Constraint Satisfaction Problems
Global Constraints

Stefan Wölfl, Christian Becker-Asano, and Bernhard Nebel
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1 Motivation

- Global Constraints
- All-different
- Sum and Cardinality
- Circuit
Global constraints

What are global constraints?

- Type of similar constraint relations . . .
- . . . differing in the number of variables
- **Semantically redundant**: same constraint can be expressed by a conjunction of simpler constraints
- **Similar structure**: can be exploited by constraint solvers

Examples:

- sum constraint, knapsack constraint, element constraint, all-different constraint, cardinality constraints
All-different constraint

Definition

Let $v_1, \ldots, v_n$ be variables each with a domain $D_i \ (1 \leq i \leq n)$.

$$\text{alldifferent}(v_1, \ldots, v_n) := \{(d_1, \ldots, d_n) \in D_1 \times \cdots \times D_n : d_i \neq d_j \text{ for } i \neq j\}$$

The all-different constraint is a simple, but widely used global constraint in constraint programming.

It allows for compact modeling of CSP problems.
Example: $n$-Queens Problem

No-attack constraints:

\[ v_i \neq v_j \text{ for } 1 \leq i < j \leq n \]
\[ v_i - v_j \neq i - j \text{ for } 1 \leq i < j \leq n \]
\[ v_j - v_i \neq i - j \text{ for } 1 \leq i < j \leq n \]

Abbildung: 4-queens problem

Problem representation:

Variables $v_i$ for each column $1, \ldots, n$; $v_i$ can take a “row value” $1, \ldots, n$.

\[ \text{alldifferent}(v_1, \ldots, v_n) \]
\[ \text{alldifferent}(v_1 - 1, \ldots, v_n - n) \]
\[ \text{alldifferent}(v_1 + 1, \ldots, v_n + n) \]
Let $v_1, \ldots, v_n, z$ be variables with subsets of $\mathbb{Q}$ as domain. For each $v_i$, let $c_i \in \mathbb{Q}$ be some fixed scalar, $c = (c_1, \ldots, c_n)$.

**Definition**

The **sum constraint** is defined as:

$$\text{sum}(v_1, \ldots, v_n, z; c) := \{(d_1, \ldots, d_n, d) \in \left( \prod_{1 \leq i \leq n} D_i \right) \times D_z : d = \sum_{1 \leq i \leq n} c_id_i\}.$$
Global cardinality constraint

\( v_1, \ldots, v_n: \) “assignment variables” with \( D_{v_i} \subseteq \{d_1^*, \ldots, d_m^*\} \).

\( c_1, \ldots, c_m: \) “count variables” with sets of integers as domains.

**Definition**

The **global cardinality constraint** is defined as:

\[
gcc(v_1, \ldots, v_n, c_1, \ldots, c_m) := \{ (d_1, \ldots, d_n, o_1, \ldots, o_m) \in \prod_{1 \leq i \leq n} D_{v_i} \times \prod_{1 \leq j \leq m} D_{c_j} : \\
\text{for each } j, \ d_j^* \text{ occurs in } (d_1, \ldots, d_n) \text{ exactly } o_j \text{ times}\}
\]

The global cardinality constraint can be considered a generalization of the all-different constraint.
Motivation

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Circuit constraint

Let \( s = (s_1, \ldots, s_n) \) be a permutation of \( \{1, \ldots, n\} \).
Define \( C_s \) as the smallest set that contains 1 and with each element \( i \) also \( s_i \).
\((s_1, \ldots, s_n)\) is called cyclic if \( C_s = \{1, \ldots, n\} \).

Definition

Let \( v_1, \ldots, v_n \) be variables with domains \( D_i = \{1, \ldots, n\} \) \((1 \leq i \leq n)\).

\[
\text{circuit}(v_1, \ldots, v_n) := \left\{ (d_1, \ldots, d_n) \in D_1 \times \cdots D_n : (d_1, \ldots, d_n) \text{ is cyclic} \right\}
\]

Given an assignment \( a = (d_1, \ldots, d_n) \), define

\[
A := \{(v_i, v_{d_i}) : d_i \in D_i, 1 \leq i \leq n\}.
\]

Then, \( a \) satisfies \( \text{circuit}(v_1, \ldots, v_n) \) if and only if \( (V, A) \) is a
Traveling Salesperson Problem (TSP):

Given a set of $n$ cities and distances $c_{ij}$ between city $i$ and city $j$, find the shortest route that visits all cities and finishes in the starting city.

TSP is not a constraint satisfaction problem, but a constraint optimization problem ...
Constraint optimization problem

Definition

A constraint optimization problem (COP) is a constraint satisfaction problem together with an objective function $f$ that assigns to each variable assignment $a$ a value $f(a) \in \mathbb{Q}$.

- **Minimization COP**: Find a solution $a$ that minimizes $f(a)$.
- **Maximization COP**: Find a solution $a$ that maximizes $f(a)$.
- **Optimal solution**: Solution to a minimization (maximization) COP.

Decision problem associated to a COP:

Given an instance of a COP, $(N, f)$, and some threshold $t \in \mathbb{Q}$, is there a solution $a$ of $P$ such that $f(a) \geq t$ ($f(a) \leq t$, resp.)?
The decision problem of TSP

\( v_i \) : variable for city \( i \) with domain \( D_i := \{1, \ldots, n\} \setminus \{i\} \)
(read as: value of \( v_i \) is the city to be visited next)

\( c_{ij} \) : distance between cities \( i \) and \( j \) (may not be symmetric)

\( t \) : bound for the total tour length

Then:

\[
\text{circuit}(v_1, \ldots, v_n) \\
\sum_{1 \leq i \leq n} c_{iv_i} \leq t
\]
2 Filtering

- Arc consistency
- All-different Constraint
Filtering

- Constraint propagation techniques aim at filtering variable domains: remove useless values (that cannot participate in any solution) as early as possible.

- Filtering allows false-positives (values are kept though they are useless),

- …… but not false-negatives (useful values may not be removed).

- A constraint is “good” if it allows significant filtering (pruning of domain values) with low computational efforts.

- Constraint solver may benefit from exploiting the structure of such good constraints.
In general, enforcing generalized arc consistency on a constraint network requires exponential time w.r.t. the largest arity of some constraint relation in the network. Recall: Enforcing generalized arc consistency runs in time

\[ O(er^r) \]

where \( e \) is the number of constraints and \( r \) is the largest arity of some constraint in the network,

Though general constraints have often high arity, there exist efficient methods to enforce generalized arc consistency.

In the following we consider the all-different constraints.
Value graphs

Definition

An undirected graph \( G = \langle V, E \rangle \) is bipartite if there exists a partition \( S \cup T \) of \( V \) such that for each \( \{x, y\} \in E \), \( x \in S \) iff \( y \in T \). A directed graph \( G = \langle V, A \rangle \) is bipartite if there exists a partition \( S \cup T \) of \( V \) such that \( A \subseteq (S \times T) \cup (T \times S) \). 

\( G \) is then written in the form \( G = \langle S, T, E \rangle \) (resp. \( G = \langle S, T, A \rangle \)).

Definition

Let \( V \) be a set of variables and \( D \) be the union of all domains \( D_v \) for \( v \in V \). The value graph of \( V \) is defined as the following bipartite graph:

\[
G = \langle V, D, E \rangle
\]

where \( E = \{ \{v, d\} : v \in V, d \in D_v \} \).
Example: Value graph

Consider variables $v_1, \ldots, v_4$ with $D_1 = \{b, c, d, e\}$, $D_2 = \{b, c\}$, $D_3 = \{a, b, c, d\}$, $D_4 = \{b, c\}$.

Value graph:
Matchings

Let $G = \langle V, E \rangle$ be an undirected (simple) graph.

**Definition**

A **matching** in $G$ is a set $M \subseteq E$ of pairwisely disjoint edges. A matching $M$ **covers** a set $S \subseteq V$ if $S \subseteq \bigcup M$, i.e., each $v \in S$ is contained in some edge in $M$. $v \in V$ is **$M$-free** if $M$ does not cover $\{v\}$.

**Definition**

Let $M$ be a matching in $G$. A path $P = v_0, e_1, \ldots, e_k, v_k$ in $G$ is **$M$-alternating** if all the edges $e_i$ are alternatingly out of and in $M$. An $M$-alternating path $P = v_0, e_1, \ldots, e_k, v_k$ is called **$M$-augmenting** if $v_0$ and $v_k$ are $M$-free.
Max-cardinality matching

Let $G = \langle V, E \rangle$ be a graph and $M$ be a matching in $G$.

Theorem (Peterson)

$M$ is a max-cardinality matching (i.e., it is a matching of maximum cardinality) if and only if there is no $M$-augmenting path in $G$.

Remark: If $M$ is a matching and $v_0, \ldots, v_k$ is an $M$-augmenting path, then

$$M' := M \triangledown \{\{v_i, v_{i+1}\} : 0 \leq i \leq k - 1\}$$

is a matching with $|M'| = |M| + 1$.

Hence a max-cardinality matching can be obtained by repeatedly searching for an $M$-augmenting path in $G$ ...
Max-cardinality matching on bipartite graphs

Let $G = \langle U, W, E \rangle$ be a bipartite graph and $M$ be some matching in $G$.

Define a directed bipartite graph $G_M = \langle U, W, A \rangle$ by

$$A := \{(w, u) : \{u, w\} \in M, u \in U, w \in W\} \cup \{(u, w) : \{u, w\} \in E \setminus M, u \in U, w \in W\}$$

Each directed path in $G_M$ is $M$-alternating.

If such a path starts and ends in an $M$-free vertex (starts in $U$, ends in $W$), it is an $M$-augmenting path in $G$.

If no $M$-augmenting path can be found, $M$ is a max-cardinality matching.

This can be used to compute a max-cardinality matching in time $O(|U| \cdot |A|)$ (van der Waerden and König)

...can be improved to $O(\sqrt{|U|} \cdot |A|)$ (Hopcroft and Karp)
Example: Computing a max-cardinality matching

\[ M = \{ \{v_4, b\}, \{v_2, c\}, \{v_1, e\}, \{v_3, a\} \} \]
All-different constraint and matching

Let $V = \{v_1, \ldots, v_n\}$ be a set of variables and $G$ be the value graph of $V$. Let $(d_1, \ldots, d_n)$ be a variable assignment.

**Lemma**

$$(d_1, \ldots, d_n) \in \text{alldifferent}(v_1, \ldots, v_n) \text{ if and only if } M = \{(v_1, d_1), \ldots, (v_n, d_n)\} \text{ is a matching in } G.$$
Lemma

The constraint \texttt{alldifferent}(v_1, \ldots, v_n) is generalized arc-consistent if and only if every edge in $G$ belongs to a matching in $G$ that covers $V$.

Proof.

Simple (exercise!).
Theorem

Let $G$ be a graph and let $M$ be a max-cardinality matching in $G$. An edge $e$ belongs to some max-cardinality matching in $G$ if and only if one of the following conditions holds:

- $e \in M$.
- $e$ is on an even-length $M$-alternating path starting at an $M$-free vertex;
- $e$ is on an even-length $M$-alternating cycle.
Enforcing arc consistency on all-different constraints

1. Compute a max-cardinality matching $M$ in the value graph of $V$ (can be done in time $O(\sqrt{nm})$ where $m = \sum_{1 \leq i \leq n} |D_i|$)

2. Identify the even $M$-alternating paths starting in an $M$-free vertex and the $M$-alternating cycles:
   1. Define dir. bipartite graph $G_M^* = \langle V, D_V, A \rangle$ with $A = \{(v, d) : v \in V, \{v, d\} \in M\} \cup \{(d, v) : v \in V, \{v, d\} \in E \setminus M\}$
   2. Compute the strongly connected components in $G_M$ (in time $O(n + m)$)
   3. Mark arcs between vertices in the same component as “used”: they belong to an even $M$-alternating cycle
   4. Mark arcs as “used” that belong to a $M$-alternating path in $G_M$ that starts in an $M$-free vertex (breadth-first search in time $O(m)$).

3. Update $D_v \leftarrow D_v \setminus \{d\}$ for all edges $\{v, d\}$ where the corresponding arc is not marked as “used”.

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Example: Enforcing arc-consistency

Start from max-cardinality matching
Example: Enforcing arc-consistency

Compute strongly connected components
(e.g. by Kosaraju’s algorithm)
Example: Enforcing arc-consistency

Mark “used” arcs
Example: Enforcing arc-consistency

\[ \begin{array}{cccc}
  a & b & c & d \\
  v_1 & v_2 & v_3 & v_4 \\
  e
\end{array} \]

\[ \ldots \text{ and remove unused arcs} \]
Example: Enforcing arc-consistency

The all-different constraint is now arc-consistent
Willem-Jan van Hoeve and Irit Katriel. 
Global Constraints, 
Handbook of Constraint Programming, Elsevier, 2006