Short-Term Plasticity Neurons Learning to Learn and Forget

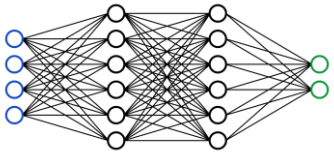
Hector Garcia Rodriguez

Qinghai Guo

Timoleon Moraitis

Motivation: Biological vs Artificial Neural Networks

Artificial NNs



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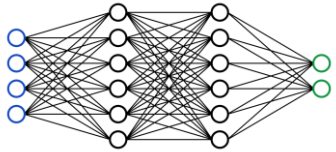

Biological NNs

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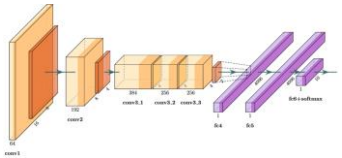
- Limitations compared to animals and humans.
    1. Long training, big data

    2. Difficulty in dynamic environments

    3. Ad hoc, task-specific architectures



    4. High computational demands

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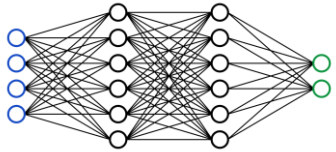

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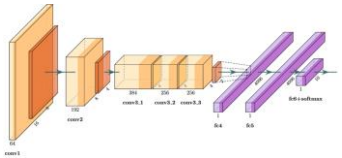

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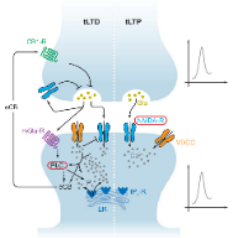

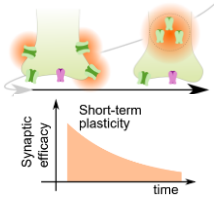

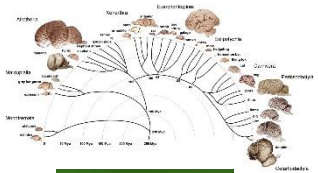

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2. Dynamically changing chemical concentrations
3. Shared principles across brain areas and species
4. Extreme energy efficiency in neurons and synapses

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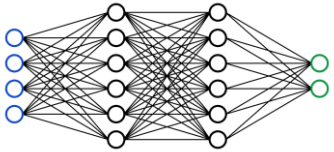

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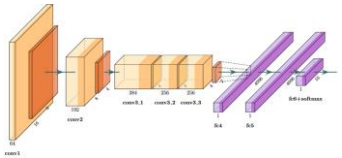

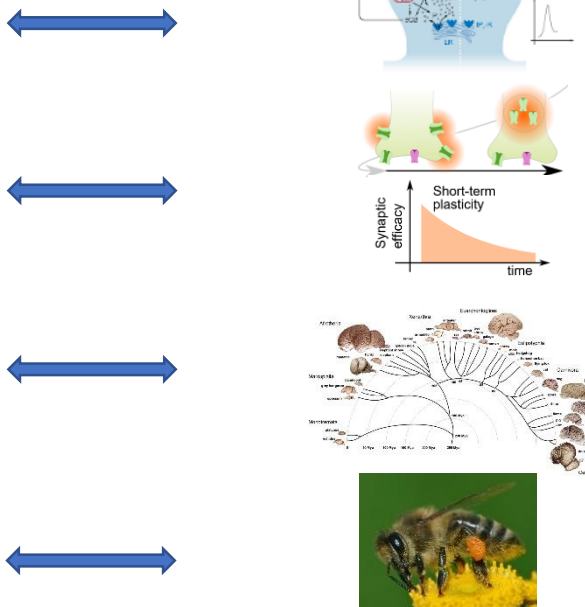

Biological NNs

- Unique mechanisms, missing from ANNs.
- The mechanisms are closely related to the advantages.
  1. Complex synaptic **plasticity** for learning
  2. **Dynamically** changing chemical concentrations
  3. **Shared** principles across brain areas and species
  4. Extreme energy **efficiency** in neurons and synapses

Background: Neuromorphic Computing

Conversion of biophysical operations into (hardware) models of computation.

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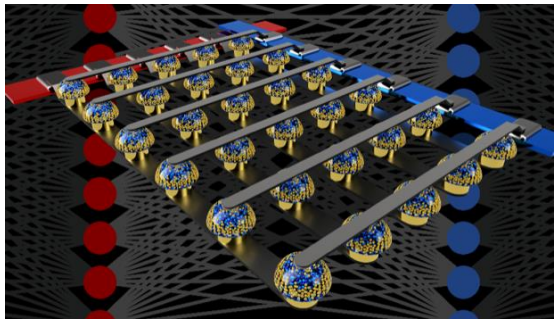

Ambrogio et al., 2018

Energy efficiency through physics of electronics.

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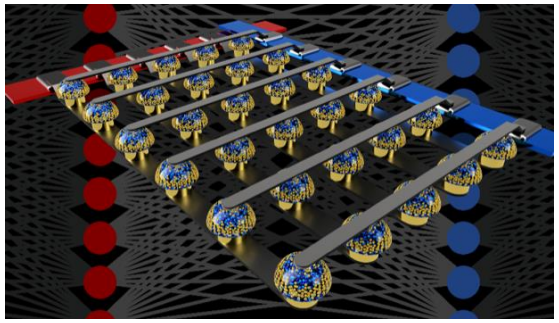

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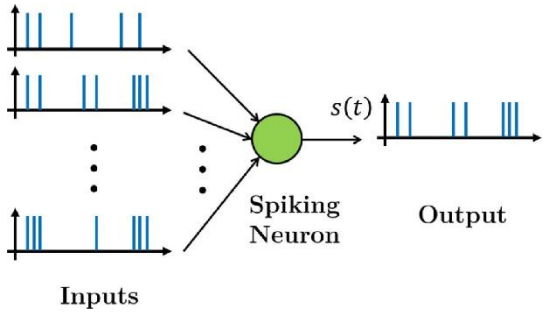

Anwani & Rajendran, 2019

The field has focused on Spiking Neural Networks.

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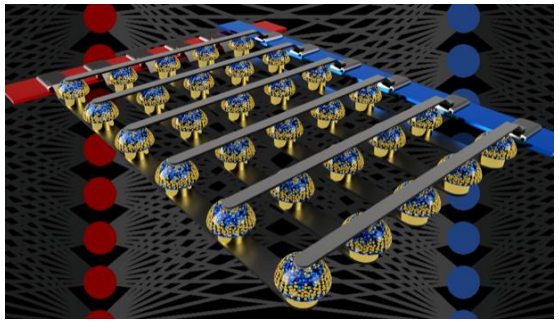

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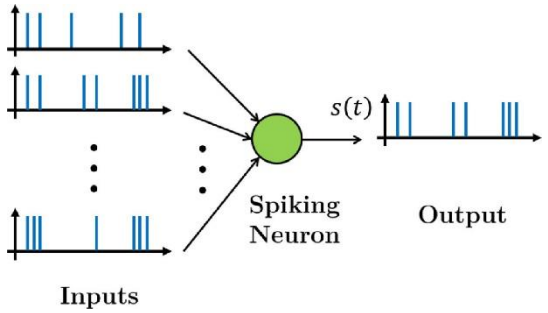


Anwani & Rajendran, 2019

The field has focused on Spiking Neural Networks.

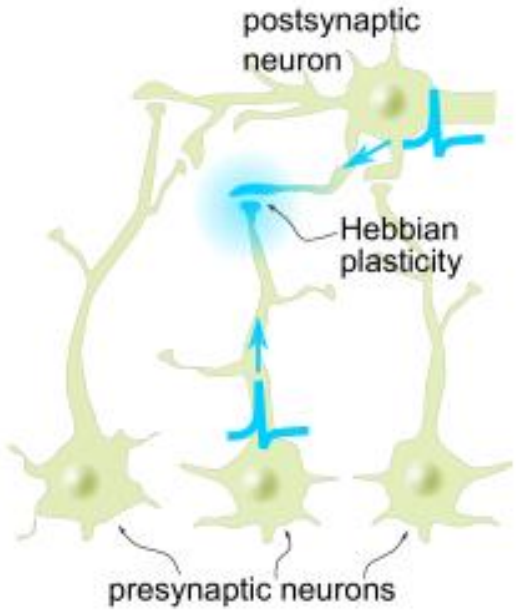
- We also used a neuromorphic mechanism (STP).

But:

- We improved **both *efficiency* and *proficiency***.
- We showed advantages **beyond SNNs, in state-of-the-art** ML.

Background: Plasticity

- E.g. Hebbian plasticity, “Fast Weights”
- Local learning in the brain



Moraitis et al., 2020

Background: Plasticity and Short-Term Plasticity

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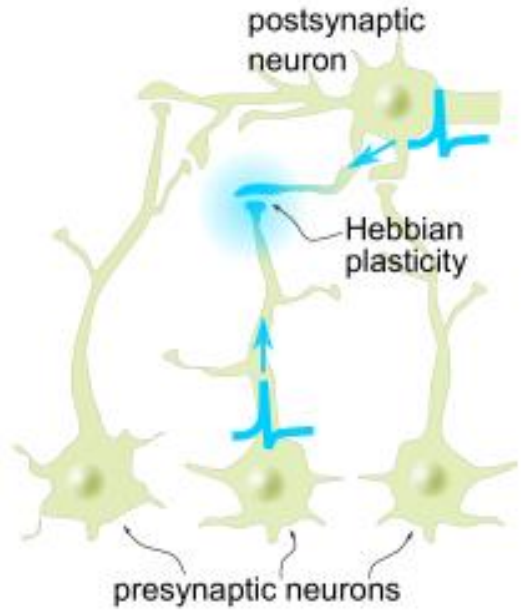
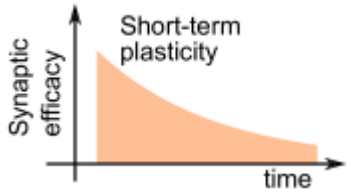
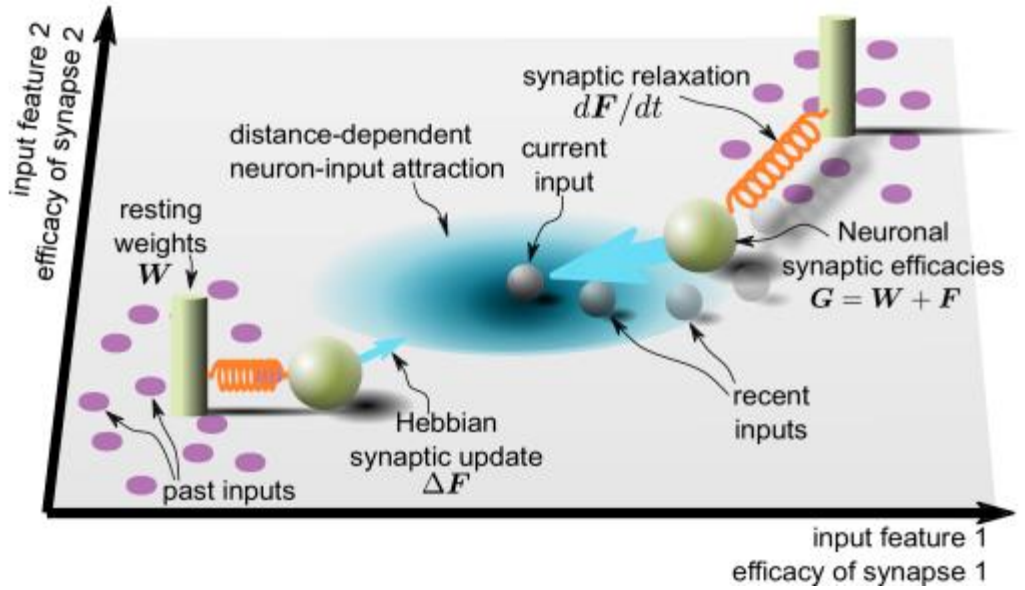


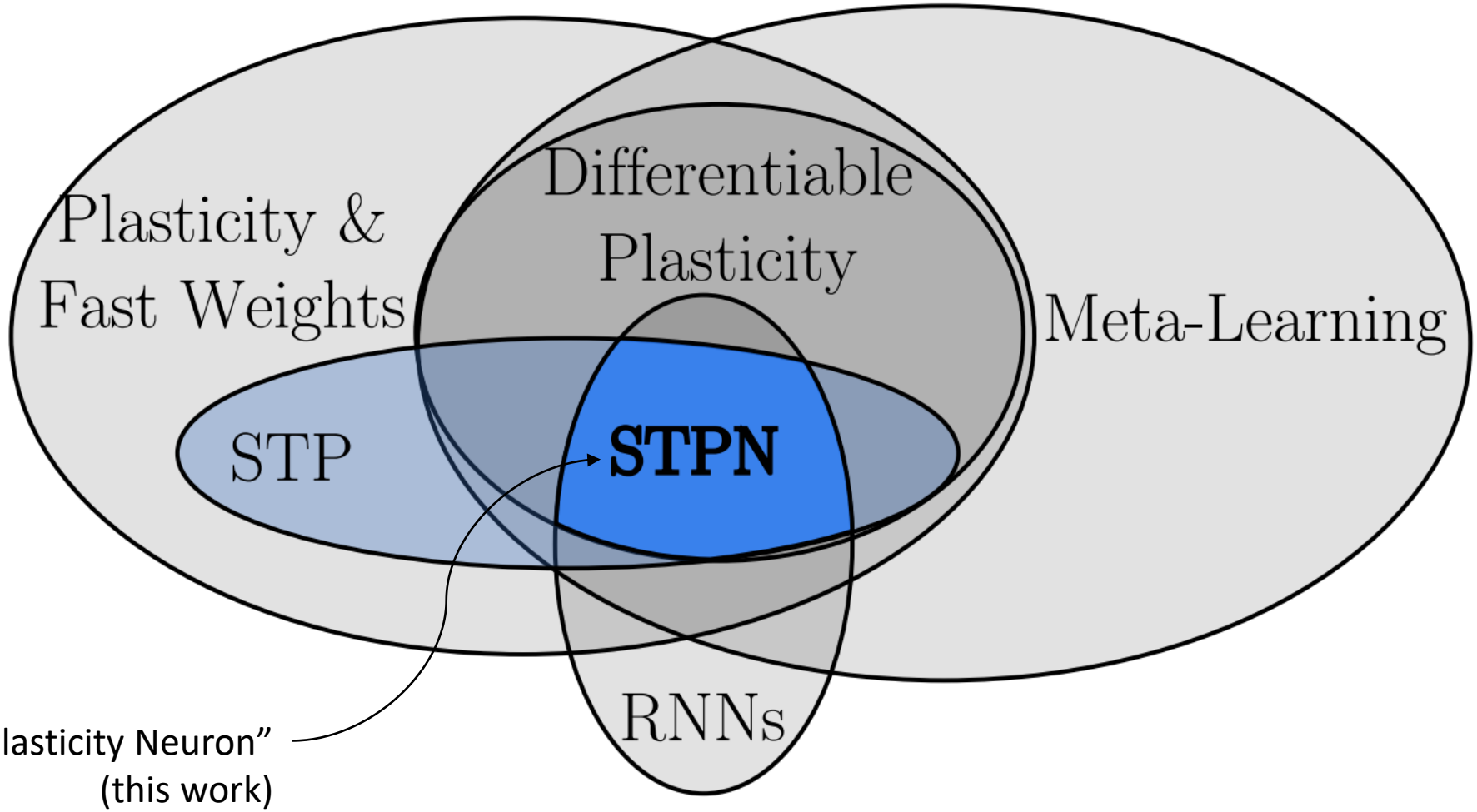
- Short-term plasticity (STP)
- Decaying effect of weight updates





➢ Hebbian STP: models certain dynamic environments optimally, in theory (Moraitis et al. 2020).

Background concepts



The Short-Term Plasticity Neuron (STPN)

$$\boldsymbol{h}^{(t)} = \sigma(\boldsymbol{G}^{(t)}\boldsymbol{x}^{(t)})$$

- Split synaptic efficacy G into long-term weight W and short-term component F

$$\boldsymbol{G}^{(t)} = \boldsymbol{W} + \boldsymbol{F}^{(t)}$$

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- Update short-term component with Hebbian product and decay dynamics

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learning

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learning forgetting

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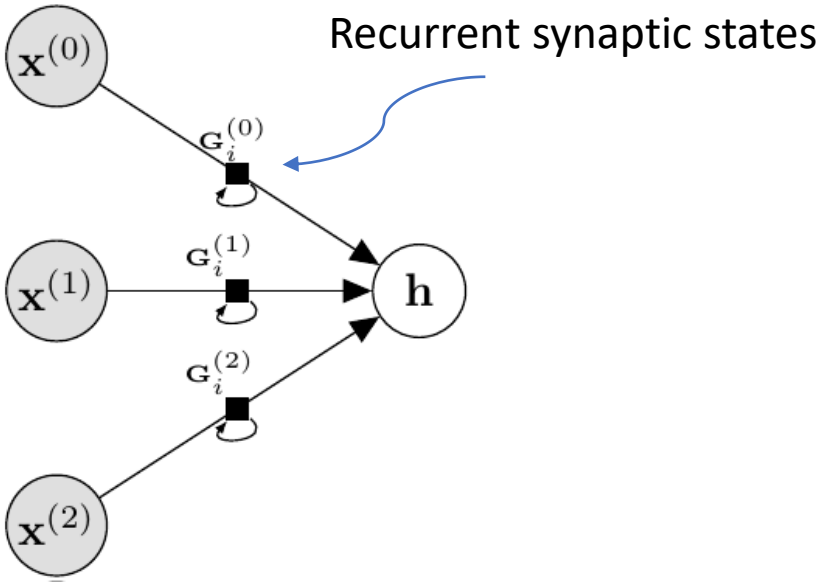
learning

forgetting

Recurrent synaptic state

The Short-Term Plasticity Neuron (STPN)

STPN-F (feed-forward)



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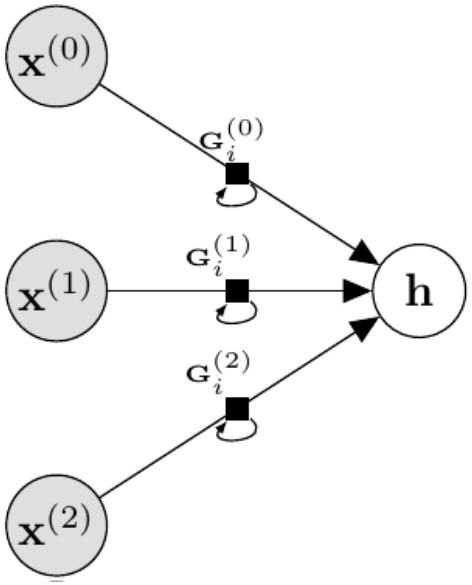

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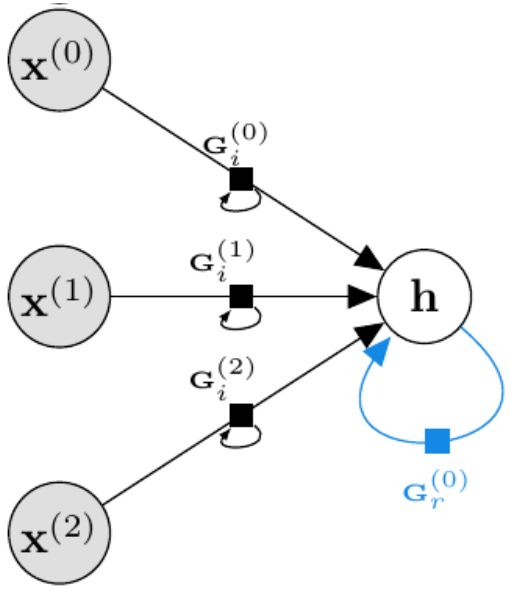
STPN-R (recurrent)



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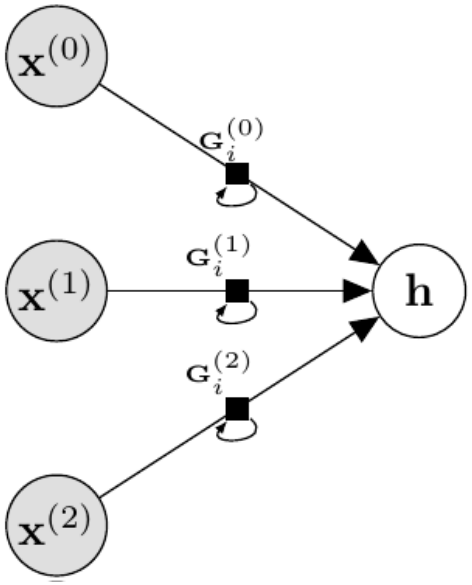

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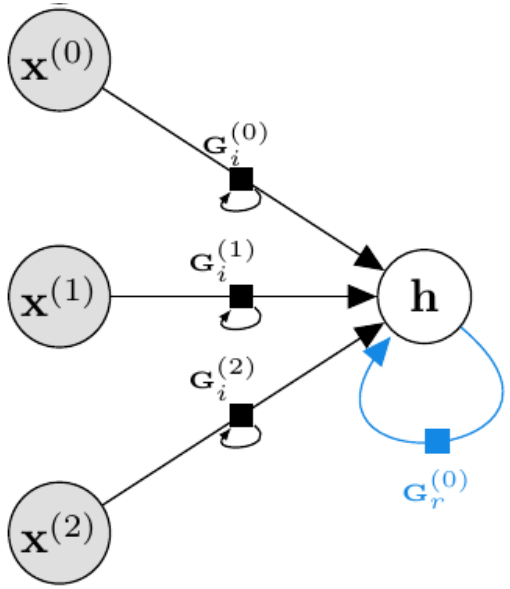

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…STPN-L? (LSTM-like)

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STP on F (and G):

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learning

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learning forgetting

BPTT on γ and λ (and W):

learning to learn and forget

Experiments: Tasks

- Supervised Learning
- Reinforcement Learning
- 4 tasks

Experiments: Tasks

Associative Retrieval Task
Ba et al., 2016

input

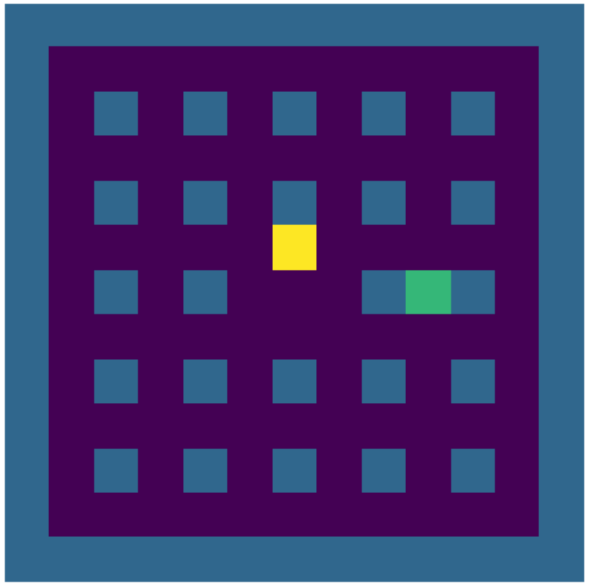
c9 k8 j3 f1 ?? k

target

8

- Memorisation and retrieval of associations presented sequentially

Maze exploration
Miconi et al., 2018

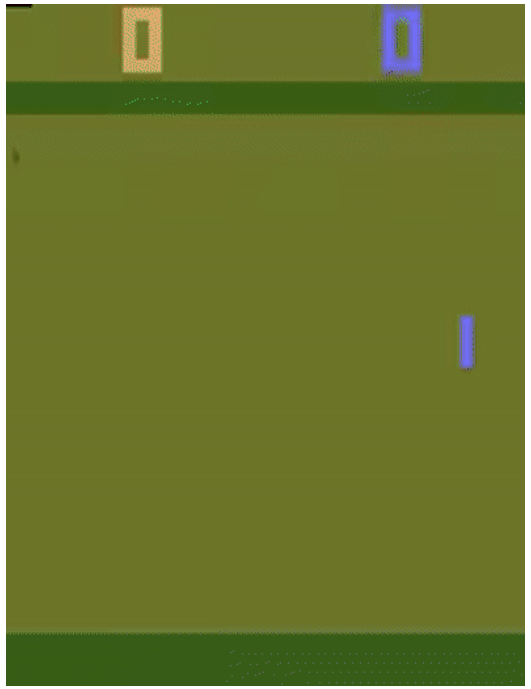


- Meta-learning to:
  - Adapt to variations in the maze
  - Change between exploration and exploitation

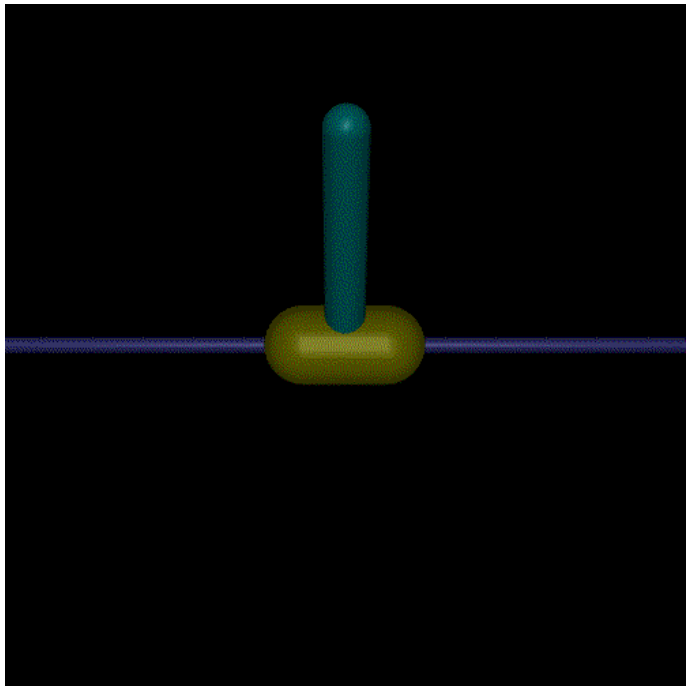
- Previously used to test models with *fast weights*

Experiments: Tasks

Atari Pong
Bellemare et al., 2013



MuJoCo Inverted Pendulum
Todorov et al., 2012

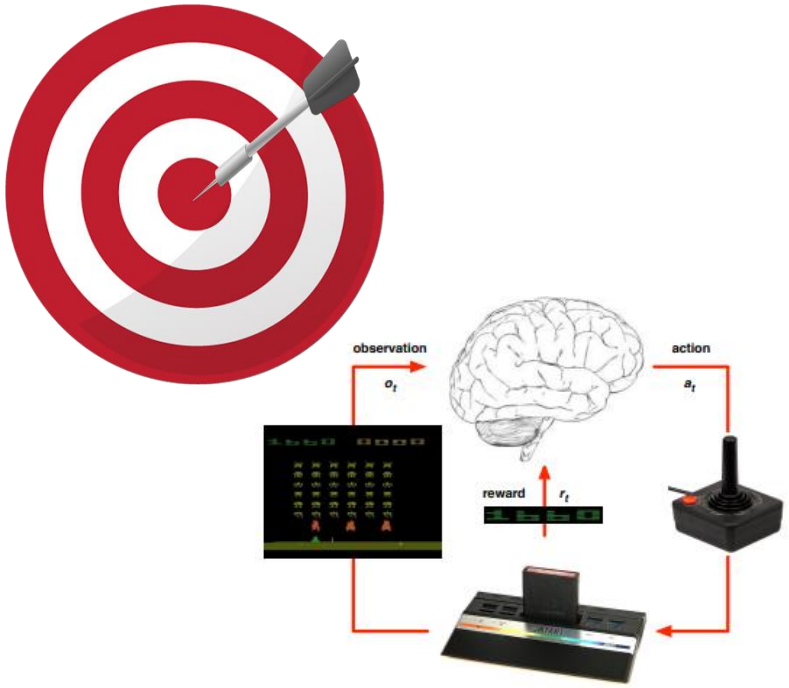


- More complex tasks, previously not tested for models with *fast weights*
- RNNs part of competitive solutions

Experiments: Metrics

We evaluated:

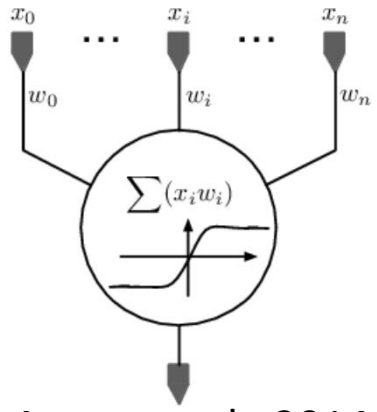
- Proficiency (Accuracy, reward)



- Efficiency (1/energy)
  - Power consumption of weighting operations
  - Assuming analog biological implementation/neuromorphic hardware

$$P = V^2 g$$

Electric power consumption — Input (voltage) — Synaptic efficacy (conductance)



Amant et al., 2014

Experiments: Baselines

We compared STPN with:

- *Fast weights* SOTA models
  - Fast weights RNN (Ba et al., 2016)
  - Differentiable plasticity (Miconi et al., 2019)
- Commonly used NNs
  - LSTM
  - RNN
  - MLP

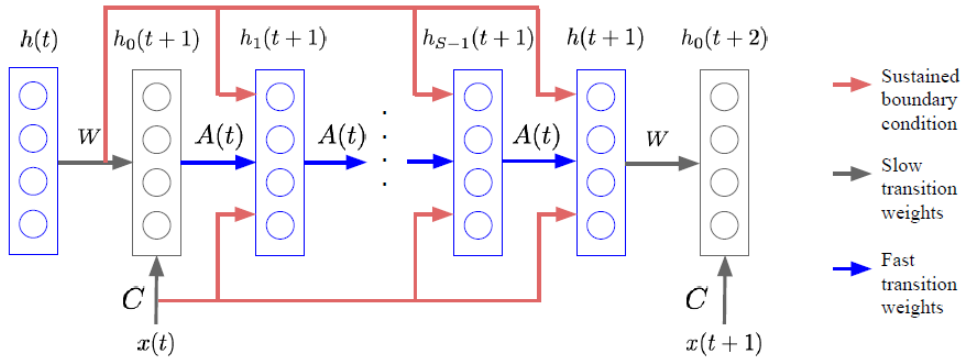
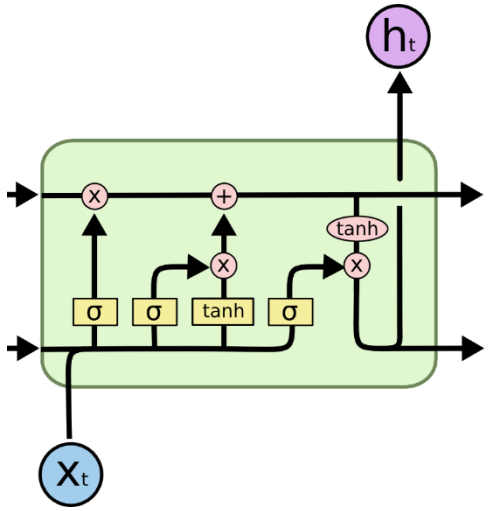


Figure 1: The fast associative memory model.

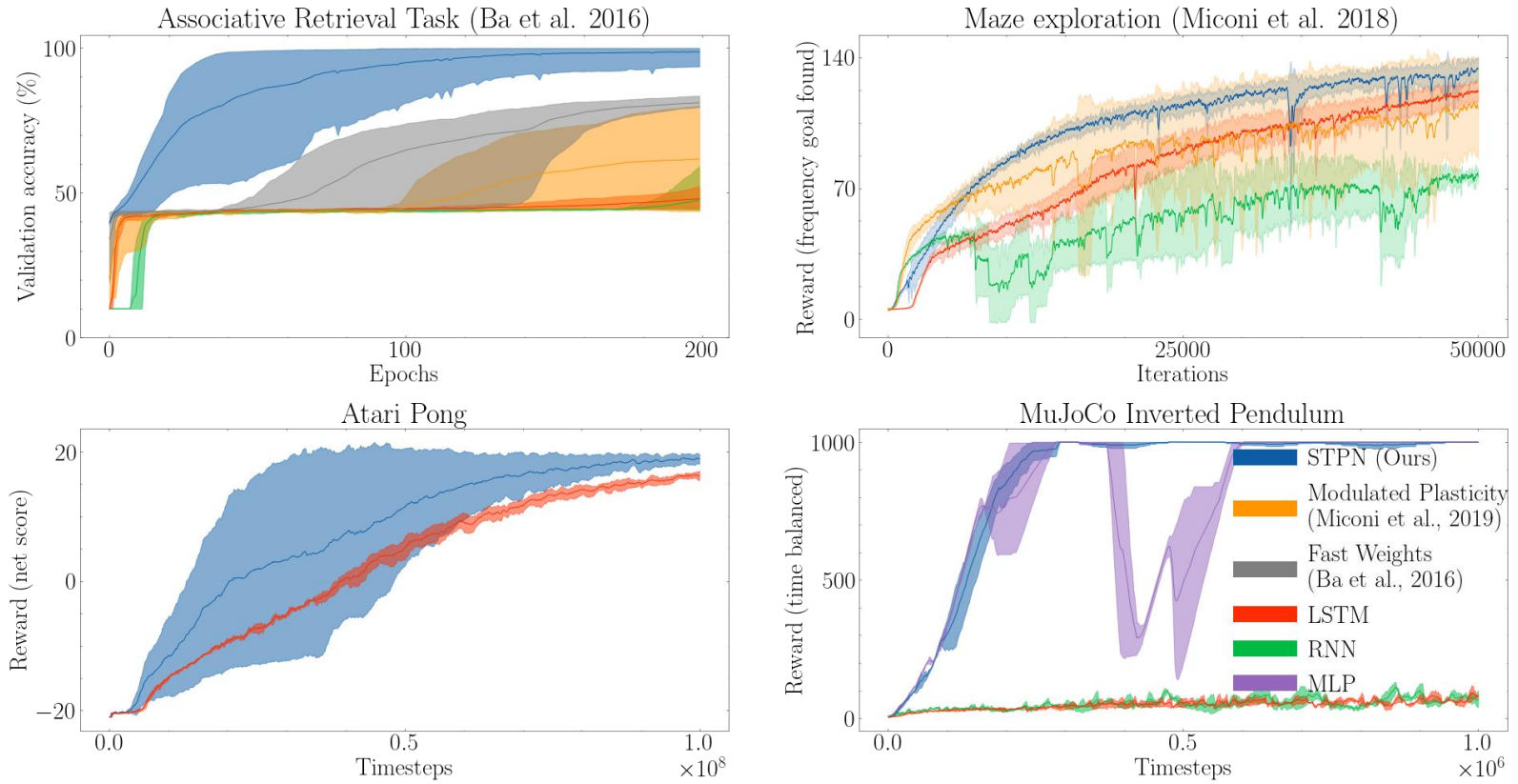
Ba et al., 2016



LSTM Illustration by Olah C., 2015

Results: Proficiency

- STPN obtained highest accuracy and reward
  - Than all baselines
  - In all tasks



Results: Efficiency

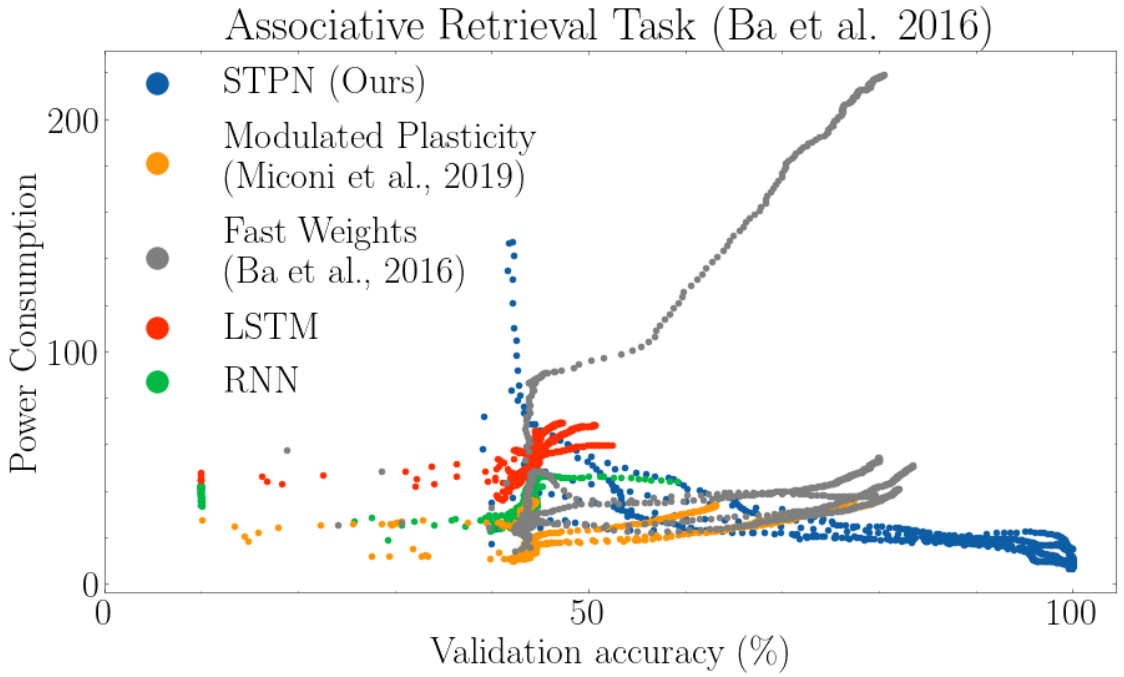
- STPN is also significantly more energy-efficient, up to 10x
  - Than all baselines
  - In all tasks

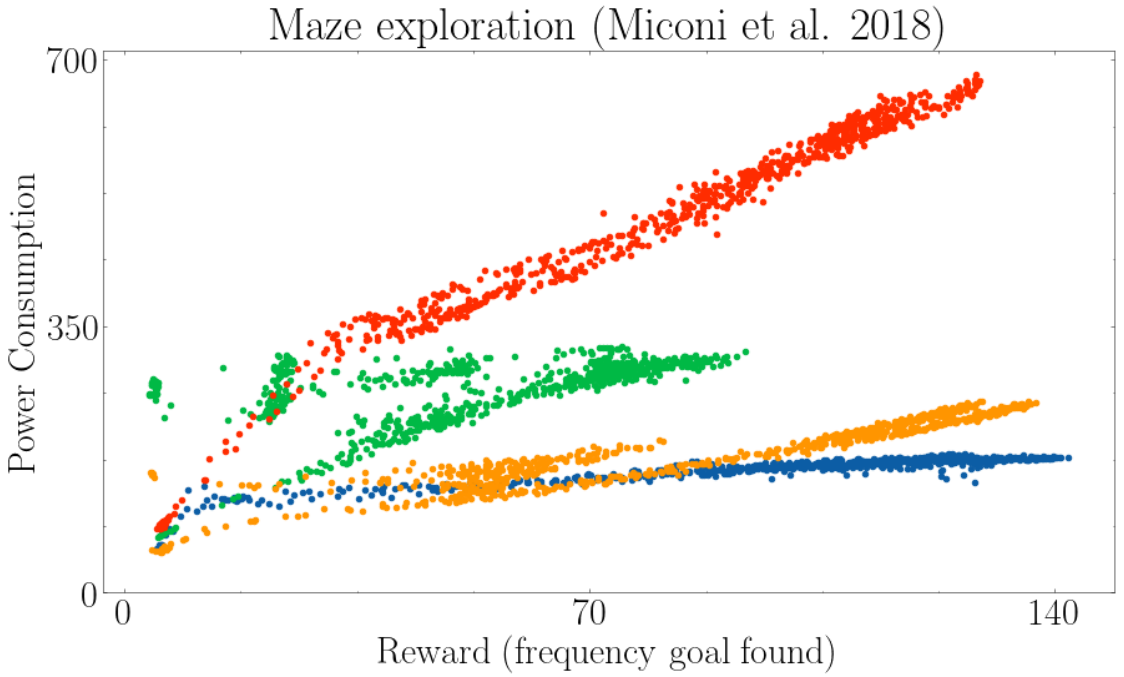
Table 4. Power consumption of trained models during inference. Average over multiple inference runs and timesteps within a run, reported mean and standard deviation over seeds.

Model	Associative Retrieval	Maze Exploration	Pong	Inverted Pendulum
STPN (Ours)	**10.9 ± 3.8**	**181.1 ± 2.9**	**52.7 ± 6.4**	**7.9 ± 2.5**
LSTM	65.6 ± 3.4	649.1 ± 15.3	576.8 ± 33.5	758.8 ± 81.7
RNN	43.0 ± 4.9	330.6 ± 24.3	-	143.0 ± 22.4
Modulated plasticity	32.0 ± 7.4	231.6 ± 23.9	-	-
Fast Weights	80.6 ± 69.4	-	-	-
MLP	-	-	-	115.8 ± 33.9

Results: Efficiency

- Power consumption remains low even as proficiency increases.
  - Despite no explicit optimization of efficiency.
  - Learning to depress irrelevant synapses improves both.





Summary

- STPN: a **new recurrent model** founded on ML theory and neuroscience
- Trainable STP through **recurrency within each synapse**
- **Meta-learning** to learn ***and forget*** through BPTT + STP
- **Highest accuracy** and reward
  - In **multiple tasks**
  - Than **SOTA** recurrent and plastic models
- A new method for **energy efficiency in neuromorphic** hardware
- Increases importance of **STP's role in biology**
- Learning to forget might tackle ***catastrophic* forgetting**