Topic 4: Modelling (for CP and LCG)[1]
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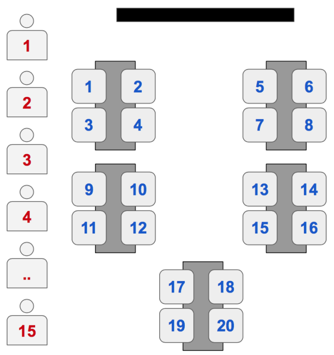
Outline

Outline

Recap

1. Modelling: express problem in terms of
   - parameters,
   - decision variables,
   - constraints, and
   - objective.
2. Solving: solve using a state-of-the-art solver.

Example (Student Seating Problem)



nStudents = 15
nPgms = 3
nChairs = 20 $\geq$ nStudents
nTables = 5
Chairs = [1..4, 5..8, 9..12, 13..16, 17..20]

Given:

- `nStudents` students,
- `nPgms` study programmes
- `nChairs` chairs around `nTables` tables, and
- `Chairs[t]` as the set of chairs of table `t`,

find a seating arrangement such that:

1. each table has students of distinct study programmes;
2. each table has either at least half or none of its chairs occupied;
3. a maximum number of student preferences on being seated at the same table are satisfied.

What are suitable decision variables for this problem?

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Viewpoints & Dummy Values

Implied Constraints

Redundant Variables & Channelling Constraints

Pre-Computation

A viewpoint is a choice of decision variables.

Example (Student Seating Problem)

Viewpoint 1: Which chair does each student sit on?

```
% Chair[s] = the chair of student s:
array[1..nStudents] of var 1..nChairs: Chair;
constraint all_different(Chair); % max 1 student per chair
```

Viewpoint 2: Which student, if any, sits on each chair?

```
int: dummyS = 0;  % Advice: also experiment with nStudents+1
set of int: StudentsAndDummy = 1..nStudents union {dummyS};
% Student[c] = the student, possibly dummy, sitting on chair c:
array[1..nChairs] of var StudentsAndDummy: Student;
constraint global_cardinality_closed(Student, [dummyS]++[i|i in 1..nStudents],
   [nChairs - nStudents] ++ [1 | i in 1..nStudents]);
   %all_different(Student) % use when nStudents+1..nChairs are dummy students
```

We revisit this problem at slide 19 and the choice of dummy values in Topic 5: Symmetry, as well as in Topic 8: Reasoning & Search in CP & LCG.

Let us see how viewpoints differ when stating constraints.

Example (Objects, Shapes, and Colours)

There are $\mathtt{n}$ objects, $\mathtt{s}$ shapes, and $\mathtt{c}$ colours, with $\mathtt{s} \geq \mathtt{n}$.
Assign a shape and a colour to each object such that:

1. the objects have distinct shapes;
2. the numbers of objects of the actually used colours are distinct;
3. other constraints, yielding NP-hardness and actually distinguishing the objects from the shapes, are satisfied.

This problem can be modelled from different viewpoints:

1. Which colour, if any, does each shape have?
2. Which shapes, if any, does each colour have?
3. Which shape and colour does each object have?
4. ...

Each viewpoint comes with benefits and drawbacks.

Example (Objects, Shapes, and Colours)

Viewpoint 1: Which colour, if any, does each shape have?

```
1 int: n; % number of objects
2 int: s; % number of shapes
3 constraint assert(s >= n, "Not enough shapes");
4 int: c; % number of colours
5 int: dummyColour = 0;  % Advice: also experiment with c+1
6 set of int: ColoursAndDummy = 1..c union {dummyColour};
7 % Colour[i] = the colour, possibly dummy, of the object of shape i:
8 array[1..s] of var ColoursAndDummy: Colour;
9 % There are n objects:
10 constraint count(Colour,dummyColour) = s - n;
11 % The numbers of objects of the actually used colours are distinct:
12 constraint all_different_except(
     global_cardinality(Colour,1..c),{0});
13 % The objects have distinct shapes:
14 %   follows from lines 6 and 8!
15 % ... state here the other constraints ...
16 solve satisfy;
```

So what are the shape and colour of a particular object?!

☞ Map the objects onto the shapes with non-dummy colour!

Example (Objects, Shapes, and Colours)

Viewpoint 2: Which shapes, if any, does each colour have?

```
int: n; % number of objects
int: s; % number of shapes
constraint assert(s >= n, "Not enough shapes");
int: c; % number of colours
%
%
% Shapes[i] = the set of shapes of colour i:
array[1..c] of var set of 1..s: Shapes;
% There are n objects:
constraint sum(colour in 1..c)(card(Shapes[colour])) = n;
% The numbers of objects of the actually used colours are distinct:
constraint all_different_except(
    [card(Shapes[colour]) | colour in 1..c],{0});
% The objects have distinct shapes:
constraint all_disjoint(Shapes);
% ... state here the other constraints ...
solve satisfy;
```

Post-process: map the objects onto actually used shapes.

Can we also model this viewpoint without set variables? ☞ Yes, see next slide!

Example (Objects, Shapes, and Colours)

Viewpoint 2 revisited: Which shapes, if any, does each colour have?

```
int: n; % number of objects
int: s; % number of shapes
constraint assert(s >= n, "Not enough shapes");
int: c; % number of colours
%
%
% NbrObj[i,j] = the number of objects of colour i and shape j:
array[1..c,1..s] of var 0..1: NbrObj;
% There are n objects:
constraint sum(NbrObj) = n;
% The numbers of objects of the actually used colours are distinct:
constraint all_different_except(
   [sum(NbrObj[colour,..]) | colour in 1..c],{0});
% The objects have distinct shapes:
constraint forall(shape in 1..s)(sum(NbrObj[..,shape]) <= 1);
% ... state here the other constraints ...
solve satisfy;
```

Which model for viewpoint 2 is clearer or better? ☞ Ask others and try!

Example (Objects, Shapes, and Colours)

Viewpoint 3: Which shape and colour does each object have?

```
1  int: n; % number of objects
2  int: s; % number of shapes
3  constraint assert(s >= n, "Not enough shapes");
4  int: c; % number of colours
5  %
6  %
7  % ShapeColour[i] = (shape: j, colour: k) when object i has shape j & colour k:
8  array[1..n] of record(var 1..s: shape, var 1..c: colour): ShapeColour;
9  % There are n objects:
10 %   follows from line 8!
11 % The numbers of objects of the actually used colours are distinct:
12 constraint all_different_except(
     global_cardinality_closed([ShapeColour[i].colour | i in 1..n],1..c),{0});
13 % The objects have distinct shapes:
14 constraint all_different([ShapeColour[i].shape | i in 1..n]);
15 % ... state here the other constraints ...
16 solve satisfy;
```

Using `record`s of two decision variables, we do not need to declare two parallel arrays in line 8 with the same index set but different domains.

Which viewpoint is better in terms of:

- Size of the search space:
  - Viewpoint 1: $\mathcal{O}((\mathtt{c}+1)^{\mathtt{s}})$, which is independent of $\mathtt{n}$
  - Viewpoint 2: $\mathcal{O}(2^{\mathtt{s}\cdot\mathtt{c}})$, which is independent of $\mathtt{n}$
  - Viewpoint 3: $\mathcal{O}(\mathtt{s}^{\mathtt{n}}\cdot\mathtt{c}^{\mathtt{n}})$

  Does this actually matter?
- Ease of formulating the constraints and the objective:
  - It depends on the unstated other constraints.
  - Ideally, we want a viewpoint that allows global constraints to be used.
- Performance:
  - Hard to tell: we have to run experiments!
- Readability:
  - Who is going to read the model?
  - What is their background?

There are no correct answers here:
we actually need to think about this and run experiments.

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Outline

Example (Magic Series of length `n`: model)

The element at index `i` in `I = 0..(n-1)` is the number of occurrences of `i`.
Solutions: `Magic=[1,2,1,0]` and `Magic=[2,0,2,0]` for `n=4`.

Decision variables: `Magic` =

0	1	⋯	n−1
∈ I	∈ I	⋯	∈ I

Problem Constraint:

```
forall(i in I)(Magic[i] = sum(j in I)(Magic[j] = i))
```

or, logically equivalently but better:

```
forall(i in I)(Magic[i] = count(Magic,i))
```

or, logically equivalently and even better:

```
global_cardinality_closed(Magic, array1d(I,I), Magic)
```

Implied Constraints:

```
sum(Magic) = n /\ sum(i in I)(i * Magic[i]) = n
```

Depending on the formulation above of the problem constraint,
the implied constraints accelerate a CP solver up to 100 times for `n=150`.

Definition

An implied constraint, also called a redundant constraint, is a constraint that logically follows from other constraints.

Benefit:
Solving may be faster, without losing any solutions.
However, not all implied constraints accelerate the solving.

Good practice in MiniZinc:
Flag implied constraints using `implied_constraint`. This allows backends to handle them differently, if wanted (see Topic 9: Modelling for CBLS):

`predicate implied_constraint(var bool: c) = c;` vs
`predicate implied_constraint(var bool: c) = true;`

Example

```
constraint implied_constraint(sum(Magic) = n);
```

In Topic 5: Symmetry,
we see the equally recommended `symmetry_breaking_constraint`.

Outline

Example (`n`-queens)

Use both the n^2 decision variables `Queen[r,c]` in `0..1`
and the `n` decision variables `Row[c]` in `1..n`.

Definition

A redundant decision variable denotes information already denoted by other variables: mutual redundancy (same information) vs non-mutual redundancy.

Benefit: Easier modelling, or faster solving, or both.
Careful, the terminology differs: derived parameters vs redundant variables.

Examples (see Topic 6: Case Studies)

- Each `Queen[..,c]` slice is mutually redundant with the variable `Row[c]`.
- Best model of Black-Hole Patience: mutual redundancy.
- Models 1 and 3 of Warehouse Location: non-mutual redundancy.
- Sport Scheduling: mutual redundancy.

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Example (n-queens)

One-way channelling from each decision variable `Row[c]` to one of its mutually redundant decision variables of the slice `Queen[..,c]`:

```
constraint forall(c in 1..n)(Queen[Row[c],c] = 1);
```

What sets the other decision variables of the slice `Queen[..,c]`?

Definition

A channelling constraint fixes the value of either some (1-way channelling) or all (2-way channelling) decision variables when the values of the decision variables they are redundant with are fixed.

This applies to both sets of decision variables.

Examples (see Topic 6: Case Studies)

- Best model of Black-Hole Patience: 2-way channelling.
- Models 1 and 3 of Warehouse Location: 1-way channelling.
- Sport Scheduling: 2-way channelling.

Example (Student Seating, viewpoint 2 revisited)

```
int: dummyS = 0;   % Advice: also experiment with nStudents+1
set of int: StudentsAndDummy = 1..nStudents union {dummyS};
% Student[c] = the student, possibly dummy, sitting on chair c:
array[1..nChairs] of var StudentsAndDummy: Student;
constraint global_cardinality_closed(Student, [dummyS]++[i|i in 1..nStudents],
   [nChairs - nStudents] ++ [1 | i in 1..nStudents]);
int: dummyP = 0;   % Advice: also experiment with nPgms+1
set of int: PgmsAndDummy = 1..nPgms union {dummyP};
% Pgm[s] = the given study programme of student s:
array[1..nStudents] of 1..nPgms: Pgm;
% Programme[c] = the programme of the student on chair c:
array[1..nChairs] of var PgmsAndDummy: Programme = % non-mut. red. w/ Student
   % 1-way channelling from Student to Programme, in case dummyS = 0:
   [array1d(StudentsAndDummy, [dummyP] ++ Pgm)[Student[c]] | c in 1..nChairs];
% (1) Each table has students of distinct study programmes:
constraint forall(T in Chairs)
   (all_different_except([Programme[c] | c in T], {dummyP}));
... % constraint (2) and objective (3) of slide 5
```

Note that `Student` uniquely determines `Programme` via `Pgm`, but not vice-versa: one can also formulate (1) directly with `Student` via `Pgm`.

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Outline

1. Viewpoints & Dummy Values

2. Implied Constraints

3. Redundant Variables & Channelling Constraints

4. Pre-Computation

Example (Prize-Pool Division)

Consider a maximisation problem where the objective function is the division of an unknown prize pool by an unknown number of winners:

```
...
array[1..5] of int: Pools = [1000,5000,15000,20000,25000];
var 1..5: x; % index of the actual prize pool within Pools
var 1..500: nbrWinners; % the number of winners
constraint ... x ... nbrWinners ...;
solve maximize Pools[x] div nbrWinners; % implicit: element!
```

Observation: We should beware of using the `div` function on decision variables, because:

- It yields weak reasoning, at least in CP and LCG solvers.
- Its reasoning takes unnecessary time and memory.

Idea: We can precompute all possible objective values, as derived parameters.

Example (Prize-Pool Division, revisited)

Precompute a 2d array of derived parameters, indexed by `1..5` and `1..500`, for each possible value pair of `x` and `nbrWinners`:

```
array[1..5] of int: Pools = [1000,5000,15000,20000,25000];
var 1..5: x; % index of the actual prize pool within Pools
var 1..500: nbrWinners; % the number of winners
constraint ... x ... nbrWinners ...;
array[1..5,1..500] of int: ObjVal = array2d(1..5, 1..500,
  [Pools[p] div n | p in 1..5, n in 1..500]); % div on par!
solve maximize ObjVal[x,nbrWinners]; % implicit: 2d-element!
```

Example (Kakuro Puzzle, reminder from Topic 3: Constraint Predicates)

We precomputed `all_different_sum(`X,σ`)` for $|X| \in 2..7$ and $\sigma \in 3..35$, say `table([x,y],[|1,3|3,1|])` for `all_different_sum([x,y],4)` and `table([y,z],[|1,2|2,1|])` for `all_different_sum([y,z],3)`, because MiniZinc has no `all_different_sum` predicate and its definition by a conjunction of `all_different` and `sum` has too poor reasoning.