

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

Federico A. Galatolo

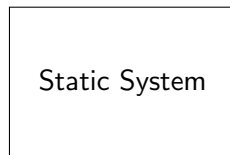
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University of Pisa

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Time-Series Static Classification

X_0	X_1	X_2	X_3	\dots	X_{n-2}	X_{n-1}
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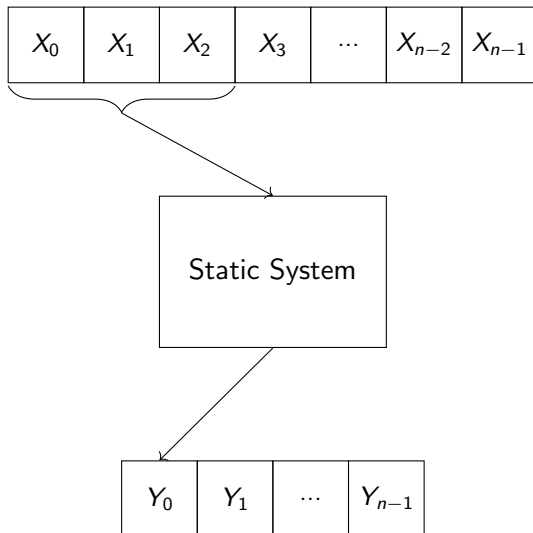
- MLP
- CNN
- ...



Y_0	Y_1	\dots	Y_{n-1}
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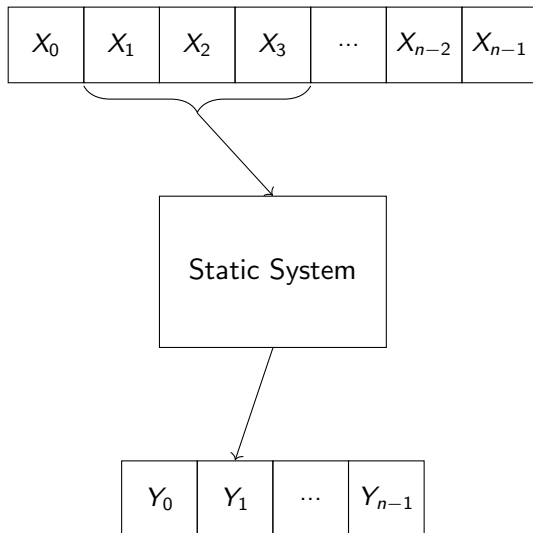
Time-Series Static Classification

- MLP
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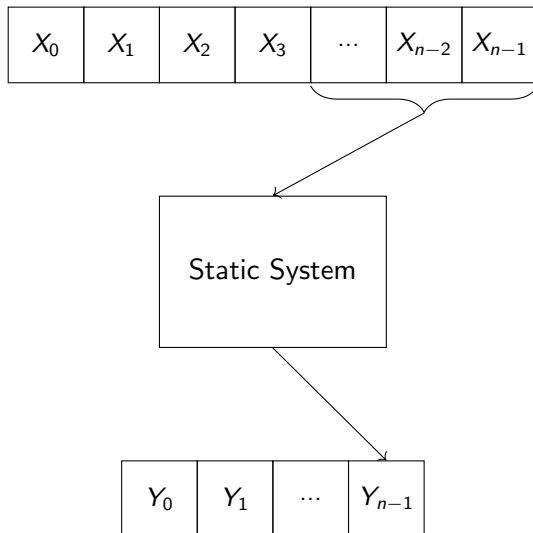
Time-Series Static Classification

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Time-Series Static Classification

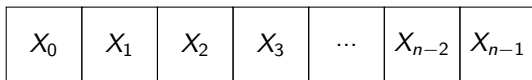
- MLP
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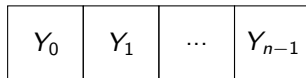
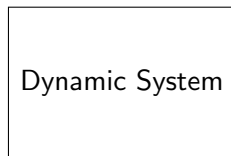
Time-Series Static Classification

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

Time-Series Dynamic Classification

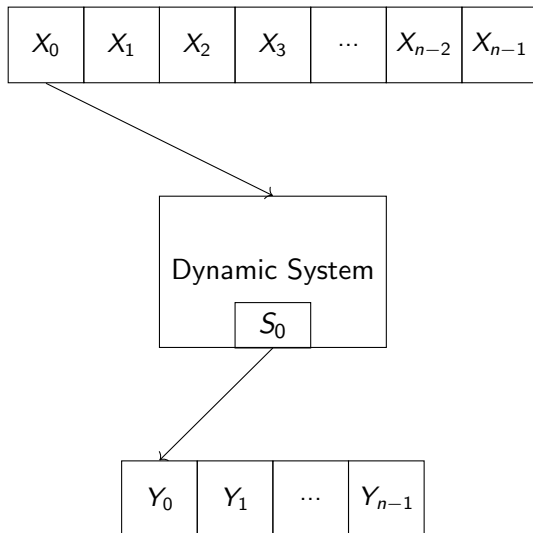


- RNN
- LSTM
- ...



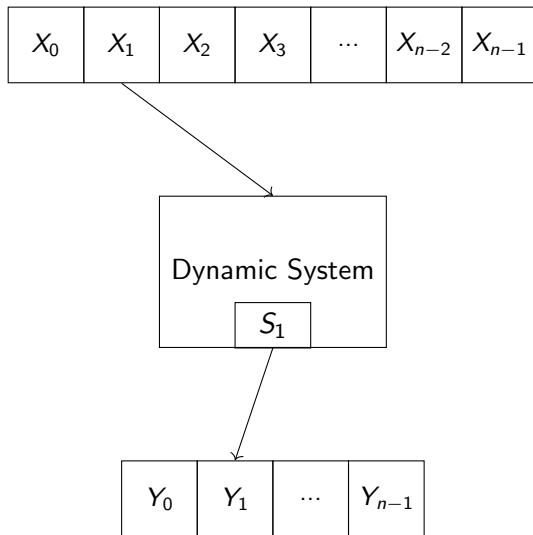
Time-Series Dynamic Classification

- RNN
- LSTM
- ...



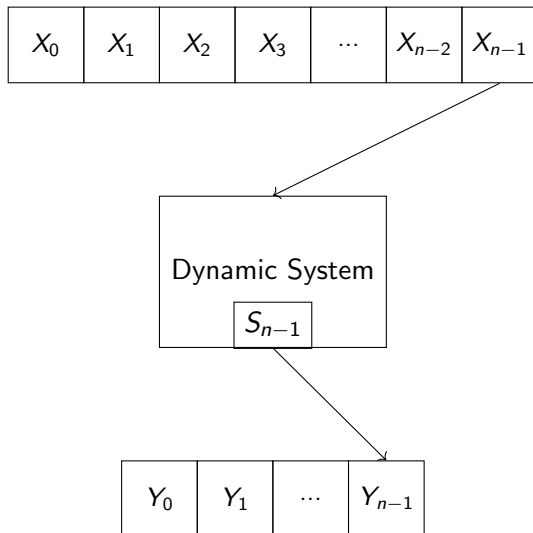
Time-Series Dynamic Classification

- RNN
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Time-Series Dynamic Classification

- RNN
- LSTM
- ...

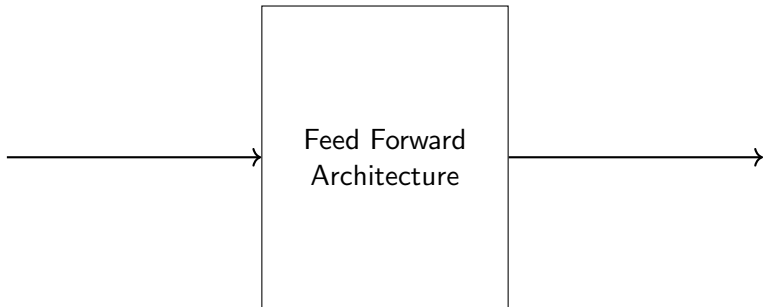


Time-Series Dynamic Classification

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

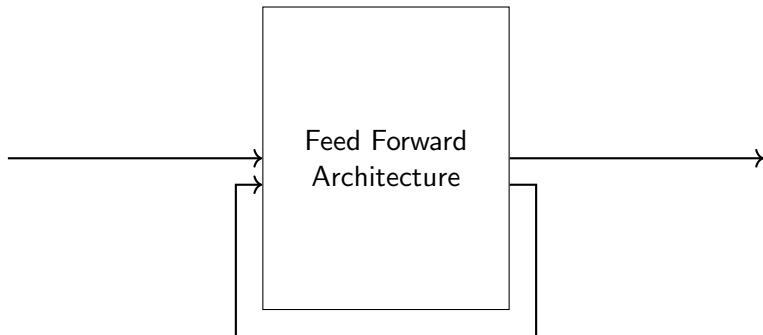
RNN \neq LSTM

- 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



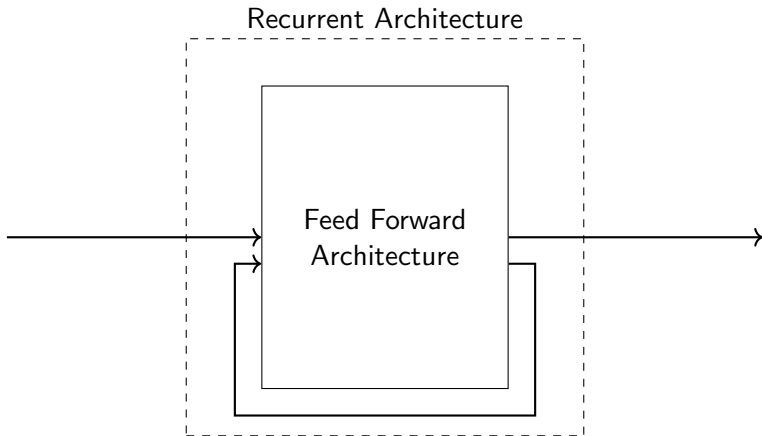
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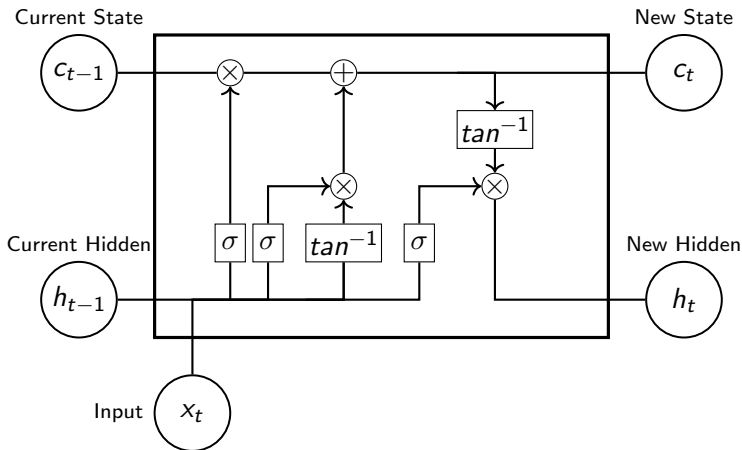


RNN \neq LSTM

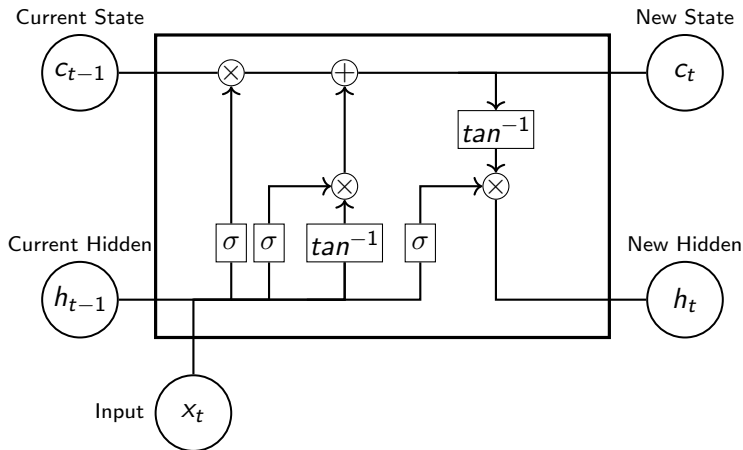
- RNN and LSTM are often used as synonyms in literature
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A deep look inside an LSTM cell

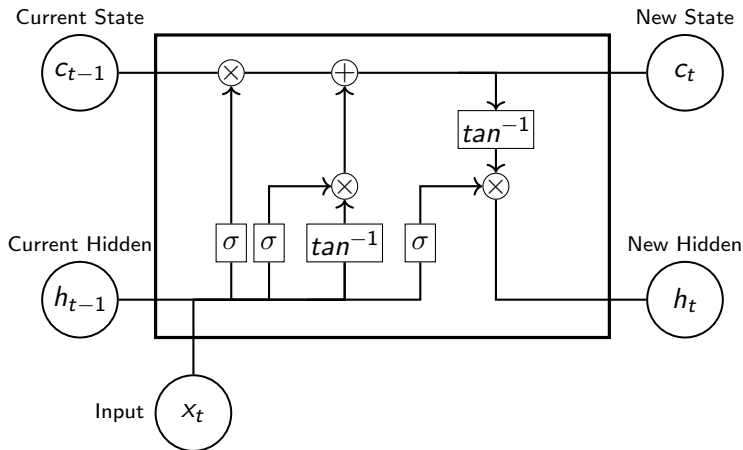


A deep look inside an LSTM cell



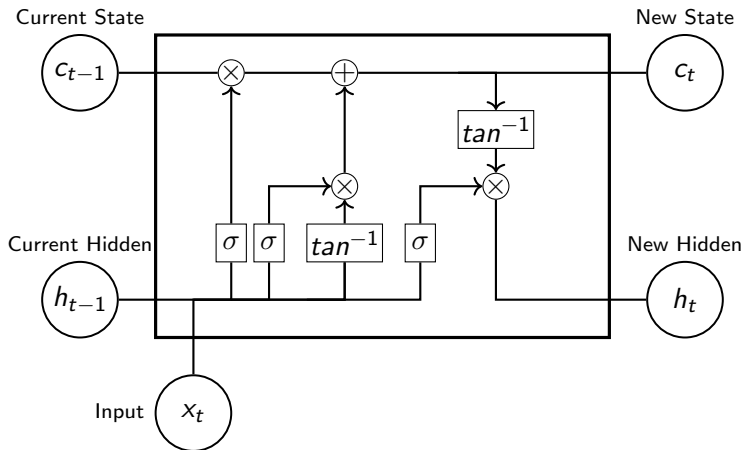
- $$f_t = \sigma(W_f x_t + U_f h_t + b_f)$$

A deep look inside an LSTM cell



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

A deep look inside an LSTM cell

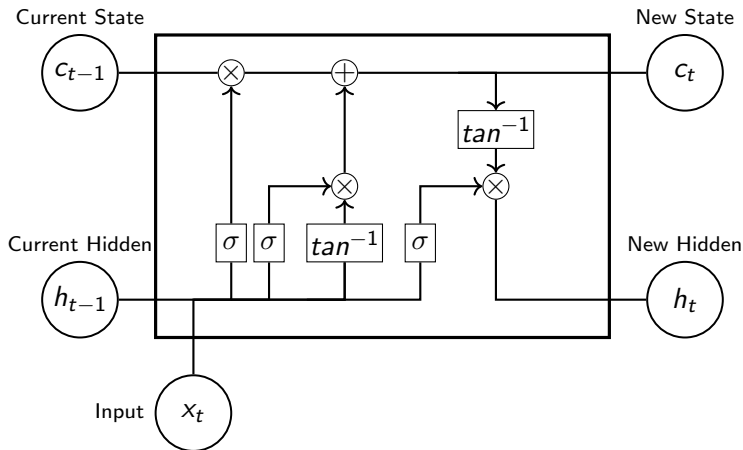


- $f_t = \sigma(W_f x_t + U_f h_t + b_f)$

- $i_t = \sigma(W_i x_t + U_i h_t + b_i)$

- $i_c = \tanh^{-1}(W_c x_t + U_c h_t + b_c)$

A deep look inside an LSTM cell



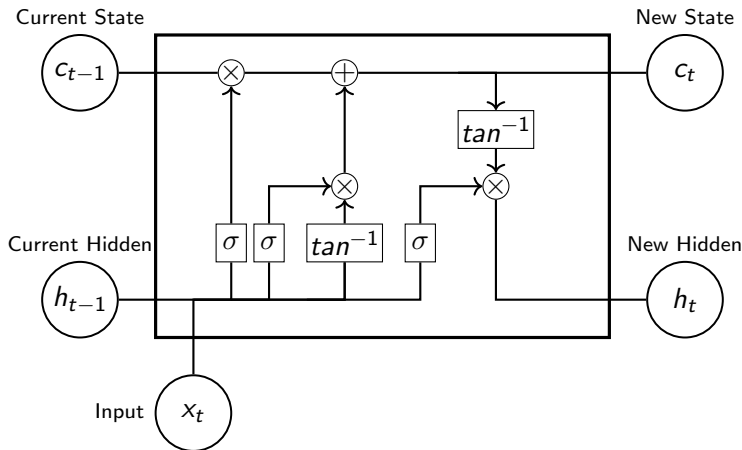
- $f_t = \sigma(W_f x_t + U_f h_t + b_f)$

- $i_t = \sigma(W_i x_t + U_i h_t + b_i)$

- $\tilde{c}_t = \tanh^{-1}(W_c x_t + U_c h_t + b_c)$

- $c_t = f_t \otimes c_{t-1} \oplus \tilde{c}_t$

A deep look inside an LSTM cell



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

- $i_t = \sigma(W_i x_t + U_i h_t + b_i)$

- $i_c = \tanh^{-1}(W_c x_t + U_c h_t + b_c)$

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

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

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

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

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

Can we do better?

Can we do **simpler**?

Let's take a step back

Let's take a step back



Let's take a step back



Let's take a step back



- 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

Let's take a step back



- 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

Biological Stigmergy

Implemented in nature via pheromonic marks



Mark

Biological Stigmergy

Implemented in nature via pheromonic marks

Stimulus

Mark

Biological Stigmergy

Implemented in nature via pheromonic marks

Stimulus

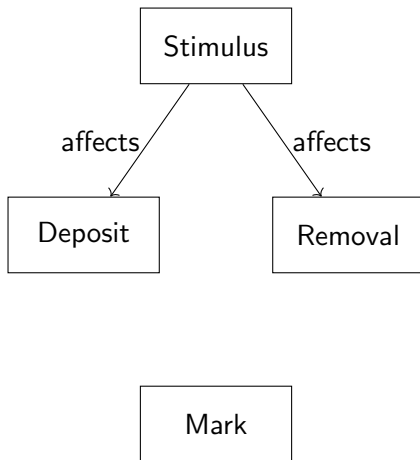
Deposit

Removal

Mark

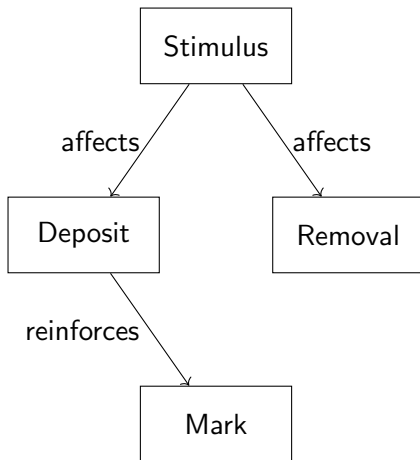
Biological Stigmergy

Implemented in nature via pheromonic marks



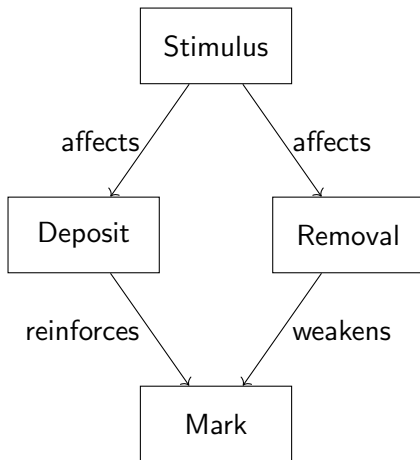
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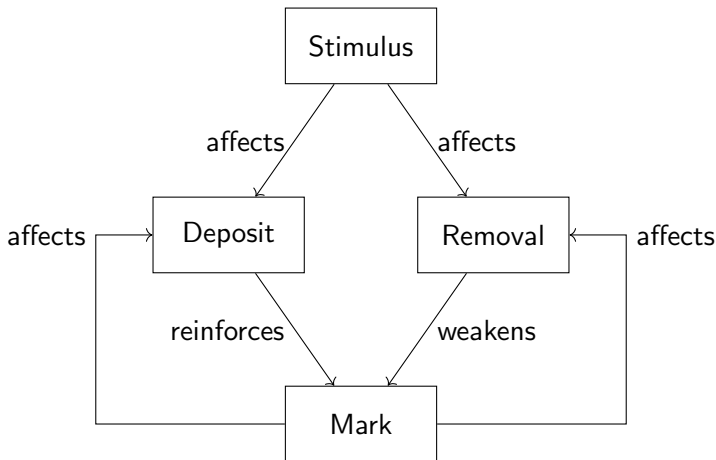
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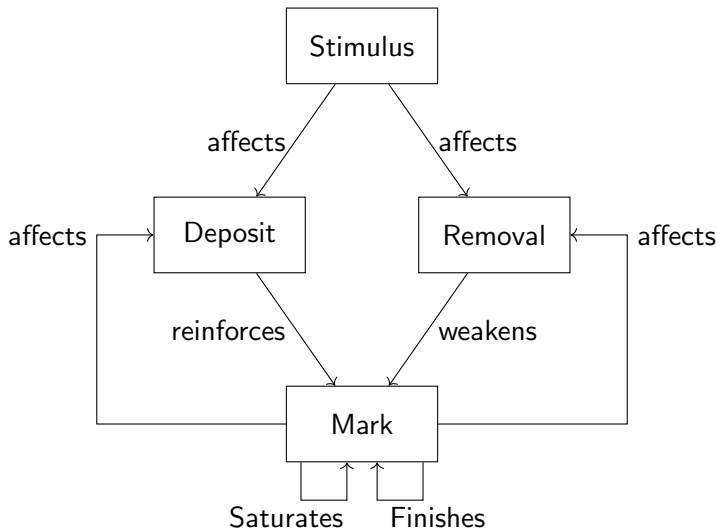
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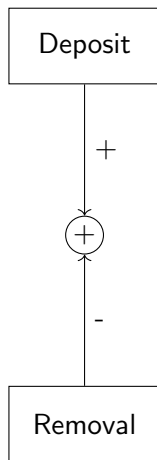


Computational Stigmergy

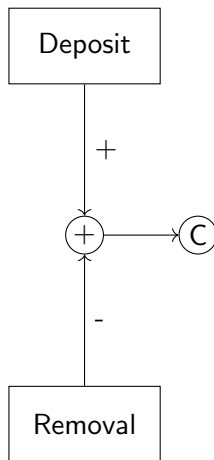
Deposit

Removal

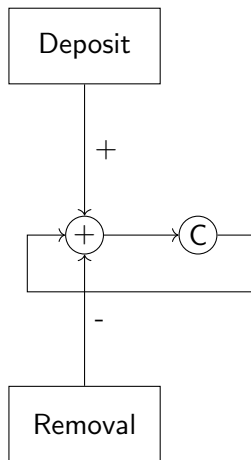
Computational Stigmergy



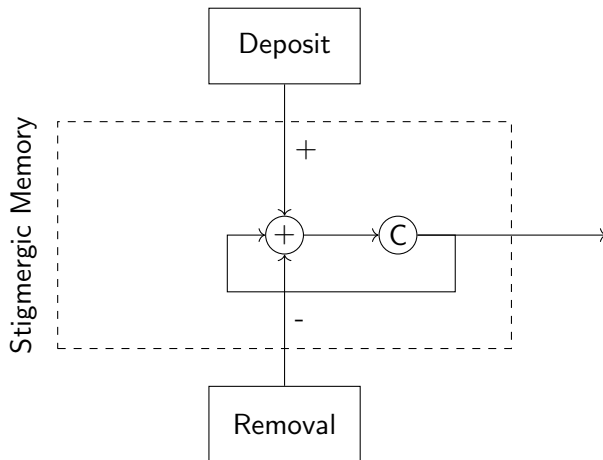
Computational Stigmergy



Computational Stigmergy

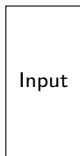


Computational Stigmergy

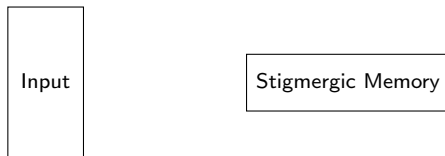


Stigmergic Memory ML Architecture

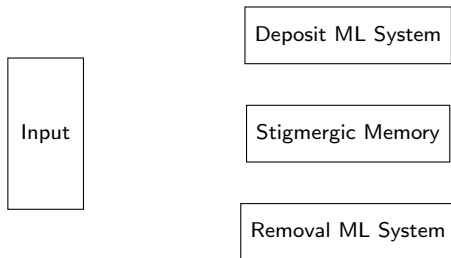
Stigmergic Memory ML Architecture



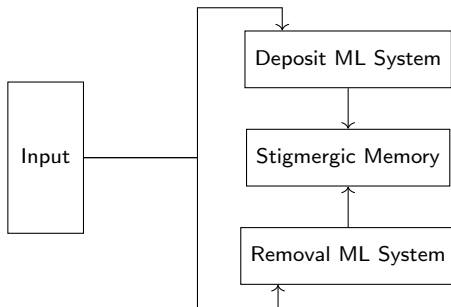
Stigmergic Memory ML Architecture



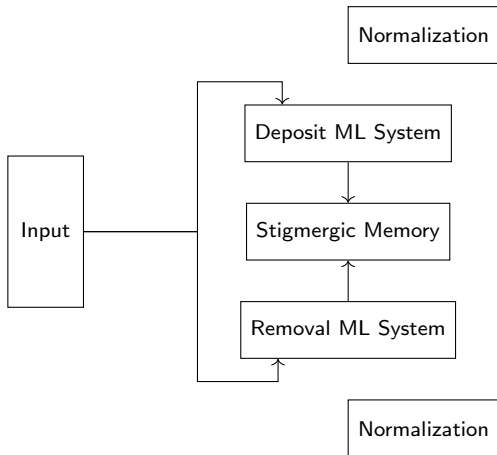
Stigmergic Memory ML Architecture



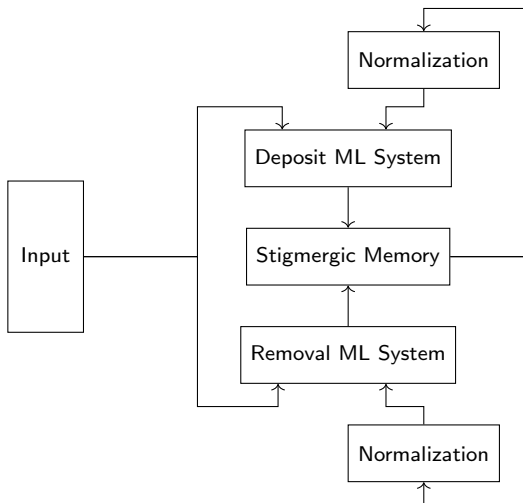
Stigmergic Memory ML Architecture



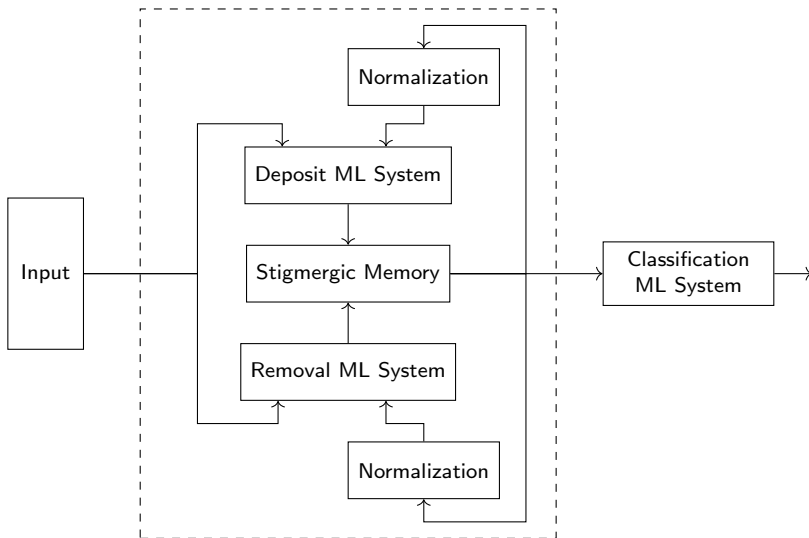
Stigmergic Memory ML Architecture



Stigmergic Memory ML Architecture

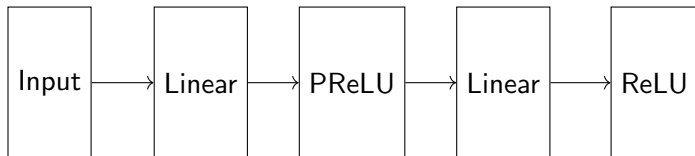


Stigmergic Memory ML Architecture



Experimental Stigmergic ML Systems

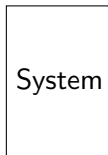
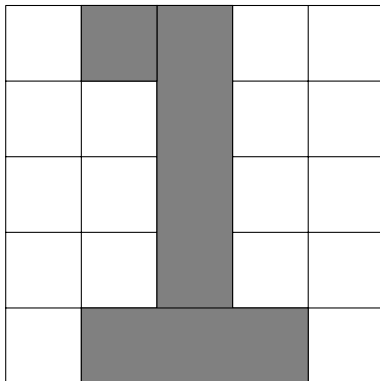
Neural Networks used as Deposit, Removal and Classification Systems



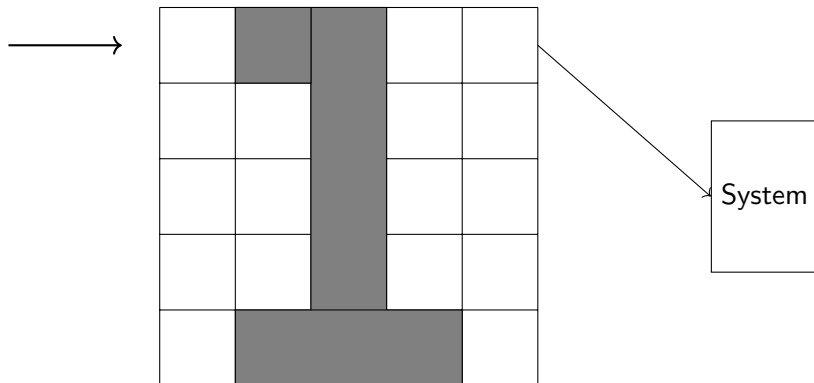
Experimental Architectures

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

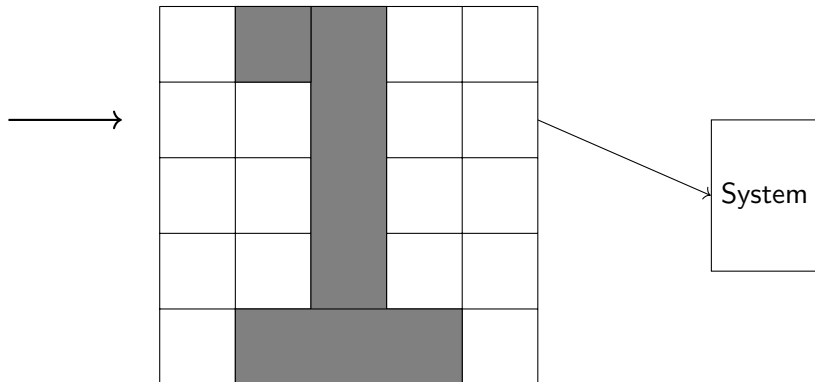
Experimental Results: Spatial MNIST



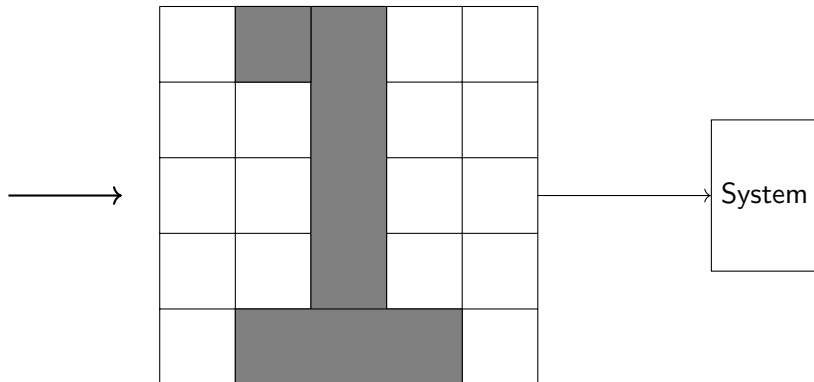
Experimental Results: Spatial MNIST



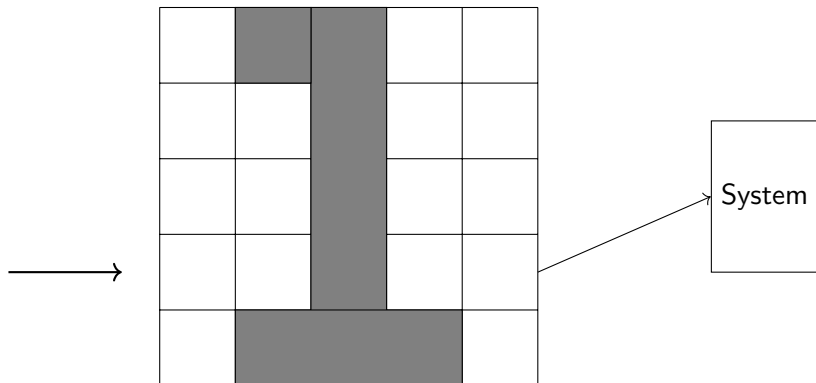
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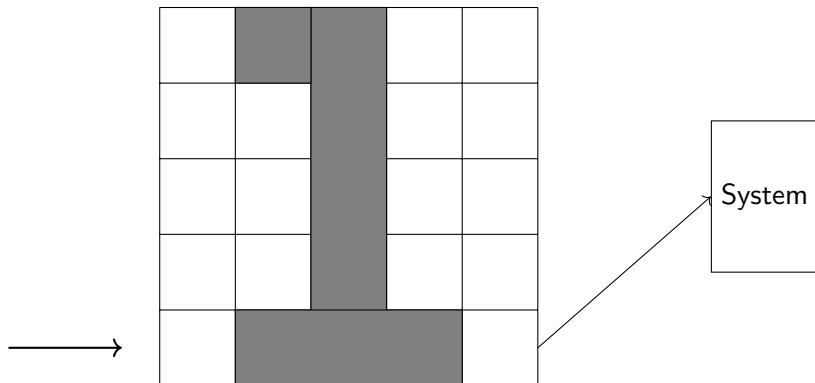
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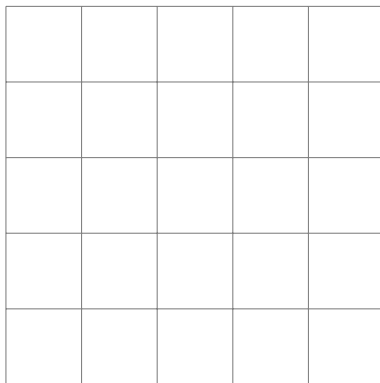


Experimental Results: Spatial MNIST

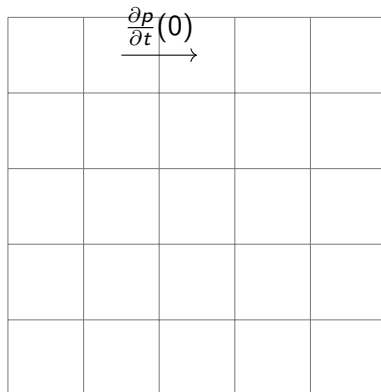
Architecture	N. Parameters	Accuracy
Stigmergic Memory	3190	$96.5 \pm 0.5 \%$
Static Feed Forward	328810	$95.1 \pm 0.02 \%$
LSTM	3360	$94.3 \pm 0.1 \%$
RNN	3482	$76.6 \pm 0.3 \%$

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

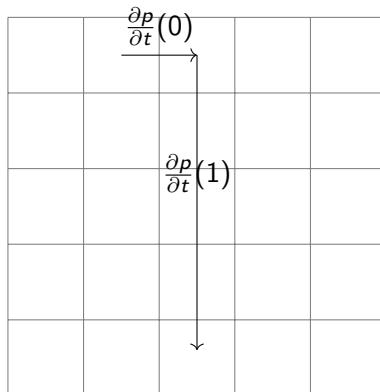
Experimental Results: Temporal MNIST



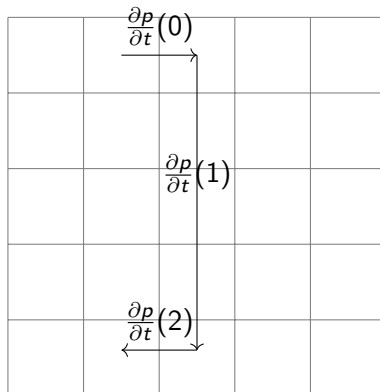
Experimental Results: Temporal MNIST



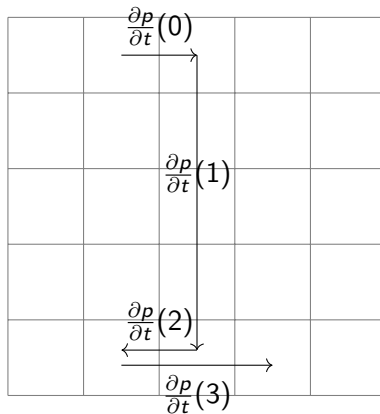
Experimental Results: Temporal MNIST



Experimental Results: Temporal MNIST



Experimental Results: Temporal MNIST



Experimental Results: Temporal MNIST

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

- Outperforms Vanilla RNNs
- Same performances as LSTMs

Keep in touch

You can find the pytorch implementation on GitHub



<https://github.com/galatolofederico/icpram2019>

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