

Tutorial: Constraint-Based Local Search

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Outline

(Meta-)
Heuristics for
Local Search

1 (Meta-) Heuristics for Local Search

Constraint-
Based Local
Search

2 Constraint-Based Local Search

The Comet
System

3 The Comet System

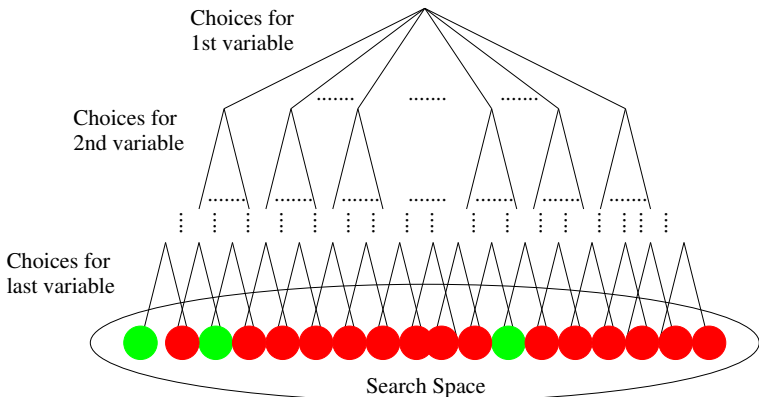
Bibliography

4 Bibliography



So Far: Inference + Systematic Search

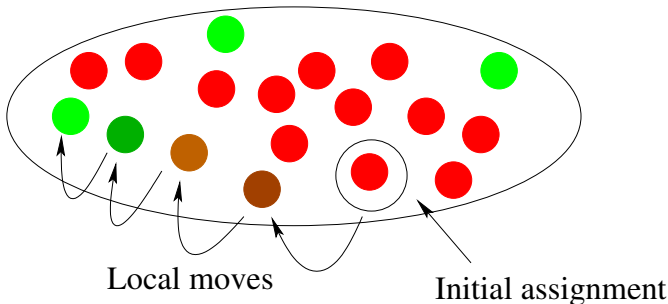
- Values are found **1-by-1** for the decision variables.
- Stop when solution or unsatisfiability proof is obtained.
- Search space from a systematic search viewpoint:





Now: Inference + Local Search

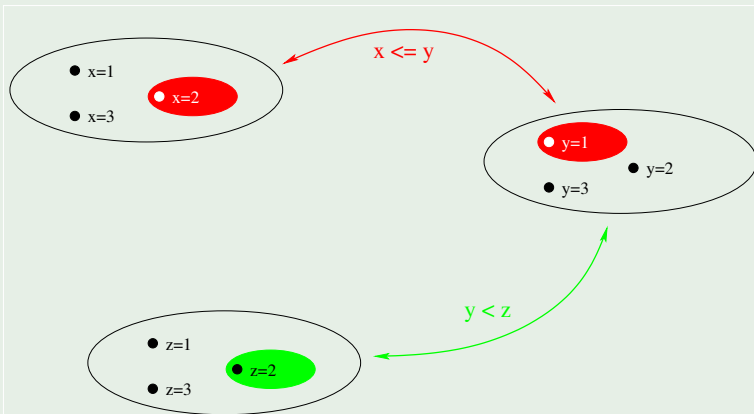
- Values are given to all the variables **at the same time**.
- Search proceeds by **moves**, which make small updates to complete assignments, upon probing the impacts of many candidate moves, called the **neighbourhood**.
- Stop when a good enough assignment has been found or when an allocated resource (running time, or a number of iterations) has been exhausted.





Example $(x, y, z \in \{1, 2, 3\} \wedge x \leq y \wedge y < z)$

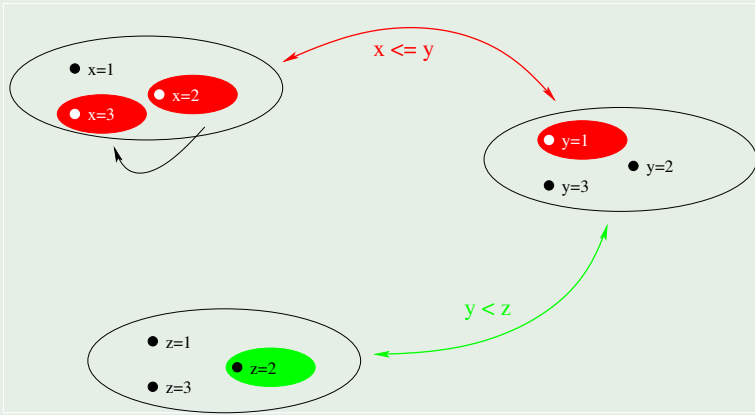
Unsatisfying assignment (the constraint $x \leq y$ is **violated**;
the decision variables x and y are **violating** wrt $x \leq y$):





Example $(x, y, z \in \{1, 2, 3\} \wedge x \leq y \wedge y < z)$

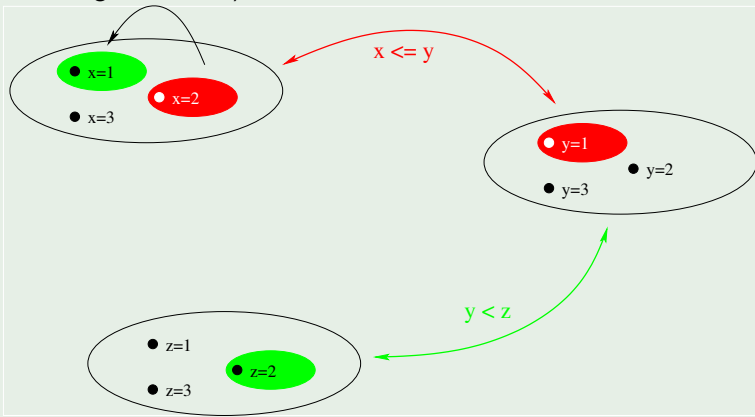
Candidate local move $x := 3$, reaching another unsatisfying assignment (the constraint $x \leq y$ is still **violated**; the decision variables x and y are still **violating** wrt $x \leq y$):





Example $(x, y, z \in \{1, 2, 3\} \wedge x \leq y \wedge y < z)$

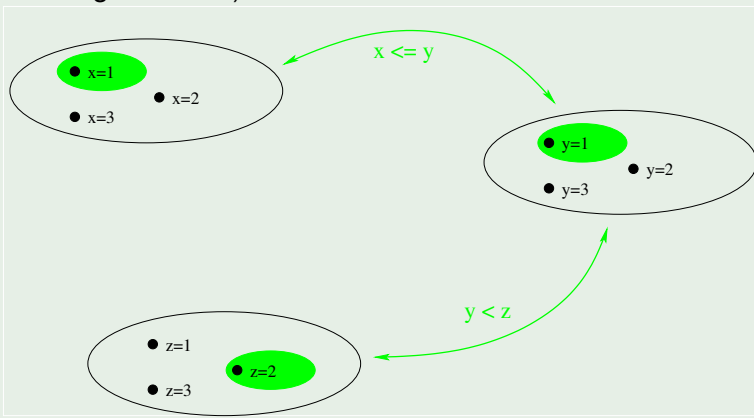
Another candidate local move $x := 1$, reaching a satisfying assignment (there are no more violated constraints or violating variables):





Example $(x, y, z \in \{1, 2, 3\} \wedge x \leq y \wedge y < z)$

Another candidate local move $x := 1$, reaching a **satisfying** assignment (there are no more violated constraints or violating variables):





Systematic search:

- + **Will** find an (optimal) solution, if one exists.
- + Will give a proof of unsatisfiability, otherwise.
- May take a **long time** to complete.
- Sometimes does not scale well to large instances.
- May need a lot of tweaking: branching heuristics, ...

Local search:

- + **May** find an (optimal) solution, if one exists.
- Can never give a proof of unsatisfiability, otherwise.
- Can never guarantee that the found solution is optimal.
- + Often scales well to large instances.
- May need a lot of tweaking: heuristics, parameters, ...

Local search trades completeness and quality for speed!



Local Search: Sample Heuristics

Example

Systematic (partial) exploration of the neighbourhood:

- **First improving neighbour**: Make the first move that improves on the current assignment.
- **Steepest/Gradient descent**: Make a random best move.
- **Min-conflict**: Make a random best move that modifies a violating variable.
- ...

Random walk:

- **Random improvement**: Select a random move and make it if it improves on the current assignment.
- ...



Local Search: Sample Meta-Heuristics

(Meta-) Heuristics for Local Search

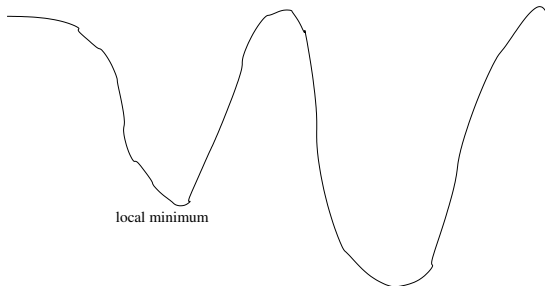
Constraint-Based Local Search

The Comet System

Bibliography

Meta-heuristics collect information on the moves made and are used for escaping **local minima** (of the weighted sum of the objective function and the total amount of violation of the constraints) and guiding the search towards global optima:

- Random restarts
- **Tabu search**
- **Simulated annealing**
- ...





Evaluation of Local Search

- It is **hard to reuse** (parts of) a local search algorithm of one problem for other problems.
- We want **reusable** software components!

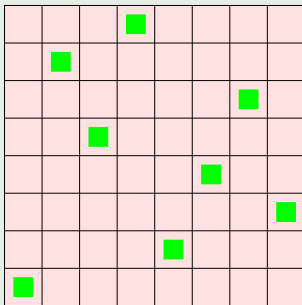
In **constraint-based local search (CBLS)**:

- A problem is modelled as a conjunction of **constraints**, which declaratively encapsulate inference algorithms specific to common combinatorial substructures and are thus reusable.
- A master search algorithm operates on the model, guided by user-indicated/designed (meta-)heuristics.

CBLS by itself makes **no** contributions to the design of local search (meta-)heuristics, but it facilitates their formulation and improves their reusability.



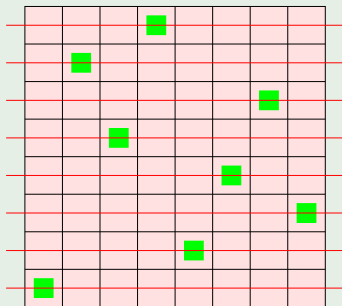
Example (8 Queens)



Place 8 queens on the chess board such that no two queens attack each other:



Example (8 Queens)

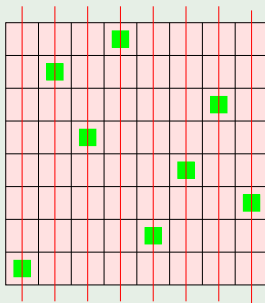


Place 8 queens on the chess board such that no two queens attack each other:

- 1 No two queens are on the same row.



Example (8 Queens)

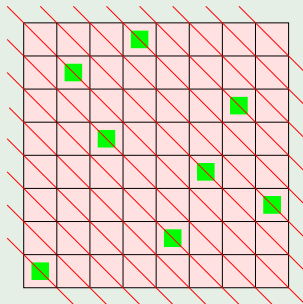


Place 8 queens on the chess board such that no two queens attack each other:

- 1 No two queens are on the same row.
- 2 No two queens are on the same column.



Example (8 Queens)

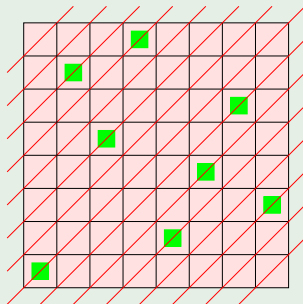


Place 8 queens on the chess board such that no two queens attack each other:

- 1 No two queens are on the same row.
- 2 No two queens are on the same column.
- 3 No two queens are on the same down diagonal.



Example (8 Queens)



Place 8 queens on the chess board such that no two queens attack each other:

- 1 No two queens are on the same row.
- 2 No two queens are on the same column.
- 3 No two queens are on the same down diagonal.
- 4 No two queens are on the same up diagonal.



Example (8 Queens: Model)

Let the row of the queen on column i be represented by a decision variable Q_i with values in $\{1, \dots, 8\}$:

- 1 No two queens are on the same row:
- 2 No two queens are on the same column:
- 3 No two queens are on the same down diagonal:
- 4 No two queens are on the same up diagonal:



Example (8 Queens: Model)

Let the row of the queen on column i be represented by a decision variable Q_i with values in $\{1, \dots, 8\}$:

- 1 No two queens are on the same row:

$$\forall i < j \in \{1, \dots, 8\} : Q_i \neq Q_j,$$

that is ALLDIFF($\{Q_1, \dots, Q_8\}$)

- 2 No two queens are on the same column:

- 3 No two queens are on the same down diagonal:

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\Rightarrow Guaranteed by the choice of the decision variables.

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\Rightarrow Guaranteed by the choice of the decision variables.

- 3 No two queens are on the same down diagonal:

$$\Rightarrow \forall i < j \in \{1, \dots, 8\} : Q_i - i \neq Q_j - j,$$

that is ALLDIFF($\{Q_1 - 1, \dots, Q_8 - 8\}$)

- 4 No two queens are on the same up diagonal:



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that is ALLDIFF($\{Q_1 - 1, \dots, Q_8 - 8\}$)

- 4 No two queens are on the same up diagonal:

$$\Rightarrow \forall i < j \in \{1, \dots, 8\} : Q_i + i \neq Q_j + j,$$

that is ALLDIFF($\{Q_1 + 1, \dots, Q_8 + 8\}$)



Constraints in Local Search

Every constraint is equipped with:

- A **constraint violation function**, which gives a measure of how much the constraint is violated under the current assignment: the violation is 0 if and only if the constraint is satisfied, and positive otherwise.
- A **variable violation function**, which gives a measure of how much a suitable change of a decision variable may decrease the constraint violation.
- ... (to be continued)

At the constraint system level:

- The **system constraint violation** of a constraint system $\{c_1, \dots, c_n\}$ is the sum of the violations of the c_j .
- The **system variable violation** of a variable is the sum of its variable violations in all the system constraints.



Violations

Example ($x \neq y$)

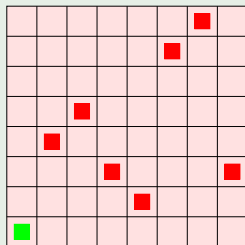
- When $x = 4$ and $y = 4$:
 - The constraint violation is 1: the constraint is violated.
 - The variable violations of x and y are both 1.
- When $x = 4$ and $y = 5$:
 - The constraint violation is 0: the constraint is satisfied.
 - The variable violations of x and y are both 0.

Example (ALLDIFFERENT($\{x_1, x_2, x_3, x_4\}$))

- When $x_1 = 5$, $x_2 = 5$, $x_3 = 5$, and $x_4 = 6$:
 - The constraint violation is 2, since at least two variables must be changed to reach a satisfying assignment.
 - The variable violations of x_1 , x_2 , and x_3 are 1.
 - The variable violation of x_4 is 0.



Example (8 Queens: Violations)

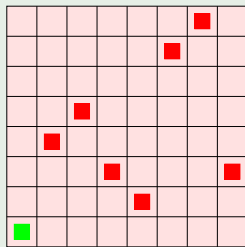


0 1 1 2 1 1 1 1 ← system variable violations

- 1 ALLDIFF($\{Q_1, \dots, Q_8\}$)
- 2 ALLDIFF($\{Q_1 - 1, \dots, Q_8 - 8\}$)
- 3 ALLDIFF($\{Q_1 + 1, \dots, Q_8 + 8\}$)



Example (8 Queens: Violations)

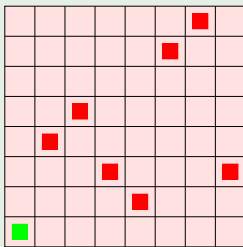


0 1 1 2 1 1 1 1 ← system variable violations

- 1 ALLDIFF($\{Q_1, \dots, Q_8\}$)
☞ Violation of ALLDIFF($\{8, 5, 4, 6, 7, 2, 1, 6\}$) is 1.
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- 3 ALLDIFF($\{Q_1 + 1, \dots, Q_8 + 8\}$)



Example (8 Queens: Violations)

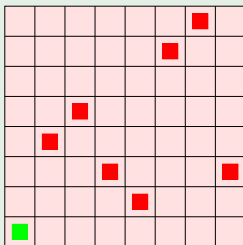


0 1 1 2 1 1 1 1 ← system variable violations

- 1** $\text{ALLDIFF}(\{Q_1, \dots, Q_8\})$
☞ Violation of $\text{ALLDIFF}(\{8, 5, 4, 6, 7, 2, 1, 6\})$ is 1.
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☞ Violation of $\text{ALLDIFF}(\{7, 3, 1, 2, 2, -4, -6, -2\})$ is 1.
- 3** $\text{ALLDIFF}(\{Q_1 + 1, \dots, Q_8 + 8\})$



Example (8 Queens: Violations)

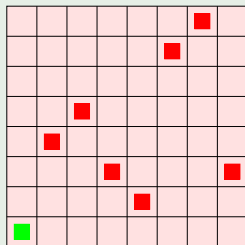


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- 3** $\text{ALLDIFF}(\{Q_1 + 1, \dots, Q_8 + 8\})$
☞ Violation of $\text{ALLDIFF}(\{9, 7, 7, 10, 12, 8, 8, 14\})$ is 2.



Example (8 Queens: Violations)



0 1 1 2 1 1 1 1 ← system variable violations

- 1** $\text{ALLDIFF}(\{Q_1, \dots, Q_8\})$
☞ Violation of $\text{ALLDIFF}(\{8, 5, 4, 6, 7, 2, 1, 6\})$ is 1.
- 2** $\text{ALLDIFF}(\{Q_1 - 1, \dots, Q_8 - 8\})$
☞ Violation of $\text{ALLDIFF}(\{7, 3, 1, 2, 2, -4, -6, -2\})$ is 1.
- 3** $\text{ALLDIFF}(\{Q_1 + 1, \dots, Q_8 + 8\})$
☞ Violation of $\text{ALLDIFF}(\{9, 7, 7, 10, 12, 8, 8, 14\})$ is 2.

The system constraint violation is $1 + 1 + 2 = 4$.



Constraints in Local Search (continued)

Every constraint is **also** equipped with:

- An **assignment delta function**, which gives the increase in constraint violation upon a probed $x := v$ assignment move for decision variable x and domain value v .
- A **swap delta function**, which gives the increase in constraint violation upon a probed $x :=: y$ swap move between two decision variables x and y .

The more negative a delta the better!

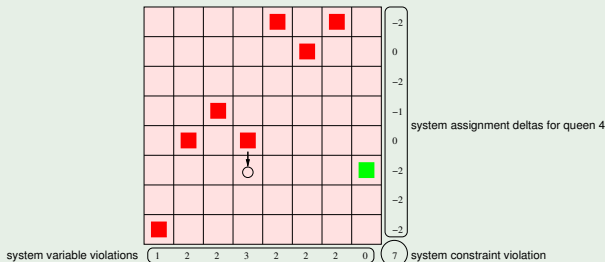
At the constraint system level:

- The **system assignment delta** of $x := v$ in a system $\{c_1, \dots, c_n\}$ is the sum of assignment deltas of all c_i .
- The **system swap delta** of $x :=: y$ in a system $\{c_1, \dots, c_n\}$ is the sum of the swap deltas of all c_i .

Other kinds of moves can be added.



Example (8 Queens: Differentiation)



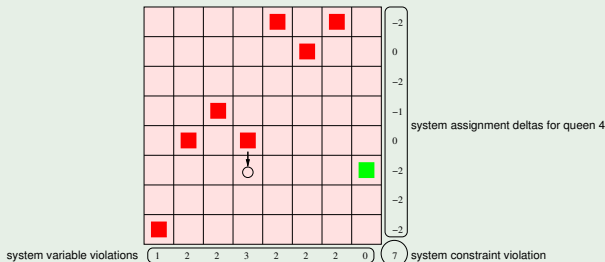
1 ALLDIFF($\{Q_1, \dots, Q_4, \dots, Q_8\}$)

2 ALLDIFF($\{Q_1 - 1, \dots, Q_4 - 4, \dots, Q_8 - 8\}$)

3 ALLDIFF($\{Q_1 + 1, \dots, Q_4 + 4, \dots, Q_8 + 8\}$)



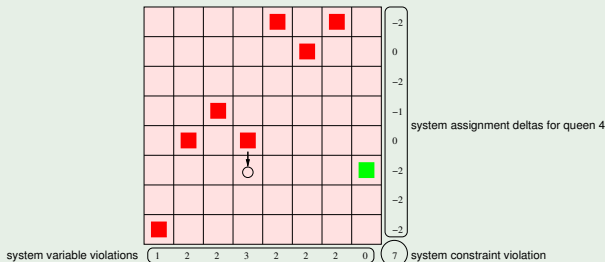
Example (8 Queens: Differentiation)



- 1 ALLDIFF($\{Q_1, \dots, Q_4, \dots, Q_8\}$)
 ↗ Delta of $Q_4 := 6$ in ALLDIFF($\{8, 5, 4, 5, 1, 2, 1, 6\}$) is ± 0 .
- 2 ALLDIFF($\{Q_1 - 1, \dots, Q_4 - 4, \dots, Q_8 - 8\}$)
- 3 ALLDIFF($\{Q_1 + 1, \dots, Q_4 + 4, \dots, Q_8 + 8\}$)



Example (8 Queens: Differentiation)



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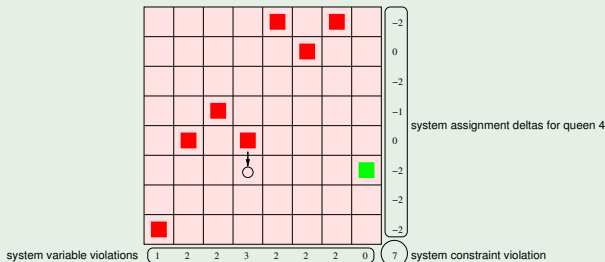
2 ALLDIFF($\{Q_1 - 1, \dots, Q_4 - 4, \dots, Q_8 - 8\}$)

☞ Delta of $Q_4 := 6$ in ALLDIFF($\{7, 3, 1, 1, -4, -4, -6, -2\}$) is -1 .

3 ALLDIFF($\{Q_1 + 1, \dots, Q_4 + 4, \dots, Q_8 + 8\}$)



Example (8 Queens: Differentiation)



$$1 \quad \text{ALLDIFF}(\{Q_1, \dots, Q_4, \dots, Q_8\})$$

☞ Delta of $Q_4 := 6$ in $\text{ALLDIFF}(\{8, 5, 4, 5, 1, 2, 1, 6\})$ is ± 0 .

$$2 \quad \text{ALLDIFF}(\{Q_1 - 1, \dots, Q_4 - 4, \dots, Q_8 - 8\})$$

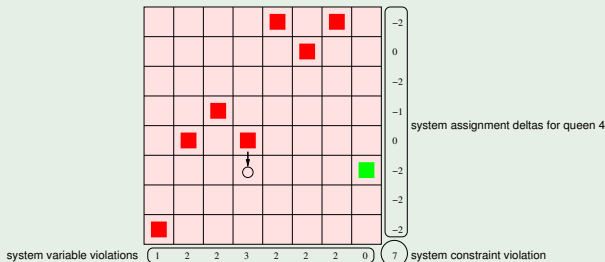
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$$3 \quad \text{ALLDIFF}(\{Q_1 + 1, \dots, Q_4 + 4, \dots, Q_8 + 8\})$$

☞ Delta of $Q_4 := 6$ in $\text{ALLDIFF}(\{9, 7, 7, 9, 6, 8, 8, 14\})$ is -1 .



Example (8 Queens: Differentiation)



$$1 \quad \text{ALLDIFF}(\{Q_1, \dots, Q_4, \dots, Q_8\})$$

☞ Delta of $Q_4 := 6$ in $\text{ALLDIFF}(\{8, 5, 4, 5, 1, 2, 1, 6\})$ is ± 0 .

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☞ Delta of $Q_4 := 6$ in $\text{ALLDIFF}(\{7, 3, 1, 1, -4, -4, -6, -2\})$ is -1 .

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☞ Delta of $Q_4 := 6$ in $\text{ALLDIFF}(\{9, 7, 7, 9, 6, 8, 8, 14\})$ is -1 .

The system assignment delta of $Q_4 := 6$ is $0 + (-1) + (-1) = -2$.



Constraints in Local Search (end)

- The functions equipping a constraint can be used to guide the local search:
 - The constraint violation function helps to **select a promising constraint** for selecting variable(s) to change in a move.
 - The variable violation function helps to **select promising variable(s)** to change in a move.
 - The delta functions help to make a **move in the good direction** for a constraint or variable.
- The violation functions are the counterpart of the subsumption checking of systematic search.
- The delta functions are the counterpart of the propagators of systematic search.
- These functions must be implemented for highest time/space efficiency, as they are queried in the exploration of the neighbourhood at each iteration.



The COMET System

COMET is a language and a tool for the modelling and solving of constraint problems.

COMET has a CBLIS back-end, as well as CP (systematic search with propagation) and MIP (mixed integer linear programming) back-ends:

- High-level software components (**constraints**) for representing constraint **models** of problems.
- High-level constructs for specifying **search** algorithms.
- An **open architecture** allowing user-defined extensions.

COMET (marketed by <http://dynadec.com/>) is free of charge for academic purposes.



Modelling in COMET

(Meta-)
Heuristics for
Local Search

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Bibliography

Example (8 Queens: COMET Model)

```
import cotls;  
Solver<LS> m();  
int n = 8;  
range Size = 1..n;  
UniformDistribution distr(Size);  
var{int} Q[Size](m,Size) := distr.get();  
ConstraintSystem<LS> S(m);  
S.post(alldifferent(Q));  
S.post(alldifferent(all(i in Size) Q[i]-i));  
S.post(alldifferent(all(i in Size) Q[i]+i));  
m.close();
```

Define an array of 8 decision variables and initialise each variable with a random value in the domain $\{1, \dots, 8\}$.



Constraint-Based Local Search in COMET

Example (8 Queens: COMET CBLS)

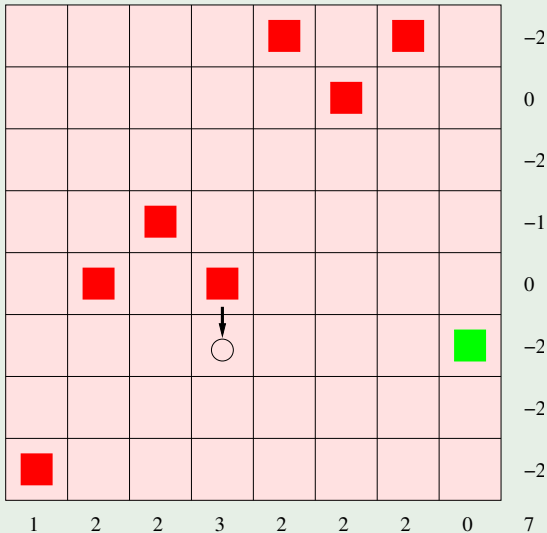
```
int iter = 0;
while (S.violations() > 0 && iter < 50 * n) {
  selectMax(i in 1..n)(S.violations(Q[i]))
  selectMin(r in 1..n)(S.getAssignDelta(Q[i],r))
  Q[i] := r;
  iter++;
}
```

In words:

while there are a violated constraint and iterations left **do**
 select a variable $Q[i]$ with the maximum system violation
 select a value r with the min system assignment delta for $Q[i]$
 assign value r to decision variable $Q[i]$
 increment the iteration counter

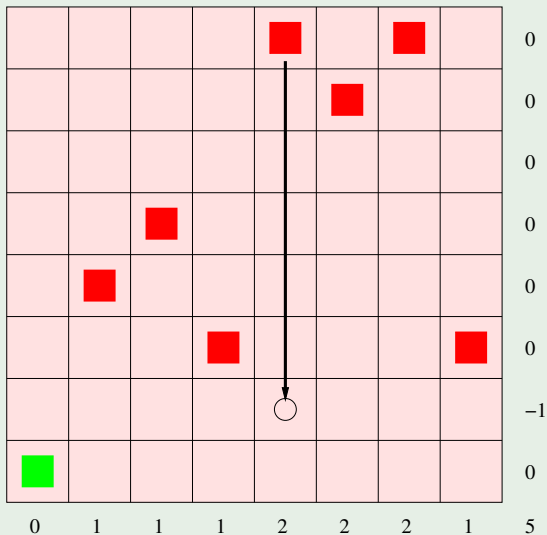


Example (8 Queens: Sample Run)



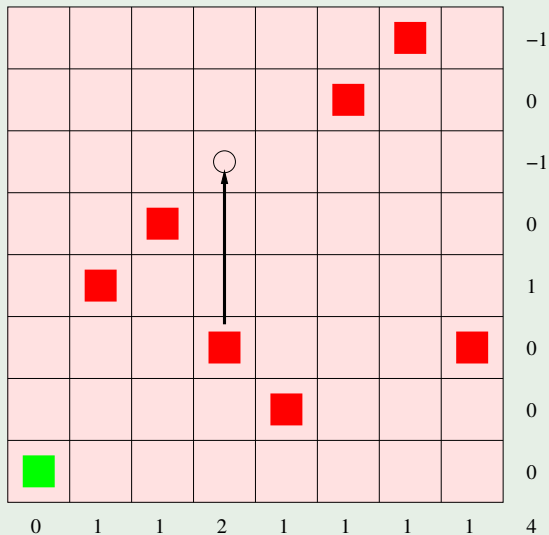


Example (8 Queens: Sample Run)





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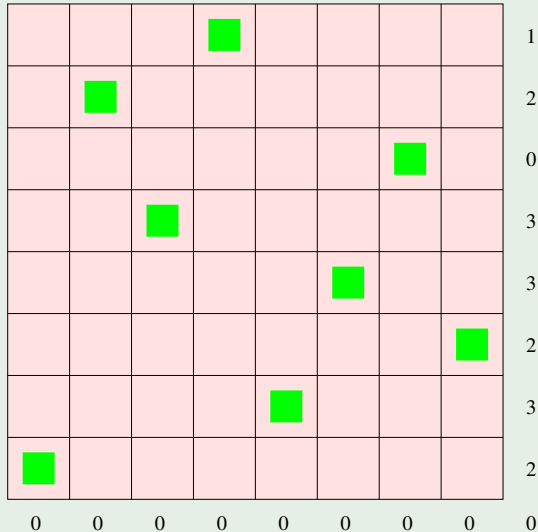


Example (8 Queens: Sample Run)

... and so on, until ...



Example (8 Queens: Sample Run)



(Meta-)
Heuristics for
Local Search

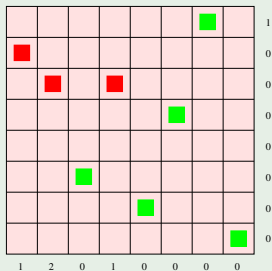
Constraint-
Based Local
Search

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Bibliography



Example (8 Queens: Local Minimum)



- Queen 2 is selected, as the only most violating queen.
- Queen 2 is placed on one of rows 2 to 8, as the system violation will increase by 1 if she is placed on row 1.
- Queen 2 remains the only most violating queen!
- Queen 2 is selected over and over again.



Reference

Some of the material in this presentation is inspired from:



Pascal Van Hentenryck and Laurent Michel.

[Constraint-Based Local Search.](#)

The MIT Press, 2005.

ISBN: 0-262-22077-6