AIMH Lab for Sustainable Bio-Inspired AI

G. Lagani, F. Falchi, C. Gennaro, G. Amato
ISTI-CNR, Pisa

Ital-IA 2023

Outline

- Introduction and motivation
- Bio-inspired cultured neural networks for AI
- Hebbian plasticity models for Deep Learning
- Conclusions and future perspectives

Introduction and Motivation

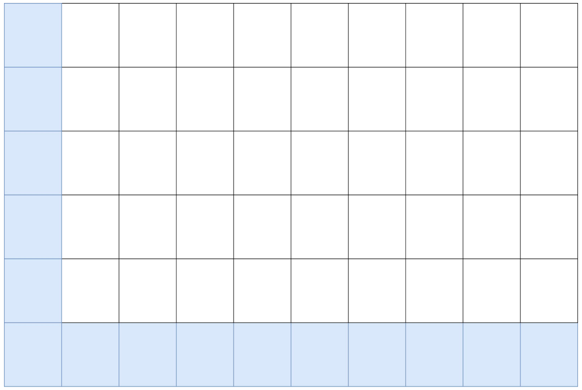
- Deep Neural Networks (DNN) achieve outstanding results thanks to **backprop** training
  - Neuroscientifically implausible
  - Very high **energy cost**
- Plasticity in biological neurons is better explained by **Hebbian** and **Spiking** models
  - **Energy efficient**
  - Data efficient
- Goal: apply **bio-inspired** models to deep learning problems
- Related work: biologically **plausible** learning solutions
  - Surrogate gradients
  - REINFORCE
  - Contrastive Hebbian Learning, Predictive Coding
  - Signal propagation, Forward-Forward
  - Feedback Alignment, TargetProp

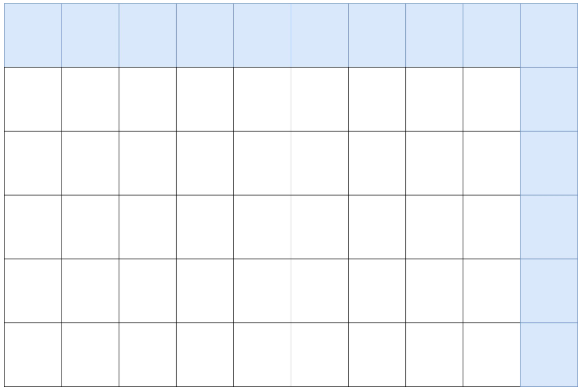
Cultured Networks on MEAs for AI

- Cultures of biological neurons can be developed *in vitro*
- Interfaces for stimulation/recording
  - **Multi-Electrode Arrays** (MEAs)
  - Light/optogenetics (preliminary)
- Goal: use biological networks for AI tasks
- **Software simulation** can guide the design process
  → Spiking Neural Network (SNN) models

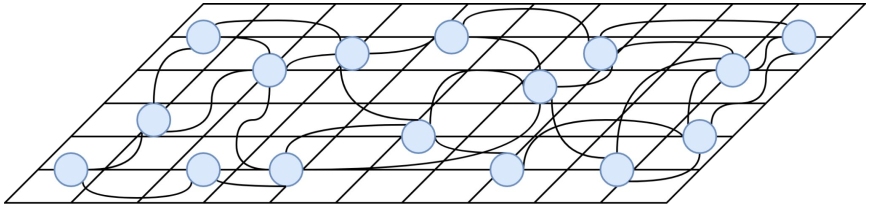
Cultured Networks on MEA

Real-world experiment from Ruaro et al. 2005





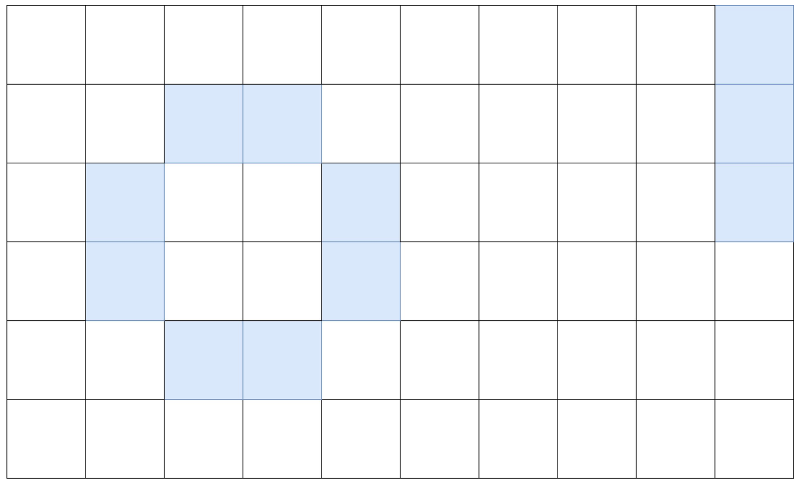
Digital twin



Parameter	Value
Resting membrane potential	-70 mV
Threshold membrane potential	-50 mV
Reset membrane potential	-70 mV
Refractory period	5 ms
Membrane potential decay time	50 ms
STDP trace decay time	$\tau_+ = \tau_- = 20ms$
Learning rate	$A_+ = 10^{-2}, A_- = 10^{-4}$
EXC_STRENGTH	1
INH_STRENGTH	10
σ_E	1.2 mm
σ_I	0.15 mm
Electrode stimulation range	0.3mm

Ruaro et al. 2005, “Toward the neurocomputer: image processing and pattern recognition with neuronal cultures”, in *IEEE Transactions in Biomedical Engineering*

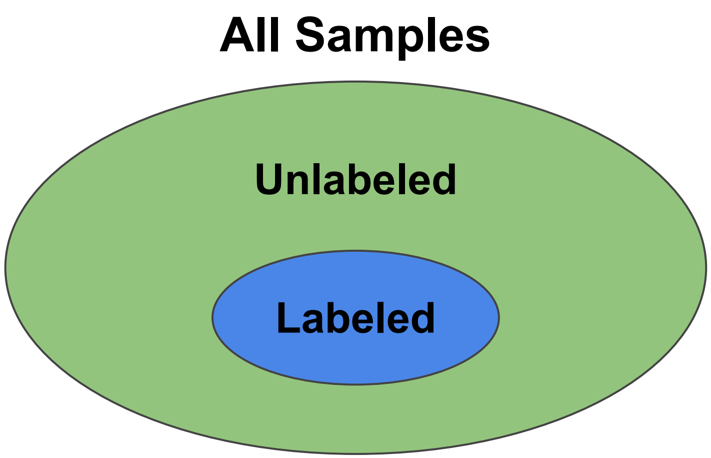
Using Digital Twin for Digit Recognition



- 0-1 digits from **MNIST** are shown on the left 6x6 part of the grid
- **Label** signal given on the right
- **STDP** reinforces correlation
- The culture from the previous experiment achieves **88% accuracy** on this task
- Further **tuning** of design parameter allows to achieve **95% accuracy**
- The simulator can **guide the creation** of real-world cultures for AI

Lagani et al. 2021, “Assessing Pattern Recognition Performance of Neuronal Cultures through Accurate Simulation”. In 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 726-729). IEEE.

Sample Efficiency and Semi-Sup. Learning



Sample efficiency regime (%): $s = \frac{|Labeled|}{|All\ Samples|}$

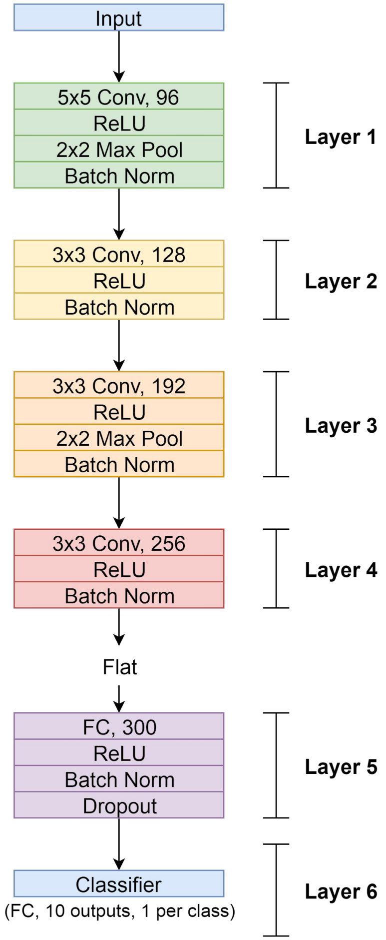
Semi-supervised learning:

- Unsupervised pre-training
- Pseudo-labels/consistency methods

Lagani et al. 2021. "Evaluating Hebbian Learning in a Semi-supervised Setting". In International Conference on Machine Learning, Optimization, and Data Science (pp. 365-379). Springer, Cham.
Lagani et al. 2021. "Hebbian semi-supervised learning in a sample efficiency setting". Neural Networks, 143, 719-731.

Semi-Supervised Hebbian Learning for DNNs

- **Hebbian** unsupervised pre-training applied to deep CNNs
  - Soft-Winner-Takes-All (SWTA)
  - Hebbian Principal Component Analysis (HPCA)
- End-to-end **fine-tuning** by SGD
- Experiments on CIFAR10, CIFAR100, Tiny ImageNet, **ImageNet**
- Compared to **VAE** pre-training
- In various **regimes** of sample efficiency



Lagani et al. 2021. “Training Convolutional Neural Networks with Competitive Hebbian Learning Approaches”. In International Conference on Machine Learning, Optimization, and Data Science (pp. 25-40). Springer, Cham.

Lagani et al. 2022. “ Comparing the performance of Hebbian against backpropagation learning using convolutional neural networks”. Neural Computing and Applications, 34(8), 6503, 6519.

Results

Regime	Method	CIFAR10	CIFAR100	Tiny ImageNet	ImageNet
1%	VAE	22.54	12.28	5.55	2.72
	SWTA	30.23	15.30	6.20	6.69
	HPCA	**39.75**	**22.63**	**11.38**	**8.65**
2%	VAE	26.78	15.25	6.74	6.14
	SWTA	36.59	20.76	8.56	11.52
	HPCA	**45.51**	**30.83**	**15.71**	**13.64**
3%	VAE	29.00	16.44	7.74	15.35
	SWTA	41.54	23.69	10.26	15.67
	HPCA	**48.80**	**35.04**	**18.23**	**17.28**
4%	VAE	31.15	17.89	8.45	**23.97**
	SWTA	45.31	26.91	11.52	19.95
	HPCA	**51.28**	**38.89**	**20.55**	20.39
5%	VAE	32.75	18.48	9.29	**29.04**
	SWTA	48.35	29.57	12.55	24.87
	HPCA	**52.20**	**41.42**	**22.46**	23.28
10%	VAE	45.67	23.80	13.51	**43.73**
	SWTA	**58.00**	38.26	16.70	41.54
	HPCA	57.35	**48.93**	**28.13**	34.27
25%	VAE	68.70	52.59	**37.89**	**61.33**
	SWTA	**69.85**	56.26	24.96	59.34
	HPCA	64.77	**58.70**	37.10	56.92
100%	VAE	85.23	**79.97**	**60.23**	76.84
	SWTA	**85.37**	79.80	54.94	76.10
	HPCA	84.38	74.42	53.96	**77.28**

Lagani et al. 2022. “FastHebb: Scaling Hebbian Training of Deep Neural Networks to ImageNet Level”. In Similarity Search and Applications: 15th International Conference, SISAP 2022 (pp. 251-264). Springer, Cham.

Conclusions and Future Perspectives

- **Hebbian alone** is still far from supervised backprop
  - Alternative feature extraction strategies can be explored (Independent Component Analysis, Sparse Coding, etc.)
  - Tighter integration of supervision with Hebbian algorithms (e.g. Forward-Forward)
  - Top-down connections enable backprop approximations with Hebbian updates
  - The brain could orchestrate different strategies

- Extension to other **architectures** and **tasks** is non-trivial
  - Residual networks
  - Attention-based architectures/transformers

- Extension of Hebbian approaches to **SNNs**

Thank you!

gabriele.lagani@phd.unipi.it