Supervised Learning of Neural Random-Access Machines with Differential Evolution

Candidate

Valerio Belli

Supervisors

Valentina Poggioni, Marco Baioletti

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University of Perugia

Departments of Mathematics and Computer Science

Intelligent and Mobile Computing

Introduction

The success of Deep Learning is undeniable.

A new family of models, based on **controller-interface abstraction**, has been introduced. The precursor is **Neural Turing Machine** (**NTM**) [Graves et al., 2014] which works with **attentional "focus" mechanisms** to interact with an external memory.

The **Neural Random-Access Machines** (NRAM) [Kurach et al., 2015] evolve the NTM implementing the concepts of **pointers manipulation and de-referencing** through primitive operations to interact also with a memory.

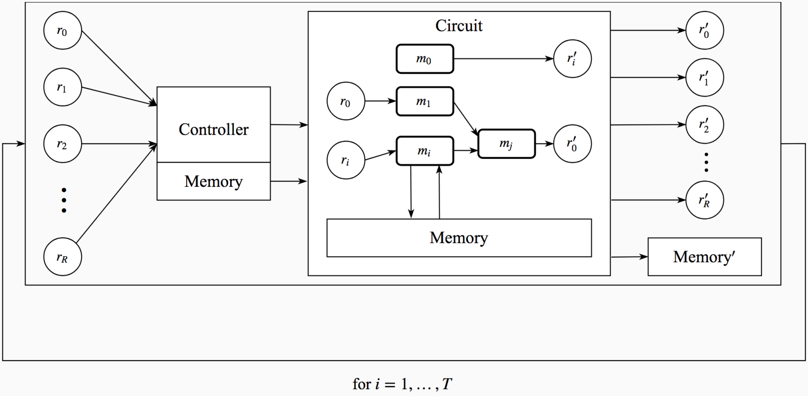
We implemented and trained **NRAM** in order to study the benefits of Differential Evolution on these type of models.

Outline

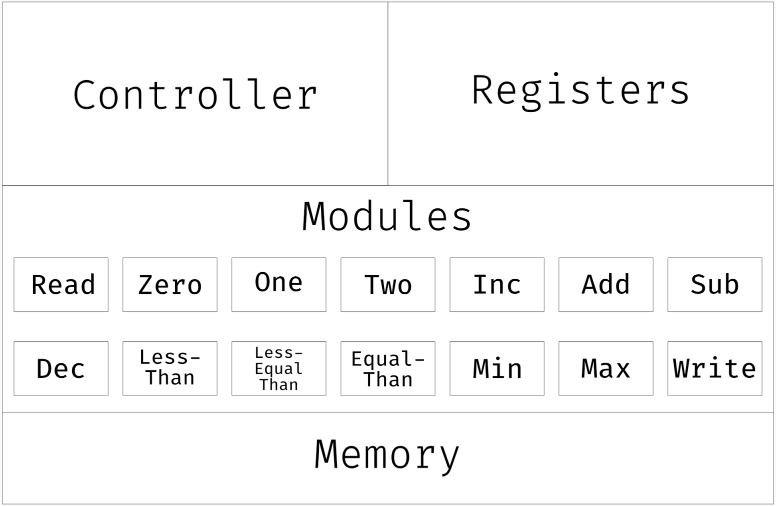
1. Neural Random-Access Machines
2. Neural Network optimization & DENN
3. Implementation & Faced problems
4. Results, Conclusions & Future works

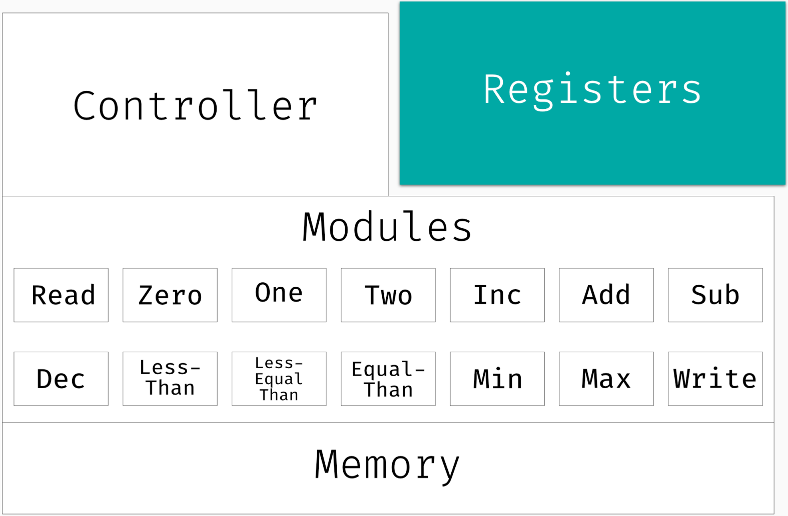
Neural Random-Access Machines

High view of the Neural Random-Access Machines model.

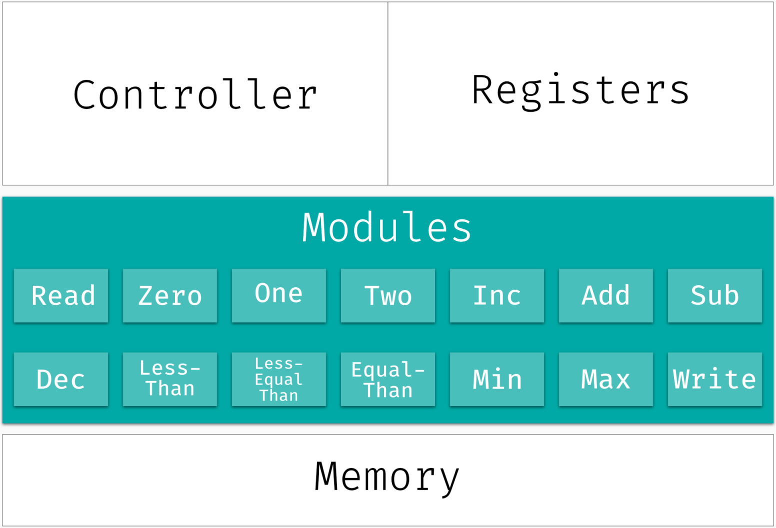


NRAM → Components




Controller
Registers
Modules
Read
Zero
One
Two
Inc
Add
Sub
Dec
Less-Than
Less-Equal Than
Equal-Than
Min
Max
Write
Memory

The registers $\mathcal{R} \in \mathbb{R}^{R \times M}$ is a set of R memory cells. Each register contains a probability distribution in $\mathbb{R}^M$ over the set $\{0, \ldots, M-1\}$.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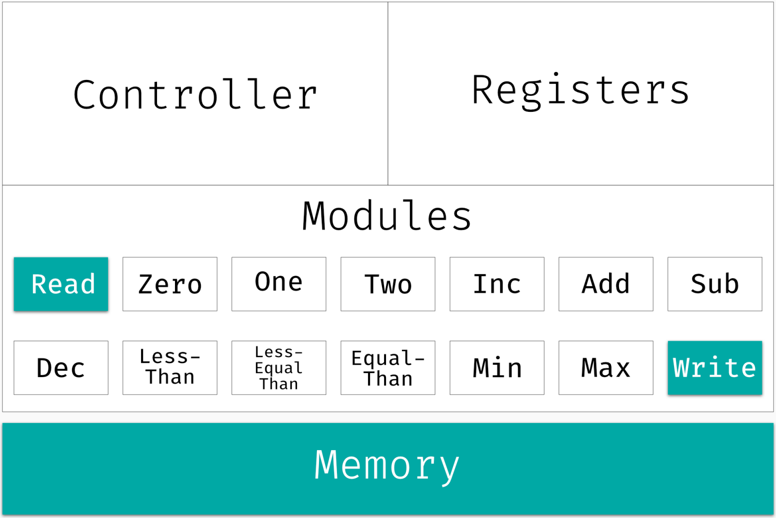
Controller
Registers
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Read
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Two
Inc
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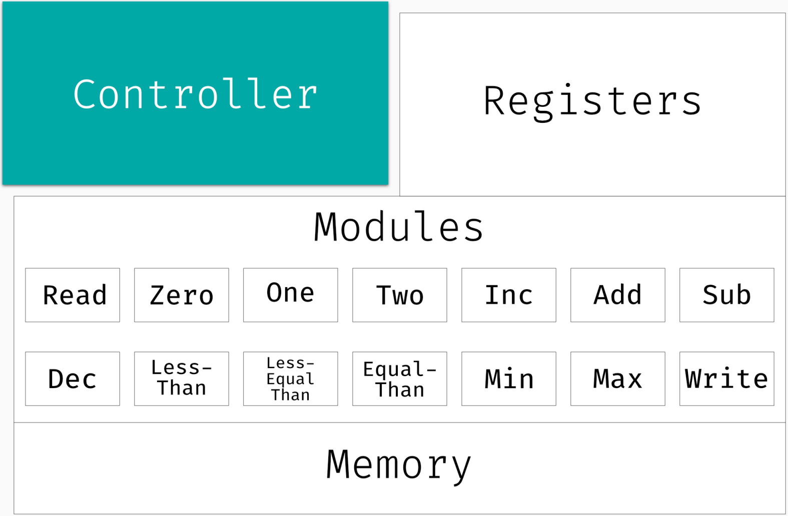
Sub
Dec
Less-Than
Less-Equal Than
Equal-Than
Min
Max
Write
Memory

The memory $\mathcal{M} \in \mathbb{R}^{M \times M}$ is a support of M cells, where each value is represented by a probability distribution in $\mathbb{R}^M$ over the set $\{0, \ldots, M-1\}$.

The NRAM interacts with the memory through:

- **Read**: takes a pointer and returns the pointed value of the memory.
- **Write**: takes a pointer and a value, modifies the memory.


Controller
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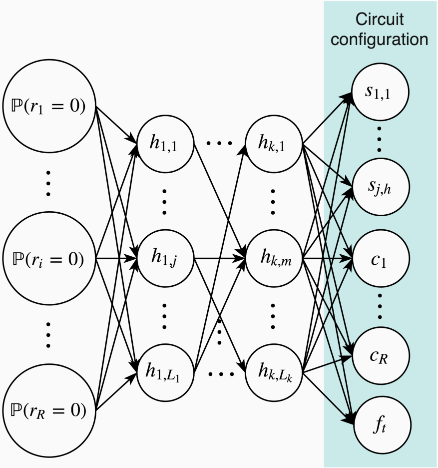
Min
Max
Write
Memory

- It is a neural network
- It takes as input $\mathbb{P}(r_i = 0)$, for $i = 1, \ldots, R$
- It emits configurations for fuzzy circuits (how the registers and modules are connected together)
- From an high view, each $s_{i,j}$ and c_h is a probability distribution generated with the **softmax** function



NRAM $\rightarrow$ Termination of NRAM

The NRAM terminates its execution in two ways:

- Reaching the **last timestep** T
- Through an **internal criterion**:
  - In each timestep, NRAM emits the willingness of terminate the execution $f_t = \sigma(x_i)$
  - The execution stops if $f_t = 1.0$.

Let $\mathcal{M} \in \mathbb{R}^{M \times M}$ the output memory and $\mathbf{y} \in \{0, \ldots, M-1\}^M$ the expected memory, the **cost function** is the **expected negative log-likelihood**

$$-\sum_{i=1}^{T} \left(p_t \cdot \sum_{i=1}^{M} log\left(\mathcal{M}_{i,\mathbf{y}_i}^{(t)} \right) \right)$$

where p_t is computed as

$$p_t = f_t \cdot \prod_{i=1}^{t-1} (1 - f_i)$$

Neural Network optimization & DENN

NN optimization & DENN → Gradient Descent & back-propagation

Gradient Descent and back-propagation optimization is divided in **computing of the gradient** and **updating of the network parameters**.

We used **ADAM** (Adaptive Moment estimation) [Kingma and Ba, 2014] as in [Kurach et al., 2015] as gradient-based optimization algorithm. Uses the concept of **momentum** to regularize the descent of the gradient.

Differential Evolution

- Meta-heuristic
- Searches a solution through the parallel evolution of a set of candidate solutions
- Candidate solutions set called **population**
  - Composed by **N** D-dimensional numerical vectors, called **Individuals**

Its functioning is iterative

1. **Mutation**: driven by a constant *F* creates a new population called **donor set** (several methods, e.g. **DEGL** and **Current-to-pbest**)
2. **Crossover**: driven by a constant *CR* creates a new population called **trial set** (several methods, e.g. **bin**)
3. **Selection**: generates the new population for the next generation comparing one-by-one the trial vectors with the corresponding target vectors.

Exist various self-adaptive variants of Differential Evolution which alleviate the problem dependence of *F* and *CR*:

- JADE
- SHADE
- L-SHADE

NN optimization & DENN → DENN (Differential Evolution for Neural Network)

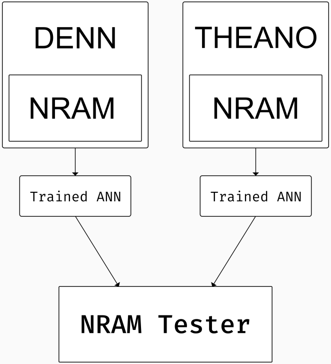
DENN [Baioletti et al., 2018] is a **framework** which implements the concepts of the Differential Evolution to train ANN:

- Created by Gabriele Di Bari and Mirco Tracolli
- It is written in C++ based on the library Eigen
- Each individual is composed by the weights and biases of the network
- The mutation and crossover operators are applied in a component-wise way

Implementation & Faced problems

Three applications

- **NRAM-DENN**: training with Differential Evolution
- **NRAM-Theano**: training with Gradient Descent-ADAM
- **NRAM-Tester**: execution and generalization testing



Implementation & Faced problems → Additional used techniques

NRAM-Theano:

- **Gradient clipping**: gradient clipped in $[C_1, C_2]$ to avoid the common problem of the Gradient Explosion;
- **Noise**: added a noise to the computed gradient to enhance the exploration;

NRAM-DENN:

- **Curriculum Learning**: it is used to enhance the training of the ANN through increasing difficulties of the datasets.

Tested problems:

- **Access**: accessing of a value of an input sequence
- **Increment**: incrementing by one of a input sequence
- **Copy**: copying an input sequence to a part of the memory
- **Reverse**: copying an input sequence in a reverse order to a part of the memory

Implementation & Faced problems → Datasets

The datasets are generated at runtime; each batch of samples is composed by:

- **initial memory content**
- **expected memory content**
- **cost mask**
- **error rate mask**

Initial memory content								
5	5	1	4	7	<u>0</u>	0	0	0

Expected memory content								
5	5	1	4	7	7	4	1	5

Cost mask								
0	1	1	1	1	1	1	1	1

Error mask								
0	0	0	0	0	1	1	1	1

Table 1: Reverse task.

Results, Conclusions & Future works

Task	Train complexity		Reached cost 0		Train error		Generalization	
	No CL	CL	No CL	CL	No CL	CL	No CL	CL
Access	—	$\mathrm{len}(A) \leq 20$	×	✓	—	0	×	Perfect
Increment	—	$\mathrm{len}(A) \leq 15$	×	✓	—	0	×	Perfect
Copy	—	$\mathrm{len}(A) \leq 15$	×	✓	—	0	×	Perfect
Reverse	—	$\mathrm{len}(A) \leq 15$	×	✓	—	0	×	Perfect

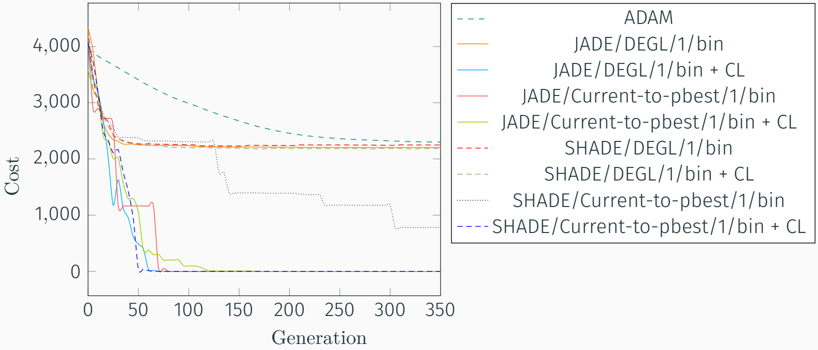
Table 2: Results of the tests with ADAM in [Kurach et al., 2015].

Task	Train complexity		Reached cost 0		Train error		Generalization	
	No CL	CL	No CL	CL	No CL	CL	No CL	CL
Access	$\mathrm{len}(A) = 8$ $t = 5$	$\mathrm{len}(A) \leq 10$	✓	✓	0	0	Perfect	Perfect
Increment	$\mathrm{len}(A) = 9$ $t = 4$	$\mathrm{len}(A) \leq 10$	✓	✓	0	0	Perfect	Perfect
Copy	$\mathrm{len}(A) = 5$ $t = 11$	$\mathrm{len}(A) \leq 9$	×	×	—	—	—	—
Reverse	$\mathrm{len}(A) = 4$ $t = 9$	$\mathrm{len}(A) \leq 8$	✓	✓	0	0	Perfect	Perfect

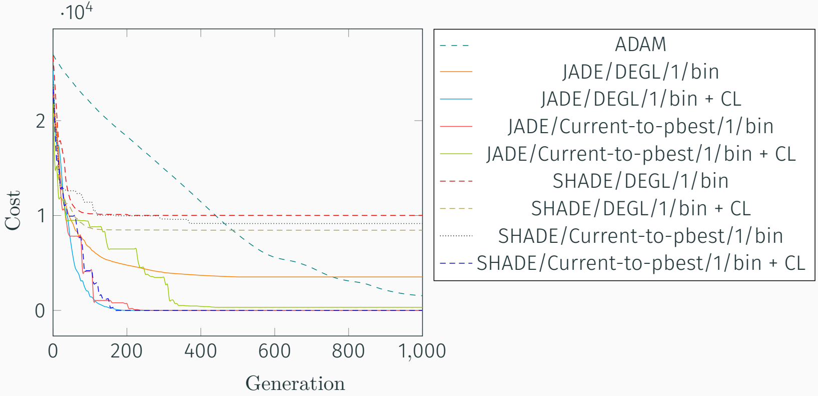
Table 3: Results of the tests with Differential Evolution.

Task	JADE/DEGL/1		JADE/c-to-pb/1		SHADE/DEGL/1		SHADE/c-to-pb/1	
	No CL	CL	No CL	CL	No CL	CL	No CL	CL
Access	×	✓	✓	✓	×	×	×	✓
Increment	×	×	✓	×	×	×	×	✓
Copy	×	×	×	×	×	×	×	×
Reverse	×	✓	✓	×	✓	✓	×	✓

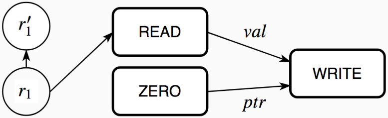
Table 4: Results of DE variants



4,000
3,000
2,000
1,000
0
Cost
0
50
100
150
200
250
300
350
Generation
ADAM
JADE/DEGL/1/bin
JADE/DEGL/1/bin + CL
JADE/Current-to-pbest/1/bin
JADE/Current-to-pbest/1/bin + CL
SHADE/DEGL/1/bin
SHADE/DEGL/1/bin + CL
SHADE/Current-to-pbest/1/bin
SHADE/Current-to-pbest/1/bin + CL

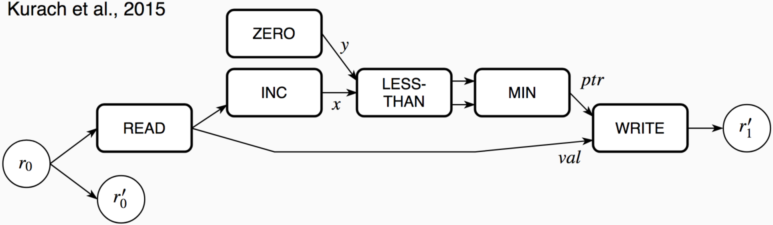

$\cdot 10^4$
2
1
0
Cost
0
200
400
600
800
1,000
Generation
ADAM
JADE/DEGL/1/bin
JADE/DEGL/1/bin + CL
JADE/Current-to-pbest/1/bin
JADE/Current-to-pbest/1/bin + CL
SHADE/DEGL/1/bin
SHADE/DEGL/1/bin + CL
SHADE/Current-to-pbest/1/bin
SHADE/Current-to-pbest/1/bin + CL

DENN with Curriculum Learning

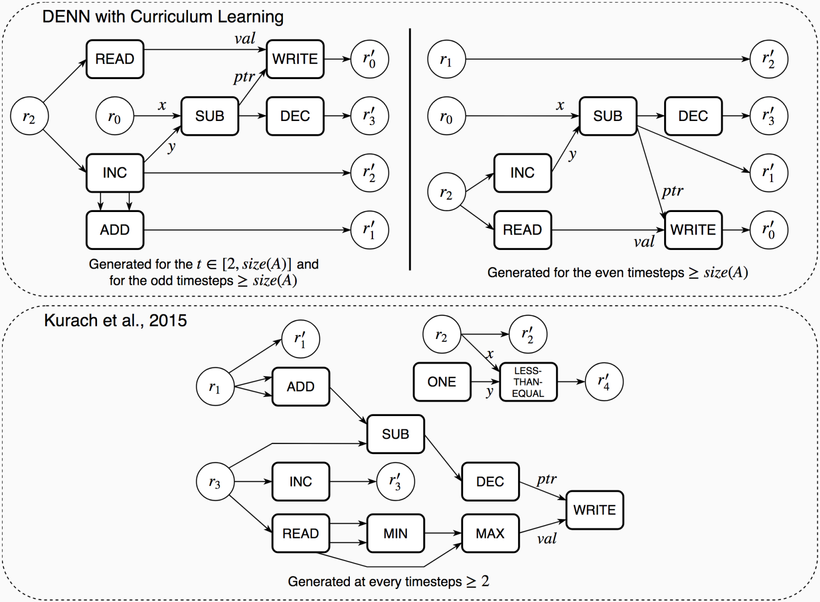


Generated for every timesteps ≥ 2.

Kurach et al., 2015



Generated for every timesteps ≥ 2.


DENN with Curriculum Learning
READ
val
WRITE
r'_0
ptr
r_2
r_0
x
SUB
DEC
r'_3
y
INC
r'_2
ADD
r'_1
Generated for the $t \in [2, size(A)]$ and
for the odd timesteps $\geq size(A)$
r_1
r'_2
r_0
x
SUB
DEC
r'_3
INC
y
r'_1
r_2
ptr
READ
val
WRITE
r'_0
Generated for the even timesteps $\geq size(A)$
Kurach et al., 2015
r'_1
r_1
ADD
r_2
r'_2
x
ONE
y
LESS-THAN-EQUAL
r'_4
SUB
r_3
INC
r'_3
DEC
ptr
WRITE
READ
MIN
MAX
val
Generated at every timesteps ≥ 2

DENN behave well in this type of model:

- Differential Evolution behave differently with these problems w.r.t. ADAM producing different results
- Best performing variants are those with **Current-to-pbest**
- Found controllers generate simpler circuits w.r.t. in [Kurach et al., 2015]

Create a new dynamic system for the gate selection.

Write an enhanced NRAM model that does not require the differentiability condition.

Thanks for the attention!