Topic 17: Constraint-Based Local Search
(Version of 2nd November 2019)

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Course 1DL441:
Combinatorial Optimisation and Constraint Programming,
whose part 1 is Course 1DL451:
Modelling for Combinatorial Optimisation

1Based on an early version by Magnus Ågren (2008)
1. (Meta-) Heuristics for Local Search
   Local Search
   Heuristics
   - Example 1: Graph Partitioning
   - Example 2: Travelling Salesperson

   Meta-Heuristics

2. Constraint-Based Local Search
   Modelling
   Violation Functions
   Probing Functions
   Comparison with CP

3. Example: The Comet System

4. Hybrid Methods

5. Bibliography
Outline

1. (Meta-) Heuristics for Local Search
   Local Search
   Heuristics
     - Example 1: Graph Partitioning
     - Example 2: Travelling Salesperson
   Meta-Heuristics

2. Constraint-Based Local Search
   Modelling
   Violation Functions
   Probing Functions
   Comparison with CP

3. Example: The Comet System

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1. (Meta-) Heuristics for Local Search

Local Search Heuristics
- Example 1: Graph Partitioning
- Example 2: Travelling Salesperson

Meta-Heuristics

2. Constraint-Based Local Search Modelling

Violation Functions

Probing Functions

Comparison with CP

3. Example: The Comet System

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So Far: Inference + Systematic Search

- The variables become fixed 1-by-1.
- Stop when solution or unsatisfiability proof is obtained.
- Search space from a systematic-search viewpoint:
Now: Inference + Local Search

- All variables are **always** fixed, from initial assignment.
- Search proceeds by local moves: each move modifies the values of a few variables in the current assignment, and is selected upon probing the cost impacts of several candidate moves, called the neighbourhood.
- Stop when a good enough assignment has been found, or when an allocated resource has been exhausted, such as time spent or iterations made.
Example (BIBD: AED assignment after $i$ moves)

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3. Balance: Every grain pair is grown in 1 common plot. But, e.g., oats & rye are grown in $2 \neq 1$ common plots.
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1. **Equal growth load:** Every plot grows 3 grains. But plot5 grows $2 \neq 3$ grains; plot6 grows $4 \neq 3$ grains.

2. **Equal sample size:** Every grain is grown in 3 plots. Satisfied by initial assignment and each move: *implicit*.

3. **Balance:** Every grain pair is grown in 1 common plot. But, e.g., corn & oats are grown in $2 \neq 1$ common plots.

Selected move: let plot5 instead of plot6 grow corn.
### Example (BIBD: AED assignment after \( i + 2 \) moves)

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1. **Equal growth load:** Every plot grows 3 grains. Currently satisfied: **zero violation.**

2. **Equal sample size:** Every grain is grown in 3 plots. Satisfied by initial assignment and each move: **implicit.**

3. **Balance:** Every grain pair is grown in 1 common plot. Currently satisfied: **zero violation.**

**Stop search:** All constraints are satisfied (no optimisation).
Consider a constraint problem with constraints \( \{c_1, \ldots, c_n\} \) and optionally an objective function \( f \), which is here to be minimised, without loss of generality:

**Definition**

A **satisfying** (or **feasible**) assignment maps all the decision variables to domain values that satisfy all the constraints \( c_i \).

**Property:** A satisfying assignment actually is a solution to a constraint satisfaction problem (CSP), but it may be **sub-optimal** for a constrained optimisation problem (COP).

Assume function \( \text{COST} \) gives the cost of an assignment \( s \):

- **CSP:** \( \text{COST}(s) = \sum_{i=1}^{n} \text{VIOLATION}(c_i, s) \)
- **COP:** \( \text{COST}(s) = \alpha \cdot \sum_{i=1}^{n} \text{VIOLATION}(c_i, s) + \beta \cdot f(s) \)

for problem-specific \( \text{VIOLATION} \) and parameters \( \alpha \) and \( \beta \).
Definition

A soft constraint \( c \) has a function \( \text{VIOLATION}(c, s) \) that returns zero if \( c \) is satisfied under the assignment \( s \), else a positive value proportional to its dissatisfaction.

Example: \( \text{VIOLATION}(x \leq y, s) = \begin{cases} 0 & \text{if } s(x) \leq s(y) \\ s(x) - s(y) & \text{else} \end{cases} \)

Definition

A one-way constraint is kept satisfied during search, as one of its variables is defined by a total function on the others.

Example: For \( p = x \cdot y \): if \( x \) or \( y \) is reassigned by a move to assignment \( s \), then \( s(p) \) is to be set to \( s(x) \cdot s(y) \).

Definition

A violating variable in a constraint \( c \) unsatisfied, or violated, under assignment \( s \) can be reassigned, not necessarily within its domain, so that \( \text{VIOLATION}(c, s) \) decreases.
Example $(x, y, z \in \{1, 2, 3\} \land x \leq y \land y < z)$

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

$x=1$
$x=3$

$x=2$

$y=1$
$y=3$

$y=2$

$z=1$
$z=3$

$z=2$

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

$x \leq y$

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

Probed 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 \((x, y, z \in \{1, 2, 3\} \land x \leq y \land y < z)\)

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

\[
\begin{align*}
\text{Example (x, y, z ∈ \{1, 2, 3\} ∧ x ≤ y ∧ y < z)} & \\
\text{Another probed move } x := 1, \text{ reaching a satisfying} & \\
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Another probed move \(x := 1\), reaching a satisfying assignment (there are no more violated constraints or violating variables):

- \(x = 1\)
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- \(x = 3\)
- \(y = 1\)
- \(y = 2\)
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- \(z = 1\)
- \(z = 2\)
- \(z = 3\)

\(x \leq y\)

\(y < z\)
Systematic Search (as in SAT, SMT, MIP, CP):

+ 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: search strategies, . . .

Local Search: (Hoos and Stützle, 2004)

+ May find an (optimal) solution, if one exists.
  – Can rarely give a proof of unsatisfiability, otherwise.
  – Can rarely guarantee that a found solution is optimal.
+ Often scales much better to large instances.
  – May need a lot of tweaking: heuristics, parameters, . . .

Local search trades completeness and quality for speed!
Outline

1. (Meta-) Heuristics for Local Search
   - Local Search Heuristics
     - Example 1: Graph Partitioning
     - Example 2: Travelling Salesperson
   - Meta-Heuristics

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Local-Search Heuristics: Outline

- Start from an initial assignment.
- Iteratively move to a neighbour assignment.
- Aim for a satisfying assignment minimising COST.
- Main operation: Move from the current assignment to a selected assignment among its legal neighbours:

\[
\text{SELECT}(\text{LEGAL}(\text{NEIGHBOURS}(s),s),s)
\]

\[
\text{LEGAL}(\text{NEIGHBOURS}(s),s)
\]
Local-Search Heuristics: Generic Algorithm

\[ s := \text{INITIAL ASSIGNMENT()} \]
\[ k := 0; s^* := s \quad // s^* \text{ is the so far best assignment} \]
\[ \text{while } \sum_{i=1}^{n} \text{VIOLATION}(c_i, s) > 0 \text{ and } k < \mu \text{ do} \]
\[ k := k + 1; s := \text{SELECT(LEGAL(NEIGHBOURS(s), s), s)} \]
\[ \text{if } \text{COST}(s) < \text{COST}(s^*) \text{ then } s^* := s \]
\[ \text{return } s^* \]

where (may need a meta-heuristic to escape local optima):

- **NEIGHBOURS(s)** returns the neighbours of \( s \).
- **LEGAL(\( N \), s)** returns the legal neighbours in \( N \) w.r.t. \( s \).
- **SELECT(\( M \), s)** returns a selected element of \( M \) w.r.t. \( s \).
Examples (LEGAL)

Improving\((N, s) = \{n \in N \mid \text{COST}(n) < \text{COST}(s)\}\)

NonWorsening\((N, s) = \{n \in N \mid \text{COST}(n) \leq \text{COST}(s)\}\)

ViolatingVar\((N, s) = \{n \in N \mid n(x) \neq s(x) \text{ for a violating variable } x\}\)

All\((N, s) = N\)

Examples (SELECT)

First\((M, s) = \text{the first element in } M\)

Best\((M, s) = \text{random}\left(\left\{ n \in M \mid \text{COST}(n) = \min_{t \in M} \text{COST}(t) \right\}\right)\)

RandomImproving\((M, s) = \text{let } n = \text{random}(M) \text{ in if } \text{COST}(n) < \text{COST}(s) \text{ then } n \text{ else } s\)
Local Search: Sample Heuristics

Examples (Heuristics for SELECT ○ LEGAL)

Systematic (partial) exploration of the neighbourhood:
- First improving neighbour: First(Improving($N$, $s$), $s$)
- Steepest / Gradient descent: Best(Improving($N$, $s$), $s$)
- Min-conflict: Best(ViolatingVar($N$, $s$), $s$)
- . . .

Random walk (pick a neighbour and decide on selecting it):
- Random improvement: RandomImproving(All($N$, $s$), $s$)
- . . .
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     - Example 1: Graph Partitioning
     - Example 2: Travelling Salesperson
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Example (Graph Partitioning)

- **Problem:** Given a graph $G = (V, E)$, find a balanced partition $\langle P_1, P_2 \rangle$ of $V$ that minimises the number of edges with end-points in both $P_1$ and $P_2$.

- **Definition:** A balanced partition $\langle P_1, P_2 \rangle$ of $V$ satisfies $P_1 \cup P_2 = V$, $P_1 \cap P_2 = \emptyset$, and $-1 \leq |P_1| - |P_2| \leq 1$.

**Example:**

We now design a greedy local-search heuristic.
Example (Graph Partitioning: Choices)

1. The **initial assignment** (**INITIAL ASSIGNMENT**).

2. The **neighbourhood function** (**NEIGHBOURS**).

3. The **cost** of an assignment (**COST**).

4. The **legal-neighbour filtering function** (**LEGAL**).

5. The **neighbour selection function** (**SELECT**).
Example (Graph Partitioning: Choices)

1. The **initial assignment** \((\text{INITIAL}\text{ASSIGNMENT})\).
   A random balanced partition \(\langle P_1, P_2 \rangle\) of \(G = (V, E)\).

2. The **neighbourhood function** \((\text{NEIGHBOURS})\).

3. The **cost** of an assignment \((\text{COST})\).

4. The **legal-neighbour filtering function** \((\text{LEGAL})\).

5. The **neighbour selection function** \((\text{SELECT})\).
Example (Graph Partitioning: Choices)

1. The **initial assignment** (**INITIAL_ASSIGNMENT**). A random balanced partition \( \langle P_1, P_2 \rangle \) of \( G = (V, E) \).

2. The **neighbourhood function** (**NEIGHBOURS**). Swapping two vertices:

3. The **cost** of an assignment (**COST**).

4. The **legal-neighbour filtering function** (**LEGAL**).

5. The **neighbour selection function** (**SELECT**).
### Example (Graph Partitioning: Choices)

1. **The initial assignment** *(INITIAL ASSIGNMENT).*
   A random balanced partition $\langle P_1, P_2 \rangle$ of $G = (V, E)$.

2. **The neighbourhood function** *(NEIGHBOURS).*
   Swapping two vertices: $\text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{\langle P_1 \setminus \{a\} \cup \{b\}, P_2 \setminus \{b\} \cup \{a\} \rangle \mid a \in P_1 \land b \in P_2\}$

3. **The cost** of an assignment *(COST).*

4. **The legal-neighbour filtering function** *(LEGAL).*

5. **The neighbour selection function** *(SELECT).*
Example (Graph Partitioning: Choices)

1. The **initial assignment** (**INITIAL ASSIGNMENT**). A random balanced partition \( \langle P_1, P_2 \rangle \) of \( G = (V, E) \).

2. The **neighbourhood function** (**NEIGHBOURS**). Swapping two vertices: \( \text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{ \langle P_1 \setminus \{a\} \cup \{b\}, P_2 \setminus \{b\} \cup \{a\} \rangle \mid a \in P_1 \land b \in P_2 \} \)

3. The **cost** of an assignment (**COST**). The number of edges with end-points in both \( P_1 \) and \( P_2 \), as the balance constraints cannot be violated:

4. The **legal-neighbour filtering function** (**LEGAL**).

5. The **neighbour selection function** (**SELECT**).
Example (Graph Partitioning: Choices)

1. The **initial assignment** (INITIAL_ASSIGNMENT). A random balanced partition \( \langle P_1, P_2 \rangle \) of \( G = (V, E) \).

2. The **neighbourhood function** (NEIGHBOURS). Swapping two vertices: \( \text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{ \langle P_1 \setminus \{a\} \cup \{b\}, P_2 \setminus \{b\} \cup \{a\} \rangle \mid a \in P_1 \land b \in P_2 \} \)

3. The **cost** of an assignment (COST). The number of edges with end-points in both \( P_1 \) and \( P_2 \), as the balance constraints cannot be violated:
\[
\text{COST}(\langle P_1, P_2 \rangle) = f(\langle P_1, P_2 \rangle) = \left| \{(a, b) \in E \mid a \in P_1 \land b \in P_2 \} \right|
\]

4. The **legal-neighbour filtering function** (LEGAL).

5. The **neighbour selection function** (SELECT).
Example (Graph Partitioning: Choices)

1. The initial assignment (INITIAL_ASSIGNMENT). A random balanced partition \( \langle P_1, P_2 \rangle \) of \( G = (V, E) \).

2. The neighbourhood function (NEIGHBOURS). Swapping two vertices: \( \text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{ \langle P_1 \setminus \{ a \} \cup \{ b \}, P_2 \setminus \{ b \} \cup \{ a \} \rangle \mid a \in P_1 \land b \in P_2 \} \)

3. The cost of an assignment (COST). The number of edges with end-points in both \( P_1 \) and \( P_2 \), as the balance constraints cannot be violated: \( \text{COST}(\langle P_1, P_2 \rangle) = f(\langle P_1, P_2 \rangle) = \|\{(a, b) \in E \mid a \in P_1 \land b \in P_2\}\| \)

4. The legal-neighbour filtering function (LEGAL). The improving neighbours:

5. The neighbour selection function (SELECT).
Example (Graph Partitioning: Choices)

1. The **initial assignment** (INITIAL_ASSIGNMENT). A random balanced partition \( \langle P_1, P_2 \rangle \) of \( G = (V, E) \).

2. The **neighbourhood function** (NEIGHBOURS). Swapping two vertices: \( \text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{\langle P_1 \setminus \{a\} \cup \{b\}, P_2 \setminus \{b\} \cup \{a\} \rangle \mid a \in P_1 \land b \in P_2\} \)

3. The **cost** of an assignment (COST). The number of edges with end-points in both \( P_1 \) and \( P_2 \), as the balance constraints cannot be violated: \( \text{COST}(\langle P_1, P_2 \rangle) = f(\langle P_1, P_2 \rangle) = |\{(a, b) \in E \mid a \in P_1 \land b \in P_2\}| \)

4. The **legal-neighbour filtering function** (LEGAL). The improving neighbours: \( \text{LEGAL}(N, s) = \text{Improving}(N, s) \)

5. The **neighbour selection function** (SELECT).
Example (Graph Partitioning: Choices)

1. **The initial assignment** (INITIAL_ASSIGNMENT). A random balanced partition \(\langle P_1, P_2 \rangle\) of \(G = (V, E)\).

2. **The neighbourhood function** (NEIGHBOURS). Swapping two vertices: \(\text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{ \langle P_1 \setminus \{a\} \cup \{b\}, P_2 \setminus \{b\} \cup \{a\} \rangle \mid a \in P_1 \land b \in P_2 \}\).

3. **The cost** of an assignment (COST). The number of edges with end-points in both \(P_1\) and \(P_2\), as the balance constraints cannot be violated: \(\text{COST}(\langle P_1, P_2 \rangle) = f(\langle P_1, P_2 \rangle) = \mid \{ (a, b) \in E \mid a \in P_1 \land b \in P_2 \} \mid\).

4. **The legal-neighbour filtering function** (LEGAL). The improving neighbours: \(\text{LEGAL}(N, s) = \text{Improving}(N, s)\).

5. **The neighbour selection function** (SELECT). A random best legal neighbour:
Example (Graph Partitioning: Choices)

1. **The initial assignment** (INITIAL_ASSIGNMENT).
   A random balanced partition \( \langle P_1, P_2 \rangle \) of \( G = (V, E) \).

2. **The neighbourhood function** (NEIGHBOURS).
   Swapping two vertices: \( \text{NEIGHBOURS}(\langle P_1, P_2 \rangle) = \{\langle P_1 \setminus \{a\} \cup \{b\}, P_2 \setminus \{b\} \cup \{a\} \rangle | a \in P_1 \land b \in P_2\} \)

3. **The cost** of an assignment (COST).
   The number of edges with end-points in both \( P_1 \) and \( P_2 \), as the balance constraints cannot be violated:
   \( \text{COST}(\langle P_1, P_2 \rangle) = f(\langle P_1, P_2 \rangle) = \{|(a, b) \in E | a \in P_1 \land b \in P_2\}| \)

4. **The legal-neighbour filtering function** (LEGAL).
   The improving neighbours:
   \( \text{LEGAL}(N, s) = \text{Improving}(N, s) \)

5. **The neighbour selection function** (SELECT).
   A random best legal neighbour:
   \( \text{SELECT}(M, s) = \text{Best}(M, s) \)
Example (Graph Partitioning: Sample Run)

\[ f(<P1,P2>) = 5 \]
Example (Graph Partitioning: Sample Run)

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Example 2: Travelling Salesperson

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Example (Graph Partitioning: Sample Run)

Example 1: Graph Partitioning

Let $P_1$ and $P_2$ be two partitions of a graph. The function $f(<P_1,P_2>)$ represents the cost of partitioning.

- Initial state: $f(<P_1,P_2>) = 5$
- After partitioning: $f(<P_1,P_2>) = 2$
Example (Graph Partitioning: Sample Run)

and 22 other probed neighbours \( \langle P_1, P_2 \rangle \), but none of which with \( f(\langle P_1, P_2 \rangle) < 2 \)
Example (Graph Partitioning: Sample Run)

\[
f(<P_1,P_2>) = 5 \quad \text{and} \quad f(<P_1,P_2>) = 2\]

\[
\text{P1} \quad \text{P2}
\]

\[
\text{P1} \quad \text{P2}
\]
and 24 other probed neighbours \( \langle P_1, P_2 \rangle \), obviously none of which with \( f(\langle P_1, P_2 \rangle) < 0 \): the trivial lower bound was reached, so search can stop, with proven optimality (this is rare, in general)!
Example (Graph Partitioning)

**Fundamental property** of the chosen neighbourhood:
If an assignment \( s \) is a balanced partition, then each partition in \( \text{NEIGHBOURS}(s) \) is also balanced.

- Only satisfying assignments are considered, including the randomly generated initial assignment.
- The balance constraints are **not** checked explicitly.
- This is a common and often crucial technique: some constraints are **explicit** (either soft or one-way), while other constraints are **implicit**, in the sense that they are satisfied by the generated initial assignment and kept satisfied during search by the neighbourhood. Constraints are **hard** (either implicit or one-way) or **soft**.
- The size of the neighbourhood is \((|V| \div 2)^2\).
- The search space is **connected**: any optimal solution can be reached from any assignment.
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**Example (Travelling Salesperson)**

- **Problem**: Given a set of cities with connecting roads, find a tour (a Hamiltonian circuit) that visits each city exactly once, with the minimum travel distance.

- **Representation**: We see the set of cities as vertices $V$ and the set of roads as edges $E$ in a (not necessarily complete) undirected graph $G = (V, E)$.

**Example**:

We now design a greedy local-search heuristic.
Example (Travelling Salesperson: Choices)

1. The **initial assignment** \( (\text{INITIAL ASSIGNMENT}) \).

2. The **neighbourhood function** \( (\text{NEIGHBOURS}) \).

3. The **cost** of an assignment \( (\text{COST}) \).

4. The **legal-neighbour filtering function** \( (\text{LEGAL}) \).

5. The **neighbour selection function** \( (\text{SELECT}) \).
Example (Travelling Salesperson: Choices)

1. The initial assignment (INITIAL_ASSIGNMENT).
   A random edge set $s \subseteq E$ that forms a tour: NP-hard!

2. The neighbourhood function (NEIGHBOURS).

3. The cost of an assignment (COST).

4. The legal-neighbour filtering function (LEGAL).

5. The neighbour selection function (SELECT).
Example (Travelling Salesperson: Choices)

1. The initial assignment (INITIAL ASSIGNMENT).
   A random edge set $s \subseteq E$ that forms a tour: NP-hard!
   Complete $E$ by adding infinite-distance edges:
   now any random permutation of $V$ yields a tour.

2. The neighbourhood function (NEIGHBOURS).

3. The cost of an assignment (COST).

4. The legal-neighbour filtering function (LEGAL).

5. The neighbour selection function (SELECT).
Example (Travelling Salesperson: Choices)

1. The **initial assignment** (**INITIAL_ASSIGNMENT**). A random edge set $s \subseteq E$ that forms a tour: NP-hard! Complete $E$ by adding infinite-distance edges: now any random permutation of $V$ yields a tour.

2. The **neighbourhood function** (**NEIGHBOURS**). Replace two edges by two other edges so that the assignment remains a tour:

3. The **cost** of an assignment (**COST**).

4. The **legal-neighbour filtering function** (**LEGAL**).

5. The **neighbour selection function** (**SELECT**).
Example (Travelling Salesperson: Choices)

1. The **initial assignment** (**INITIAL_ASSIGNMENT**). A random edge set $s \subseteq E$ that forms a tour: NP-hard! Complete $E$ by adding infinite-distance edges: now any random permutation of $V$ yields a tour.

2. The **neighbourhood function** (**NEIGHBOURS**). Replace two edges by two other edges so that the assignment remains a tour: $\text{NEIGHBOURS}(s) = \{s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} | i, j \in V \text{ where } (i, j) \notin s\}$

3. The **cost** of an assignment (**COST**).

4. The **legal-neighbour filtering function** (**LEGAL**).

5. The **neighbour selection function** (**SELECT**).
Example (Travelling Salesperson: Choices)

1. **The initial assignment** \( \text{(INITIAL\text{ASSIGNMENT)}).} \)
   A random edge set \( s \subseteq E \) that forms a tour: NP-hard!
   Complete \( E \) by adding infinite-distance edges: now any random permutation of \( V \) yields a tour.

2. **The neighbourhood function** \( \text{(NEIGHBOURS).} \)
   Replace two edges by two other edges so that the assignment remains a tour: 
   \[
   \text{NEIGHBOURS}(s) = \{s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} \mid i, j \in V \text{ where } (i, j) \notin s\}
   \]

3. **The cost** of an assignment \( \text{(COST).} \)
   The sum of all distances, as the tour constraint cannot be violated:

4. **The legal-neighbour filtering function** \( \text{(LEGAL).} \)

5. **The neighbour selection function** \( \text{(SELECT).} \)
Example (Travelling Salesperson: Choices)

1. The **initial assignment** *(INITIAL_ASSIGNMENT)*.
   A random edge set \( s \subseteq E \) that forms a tour: NP-hard!
   Complete \( E \) by adding infinite-distance edges:
   now any random permutation of \( V \) yields a tour.

2. The **neighbourhood function** *(NEIGHBOURS)*.
   Replace two edges by two other edges so that the assignment remains a tour:
   \( \text{NEIGHBOURS}(s) = \{s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} | i, j \in V \text{ where } (i, j) \notin s\} \)

3. The **cost** of an assignment *(COST)*.
   The sum of all distances, as the tour constraint cannot be violated:
   \( \text{COST}(s) = f(s) = \sum_{(a, b) \in s} \text{Distance}(a, b) \)

4. The **legal-neighbour filtering function** *(LEGAL)*.

5. The **neighbour selection function** *(SELECT)*.
Example (Travelling Salesperson: Choices)

1. The **initial assignment** (**INITIAL ASSIGNMENT**). A random edge set \( s \subseteq E \) that forms a tour: NP-hard! Complete \( E \) by adding infinite-distance edges: now any random permutation of \( V \) yields a tour.

2. The **neighbourhood function** (**NEIGHBOURS**). Replace two edges by two other edges so that the assignment remains a tour: \( \text{NEIGHBOURS}(s) = \{ s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} | i, j \in V \text{ where } (i, j) \notin s \} \)

3. The **cost** of an assignment (**COST**). The sum of all distances, as the tour constraint cannot be violated: \( \text{COST}(s) = f(s) = \sum_{(a, b) \in s} \text{Distance}(a, b) \)

4. The **legal-neighbour filtering function** (**LEGAL**). The improving neighbours:

5. The **neighbour selection function** (**SELECT**).
Example (Travelling Salesperson: Choices)

1. The **initial assignment** (**INITIAL ASSIGNMENT**). A random edge set \( s \subseteq E \) that forms a tour: NP-hard! Complete \( E \) by adding infinite-distance edges: now any random permutation of \( V \) yields a tour.

2. The **neighbourhood function** (**NEIGHBOURS**). Replace two edges by two other edges so that the assignment remains a tour: 
\[
\text{NEIGHBOURS}(s) = \{s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} \mid i, j \in V \text{ where } (i, j) \notin s\}
\]

3. The **cost** of an assignment (**COST**). The sum of all distances, as the tour constraint cannot be violated: 
\[
\text{COST}(s) = f(s) = \sum_{(a, b) \in s} \text{Distance}(a, b)
\]

4. The **legal-neighbour filtering function** (**LEGAL**). The improving neighbours: 
\[
\text{LEGAL}(N, s) = \text{Improving}(N, s)
\]

5. The **neighbour selection function** (**SELECT**).
### Example (Travelling Salesperson: Choices)

1. The **initial assignment** (**INITIAL_ASSIGNMENT**).  
   A random edge set \( s \subseteq E \) that forms a tour: NP-hard!  
   Complete \( E \) by adding infinite-distance edges:  
   now any random permutation of \( V \) yields a tour.

2. The **neighbourhood function** (**NEIGHBOURS**).  
   Replace two edges by two other edges so that the  
   assignment remains a tour:  
   \[
   \text{NEIGHBOURS}(s) = \{ s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} \mid i, j \in V \text{ where } (i, j) \not\in s \}
   \]

3. The **cost** of an assignment (**COST**).  
   The sum of all distances, as the tour constraint cannot  
   be violated:  
   \[
   \text{COST}(s) = f(s) = \sum_{(a, b) \in s} \text{Distance}(a, b)
   \]

4. The **legal-neighbour filtering function** (**LEGAL**).  
   The improving neighbours:  
   \[
   \text{LEGAL}(N, s) = \text{Improving}(N, s)
   \]

5. The **neighbour selection function** (**SELECT**).  
   A random best legal neighbour:
Example (Travelling Salesperson: Choices)

1. The **initial assignment** (**INITIAL ASSIGNMENT**). A random edge set $s \subseteq E$ that forms a tour: NP-hard! Complete $E$ by adding infinite-distance edges: now any random permutation of $V$ yields a tour.

2. The **neighbourhood function** (**NEIGHBOURS**). Replace two edges by two other edges so that the assignment remains a tour: $\text{NEIGHBOURS}(s) = \{s \setminus \{(i, i'), (j, j')\} \cup \{(i, j), (i', j')\} | i, j \in V \text{ where } (i, j) \notin s\}$

3. The **cost** of an assignment (**COST**). The sum of all distances, as the tour constraint cannot be violated: $\text{COST}(s) = f(s) = \sum_{(a, b) \in s} \text{Distance}(a, b)$

4. The **legal-neighbour filtering function** (**LEGAL**). The improving neighbours: $\text{LEGAL}(N, s) = \text{Improving}(N, s)$

5. The **neighbour selection function** (**SELECT**). A random best legal neighbour: $\text{SELECT}(M, s) = \text{Best}(M, s)$
Example (Travelling Salesperson: Sample Run)

Three consecutive improving satisfying assignments:

- First assignment: s: s: 12
  - f(s) = 709
- Second assignment: s: s: 12
  - f(s) = 656
- Third assignment: s: s: 12
  - f(s) = 530
Example (Travelling Salesperson)

**Fundamental property** of the chosen neighbourhood:
If an assignment \( s \) is a tour,
then each assignment in \( \text{NEIGHBOURS}(s) \) is also a tour.

- Only satisfying assignments are considered, including the randomly generated initial assignment, but sub-optimality surely occurs if some of the added infinite-distance edges are used.
- The tour constraint is not checked explicitly.
- Making all constraints implicit is not always possible: moves to unsatisfying assignments must also be considered (as discussed in the next section).
- This neighbourhood is called 2-opt: two edges on the current tour are replaced.
- The size of the neighbourhood is \( |V| \cdot (|V| - 2) \), that is \( 6 \cdot 4 = 24 \) neighbours for our instance.
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Heuristics drive the search to (good enough) solutions:
- Which decision variables are modified in a move?
- Which new values do they get in the move?

Meta-heuristics drive the search to global optima of \textit{Cost}:
- Avoid cycles of moves & escape local optima of \textit{Cost}.
- Explore many parts of the search space.
- Focus on promising parts of the search space.
Examples (Meta-heuristics)

- **Tabu search** (1986):
  forbid recent moves from being done again.

- **Simulated annealing** (1983):
  consider random moves and make worsening ones with a probability that decreases over time.

- **Genetic algorithms** (1975):
  use a pool of current assignments and cross them.
In order to escape local optima, we must be able to accept worse assignments, that is assignments that increase the value of $\text{COST}$.

To avoid ending up in cycles, tabu search remembers the last $\lambda$ assignments in a tabu list and makes them tabu (or taboo): moves in this list cannot be chosen, even if this implies increasing the value of $\text{COST}$.
Tabu Search

\[ s := \text{INITIAL\textsc{Assignment}}() \]
\[ k := 0; s^* := s \quad // s^* \text{ is the so far best assignment} \]
\[ \tau := [s] \quad // \text{initialise the tabu list} \]

\textbf{while} \( \sum_{i=1}^{n} \text{VIOLATION}(c_i, s) > 0 \land k < \mu \) \textbf{do}

\[ k := k + 1; s := \text{Best(NonTabu(NEIGHBOURS(s), \tau), \tau)} \]
\[ \tau := \tau :: s \quad // \text{but keep only the last } \lambda \text{ assignments} \]
\textbf{if} \( \text{COST}(s) < \text{COST}(s^*) \) \textbf{then}

\[ s^* := s \]

\textbf{return} \quad s^*

\textbf{function} \text{NonTabu}(N, \tau)
\textbf{return} \quad \{ n \in N \mid n \notin \tau \}
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Evaluation of Local Search

We have seen local-search algorithms for two problems:

- 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) (Van Hentenryck and Michel, 2005):

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

CBLS by itself makes no contributions to the state of the art of neighbourhoods, heuristics, and meta-heuristics, but it simplifies their formulation and improves their reusability.
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Definition

Each constraint predicate has a violation function: the violation of a constraint is zero if it is currently satisfied, else a positive value proportional to its dissatisfaction.

Example

For $a \leq b$, let $\alpha$ and $\beta$ be the current values of $a$ and $b$: define the violation to be $\alpha - \beta$ if $\alpha \nleq \beta$, and 0 otherwise.

Definition

A constraint with violation is explicit in a CBLS model and soft: it can be violated during search but ought to be satisfied in a solution.

The constraint violations are queried during search.
Definition

A **one-way constraint** is explicit in a CBLS model and **hard**: it is kept satisfied during search by the solver.

Example

For \( p = a \times b \), whenever the value \( \alpha \) of \( a \) or the value \( \beta \) of \( b \) is modified by a move, the value of \( p \) is automatically modified by the solver so as to remain equal to \( \alpha \cdot \beta \).

CBLS solvers offer a syntax for one-way constraints, such as \( p <= a \times b \) in OscaR.cbls, but CP solvers (such as Gecode) and technology-independent modelling languages (such as MiniZinc) do not make such a distinction.
**Definition**

An **implicit constraint** is not in a CBLS model but hard: it is kept satisfied during search by choosing a satisfying initial assignment and only making satisfaction-preserving moves, by the use of a **constraint-specific neighbourhood**.

**Example**

For **all_different** when there are as many variables as values: the initial assignment gives distinct values to all the variables (by random permutation), and the neighbourhood only has moves that swap the values of two variables.

When building a CBLS model, a MiniZinc backend must:

- Aptly assort the otherwise all explicit & soft constraints.
- Add suitable neighbourhood, heuristic, meta-heuristic.

This is **much** more involved than just flattening and solving.
Example (8 Queens)

Place 8 queens on a chess board such that no two queens attack each other:
Example (8 Queens)

Place 8 queens on a 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 a 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 a 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 a 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: CBLS Models)

Let variable $R[i]$ represent the row of the queen in col. $i$:

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: CBLS Models)

Let variable $R[i]$ represent the row of the queen in col. $i$:

1. No two queens are on the same row:
   \[ \forall i, j \in 1..8 \text{ where } i < j : R[i] \neq R[j], \]
   that is distinct([$R[1], \ldots, R[8]$])

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: CBLS Models)

Let variable $R[i]$ represent the row of the queen in col. $i$:

1. No two queens are on the same row:
   $\forall i, j \in 1..8 \ where \ i < j : R[i] \neq R[j],$
   that is $\text{distinct}([R[1], \ldots, R[8]])$

2. No two queens are on the same column:
   Guaranteed by the choice of the decision variables.

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

4. No two queens are on the same up-diagonal:
Example (8 Queens: CBLS Models)

Let variable $R[i]$ represent the row of the queen in col. $i$:

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   that is $\text{distinct}([R[1], \ldots, R[8]])$

2. No two queens are on the same column: Guaranteed by the choice of the decision variables.

3. No two queens are on the same down-diagonal:
   $\forall i, j \in 1..8 \text{ where } i < j : R[i] - i \neq R[j] - j,$
   that is $\text{distinct}([R[1] - 1, \ldots, R[8] - 8])$

4. No two queens are on the same up-diagonal:
Example (8 Queens: CBLS Models)

Let variable $R[i]$ represent the row of the queen in col. $i$:

1. No two queens are on the same row:
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   that is $\text{distinct}([R[1], \ldots, R[8]])$

2. No two queens are on the same column:
   Guaranteed by the choice of the decision variables.

3. No two queens are on the same down-diagonal:
   \[ \forall i, j \in 1..8 \text{ where } i < j : R[i] - i \neq R[j] - j, \]
   that is $\text{distinct}([R[1] - 1, \ldots, R[8] - 8])$

4. No two queens are on the same up-diagonal:
   \[ \forall i, j \in 1..8 \text{ where } i < j : R[i] + i \neq R[j] + j, \]
   that is $\text{distinct}([R[1] + 1, \ldots, R[8] + 8])$
Example (8 Queens: CBLS Models)

Let variable $R[i]$ represent the row of the queen in col. $i$:

1. No two queens are on the same row:
   \[ \forall i, j \in 1..8 \text{ where } i < j : R[i] \neq R[j], \]
   that is distinct([$R[1]$, ..., $R[8]$])

2. No two queens are on the same column:
   Guaranteed by the choice of the decision variables.

3. No two queens are on the same down-diagonal:
   \[ \forall i, j \in 1..8 \text{ where } i < j : R[i] - i \neq R[j] - j, \]
   that is distinct([$R[1] - 1$, ..., $R[8] - 8$])

4. No two queens are on the same up-diagonal:
   \[ \forall i, j \in 1..8 \text{ where } i < j : R[i] + i \neq R[j] + j, \]
   that is distinct([$R[1] + 1$, ..., $R[8] + 8$])

Better model: Make the row constraint implicit, by using a random permutation of 1..8 as initial assignment and using a neighbourhood that keeps the row constraint satisfied.
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**Constraint Predicates in Local Search**

The predicate of a soft constraint \( c \) is equipped with:

- **A constraint violation function** \( \text{VIOLATION}(c, s) \), which estimates how much \( c \) is violated under the current assignment \( s \): \( \text{VIOLATION}(c, s) = 0 \) if and only if \( c \) is satisfied, and \( \text{VIOLATION}(c, s) > 0 \) otherwise.

- **A variable violation function** \( \text{VIOLATION}(c, s, x) \), which estimates how much a suitable change of the value of the decision variable \( x \) can decrease \( \text{VIOLATION}(c, s) \).

. . . (to be continued)

At the constraint-system level, one can query:

- **The system constraint violation** under \( s \) of a constraint system \( \{c_1, \ldots, c_n\} \) is \( \sum_{i=1}^{n} \text{VIOLATION}(c_i, s) \).

- **The system variable violation** under \( s \) of a variable \( x \) in a system \( \{c_1, \ldots, c_n\} \) is \( \sum_{i=1}^{n} \text{VIOLATION}(c_i, s, x) \).
Example \((x \neq y)\)

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.

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.

Example \((\text{distinct}([a, b, c, d]))\)

When \(a = 5\), \(b = 5\), \(c = 5\), \(d = 6\), all with domain \(D\):
- The constraint violation is 2, since at least two variables must be changed to reach a satisfying assignment:
  \[\text{VIOLATION} = \sum_{v \in D} \max(\text{occ}[v] - 1, 0),\]
  where \(\text{occ}[v]\) stores the current number of occurrences of value \(v\).
- The variable violations of \(a\), \(b\), \(c\) are 1, and 0 for \(d\).
Let the upper-left corner have the coordinates $(1, 1)$:

- $\text{distinct}([R[1], \ldots, R[8]])$
- $\text{distinct}([R[1] - 1, \ldots, R[8] - 8])$
- $\text{distinct}([R[1] + 1, \ldots, R[8] + 8])$
Let the upper-left corner have the coordinates \((1, 1)\):

- \(\text{distinct}([R[1], \ldots, R[8]])\)
  
  The violation of \(\text{distinct}([8, 5, 4, 6, 7, 2, 1, 6])\) is 1.

- \(\text{distinct}([R[1] - 1, \ldots, R[8] - 8])\)

- \(\text{distinct}([R[1] + 1, \ldots, R[8] + 8])\)
Example (8 Queens: Violations)

Let the upper-left corner have the coordinates $(1, 1)$:

- $\text{distinct}([R[1], \ldots, R[8]])$
  The violation of $\text{distinct}([8, 5, 4, 6, 7, 2, 1, 6])$ is 1.

- $\text{distinct}([R[1] - 1, \ldots, R[8] - 8])$
  The violation of $\text{distinct}([7, 3, 1, 2, 2, -4, -6, -2])$ is 1.

- $\text{distinct}([R[1] + 1, \ldots, R[8] + 8])$
Let the upper-left corner have the coordinates \((1, 1)\):

- \(\text{distinct}([R[1], \ldots, R[8]])\)
  The violation of \(\text{distinct}([8, 5, 4, 6, 7, 2, 1, 6])\) is 1.

- \(\text{distinct}([R[1] - 1, \ldots, R[8] - 8])\)
  The violation of \(\text{distinct}([7, 3, 1, 2, 2, -4, -6, -2])\) is 1.

- \(\text{distinct}([R[1] + 1, \ldots, R[8] + 8])\)
  The violation of \(\text{distinct}([9, 7, 7, 10, 12, 8, 8, 14])\) is 2.
Let the upper-left corner have the coordinates \((1, 1)\):

- \(\text{distinct}([R[1], \ldots, R[8]])\)
  The violation of \(\text{distinct}([8, 5, 4, 6, 7, 2, 1, 6])\) is 1.

- \(\text{distinct}([R[1] - 1, \ldots, R[8] - 8])\)
  The violation of \(\text{distinct}([7, 3, 1, 2, 2, -4, -6, -2])\) is 1.

- \(\text{distinct}([R[1] + 1, \ldots, R[8] + 8])\)
  The violation of \(\text{distinct}([9, 7, 7, 10, 12, 8, 8, 14])\) is 2.

The system constraint violation is \(1 + 1 + 2 = 4\).
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Constr. Predicates in Local Search (cont’d)

The predicate of a soft constraint \( c \) is also equipped with:

- An assignment delta function \( \text{DELTA}(c, s, x := v) \), which estimates the increase of \( \text{VIOLATION}(c, s) \) upon a probed \( x := v \) assignment move for variable \( x \) and its domain value \( v \).

- A swap delta function \( \text{DELTA}(c, s, x :=: y) \), which estimates the increase of \( \text{VIOLATION}(c, s) \) upon a probed \( x :=: y \) swap move for two variables \( x \) and \( y \).

The more negative a delta the better the probed move!

At the constraint-system level, one can query:

- The system assignment delta under \( s \) of \( x := v \) in a system \( C \subseteq \{c_1, \ldots, c_n\} \) is \( \sum_{c \in C} \text{DELTA}(c, s, x := v) \).

- The system swap delta under \( s \) of \( x :=: y \) in a system \( C \subseteq \{c_1, \ldots, c_n\} \) is \( \sum_{c \in C} \text{DELTA}(c, s, x :=: y) \).

Other kinds of moves can be added.
Example (8 Queens: Computing Deltas in $\mathcal{O}(1)$ Time)

- $\text{distinct}([R[1], \ldots, R[4], \ldots, R[8]])$
- $\text{distinct}([R[1] + 1, \ldots, R[4] + 4, \ldots, R[8] + 8])$

The violation increases by $[\text{occ}[v] \geq 1] - [\text{occ}[s(x)] \geq 2]$ upon $x := v$. 
Example (8 Queens: Computing Deltas in $O(1)$ Time)

\[
\text{system assignment deltas for queen 4}
\begin{array}{cccccc}
1 & 2 & 2 & 2 & 2 & 2 \\
-2 & -2 & -2 & 0 & 0 & 3 \\
\end{array}
\]
\[
\text{system constraint violation} = 2 + 2 + 3
\]

- \(\text{distinct}([R[1], \ldots, R[4], \ldots, R[8]])\)
  Delta of \(R[4] := 6\) in \(\text{distinct}([8, 5, 4, 5, 1, 2, 1, 6])\) is \(\pm 0\).


The violation increases by \([\text{occ}[v] \geq 1] - [\text{occ}[s(x)] \geq 2]\) upon \(x := v\).
Example (8 Queens: Computing Deltas in $O(1)$ Time)

- $\text{distinct}([R[1], \ldots, R[4], \ldots, R[8]])$
  Delta of $R[4] := 6$ in $\text{distinct}([8, 5, 4, 5, 1, 2, 1, 6])$ is $\pm 0$.

  Delta of $R[4] := 6$ in $\text{distinct}([7, 3, 1, 1, -4, -4, -6, -2])$ is $-1$.

- $\text{distinct}([R[1] + 1, \ldots, R[4] + 4, \ldots, R[8] + 8])$

The violation increases by $[\text{occ}[v] \geq 1] - [\text{occ}[s(x)] \geq 2]$ upon $x := v$. 
Example (8 Queens: Computing Deltas in $\mathcal{O}(1)$ Time)

- $\text{distinct}([R[1], \ldots, R[4], \ldots, R[8]])$
  
  Delta of $R[4] := 6$ in $\text{distinct}([8, 5, 4, 5, 1, 2, 1, 6])$ is $\pm 0$.

  
  Delta of $R[4] := 6$ in $\text{distinct}([7, 3, 1, 1, -4, -4, -6, -2])$ is $-1$.

- $\text{distinct}([R[1] + 1, \ldots, R[4] + 4, \ldots, R[8] + 8])$
  
  Delta of $R[4] := 6$ in $\text{distinct}([9, 7, 7, 9, 6, 8, 8, 14])$ is $-1$.

The violation increases by $[\text{occ}[v] \geq 1] - [\text{occ}[s(x)] \geq 2]$ upon $x := v$. 
Example (8 Queens: Computing Deltas in $O(1)$ Time)

- $\text{distinct}([R[1], \ldots, R[4], \ldots, R[8]])$
  - Delta of $R[4] := 6$ in $\text{distinct}([8, 5, 4, 5, 1, 2, 1, 6])$ is $\pm 0$.

  - Delta of $R[4] := 6$ in $\text{distinct}([7, 3, 1, 1, -4, -4, -6, -2])$ is $-1$.

- $\text{distinct}([R[1] + 1, \ldots, R[4] + 4, \ldots, R[8] + 8])$
  - Delta of $R[4] := 6$ in $\text{distinct}([9, 7, 7, 9, 6, 8, 8, 14])$ is $-1$.

The system assignment delta of $R[4] := 6$ is $0 + (-1) + (-1) = -2$. 
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The functions equipping a constraint predicate can be queried in order to guide the local search:

- The constraint violation functions can be queried to find promising constraint(s) in order to select promising decision variable(s) to reassign in a move.
- The variable violation functions can be queried to select promising decision variable(s) to reassign in a move.
- The probing functions can be queried to select a move in a good direction for a variable or constraint (system).

The violation functions are the counterpart of the subsumption checking of systematic CP-style solving.

The probing functions are the counterpart of the propagators of systematic CP-style solving.

These functions must be implemented for highest time and space efficiency, as they may be queried in the probing of the neighbourhood at each search iteration.
Symmetry Handling in Local Search

When solving combinatorial problems by local search, the idea is often to exploit the presence of symmetries by doing nothing, rather than by making the search space smaller, as with CP / MIP / SAT / SMT-style systematic search.
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The Comet System

Comet was a language and a tool for the modelling and solving of constraint problems.

Comet had a CBLS back-end (Van Hentenryck and Michel, 2005), as well as CP (systematic search with propagation) and MIP (mixed integer linear programming) back-ends:

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

Comet was free of charge for academic purposes. It inspired, among others, the CBLS back-end of OscaR, available for free at https://oscarlib.bitbucket.io.
Example (8 Queens: Comet CBLS Model)

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

Define an array $R$ of 8 variables and initialise each variable with a random (possibly repeated) value in the domain 1..8.

Better: Make the constraint $\text{alldifferent}(R)$ implicit, by using a random permutation of 1..8 as initial assignment.
Example (8 Queens: Comet CBLS Search)

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

In words:
initialise the iteration counter to zero
while there are a violated constraint in system S and iterations left do
select a variable \( R[i] \) with the maximum violation in system S
select a value \( r \) with the minimum assignment delta for \( R[i] \) in S
assign value \( r \) to decision variable \( R[i] \)
increment the iteration counter

Better (continued): Keep the row constraint satisfied by a neighbourhood of swap moves \( R[i] := R[j] \).
Example (8 Queens: Sample Run)
Example (8 Queens: Sample Run)
Example (8 Queens: Sample Run)
Example (8 Queens: Sample Run)

... and so on, until ...
Example (8 Queens: Sample Run)
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.

A meta-heuristic is needed to escape this local minimum.
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Compare with the generic algorithm of slide 16:

Example (Large Neighbourhood Search (Shaw, 1998))

\[
\begin{align*}
p & := \text{the CSP where all variables have their full domains} \\
s & := \text{First} (\text{Solutions}(p)) \quad \text{// systematic search} \\
k & := 0; \ s^* := s \quad \text{// } s^* \text{ is the so far best assignment} \\
\textbf{while } k < \mu \textbf{ do} \\
& \quad k := k + 1 \\
p & := \text{the COP where some variables are frozen} \\
\text{ (e.g., fixed to their values in } s^* \text{), the other variables} \\
\text{are thawed (e.g., have their full domains), and the} \\
\text{objective function is strictly bounded by } f(s^*) \\
s & := \text{Select} (\text{Solutions}(p), -) \quad \text{// limited syst. search} \\
\textbf{if } s \text{ exists } \textbf{then } s^* := s \\
\textbf{return } s^*
\end{align*}
\]
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