## Mathematical programming by Local Search

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Who?







## Innovation 24



Large industrial group with businesses in construction, telecom, media *www.bouygues.com* 

#### **Innovation24** Operation Research subsidiary of the Bouygues group

# **LocalSolver** Flagship product of Innovation 24

www.localsolver.com





Why?







## Practical observations

What is the most powerful tool provided by OR today? → Mixed Integer Linear Programming (MIP)

- Simple and generic formalism
- Easy-to-use solvers: "model-and-run" approach
- Now an indispensable tool for practitioners
- Constraint Programming (CP) is following the way

What do practitioners when MIP/CP solvers are ineffective?  $\rightarrow$  Local Search (LS)

- Core principle: improving the incumbent by exploring neighborhoods
- Provides quality solutions in minutes
- Extra costs (development, maintenance)





## Our goals

#### A solver aligned with enterprise needs

- Provides high-quality solutions in seconds
- Scalable: tackles problems with millions of decisions
- Proves infeasibility or optimality when possible (best effort)

#### A solver aligned with practitioner needs

- « Model & Run »
  - Simple mathematical modeling formalism
  - Direct resolution: no need of complex tuning

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- Full-version free trials with support
- Competitive pricing

http://www.localsolver.com/pricing.html

Free for academics

Quick tour

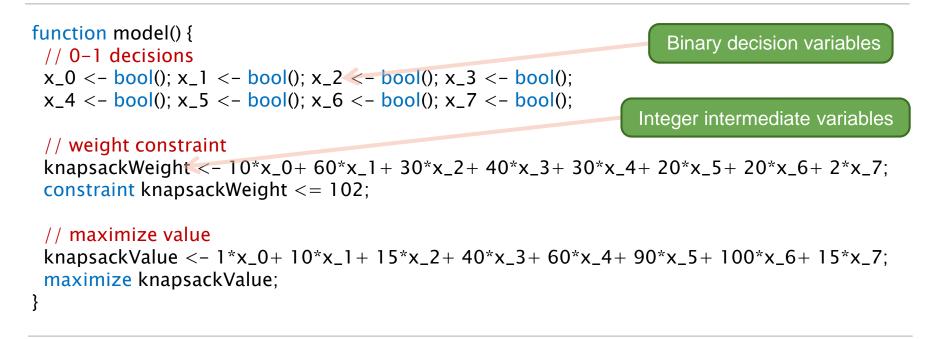


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7 28

## Classical knapsack

8 items to pack in a sack: maximize the total value of items while not exceeding a total weight of 102 kg





You write the model: nothing else to do!

declarative approach = model & run





## Multiobjective nonlinear knapsack

```
function model() {
    // 0-1 decisions
    x[0..7] <- bool();</pre>
```

Nonlinear operators: prod, min, max, and, or, if-then-else, ...

// weight constraint
knapsackWeight <- 10\*x[0]+ 60\*x[1]+ 30\*x[2]+ 40\*x[3]+ 30\*x[4]+ 20\*x[5]+ 20\*x[6]+ 2\*x[7];
constraint knapsackWeight <= 102;</pre>

// maximize value
knapsackValue <- 1\*x[0]+ 10\*x[1]+ 15\*x[2]+ 40\*x[3]+ 60\*x[4]+ 90\*x[5]+ 100\*x[6]+ 15\*x[7];
maximize knapsackValue;</pre>

// secondary objective: minimize product of minimum and maximum values
knapsackMinValue <- min[i in 0..7](x[i] ? values[i] : 1000);
knapsackMaxValue <- max[i in 0..7](x[i] ? values[i] : 0);
knapsackProduct <- knapsackMinValue \* knapsackMaxValue;
minimize knapsackProduct;</pre>

}



Lexicographic objectives

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## Mathematical operators

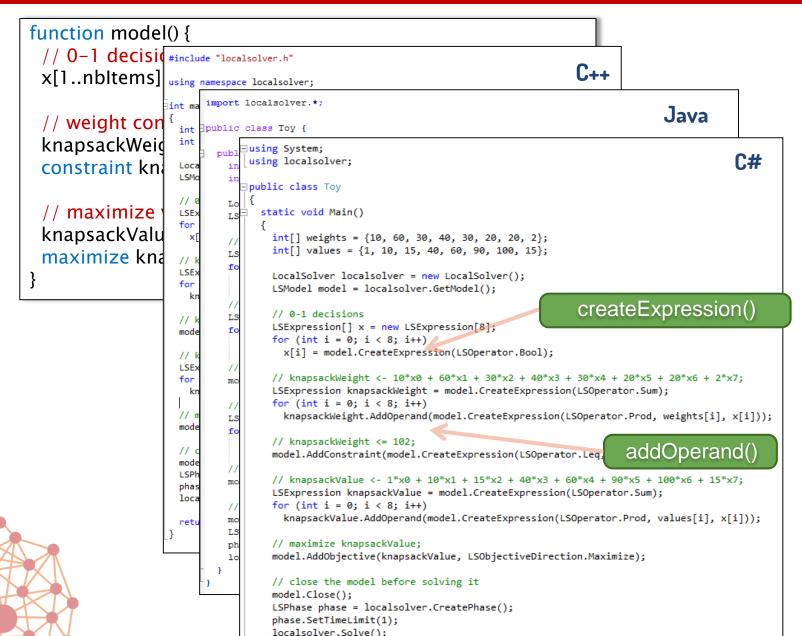
	Arithmeti	С	Logical	Relational
sum	prod	abs	not	==
min	max	dist	and	!=
div	mod	exp	or	<=
sqrt	log	pow	xor	>=
log	exp	tan	if	<
COS	sin	round	array + at	>
floor	ceil			

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10 28



## From LSP to APIs



### Let's go inside







#### Scheduling cars on a production line

#### Objective = distributing options

- E.g. : at most 2 sun-roofs in any sequence of 5 cars («P/Q»)
- measure: in each window of length 5, penalty based on overcapacities = max(n-2,0) with n the number of sun-roofs.

### A *class* is a set of identical cars

• Her with 3 options A, B and C: AB is the class of cars featuring options A and B



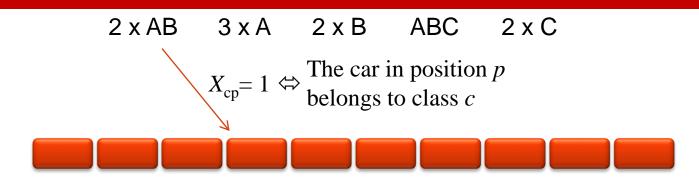








#### Model



X[c in 1..nbClasses][p in 1..nbPositions] <- bool();

```
for[c in 1..nbClasses]
    constraint sum[p in 1..nbPositions](X[c][p]) == card[c];
```

```
for[p in 1..nbPositions]
    constraint sum[c in 1..nbClasses](X[c][p]) == 1;
```

```
nbVehicles[o in 1..nbOptions][j in 1..nbPositions-Q[o]+1] <-
sum[k in 1..Q[o]](op[o][j+k-1]);
```

```
violations[o in 1..nbOptions][j in 1..nbPositions-Q[o]+1] <- max(nbVehicles[o][j] - P[o], 0);
```

obj<- sum[o in 1..nbOptions][p in 1..nbPositions-Q[o]+1](violations[o][p]);

#### That's all!

## Solving

#### How does LocalSolver solves this model?

- 1. Find an initial solution (here a random assignment of cars)
- 2. Apply generic moves







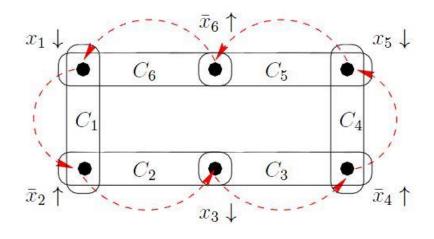
## Small-neighborhood moves

#### Classical moves for Boolean Programming: "k-flips"

- Moves lead in majority to infeasible solutions
- Feasibility is hard to recover, implying a slow convergence
- Then no solver integrates an effective "pure local search" approach

#### Our moves tend to preserve the feasibility

- Can be viewed as a destroy-and-repair approach
- Can be viewed as ejection chains in the constraint hypergraph
- Can be specific to special combinatorial structures (when detected)

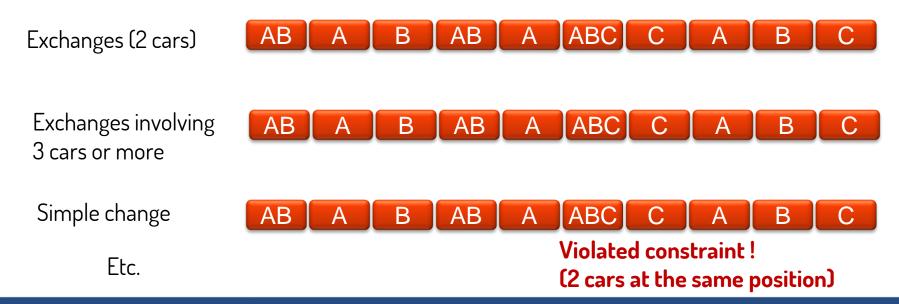




## Solving

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- Key points :
  - Simple changes will be eliminated after a few seconds since they fail systematically.
  - The global search strategy is a randomized simulated annealing (parameterized)
  - LocalSolver launches several concurrent search (the number of threads is a parameter)
  - Some moves will be focused on windows with overcapacities

### For more details



T. Benoist, B. Estellon, F. Gardi, R. Megel, K. Nouioua. LocalSolver 1.x: a black-box local-search solver for 0-1 programming. *4OR, A Quarterly Journal of Operations Research* 9(3), pp. 299-316.

http://www.localsolver.com/technology.html







### Benchmarks







## Car sequencing in Renault's plants

Some instances are public. This problem was submitted as ROADEF Challenge in 2005: <u>http://challenge.roadef.org/2005/en</u>

#### Example: instance 022\_EP\_ENP\_RAF\_S22\_J1

- Small instance: 80,000 variables, including 44,000 binary decisions
- State of the art: **3,109** obtained by a specific local search algorithm

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• Best lower bound: 3,103

#### Results

- Gurobi 5.0: 3.116647e+07 in 10 min | 25,197 in 1 hour
- LocalSolver 3.0: 3,478 in 10 sec | 3,118 in 10 min

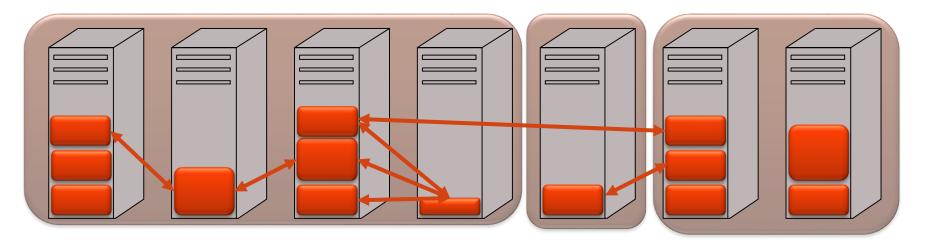




### 2012 ROADEF Challenge



Reassignment of processes to machines, with different kinds of constraints (mutual exclusion, resources, etc.)



More than 100 000 binary decisions Only 1 day of work LocalSolver qualified for final round (ranked 24/80)

## MIPLIB

#### Some results obtained on the hardest MIPLIB instances

- Lower objective is better
- 5 minutes time limit for both LocalSolver and MIP
- Models are not suitably modeled for LocalSolver

**Minimization** 

Problem	Variables	LS 3.1	MIP	
ds-big	4.9 M	9 844	62 520	
ivu06-big	27.0 M	479	9 416	
ivu52	2.5 M	4 907	16 880	
mining	5.3 M	- 65 720 600	902 969 000	
ns1853823	1.1 M	2 820 000	4 670 000	
rmine14	1.3 M	- 3 470	-171	
rmine21	6.7 M	- 3 658	- 185	
rmine25	14.0 M	- 3 052	- 161	



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Business cases







### Business cases



- Supply Chain Optimization
- Workforce planning



TV Media Planning



Logistic clustering



Street lighting maintenance planning



Network deployment planning



Energy optimization for tramway lines



- Placement of nuclear fuel assemblies in pools
- Painting shop scheduling



Transportation of equipment LocalSolver



## Supply Chain Optimization



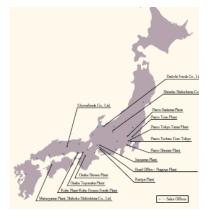


#### **Global Supply Chain**

- Both production and logistics optimization
- More than 10 factories, each with several production lines
- Large number of stores and distribution centers

### A challenging context for LocalSolver

- 20,00,000-variable model including 3 millions binaries
- A rich model involving setup costs, delivery times, packaging...
- A vain attempt to solve the problem with MIP solvers
- LocalSolver finds a high-quality solution in minutes











Tomorrow at 8:30 in this room

### Long Term Planning with LocalSolver

by Romain Megel







26 28

Roadmap







Integrating MIP, CP, SAT techniques with LS into an all-in-one solver for large-scale mixed-variable non-convex optimization

Feasibility search Optimization       Model rewriting Pattern detection       Simulated annealing Restarts (feas/infeas)       Combinatorial       Continuous         Variable elimination Constraint inference Domain reduction       Variable elimination Constraint inference Domain reduction       Simulated annealing Restarts (feas/infeas)       Small moves Compound moves       Small moves Compound moves         Infeasibility proof Lower bound       Divide & Conquer       Propagation       Relaxation         Tree search Interval branching       Discrete propagation       Dual linear relaxation		Preprocessing	Search strategy	Neighborhoods	
Domain reduction     Divide & Conquer     Propagation     Relaxation       Infeasibility proof     Lower bound     Tree search     Discrete propagation     Dual linear relaxation	•	Pattern detection Variable elimination	Restarts (feas/infeas) Randomization	Small moves Compound moves	ed Small moves Compound moves
Lower bound	Y Infeasibility proof				
	Lower bound				4

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28





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## Customers & Partners



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## Growing community!





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