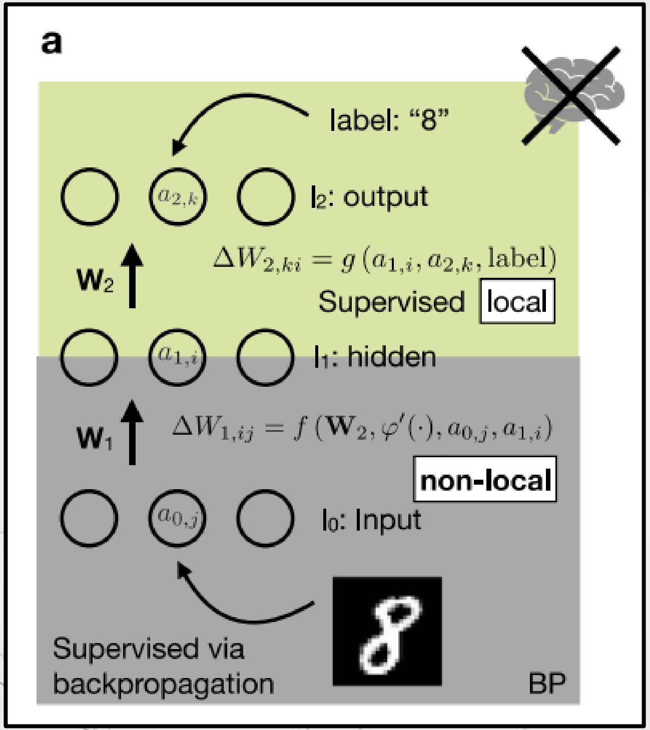
https://www.guru99.com/backpropogation-neural-network.html



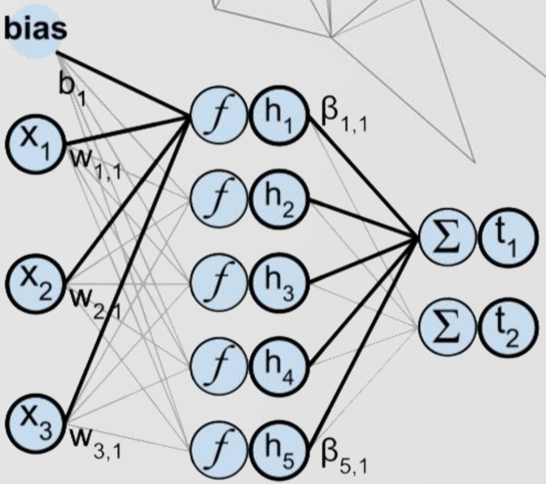


https://www.kurzweilai.net/ibm-scientists-emulate-neurons-with-phase-change-technology

Supervised Learning



https://github.com/cazala/mnist



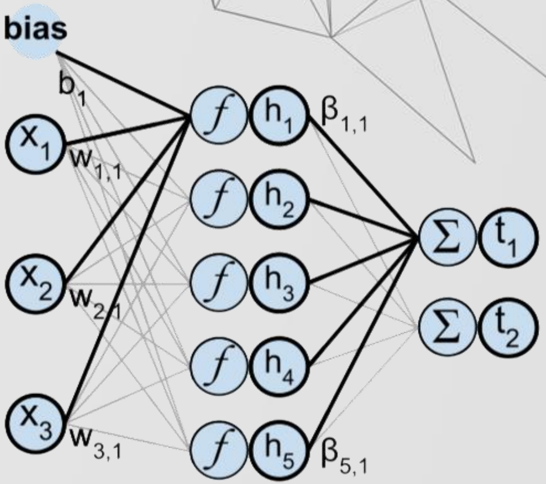
https://towardsdatascience.com/ml-for-ts-3-extreme-learning-machines-3fcf5991e390

Alternatives to Supervised Training

1. fix weights in the first layer(s) at random values , as proposed by general approximation theory

2. The other alternative is unsupervised training in the first layer(s)

In both cases, only the weights of a readout layer are learned with supervised training

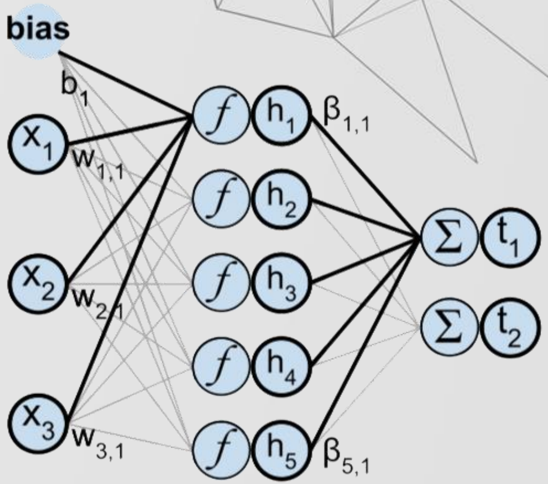


https://towardsdatascience.com/ml-for-ts-3-extreme-learning-machines-3fcf5991e390

Random Weights	Unsupervised
RP	ICA
RG	PCA
	SC

Random Projections

$$\mathbf{W}_1 \sim \mathcal{N}(0, \sigma^2) \;\; \sigma^2 = \frac{1}{100\ n_0}$$
$$\mathbf{b}_1 \sim \mathcal{U}([0, 0.1])$$



https://towardsdatascience.com/ml-for-ts-3-extreme-learning-machines-3fcf5991e390

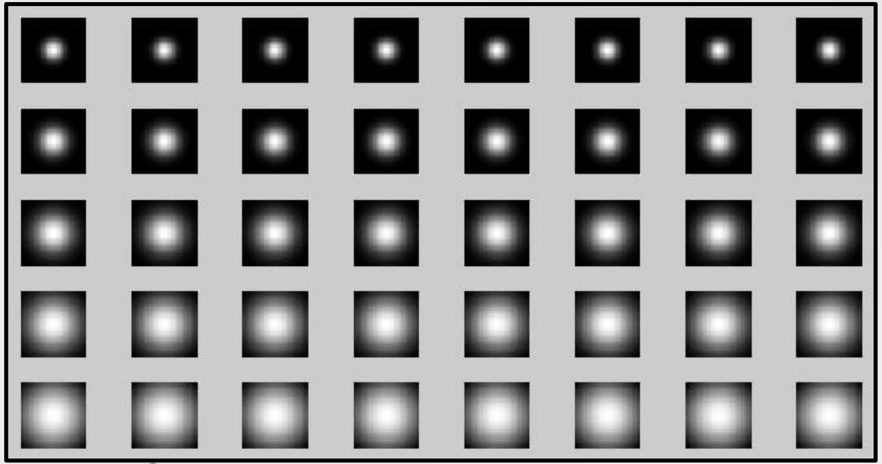
Random Weights

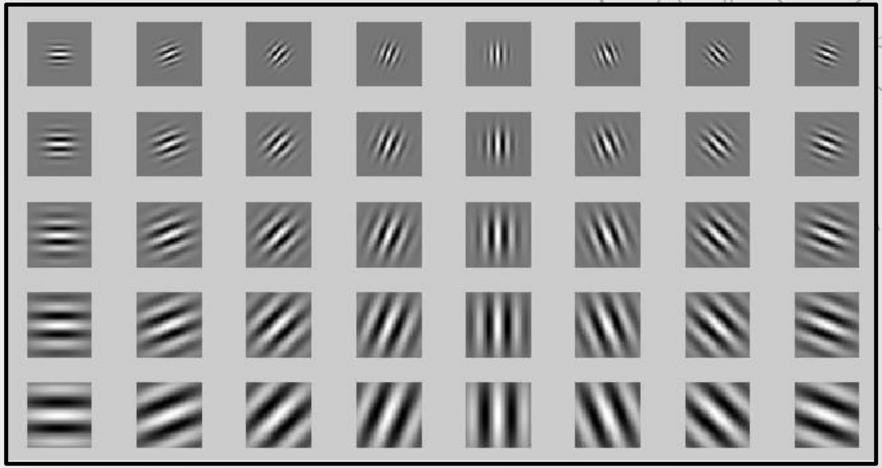
- RP
- RG

Unsupervised

- ICA
- PCA
- SC

Random Gabor Filters



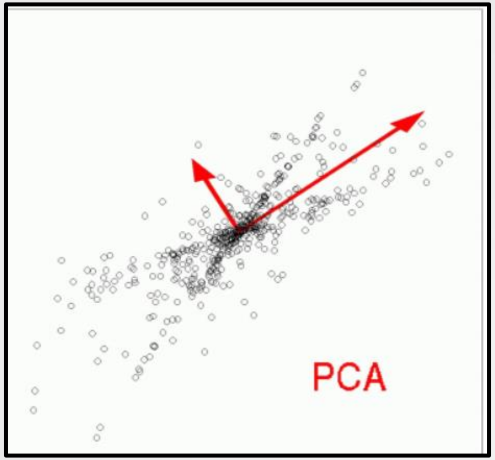


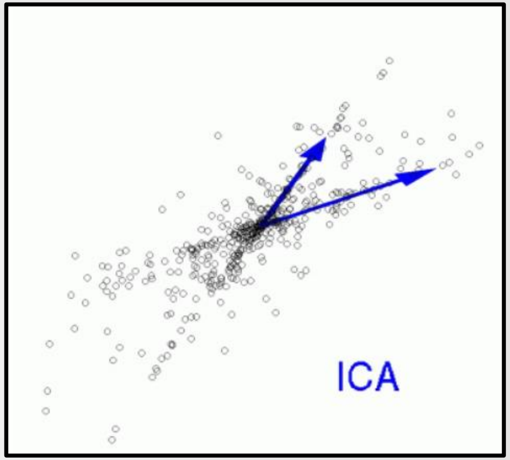
https://www.semanticscholar.org/paper/Local-binary-pattern%3A-An-improved-LBP-to-extract-to-Kumar-Kumar/f05b226b35f6871d9b3cda9691dba67d238d683d

Random Weights
- RP
- RG

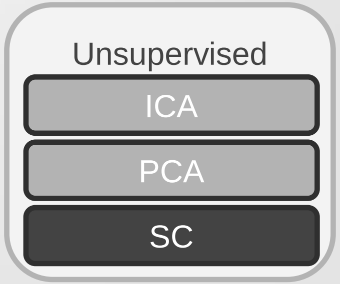
Unsupervised
- ICA
- PCA
- SC

Random Gabor Filters





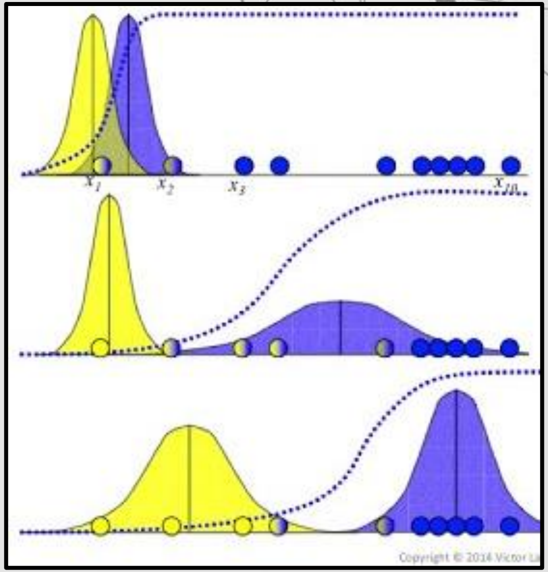
http://compneurosci.com/wiki/images/4/42/Intro_to_PCA_and_ICA.pdf



Sparse Coding

$$\mathbf{W}^{opt}, \mathbf{a}_1^{opt} = \operatorname{argmin} \mathcal{L}(\mathbf{W}, \mathbf{a}_1)$$

$$\mathcal{L}(\mathbf{W}, \mathbf{a}_1) = \frac{1}{2}\|\mathbf{a}_0 - \mathbf{W}^\top \mathbf{a}_1\|_2^2 + \lambda \|\mathbf{a}_1\|_1.$$



https://www.youtube.com/watch?v=XLKoTqGao7U

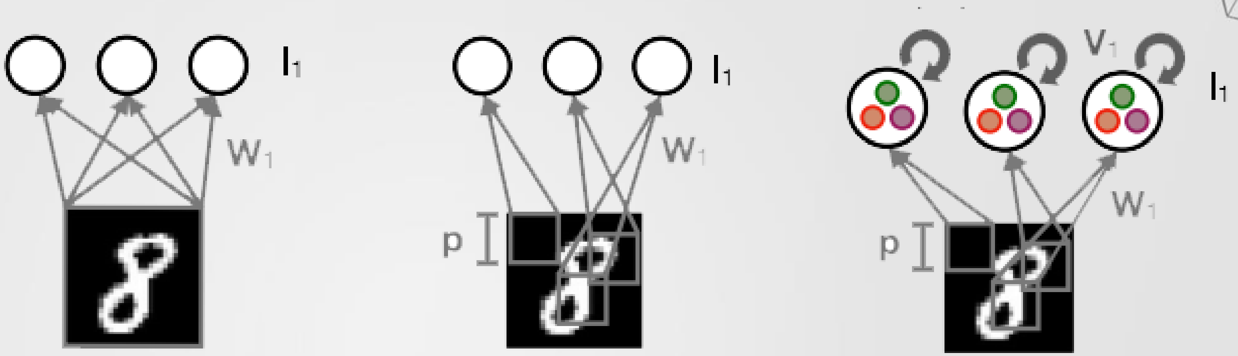
Random Weights

- RP
- RG

Unsupervised

- ICA
- PCA
- SC

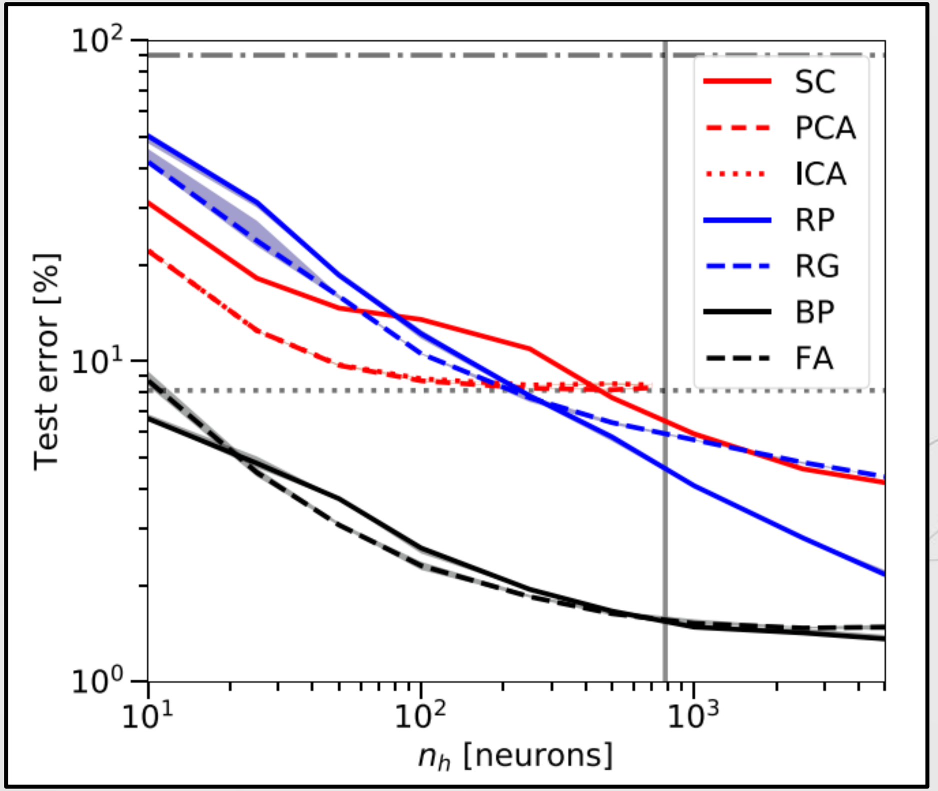
localized receptive fields



Localized

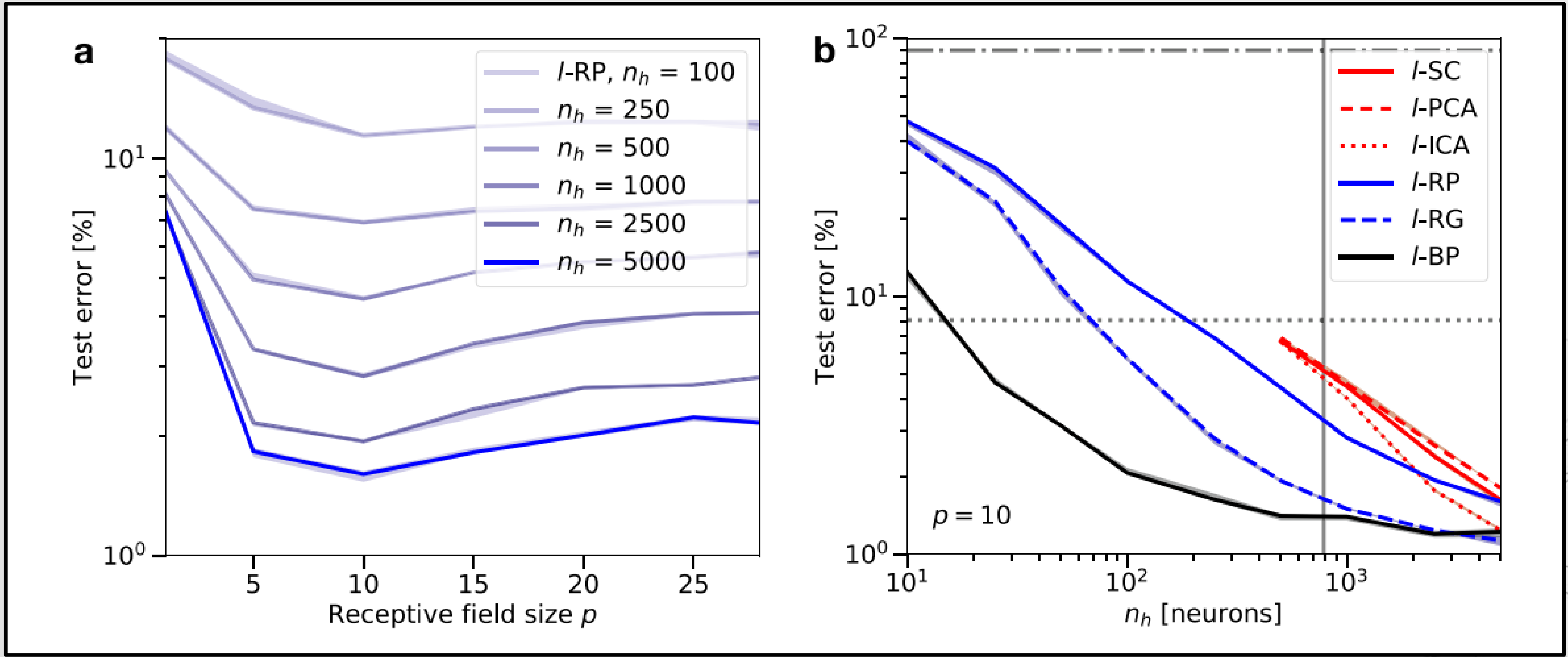
- Random Weights
  - RP
  - RG
- Unsupervised
  - ICA
  - PCA
  - SC

Results



10^2
10^1
10^0
Test error [%]
10^1
10^2
10^3
n_h [neurons]
SC
PCA
ICA
RP
RG
BP
FA

Results

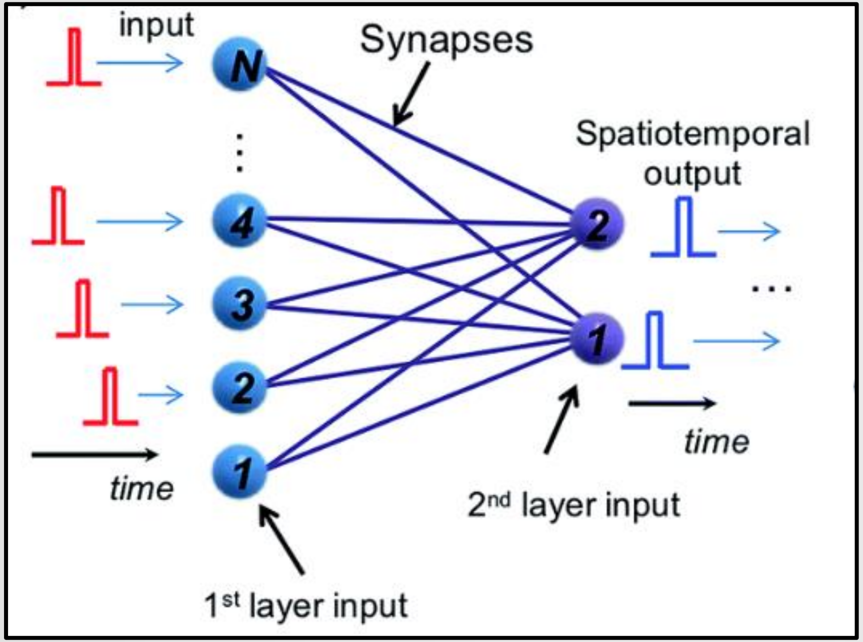


a
l-RP, n_h = 100
n_h = 250
n_h = 500
n_h = 1000
n_h = 2500
n_h = 5000
Test error [%]
10^1
10^0
5
10
15
20
25
Receptive field size p
b
10^2
10^1
10^0
Test error [%]
l-SC
l-PCA
l-ICA
l-RP
l-RG
l-BP
$p = 10$
10^1
10^2
10^3
n_h [neurons]

Results

Model	Neural coding	Learning type	Comments	Test accuracy (%)
Conv. SNN (Wu, Deng, Li, Zhu, & Shi, 2018)	Spikes	Supervised	5 conv. layers, Spatio-Temporal BP	*99.3*
Conv. SNN (Diehl, et al., 2015)	Rate	Supervised	Conversion: rate → spike	*99.1*
Conv. Spiking AE (Panda & Roy, 2016)	Spikes	Un/Supervised	Stacked conv. AE with BP + sym. weights	*99.1*
l-**RG** (this paper)	Rate	Un/Supervised	Only output layer learned	**98.9**
l-**BP** (this paper)	Rate	Supervised	BP-benchmark of this paper	**98.8**
l-**ICA** (this paper)	Rate	Un/Supervised	ICs as features for SGD	**98.8**
l-**FA** (Bartunov et al., 2018) (& this paper)	Rate	Supervised	FA with localized rec. fields	**98.7**
SNN (Lee, Delbruck, & Pfeiffer, 2016)	Spikes	Supervised	BP approx., weight symmetry	98.7
spiking LIF *l*-**RG** (this paper)	Spikes	Supervised	STDP (only output layer learned)	**98.6**
(Stoch.) Diff. Target Prop. (Lee, Zhang, Fischer, & Bengio, 2015)	Rate	Supervised	Layer-wise AE, Target Prop.	98.5
Nonlin. Hebb + SGD (Krotov, Hopfield, & Lee, 2019)	Rate	Un/Supervised	nonlin. Hebb + SGD (similar to this paper)	98.5
l-**RP** (this paper)	Rate	Supervised	Only output layer learned	**98.4**
l-**SC** (this paper)	Rate	Un/Supervised	SC for 1. layer, SGD for 2. layer	**98.4**
Conv. SNN (Kheradpisheh et al., 2018)	Spikes	Unsupervised	3 Conv. layers, STDP, ext. SVM	*98.4*
SNN (O'Connor, Gavves, & Welling, 2017)	Pseudo-spike	Supervised	Sparse, discrete activities, STDP	98.3
Direct FA (Nøkland, 2016)	Rate	Supervised	Many hidden layers	98.3
Spiking FA (Lillicrap et al., 2016)	Spikes	Supervised	3 hidden layers	98.2
spiking LIF *l*-**RP** (this paper)	Spikes	Supervised	STDP (only output layer learned)	**98.2**
l-**PCA** (this paper)	Rate	Un/Supervised	PCs as features for SGD	**98.2**
Q-AGREL (RL-like) (Pozzi, Bohté, & Roelfsema, 2018)	Rate	RL-like	RL-like BP-approx.	98.2
Forward propagation (FP) (Kohan, Rietman, & Siegelmann, 2018)	Rate	Supervised	FP: BP approximation	98.1
Spiking FA (Neftci, Augustine, Paul, & Detorakis, 2017)	Spikes	Supervised	Direct FA	98

Spiking localized random projections



https://pubs.rsc.org/image/article/2019/fd/c8fd00097b/c8fd00097b-f8_hi-res.gif

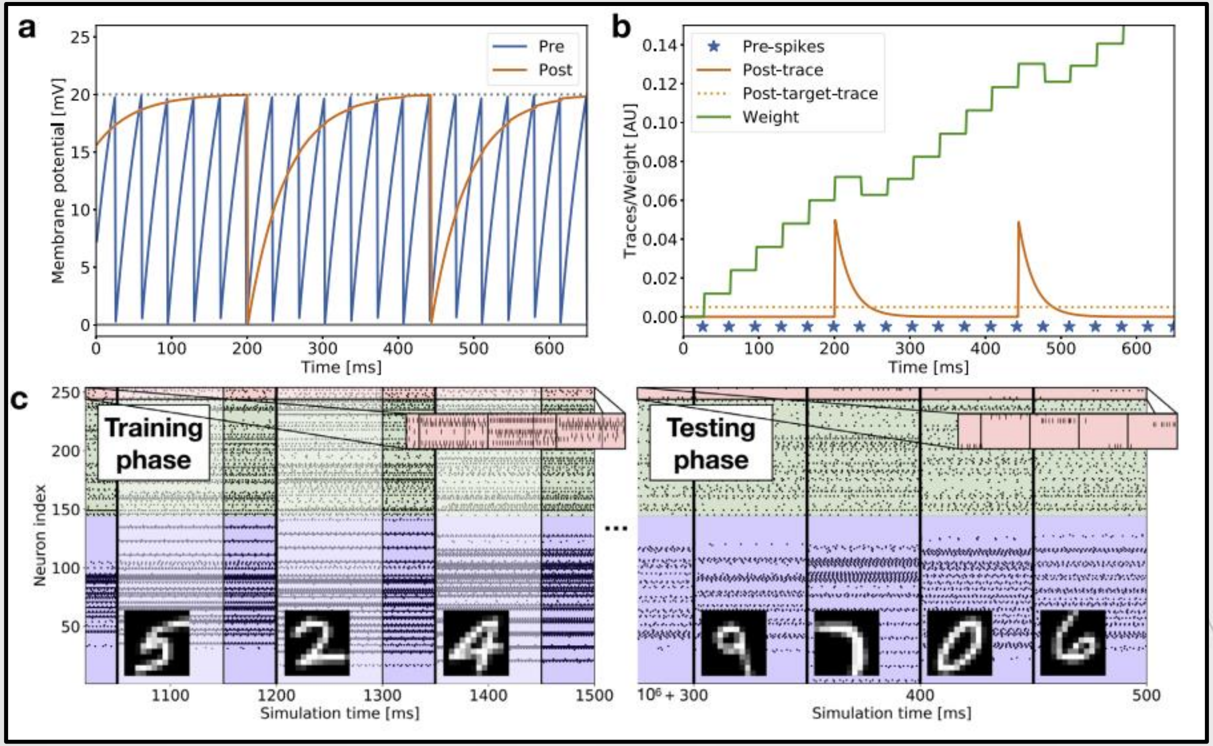
$$\tau_m \frac{du_i(t)}{dt} = -u_i(t) + RI_i(t)$$

$$\text{with } \; I_i(t) = I_i^{ff}(t) + I_i^{ext}(t) = \sum_{j,f} w_{ij}\epsilon\left(t - t_j^f\right) + I_i^{ext}(t)$$

$$\tau_{\mathrm{tr}} \frac{d\mathrm{tr}_i(t)}{dt} = -\mathrm{tr}_i(t) + \sum_f \delta\left(t - t_i^f\right)$$

$$\Delta w_{2,ij} = \alpha \cdot \left(\mathrm{tgt}_i^{\mathrm{post}}(t) - \mathrm{tr}_i^{\mathrm{post}}(t)\right) \delta\left(t - t_j^f\right)$$

Results



		SP	*l*-PCA	*l*-ICA	*l*-SC	*l*-RP	*l*-RG	*l*-BP
Rate	CIFAR10	41.1 ± 0.1	50.8 ± 0.3	53.9 ± 0.3	50.2 ± 0.2	52.0 ± 0.4	55.6 ± 0.2	**58.3** ± **0.2**
	MNIST	91.9 ± 0.1	98.2 ± 0.02	**98.8** ± **0.03**	98.4 ± 0.07	98.4 ± 0.1	**98.9** ± **0.05**	**98.8** ± **0.1**
Spiking	MNIST	–				98.2 ± 0.05	98.6 ± 0.1	–

Thanks

any questions?