Using stigmergy as a computational memory in the design of recurrent neural networks

Federico A. Galatolo

Department of Information Engineering
University of Pisa

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Time-Series Static Classification

X_0	X_1	X_2	X_3	$\cdots$	X_{n-2}	X_{n-1}

- MLP
- CNN
- ...

Static System

Y_0	Y_1	$\cdots$	Y_{n-1}

Time-Series Static Classification

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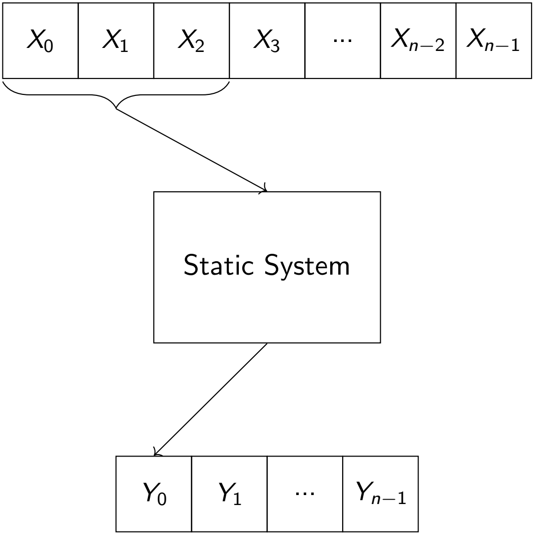
- ...



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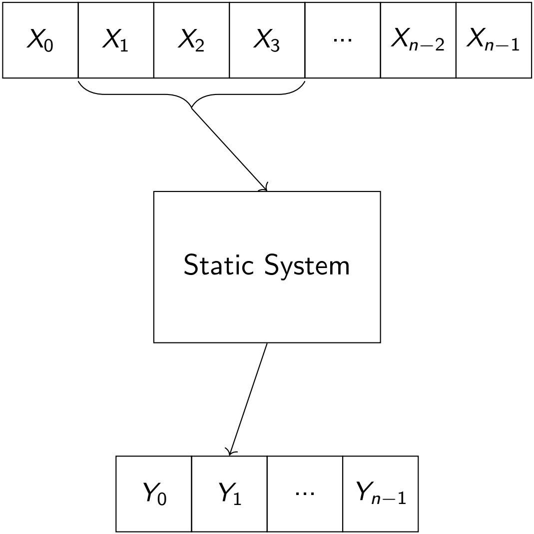

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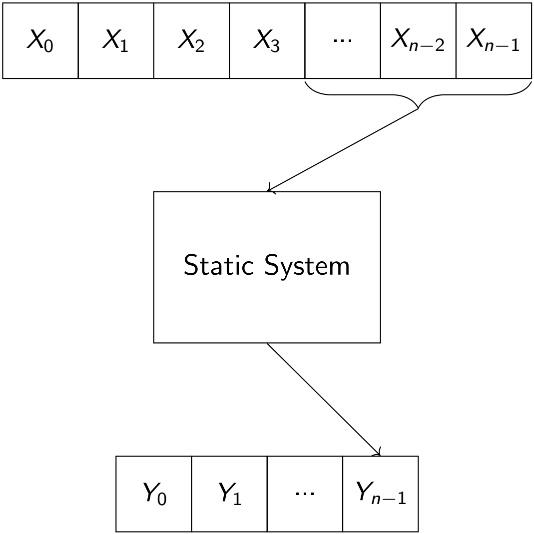

Time-Series Static Classification

- ✓ You can use any existing ML Architecture
- × Window size choice
- × Long-lived relationships are impossible to infer

Time-Series Dynamic Classification

X_0	X_1	X_2	X_3	$\cdots$	X_{n-2}	X_{n-1}

- RNN
- LSTM
- ...

Dynamic System

Y_0	Y_1	$\cdots$	Y_{n-1}

Time-Series Dynamic Classification

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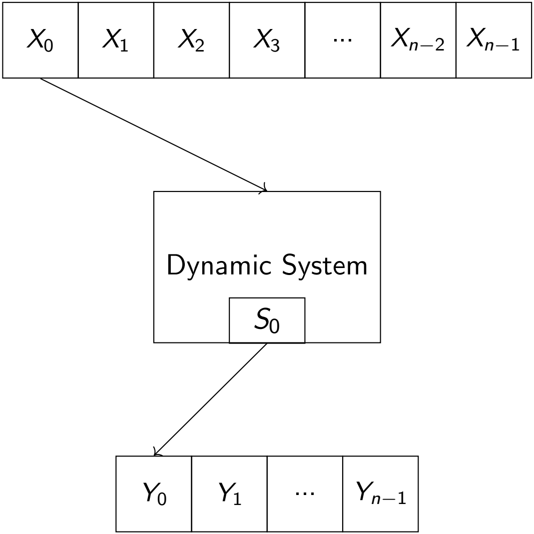

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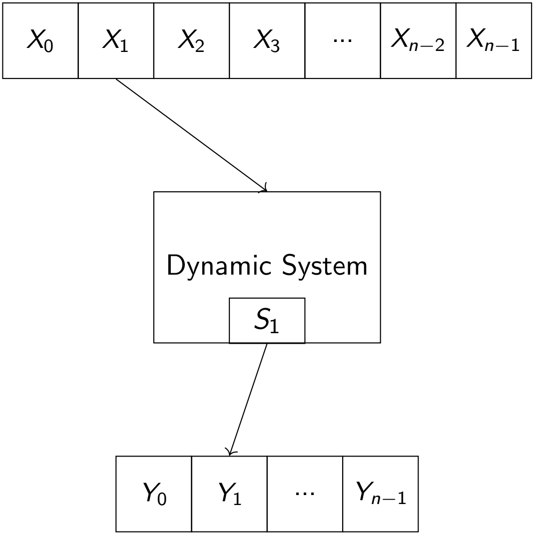

Time-Series Dynamic Classification

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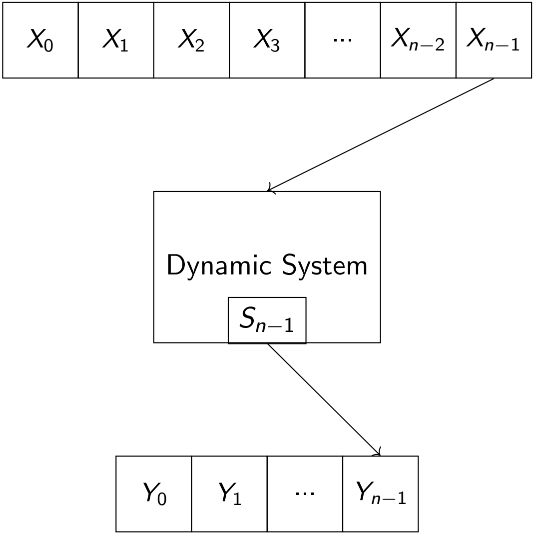
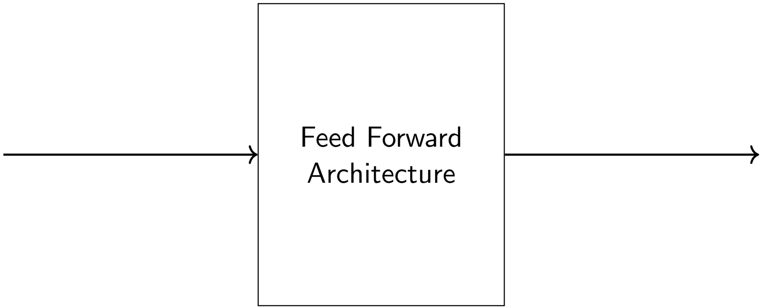


Time-Series Dynamic Classification

- ✓ The system knows the concept of time
- ✓ Can autonomously decide what to remember and forget
- × Ad-Hoc solutions
- × Highly engineered

RNN $\neq$ LSTM

- RNN and LSTM are often used as synonyms in literature
- Has been proven that “Vanilla recursion” performs poorly
- LSTM are the state of the art for Time Series Classification



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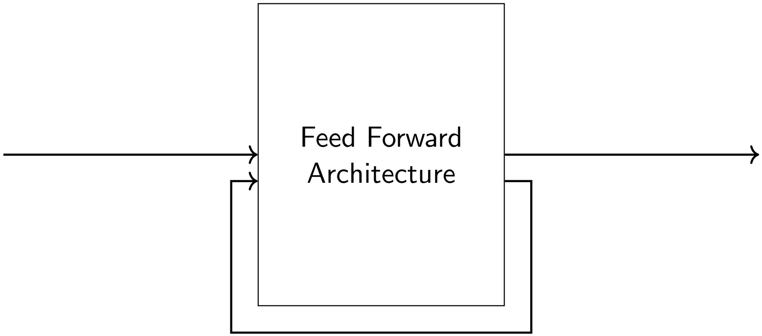

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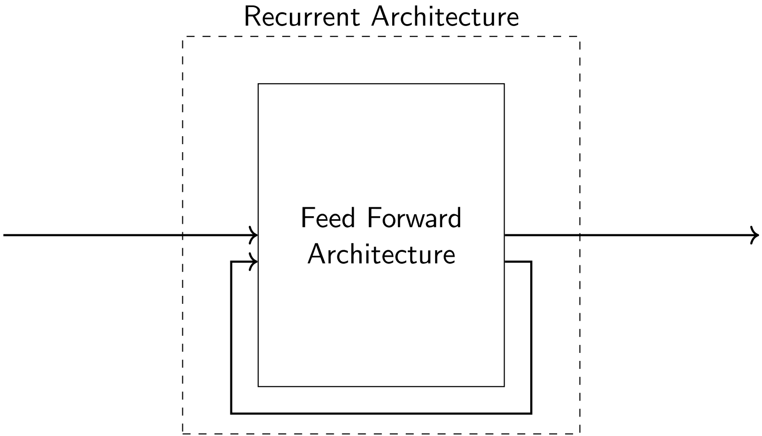
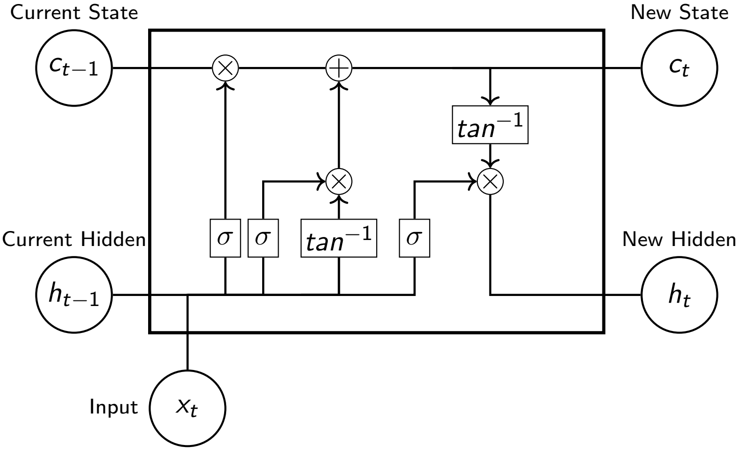


A deep look inside an LSTM cell



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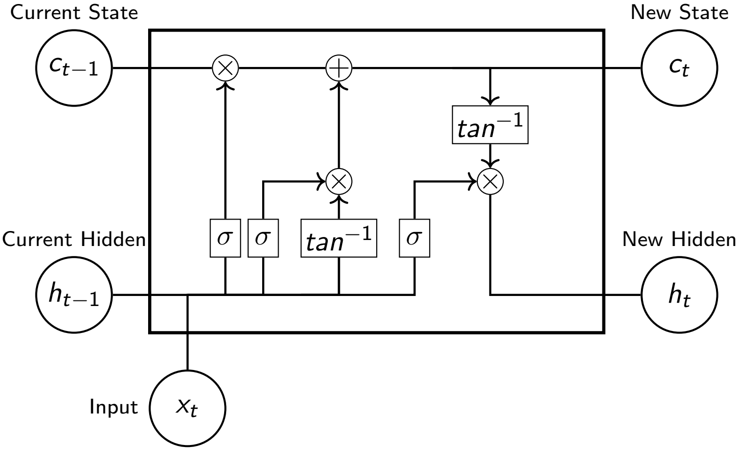
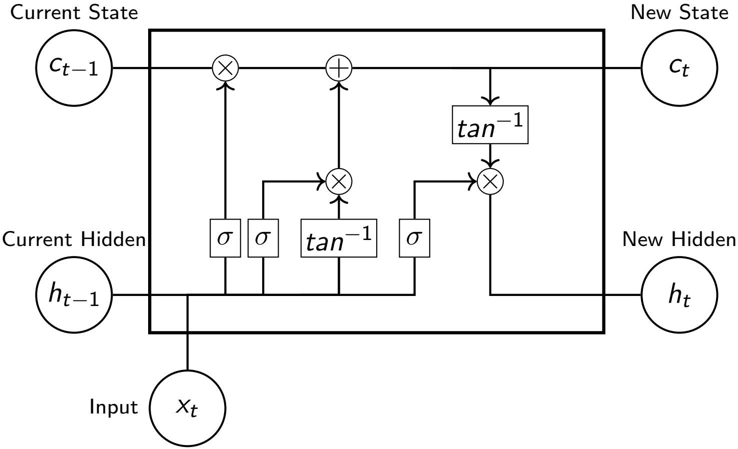


- $f_t = \sigma(W_f x_t + U_f h_t + b_f)$

A deep look inside an LSTM cell



- $f_t = \sigma(W_f x_t + U_f h_t + b_f)$
- $i_t = \sigma(W_i x_t + U_i h_t + b_i)$

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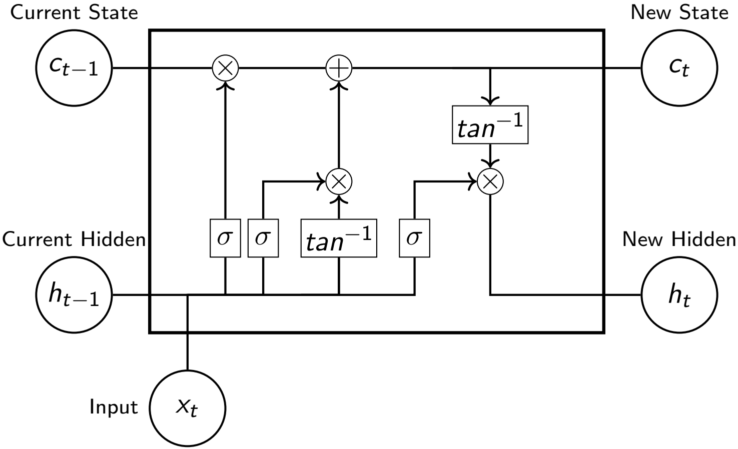

- $f_t = \sigma(W_f x_t + U_f h_t + b_f)$
- $i_t = \sigma(W_i x_t + U_i h_t + b_i)$
- $i_c = tan^{-1}(W_c x_t + U_c h_t + b_c)$

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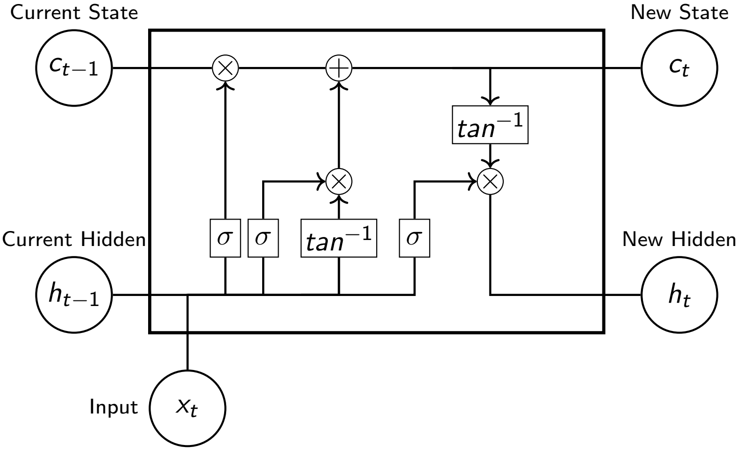

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- $c_t = f_t \circ c_{t-1}$

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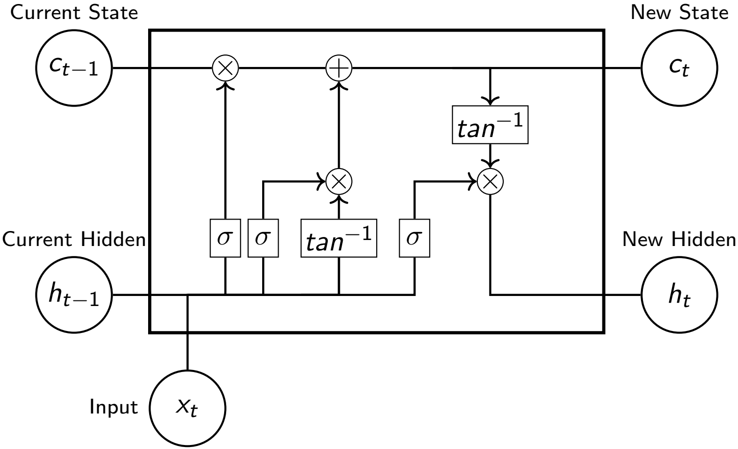

- $f_t = \sigma(W_f x_t + U_f h_t + b_f)$
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- $i_c = tan^{-1}(W_c x_t + U_c h_t + b_c)$
- $c_t = f_t \circ c_{t-1} + i_t \circ i_c$

A deep look inside an LSTM cell

- $f_i = \sigma(W_f x_i + U_f h_{i-1} + b_f)$
- $i_i = \sigma(W_i x_i + U_i h_{i-1} + b_i)$
- $o_i = \sigma(W_o x_i + U_o h_{i-1} + b_o)$
- $c_i = \sigma(f_i \circ c_{i-1} + i_i \circ tan^{-1}(W_c X_i + U_c h_{i-1} + b_c))$
- $h_t = o_i * tan^{-1}(c_i)$

Using

- $W_f,\ W_i,\ W_o,\ W_C \in R^{n\times h}$
- $U_f,\ U_i,\ U_o,\ U_c \in R^{h\times h}$
- $b_f,\ b_i,\ b_o,\ b_c \in R^h$

A deep look inside an LSTM cell

- $f_i = \sigma(W_f x_i + U_f h_{i-1} + b_f)$
- $i_i = \sigma(W_i x_i + U_i h_{i-1} + b_i)$
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Using

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Can we do better?

A deep look inside an LSTM cell

- $f_i = \sigma(W_f x_i + U_f h_{i-1} + b_f)$
- $i_i = \sigma(W_i x_i + U_i h_{i-1} + b_i)$
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Using

- $W_f,\ W_i,\ W_o,\ W_C \in R^{n \times h}$
- $U_f,\ U_i,\ U_o,\ U_c \in R^{h \times h}$
- $b_f,\ b_i,\ b_o,\ b_c \in R^h$

Can we do better?

Can we do **simpler**?

Let's take a step back

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- Complex behaviors can **emerge** from simple ones
- Emergence is a key phenomenon in nature
- **Stigmergy** is one of the tools nature uses to achieve emergence

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- Complex behaviors can **emerge** from simple ones
- Emergence is a key phenomenon in nature
- **Stigmergy** is one of the tools nature uses to achieve emergence

Can we **emerge** a computational memory using the **stigmergy**?

Biological Stigmergy

Implemented in nature via pheromonic marks

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Mark

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Stimulus

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Stimulus

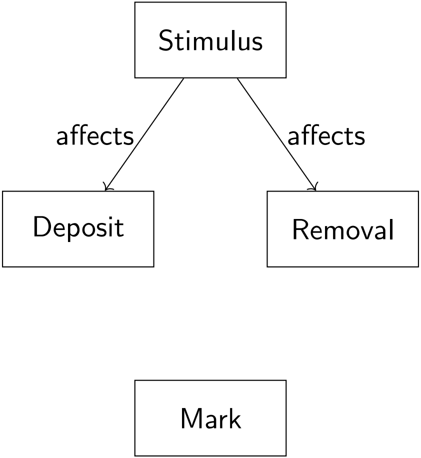
Deposit

Removal

Mark

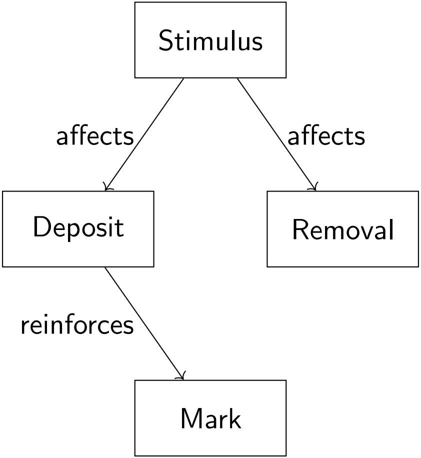
Biological Stigmergy

Implemented in nature via pheromonic marks



Biological Stigmergy

Implemented in nature via pheromonic marks



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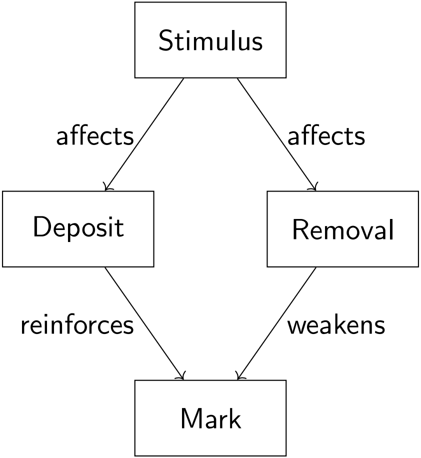

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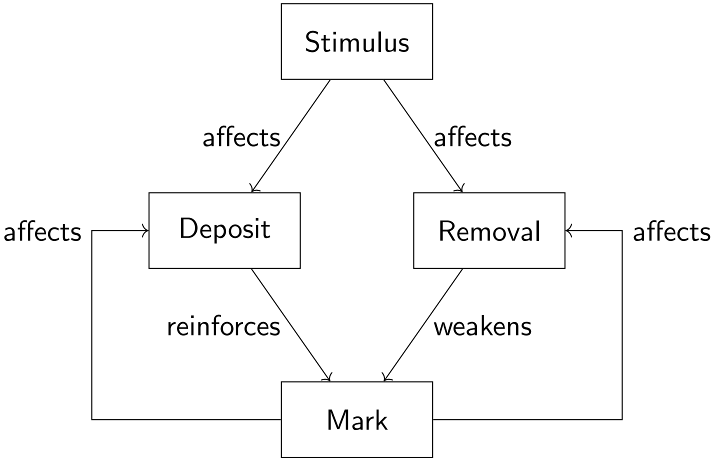

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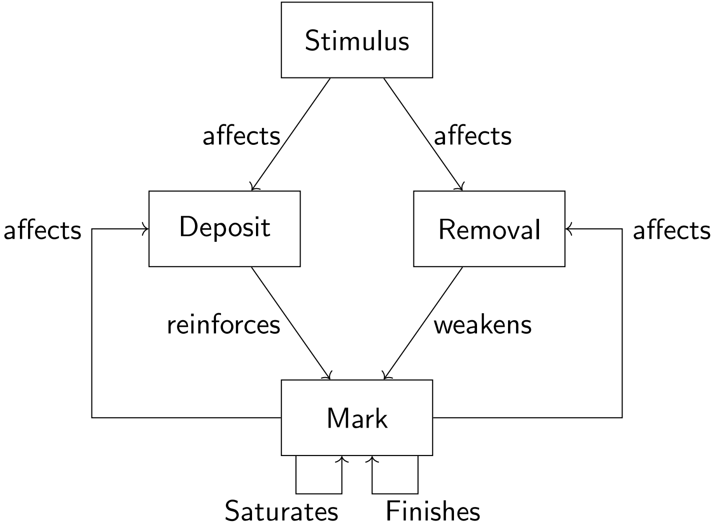
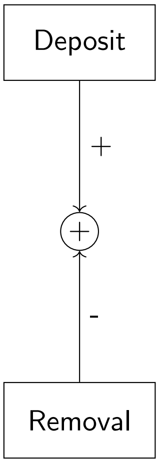


Computational Stigmergy

Deposit

Removal

Computational Stigmergy



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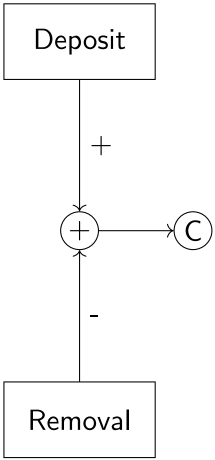

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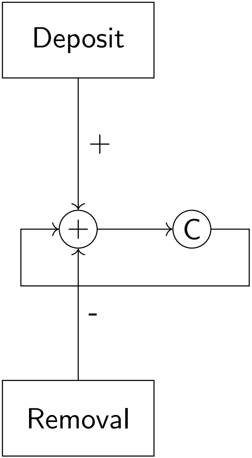

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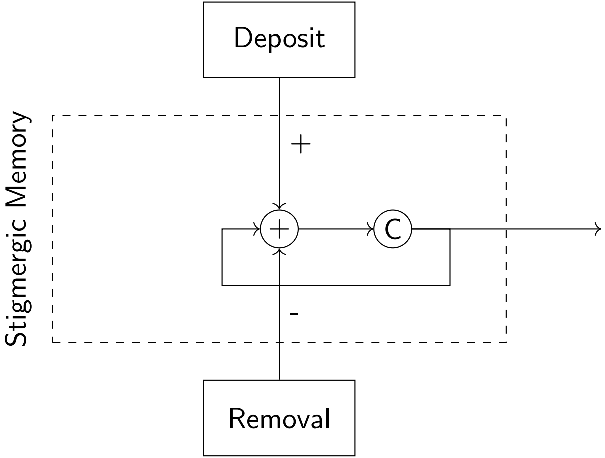

Stigmergic Memory ML Architecture

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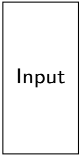

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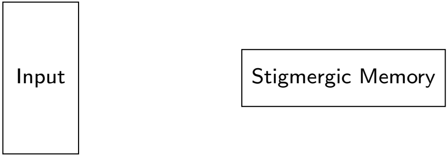

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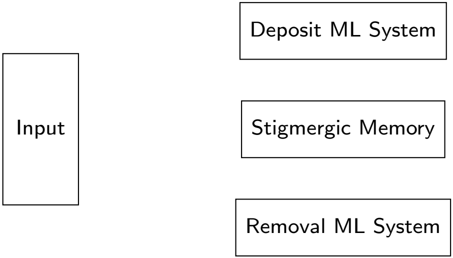

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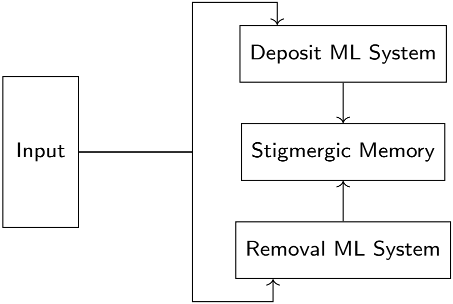

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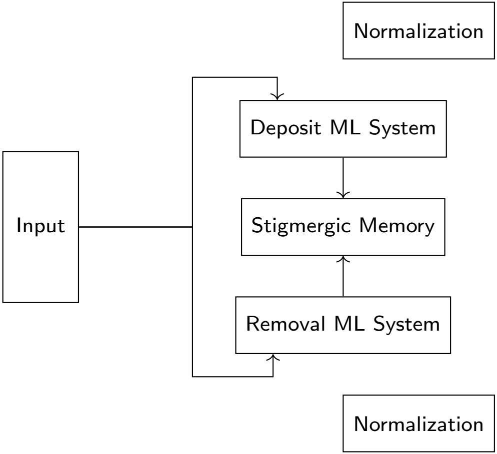

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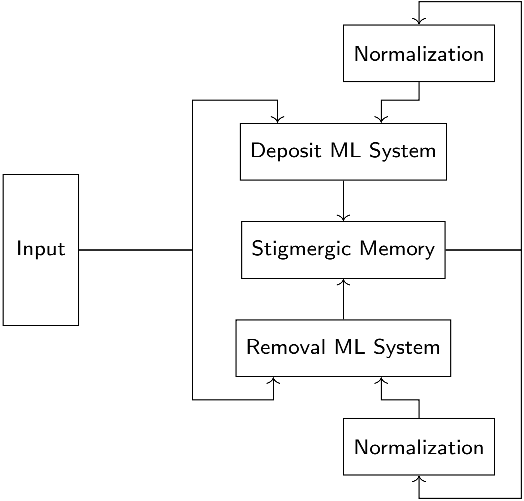

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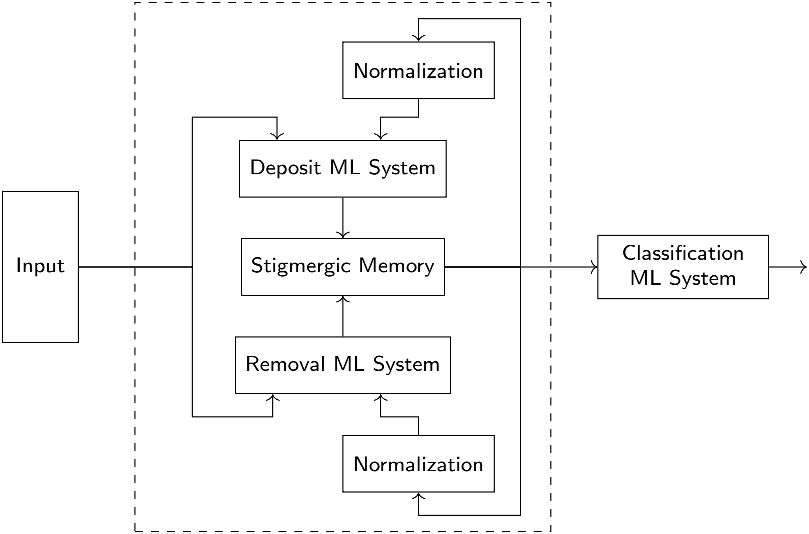
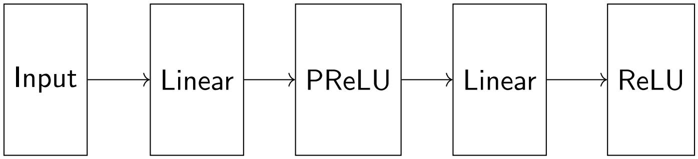


Experimental Stigmergic ML Systems

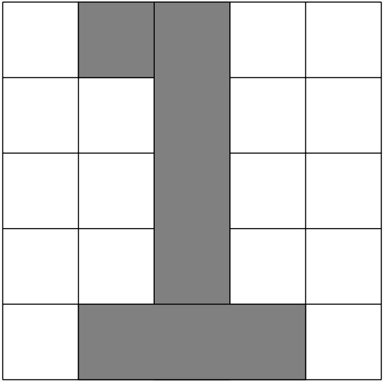
Neural Networks used as Deposit, Removal and Classification Systems

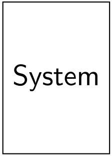


Experimental Architectures

- Stigmergic Memory NNs
- LSTMs
- Vanilla RNNs
- FF NNs (only with spatial dataset)

Experimental Results: Spatial MNIST





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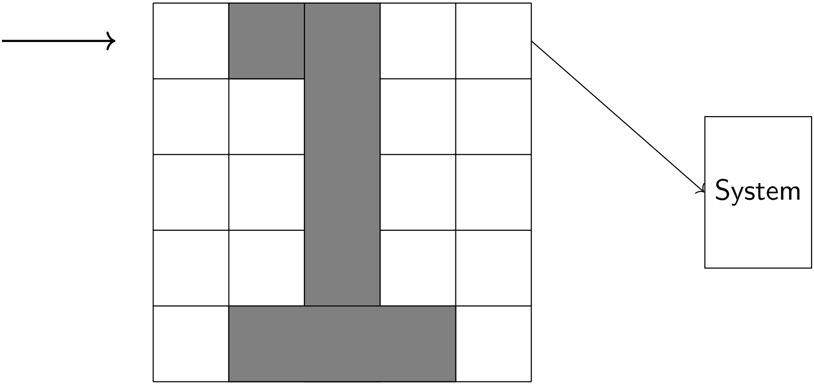

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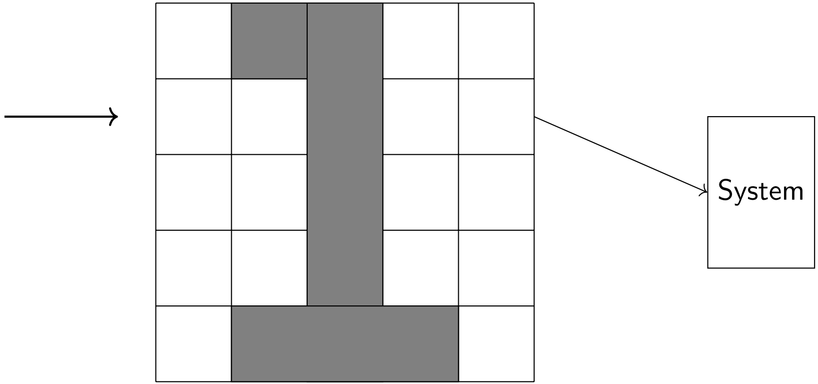

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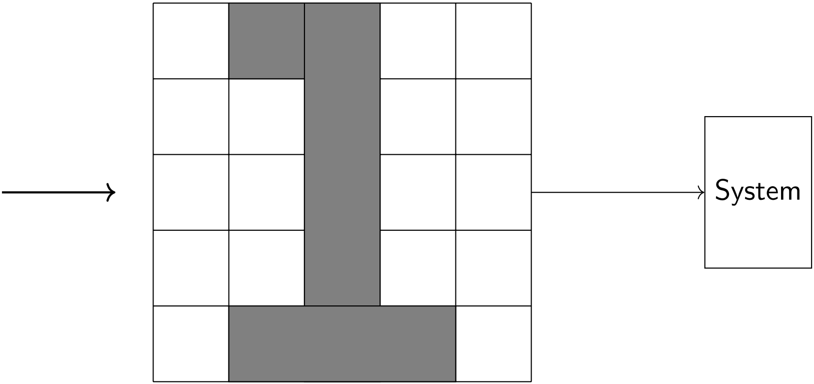

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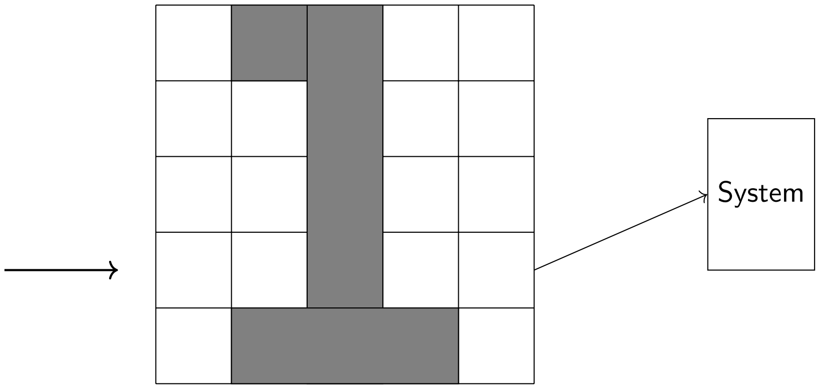

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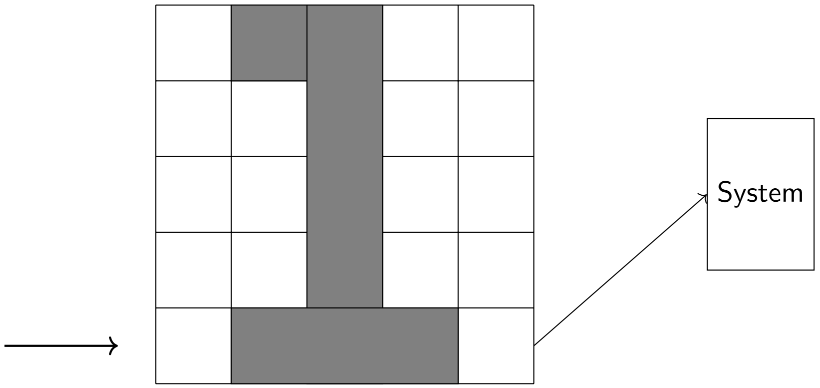
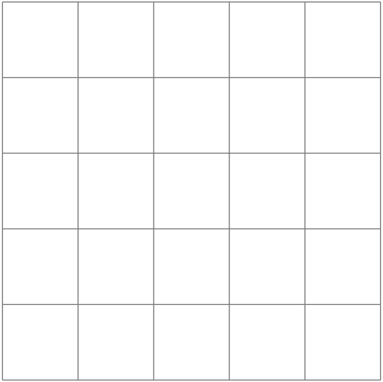


Experimental Results: Spatial MNIST

Architecture	N. Parameters	Accuracy
Stigmergic Memory	3190	96.5 ± 0.5 %
Static Feed Forward	328810	95.1 ± 0.02 %
LSTM	3360	94.3 ± 0.1 %
RNN	3482	76.6 ± 0.3 %

- Outperforms LSTMs, Vanilla RNNs and FFs
- Best performances, smaller number of parameters

Experimental Results: Temporal MNIST



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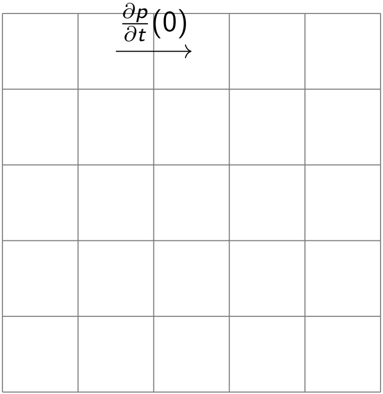

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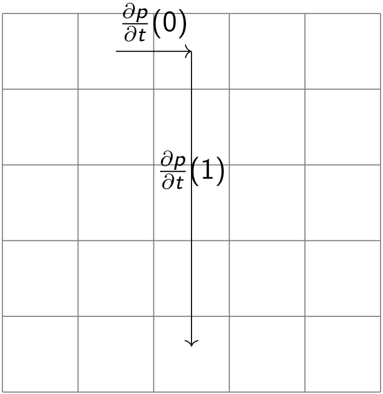

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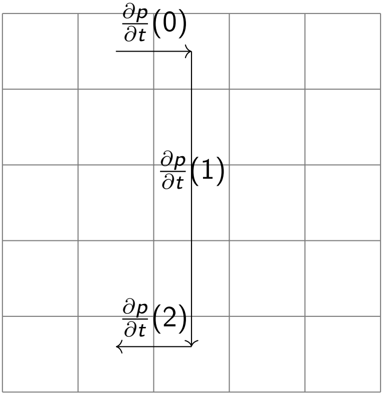

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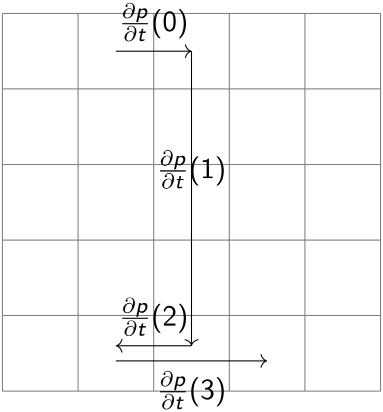

Experimental Results: Temporal MNIST

Architecture	N. Parameters	Accuracy
LSTM	5490	94.96 ± 0.2 %
Stigmergic Memory	5420	94.67 ± 0.7 %
RNN	5480	72.95 ± 11 %

- Outperforms Vanilla RNNs
- Same performances as LSTMs

Keep in touch

You can find the pytorch implementation on GitHub

https://github.com/galatolofederico/icpram2019

federico.galatolo@ing.unipi.it

galatolo.me

@galatolo

@galatolofederico