



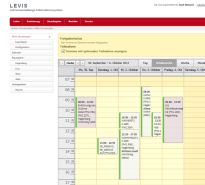
Solving Soft Constraint Problems in MiniBrass

Alexander Schiendorfer et al.





“How many muffins of each kind?”



“When does which lecture take place?”



“Who performs which tasks?”



“What’s up on the weekend?”

What do these problems have in common?

Decisions

- The number of chocolate or banana muffins
- The lectures in the curriculum
- Friday and saturday activity

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Possibilities

- Chocolate muffins: $\{0, \dots, 20\}$
- Lecture “Algorithms 101”: $\{LH1, LH2, LH3, \dots\}$

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Dependencies

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- There can only be one class per room (at a time).
- There can only be one all-you-can-eat buffet per weekend.

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Preferences

- There *should* be no algorithm lab on Friday, 8am
- Bernd would like to have steaks, Ada prefers sushi → Ada's preference is *more important*
- I'd rather not clean nor vacuum. But if I have to do either, cleaning is *worse*

What do these problems have in common?

PREFERENCES (soft constraints)

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and/or

Goals

- Maximize the revenue of our chocolate/banana mix
- Maximize the number of lecture-free days

a **constraint satisfaction (optimization) problem** (CSP/COP),
discrete if some decisions are over integers

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Goals (*utility functions*)

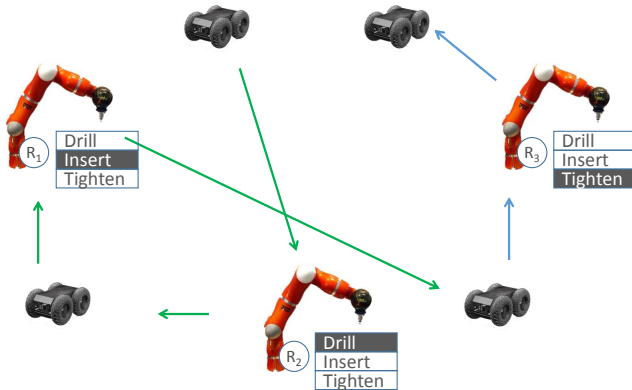
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a **constraint satisfaction (optimization) problem** (CSP/COP),
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Adaptive production cells



Goal: Assign tasks to robots such that a correct **resource flow** emerges



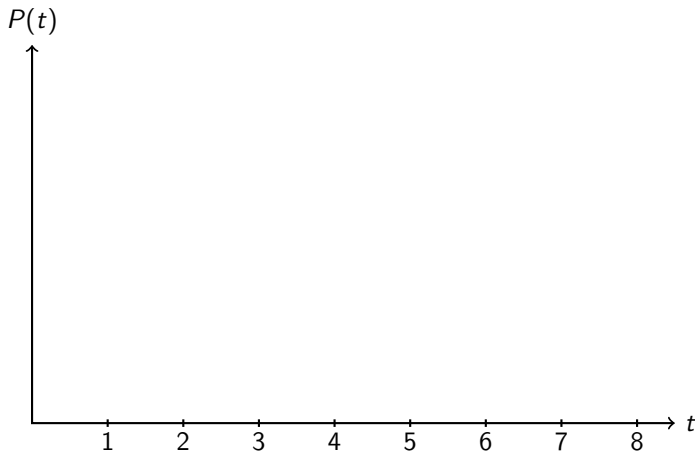
(Seebach et al., 2010), SASO

Decentralized energy management



Discrete Optimization Problems in FAS* (2)

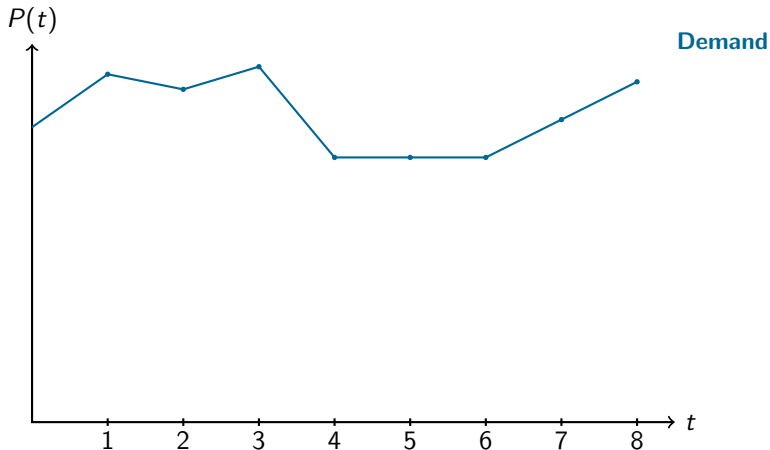
Goal: Schedule power plants such that they meet the demand



(Anders et al., 2013), SASO

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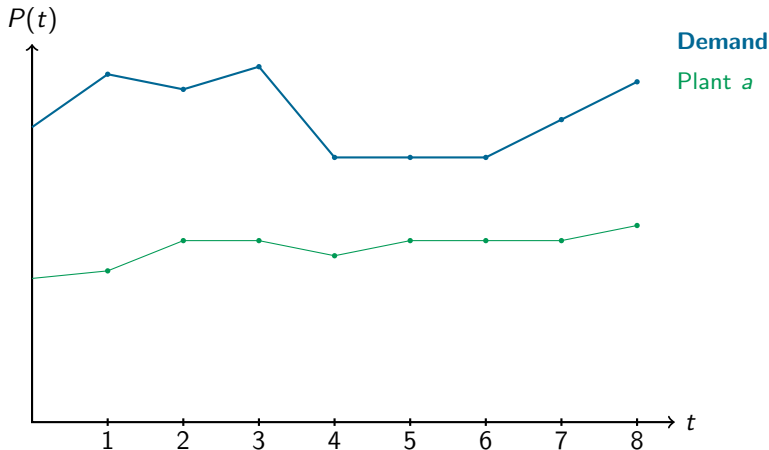
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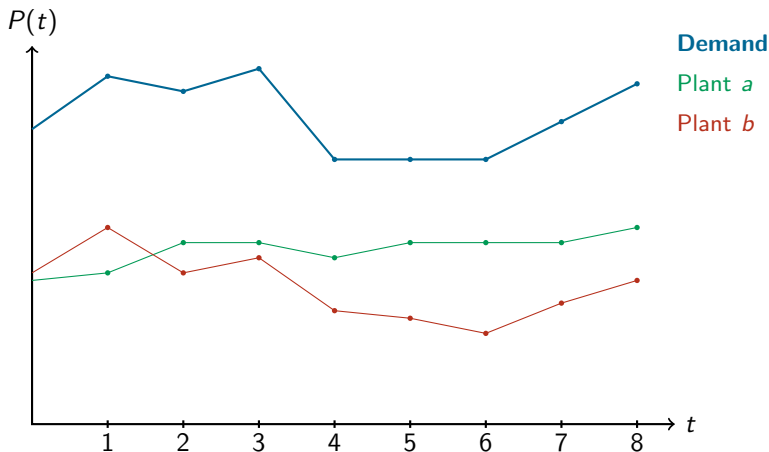
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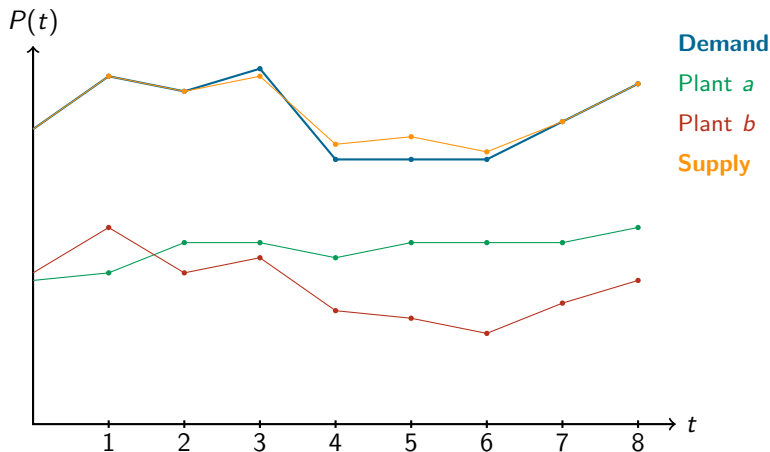
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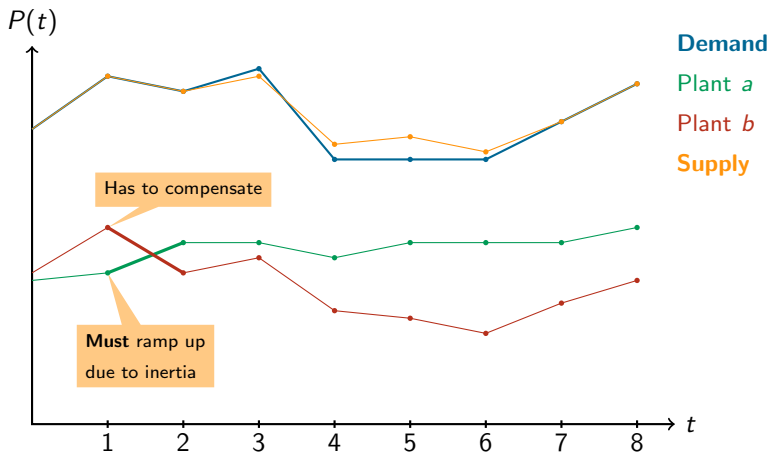
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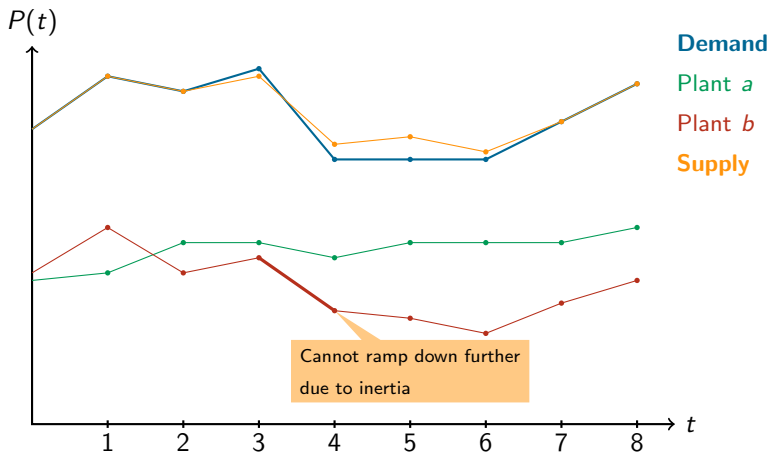
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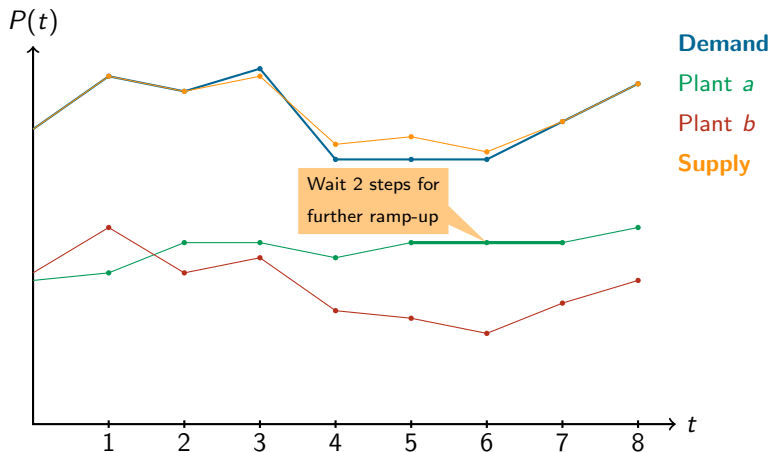
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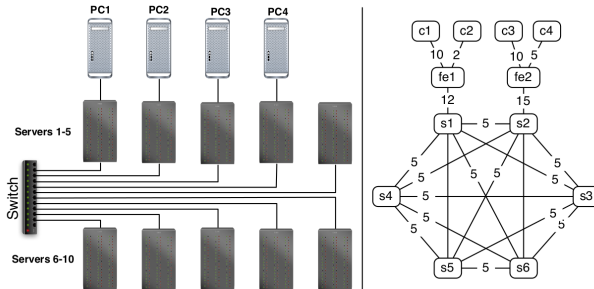
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Goal: Schedule power plants such that they meet the demand



(Anders et al., 2013), SASO

ESDS Deployment Problem (*eventually serializable data services*)



(Michel et al., 2008), CPAIOR

Why is it useful to you?

As a tool ...

- If you identify discrete optimization problems in your (self-organizing, autonomic, cloud) application, you can solve them with reliable tools.
- Modeling languages provide *easy* access to powerful solvers
- → *independent* of the concrete technology (SAT, CSP, Mathematical Programming)

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As a research opportunity ...

- Studying interactions of complex networks of optimizing agents offers interesting problems (*global systems science*)
- Integration of optimization problems into architectures for decision-making
- Solving large-scale problems by decomposition through self-organization

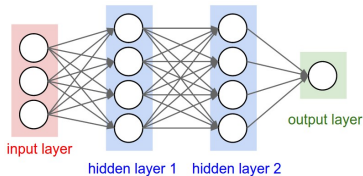
Constraint programming (first half of the tutorial)

- Declarative programming (similar to SQL, Prolog)
- Separation of **model** and *algorithm*
- Suitable for combinatorial problems with hard constraints (e.g. physics!)
- Modeling language **MiniZinc**

Soft constraint programming (second half of the tutorial)

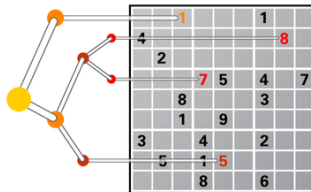
- Modeling of **user preferences**
- Find solutions that are *as good as possible*
- What does “good” mean?
- Modeling language **MiniBrass**

Data-driven AI



- Machine Learning
- Signal Processing
- Computer Vision

Decision-driven AI



- Constraint Programming
- Combinatorial Optimization
- Heuristic Optimization
- Planning / Scheduling

```
var 0..2: x;  
var 0..2: y;  
  
constraint x < y;  
  
solve maximize x + y;
```

<http://www.minizinc.org>

```
x = 1;  
y = 2;  
-----  
=====
```

A second example

```
var 0..2: x; % this notation is shorthand for the set {0,1,2}
var 0..2: y;
var 0..1: z; % {0,1}

% c1
constraint x != y /\ y != z /\ x != z;
% c2
constraint x + 1 = y;

solve satisfy;
```

Can you give a solution to this problem?

A second example

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var 0..2: x; % this notation is shorthand for the set {0,1,2}
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Can you give a solution to this problem?

- $\Theta = \{(x \rightarrow 1, y \rightarrow 2, z \rightarrow ?), (x \rightarrow 0, y \rightarrow 1, z \rightarrow ?)\}$ satisfy c_2 ;

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- $\Theta = \{(x \rightarrow 1, y \rightarrow 2, z \rightarrow ?), (x \rightarrow 0, y \rightarrow 1, z \rightarrow ?)\}$ satisfy c_2 ;
- $(x \rightarrow 0, y \rightarrow 1, z \rightarrow ?)$ cannot be extended to a solution since z has to be 0 or $1 \rightarrow$ has to violate c_1
- Hence, the only solution is $(x \rightarrow 1, y \rightarrow 2, z \rightarrow 0)$

- ① Once stated (formally) – solved many times
 - Constraint-Solving
 - SAT – Boolean Satisfiability
 - MIP – Mixed Integer Programming
 - Heuristic Optimization – Genetic etc.
- ② Efficient and reliable algorithms provided by solvers
 - Same algorithms for a variety of different problems
 - Dedicated algorithms for recurring combinatorial substructures (alldifferent)
- ③ Prototyping
 - Specification becomes much clearer
 - Bespoke algorithm for concrete problem can be developed later

```
SELECT firstname, lastname  
FROM employees  
WHERE age < 30
```

instead of

```
Collection<Person> youngs = new ArrayList<>();  
for(Person p : allEmployees) {  
    if(p.getAge() < 30)  
        youngs.add(p);  
}
```

Motivation

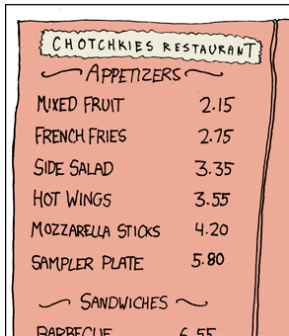
Constraint modeling for optimization problems \approx SQL for database access

Theorem

The decision problem associated to a constraint satisfaction/optimization problem is NP-complete.

MY HOBBY:

EMBEDDING NP-COMPLETE PROBLEMS IN RESTAURANT ORDERS



CHOTCHKIES RESTAURANT	
~ APPETIZERS ~	
MIXED FRUIT	2.15
FRENCH FRIES	2.75
SIDE SALAD	3.35
HOT WINGS	3.55
MOZZARELLA STICKS	4.20
SAMPLER PLATE	5.80
~ SANDWICHES ~	
BARBECUE	6.55



<https://xkcd.com/287/>

Rationale

One modeling language – many solvers

Supported solvers (selection)

- Gecode (CP)
- JaCoP (CP)
- Google Optimization Tools (CP)
- Choco (CP)
- G12 (CP/LP/MIP)



A relevant example ...

```
var 0..100: b; % no. of banana muffins
var 0..100: c; % no. of chocolate muffins

% flour
constraint 250*b + 200*c <= 4000;
% bananas
constraint 2*b <= 6;
% sugar
constraint 75*b + 150*c <= 2000;
% butter
constraint 100*b + 150*c <= 500;
% cocoa
constraint 75*c <= 500;

% maximize our profit
solve maximize 400*b + 450*c;

output ["no. of banana muffins = ", show(b), "\n", % b = 2
        "no. of chocolate muffins = ", show(c), "\n"]; % c = 2
```

Parameters: input data for the problem, constants

```
int: n;  
n = 3;  
% equivalent to:  
int: n = 3;  
par int: n = 3;  
% or with bounded domains  
0..10: m; % a fixed value (input by a user) between 0 and 10  
% set types  
set of int: AGENTS = 1..n; % {1, ..., n}
```

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Decision Variables: variables to be assigned by a solver

```
var int: n;  
var 0..10: x;  
% immediate declaration (useful for dependent expressions)  
var int: y = 2*x;
```

Arrays: for parameters/variables of different sizes

```
int: n;  
array[1..n] of int: height; % height[i] denotes the height of truck i  
% also for decisions  
array[1..n] of var bool: x; % x[i] holds if we select item i  
% typical usage  
set of int: ITEMS = 1..n;  
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```

Sets: set type for parameters and decisions (only set of int/subtype int)

```
set of int: AGENTS = 1..n;  
set of int: CAP = 1..m;  
array[AGENTS] of set of CAP: offers; % [{1}, {2}, {1,2}]  
  
var set of AGENT: selectedTeam;
```

Allowed primitive types for variables/parameters are

- Integer `int` or subtypes:
 - range `1..n`
 - explicit set `{1,5,7}`
- Floating point number `float` or subtypes:
 - range `0.0 .. 1.0`
 - explicit set `{1.0, 2.5, 3.7}`
- Boolean `bool`
- Arrays, Sets

Constraints: to restrict assignments

```
var 0..10: x; var 0..10: y; var 0..10: z;  
constraint x + y = z;  
constraint x mod 2 = 0;  
% 'forall' concept for arrays  
par int: n; array[1..n] of var 0..10: t;  
% each t[i] should be even:  
constraint forall(i in 1..n) (t[i] mod 2 = 0);
```

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Solve Item: provides the objective (one per model)

```
solve satisfy; % for a satisfaction problem  
solve maximize sum(i in 1..n) (t[i]);  
solve minimize x + y;
```

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String Output: one output item per model

```
var 0..10: x;  
output ["The value of x is: \"(x)\""]
```

Exercise 1

Build a MiniZinc model `xopt.mzn` with a decision variable x taking values from 0 to 10, with constraints to ensure that x is divisible by 4, which outputs the value of x that gives the minimum value of $(x - 7)^2$.

Test it using the precompiled IDE-bundle. Suppose you cannot use the `mod` function, how would you alternatively model that x is divisible by 4?

Exercise 2 Define a MiniZinc model `array.mzn` which takes an integer parameter n defining the length of an array of numbers x taking values from 0 to 9. Constrain the array so the sum of the numbers in the array is equal to the product of the numbers in the array. Output the resulting array. Test your model using the “all solutions” setting active in the IDE.

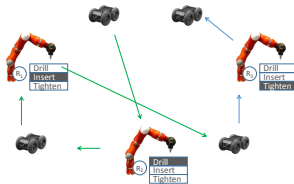
Add a constraint to ensure that the numbers in the array are non-decreasing, i.e. $x[1] \leq x[2] \leq \dots \leq x[n]$. This should reduce the number of similar solutions. How big a number can you solve with your model? Why do you think this happens?

- A very important, recurring problem is *deciding* a finite **function**.
- Given
 - Domain DOM
 - Codomain COD
- Find a function $f : \text{DOM} \rightarrow \text{COD}$
- Satisfying some criteria (e.g. *injectivity*)

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Examples:

- Task allocation (maps tasks to workers, exactly one worker per task)
- Exam schedules (map students to appointments, certainly different appointments)



- Task allocation problem

- n robots
- m tasks
- Assign each robot a *different* task and maximize the profit

- Example:

- $n = 4$, $m = 5$

	t1	t2	t3	t4	t5
r1	7	1	3	4	6
r2	8	2	5	1	4
r3	4	3	7	2	5
r4	3	1	6	3	6


```
% problem data
int: n; set of int: ROBOTS = 1..n;
int: m; set of int: TASKS = 1..m;
array[ROBOTS,TASKS] of int: profit;

% decisions
array[ROBOTS] of var TASKS: allocation;

% goal
solve maximize sum(r in ROBOTS) (profit[r, allocation[r]] );

% have robots work on different tasks
constraint forall(r1 in ROBOTS, r2 in ROBOTS where r1 < r2)
  ( allocation[r1] != allocation[r2] );
```

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```

- In principle, *fine*, but ...
 - Not very concise – can be messed up
 - $O(n^2)$ individual constraints between two variables

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- In principle, *fine*, but ...
 - Not very concise – can be messed up
 - $O(n^2)$ individual constraints between two variables
- But in fact, this substructure is so common that it deserves a *name*
 - `alldifferent`

```
constraint alldifferent(allocation);
```

- `alldifferent`($[x_1, \dots, x_n]$) is true if and only if all variables x_1 to x_n take a different value
- e.g. `alldifferent`($[2, 3, 5]$) holds but `alldifferent`($[2, 2, 3]$) does not.

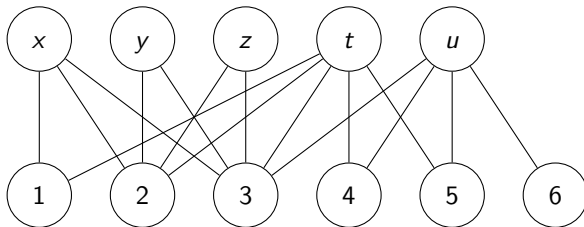
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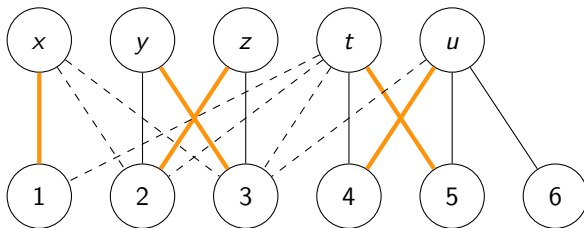
include "alldifferent.mzn"; % we have to import from the library
% have robots work on different tasks
constraint alldifferent(allocation);
```

```
var {1,2,3}: x;    var {2,3}: y;    var {2,3}: z;  
var {1,2,3,4,5}: t; var {3,4,5,6}: u;  
constraint alldifferent([x,y,z,t,u]);
```



```
var {1}: x;        var {2,3}: y;    var {2,3}: z;  
var {4,5}: t;      var {4,5,6}: u;  
constraint alldifferent([x,y,z,t,u]);
```

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var {1,2,3}: x;    var {2,3}: y;    var {2,3}: z;  
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```
var {1}: x;        var {2,3}: y;    var {2,3}: z;  
var {4,5}: t;      var {4,5,6}: u;  
constraint alldifferent([x,y,z,t,u]);
```



Assume an employee scheduling problem (rostering)
(Shifts: 1 = morning, 2 = afternoon, 3 = night):

	Monday	Tuesday	Wednesday	Thursday	Friday
Nurse 1	off	1	2	3	2
Nurse 2	1	off	1	1	1
Nurse 3	1	2	off	1	2
Nurse 4	2	2	2	off	3
Nurse 5	3	3	2	3	off



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- Consider work regulations
 - At least one nurse has to be assigned to every shift per day
 - Each nurse may at most work two night shifts
 - Each nurse needs to have one day off

worksShift	Monday	Tuesday	Wednesday	Thursday	Friday
Nurse 1	off	1	2	3	2
Nurse 2	1	off	1	1	1

- $\text{cardinality}(X \mid v, l, u)$
 - $X = \{x_1, \dots, x_n\}$
 - $v = (v_1, \dots, v_m)$
 - $l = (l_1, \dots, l_m)$ contain *lower* and $u = (u_1, \dots, u_m)$ *upper* bounds for values v_i

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 - $X = \{x_1, \dots, x_n\}$
 - $v = (v_1, \dots, v_m)$
 - $l = (l_1, \dots, l_m)$ contain *lower* and $u = (u_1, \dots, u_m)$ *upper* bounds for values v_i
- For instance, for each nurse i :
 - $\text{cardinality}([\text{worksShift}[i, \cdot]] \mid (0, 1, 2, 3), (1, 0, 0, 0), (5, 5, 5, 2))$
- In MiniZinc:

```
constraint forall(i in NURSES) (  
    global_cardinality_low_up([worksShift[i,d] | d in DAYS],  
                              [0,1,2,3], [1,0,0,0], [1,5,5,2] ) );
```

Exercise 3

Given a group of n people, we must arrange them for a photo. The best photo is when people are next to their friends, so the aim is to arrange them so that each person is next to (to the left or right) with as many friends as possible. The data for the problem is given as

```
n = <size of problem> ;  
array[1..n,1..n] of par bool: friend;
```

where `friend[f1, f2]` means `f1` and `f2` are friends. You can assume that the friend array is symmetric. You should output a list of the people in their position to maximize the number of adjacent friends. For example given the data `groupphoto1.dzn`, you should output the placement of the guests as well as the objective value, i.e.,

```
Obj = 7; [4, 3, 5, 6, 8, 7, 1, 2]
```



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