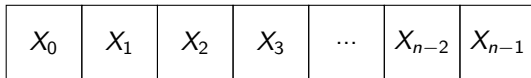


Using stigmergy as a computational memory in the design of recurrent neural networks

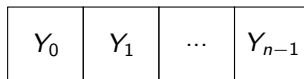
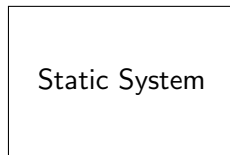
Federico A. Galatolo

20 February 2019

Time-Series Static Classification

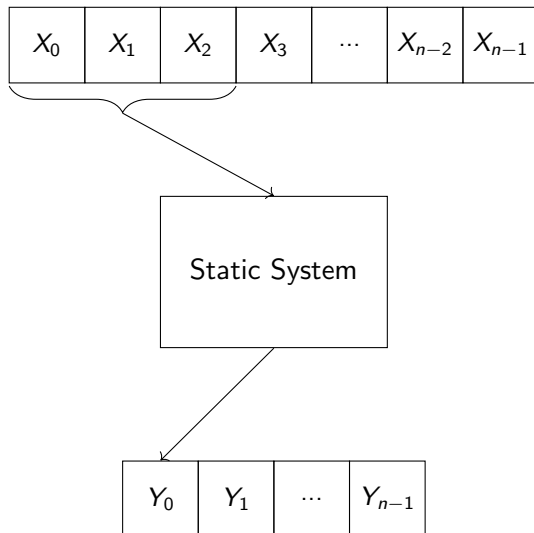


- ▶ MLP
- ▶ CNN
- ▶ ...



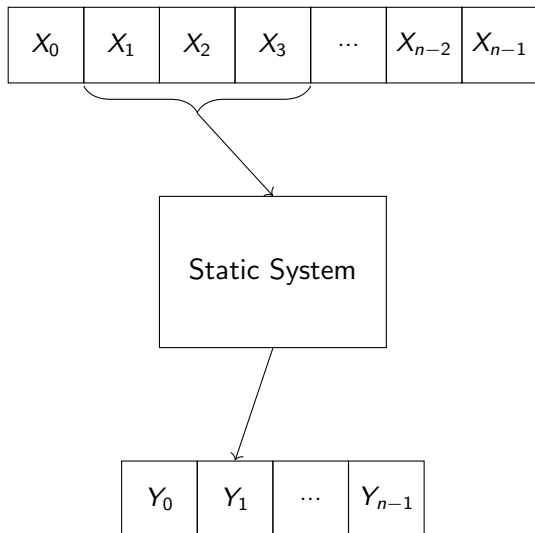
Time-Series Static Classification

- ▶ MLP
- ▶ CNN
- ▶ ...



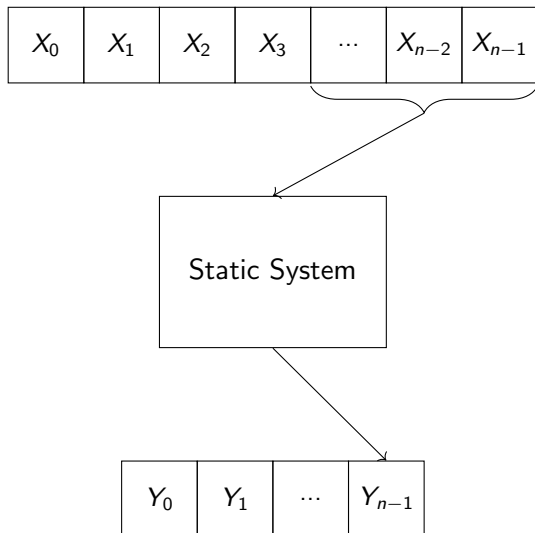
Time-Series Static Classification

- ▶ MLP
- ▶ CNN
- ▶ ...



Time-Series Static Classification

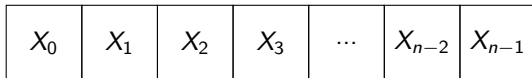
- ▶ MLP
- ▶ CNN
- ▶ ...



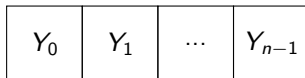
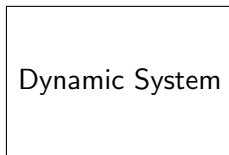
Time-Series Static Classification

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

Time-Series Dynamic Classification

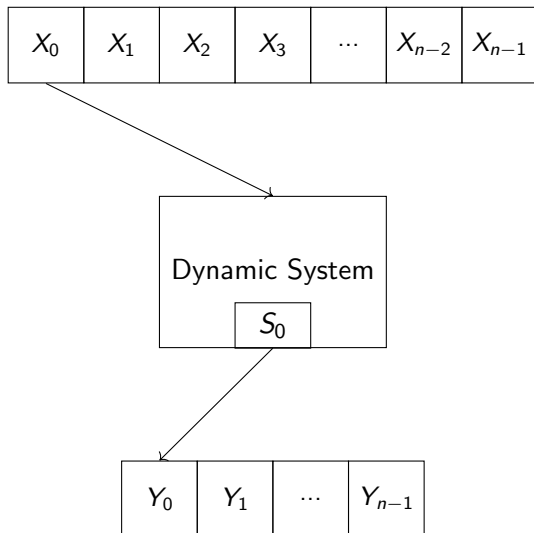


- ▶ RNN
- ▶ LSTM
- ▶ ...



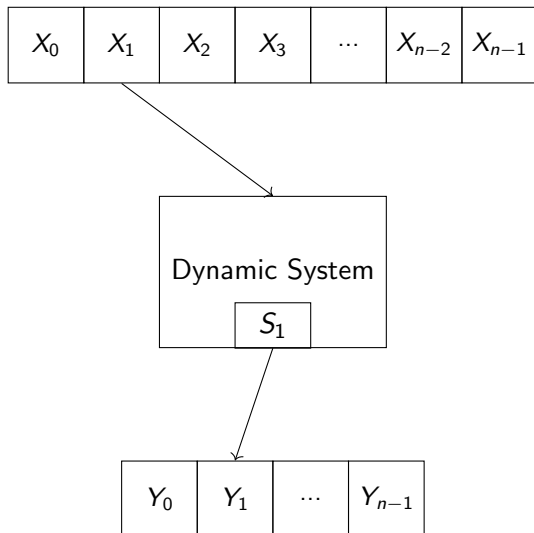
Time-Series Dynamic Classification

- ▶ RNN
- ▶ LSTM
- ▶ ...

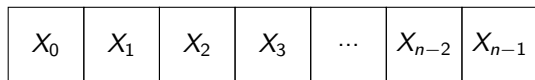


Time-Series Dynamic Classification

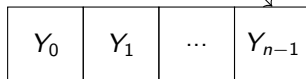
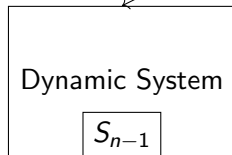
- ▶ RNN
- ▶ LSTM
- ▶ ...



Time-Series Dynamic Classification



- ▶ RNN
- ▶ LSTM
- ▶ ...

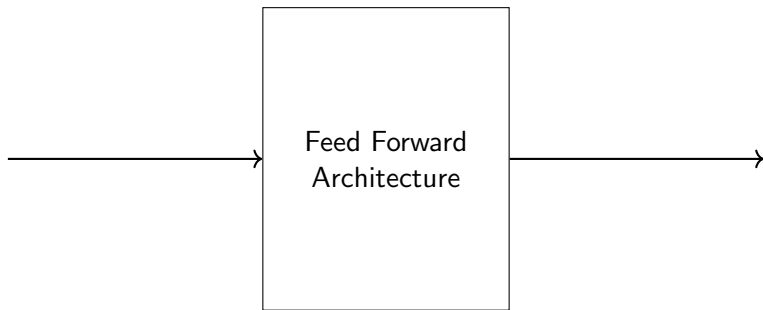


Time-Series Dynamic Classification

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

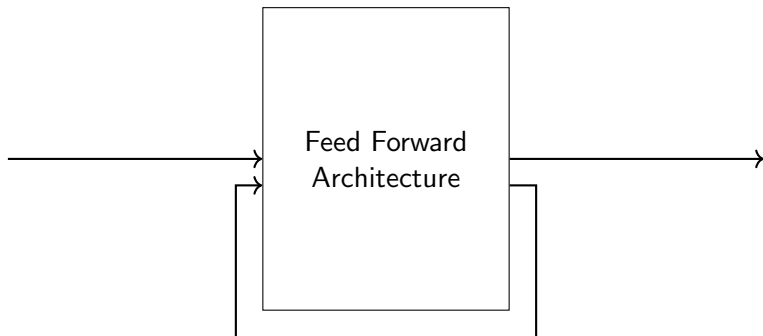
RNN \neq LSTM

- ▶ 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



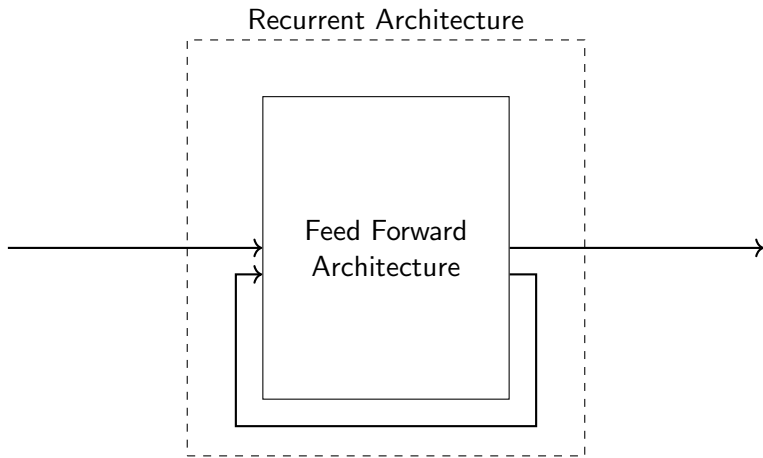
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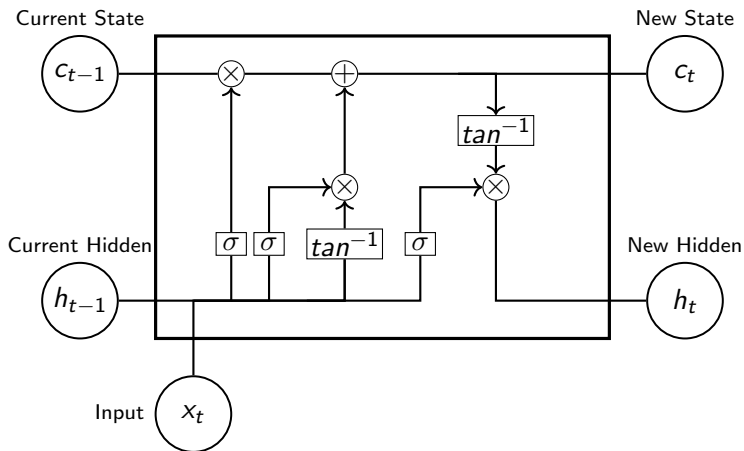


RNN \neq LSTM

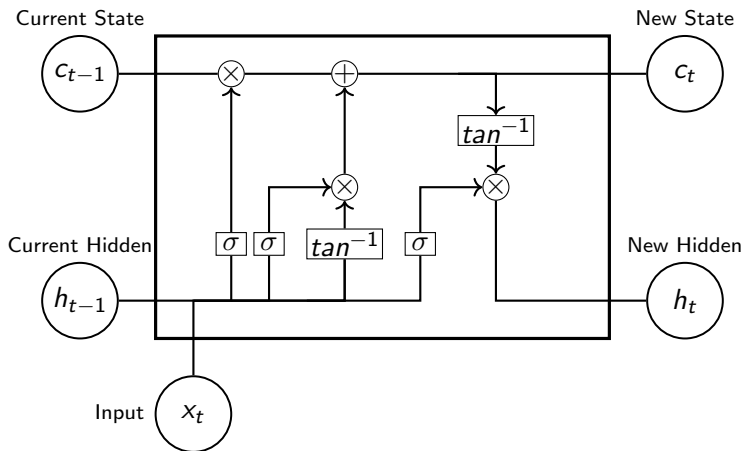
- ▶ RNN and LSTM are often used as synonyms in literature
- ▶ Has been proven that “Vanilla recursion” performs poorly
- ▶ LSTM are the state of the art for Time Series Classification



A deep look inside an LSTM cell

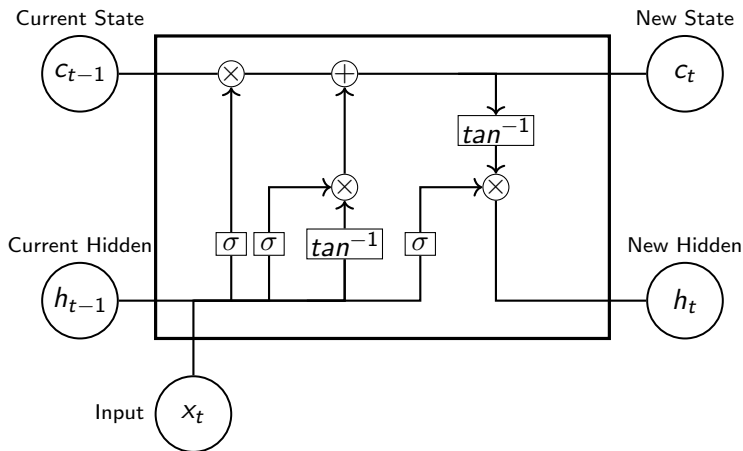


A deep look inside an LSTM cell



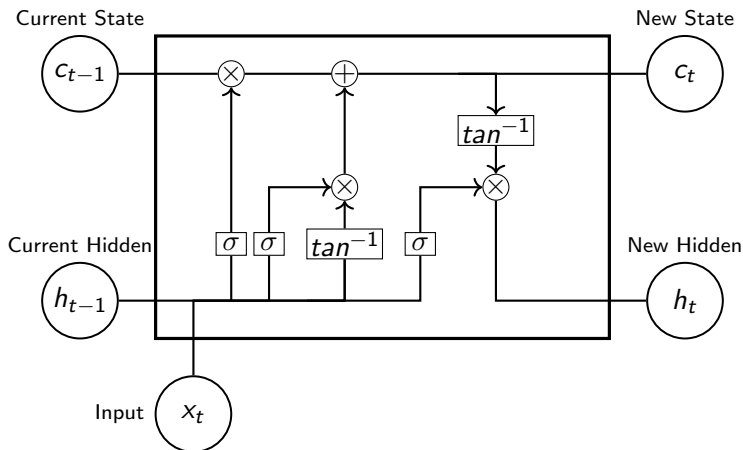
► $f_t = \sigma(W_f x_t + U_f h_t + b_f)$

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

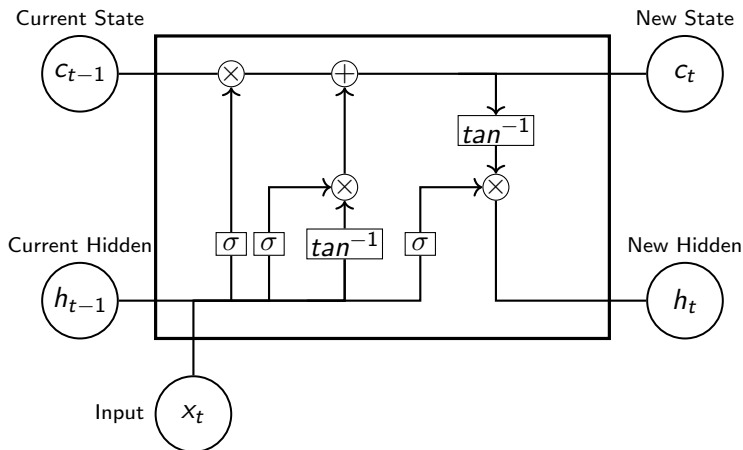


$$\blacktriangleright f_t = \sigma(W_f x_t + U_f h_t + b_f)$$

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

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

A deep look inside an LSTM cell



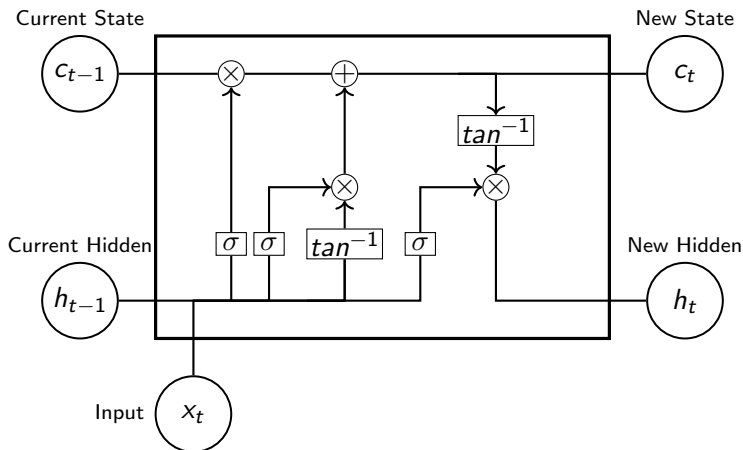
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$$\blacktriangleright i_c = \tanh^{-1}(W_c x_t + U_c h_t + b_c)$$

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

A deep look inside an LSTM cell



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

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

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

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

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

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

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?

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?

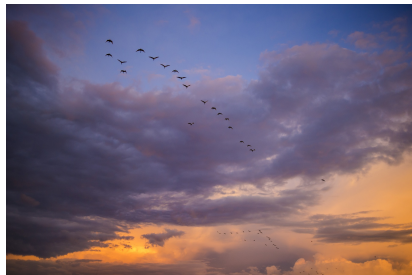
Can we do **simpler**?

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

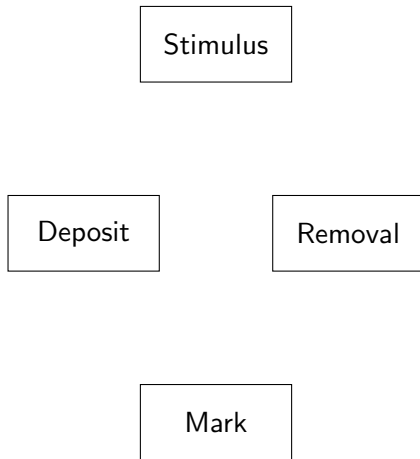
Stimulus

A diagram illustrating biological stigmergy. It consists of two rectangular boxes. The top box is labeled 'Stimulus' and the bottom box is labeled 'Mark'. There are no lines or arrows connecting the two boxes, suggesting a sequential or independent process.

Mark

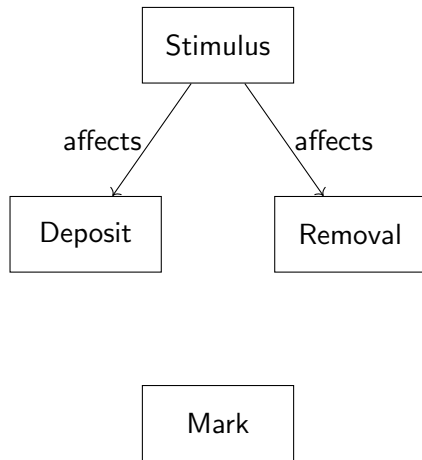
Biological Stigmergy

Implemented in nature via pheromonic marks



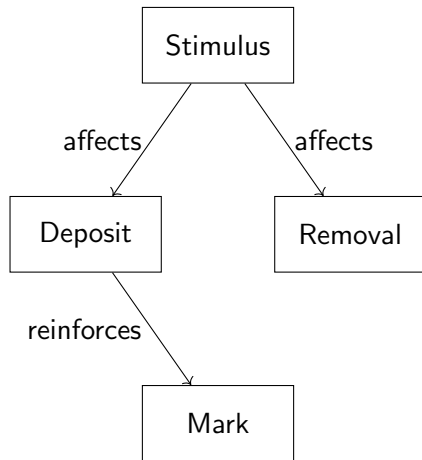
Biological Stigmergy

Implemented in nature via pheromonic marks



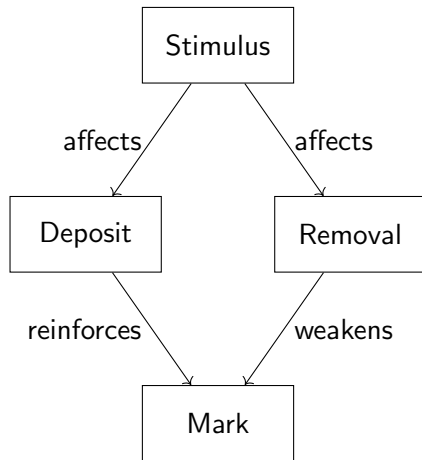
Biological Stigmergy

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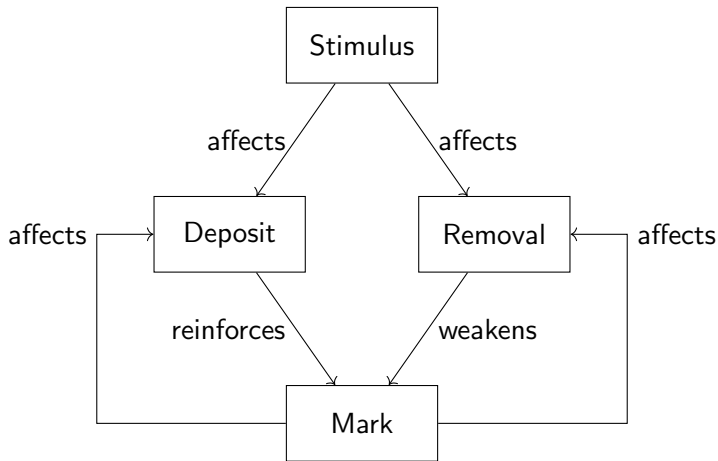
Biological Stigmergy

Implemented in nature via pheromonic marks



Biological Stigmergy

Implemented in nature via pheromonic marks

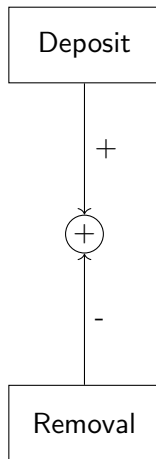


Computational Stigmergy

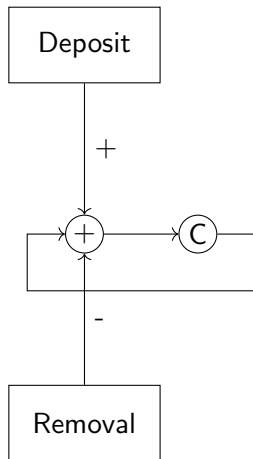
Deposit

Removal

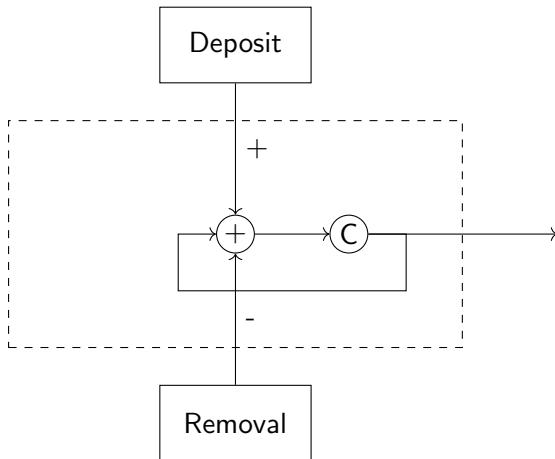
Computational Stigmergy



Computational Stigmergy



Computational Stigmergy



Stigmergic Memory Neural Network