

## Integer vs. constraint programming

### Practical Problem Solving

- Model building: Language
- Model solving: Algorithms

### IP vs. CP: Language

	IP	CP
Variables	(mostly) 0-1	Finite domain
Constraints	Linear equations and inequalities	Arithmetic constraints <b>Symbolic/global constraints</b>

### Example

- Variables:  $x_1, \dots, x_n \in \{0, \dots, m-1\}$
- Constraint: Pairwise different values

### Example <sup>(2)</sup>

- Integer programming: Only linear equations and inequalities

$$\begin{aligned}
 x_i \neq x_j &\iff x_i < x_j \vee x_i > x_j \\
 &\iff x_i \leq x_j - 1 \vee x_i \geq x_j + 1
 \end{aligned}$$

- Eliminating disjunction

$$\begin{aligned}
 x_i - x_j + 1 \leq my_1, \quad x_j - x_i + 1 \leq my_2, \quad y_1 + y_2 = 1, \\
 y_1, y_2 \in \{0, 1\}, \quad 0 \leq x_i, x_j \leq m - 1,
 \end{aligned}$$

- New variables:  $z_{ik} = 1$  iff  $x_i = k$ ,  $i = 1, \dots, n$ ,  $k = 0, \dots, m-1$

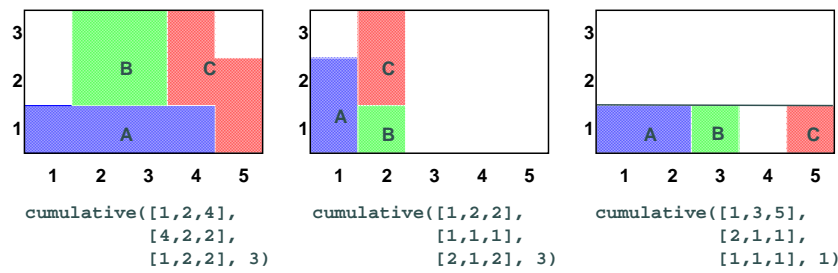
$$z_{i0} + \dots + z_{im-1} = 1, \quad z_{1k} + \dots + z_{nk} \leq 1,$$

- Constraint programming  $\rightsquigarrow$  **symbolic constraint**

$$\text{alldifferent}(x_1, \dots, x_n)$$

### Symbolic/global constraints

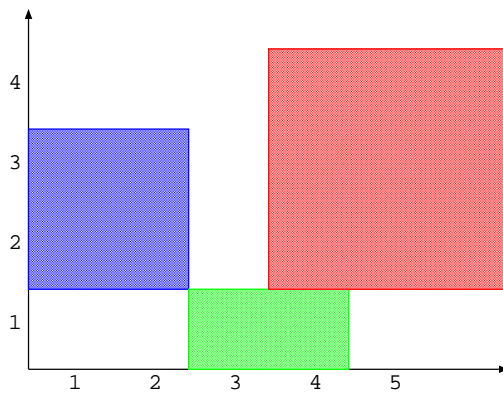
- $\text{alldifferent}([x_1, \dots, x_n])$
- $\text{cumulative}([s_1, \dots, s_n], [d_1, \dots, d_n], [r_1, \dots, r_n], c, e)$ .
  - $n$  tasks: starting time  $s_i$ , duration  $d_i$ , resource demand  $r_i$
  - resource capacity  $c$ , completion time  $e$



### Diffn Constraint

Beldiceanu/Contejean'94

- Nonoverlapping of  $n$ -dimensional rectangles  $[O_1, \dots, O_n, L_1, \dots, L_n]$ , where  $O_i$  (resp.  $L_i$ ) denotes the origin (resp. length) in dimension  $i$
- $\text{diffn}([ [O_{11}, \dots, O_{1n}, L_{11}, \dots, L_{1n}], \dots, [O_{m1}, \dots, O_{mn}, L_{m1}, \dots, L_{mn}] ])$



$\text{diffn}([ [1,2,2,2], [3,1,2,1], [4,2,3,3] ])$

- General form:  $\text{diffn}(\text{Rectangles}, \text{Min\_Vol}, \text{Max\_Vol}, \text{End}, \text{Distances}, \text{Regions})$

### IP vs. CP: Algorithms

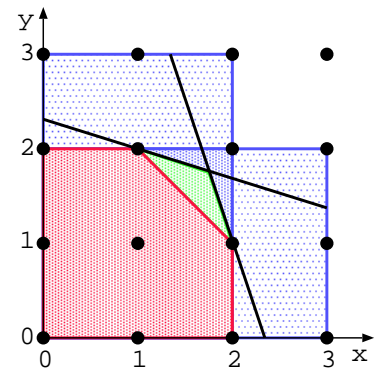
	IP	CP
<i>Inference</i>	Linear programming Cutting planes	Domain filtering Constraint propagation
<i>Search</i>	Branch-and-relax Branch-and-cut	Branch-and-bound
Bounds on the objective function	Two-sided	One-sided

### Local vs. global reasoning

Linear arithmetic constraints

$$\begin{aligned}
 3x + y &\leq 7, \\
 3y + x &\leq 7, \\
 x + y &= z, \\
 x, y &\in \{0, \dots, 3\}
 \end{aligned}$$

- CP  $x, y \leq 2, z \leq 4$
- LP  $x, y \leq 2, z \leq 3.5$
- IP  $x, y \leq 2, z \leq 3$



Global reasoning in CP ?  $\rightsquigarrow$  global constraints!

### Global reasoning in CP

Example

- $x_1, x_2, x_3 \in \{0, 1\}$
- pairwise different values
- **Local** consistency. 3 disequalities:  $x_1 \neq x_2, x_1 \neq x_3, x_2 \neq x_3$   
 $\rightsquigarrow x_1, x_2, x_3 \in \{0, 1\}$ , i.e., no domain reduction is possible
- **Global** constraint: `alldifferent( $x_1, x_2, x_3$ )`  
 $\rightsquigarrow$  detects infeasibility (uses bipartite matching)

Global reasoning in CP: inside global constraints

### Summary

	ILP	CP(FD)
<i>Language</i>	Linear arithmetic —	Arithmetic constraints <b>Symbolic constraints</b>
<i>Algorithms</i>	Global consistency (LP) Cutting planes	Local consistency Domain reduction
	Branch-and-bound Branch-and-cut	User-defined enumeration

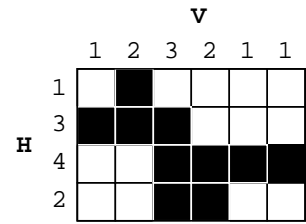
- Symbolic constraints  $\rightsquigarrow$  more expressivity + more efficiency
- Unifying framework for CP and IP: *Branch-and-infer* (Bockmayr/Kasper 98), . . . , SCIP

### Discrete Tomography

- Binary matrix with  $m$  rows and  $n$  columns
  - Horizontal projection numbers  $(h_1, \dots, h_m)$
  - Vertical projection numbers  $(v_1, \dots, v_n)$

• *Properties*

- Horizontal convexity (h)
- Vertical convexity (v)
- Connectivity (polyomino) (p)



• *Complexity* (Woeginger'01)

- polynomial: ( ), (p,v,h)
- NP-complete: (p,v), (p,h), (v,h), (v), (h), (p)

**IP Model**

- *Variables*  $x_{ij} = \begin{cases} 0 & \text{cell}(i,j) \text{ is labeled white} \\ 1 & \text{cell}(i,j) \text{ is labeled black} \end{cases}$

• *Constraints I: Projections*

$$\sum_{j=1}^n x_{ij} = h_i, \quad \sum_{i=1}^m x_{ij} = v_j$$

• *Constraints II: Convexity*



$$h_i x_{ik} + \sum_{l=k+h_i}^n x_{il} \leq h_i, \quad v_j x_{kj} + \sum_{l=k+v_j}^m x_{lj} \leq v_j$$

**IP Model (contd)**

• *Constraints III: Connectivity*

$$\sum_{k=j}^{j+h_i-1} x_{ik} - \sum_{k=j}^{j+h_i-1} x_{i+1,k} \leq h_i - 1$$

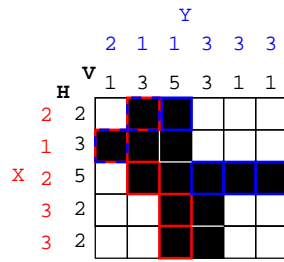


- Various linear arithmetic models possible, e.g. convexity
- Enormous differences in size and running time, e.g. 1 day vs. < 1 sec
- Large number of constraints (~ 3mn in the above model)

**Finite Domain Model**

• *Variables*

- $x_i$  start of horizontal convex block in row  $i$ , for  $1 \leq i \leq m$
- $y_j$  start of vertical convex block in column  $j$ , for  $1 \leq j \leq n$



• Domain

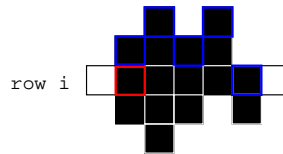
- $x_i \in [1, \dots, n - h_i + 1]$ , for  $1 \leq i \leq m$
- $y_j \in [1, \dots, m - v_j + 1]$ , for  $1 \leq j \leq n$

### Conditional Propagation

- Projection/Convexity modelled by FD variables
- Compatibility of  $x_i$  and  $y_j$

$$x_i \leq j < x_i + h_i \iff y_j \leq i < y_j + v_j$$

for  $1 \leq i \leq m$  and  $1 \leq j \leq n$

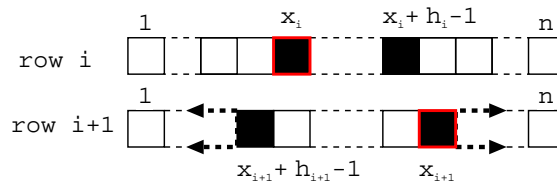


• Conditional propagation

if  $x_i \leq j$  then (if  $j < x_i + h_i$  then ( $y_j \leq i, i < y_j + v_j$ ))

### Finite Domain Model (contd)

• Connectivity



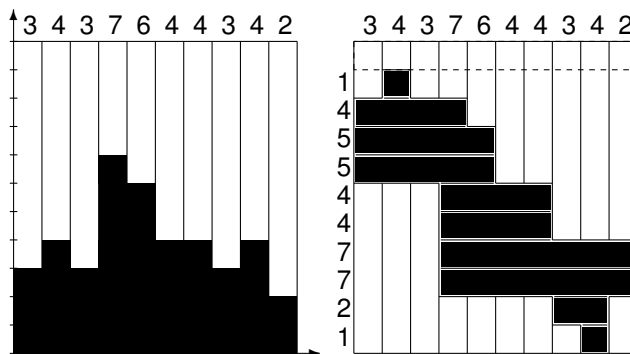
• Block  $i$  must start before the end of block  $i + 1$

$$x_i \leq x_{i+1} + h_{i+1} - 1, \text{ for } 1 \leq i \leq m - 1$$

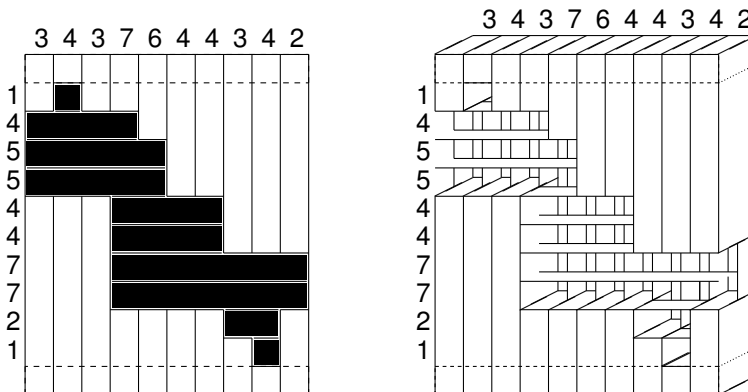
• Block  $i + 1$  must start before the end of block  $i$

$$x_{i+1} \leq x_i + h_i - 1, \text{ for } 1 \leq i \leq m - 1$$

### Cumulative



**2d and 3d Diffn Model**



**Propositional satisfiability**

- $x_1, \dots, x_n \in \{0, 1\}$  0-1 variables (or atomic formulae in propositional logic)
- A *literal*  $L$  is a 0-1 variable  $x$  or its negation  $\bar{x} = 1 - x$ .
- A *clause* is set of literals  $C = \{L_1, \dots, L_k\}$  corresponding to the logical disjunction  $L_1 \vee \dots \vee L_k$  or the *clausal inequality*  $L_1 + \dots + L_k \geq 1$ .
- A *clause set* is a set of clauses  $S = \{C_1, \dots, C_m\}$  corresponding to the logical conjunction  $C_1 \wedge \dots \wedge C_m$ .
- A clause set  $S$  is *satisfiable* if there exists an assignment  $I : \{x_1, \dots, x_n\} \rightarrow \{0, 1\}$  making the logical formula true (equivalently, if the system of clausal inequalities has a 0-1 solution).

**Examples**

1. Clause set

$$S = \{ \{x_1, x_2\}, \{\bar{x}_1, \bar{x}_2\} \}$$

Corresponding logical formula:  $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

Corresponding system of clausal inequalities:  $x_1 + x_2 \geq 1, -x_1 - x_2 \geq -1$

Satisfying assignments:  $I(x_1) = 1, I(x_2) = 0$  and  $I'(x_1) = 0, I'(x_2) = 1$ .

2. The clause set

$$S = \{ \{x_1, x_2\}, \{\bar{x}_1, \bar{x}_2\}, \{x_1, \bar{x}_2\}, \{\bar{x}_1, x_2\} \}$$

is unsatisfiable.

## SAT problem

- *SAT problem*: Given a set of clauses  $S$ , is  $S$  satisfiable?
- **Theorem (Cook'71)**: SAT is NP-complete.
- There exist highly efficient SAT solvers.
- Enormous progress has been made during the last 10-15 years, see e.g. <http://www.satlive.org/>  
 $\rightsquigarrow$  SAT competitions
- SAT is a third general approach for solving constraint satisfaction/optimization problems (in addition to IP and CP)

## Davis-Putnam procedure

```

function Satisfiable(S) return boolean
  /* unit resolution */
  repeat
    for each clause  $\{L\}$  in  $S$  of length 1 do
      delete from  $S$  every clause containing  $L$ 
      delete  $\bar{L}$  in every clause of  $S$  containing  $\bar{L}$ 
    od
    if  $S = \emptyset$  then true
    else if  $S$  contains the empty clause  $C = \emptyset$  then false
    fi
  until no further changes
  /* branching */
  choose a literal  $L$  occurring in  $S$ 
  if Satisfiable( $S \cup \{L\}$ ) then true
  else if Satisfiable( $S \cup \{\bar{L}\}$ ) then true
  else false
  fi
end function

```

## Example

Let  $S$  be the clause set

$$\begin{array}{l}
 \{ x_1, x_2, x_3, x_4, x_5 \}, \\
 \{ x_1, x_2, x_3, \bar{x}_4 \}, \\
 \{ \bar{x}_1, \bar{x}_2, \bar{x}_3, x_5 \}, \\
 \{ \bar{x}_2, x_3 \}, \\
 \{ \bar{x}_1, x_2 \}, \\
 \{ x_1, \bar{x}_2, \bar{x}_5 \}, \\
 \{ \bar{x}_5 \}.
 \end{array}$$

Satisfying assignment:  $I(x_1) = 0, I(x_2) = 1, I(x_3) = 1, I(x_5) = 0$ .