

# Constraint Programming

Connections with HPC

Jean-Guillaume FAGES, PhD  
COSLING CEO



# Outline

- 1 What is Constraint-Programming?
- 2 How does it work?
- 3 How does HPC contributes to Constraint-Programming?

# What is Constraint-Programming?

# A Paradigm



## Constraint-Programming

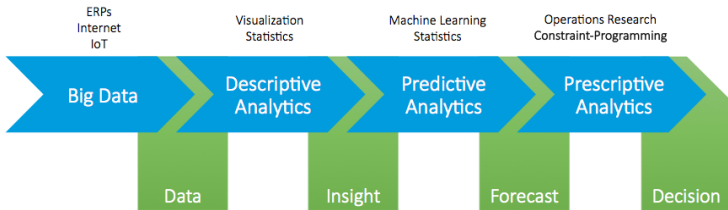
A programming paradigm between AI and OR to solve constrained decision problems in a generic way.

# A Paradigm



## Constraint-Programming

A programming paradigm between AI and OR to solve constrained decision problems in a generic way.



# Problem oriented paradigm

## Focus

- It is not about Data (input)
  - It is about solving problems
  - Models are problem-specific
- CP is a generic toolbox to design algorithms

# Applications

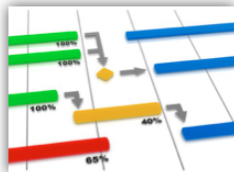


# Applications





# Applications



# Applications



How does it work?

# Definition



## Constraint Satisfaction Problem (CSP)

Defined by

- a set of variables  $X = \{x_1, \dots, x_n\}$  (unknowns)
- a set of domains  $D = \{d_1, \dots, d_n\}$  (possible values)
- a set of constraints  $C = \{c_1, \dots, c_m\}$  (restrictions)

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Variable	Domain	Example
Binary	two integers	$\{0, 1\}$
Integer (bounded)	integer interval	$\llbracket 3, 11 \rrbracket$
Integer (enum)	integer set	$\{-2, \dots, 3, 12\}$
Set	(int) set interval	$\llbracket \{2\}, \{0, 2, 3, 5\} \rrbracket$
Graph	graph interval	$\llbracket \text{[graph 1]}, \text{[graph 2]} \rrbracket$
Real	real interval	$\llbracket 3.14, 12.7 \rrbracket$

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Constraints	Examples
Arithmetic	$+, -, \times, \div, =, >, \leq, \neq$
Logical	$\vee, \wedge, \Rightarrow, \Leftrightarrow$
Set	$\cap, \cup, \subseteq, \text{card}, \text{partition}$
Global	<i>AllDifferent, Cumulative, Regular, Circuit...</i>
Graph	<i>Degrees, NCliques, NSCC, Tree</i>

**No restrictions!**

# Example: TSP

```

// --- Circuit: successors[i] = k <=> once at client i, travel to client k
IntVar[] successors = model.intVarArray("succ",n, 0, n - 1, false);
model.circuit(successors).post();

// --- Unit travel cost
IntVar[] travelDistances = model.intVarArray(n, min, max, true);
for(int i=0; i<n ; i++){
    model.element(travelDistances[i], distances[i], successors[i]).post();
}

// --- Objective function
IntVar totalDistance = model.intVar("total distance",min*n, max*n, true);
model.sum(travelDistances, "=", totalDistance).post();
model.setObjective(Model.MINIMIZE, totalDistance);

// --- Solving
Solver s = model.getSolver();
while (s.solve()){
    System.out.println(totalDistance);
}

```



# The Holy Grail



*Constraint Programming represents one of the closest approaches computer science has yet made to the Holy Grail of programming: the user states the problem, the computer solves it. [Eugene Freuder]*



# Main algorithm



## Solving loop

- **Filtering**
  - Search space reduction (inconsistent values removal)
  - Propagating deductions until **fixpoint**
- **Search**
  - Search space exploration (hypothesis)
  - Applying branching **heuristics** to compute **decisions**

Until all variables are fixed to a value (solution)

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## Optimization

- Compute solution
- Post  $z < c$  (cost of previous solution)

Until no better solution exists

# Filtering



## From constraints to filtering

Every constraint comes with one or many **filtering algorithms** to remove inconsistent values (domain modifications)

## From constraints to filtering

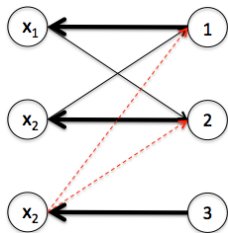
Every constraint comes with one or many **filtering algorithms** to remove inconsistent values (domain modifications)

## Example

- $x = \{0, 1, 2, 3, 5, 6\}$  and  $y = \{2, 3, 5, 6, 10\}$
- constraint:  $x > y$
- Filtering  $x \rightarrow y : y = \{2, 3, 5, \cancel{6}, \cancel{10}\}$
- Filtering  $x \leftarrow y : x = \{\emptyset, \cancel{1}, \cancel{2}, 3, 5, 6\}$

## From constraints to filtering

Every constraint comes with one or many **filtering algorithms** to remove inconsistent values (domain modifications)



### Example: *AllDifferent*

Let  $X = \{x_1, x_2, x_3\}$   
 with  $x_1 \in \{1, 2\}$ ,  $x_2 \in \{1, 2\}$  and  $x_3 \in \{1, 2, 3\}$   
 such that  $x_1 \neq x_2$ ,  $x_1 \neq x_3$ ,  $x_2 \neq x_3$

$x_1 \in \{1, 2\}$ ,  $x_2 \in \{1, 2\}$  and  $x_3 \in \{1, 2, 3\}$

## From constraints to filtering

Every constraint comes with one or many **filtering algorithms** to remove inconsistent values (domain modifications)

## Scope

- Each filtering algorithm is **local** to a constraint
- Filtering algorithms are called **incrementally** until reaching a fix point

## Search

Heuristic domain modification to drive the solving process

- Triggers propagation and filtering
- Guides how to reach a solution

## Binary branching

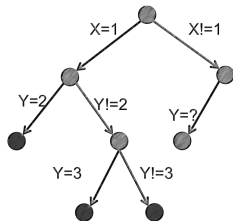
At each node a **decision** ( $var, op, val$ ) is taken

- Left child: apply decision (guess)
- Right child: negate decision (deduction)

## Search heuristics

Which decision (*var*, *op*, *val*) to generate?

- Huge impact on results

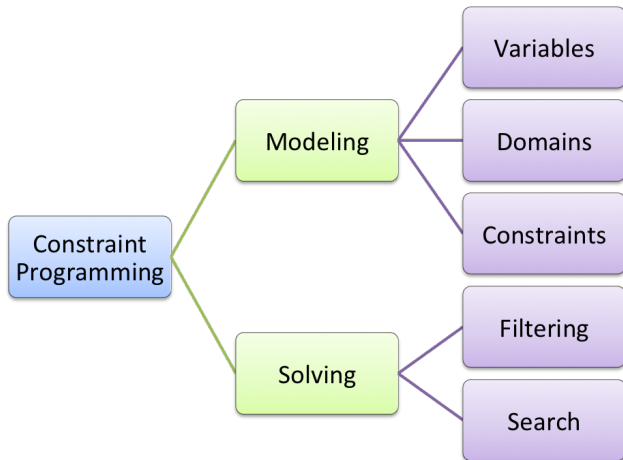


## Many strategies

- Black-box v.s. User-defined strategy
- Best-First v.s. Fail-First principle



# Summary



# How does HPC contributes to Constraint-Programming?

# Parallelism



## Parallelism

Can we achieve significant gains using parallel computing?

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Can we achieve significant gains using parallel computing?

## Filtering parallelization

Filtering algorithms could be called in parallel, but:

- Domain cloning overhead
  - Unit propagation is (usually) fast
  - Propagation is an iterative process
- ⇒ Not used in practice

## Parallelism

Can we achieve significant gains using parallel computing?

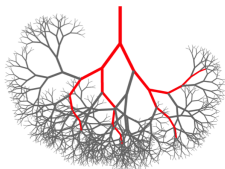
## Search parallelization

- Solver portfolios
- Distributed search
  - Work stealing
  - Embarrassingly Parallel Search

# Portfolio approaches

## Portfolio

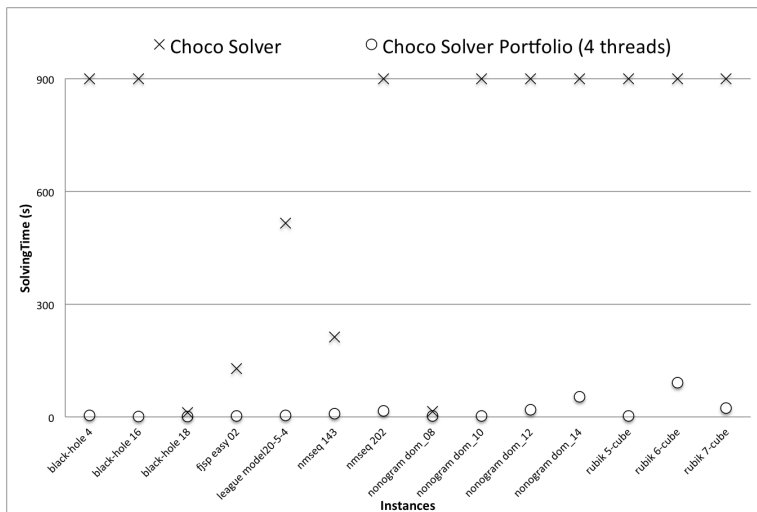
- Several instances of **same model** but **Different search strategies** run in parallel
- Satisfaction: no communication at all (luck)
- Optimization: Bound sharing (collaboration)



## Many strategies

- Exponential speedup
- State-of-the-art for few cores

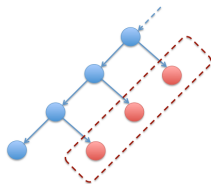
# Portfolio approaches



# Distributed DFS

## Work stealing [Jaffar et. al.]

- Master records solutions & bounds
- Workers (dynamical)
  - Pop or steal node
  - Explore node
  - Push right child in stack



## Issue

- Communication cost
- Hard to find a balanced distribution
- Hard to scale beyond 100 cores



# Distributed DFS



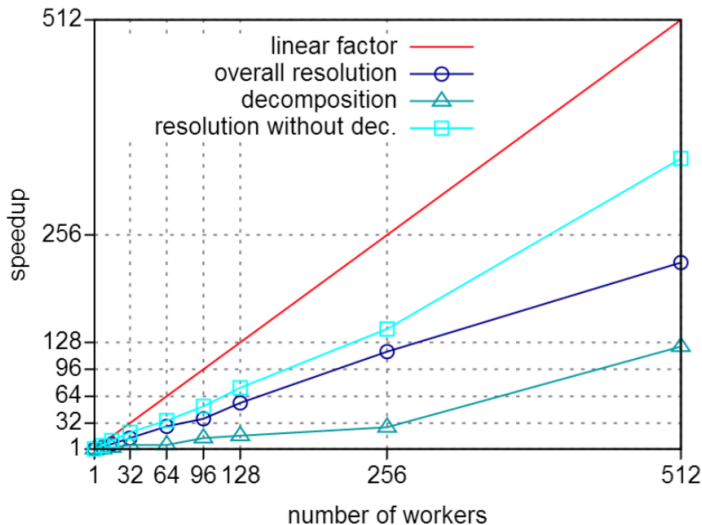
## Embarrassingly Parallel Search [Regin et. al.]

- **Static** decomposition into **consistent** subproblems
- Based on depth-bounded DFS
- Communicate with master only when subproblem is solved
- $\approx 40$  subproblems per workers  $\rightarrow$  balanced workload

## Issue

- Almost no communication cost but decomposition cost
- State of the art over large number of cores

# EPS speedup



# Distributed DFS



## Insight

- Independent subproblems are efficiently solved in parallel
- Automated decomposition may be costly/intricate

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## Good news!

It is often possible to decompose a problem

- Stochastic optimization based on different scenarios
- Optimization of different orders (logistics)
- Routing optimization of different areas (transportation)
- Frequent user request presolving (web-app)

# Conclusion



## HPC

- Simple and affordable
- Pushes forward the limits of Constraint Programming
- Opens real-time application opportunities

# Thank you for your attention



## Contact

- Jean-Guillaume FAGES, PhD
- [jg.fages@cosling.com](mailto:jg.fages@cosling.com)
- [www.cosling.com](http://www.cosling.com)
- +33683311966

# References

## Main references

- Handbook of Constraint Programming
- J.-C. Regin, A Filtering Algorithm for Constraints of Difference in CSPs
- Global Constraint Catalogue:  
<http://sofdem.github.io/gccat/>
- A. Malapert, J-C. Regin, M. Rezgui: Embarrassingly Parallel Search in Constraint Programming

## Journals & conferences

- Artificial Intelligence, Constraints
- CP, CPAIOR, AAAI, ECAI, JFPC