

Advanced School in Artificial Intelligence

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# Programming with Constraints

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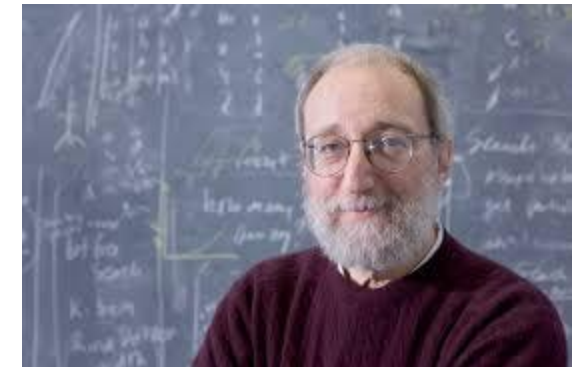
# Constraint Programming



- **Constraint Programming (CP)** is a *declarative* paradigm to model and solve CSPs and COPs
- **Declarative** = focus on **what** to solve, rather than how to do it

*“ Constraint Programming represents one of the closest approaches Computer Science has yet made to the Holy Grail of programming: **the user states the problem, the computer solves it** ”*

Eugene C. Freuder (1997)  
Professor Emeritus, University College Cork



# Modelling CP problems



- Converting a real-life problem into a mathematical model that “*better abstracts*” can be **tricky**
  - It requires **expertise**, the concept of “best abstraction” is informal and not univocal
- The same problem can have different yet **equivalent models**
  - the same solver can have **different performance** on equivalent models
- Different solvers can perform differently on the **same model**
  - The user may define a model according to the solver that will solve it
  - *Portfolio solvers*

# Encoding CP problems



- Given a mathematical model for a problem, we need to **encode** it in a language understandable by the solver(s) that will solve it
- Officially, **no standard** language to encode CP problems
- However, one of the most known is called **MiniZinc**
  - <https://www.minizinc.org/>
- MiniZinc is high-level and **solver-independent**
  - *“Model once, solve anywhere”*
- Who develops/developed MiniZinc?
  - **Monash University**, CSIRO Data61, University of Melbourne



# MiniZinc



- MiniZinc is modelling language, **not a solver!** It allows the user to specify:
  - **Parameters**
    - MiniZinc also provides **separation** model/data
  - **Variables** of different **type**, and corresponding **domains**
    - Boolean, integers, floats, set of integers, ...
  - **Constraints** over the variables
    - Arithmetical, logical, **global**
  - **Objective** (minimization/maximization)
  - ...and much more!



# Example: Sudoku



```
1 include "globals.mzn";
2
3 function array[int] of var int:
4 subgrid(array[int,int] of var int: grid, int: i, int: j) =
5   [grid[3*(i-1)+p, 3*(j-1)+q] | p in 1..3, q in 1..3];
6
7 array[1..9,1..9] of var 1..9: grid = [|
8   5, 3, _, _, 7, _, _, _ |
9   6, _, _, 1, 9, 5, _, _ |
10  _, 9, 8, _, _, _, _, 6 |
11  8, _, _, 6, _, _, 3 |
12  4, _, 8, _, 3, _, 1 |
13  7, _, _, 2, _, _, 6 |
14  _, 6, _, _, _, 2, 8, _ |
15  _, _, 4, 1, 9, _, 5 |
16  _, _, _, 8, _, 7, 9
17 |];
18 constraint forall (i in 1..9) (all_different([grid[i,j] | j in 1..9]));
19 constraint forall (j in 1..9) (all_different([grid[i,j] | i in 1..9]));
20 constraint forall (i in 1..3, j in 1..3) (all_different(subgrid(grid, i,j)));
21
22 solve satisfy;
```

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

# Example: Sudoku



Output

Finished in 127msec  
Compiling sudoku.mzn  
Running sudoku.mzn

5	3	4	6	7	8	9	1	2
6	7	2	1	9	5	3	4	8
1	9	8	3	4	2	5	6	7
8	5	9	7	6	1	4	2	3
4	2	6	8	5	3	7	9	1
7	1	3	9	2	4	8	5	6
9	6	1	5	3	7	2	8	4
2	8	7	4	1	9	6	3	5
3	4	5	2	8	6	1	7	9

-----  
Finished in 130msec

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

# Example: Subset-sum



- **subset-sum problem:** are there **N** numbers in a set **S** adding up to **K**?

```
1 % Are there N numbers in a set S adding up to K?
2 include "globals.mzn";
3
4 set of int: S = {7, 10, 23, 13, 4, 16};
5 int: N = 4;
6 int: K = 50;
7
8 array[1..N] of var S: X;
9 constraint all_different(X);
10 constraint sum(X) = K;
11
12 solve satisfy;
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**CSP**

# Getting started

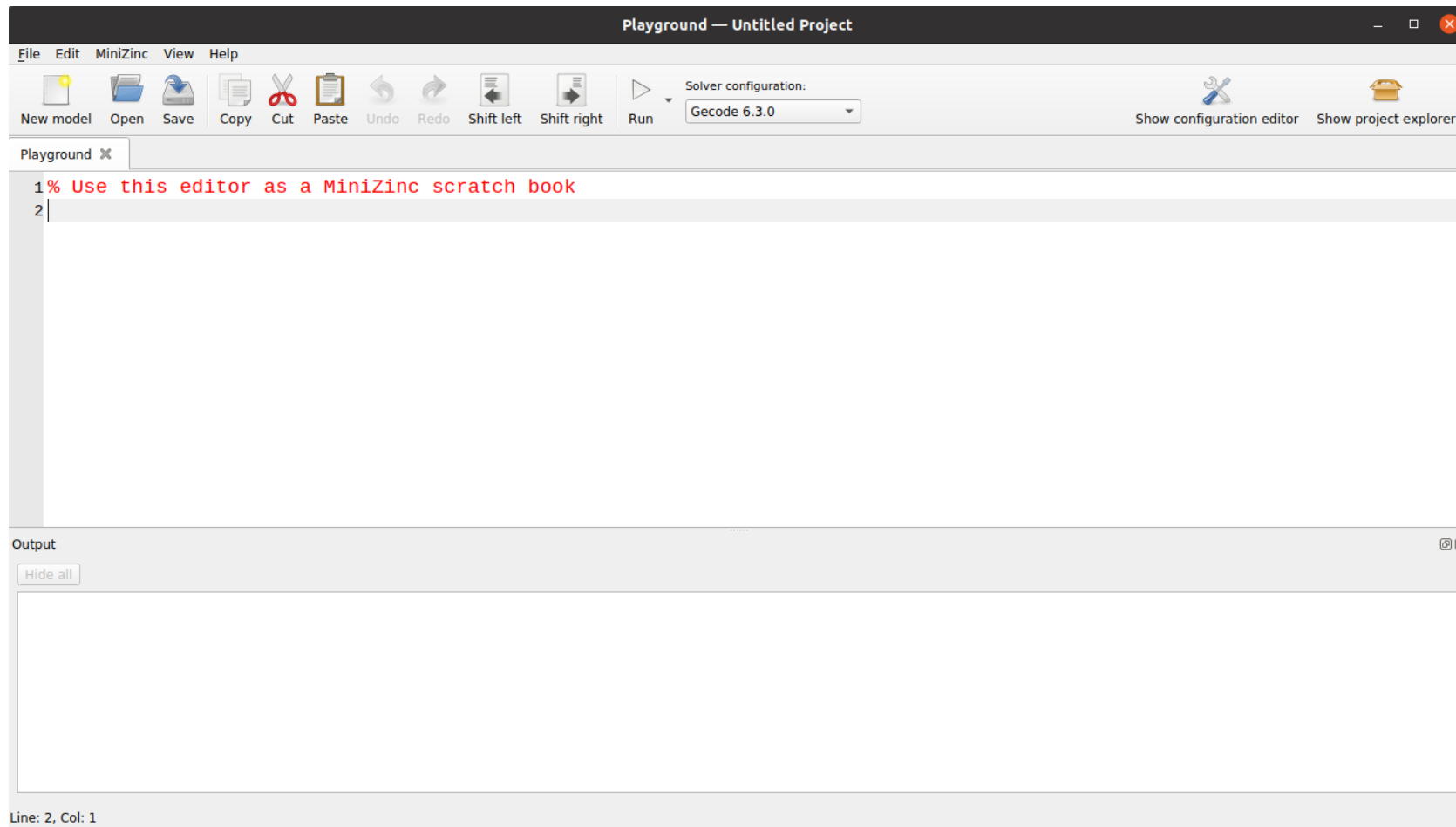


- **Download** and Install **MiniZinc**: <https://www.minizinc.org/software.html>
  - Bundled binary packages recommended
- **MiniZinc IDE**: Integrated Development Environment to:
  - **Develop** MiniZinc models (editor)
  - **Compile** MiniZinc models into FlatZinc, a low-level language understood by a large range of solvers
    - Solvers solve the derived FlatZinc, not the MiniZinc model
  - **Solve** a compiled model by one of the integrated solvers
    - Chuffed
    - Gecode
    - Coin-BC
    - ...

# Getting Started



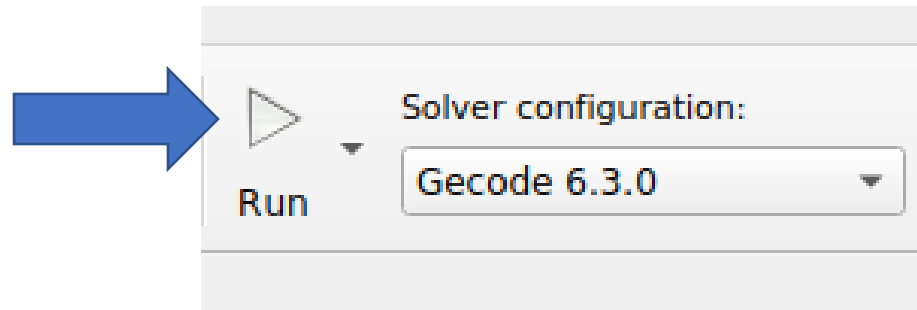
- Now open the **MiniZinc IDE**. It should appear something like:



# MiniZinc IDE



- **Exercise:** Implement the above models (or other models!) with MiniZinc and solve them
  - The FlatZinc compilation is transparent for the user, just pick a solver and click "**Run**"!



- Use **different solvers**:
  - Chuffed
  - COIN-BC
  - Gecode
  - ...
- ...Is the **output** always the same?

```
Running subset-sum.mzn
X = [10, 7, 13, 4];
-----
Finished in 139msec.
```



# Solving CP problems



- Once a CP model is defined, a **constraint solver** is used to solve the constraints and (possibly) return a solution
- CP solving basically works in two steps:
  - **Propagation**: the domains of the variables are **pruned** until no more pruning is possible (not complete)
    - E.g., propagating  $x < y$  with  $D(x) = [1,5]$ ,  $D(y) = [-2,4]$  results in  $D(x) \leftarrow [1,3]$  and  $D(y) \leftarrow [2,4]$ . This in turn may trigger other propagators until a **fixpoint** is reached
  - **Search**: we “guess” the value of a variable (heuristics) and if we have a failure we **backtrack**, until either all the variables are **assigned** (we have a solution) or **unsatisfiability** is proven (all the alternatives fail)

# Solving CP problems



- A powerful technique for solving (not only) CP problems is called **clause learning**
  - a.k.a. **no-goods** learning
  - Basically, redundant constraints are **learned** during the solving process to **avoid to repeat** the same "*bad choices*" during the search process
- Examples of effective CP solvers using clause learning are **Chuffed** (part of MiniZinc bundle), **OR-Tools** (developed by Google), and **Opturion** (commercial software)
  - <https://github.com/chuffed/chuffed>
  - <https://developers.google.com/optimization>
  - <https://www.opturion.com/>
- Other well-known CP solvers: Gecode, iZplus, Picat, Choco, etc...
  - See *MiniZinc Challenge*: <https://www.minizinc.org/challenge.html>

# Exercise



- We are **master brewers**. We bought the right ingredients (Corn, Hop, Malt) and we need to **decide** how many **Ales** and **Beers** as possible, given the **resources available**, to maximize the potential **profit**:

Beverage	Corn	Hops	Malt	Profit
Ale	5	4	35	13
Beer	15	4	20	23
Q.ty available	480	160	1190	

- First define a **model** for this problem
  - Identify **variables** (decisions), **domains** (options), **constraints** (requirement), **objective function** (goal)
- Then **implement** it and **solve** it with MiniZinc
  - Hint*: use **solve maximize** instead of solve satisfy...