Grid-enabled parameter initialization for high performance machine learning tasks

Kyriakos Chatzidimitriou, Fotis Psomopoulos and Pericles Mitkas

Thessaloniki, Greece

Presentation Overview

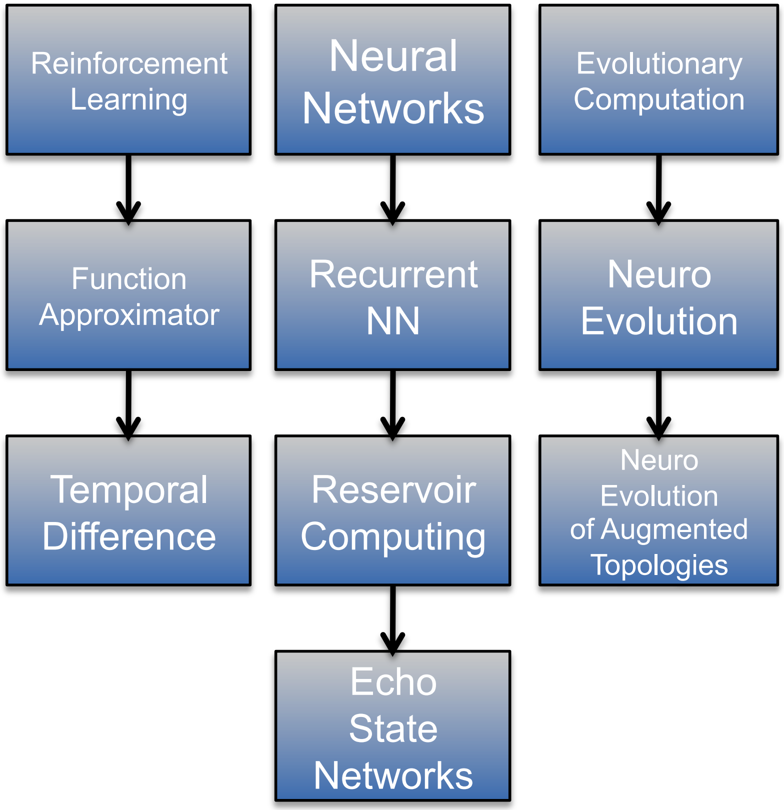
- **Introduction to the scope of work**
- **The algorithm**
  - NeuroEvolution of Augmented Reservoir (NEAR) = NeuroEvolution of Augmented Topologies + Echo State Networks (NEAT + ESN)
- **Questions we want to answer**
- **Testbeds**
  - Supervised learning
  - Reinforcement learning
- **Experimental setup**
- **Results obtained**
- **Conclusions**
- **Future work**

Introduction

Approach – Problem – Solution

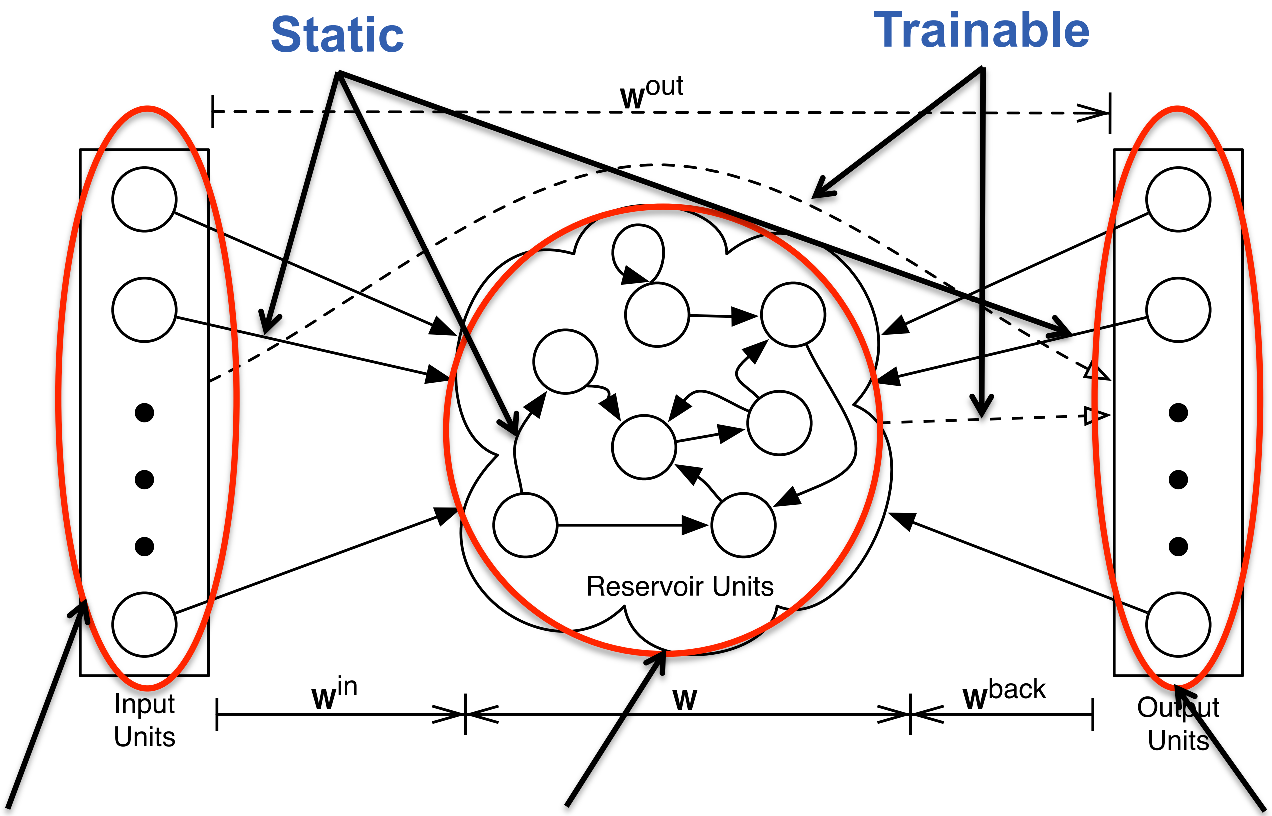
- **Reinforcement Learning paradigm**
  ➔ appropriate for agents
- **Real world/complex tasks**
  ➔ Function Approximator
- **Echo State Networks**
  ➔ Non-linear/Non-Markovian tasks
- **Evolution and learning**
  ➔ adapt the reservoir to the problem at hand
- **How?**
  ➔ NeuroEvolution (NEAT) and Temporal Difference learning

Hierarchy of involved areas



Echo State Networks

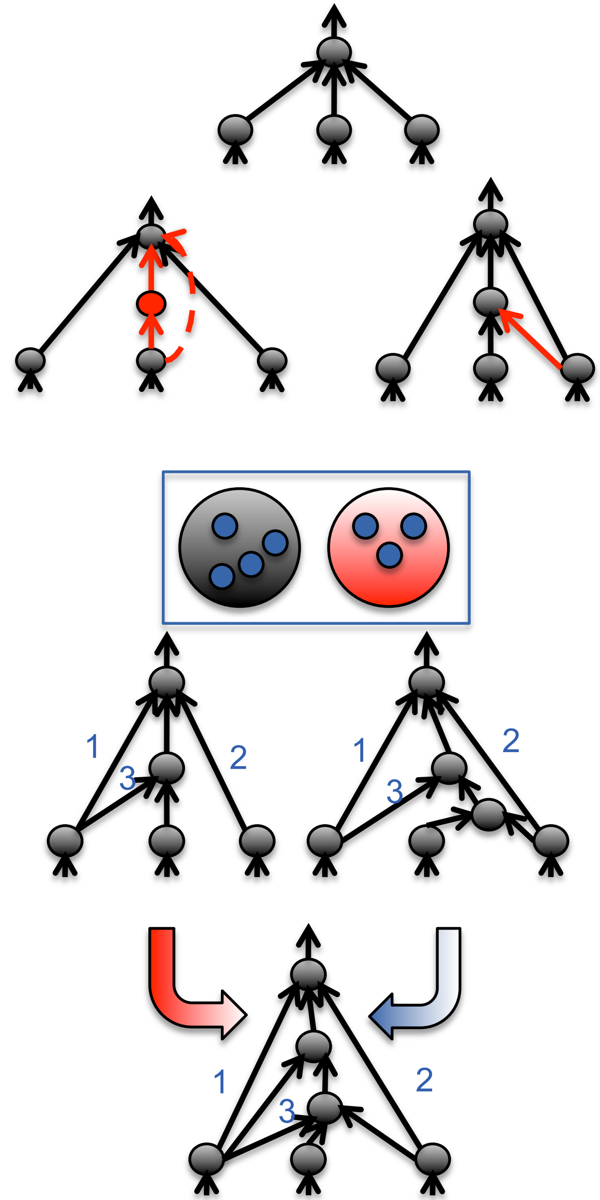
- **An Echo State Network (ESN) [Jaeger, 2001 & 2002]**



Input	Reservoir	Output
Linear Features	Non-linear Features - Memory	Linear/Non-linear Combination

NeuroEvolution of Augmented Topologies

- **Start minimally & complexify**
- **Weight & structural mutation**
- **Speciation through clustering to protect innovation**
- **Crossover networks through historical markings on connections**



[Stanley, PhD, 2004]

NeuroEvolution of Augmented Reservoirs (NEAR)

- **Use NEAT as a meta-search method**
- **Start from minimal reservoirs (1 neuron)**
- **Perform weight and structural mutation**
  - Add neurons, add connections
- **Maintain ESN constraints**
- **Apply speciation through clustering**
  - Similarity metric ~ Reservoir's Macroscopic Features (Spectral Radius, Reservoir Neurons & Sparseness)
- **Apply crossover using historical markings on neurons**
- **Identical performance and in some cases better against "rival" algorithms**
- **Work under review**

Questions

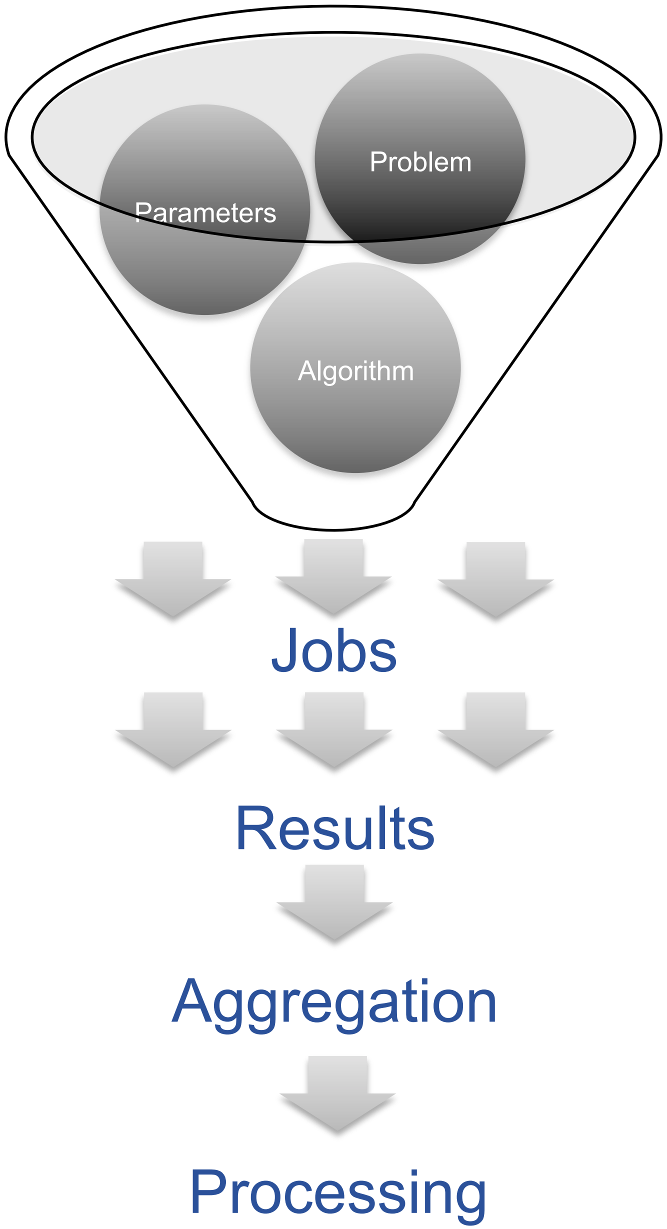
- **We ask the following questions:**

Selection	• Degree of elitism
Reproduction	• With crossover • Mutation only
Fitness	• Speciation • Individualism
Crossover	• Continuous complexification • Survival of the fittest
Reservoir	• Sparse • Dense

- **Questions are formulated as sets of parameters**
- **Experimentation to answer them**

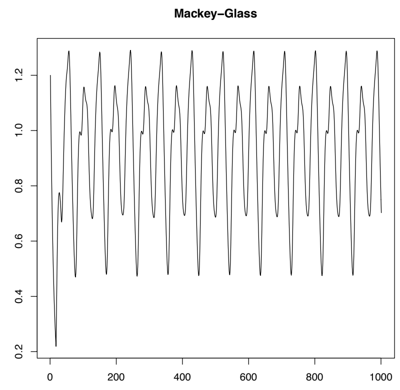
Set up

- 7 problems
- 5 parameters
- 64 parameter sets
- 30 runs per experiment
- A total of 13440 evolutionary procedures
- Population of 100 individuals
- Evolutionary process of 100 generations
- 13.44 10^7 networks were evaluated

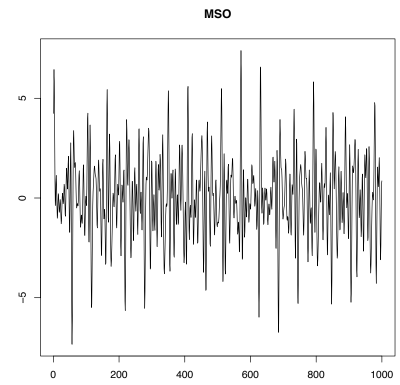


Testbeds – Time Series

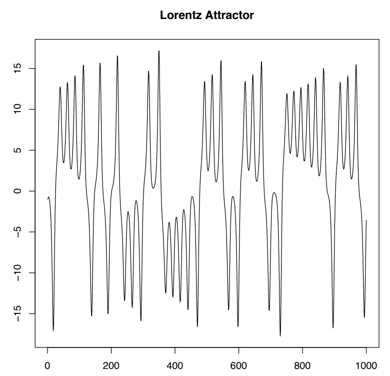
- **Time Series**
  - Mackey-Glass
  - Multiple Superimposed Oscillator
  - Lorentz Attractor
- **Predict the next value of sequence**
- **Train on sequence *T***
- **Calculate fitness, *1/NRMSE*, by feeding output to input on F chunks of sequence *T***
- **Validate on sequence *V***



Mackey Glass



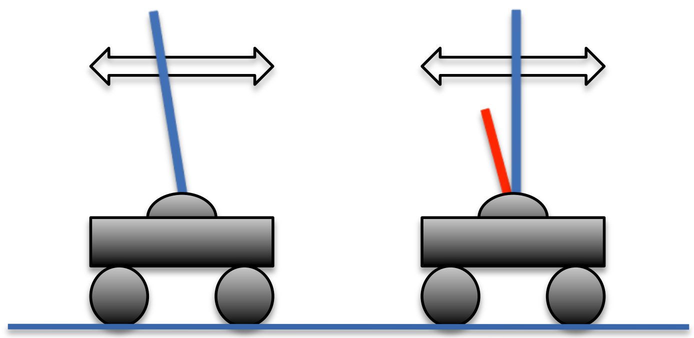
MSO



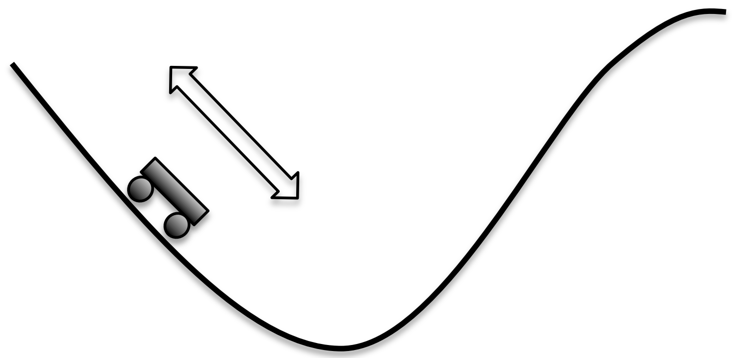
Lorentz Attractor

Testbeds – Reinforcement Learning

- **Reinforcement Learning**
  - **Single and Double pole balancing**
    Balance one pole, or two poles of different lengths and masses for more than 100.000 time steps



  - **2D and 3D mountain car**
    Escape from a valley by moving the car in two or three dimensions, starting from random states
    - 10 runs for 3D due to extremely large execution time



Mackey-Glass

- **Performance measure: Validation NRMSE**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	**$1.09\ 10^{-3}$**	40%	Yes	No	**Yes**	**No**
2	$3.04\ 10^{-3}$	30%	Yes	No	**Yes**	**No**
3	$3.50\ 10^{-3}$	10%	No	No	**Yes**	**No**
4	$3.61\ 10^{-3}$	40%	Yes	Yes	**Yes**	**No**
5	$4.35\ 10^{-3}$	10%	No	No	No	Yes
…	…	…	…	…	…	…
60	$3.27\ 10^{-1}$	40%	Yes	No	No	Yes
61	$3.55\ 10^{-1}$	10%	Yes	No	No	No
62	**$2.22\ 10^{2}$**	40%	**No**	No	No	Yes
63	**$3.07\ 10^{7}$**	30%	**No**	No	Yes	No
64	**$3.07\ 10^{7}$**	20%	**No**	Yes	Yes	Yes

- **Inconclusive**

MSO

- **Performance measure: Validation NRMSE**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	$8.8\ 10^{-1}$	10%	No	No	No	No
2	$8.86\ 10^{-1}$	20%	No	No	No	No

- **The most difficult task**
- **Know to be an especially difficult task for ESNs**
- **Even the best results exhibit poor error behavior**
- **The poor performance does not allow us to derive concrete conclusions**

Lorentz Attractor

- **Performance measure: Validation NRMSE**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	$7.56\ 10^{-2}$	40%	Yes	**No**	Yes	No
2	$7.63\ 10^{-2}$	40%	Yes	**No**	Yes	Yes
3	$7.64\ 10^{-2}$	10%	No	**No**	No	Yes
4	$7.67\ 10^{-2}$	20%	Yes	**No**	No	Yes
5	$7.69\ 10^{-2}$	40%	No	**No**	Yes	Yes
…	…	…	…	…	…	…
60	$1.02\ 10^{-1}$	**10%**	**Yes**	No	No	No
61	$1.09\ 10^{-1}$	**10%**	**Yes**	Yes	No	No
62	$1.10\ 10^{-1}$	**10%**	**Yes**	No	No	Yes
63	$1.18\ 10^{-1}$	**10%**	**Yes**	No	Yes	No
64	$1.20\ 10^{-1}$	**10%**	**Yes**	Yes	Yes	No

2D Mountain Car

- **Performance measure: avg # steps escaping the valley from 1000 random starting states**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	-50.90	40%	No	No	Yes	No
2	-51.15	10%	Yes	No	Yes	Yes
3	-51.21	10%	No	Yes	No	No
4	-51.24	20%	Yes	No	No	No
5	-51.28	40%	Yes	No	No	No
…	…	…	…	…	…	…
60	-53.52	20%	**Yes**	**Yes**	No	Yes
61	-53.67	30%	**Yes**	**Yes**	Yes	No
62	-53.68	30%	**Yes**	**Yes**	Yes	Yes
63	-53.72	10%	**Yes**	**Yes**	Yes	No
64	-54.12	30%	**Yes**	**Yes**	No	No

- **Inconclusive**
- **Similar results versus classic CMAC SARSA and the recent NEAT+Q**

3D Mountain Car

- **Performance measure: avg # steps escaping the valley from 1000 random starting states**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	-157.17	40%	Yes	No	Yes	Yes
2	-165.80	40%	No	No	No	Yes
3	-167.61	30%	No	No	No	No
4	-170.13	10%	No	Yes	Yes	No
5	-174.57	10%	No	No	Yes	Yes
…	…	…	…	…	…	…
60	-224.72	10%	No	Yes	No	No
61	-228.81	20%	Yes	No	No	No
62	-230.63	10%	Yes	No	Yes	Yes
63	-234.64	40%	No	No	Yes	Yes
64	-238.75	20%	Yes	No	No	Yes

- **Inconclusive**

Single Pole Balancing

- **Performance measure: # Nets evaluated**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	186.48	**10%**	No	No	No	No
2	189.64	**10%**	No	No	No	Yes
3	195.64	**10%**	No	Yes	Yes	Yes
4	195.92	**20%**	Yes	No	No	Yes
5	196.22	**10%**	No	Yes	No	No
…	…	…	…	…	…	…
60	249.52	**30%**	**Yes**	**Yes**	Yes	Yes
61	258.88	**40%**	**Yes**	**Yes**	Yes	No
62	261.38	**20%**	**Yes**	**Yes**	No	Yes
63	268.96	**20%**	**Yes**	**Yes**	No	Yes
64	277.74	**40%**	**Yes**	**Yes**	No	Yes

Double Pole Balancing

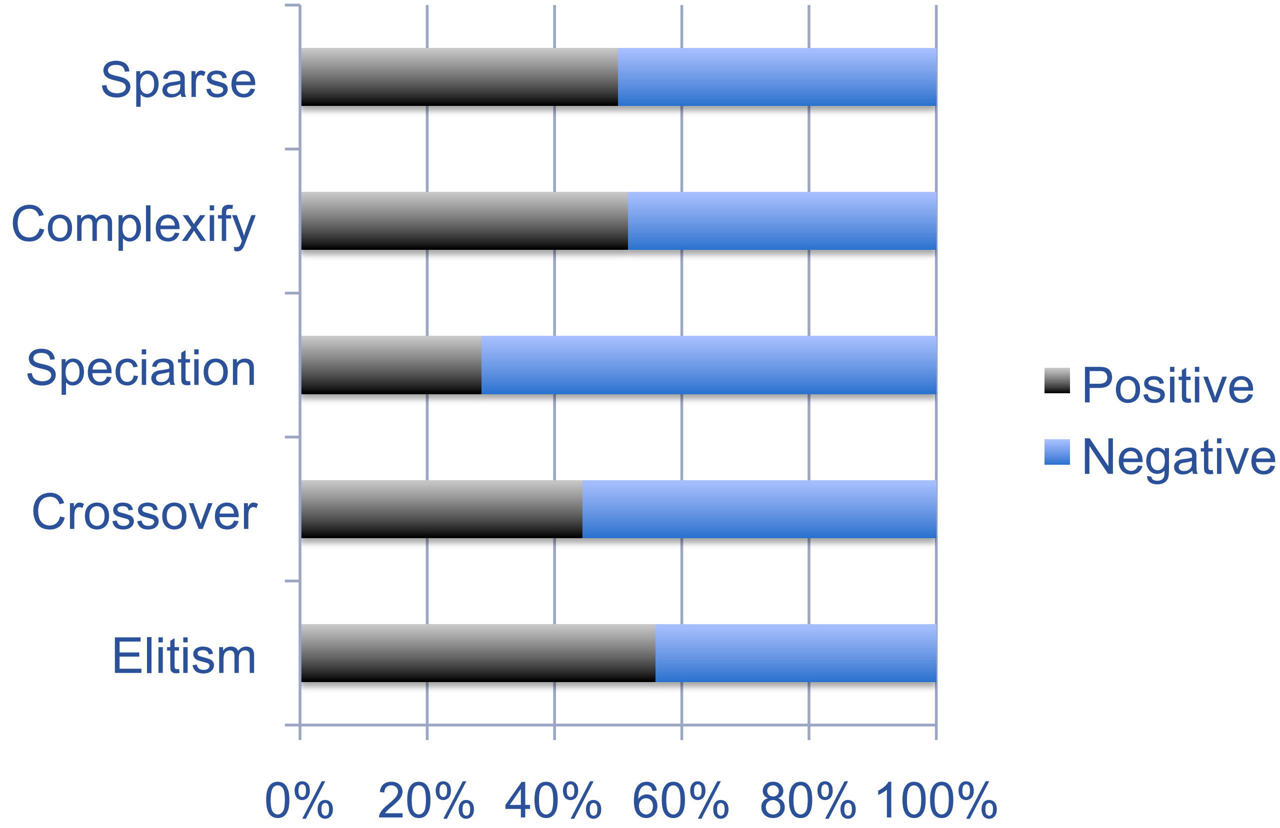
- **Performance measure: # Nets evaluated**

Rank	Perf.	Elitism	Crossover	Speciation	Complexify	Sparse
1	393.54	10%	Yes	No	Yes	No
2	408.94	10%	Yes	Yes	Yes	No
3	415.26	10%	Yes	No	Yes	Yes
4	423.08	10%	Yes	No	No	Yes
5	424.32	10%	Yes	No	No	No
…	…	…	…	…	…	…
60	737.40	30%	No	No	Yes	No
61	743.38	40%	No	No	Yes	No
62	752.88	30%	No	Yes	Yes	No
63	782.54	40%	No	No	No	No
64	788.52	40%	No	No	Yes	Yes

- **Important parameters: Elitism, Crossover**

Summarize

- **Testbeds very different**
- **Free lunch theorem holds for parameters**
- **Results inconclusive besides speciation**
  - Actually good
  - Multiple ways of finding a good solution without in many environments without worrying much about specific parameter settings
  - The case the algorithm does not work well (MSO) is mainly due to the restriction of the model itself



Execution period on Grid

- **Execution for 1 run on Grid**
  - MG ~ 1509.23 sec
  - MSO ~ 977.33 sec
  - Lorentz ~ 2596.66 sec
  - 2DMC ~ 3157.30 sec
  - 3DMC ~ 17347 sec
  - SPB ~ 15.52 sec
  - DPB ~ 183.12 sec
- **Total time ~ 27.3 10^6 ~ 316 days of sequential execution time**
- **Experimentation period on Grid ~ 60 days**
  - allowing for testing, errors, outage, inactivity periods etc.

Future Work

- **Add more testbeds to the grid search**
  - Non-markov cases that make pole balancing and mountain car problems more difficult (Implememted)
  - Server Job Scheduling (Implemented)
- **More research on speciation and clustering similarity metric**
- **Increase generations when searching for a suitable network for the MSO testbed**

Thank you for your attention!

Fotis Psomopoulos

fpsom@issel.ee.auth.gr

Intelligent Systems and Software Engineering Labgroup

Informatics and Telematics Institute
Centre for Research and Technology-Hellas

Electrical and Computer Eng. Dept.
Aristotle University of Thessaloniki

Thessaloniki, Greece