

# PyDGGA: Distributed GGA for Automatic Configuration

Carlos Ansótegui <sup>1</sup>    Josep Pon <sup>1</sup>    Meinolf Sellmann <sup>2</sup>  
Kevin Tierney <sup>3</sup>

LOG group, University of Lleida, Spain  
carlos.ansotegui@diei.udl.cat  
josep.pon@udl.cat

General Electric, USA  
meinolf@ge.com

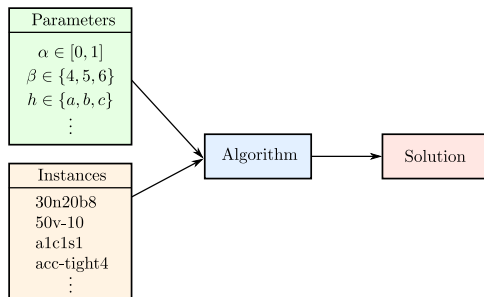
Decision and Operation Technologies Group, Bielefeld University, Germany  
kevin.tierney@uni-bielefeld.de

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# Parameters

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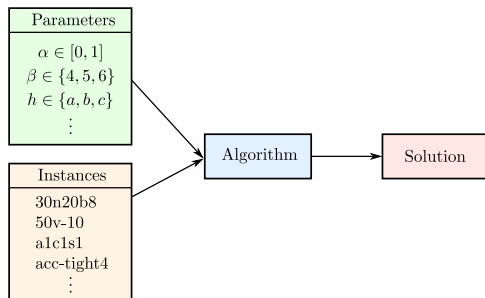
Algorithms have many parameters that influence their performance.



# Parameters

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Algorithms have many parameters that influence their performance.



- ▶ With good parameter settings (configurations), problems can be solved faster (or better).

# Parameter

## What are parameters?

Parameters are settings (configurations) of an algorithm (or solver) that change the way an algorithm solves a problem.

## Parameter Types

- ▶ Continuous: e.g.  $[1.0, 5.0]$
- ▶ Discrete: e.g.  $[1, \dots, 10]$
- ▶ Categorical: e.g.  $\{a, b, c, d\}$
- ▶ Ordinal: e.g.  $\{low, medium, high\}$  (Ordered set)

## SparrowToRiss parameters example

- ▶  $\text{prUips} \in \{-1, 0, 1\}$
- ▶  $\text{prDouble} \in \{\text{yes}, \text{no}\}$
- ▶  $\text{prProbleL} \in [500000, 7500000]$
- ▶  $\text{firstReduceDB} \in [2000, 8000]$
- ▶  $\text{incReduceDB} \in [300, 450]$
- ▶  $\text{rlevel} \in \{0, 1, 2\}$
- ▶  $\text{quickRed} \in \{\text{yes}, \text{no}\}$
- ▶  $\text{rndFreq} \in [0.00, 0.01]$
- ▶  $\text{minLBDMinimizingClause} \in [4, 9]$
- ▶  $\text{minSizeMinimizingClause} \in [3, 50]$
- ▶  $\text{incLBD} \in \{\text{yes}, \text{no}\}$
- ▶  $\text{xor} \in \{\text{yes}, \text{no}\}$
- ▶ ... the list extends to about 222 parameters

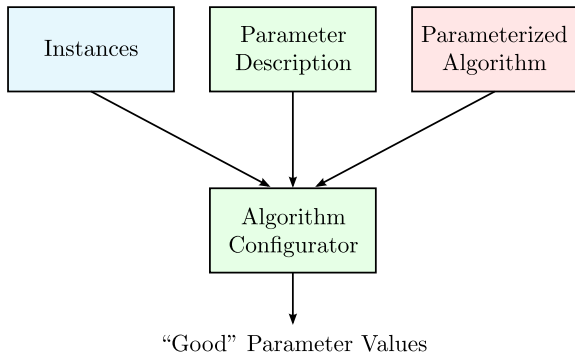
## SparrowToRiss parameters example

- ▶  $\text{prUips} \in \{-1, 0, 1\} \rightarrow \mathbf{0}$
- ▶  $\text{prDouble} \in \{\text{yes}, \text{no}\} \rightarrow \mathbf{\text{yes}}$
- ▶  $\text{prProbleL} \in [500000, 7500000] \rightarrow \mathbf{5000000}$
- ▶  $\text{firstReduceDB} \in [2000, 8000] \rightarrow \mathbf{4000}$
- ▶  $\text{incReduceDB} \in [300, 450] \rightarrow \mathbf{300}$
- ▶  $\text{rlevel} \in \{0, 1, 2\} \rightarrow \mathbf{1}$
- ▶  $\text{quickRed} \in \{\text{yes}, \text{no}\} \rightarrow \mathbf{\text{yes}}$
- ▶  $\text{rndFreq} \in [0.00, 0.01] \rightarrow \mathbf{0.005}$
- ▶  $\text{minLBDMinimizingClause} \in [4, 9] \rightarrow \mathbf{6}$
- ▶  $\text{minSizeMinimizingClause} \in [3, 50] \rightarrow \mathbf{30}$
- ▶  $\text{incLBD} \in \{\text{yes}, \text{no}\} \rightarrow \mathbf{\text{no}}$
- ▶  $\text{xor} \in \{\text{yes}, \text{no}\} \rightarrow \mathbf{\text{no}}$
- ▶ ... the list extends to about 222 parameters

# Automatic Algorithm Configuration

- ▶ Instead of experimental design (or parameter tuning by hand), algorithms can be automatically configured.
- ▶ Non-model-based algorithm configurators:
  - ▶ **CALIBRA**: Fractional factorial design with local search (Adenso-Diaz and Laguna, 2006)
  - ▶ **ParamILS**: Iterated Local Search (Hutter, Hoos und Stützle 2007/2009)
  - ▶ **GGA**: Genetic algorithms (Ansotegui, Sellmann and Tierney 2009)
  - ▶ **(Iterated) F-Race**: Racing with statistical tests (Birattari, et al. 2002/2010)
- ▶ Model based algorithm configurators:
  - ▶ **SMAC**: Random forest learning (Hutter, Hoos, Leyton-Brown 2011)
  - ▶ **GGA++**: Genetic algorithms with random forest model crossover (Ansotegui, et al. 2015)

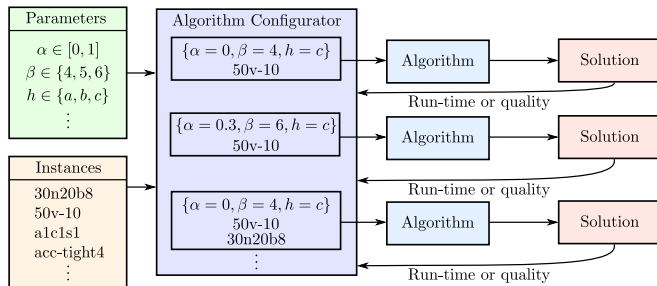
# Automated Algorithm Configuration





# Parameter Tuning

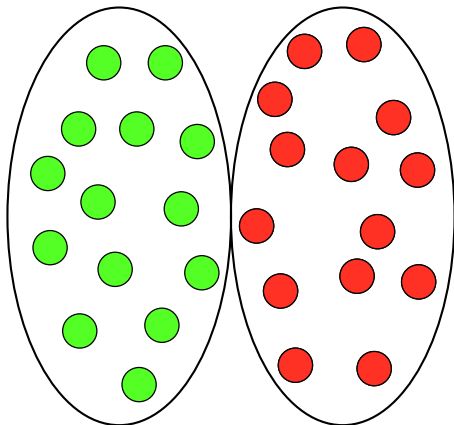
- ▶ Algorithm configurators try different parameter settings on selected instances and measure the performance of the target algorithm.



# GGA

- ▶ Genetic algorithm based algorithm configurator
- ▶ “Gender-based GA” for diversification
- ▶ Intensification through strong selection procedure
- ▶ Supports all continuous, discrete and categorical parameters
- ▶ Can handle certain types of conditionality and forbidden parameter sequences
- ▶ First published in 2009

## GGA: Population

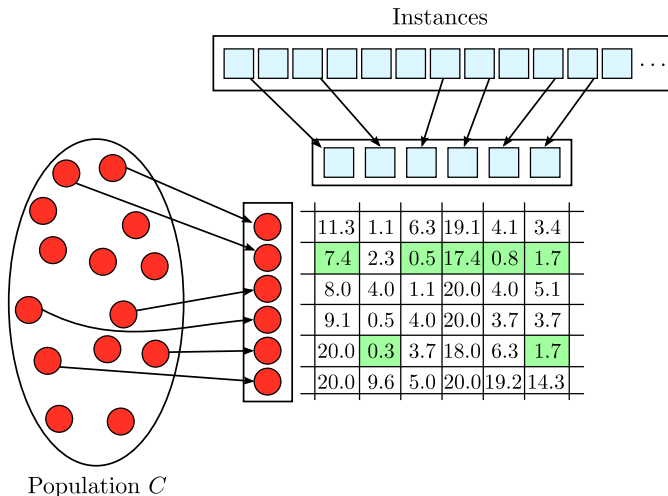


Partition: Population  $N$  and  $C$

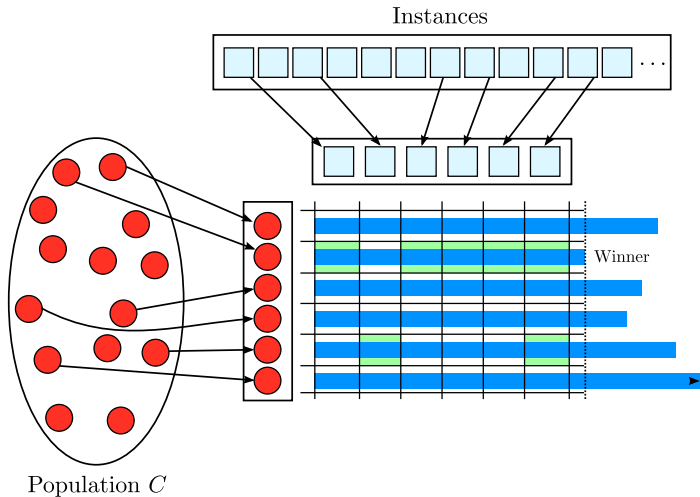
Population  $N$ : “Genome storage”

Population  $C$ : Competing against each other in competitions

# Selection (mini-tournament)

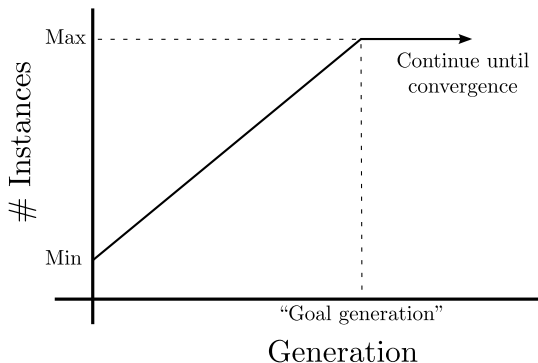


# Selection (mini-tournament)

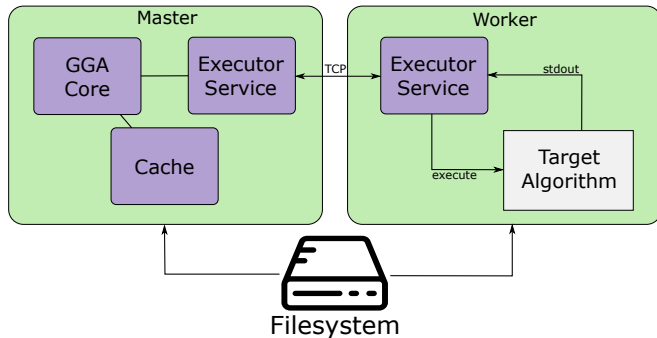


## Instance selection

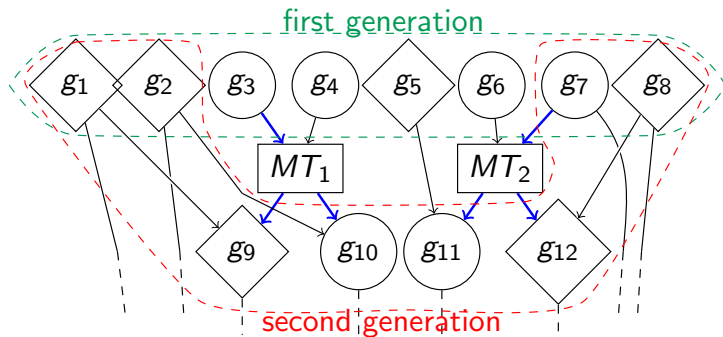
- ▶ GGA tunes a subset of instances that increases linearly in size according to the current generation.
- ▶ The subset of instances is chosen randomly at each generation



# PyDGGA: Architecture

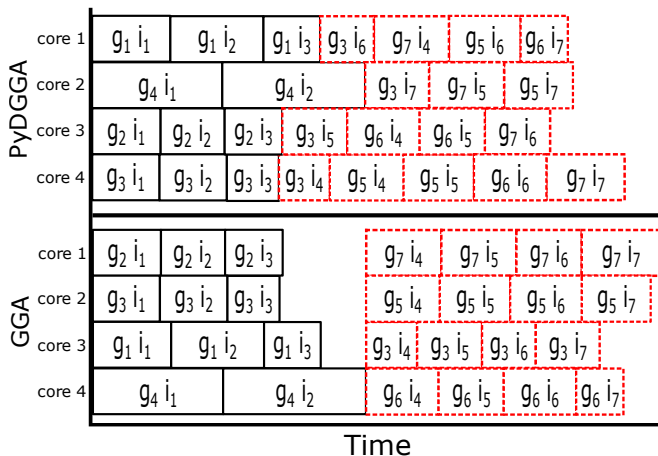


# PyDGGA: Simulation





# PyDGGA: Scheduler



# Hands-on Demo

Elite mini-tournament, Stop/Resume, Improved Configuration constraints, ...

Available from <https://ulog.udl.cat>

# Results

Table: SparrowToRiss PAR10 performance (# solved instances)

	BMC	CF	IBM	GI	N-Rooks
Default	346 (262)	297 (276)	113 (232)	247 (307)	116 (348)
PyDGGA	<b>171 (267)</b>	<b>89 (283)</b>	<b>10 (232)</b>	<b>91 (317)</b>	<b>6.3 (351)</b>

Table: CPLEX PAR10 performance (# solved instances)

	Assortment	CLS	COR-LAT	RCW
Default	2429 (52)	3.04 (50)	37 (999)	562 (844)
PyDGGA	<b>718 (58)</b>	<b>2.01 (50)</b>	<b>7 (1000)</b>	<b>344 (855)</b>

## Conclusions & Future Work

PYDGGGA is able to improve the performance of an algorithm, using the resources of a distributed computing environment efficiently.

- ▶ Integrate surrogate models
- ▶ Improve evaluations scheduling
- ▶ Simplify setup by means of technologies, such as Zero-configuration networking.