Proceedings of the 2022 XCSP3 Competition

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▶ **To cite this version:**

HAL Id: hal-03937145

https://univ-artois.hal.science/hal-03937145

Submitted on 13 Jan 2023

XCSP^3 Competition 2022
Proceedings

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September 1, 2022

This document represents the proceedings of the XCSP^3 Competition 2022. The website containing all **detailed results** is available at: http://www.cril.univ-artois.fr/XCSP22/

The organization of this 2022 competition involved the following tasks:

- adjusting general details (dates, tracks, . . .) by G. Audemard, C. Lecoutre and E. Lonca

- selecting instances (problems, models and data) by C. Lecoutre

- receiving, testing and executing solvers on CRIL cluster by E. Lonca

- validating solvers and rankings by C. Lecoutre and E. Lonca

- developping the 2022 website dedicated to results by G. Audemard

Contents

Chapter 1

About the Selection of Problems in 2022

Remember that the complete description, **Version 3.0.7**, of the format (XCSP³) used to represent combinatorial constrained problems can be found in [4]. For the 2022 competition, we have limited XCSP³ to its kernel, called XCSP³-core [5]. This means that the scope of XCSP³ is restricted to:

- integer variables,

- CSP and COP problems,

- a set of 21 popular (global) constraints for Standard tracks:

  - generic constraints: `intension` and `extension`
  - language-based constraints: `regular` and `mdd`
  - comparison constraints: `allDifferent`, `allEqual`, `ordered` and `lex`
  - counting/summing constraints: `sum`, `count`, `nValues` and `cardinality`
  - connection constraints: `maximum`, `minimum`, `element` and `channel`
  - packing/scheduling constraints: `noOverlap` and `cumulative`
  - `circuit`, `instantiation` and `slide`

  and a small set of constraints for Mini-solver tracks.

For the 2022 competition, 41 problems have been selected. They are succinctly presented in Table 1.1. For each problem, the type of optimization is indicated (if any), as well as the involved constraints. At this point, do note that making a good selection of problems/instances is a difficult task. In our opinion, important criteria for a good selection are:

- the novelty of problems, avoiding constraint solvers to overfit already published problems;

- the diversity of constraints, trying to represent all of the most popular constraints (those from XCSP³-core) while paying attention to not over-representing some of them (in particular, second class citizens);

- the scaling up of problems.

Novelty.   Many problems are new in 2022, with most of the models written in PyCSP³. Two problems have been submitted, in response to the call.

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CSP Problems	Global Constraints (including extension)
Aztec Diamond	extension (∗)
Blocked Queens	allDifferent
Car Sequencing	cardinality, extension, sum
Costas Arrays	allDifferent
Crosswords	extension
Crypto	extension (∗)
Diamond Free	lex, sum
Eternity	allDifferent, extension
Hadamard	sum
Hidato	allDifferent, extension (∗)
Knight Tour	circuit
Molnar	lex, sum
Number Partitioning	allDifferent, sum
Rostering	allDifferent, regular
Ortho. Latin Squares	allDifferent, extension
Pseudo-Boolean	sum
Quasigroup	allDifferent, element
Room Mate	
Solitaire Batleship	cardinality, count, extension, regular, sum
Sports Scheduling	allDifferent, cardinality, count, extension
Superpermutation	allDifferent, element

COP Problems	Optimization	Global Constraints (including extension)
Aircraft Landing	min EXPR	allDifferent, extension, noOverlap
Clock Triplets	min VAR	allDifferent, sum
Coins Grid	min SUM	sum
CVRP	min SUM	allDifferent, cardinality, element, sum
Cyclic Bandwith	min MAXIMUM	allDifferent
DC	min SUM	extension, sum
Echelon Stock	min SUM	sum
Filters	min MAXIMUM	noOverlap
Itemset Mining	max SUM	count, lex, sum
Multi-Agent Path Finding	min MAXIMUM min SUM	allDifferent, extension
Nurse Rostering	min SUM	count, extension, regular, slide, sum
Nursing Workload	min SUM	cardinality, sum
RCPSP	min VAR	cumulative
RLFAP	min MAXIMUM min N_VALUES min SUM	
Spot5	min SUM	extension
TAL	min SUM	count, extension
Triangular	max SUM	sum
Warehouse	min SUM	count, element
War or Peace	min SUM	sum

Table 1.1: Selected Problems for the main tracks of the 2022 Competition. VAR/EXPR means that a variable/expression must be optimized. For RLFAP and Multi-agent Path Finding, the type of objective differs depending on instances. When extension is followed by (∗), it means that short tables are involved.

Diversity. Of course, not all types of constraints are equally involved in the selected benchmark. In the next edition, we shall attempt to foster the representation of CP-representative global constraints such as `cumulative` and `noOverlap`, and possibly, to introduce a couple of new ones (e.g., `binPacking`).

Scaling up. It is always interesting to see how constraint solvers behave when the instances of a problem become harder and harder. This is what we call the scaling behavior of solvers. For most of the problems in the 2022 competition, we have selected series of instances with regular increasing difficulty. It is important to note that assessing the difficulty of instances was determined with ACE, which is the main reason why ACE is off-competition (due to this strong bias).

Selection. This year, the selection of problems and instances has been performed by Christophe Lecoutre. As a consequence, the solver ACE was labelled off-competition.

Chapter 2

Problems and Models

In the next sections, you will find all models used for generating the XCSP[3] instances of the 2022 competition (for main CSP and COP tracks). Almost all models are written in PyCSP[3] [8], Version 2.0, officially released in December 2021; see https://pycsp.org/.

2.1 CSP

2.1.1 Aztec Diamond

Description. An Aztec diamond of order n consists of $2n$ centered rows of unit squares, of respective lengths $2, 4, \ldots, 2n-2, 2n, 2n-2, \ldots, 4, 2$. An Aztec diamond of order n has exactly $2^{(n*(n+1)/2)}$ tilings by dominos. See wikipedia.org. Building a solution analytically may be easy. However, a CP model is interesting as one can easily add side constraints to form Aztec diamonds with some specific properties (although this is not the case here).

Data. Only one integer is required to specify a specific instance. Values of n used for the competition are:

> 25, 50, 75, 100, 150, 200, 250, 300

Model. The PyCSP[3] model, in a file 'AztecDiamond.py', used for the competition is:

PyCSP[3] Model 1

```python
from pycsp3 import *

n = data # order of the Aztec diamond

def valid(i, j):
   if i < 0 or i >= n * 2 or j < 0 or j >= n * 2:
      return False
   if i < n - 1 and (j < n - 1 - i or j > n + i):
      return False
   if i > n and (j < i - n or j > 3 * n - i - 1):
      return False
   return True

def inner(i, j):
    return valid(i, j - 1) and valid(i, j + 1) and valid(i - 1, j) and valid(i + 1, j)
```

```
# all valid cells
valid_cells = [(i, j) for i in range(2 * n) for j in range(2 * n) if valid(i, j)]

# all inner cells, i.e., valid cells that are not situated on the border of the diamond
inners = [(i, j) for i, j in valid_cells if inner(i, j)]

# all border cells, i.e., valid cells that are situated on the border of the diamond
borders = [(i, j) for i, j in valid_cells if not inner(i, j)]


# x[i][j] is the position (0: left, 1: right, 2:top, 3: bottom) of the second part of the
    domino whose first part occupies the cell ar row i and column j
x = VarArray(size=[2 * n, 2 * n], dom=lambda i, j: range(4) if valid(i, j) else None)

satisfy(
   # constraining cells situated on the top left border
   [(x[i][j], x[i][j + 1], x[i + 1, j]) in {(1, 0, ANY), (3, ANY, 2)}
       for i, j in borders if not valid(i, j - 1) and not valid(i - 1, j)],

   # constraining cells situated on the top right border
   [(x[i][j], x[i][j - 1], x[i + 1, j]) in {(0, 1, ANY), (3, ANY, 2)}
     for i, j in borders if not valid(i, j + 1) and not valid(i - 1, j)],

   # constraining cells situated on the bottom left border
   [(x[i][j], x[i][j + 1], x[i - 1, j]) in {(1, 0, ANY), (2, ANY, 3)}
     for i, j in borders if not valid(i, j - 1) and not valid(i + 1, j)],

   # constraining cells situated on the bottom right border
   [(x[i][j], x[i][j - 1], x[i - 1, j]) in {(0, 1, ANY), (2, ANY, 3)}
     for i, j in borders if not valid(i, j + 1) and not valid(i + 1, j)],

   # constraining inner cells
   [(x[i][j], x[i][j - 1], x[i, j + 1], x[i - 1][j], x[i + 1][j]) in {(0, 1, ANY, ANY, ANY),
       (1, ANY, 0, ANY, ANY), (2, ANY, ANY, 3, ANY), (3, ANY, ANY, ANY, 2)}
     for i, j in inners]
)
```

The model involves a two-dimensional array of variable x, and several groups (lists) of starred table constraints (ANY is '*'). A series of 8 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

```
python AztecDiamond.py -data=100
```

2.1.2   Blocked Queens

This is Problem 080 on CSPLib, called Blocked n-Queens Problem.

Description (excerpt from CSPLib).   The blocked n-queens problem is a variant of n-queens which has been proven to be NP-complete as a decision problem and #P-complete as a counting problem. The blocked n-queens problem is a variant where, as well as n, the input contains a list of squares which are blocked. A solution to the problem is a solution to the n-Queens problem containing no queens on any of the blocked squares.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "n": 6,
   "blocks": [[0,2], [3,4], [5,1]]
}
```

A series of 400 instances (not in JSON format) can be found on CSPLib. They were used in ASP competitions. The problem was also the subject of the LP/CP programming contest at ICLP 2016.

Model.   The PyCSP[3] model, in a file 'BlockedQueens.py', used for the competition is:

🖋 PyCSP[3] Model 2

```python
from pycsp3 import *

n, blocks = data

# q[i] is the column where is put the ith queen (at row i)
q = VarArray(size=n, dom=range(n))

satisfy(
   # respecting blocks
   [q[i] != j for (i, j) in blocks],

   # no two queens on the same column
   AllDifferent(q),

   # no two queens on the same diagonal
   [abs(q[i] - q[j]) != abs(i - j) for i, j in combinations(n, 2)]
)
```

The model involves a global constraint `AllDifferent` and some unary and binary intensional constraints. A series of 8 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

   `python BlockedQueens.py -data=28-1449787798 -dataparser=BlockedQueens_Parser.py`

where '28-1449787798' is a data file in Essence format and 'BlockedQueens_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.3   Car Sequencing

This is Problem 001 on CSPLib.

Description (excerpt from CSPLib).   A number of cars are to be produced; they are not identical, because different options are available as variants on the basic model. The assembly line has different stations which install the various options (air-conditioning, sun-roof, etc.). These stations have been designed to handle at most a certain percentage of the cars passing along the assembly line. Furthermore, the cars requiring a certain option must not be bunched together, otherwise the station will not be able to cope. Consequently, the cars must be arranged in a sequence so that the capacity of each station is never exceeded. For instance, if a particular station can only cope with at most half of the cars passing along the line, the sequence must be built so that at most 1 car in any 2 requires that option.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
  "carClasses": [
    { "demand": 1, "options": [1, 0, 1, 1, 0] },
```

```
            { "demand": 2, "options": [0, 1, 0, 0, 1] },
            { "demand": 2, "options": [0, 1, 0, 1, 0] },
            { "demand": 2, "options": [1, 1, 0, 0, 0] }
        ],
        "optionLimits": [
            { "num": 1, "den": 2 },
            { "num": 2, "den": 3 },
            { "num": 1, "den": 3 },
            { "num": 2, "den": 5 },
            { "num": 1, "den": 5 }
        ]
    }
```

Model. The PyCSP^3 model, in a file 'CarSequencing.py', used for the competition is:

✎ PyCSP^3 Model 3

```python
from pycsp3 import *

classes, limits = data
demands = [demand for demand, _ in classes]
nCars, nClasses, nOptions = sum(demands), len(classes), len(limits)

# c[i] is the class of the ith assembled car
c = VarArray(size=nCars, dom=range(nClasses))

# o[i][k] is 1 if the ith assembled car has option k
o = VarArray(size=[nCars, nOptions], dom={0, 1})

satisfy(
    # building the right numbers of cars per class
    Cardinality(c, occurrences={j: demands[j] for j in range(nClasses)})
)

if not variant():
    satisfy(
        # computing assembled car options
        imply(c[i] == j, o[i][k] == options[k]) for i in range(nCars)
            for j, (_, options) in enumerate(classes) for k in range(nOptions)
    )
elif variant('table'):
    satisfy(
        # computing assembled car options
        (c[i], *o[i]) in {(j, *options) for j, (_, options) in enumerate(classes)}
            for i in range(nCars)
    )

def sum_from_full_consecutive_blocks(k, nb):
    # nb stands for the number of consecutive blocks (of cars) set to their maximal capacity
    n_cars_with_option = sum(demand for (demand, options) in classes if options[k] == 1)
    remaining = n_cars_with_option - nb * limits[k].num
    possible = nCars - nb * limits[k].den
    return Sum(o[:possible, k]) >= remaining if remaining > 0 and possible > 0 else None

satisfy(
    # respecting option frequencies
    [Sum(o[i:i + den, k]) <= num for k, (num, den) in enumerate(limits)
        for i in range(nCars) if i <= nCars - den],
```

```
    # additional constraints by reasoning from consecutive blocks tag(redundant-constraints)
    [sum_from_full_consecutive_blocks(k, nb) for k in range(nOptions)
      for nb in range(ceil(nCars // limits[k].den) + 1)]
)
```

This model involves 2 arrays of variables and 4 types of constraints: `Cardinality`, `Intension`, `Extension` and `Sum`. Actually, depending on the chosen variant, either `Extension` constraints are posted, or binary `Intension` constraints are posted with predicates like $c_i = j \Rightarrow o_{i,k} = v$ where v is the value (0 or 1) of the kth option of the jth class. The last group of constraints corresponds to redundant constraints. A series of 10 instances has been selected for the competition (8 for variant 'table'). For generating an XCSP³ instance (file), you can execute for example:

```
python CarSequencing.py -data=90-01 -dataparser=CarSequencing_Parser.py
python CarSequencing.py -variant=table -data=90-01 -dataparser=CarSequencing_Parser.py
```

where '90-01' is a data file and 'CarSequencing_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that when you omit to write '-variant=table', you get the main variant. Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.4 Costas Arrays

This is Problem 076 on CSPLib.

Description (excerpt from CSPLib). A costas array is a pattern of n marks on an $n \times n$ grid, one mark per row and one per column, in which the $n \times (n-1)/2$ vectors between the marks are all different. Such patterns are important as they provide a template for generating radar and sonar signals with ideal ambiguity functions.

Data. Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

    15, 16, 17, 18, 19, 20, 22, 24, 26, 28

Model. The PyCSP³ model, in a file 'CostasArray.py', used for the competition is:

🖌 **PyCSP³ Model 4**

```
from pycsp3 import *

n = data

# x[i] is the row where is put the ith mark (on the ith column)
x = VarArray(size=n, dom=range(n))

satisfy(
    # all marks are on different rows (and columns)
    AllDifferent(x),

    # all displacement vectors between the marks must be different
    [AllDifferent(x[i] - x[i + d] for i in range(n - d)) for d in range(1, n - 1)]
)
```

This model involves 1 array of variables and several constraints `AllDifferent`. A series of 10 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

```
python CostasArray.py -data=20
```

2.1.5 Crosswords (Satisfaction)

This problem has already been used in previous XCSP competitions, because it notably permits to compare filtering algorithms on large table constraints.

Description. Given a grid with imposed black cells (spots) and a dictionary, the problem is to fulfill the grid with the words contained in the dictionary.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
   "spots": [[0,1,0,0,0], [0,0,0,0,0], [0,0,1,0,0], [0,0,0,0,0], [0,0,0,0,1]],
   "dict": "ogd2008"
}
```

Model. A model similar to the following one, in a file 'Crossword.py', was used in 2018:

🖌 PyCSP[3] Model 5

```python
from pycsp3 import *

spots, dict_name = data

# loading words of the dictionary
words = dict()
for line in open(dict_name):
    code = alphabet_positions(line.strip().lower())
    words.setdefault(len(code), []).append(code)

# For Hole, i and j are indexes (one of them being a slice) and r is the size
Hole = namedtuple("Hole", "i j r")

def build_hole(row, col, size, horizontal):
    sl = slice(col, col + size)
    return Hole(row, sl, size) if horizontal else Hole(sl, row, size)

def find_holes(matrix, transposed):
    p, q = len(matrix), len(matrix[0])
    t = []
    for i in range(p):
        start = -1
        for j in range(q):
            if matrix[i][j] == 1:
                if start != -1 and j - start >= 2:
                    t.append(build_hole(i, start, j - start, not transposed))
                start = -1
            elif start == -1:
                start = j
            elif j == q - 1 and q - start >= 2:
                t.append(build_hole(i, start, q - start, not transposed))
    return t
```

```
holes = find_holes(spots, False) + find_holes(columns(spots), True)
n, m, nHoles = len(spots), len(spots[0]), len(holes)

# x[i][j] is the letter, number from 0 to 25, at row i and column j (when no spot)
x = VarArray(size=[n, m], dom=lambda i, j: range(26) if spots[i][j] == 0 else None)

satisfy(
   # fill the grid with words
   x[i, j] in words[r] for (i, j, r) in holes
)
```

This model only involves 1 array of variables and 1 group of ordinary table constraints. For clarity, we use an auxiliary named tuple `Hole`. A series of 13 instances, with only blank grids, has been selected for the competition. Note that it is not possible to write x[i][j] when i is a slice; this must be x[i, j]. For generating an XCSP^3 instance (file), you can execute for example:

```
python Crossword.py -data=[vg-04-05,dict=ogd2008] -dataparser=Crossword_Parser.py
```

where 'vg-04-05' is a data file representing a grid, 'ogd2008' is the name of a dictionary file (we need to use 'dict=' as a prefix, otherwise the dictionary will be appended to the first file) and 'Crossword_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

Important: The series of instances, used for the 2022 competition comes from the 2018 competition, and compiling instances from the PyCSP^3 model above may produce slighlty different files.

2.1.6   Crypto

A series of 10 instances has been generated (independently of PyCSP^3), and submitted to the 2022 competition by Martin Mariusz Lester. This benchmark encodes 10 instances of breaking the weak stream cipher Crypto1. M. M. Lester generated the instances using the tool Grain of Salt (which produces CNF format SAT instances), then translated them into XCSP^3 instances. Martin picked instances that were relatively harder for MiniSAT to solve (2-4 minutes). He hypothesised that these instances would be hard for any XCSP^3 solver that does not use a SAT solver as the backend, with XCSP^3 solvers using more modern solvers faring best. Perhaps this benchmark is not very interesting from the perspective of using XCSP^3 as an intermediate language, as it is a translation back from a low-level language that loses all of the structure. Nonetheless, it may serve as a reminder that these kinds of encodings exist.

2.1.7   Diamond Free

This is Problem 050 on CSPLib, called Diamond-free Degree Sequences.

Description (excerpt from CSPLib). A diamond is a set of four vertices in a graph such that there are at least five edges between those vertices. Conversely, a graph is diamond-free if it has no diamond as an induced subgraph, i.e. for every set of four vertices the number of edges between those vertices is at most four.

Data. Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

30, 40, 50, 60, 70, 80

Model.   The PyCSP[3] model, in a file 'DiamondFree.py', used for the competition is:

PyCSP[3] Model 6

```
from pycsp3 import *

n = data

# x is the adjacency matrix
x = VarArray(size=[n, n], dom=lambda i, j: {0, 1} if i != j else {0})

# y[i] is the degree of the ith node
y = VarArray(size=n, dom={i for i in range(1, n) if i % 3 == 0})

# s is the sum of all degrees
s = Var(dom={i for i in range(n, n * (n - 1) + 1) if i % 12 == 0})

satisfy(
   # ensuring the absence of diamond in the graph
   [Sum(x[i][j], x[i][k], x[i][l], x[j][k], x[j][l], x[k][l]) <= 4
      for i, j, k, l in combinations(n, 4)],

   # ensuring that the graph is undirected (symmetric)
   [x[i][j] == x[j][i] for i, j in combinations(n, 2)],

   # computing node degrees
   [Sum(x[i]) == y[i] for i in range(n)],

   # computing the sum of node degrees
   Sum(y) == s,

   # tag(symmetry-breaking)
   [Decreasing(y), LexIncreasing(x)]
)
```

This model involves 2 arrays of variables, a stand-alone variable and 4 types of constraints: `Sum`, `Intension`, `Decreasing` and `LexIncreasing`. A series of 6 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

```
python DiamondFree.py -data=40
```

2.1.8   Eternity

Eternity II is a famous edge-matching puzzle, released in July 2007 by TOMY, with a 2 million dollars prize for the first submitted solution; see, e.g., [3]. Here, we are interested in instances derived from the original problem by the BeCool team of the UCL ("Université Catholique de Louvain") who proposed them for the 2018 competition.

Description.   On a board of size $n \times m$, you have to put square tiles (pieces) that are described by four colors (one for each direction : top, right, bottom and left). All adjacent tiles on the board must have matching colors along their common edge. All edges must have color '0' on the border of the board.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "n": 3,
   "m": 3,
```

```
    "pieces": [
        [0,0,1,1], [0,0,1,2], [0,0,2,1], [0,0,2,2], [0,1,3,2],
        [0,1,4,1], [0,2,3,1], [0,2,4,2], [3,3,4,4]
    ]
}
```

Model. The PyCSP³ model, in a file 'Eternity.py', used for the competition is:

PyCSP³ Model 7

```python
from pycsp3 import *

n, m, pieces = data
assert n * m == len(pieces), "badly formed data"
max_value = max(max(piece) for piece in pieces) # max possible value on pieces

table = {(i, piece[r % 4], piece[(r + 1) % 4], piece[(r + 2) % 4], piece[(r + 3) % 4])
            for i, piece in enumerate(pieces) for r in range(4)}

# x[i][j] is the index of the piece at row i and column j
x = VarArray(size=[n, m], dom=range(n * m))

# t[i][j] is the value at the top of the piece at row i and column j
t = VarArray(size=[n + 1, m], dom=range(max_value + 1))

# l[i][j] is the value at the left of the piece at row i and column j
l = VarArray(size=[n, m + 1], dom=range(max_value + 1))

satisfy(
    # all pieces must be placed (only once)
    AllDifferent(x),

    # all pieces must be valid (i.e., must correspond to those given initially,
    # possibly after applying some rotation)
    [(x[i][j], t[i][j], l[i][j + 1], t[i + 1][j], l[i][j]) in table
        for i in range(n) for j in range(m)],

    # putting special value 0 on borders
    [z == 0 for z in t[0] + l[:, -1] + t[-1] + l[:, 0]]
)
```

This model involves 3 arrays of variables and 3 types of constraints: `AllDifferent`, `Extension` and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Eternity.py -data=06-06 -dataparser=Eternity_Parser.py
```

where '06-06' is a data file representing a puzzle and 'Eternity_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.9 Hadamard

This is Problem 084 on CSPLib, called 2cc Hadamard matrix Legendre pairs.

Description. For every odd positive integer n (and $m = (n-1)/2$), the 2cc Hadamard matrix Legendre pairs are defined from m quadratic constraints and 2 linear constraints.

Data. Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

17, 19, 21, 23, 25, 27, 29, 31, 35, 41

Model. The PyCSP[3] model, in a file 'Hadamard.py', used for the competition is:

✎ PyCSP[3] Model 8

```python
from pycsp3 import *

n = data
assert n % 2 == 1
m = (n - 1) // 2

# x[i] is the ith value of the first sequence
x = VarArray(size=n, dom={-1, 1})

# y[i] is the ith value of the second sequence
y = VarArray(size=n, dom={-1, 1})

satisfy(
   Sum(x) == 1,
   Sum(y) == 1,

   # quadratic constraints
   [
      Sum(x[i] * x[(i + k) % n] for i in range(n))
    + Sum(y[i] * y[(i + k) % n] for i in range(n))
    == -2 for k in range(1, m + 1)
   ]
)
```

This model involves 2 arrays of variables and several constraints `Sum`. A series of 10 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

```
python Hadamard.py -data=23
```

2.1.10   Hidato

Description. Hidato, also known as Hidoku is a logic puzzle game invented by Gyora M. Benedek, an Israeli mathematician. The goal of Hidato is to fill the grid with consecutive numbers that connect horizontally, vertically, or diagonally. See wikipedia.org.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "n": 5,
  "m": 5,
  "clues": [
     [0, 0, 20, 0, 0],
     [0, 0, 0, 16, 18],
     [22, 0, 15, 0, 0],
     [23, 0, 1, 14, 11],
     [0, 25, 0, 0, 12]
  ]
}
```

Model. The PyCSP³ model, in a file 'Hidato.py', used for the competition is:

✎ **PyCSP³ Model 9**

```
from pycsp3 import *

n, m, clues = data # clues are given by strictly positive values

# x[i][j] is the value in the grid at row i and column j
x = VarArray(size=[n, m], dom=range(1, n * m + 1))

satisfy(
   # all values must be different
   AllDifferent(x),

   # respecting clues
   [x[i][j] == clues[i][j] for i in range(n) for j in range(m) if clues and clues[i][j] > 0]
)

if variant('table'):

   def table(i, j):
      corners = {(0, 0), (0, m - 1), (n - 1, 0), (n - 1, m - 1)}
      r = 3 if (i, j) in corners else 5 if i in (0, n - 1) or j in (0, m - 1) else 8
      return [(v, *[v + 1 if l == k else ANY for l in range(r)]) for v in range(1, n * m)
               for k in range(r)]
            + [(n * m, *[ANY] * r)]

   satisfy(
      # ensuring adjacent consecutive numbers
      (x[i][j], x.around(i, j)) in table(i, j) for i in range(n) for j in range(m)
   )

else: # variant not considered for the competition
   ...
```

This model involves 1 array of variables and 3 types of constraints: `AllDifferent`, `Extension` and `Intension`. A series of 9 instances (with variant 'table') has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

    `python Hidato.py -variant=table -data=p1.json`

or with an empty grid of size 10×10:

    `python Hidato.py -variant=table -data=[10,10,null]`

2.1.11 Knight Tour

Description. A knight's tour is a sequence of moves of a knight on a chessboard such that the knight visits every square exactly once. If the knight ends on a square that is one knight's move from the beginning square (so that it could tour the board again immediately, following the same path), the tour is closed (or re-entrant); otherwise, it is open. See wikipedia.org.

Data. Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

    10, 20, 30, 40, 50, 60, 70, 80, 90, 100

Model. The PyCSP³ model, in a file 'KnightTour2.py', used for the competition is:

> **PyCSP³ Model 10**
>
> ```
> from pycsp3 import *
>
> n = data
>
> def domain_x(i):
>    r, c = i // n, i % n
>    t = [(r - 2, c - 1), (r - 2, c + 1), (r - 1, c - 2), (r - 1, c + 2),
>        (r + 1, c - 2), (r + 1, c + 2), (r + 2, c - 1), (r + 2, c + 1)]
>    return {k * n + l for (k, l) in t if 0 <= k < n and 0 <= l < n}
>
> # x[i] is the cell number that comes in the tour (by the knight) after cell i
> x = VarArray(size=n * n, dom=domain_x)
>
> satisfy(
>    # the knights form a circuit (tour)
>    Circuit(x),
>
>    # the first move is set tag(symmetry-breaking)
>    x[0] == n + 2
> )
> ```

This model involves 1 array of variables and 2 types of constraints: `Circuit` and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python KnightTour2.py -data=50
```

2.1.12   Molnar

This is Problem 035 on CSPLib.

Description (excerpt from CSPLib).   The problem (in this variant) is to construct a $k \times k$ matrix M with values strictly greater than 1 such that both the determinant of M and the determinant of M when squared values are considered are equal to 1 The solutions to this problem are significant in classifying certain types of topological spaces.

Data.   Only two integers are required to specify a specific instance. Values of k and d used for the instances in the competition are:

(2,20), (2,25), (3,7), (3,8), (3,9), (4,3), (4,4), (4,5), (5,4), (5,5)

Model.   The PyCSP³ model, in a file 'Molnar.py', used for the competition is:

> **PyCSP³ Model 11**
>
> ```
> from pycsp3 import *
> from pycsp3.classes.entities import TypeNode
>
> k, d = data
>
> def det_terms(t):
>    if len(t) == 2:
>       return [t[0][0] * t[1][1], -(t[0][1] * t[1][0])]
>    subterms = [det_terms([[v for j, v in enumerate(row) if j != i] for row in t[1:]])
>                for i in range(len(t))]
> ```

```
       return [t[0][i] * sub if i % 2 == 0 else -(t[0][i] * sub) for i in range(len(t))
               for sub in subterms[i]]

def determinant(t):
   terms = det_terms(t)
   # we extract coeffs from terms for posting a simpler Sum constraint later
   terms = [(term.sons[0], -1) if term.type == TypeNode.NEG else (term, 1) for term in terms]
   return [t for t, _ in terms] * [c for _, c in terms]


# x[i][j] is the value of the matrix at row i and column j
x = VarArray(size=[k, k], dom=range(2, d + 1))

# y[i][j] is the square of the value of the matrix x at row i and column j
y = VarArray(size=[k, k], dom=range(4, d * d + 1))

satisfy(
   # computing y
   [y[i][j] == x[i][j] * x[i][j] for i in range(k) for j in range(k)],

   determinant(x) == 1,

   determinant(y) == 1,

   # tag(symmetryBreaking)
   LexIncreasing(x, matrix=True)
)
```

This model involves 2 arrays of variables and 3 types of constraints: `Sum`, `LexIncreasing` and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Molnar.py -data=[4,5]
```

2.1.13 Number Partitioning

This is Problem 049 on CSPLib.

Description (excerpt from CSPLib). This problem consists in finding a partition of the set of numbers $\{1, 2, \ldots, n\}$ into two sets A and B such that:

- A and B have the same cardinality

- the sum of numbers in A is equal to the sum of numbers in B

- the sum of squares of numbers in A is equal to the sum of squares of numbers in B

There is no solution for $n < 8$.

Data. Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

20, 50, 80, 110, 140, 170, 200, 230, 260, 290

Model. The PyCSP³ model, in a file 'NumberPartitioning.py', used for the competition is:

🖌 PyCSP³ Model 12

```
from pycsp3 import *

n = data
assert n % 2 == 0, "The value of n must be even"

# x[i] is the ith value of the first set
x = VarArray(size=n // 2, dom=range(1, n + 1))

# y[i] is the ith value of the second set
y = VarArray(size=n // 2, dom=range(1, n + 1))

satisfy(
   AllDifferent(x + y),

   # tag(power1)
   [
      Sum(x) == n * (n + 1) // 4,
      Sum(y) == n * (n + 1) // 4
   ],

   # tag(power2)
   [
      Sum(x[i] * x[i] for i in range(n // 2)) == n * (n + 1) * (2 * n + 1) // 12,
      Sum(y[i] * y[i] for i in range(n // 2)) == n * (n + 1) * (2 * n + 1) // 12
   ],

   # tag(symmetry-breaking)
   [
      x[0] == 1,
      Increasing(x, strict=True),
      Increasing(y, strict=True)
   ]
)
```

This model involves 2 arrays of variables and 3 types of constraints: `AllDifferent`, `Sum` and `Increasing`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python NumberPartitioning.py -data=50
```

2.1.14   (Nurse) Rostering

This problem was described by G. Pesant, C.-G. Quimper and A. Zanarini [11]

Description.   This problem was inspired by a rostering context. The objective is to schedule n employees over a span of n time periods. In each time period, $n - 1$ tasks need to be accomplished and one employee out of the n has a break. The tasks are fully ordered 1 to $n-1$; for each employee the schedule has to respect the following rules:

- two consecutive time periods have to be assigned to either two consecutive tasks, in no matter which order i.e. $(t, t + 1)$ or $(t + 1, t)$, or to the same task i.e. (t, t);

- an employee can have a break after no matter which task;

- after a break an employee cannot perform the task that precedes the task prior to the break, i.e. (t, break, t - 1) is not allowed.

The problem is modeled with one constraint `Regular` per row and one constraint `Alldifferent` per column.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "preset": [[7, 5, 8], [7, 0, 8], [3, 5, 5], [0, 5, 4], [1, 7, 7]],
   "forbidden": []
}
```

Model.   The PyCSP[3] model, in a file 'Rostering.py', used for the competition is:

🎨 PyCSP[3] Model 13

```
from pycsp3 import *

n = 10
preset, forbidden = data

def automaton():
    # q(1,i) means before break and just after reading i
    # q(2,i) means just after reading break (0) and i before
    # q(3,i) means after break and just after reading i
    q, rng = Automaton.q, range(1, n)
    t = [(q(0), 0, q(2, 0))] + [(q(2, 0), i, q(3, i)) for i in rng]
    t.extend((q(0), i, q(1, i)) for i in rng)
    # BE CAREFUL: rule made stricter below than Pesant's rule
    t.extend((q(1, i), j, q(1, j)) for i in rng for j in (i - 1, i + 1) if 1 <= j < n)
    t.extend((q(1, i), 0, q(2, i)) for i in rng)
    # BE CAREFUL: rule made stricter below than Pesant's rule
    t.extend((q(2, i), j, q(3, j)) for i in rng for j in rng if abs(i - j) != 1)
    # BE CAREFUL: rule made stricter below than Pesant's rule
    t.extend((q(3, i), j, q(3, j)) for i in rng for j in (i - 1, i + 1) if 1 <= j < n)
    return Automaton(start=q(0), final=[q(2, i) for i in rng] + [q(3, i) for i in rng],
                     transitions=t)

A = automaton()

# x[i][j] is the task (or break) performed by the ith employee at time j
x = VarArray(size=[n, n], dom=range(n))

satisfy(
    [x[i][j] == k for (i, j, k) in preset],

    [x[i][j] != k for (i, j, k) in forbidden],

    [x[i] in A for i in range(n)],

    [AllDifferent(x[:, j]) for j in range(n)]
)
```

This model involves 1 array of variables and 3 types of constraints: `Regular`, `AllDifferent` and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

```
python Rostering.py -data=roster-5-00-02.dat -dataparser=Rostering_Parser.py
```

where 'roster-5-00-02.dat' is a data file and 'Rostering_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.15   Orthogonal Latin Squares

Description.   A Latin square of order n is an n by n array filled with n different symbols (for example, values between 1 and n), each occurring exactly once in each row and exactly once in each column. Two latin squares of the same order n are orthogonal if each pair of elements in the same position occurs exactly once. The most easy way to see this is by concatenating elements in the same position and verify that no pair appears twice. There are orthogonal latin squares of any size except 1, 2, and 6. See wikipedia.org.

Data.   Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

> 5, 6, 7, 8, 9, 10, 11, 12, 15, 20

Model.   The PyCSP^3 model, in a file 'Ortholatin.py', used for the competition is:

✎ **PyCSP^3 Model 14**

```python
from pycsp3 import *

n = data

# x is the first Latin square
x = VarArray(size=[n, n], dom=range(n))

# y is the second Latin square
y = VarArray(size=[n, n], dom=range(n))

# z is the matrix used to control orthogonality
z = VarArray(size=[n * n], dom=range(n * n))

table = {(i, j, i * n + j) for i in range(n) for j in range(n)}

satisfy(
   # ensuring that x is a Latin square
   AllDifferent(x, matrix=True),

   # ensuring that y is a Latin square
   AllDifferent(y, matrix=True),

   # ensuring that values on diagonals are different tag(diagonals)
   [AllDifferent(t) for t in [diagonal_down(x), diagonal_up(x),
                              diagonal_down(y), diagonal_up(y)]],

   # ensuring orthogonality of x and y through z
   AllDifferent(z),

   # computing z from x and y
   [(x[i][j], y[i][j], z[i * n + j]) in table for i in range(n) for j in range(n)],

   # tag(symmetry-breaking)
   [(x[0][j] == j, y[0][j] == j) for j in range(n)]
)
```

This model involves 3 arrays of variables and 3 types of constraints: `AllDifferent`, `Extension` and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP^3 instance (file), you can execute for example:

> `python Ortholatin.py -data=10`

2.1.16   PB (Pseudo-Boolean)

This problem has been already used in previous XCSP competitions.

Description.   Pseudo-Boolean problems generalize SAT problems by allowing linear constraints and, possibly, a linear objective function.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "n": 144,
   "e": 704,
   "constraints": [
      { "coeffs": [1,1,1,1,1], "nums": [1,17,33,49,81], "op": "=", "limit": 1 },
      { "coeffs": [1,1,1,1,1], "nums": [2,18,34,50,82], "op": "=", "limit": 1 },
      ...
   ],
   "objective": null
}
```

Model.   The PyCSP^3 model, in a file 'PseudoBoolean.py', used for the competition is:

 PyCSP^3 Model 15

```
from pycsp3 import *

n, e, constraints, objective = data

x = VarArray(size=n, dom={0, 1})

satisfy(
   # respecting each linear constraint
   Sum(x[nums] * coeffs, condition=(op, limit)) for (coeffs, nums, op, limit) in constraints
)
```

This problem involves 1 array of variables and 1 type of constraints: `Sum`. A series of 11 instances has been selected for the competition. For generating an XCSP^3 instance (file), you can execute for example:

```
python PseudoBoolean.py -data=BeauxArts-K65.opb -dataparser=PseudoBoolean_Parser.py
```

where 'BeauxArts-K65.opb' is a data file and 'PseudoBoolean_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.17   Quasigroup

This is Problem 003 on CSPLib, called Quasigroup Existence.

Description (excerpt from CSPLib).   An order n quasigroup is a Latin square of size n. That is, a $n \times n$ multiplication table in which each element occurs once in every row and column. A quasigroup can be specified by a set and a binary multiplication operator, $*$ defined over this set. Quasigroup existence problems determine the existence or non-existence of quasigroups of a given size with additional properties. For example:

- QG3: quasigroups for which $(a * b) * (b * a) = a$

- QG5: quasigroups for which $((b * a) * b) * b = a$

- QG6: quasigroups for which $(a * b) * b = a * (a * b)$

For each of these problems, we may additionally demand that the quasigroup is idempotent. That is, $a * a = a$ for every element a.

Data.   Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

- 8, 9, 10, 11, 16 for variant base-v3

- 8, 9, 10, 11, 16 for variant base-v5

- 8, 9, 10, 11, 16 for variant base-v6

Model.   The PyCSP^3 model, in a file 'QuasiGroup.py', used for the competition is:

✎ PyCSP^3 Model 16

```python
from pycsp3 import *

n = data

# x[i][j] is the value at row i and column j of the quasi-group
x = VarArray(size=[n, n], dom=range(n))

satisfy(
    # ensuring a Latin square
    AllDifferent(x, matrix=True),

    # ensuring idempotence tag(idempotence)
    [x[i][i] == i for i in range(n)]
)

if variant("base"):
    if subvariant("v3"):
        satisfy(
            x[x[i][j], x[j][i]] == i for i in range(n) for j in range(n)
        )
    elif subvariant("v5"):
        satisfy(
            x[x[x[j][i], j], j] == i for i in range(n) for j in range(n)
        )
    elif subvariant("v6"):
        satisfy(
            x[x[i][j], j] == x[i, x[i][j]] for i in range(n) for j in range(n)
        )
elif ... # not considered for the competition
```

   Three variants of the problem are described here, involving 1 array of variables and various forms of constraints `Element`. Note the presence of the tag 'idempotence', which easily allows us to activate or deactivate the associated constraints, at parsing time. A series of 3×5 instances has been generated, for problems QG3, QG5 and QG6.
   For generating an XCSP^3 instance (file), you can execute for example:

```
python QuasiGroup.py -variant=base-v3 -data=10
python QuasiGroup.py -variant=base-v5 -data=10
python QuasiGroup.py -variant=base-v6 -data=10
```

2.1.18 Room Mate

Description (from Wikipedia). In mathematics, economics and computer science, the stable-roommate problem is the problem of finding a stable matching for an even-sized set. A matching is a separation of the set into disjoint pairs ('roommates'). The matching is stable if there are no two elements which are not roommates and which both prefer each other to their roommate under the matching. This is distinct from the stable-marriage problem in that the stable-roommates problem allows matches between any two elements, not just between classes of "men" and "women". See wikipedia.org.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "preferences": [
    [3,4,2,6,5], [6,5,4,1,3], [2,4,5,1,6],
    [5,2,3,6,1], [3,1,2,4,6], [5,1,3,4,2]
  ]
}
```

Model. The PyCSP[3] model, in a file 'RoomMate.py', used for the competition is:

✎ PyCSP[3] Model 17

```python
from pycsp3 import *

preferences = data
n = len(preferences)

def pref_rank():
    pref = [[0] * n for _ in range(n)] # pref[i][k] = j <-> guy i has guy j as kth choice
    rank = [[0] * n for _ in range(n)] # rank[i][j] = k <-> guy i ranks guy j as kth choice
    for i in range(n):
        for k in range(len(preferences[i])):
            j = preferences[i][k] - 1 # because we start at 0
            rank[i][j] = k
            pref[i][k] = j
        rank[i][i] = len(preferences[i])
        pref[i][len(preferences[i])] = i
    return pref, rank

pref, rank = pref_rank()

# x[i] is the value of k, meaning that j = pref[i][k] is the paired agent
x = VarArray(size=n, dom=lambda i: range(len(preferences[i])))

satisfy(
    (imply(x[i] > rank[i][k], x[k] < rank[k][i]),
     imply(x[i] == rank[i][k], x[k] == rank[k][i]))
        for i in range(n) for k in pref[i] if k != i
)
```

This problem involves 1 array of variables and 1 type of constraints: `Intension`. A series of 6 instances has been selected for the competition (coming from the repository developed by Patrick Prosser). For generating an XCSP[3] instance (file), you can execute for example:

```
python RoomMate.py -data=sr0400.txt -dataparser=RoomMate_Parser.py
```

where 'sr0400.txt' is a data file and 'RoomMate_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.19   Solitaire Battleship

This is Problem 014 on CSPLib.

Description (excerpt from CSPLib). As an illustration, a specific fleet consists of one battleship (four grid squares in length), two cruisers (each three grid squares long), three three destroyers (each two squares long) and four submarines (one square each). The ships may be oriented horizontally or vertically, and no two ships will occupy adjacent grid squares, not even diagonally. The digits along the right side of and below the grid indicate the number of grid squares in the corresponding rows and columns that are occupied by vessels. In each of the puzzles, one or more 'shots' have been taken to start you off. These may show water (indicated by wavy lines), a complete submarine (a circle), or the middle (a square), or the end (a rounded-off square) of a longer vessel.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "fleet":[{"size":4,"cnt":1}, {"size":3,"cnt":2},
            {"size":2,"cnt":3}, {"size":1,"cnt":4}],
   "hints":[{"type":"c","row":7,"col":10},{"type":"w","row":1,"col":6}],
   "rowSums":[2,4,3,3,2,4,1,1,0,0],
   "colSums":[0,5,0,2,2,3,1,3,2,2]
}
```

Model.   The PyCSP³ model, in a file 'SolitaireBattleship.py', used for the competition is:

✎ **PyCSP³ Model 18**

```python
from pycsp3 import *

fleet, hints, rowSums, colSums = data
surfaces = [ship.size * ship.cnt for ship in fleet]
maxSurf = max(surfaces)
pos, neg = [ship.size for ship in fleet], [-ship.size for ship in fleet]
n, nTypes = len(colSums), len(pos)

def automaton(horizontal):
    q = Automaton.q # for building state names
    t = [(q(0), 0, q(0)), (q(0), neg if horizontal else pos, "qq"), ("qq", 0, q(0))]
    for i in pos:
        v = i if horizontal else -i
        t.append((q(0), v, q(i, 1)))
        t.extend((q(i, j), v, q(i, j + 1)) for j in range(1, i))
        t.append((q(i, i), 0, q(0)))
    return Automaton(start=q(0), final=q(0), transitions=t)

horizontal_automaton, vertical_automaton = automaton(True), automaton(False)

# s[i][j] is 1 iff the cell at row i and col j is occupied by a ship segment
s = VarArray(size=[n + 2, n + 2], dom={0, 1})
```

```python
# t[i][j] is 0 iff the cell at row i and col j is unoccupied, the type (size) of the ship
#     fragment otherwise, when positive, the ship is put horizontally, vertically otherwise
t = VarArray(size=[n + 2, n + 2], dom=set(neg) | {0} | set(pos))

# cp[i] is the number of positive ship segments of type i
cp = VarArray(size=nTypes, dom=range(maxSurf + 1))

# cn[i] is the number of negative ship segments of type i
cn = VarArray(size=nTypes, dom=lambda i: {0} if fleet[i].size == 1 else range(maxSurf + 1))

def hint_ctr(c, i, j):
    if c == 'w':
        return s[i][j] == 0
    if c in {'c', 'l', 'r', 't', 'b'}:
        return [
            s[i][j] == 1,
            s[i - 1][j] == (1 if c == 'b' else 0),
            s[i + 1][j] == (1 if c == 't' else 0),
            s[i][j - 1] == (1 if c == 'r' else 0),
            s[i][j + 1] == (1 if c == 'l' else 0)
        ]
    if c == 'm':
        return [
            s[i][j] == 1,
            t[i][j] not in {-2, -1, 0, 1, 2},
            (s[i - 1][j], s[i + 1][j], s[i][j - 1], s[i][j + 1]) in {(0, 0, 1, 1), (1, 1, 0, 0)}
        ]

satisfy(
    # no ship on borders
    [(s[0][k] == 0, s[-1][k] == 0, s[k][0] == 0, s[k][-1] == 0) for k in range(n + 2)],

    # respecting the specified row tallies
    [Sum(s[i + 1]) == k for i, k in enumerate(rowSums)],

    # respecting the specified column tallies
    [Sum(s[:, j + 1]) == k for j, k in enumerate(colSums)],

    # being careful about cells on diagonals
    [(s[i][j], s[i - 1][j - 1], s[i - 1][j + 1], s[i + 1][j - 1], s[i + 1][j + 1])
        in {(0, ANY, ANY, ANY, ANY), (1, 0, 0, 0, 0)}
      for i in range(1, n + 1) for j in range(1, n + 1)],

    # tag(channeling)
    [iff(s[i][j] == 1, t[i][j] != 0) for i in range(n + 2) for j in range(n + 2)],

    # counting the number of occurrences of ship segments of each type
    Cardinality(t[1:n + 1, 1:n + 1], occurrences={pos[i]: cp[i] for i in range(nTypes)}
                                    + {neg[i]: cn[i] for i in range(nTypes)}),

    # ensuring the right number of occurrences of ship segments of each type
    [cp[i] + cn[i] == surfaces[i] for i in range(nTypes)],

    # ensuring row connectedness of ship segments
    [t[i + 1] in horizontal_automaton for i in range(n)],

    # ensuring column connectedness of ship segments
    [t[:, j + 1] in vertical_automaton for j in range(n)],

    # tag(clues)
    [hint_ctr(c, i, j) for (c, i, j) in hints] if hints else None
)
```

This problem involves 4 arrays of variables and 5 types of constraints: `Sum`, `Extension`,

`Cardinality`, `Regular` and `Intension`. A series of 8 instances has been selected for the competition (coming from Minizinc repository). For generating an XCSP[3] instance (file), you can execute for example:

```
python SolitaireBattleship.py -data=sb_13_13_5_1.dzn
                             -dataparser=SolitaireBattleship_ParserZ.py
```

where 'sb_13_13_5_1.dzn' is a data file and 'SolitaireBattleship_ParserZ.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.1.20   Sports Scheduling

This is Problem 026 on CSPLib, called the Sports Tournament Scheduling.

Description (excerpt from CSPLib).   The problem is to schedule a tournament of n teams over $n-1$ weeks, with each week divided into $n/2$ periods, and each period divided into two slots. The first team in each slot plays at home, whilst the second plays the first team away. A tournament must satisfy the following three constraints: every team plays once a week; every team plays at most twice in the same period over the tournament; every team plays every other team.

Data.   Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

8, 10, 12, 14, 16, 18, 20, 22, 24, 26

Model.   The PyCSP[3] model, in a file 'SportsScheduling.py', used for the competition is:

PyCSP[3] Model 19

```python
from pycsp3 import *

nTeams = data
nWeeks, nPeriods, nMatches = nTeams - 1, nTeams // 2, (nTeams - 1) * nTeams // 2

def match_number(t1, t2):
   return nMatches - ((nTeams - t1) * (nTeams - t1 - 1)) // 2 + (t2 - t1 - 1)

table = {(t1, t2, match_number(t1, t2)) for t1, t2 in combinations(nTeams, 2)}

# m[w][p] is the number of the match at week w and period p
m = VarArray(size=[nWeeks, nPeriods], dom=range(nMatches))

# x[w][p] is the first team for the match at week w and period p
x = VarArray(size=[nWeeks, nPeriods], dom=range(nTeams))

# y[w][p] is the second team for the match at week w and period p
y = VarArray(size=[nWeeks, nPeriods], dom=range(nTeams))

satisfy(
   # all matches are different (no team can play twice against another team)
   AllDifferent(m),

   # linking variables through ternary table constraints
   [(x[w][p], y[w][p], m[w][p]) in table for w in range(nWeeks) for p in range(nPeriods)],
```

```
    # each week, all teams are different (each team plays each week)
    [AllDifferent(x[w] + y[w]) for w in range(nWeeks)],

    # each team plays at most two times in each period
    [Cardinality(x[:, p] + y[:, p], occurrences={t: range(1, 3) for t in range(nTeams)})
      for p in range(nPeriods)],

    # tag(symmetry-breaking)
    [
      # the match '0 versus t' (with t strictly greater than 0) appears at week t-1
      [Count(m[w], value=match_number(0, w + 1)) == 1 for w in range(nWeeks)],

      # the first week is set : 0 vs 1, 2 vs 3, 4 vs 5, etc.
      [m[0][p] == match_number(2 * p, 2 * p + 1) for p in range(nPeriods)]
    ]
)

if variant("dummy"):
  # xd[p] is the first team for the dummy match of period p tag(dummy-week)
  xd = VarArray(size=nPeriods, dom=range(nTeams))

  # yd[p] is the second team for the dummy match of period p tag(dummy-week)
  yd = VarArray(size=nPeriods, dom=range(nTeams))

  satisfy(
    # handling dummy week (variables and constraints) tag(dummy-week)
    [
      # all teams are different in the dummy week
      AllDifferent(xd + yd),

      # each team plays two times in each period
      [Cardinality(x[:, p] + y[:, p] + [xd[p], yd[p]],
        occurrences={t: 2 for t in range(nTeams)}) for p in range(nPeriods)],

      # tag(symmetry-breaking)
      [xd[p] < yd[p] for p in range(nPeriods)]
    ]
  )
```

This model involves $3 + 2$ arrays of variables and 5 types of constraints: `Cardinality`, `AllDifferent`, `Count` (`Exactly1`), `Extension` and `Intension`. A series of 10 instances has been selected for the competition, for variant 'dummy'. For generating an XCSP[3] instance (file), you can execute for example:

```
python SportScheduling.py -variant=dummy -data=10
```

2.1.21 Superpermutation

Description (from Wikipedia). In combinatorial mathematics, a superpermutation on n symbols is a string that contains each permutation of n symbols as a substring. While trivial superpermutations can simply be made up of every permutation listed together, superpermutations can also be shorter (except for the trivial case of $n = 1$) because overlap is allowed. For instance, in the case of $n = 2$, the superpermutation 1221 contains all possible permutations (12 and 21), but the shorter string 121 also contains both permutations. It has been shown that for $1 \le n \le 5$, the smallest superpermutation on n symbols has length $1! + 2! + ... + n!$. The first four smallest superpermutations have respective lengths 1, 3, 9, and 33, forming the strings 1, 121, 123121321, and 123412314231243121342132413214321. However, for n = 5, there are several smallest superpermutations having the length 153. See wikipedia.org.

Data.   Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

- 3, 4, 5 for main variant

- 3, 4, 5 for variant 'table'

Model.   The PyCSP^3 model, in a file 'Superpermutation.py', used for the competition is:

PyCSP^3 Model 20

```python
from pycsp3 import *

n = data
m = sum(factorial(i) for i in range(1, n + 1)) # the length of the sequence
assert 2 <= n <= 5, "for the moment, the model is valid for n between 2 and 5"

permutations = list(permutations(list(range(1, n + 1))))
nPermutations = len(permutations)

# x[i] is the ith value of the sequence
x = VarArray(size=m, dom=range(1, n + 1))

if not variant():
    # p[j] is the index in the sequence of the first value of the jth permutation
    p = VarArray(size=nPermutations, dom=range(m))

    satisfy(
        # all permutations start at different indexes tag(redundant-constraints)
        AllDifferent(p),

        # ensuring that each permutation occurs in the sequence
        [x[p[j] + k] == permutations[j][k] for k in range(n) for j in range(nPermutations)]
    )

elif variant("table"):
    nPatterns = m - n + 1 # a pattern is a possible subsequence of length n
    gap = nPatterns - nPermutations # the gap corresponds to the flexibility we have

    table = [(i, *t) for i, t in enumerate(permutations)]
    table.extend((-1, *(v if k in (i, j) else ANY for k in range(n)))
                    for v in range(n) for i, j in combinations(n, 2))

    # y[i] is the index of the permutation x[i:i+n] or -1 if this is not a permutation
    y = VarArray(size=nPatterns, dom=range(-1, nPermutations))

    satisfy(
        # identifying each pattern (subsequence of n values)
        [(y[i], x[i:i + n]) in table for i in range(nPatterns)],

        # ensuring that each permutation occurs in the sequence
        Cardinality(y, occurrences={-1: range(gap + 1)}
                        + {i: range(1, gap + 1) for i in range(nPermutations)})
    )

satisfy(
    # setting the first permutation tag(symmetry-breaking)
    [x[i] == i + 1 for i in range(n)],

    # constraining a palindrome tag(palindrome)
    [x[i] == x[-1 - i] for i in range(m // 2)]
)
```

Two variants of the problem are described here, involving 2 arrays of variables and different types of constraints: `AllDifferent`, `Element`, `Cardinality`, `Extension` and `Intension`. A series of 2×3 instances has been generated.

For generating an XCSP[3] instance (file), you can execute for example:

```
python Superpermutation.py -data=5
python Superpermutation.py -variant=table -data=5
```

2.2 COP

2.2.1 Aircraft Landing

Description (from Choco Tutorial). Given a set of planes and runways, the objective is to minimize the total (weighted) deviation from the target landing time for each plane. There are costs associated with landing either earlier or later than a target landing time for each plane. Each plane has to land on one of the runways within its predetermined time windows such that separation criteria between all pairs of planes are satisfied. See OR-Library.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "n": 10,
  "times": [
    {"earliest": 129, "target": 155, "latest": 559},
    {"earliest": 195, "target": 258, "latest": 744},
    ...
  ],
  "costs": [
    {"early_penalty": 1000, "late_penalty": 1000},
    {"early_penalty": 1000, "late_penalty": 1000},
    ...
  ],
  "separations": [
    [99999, 3, 15, 15, 15, 15, 15, 15, 15, 15],
    [3, 99999, 15, 15, 15, 15, 15, 15, 15, 15],
    ...
  ]
}
```

Model. The PyCSP[3] model, in a file 'AircraftLanding.py', used for the competition is:

📝 PyCSP[3] Model 21

```python
from pycsp3 import *

nPlanes, times, costs, separations = data
earliest, target, latest = zip(*times)
early_penalties, late_penalties = zip(*costs)

# x[i] is the landing time of the ith plane
x = VarArray(size=nPlanes, dom=lambda i: range(earliest[i], latest[i] + 1))

# e[i] is the earliness of the ith plane
e = VarArray(size=nPlanes, dom=lambda i: range(target[i] - earliest[i] + 1))
```

```
# t[i] is the tardiness of the ith plane
t = VarArray(size=nPlanes, dom=lambda i: range(latest[i] - target[i] + 1))

satisfy(
   # planes must land at different times
   AllDifferent(x),

   # the separation time required between any two planes must be satisfied:
   [NoOverlap(origins=[x[i], x[j]], lengths=[separations[i][j], separations[j][i]])
      for i, j in combinations(nPlanes, 2)]
)

if not variant():
   satisfy(
      # computing earlinesses of planes
      [e[i] == max(0, target[i] - x[i]) for i in range(nPlanes)],

      # computing tardinesses of planes
      [t[i] == max(0, x[i] - target[i]) for i in range(nPlanes)],
   )
elif variant("table"):
   satisfy(
      # computing earlinesses and tardinesses of planes
      (x[i], e[i], t[i]) in {(v, max(0, target[i] - v), max(0, v - target[i]))
         for v in range(earliest[i], latest[i] + 1)} for i in range(nPlanes)
   )

minimize(
   # minimizing the deviation cost
   e * early_penalties + t * late_penalties
)
```

Two variants of the problem are described here (but only the variant 'table' is used for the competition), involving 3 arrays of variables and different types of constraints: `AllDifferent`, `NoOverlap` and `Extension`. A series of 13 instances (coming from OR-Library) has been selected.

For generating an XCSP[3] instance (file), you can execute for example:

```
python AircraftLanding.py -variant=table -data=airland01.txt
                          -dataparser=AircraftLanding_Parser.py
```

where 'airland01.txt' is a data file and 'AircraftLanding_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.2 Clock Triplets

Description.   Martin Gardner presented this problem:

> Now for a curious little combinatorial puzzle involving the twelve numbers on the face of a clock. Can you rearrange the numbers (keeping them in a circle) so no triplet of adjacent numbers has a sum higher than 21? This is the smallest value that the highest sum of a triplet can have.

See f1compiler.com The problem here is given in a general form.

Data.   Only two integers are required to specify a specific instance. Values of r and n used for the instances in the competition are:

(3,12), (5,15), (7,15), (7,20), (10,15), (10,20), (15,20), (15,30), (20,25), (20,35)

Model. The PyCSP³ model, in a file 'ClockTriplet.py', used for the competition is:

✍ PyCSP³ Model 22

```
from pycsp3 import *

r, n = data

# x[i] is the ith number in the circle
x = VarArray(size=n, dom=range(1, n + 1))

# z is the minimal value such that any (circular) subsequence of x of size r is <= z
z = Var(range(sum(n - v for v in range(r)) + 1))

satisfy(
    # a permutation is required
    AllDifferent(x),

    # any subsequence of size r must be less than or equal to z
    [Sum(x[j] for j in [(i + k) % n for k in range(r)]) <= z for i in range(n)],

    # tag(symmetry-breaking)
    [x[0] == 1, x[1] < x[-1]]
)

minimize(
    z
)
```

This model involves 1 array of variables, a stand-alone variable, and 3 types of constraints: `AllDifferent`, `Sum` and `intension`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python ClockTriplet.py -data=[7,20]
```

2.2.3 Coins Grid

Description. The problem, from Tony Hurlimann's working paper called 'A coin puzzle: SVOR-contest 2007', is defined as follows. In a quadratic grid (or a larger chessboard) with $n \times n$ cells, one should place c coins in such a way that the following conditions are fulfilled:

1. In each row exactly c coins must be placed.

2. In each column exactly c coins must be placed.

3. The sum of the quadratic horizontal distance from the main diagonal of all cells containing a coin must be as small as possible.

4. In each cell at most one coin can be placed.

The problem is initially illustrated with $n = 31$ and $c = 14$.

Data. Only two integers are required to specify a specific instance. Values of n and c used for the instances in the competition are:

(8,4), (10,5), (12,6), (14,7), (16,8), (19,9), (22,10), (25,11), (28,12), (31,14)

Model. The PyCSP³ model, in a file 'CoinsGrid.py', used for the competition is:

PyCSP³ Model 23

```
from pycsp3 import *

n, c = data

# x[i][j] is 1 if a coin is placed at row i and column j
x = VarArray(size=[n, n], dom={0, 1})

satisfy(
   [Sum(x[i]) == c for i in range(n)],

   [Sum(x[:, j]) == c for j in range(n)]
)

minimize(
   Sum(x[i][j] * abs(i - j) ** 2 for i in range(n) for j in range(n))
)
```

This model involves 1 array of variables, and some constraints `Sum`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python CoinsGrid.py -data=[31,14]
```

2.2.4   CVRP

This is Problem 086 on CSPLib, called Capacitated Vehicle Routing Problem.

Description.   The capacitated vehicle routing problem (CVRP) is a VRP in which vehicles with limited carrying capacity need to pick up or deliver items at various locations. The items have a quantity, such as weight or volume, and the vehicles have a maximum capacity that they can carry. See CVRPLIB.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "n": 32,
   "capacity": 100,
   "demands": [0,19,...],
   "distances":[
      [0,35,...],
      [35,0,...],
      ...
   ]
}
```

Model.   The PyCSP³ model, in a file 'CVRP.py', used for the competition is:

📎 PyCSP³ Model 24

```python
from pycsp3 import *

nNodes, capacity, demands, distances = data
nVehicles = nNodes // 4 # hard coding, which can be at least used for Set A (Augerat, 1995)

def max_tour():
    t = sorted(demands)
    i, s = 1, 0
    while i < nNodes and s < capacity:
        s += t[i]
        i += 1
    return i - 2

nSteps = max_tour()

# c[i][j] is the jth customer (step) during the tour of the ith vehicle
c = VarArray(size=[nVehicles, nSteps], dom=range(nNodes))

# d[i][j] is the demand of the jth customer during the tour of the ith vehicle
d = VarArray(size=[nVehicles, nSteps], dom=demands)

satisfy(
    AllDifferent(c, excepting=0),

    # ensuring that all demands are satisfied
    Cardinality(c, occurrences={0: nVehicles * nSteps - nNodes + 1}
                              + {i: 1 for i in range(1, nNodes)}),

    # no holes permitted during tours
    [(c[i][j] != 0) | (c[i][j+1] == 0) for i in range(nVehicles) for j in range(nSteps - 1)],

    # computing the collected demands
    [demands[c[i][j]] == d[i][j] for i in range(nVehicles) for j in range(nSteps)],

    # not exceeding the capacity of each vehicle
    [Sum(d[i]) <= capacity for i in range(nVehicles)],

    # tag(symmetry-breaking)
    Decreasing(c[:, 0])
)

minimize(
    # minimizing the total traveled distance by vehicles
      Sum(distances[0][c[i][0]] for i in range(nVehicles))
    + Sum(distances[c[i][j]][c[i][j+1]] for i in range(nVehicles) for j in range(nSteps - 1))
    + Sum(distances[c[i][-1]][0] for i in range(nVehicles))
)
```

This problem involves 2 arrays of variables and 5 types of constraints: `AllDifferent`, `Cardinality`, `Sum`, `Decreasing` and `Intension`. A series of 10 instances has been selected for the competition (coming from CVRPLIB). For generating an XCSP³ instance (file), you can execute for example:

```
python CVRP.py -data=A-n32-k5.json
```

2.2.5 Cyclic Bandwith

Description. The Cyclic Bandwidth problem is a graph embedding problem. It was first stated by Leung et al. in 1984 in relation with the design of a ring interconnection network.

Their aim was to find an arrangement on a cycle for a set of computers with a known communication pattern given by a graph, in such a way that every message sent can arrive at its destination in at most k steps. The CB problem arises also in other important application areas like VLSI designs, data structure representations, code design and interconnection networks for parallel computer systems. See E. Rodriguez-Tello's page.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
   "n": 104,
   "edges": [[30, 101], [101, 43], ... ]
}
```

Model.   The PyCSP^3 model, in a file 'CyclicBandwith.py', used for the competition is:

🖋 PyCSP^3 Model 25

```python
from pycsp3 import *

n, edges = data

# x[i] is the label of the ith node
x = VarArray(size=n, dom=range(n))

satisfy(
   AllDifferent(x)
)

minimize(
   Maximum(min(abs(x[i] - x[j]), n - abs(x[i] - x[j])) for i, j in edges)
)
```

This problem involves 1 array of variables, 1 constraint `AllDifferent` and a complex objective expression. A series of 10 instances has been selected for the competition (coming from E. Rodriguez-Tello's page). For generating an XCSP^3 instance (file), you can execute for example:

```
python CyclicBandwith.py -data=path100.rnd -dataparser=CyclicBandwith_Parser.py
```

where 'path100.rnd' is a data file and 'CyclicBandwith_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.6   DC

A series of 26 instances linked to DC (Differential Cryptanalysis) has been generated (independently of the library PyCSP^3), and submitted to the 2022 competition by François Delobel. These instances have been generated with Tagada [9] and are about finding truncated differential features for symmetric encryption algorithms. More specifically, all instances consist in finding the smallest number of active S-boxes in a truncated differential characteristic (problem called Step1-opt in the CP paper). The encryption algorithms considered are Midori, Rijndael and Skinny. There are multiple instances for each cipher, with an increasing number r of rounds.

2.2.7   Echelon Stock

This is Problem 040 on CSPLib, called Distribution Problem with Wagner-Whitin Costs.

Description (excerpt from CSPLib). A basic distribution problem is described as follows. Given:

- a supply chain structure of stocking points divided into levels

- a holding cost per unit of inventory at each stocking point, where it is assumed that a parent has lower holding cost than any of its children

- a procurement cost per stocking point (per order, not per unit of inventory received)

- a number of periods

- a demand for each leaf at each period

find an optimal ordering policy: i.e. a decision as to how much to order at each stocking point at each time period that minimises cost. The Wagner-Whitin form of the problem assumes that the holding costs and procurement costs are constant, and that the demands are known for the entire planning horizon. Furthermore, the stocking points have no maximum capacity and the starting inventory is 0.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
    "children": [[], [], [], [0, 1], [2], [3, 4]],
    "hcosts": [3, 3, 3, 2, 2, 1],
    "pcosts": [1000, 1000, 1000, 1000, 1000, 1000],
    "demands": [[100, 100, 100, 100, 100, 100, 100, 100, 100, 100, 100, 100],
        [50, 200, 50, 50, 200, 250, 250, 100, 150, 150, 50, 200],
        [250, 50, 350, 50, 250, 50, 250, 50, 350, 100, 50, 50]]
}
```

Model. The PyCSP³ model, in a file 'EchelonStock2.py', used for the competition is:

🖍 **PyCSP³ Model 26**

```
from pycsp3 import *

children, hcosts, pcosts, demands = data
n, nPeriods, nLeaves = len(children), len(demands[0]), len(demands)

# below, some simplifications
gcd = reduce(gcd, {v for row in demands for v in row})
demands = [[row[t] // gcd for t in range(nPeriods)] for row in demands]
hcosts = [hcosts[i] * gcd for i in range(n)]

sum_dmds, all_dmds = [], []
for i in range(n):
    if i < nLeaves:
        sum_dmds.append(sum(demands[i]))
        all_dmds.append([sum(demands[i][t:]) for t in range(nPeriods)])
    else:
        sum_dmds.append(sum(sum_dmds[j] for j in children[i]))
        all_dmds.append([sum(all_dmds[j][t] for j in children[i]) for t in range(nPeriods)])

def ratio1(i, coeff=1):
    parent = next(j for j in range(n) if i in children[j])
    return floor(pcosts[i] // (coeff * (hcosts[i] - hcosts[parent])))
```

```python
def ratio2(i, t_inf):
    return min(sum(demands[i][t_inf: t_sup + 1]) + ratio1(i, t_sup - t_inf + 1)
        for t_sup in range(t_inf, nPeriods))

def domain_x(i, t): # ratio2 from IC4, and all_dmds from IC6a
    return range(min(all_dmds[i][t], ratio2(i, t)) + 1) if i < nLeaves
           else range(all_dmds[i][t] + 1)

def domain_y(i, t): # {0} from IC1, ratio1 from IC3 and all_dmds from IC6b
    return {0} if t == nPeriods - 1 else range(min(all_dmds[i][t + 1], ratio1(i)) + 1)
           if i < n - 1 else range(all_dmds[i][t + 1] + 1)

# x[i][t] is the amount ordered at node i at period (time) t
x = VarArray(size=[n, nPeriods], dom=domain_x)

# y[i][t] is the amount stocked at node i at the end of period t
y = VarArray(size=[n, nPeriods], dom=domain_y)

satisfy(
    [y[i][0] == x[i][0] - demands[i][0] for i in range(nLeaves)],

    [y[i][t] - Sum(y[i][t - 1], x[i][t]) == -demands[i][t] for i in range(nLeaves)
        for t in range(1, nPeriods)],

    [y[i][0] == x[i][0] - Sum(x[j][0] for j in children[i]) for i in range(nLeaves, n)],

    [y[i][t] == y[i][t - 1] + x[i][t] - Sum(x[j][t] for j in children[i])
        for i in range(nLeaves, n) for t in range(1, nPeriods)],

    # IC2
    [(x[i][t] == 0) | disjunction(x[j][t] > 0 for j in children[i])
        for i in range(nLeaves, n) for t in range(nPeriods)],

    # IC5
    [(y[i][t - 1] == 0) | (x[i][t] == 0) for i in range(n) for t in range(1, nPeriods)],

    # tag(redundant-constraints)
    [Sum(x[i]) == sumDemands[i] for i in range(n)],

    [y[i][t - 1] + Sum(x[i][t:]) == all_dmds[i][t] for i in range(nLeaves)
        for t in range(1, nPeriods)]
)

minimize(
      Sum(hcosts[i] * y[i][t] for i in range(n) for t in range(nPeriods))
    + Sum(pcosts[i] * (x[i][t] > 0) for i in range(n) for t in range(nPeriods))
)
```

This problem involves 2 arrays of variables, 2 types of constraints `Sum` and `Intension`, and a complex objective expression. A series of 10 instances has been selected for the competition (coming from CSPLib). For generating an XCSP^3 instance (file), you can execute for example:

```
python EchelonStock2.py -data=A01.txt -dataparser=EchelonStock_Parser.py
```

where 'A01.txt' is a data file and 'EchelonStock_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.8 Filters

Description. This problem is about optimizing the scheduling of filter operations, commonly used in High-Level Synthesis. This problem/model has been originally written by Krzysztof Kuchcinski for the 2010, 2012, 2013 and 2016 Minizinc competitions. See also the models in JaCop.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
    "del_add": 1,
    "del_mul": 2,
    "number_add": 2,
    "number_mul": 3,
    "last": [40, 41, 42, 43, 44, 45, 46, 47],
    "add": [0, 1, 2, 3, 4, ...],
    "dependencies": [[8, 16, 17], [8, 19, 20], ...]
}
```

Model. The PyCSP[3] model, in a file 'Filters.py', used for the competition is:

🖌 **PyCSP[3] Model 27**

```
from pycsp3 import *

d_add, d_mul, n_add, n_mul, last, add, dependencies = data
nOperations = len(dependencies)

d = [d_add if i in add else d_mul for i in range(nOperations)]
mul = [i for i in range(nOperations) if i not in add]

# t[i] is the starting time of the ith operation
t = VarArray(size=nOperations, dom=range(101))

# r[i] is the (index of the) operator used for the ith operation
r = VarArray(size=nOperations, dom=lambda i: range(1, 1 + (n_add if i in add else n_mul)))

satisfy(
    # respecting dependencies
    [t[i] + d[i] <= t[j] for i in range(nOperations) for j in dependencies[i]],

    # no overlap concerning add operations
    NoOverlap(origins=[(t[i], r[i]) for i in add], lengths=[(d_add, 1) for i in add]),

    # no overlap concerning mul operations
    NoOverlap(origins=[(t[i], r[i]) for i in mul], lengths=[(d_mul, 1) for i in mul])
)

minimize(
    # minimizing the ending time of last operations
    Maximum(t[i] + d[i] for i in last)
)
```

This problem involves 2 arrays of variables and two types of constraints: `NoOverlap` and `Intension`. A series of 8 instances has been selected for the competition (coming from data generated by K. Kuchcinski who submitted them to several Minizinc competitions). For generating an XCSP[3] instance (file), you can execute for example:

```
python Filters.py -data=dct_1_1.dzn -dataparser=Filters_ParserZ.py
```

where 'dct_1_1.dzn' is a data file and 'Filters_ParserZ.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.9   Itemset Mining

Description.   A model for the following problem has been originally written by Tias Guns for the 2011, 2012 and 2013 Minizinc competitions. A traditional task in machine learning is the task of concept learning. Given a dataset of positive and negative examples, the aim is here to find a formula in disjunctive normal form which characterizes the positive examples as accurately as possible. In this challenge this task is modeled as a discrete constraint optimization problem; the aim is to find a formula which is as accurate as possible.

The model is based on the link between DNF formulas and pattern sets in the data mining literature. It represents the formula as a set of itemsets, and imposes constraints on both the itemsets and the set of itemsets. It is based on the 'Constraint Programming for Itemset Mining' framework called CP4IM. See also [7].

Data.   As an illustration of data specifying a toy instance of this problem, we have:

```
{
  "nItems": 7,
  "pos": [[1, 3], [2, 4, 6]],
  "neg": [[0, 2, 5], [1, 2, 6], [2, 3, 5],
  "k": 2
}
```

Model.   The PyCSP^3 model, in a file 'ItemsetMining.py', used for the competition is:

✎ PyCSP^3 Model 28

```python
from pycsp3 import *

nItems, positiveExamples, negativeExamples, k = data
nPos, nNeg = len(positiveExamples), len(negativeExamples)

# precomputing three auxiliary complementary sets
pComp = [[i for i in range(nItems) if i not in t] for t in positiveExamples] # complementary
nComp = [[i for i in range(nItems) if i not in t] for t in negativeExamples]
citm = [[t for t in range(nPos) if i not in positiveExamples[t]] for i in range(nItems)]

if k == 1:
    x = VarArray(size=[nItems], dom={0, 1})

    tp = VarArray(size=[nPos], dom={0, 1})
    tn = VarArray(size=[nNeg], dom={0, 1})

    satisfy(
        [tp[t] == (Count(x[i] for i in pComp[t]) <= 0) for t in range(nPos)
                    if len(pComp[t]) > 0],
        [tn[t] == (Count(x[i] for i in nComp[t]) <= 0) for t in range(nNeg)
                    if len(nComp[t]) > 0],
        [x[i] == (Count(tp[t] for t in citm[i]) <= 0) for i in range(nItems)
                    if len(citm[i]) > 0]
    )
```

```
   maximize(
      Sum(tp) - Sum(tn)
   )

else:
   x = VarArray(size=[k, nItems], dom={0, 1})

   tp = VarArray(size=[k, nPos], dom={0, 1})
   tn = VarArray(size=[k, nNeg], dom={0, 1})

   jtp = VarArray(size=nPos, dom={0, 1})
   jtn = VarArray(size=nNeg, dom={0, 1})

   satisfy(
      [tp[d, t] == (Count(x[d, i] for i in pComp[t]) <= 0) for d in range(k)
                     for t in range(nPos) if len(pComp[t]) > 0],
      [tn[d, t] == (Count(x[d, i] for i in nComp[t]) <= 0) for d in range(k)
                     for t in range(nNeg) if len(nComp[t]) > 0],
      [x[d, i] == (Count(tp[d, t] for t in citm[i]) <= 0) for d in range(k)
                     for i in range(nItems) if len(citm[i]) > 0],

      [jtp[t] == tp[0][t] | tp[1][t] for t in range(nPos)],
      [jtn[t] == tn[0][t] | tn[1][t] for t in range(nNeg)],

      # tag(symmetry-breaking)
      [
         LexIncreasing(tp, strict=True),
         LexIncreasing(tn, strict=True)
      ]
   )

   maximize(
      Sum(jtp) - Sum(jtn)
   )
```

This model involves 3 and 5 arrays of variables (depending on the value of k) and several types of constraints: `Count`, `Intension`, `LexIncreasing` and `Sum`. A series of 15 instances has been selected for the competition (coming from data generated by T. Guns who submitted them to Minizinc competitions). For generating an XCSP[3] instance (file), you can execute for example:

```
python ItemsetMining.py -data=audiology-k2.dzn -dataparser=ItemsetMining_ParserZ.py
```

where 'audiology-k2.dzn' is a data file and 'ItemsetMining_ParserZ.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.10 Multi-Agent Path Finding

Description.   A model for the following problem has been originally written by Neng-Fa Zhou in Picat (and translated to Minizinc by Hakan Kjellerstrand for the 2017 Minizinc competition).

> The multi-agent pathfinding (MAPF) problem amounts to finding a plan for agents to move within a graph from their starting locations to their destinations, such that no agents collide with each other at any time. MAPF can be solved suboptimally in polynomial time [14], but finding an optimal solution is NP-hard for common optimization criteria

See also [1].

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
    "agents": [[104, 31], [60, 56], [125, 211], ...],
    "horizon": 113,
    "neighbors": [[0, 15], [1, 17, 2], [2, 18, 1, 3], ...]
}
```

Model. The PyCSP³ model, in file 'MultiAgentPathFinding.py', used for the competition is:

🖌 PyCSP³ Model 29

```python
from pycsp3 import *

agents, horizon, neighbors, = data
src, dst = zip(*agents)
nAgents, nNodes = len(agents), len(neighbors)

if variant("table"):

    table = [(i, v) for i, t in enumerate(neighbors) for v in t]

    # x[t][a] is the node where is the agent a at time t
    x = VarArray(size=[horizon + 1, nAgents], dom=range(nNodes))

    # e[a] is the time when the agent a arrives at its destination
    e = VarArray(size=nAgents, dom=range(horizon + 1))

    satisfy(
        # agents must occupy different node at any time
        [AllDifferent(x[t]) for t in range(horizon + 1)],

        # agents at their destinations stays there
        [(x[t][a] != dst[a]) | (x[t + 1][a] == dst[a]) for t in range(horizon)
            for a in range(nAgents)],

        # agents can only move to connected nodes
        [(x[t][a], x[t + 1][a]) in table for t in range(horizon) for a in range(nAgents)],

        # setting agents at their initial positions
        [x[0][a] == src[a] for a in range(nAgents)],

        # setting agents at their final positions
        [x[-1][a] == dst[a] for a in range(nAgents)],

        # computing end times of agents
        [(e[a] == t + 1) == ((x[t][a] != dst[a]) & (x[t + 1][a] == dst[a]))
            for t in range(horizon) for a in range(nAgents)]
    )

    if subvariant("mks"):
        minimize(
            Maximum(e)
        )
    else:
        minimize(
            Sum(e) + nAgents
        )
```

This problem involves 2 arrays of variables and 3 types of constraints: `AllDifferent`, `Extension` and `Intension`. A series of 2×10 instances has been selected for the competition

(coming from data gently given by N.-F. Zhou). For generating an XCSP^3 instance (file), you can execute for example:

```
python MultiAgentPathFinding.py -variant=table -data=g16_p10_a05.pi
                               -dataparser=MultiAgentPathFinding_ParserPicat.py
python MultiAgentPathFinding.py -variant=table-mks -data=g16_p10_a05.pi
                               -dataparser=MultiAgentPathFinding_ParserPicat.py
```

where 'g16_p10_a05.pi' is a data file and 'MultiAgentPathFinding_ParserPicat.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.11 Nurse Rostering

This is a realistic employee shift scheduling Problem (see, for example, [10]).

Description. The description is rather complex. Hence, we refer the reader to: http://www.schedulingbenchmarks.org/nrp/.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "nDays": 14,
  "shifts": [ { "id": "D", "length": 480, "forbiddenFollowingShifts": "null" } ],
  "staffs": [
    { "id": "A",
      "maxShifts": [14],
      "minTotalMinutes": 3360,"maxTotalMinutes": 4320,
      "minConsecutiveShifts": 2,"maxConsecutiveShifts": 5,
      "minConsecutiveDaysOff": 2,
      "maxWeekends": 1, "daysOff": [0],
      "onRequests": [
        { "day": 2, "shift": "D", "weight": 2 },
        { "day": 3, "shift": "D", "weight": 2}
      ],
      "offRequests": "null"
    },
    ...
  ],
  "covers": [
      [ { "requirement": 3, "weightIfUnder": 100, "weightIfOver": 1 } ],
      [ { "requirement": 5, "weightIfUnder": 100, "weightIfOver": 1 } ],
      ...
  ]
}
```

Model. The PyCSP^3 model, in a file 'NurseRostering.py', used for the competition is:

PyCSP³ Model 30

```python
from pycsp3 import *

nDays, shifts, staffs, covers = data

if shifts[-1].id != "_off": # if not present, we add first a dummy 'off' shift
    shifts.append(shifts[0].__class__("_off", 0, None)) # with a named tuple of the same class
off = len(shifts) - 1 # value for _off
lengths = [shift.length for shift in shifts]
nWeeks, nShifts, nStaffs = nDays // 7, len(shifts), len(staffs)

on_r = [[next((r for r in staff.onRequests if r.day == day), None) if staff.onRequests
            else None for day in range(nDays)] for staff in staffs]
off_r = [[next((r for r in staff.offRequests if r.day == day), None) if staff.offRequests
            else None for day in range(nDays)] for staff in staffs]

# kmin, kmax, kday for minConsecutiveShifts, maxConsecutiveShifts, minConsecutiveDaysOff
_, maxShifts, minTimes, maxTimes, kmin, kmax, kday, maxWeekends, daysOff, _, _ = zip(*staffs)

sp = {shifts[i].id: i for i in range(nShifts)} # position of shifts in the list 'shifts'
table = {(sp[s1.id], sp[s2]) for s1 in shifts if s1.forbiddenFollowingShifts
            for s2 in s1.forbiddenFollowingShifts} # rotation

def costs(day, shift):
    if shift == off: return [0] * (nStaffs + 1)
    r, wu, wo = covers[day][shift]
    return [abs(r - i) * (wu if i <= r else wo) for i in range(nStaffs + 1)]

def automaton(k, for_shifts): # automaton_min_consecutive
    q = Automaton.q # for building state names
    range_off = range(nShifts - 1, nShifts) # a range with only one value (off)
    range_others = range(nShifts - 1) # a range with all other values
    r1, r2 = (range_off,range_others) if for_shifts else (range_others, range_off)
    t = [(q(0), r1, q(1)), (q(0), r2, q(k + 1)), (q(1), r1, q(k + 1))]
    t.extend((q(i), r2, q(i + 1)) for i in range(1, k + 1))
    t.append((q(k + 1), range(nShifts), q(k + 1)))
    return Automaton(start=q(0), final=q(k + 1), transitions=t)

# x[d][p] is the shift at day d for person p (value 'off' denotes off)
x = VarArray(size=[nDays, nStaffs], dom=range(nShifts))

# nd[p][s] is the number of days such that person p works with shift s
nd = VarArray(size=[nStaffs, nShifts],
              dom=lambda p, s: range((nDays if s == off else maxShifts[p][s]) + 1))

# np[d][s] is the number of persons working on day d with shift s
np = VarArray(size=[nDays, nShifts], dom=range(nStaffs + 1))

# wk[p][w] is 1 iff the week-end w is worked by person p
wk = VarArray(size=[nStaffs, nWeeks], dom={0, 1})

# cn[p][d] is the cost of not satisfying the on-request (if it exists) of person p on day d
cn = VarArray(size=[nStaffs, nDays],
              dom=lambda p, d: {0, on_r[p][d].weight} if on_r[p][d] else None)

# cf[p][d] is the cost of not satisfying the off-request (if it exists) of person p on day d
cf = VarArray(size=[nStaffs, nDays],
              dom=lambda p, d: {0, off_r[p][d].weight} if off_r[p][d] else None)

# cc[d][s] is the cost of not satisfying cover for shift s on day d
cc = VarArray(size=[nDays, nShifts], dom=lambda d, s: costs(d, s))
```

```
satisfy(
   # days off for staff
   [x[d][p] == off for d in range(nDays) for p in range(nStaffs) if d in daysOff[p]],

   # computing number of days
   [Count(x[:, p], value=s) == nd[p][s] for p in range(nStaffs) for s in range(nShifts)],

   # computing number of persons
   [Count(x[d], value=s) == np[d][s] for d in range(nDays) for s in range(nShifts)],

   # computing worked week-ends
   [(imply(x[w * 7 + 5][p] != off, wk[p][w]), imply(x[w * 7 + 6][p] != off, wk[p][w]))
     for p in range(nStaffs) for w in range(nWeeks)],

   # rotation shifts
   [Slide((x[i][p], x[i + 1][p]) not in table for i in range(nDays - 1))
     for p in range(nStaffs)] if len(table) > 0 else None,

   # maximum number of worked week-ends
   [Sum(wk[p]) <= maxWeekends[p] for p in range(nStaffs)],

   # minimum and maximum number of total worked minutes
   [nd[p] * lengths in range(minTimes[p], maxTimes[p] + 1) for p in range(nStaffs)],

   # maximum consecutive worked shifts
   [Count(x[i:i + kmax[p] + 1, p], value=off) >= 1 for p in range(nStaffs)
     for i in range(nDays - kmax[p])],

   # minimum consecutive worked shifts
   [x[i: i + kmin[p] + 1, p] in automaton(kmin[p], True) for p in range(nStaffs)
     for i in range(nDays - kmin[p])],

   # managing off days on schedule ends
   [(imply(x[0][p] != off, x[i][p] != off), imply(x[-1][p] != off, x[-1 - i][p] != off))
     for p in range(nStaffs) if kmin[p] > 1 for i in range(1, kmin[p])],

   # minimum consecutive days off
   [x[i: i + kday[p] + 1, p] in automaton(kday[p], False) for p in range(nStaffs)
     for i in range(nDays - kday[p])],

   # cost of not satisfying on requests
   [iff(x[d][p] == sp[on_r[p][d].shift], cn[p][d] == 0) for p in range(nStaffs)
     for d in range(nDays) if on_r[p][d]],

   # cost of not satisfying off requests
   [iff(x[d][p] == sp[off_r[p][d].shift], cf[p][d] != 0) for p in range(nStaffs)
     for d in range(nDays) if off_r[p][d]],

   # cost of under or over covering
   [(np[d][s], cc[d][s]) in enumerate(costs(d, s)) for d in range(nDays)
     for s in range(nShifts)]
)

minimize(
   Sum(cn) + Sum(cf) + Sum(cc)
)
```

This model involves 7 arrays of variables and 6 types of constraints: `Regular`, `Slide`, `Count`, `Sum`, `Intension` and `Extension`. A series of 20 instances has been selected from http://www.schedulingbenchmarks.org. For generating an XCSP[3] instance (file), you can execute for example:

```
python NurseRostering.py -data=01 -dataparser=NurseRostering_Parser.py
```

where '01' is a data file and 'NurseRostering_Parser.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

Important: The series of instances, used for the 2022 competition comes from the 2018 competition, and compiling instances from the PyCSP³ model above may produce slighlty different files.

2.2.12   Nursing Workload

This is Problem 069 on CSPLib, called Balanced Nursing Workload Problem.

Description (excerpt from CSPLib). Given a set of patients distributed in a number of hospital zones and an available nursing staff, one must assign a nurse to each patient in such a way that the work is distributed evenly between nurses. Each patient is assigned an acuity level corresponding to the amount of care he requires; the workload of a nurse is defined as the sum of the acuities of the patients he cares for. A nurse can only work in one zone and there are retrictions both on the number of patients assigned to a nurse and on the corresponding workload. We balance the workloads by minimizing their standard deviation.

Data. As an illustration of data specifying an instance of this problem, we have:

```
{
  "nNurses": 11,
  "minPatientsPerNurse": 1,
  "maxPatientsPerNurse": 3,
  "maxWorkloadPerNurse": 105,
  "demands": [[59, 57, 50, 44, 42, 40, 39, 39, 33, 33, 32, 27, 26, 22, 20, 17,
       11], [49, 47, 39, 39, 38, 30, 30, 28, 27, 15, 14]]
}
```

Model. The PyCSP³ model, in a file 'NursingWorkload.py', used for the competition is:

🖌 **PyCSP³ Model 31**

```
from pycsp3 import *

nNurses, minPatientsPerNurse, maxPatientsPerNurse, maxWorkloadPerNurse, demands = data
patients = [(i, demand) for i, t in enumerate(demands) for demand in t]
nPatients, nZones = len(patients), len(demands)

lb = sum(sorted([dem for i, t in enumerate(demands) for dem in t])[:minPatientsPerNurse])

# p[i] is the nurse assigned to the ith patient
p = VarArray(size=nPatients, dom=range(nNurses))

# w[k] is the workload of the kth nurse
w = VarArray(size=nNurses, dom=range(lb, maxWorkloadPerNurse + 1))

satisfy(
   Cardinality(p, occurrences={k: range(minPatientsPerNurse, maxPatientsPerNurse + 1)
      for k in range(nNurses)}),
```

```
      [p[i] != p[j] for i, j in combinations(range(nPatients), 2)
        if patients[i][0] != patients[j][0]],

      [w[k] == Sum(c * (p[i] == k) for i, (_, c) in enumerate(patients))
        for k in range(nNurses)],

      # tag(symmetry-breaking)
      [p[z] == z for z in range(nZones)],

      Increasing(w)
)

minimize(
      Sum(w[k] * w[k] for k in range(nNurses))
)
```

This problem involves 2 arrays of variables and 3 types of constraints: `Cardinality`, `Sum` and `Intension`. A series of 12 instances has been selected for the competition (coming from data generated by P. Schaus). For generating an XCSP[3] instance (file), you can execute for example:

```
python NurseWorkload.py -data=2zones0.txt -dataparser=NursingWorkload_Parser.py
```

where '2zones0.txt' is a data file and 'NursingWorkload_ParserZ.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.13   RCPSP

This is Problem 061 on CSPLib, called Resource-Constrained Project Scheduling Problem (RCPSP). See also PSPLIB.

Description (excerpt from CSPLib).   The resource-constrained project scheduling problem is a classical well-known problem in operations research. A number of activities are to be scheduled. Each activity has a duration and cannot be interrupted. There are a set of precedence relations between pairs of activities which state that the second activity must start after the first has finished. There are a set of renewable resources. Each resource has a maximum capacity and at any given time slot no more than this amount can be in use. Each activity has a demand (possibly zero) on each resource. The dummy source and sink activities have zero demand on all resources. The problem is usually stated as an optimisation problem where the makespan (i.e. the completion time of the sink activity) is minimized.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
  "horizon": 158,
  "resourceCapacities": [12, 13, 4, 12],
  "jobs": [
    { "duration": 0, "successors": [1, 2, 3], "requiredQuantities": [0, 0, 0, 0]
        },
    { "duration": 8, "successors": [5, 10, 14], "requiredQuantities": [4, 0, 0, 0]
        },
    ...,
    { "duration": 0, "successors": [], "requiredQuantities": [0, 0, 0, 0] }
  ]
}
```

Model.   The PyCSP[3] model, in a file 'Rcpsp.py', used for the competition is:

📕 **PyCSP[3] Model 32**

```python
from pycsp3 import *

horizon, capacities, jobs = data
nJobs = len(jobs)

# s[i] is the starting time of the ith job
s = VarArray(size=nJobs, dom=lambda i: {0} if i == 0 else range(horizon))

satisfy(
    # precedence constraints
    [s[i] + duration <= s[j] for i, (duration, successors, _) in enumerate(jobs)
        for j in successors],

    # resource constraints
    [Cumulative(tasks=[(s[i], duration, quantities[k]) for i, (duration, _, quantities) in
            enumerate(jobs) if quantities[k] > 0]) <= capacity
        for k, capacity in enumerate(capacities)]
)

minimize(
    s[-1]
)
```

This model involves 1 array of variables and 2 types of constraints: `Cumulative` and `Intension`. A series of 10 instances has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

        python Rcpsp.py -data=j120-01-01.sm -dataparser=Rcpsp_Parser.py

where 'j120-01-01.sm' is a data file and 'Rcpsp_ParserZ.py' is a parser (i.e., a Python file allowing us to load data that are not directly given in JSON format). Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.14   RLFAP

When radio communication links are assigned the same or closely related frequencies, there is a potential for interference. Consider a radio communication network, defined by a set of radio links. The radio link frequency assignment problem [6] is to assign, from limited spectral resources, a frequency to each of these links in such a way that all the links may operate together without noticeable interference. Moreover, the assignment has to comply to certain regulations and physical constraints of the transmitters. Among all such assignments, one will naturally prefer those which make good use of the available spectrum, trying to save the spectral resources for a later extension of the network. As in 2018, do note that we consider here the original COP instances.

Description   The description is rather complex. Hence, we refer the reader to [6].

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
  "domains": {
    "1": [16, 30, 44, 58, 72, 86, 100, 114, 128, 142, 156, 254, 268, ...],
    "2":[30, 58, 86, 114, 142, 268, 296, 324, 352, 380, 414, 442, 470, ...],
```

```
         ...
      },
      "vars": [
         { "number": 13, "domain": 1, "value": "null", "mobility": "null" },
         { "number": 14, "domain": 1, "value": "null", "mobility": "null" },
         ...
      ],
      "ctrs":[
         { "x": 13, "y": 14, "equality": true, "limit": 238, "weight": 0 },
         { "x": 13, "y": 16, "equality": false, "limit": 186, "weight": 0 },
         ...
      ],
      "interferenceCosts": [0, 1000, 100, 10, 1],
      "mobilityCosts": [0, 0, 0, 0, 0]
   }
```

Model.   The PyCSP³ model, in a file 'Rlfap.py', used for the competition is:

🖋 PyCSP³ Model 33

```python
from pycsp3 import *

domains, variables, constraints, interferenceCosts, mobilityCosts = data
n = len(variables)

# f[i] is the frequency of the ith radio link
f = VarArray(size=n, dom=lambda i: domains[variables[i].domain])

satisfy(
    # managing pre-assigned frequencies
    [f[i] == v for i, (_, v, mob) in enumerate(variables)
               if v and not (variant("max") and mob)],

    # hard constraints on radio-links
    [expr(op, abs(f[i] - f[j]), k) for (i, j, op, k, wgt) in constraints
        if not (variant("max") and wgt)]
)

if variant("span"):
    minimize(
        # minimizing the largest frequency
        Maximum(f)
    )

elif variant("card"):
    minimize(
        # minimizing the number of used frequencies
        NValues(f)
    )

elif variant("max"):
    minimize(
        # minimizing the sum of violation costs
        Sum(ift(f[i] == v, 0, mobilityCosts[mob])
             for i, (_, v, mob) in enumerate(variables) if v and mob)
        + Sum(ift(expr(op, abs(f[i] - f[j]), k), 0, interferenceCosts[wgt])
             for (i, j, op, k, wgt) in constraints if wgt)
    )
```

The model involves 1 array of variables, many constraints `Intension` and an objective that varies according to the chosen variant. Note that `expr` allows us to build an expression (constraint) with an operator given as first parameter (possibly, a string). The complete series of 25 instances, 11 CELAR (scen) and 14 GRAPH, has been selected for the competition. For generating an XCSP[3] instance (file), you can execute for example:

```
python Rlfap.py -variant=span -data=Rlfap-span-graph-03.json
python Rlfap.py -variant=card -data=Rlfap-card-graph-01.json
python Rlfap.py -variant=max -data=Rlfap-max-graph-05.json
```

2.2.15   Spot5

Description.   A model for the following problem has been originally written by Simon de Givry for the 2014 and 2015 Minizinc competitions. The problem is roughly described (by Simon) as follows:

- given a set S of photographs which can be taken the next day from at least one of the three instruments, w.r.t. the satellite trajectory;

- given, for each photograph, a weight expressing its importance;

- given a set of imperative constraints: non overlapping and minimal transition time between two successive photographs on the sameinstrument, limitation on the instantaneous data flow through the satellite telemetry and on the recording capacity on board;

find an admissible subset S' of S (imperative constraints met) which maximizes the sum of the weights of the photographs in S'. See also [2].

Data.   As an illustration, the structure of the data specifying an instance of this problem is:

```
{
  "domains": ...,
  "costs": ...,
  "f2x": ...,
  "f2y": ...,
  "nTuples2": ...,
  "offsets2": ...,
  "t2": ...,
  "f3x": ...,
  "f3y": ...,
  "f3z": ...,
  "nTuples3": ...,
  "offsets3": ...,
  "t3": ...
}
```

Model.   The PyCSP[3] model, in a file 'Spot5.py', used for the competition is:

```
from pycsp3 import *

domains, costs, f2x, f2y, nTuples2, offsets2, t2, \
                f3x, f3y, f3z, nTuples3, offsets3, t3 = data
n = len(domains)

# x[i] is the value for the ith variable
x = VarArray(size=n, dom=lambda i: domains[i])

satisfy(
   # binary constraints
   [(x[f2x[j]], x[f2y[j]]) in [(t2[2 * offsets2[j] + k * 2], t2[2 * offsets2[j] + k * 2 + 1])
         for k in range(nTuples2[j])] for j in range(len(f2x))],

   # ternary constraints
   [(x[f3x[j]], x[f3y[j]], x[f3z[j]]) in [
       (t3[3 * offsets3[j] + k * 3], t3[3 * offsets3[j] + k * 3 + 1], t3[3 * offsets3[j] + k
           * 3 + 2]) for k in range(nTuples3[j])] for j in range(len(f3x))]
)

minimize(
   Sum(costs[i] * (x[i] == 0) for i in range(n))
)
```

This problem involves 1 array of variables and 1 type of constraints: `Extension`. A series of 10 instances has been selected for the competition (coming from data generated by S. de Givry for Minizinc competitions). For generating an XCSP³ instance (file), you can execute for example:

```
python Spot5.py -data=0412.json
```

2.2.16   TAL

TAL is a problem of natural language processing. The series of instances, used for the 2022 competition comes from the 2018 competition. The model has not been converted in PyCSP³.

2.2.17   Triangular

Description.   This problem, taken from Daily Telegraph and Sunday Times, is to find, for an equilateral triangular grid of size n (length of a side), the maximum number of nodes that can be selected without having all selected corners of any equilateral triangle of any size or orientation. It was also used in Minizinc Competitions (2015 and 2019).

Data.   Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

10, 15, 20, 22, 25, 28, 30, 32, 35, 38

Model.   The PyCSP³ model, in a file 'Triangular.py', used for the competition is:

PyCSP³ Model 35

```
from pycsp3 import *

n = data

# x[i,j] is 1 iff the jth node in the ith row is selected
x = VarArray(size=[n, n], dom=lambda i, j: {0, 1} if i >= j else None)

satisfy(
   Sum(x[i + m][j], x[i + k][j + m], x[i + k - m][j + k - m]) <= 2 for i in range(n)
     for j in range(i + 1) for k in range(1, n - i) for m in range(k)
)

maximize(
   Sum(x)
)
```

This problem involves 1 array of variables and 1 type of constraints: `Sum`. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Triangular.py -data=25
```

2.2.18   Warehouse

This is Problem 034 on CSPLib, called Warehouse Location Problem.

Description (from CSPLib).   In the Warehouse Location problem (WLP), a company considers opening warehouses at some candidate locations in order to supply its existing stores. Each possible warehouse has the same maintenance cost, and a capacity designating the maximum number of stores that it can supply. Each store must be supplied by exactly one open warehouse. The supply cost to a store depends on the warehouse. The objective is to determine which warehouses to open, and which of these warehouses should supply the various stores, such that the sum of the maintenance and supply costs is minimized.

Data.   As an illustration of data specifying an instance of this problem, we have:

```
{
  "fixedCost": 30,
  "warehouseCapacities": [1,4,2,1,3],
  "storeSupplyCosts": [
    [20,24,11,25,30],[28,27,82,83,74],[74,97,71,96,70],[2,55,73,69,61],
    [46,96,59,83,4],[42,22,29,67,59],[1,5,73,59,56],[10,73,13,43,96],
    [93,35,63,85,46],[47,65,55,71,95]
  ]
}
```

Model.   The PyCSP³ model, in a file 'Warehouse.py', used for the competition is:

PyCSP³ Model 36

```
from pycsp3 import *

cost, capacities, costs = data # cost is the fixed cost when opening a warehouse
nWarehouses, nStores = len(capacities), len(costs)

# w[i] is the warehouse supplying the ith store
w = VarArray(size=nStores, dom=range(nWarehouses))

# o[j] is 1 if the jth warehouse is open
o = VarArray(size=nWarehouses, dom={0, 1})

# c[i] is the cost of supplying the ith store
c = VarArray(size=nStores, dom=lambda i: costs[i])

satisfy(
    # capacities of warehouses must not be exceeded
    Count(w, value=j) <= capacities[j] for j in range(nWarehouses)

    # the warehouse supplier of the ith store must be open
    [o[w[i]] == 1 for i in range(nStores)],

    # computing the cost of supplying the ith store
    [costs[i][w[i]] == c[i] for i in range(nStores)]
)

minimize(
    # minimizing the overall cost
    Sum(c) + Sum(o) * cost
)
```

This model involves 3 arrays of variables and 2 type of constraints: `Count` and `Element`. A series of 9 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python Warehouse.py -dataparser=Warehouse_Random.py 40 80 100 10 1000 0
```

where 'Warehouse_Random.py' is a generator of instances, using specified values. Note that for saving data in JSON files, you can add the option '-dataexport'.

2.2.19 War or Peace

Description. Problem based on information from hakank.org. There are n countries. Each pair of two countries is either at war or has a peace treaty. Each pair of two countries that has a common enemy has a peace treaty. What is the minimum number of peace treaties?

Data. Only one integer is required to specify a specific instance. Values of n used for the instances in the competition are:

- 8, 9, 10, 12, 14 for main variant

- 8, 9, 10, 12, 14 for variant 'or'

Model. The PyCSP³ model, in a file 'WarOrPeace.py', used for the competition is:

PyCSP³ Model 37

```
from pycsp3 import *

n = data
WAR, PEACE = 0, 1

# x[i][j] is 1 iff countries i and j have a peace treaty
x = VarArray(size=[n, n], dom=lambda i, j: {WAR, PEACE} if i < j else None)

if not variant():
   satisfy(
      (x[i][j] == PEACE)
      | (Sum((x[min(i, k)][max(i, k)] == WAR) & (x[min(j, k)][max(j, k)] == WAR)
           for k in range(n) if different_values(i, j, k)) == 0)
        for i, j in combinations(range(n), 2)
   )

elif variant("or"):
   satisfy(
      (x[i][j] == PEACE)
      | ((x[i][j] == WAR) & conjunction((x[k][i] == PEACE) | (x[k][j] == PEACE)
          for k in range(i)))
        for i, j in combinations(range(1, n), 2)
   )

minimize(
   # minimizing the number of peace treaties
   Sum(x)
)
```

This problem involves 1 array of variables and complex forms of constraints. A series of 10 instances has been selected for the competition. For generating an XCSP³ instance (file), you can execute for example:

```
python WarOrPeace.py -data=10
python WarOrPeace.py -variant=or -data=10
```

Chapter 3

Solvers

In this chapter, we introduce the solvers and teams having participated to the XCSP^3 Competition 2022.

- ACE (Christophe Lecoutre)

- ACE ABD (extension of ACE by Thibault Falque and Hughes Wattez)

- BTD, miniBTD (Mohamed Sami Cherif, Djamal Habet, Philippe Jégou, Hélène Kanso, Cyril Terrioux)

- Choco (Charles Prud'homme and Jean-Guillaume Fages)

- CoSoCo (Gilles Audemard)

- Exchequer (Martin Mariusz Lester)

- Fun-sCOP (Takehide Soh, Daniel Le Berre, Hidetomo Nabeshima, Mutsunori Banbara, Naoyuki Tamura)

- Glasgow (Ciaran McCreesh)

- MiniCPBP (Gilles Pesant and Auguste Burlats)

- Mistral (Emmanuel Hebrard and Mohamed Siala)

- Nacre (Gaël Glorian)

- Picat (Neng-Fa Zhou)

- RBO, miniRBO (Mohamed Sami Cherif, Djamal Habet, Cyril Terrioux)

- Sat4j-CSP-PB (extension of Sat4j by Thibault Falque and Romain Wallon)

- toulbar2 (David Allouche et al.)

ACE
A Generic Constraint Solver

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Version 2.0.1 – May 23, 2022

ACE (AbsCon Essence) is an open-source constraint solver, developed in Java. ACE focuses on:

- integer variables, including 0/1 (Boolean) variables,

- state-of-the-art table constraints, including ordinary, starred, and hybrid table constraints,

- popular global constraints (AllDifferent, Count, Element, Cardinality, Cumulative, etc.),

- search heuristics, as e.g., wdeg [2, 9], last-conflict [6], BIVS [5], solution-saving [8],

- mono-criterion optimization

ACE is derived from the constraint solver AbsCon that has been used as a research platform in our team at CRIL during many years. Many ideas and algorithms have been discarded from AbsCon, so as to get a constraint solver of reasonable size and understanding.

Important: ACE is not an official competitor for the 2022 XCSP^3 competition because I conducted the selection of instances. Note also that ACE is run with its default behaviour without any mechanism that could have been used to improve its performances (e.g., local search in a preprocessing step, use of several heuristics to improve diversification of search, etc.).

With the right classpath (after having cloned the code from Github), you can run the solver on any XCSP³ [4, 1, 3] instance (file) by executing:

```
java ace <xcsp3_file> [options]
```

with:

- <xcsp3_file>: an XCSP³ file representing a CSP or COP instance

- [options]: possible options to be used when running the solver

Of course, for generating XCSP³ instances, just write and compile models with the Python library PyCSP³ [7]. See http://pycsp.org/

Licence. ACE is licensed under the MIT License

Code. ACE code is available

- on Github: https://github.com/xcsp3team/ace

Acknowledgements

References

[1] G. Audemard, F. Boussemart, C. Lecoutre, C. Piette, and O. Roussel. XCSP3 and its ecosystem. **Constraints**, 25(1-2):47–69, February 2020. Springer.

[2] F. Boussemart, F. Hemery, C. Lecoutre, and L. Sais. Boosting systematic search by weighting constraints. In *Proceedings of ECAI'04*, pages 146–150, 2004.

[3] F. Boussemart, C. Lecoutre, G. Audemard, and C. Piette. *XCSP3: An Integrated Format for Benchmarking Combinatorial Constrained Problems.* Technical Report. v3.0.7 on CoRR, arXiv:1611.03398, 2016–2021. 242 pages.

[4] F. Boussemart, C. Lecoutre, G. Audemard, and C. Piette. *XCSP3-core: A Format for Representing Constraint Satisfaction/Optimization Problems.* Technical Report. v3.0.7 on CoRR, arXiv:2009.00514, 2020–2021. 106 pages.

[5] J.-G. Fages and C. Prud'homme. Making the first solution good! In *Proceedings of ICTAI'17*, pages 1073–1077, 2017.

[6] C. Lecoutre, L. Sais, S. Tabary, and V. Vidal. Reasonning from last conflict(s) in constraint programming. *Artificial Intelligence*, 173(18):1592–1614, 2009.

[7] C. Lecoutre and N. Szczepanski. *PyCSP3: Modeling Combinatorial Constrained Problems in Python.* Technical Report. v2.0 on CoRR, arXiv:2009.00326, 2020–2021. 144 pages.

[8] J. Vion and S. Piechowiak. Une simple heuristique pour rapprocher DFS et LNS pour les COP. In *Proceedings of JFPC'17*, pages 39–45, 2017.

[9] H. Wattez, C. Lecoutre, A. Paparrizou, and S. Tabary. Refining constraint weighting. In *Proceedings of ICTAI'19*, pages 71–77, 2019.

ACE ABD
An unofficial ACE extension with Agressive Bound Descent

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Version 2.0.1 – May 23, 2022

ACE ABD (AbsCon Essence with Agressive Bound Descent) is a constraint solver, developed in Java. ACE ABD focuses on:

- integer variables, including 0/1 (Boolean) variables,

- state-of-the-art table constraints, including ordinary, starred, and hybrid table constraints,

- popular global constraints (AllDifferent, Count, Element, Cardinality, Cumulative, etc.),

- search heuristics, as e.g., wdeg [1, 8], last-conflict [5], BIVS [3], solution-saving [7],

- mono-criterion optimization

- aggressive bound descent [4]

ACE ABD is derived from the open-source constraint solver ACE. This is an unofficial version of ACE composed, in particular, of an aggressive bound descent policy [4]. With the ABD policy enabled, new bounds are modified exponentially as long as the searching algorithm is successful (into

a run): for a sequence of bounds $\langle B_0, B_1, \ldots \rangle$, the solver forces a minimum gap between two successive bounds: $B_{i+1} - B_i \geq 2^i$. These gaps follow the exponential sequence: 1, 2, 4, 8, … (as indicated in the acronym where each letter is identified by its rank: $A_1 B_2 D_4$).

Important: ACE ABD is not an official competitor for the 2022 XCSP³ competition because the original solver has been used to conduct the selection of instances.

You can run the solver on any XCSP³ [2, 6] instance (file) by executing:

```
java -jar ACE-ABD.jar <xcsp3_file> [options]
```

with:

- <xcsp3_file>: an XCSP³ file representing a COP instance
- [options]: possible options to be used when running the solver

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Code.   ACE (not ACE ABD) code is available

- on Github: https://github.com/xcsp3team/ace

Acknowledgements

References

[1] F. Boussemart, F. Hemery, C. Lecoutre, and L. Sais. Boosting systematic search by weighting constraints. In *Proceedings of ECAI'04*, pages 146–150, 2004.

[2] F. Boussemart, C. Lecoutre, G. Audemard, and C. Piette. XCSP3: an integrated format for benchmarking combinatorial constrained problems. *CoRR*, abs/1611.03398, 2016.

[3] J.G. Fages and C. Prud'Homme. Making the first solution good! In *ICTAI 2017 : 29th IEEE International Conference on Tools with Artificial Intelligence*, Boston, MA, United States, November 2017.

[4] T. Falque, C. Lecoutre, B. Mazure, and H. Wattez. Descente Agressive de Borne en Optimisation sous Contraintes. In *16èmes Journées Francophones de Programmation par Contraintes (JPFC'21)*, Nice, France, June 2021.

[5] C. Lecoutre, L. Sais, S. Tabary, and V. Vidal. Reasonning from last conflict(s) in constraint programming. *Artificial Intelligence*, 173(18):1592–1614, 2009.

[6] C. Lecoutre and N. Szczepanski. PyCSP³: Modeling combinatorial constrained problems in Python. Technical report, CRIL, 2020. Available from https://github.com/xcsp3team/pycsp3.

[7] J. Vion and S. Piechowiak. Une simple heuristique pour rapprocher DFS et LNS pour les COP. In *Proceedings of JFPC'17*, pages 39–45, 2017.

[8] H. Wattez, C. Lecoutre, A. Paparrizou, and S. Tabary. Refining constraint weighting. In *Proceedings of ICTAI'19*, pages 71–77, 2019.

BTD and miniBTD
A Tree-decomposition based Approach

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(mini)BTD (Backtracking on Tree-Decomposition) is an open-source constraint solver which exploits the structure of CSP instances thanks to the notion of tree-decomposition [5]. It is written in C++ and implements the algorithm BTD-MAC+RST+Merge [3].

For the competition, we have made the following choices:

- The variable heuristic relies on Last Conflict [4] combined with a multi-armed bandit with 9 arms [1]. The i-th arm is based on CHS (for Conflict History Search [2]) with $\alpha = 0.1 * i$ and $\delta = 10^{-4}$. Note that the variable heuristic is only exploited for ordering the variables inside a cluster.

- *lexico* is used as value ordering heuristic.

- Generalized arc-consistency is enforced by a propagation-based system exploiting events.

- (mini)BTD relies on restarts performed according to a geometric restart policy based on the number of conflicts with an initial cutoff set to 50 and an increasing factor set to 1.05,

- The tree-decomposition is computed thanks to the heuristic H_5-TD-WT [3].

- The first root cluster is the cluster having the maximum ratio number of constraints to its size minus one and then, at each restart, the selected root cluster is one which maximizes the sum of the weights of the constraints whose scope intersects the cluster.

(mini)BTD is able to handle all the constraints used in the competition.

Licence.   (mini)BTD is licensed under the MIT License.

Code.   The source code is available on Github: https://github.com/Terrioux/BTD-RBO.

Command line.   (mini)BTD can be launched thanks to the following command line:

```
SOLVER TIMELIMIT BENCHNAME
```

where:

- `SOLVER` is the path to the executable BTD or miniBTD,

- `TIMELIMIT` is the number of seconds allowed for solving the instance,

- `BENCHNAME` is the name of the XML file representing the instance we want to solve.

References

[1] Mohamed Sami Cherif, Djamal Habet, and Cyril Terrioux. On the Refinement of Conflict History Search Through Multi-Armed Bandit. In *Proceedings of 32nd IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 264–271. IEEE, 2020.

[2] Djamal Habet and Cyril Terrioux. Conflict History Based Heuristic for Constraint Satisfaction Problem Solving. *J. Heuristics*, 27(6):951–990, 2021.

[3] P. Jégou, H. Kanso, and C. Terrioux. Towards a Dynamic Decomposition of CSPs with Separators of Bounded Size. In *Proceedings of the 22nd International Conference on Principles and Practice of Constraint Programming (CP)*, pages 298–315, 2016.

[4] Christophe Lecoutre, Lakhdar Sais, Sébastien Tabary, and Vincent Vidal. Reasoning from last conflict(s) in constraint programming. *Artif. Intell.*, 173(18):1592–1614, 2009.

[5] N. Robertson and P.D. Seymour. Graph minors II: Algorithmic aspects of treewidth. *Algorithms*, 7:309–322, 1986.

Choco solver
a free open-source Java library for CP

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Choco solver already has a long history : the first line of code was written in 1999 [11]. Since then, the code has been frequently re-engineered and released, up to version 4.0.8, the last current released [12]. It contains numerous variables, many (global) constraints and search procedures, to provide wide modeling perspectives.

Choco solver is used by the academy for teaching and research and by the industry to solve real-world problems, such as program verification, data center management, timetabling, scheduling and routing.

Several useful extra features are also available such as an extension that deals with graph variables, parsers to XCSP3 and FlatZinc or a minimalist profiler.

1   A Modeling API

Choco solver comes with the commonly used types of variables: integer vari-

ables with either bounded domain or enumerated one, Boolean variables, set variables and graph variables. Views [13] but also arithmetical, relational and logical expressions are supported.

Up to 100 constraints –and more than 150 propagators– are provided : from classic ones, such as arithmetical constraints, to must-have global constraints, such as ALLDIFFERENT or CUMULATIVE, and include less common even though useful ones, such as TREE. One can pick some existing propagators to compose a new constraint or create its own one in a straightforward way by implementing a filtering algorithm and a satisfaction checker.

The library supports natively real variables and constraints also, and relies on Ibex [3] to solve the continuous part of the problem [4].

2 Resolution Toolbox

`Choco solver` has been carefully designed to offer wide range of resolution configurations and good resolution performances. Backtrackable primitives and structures are based on trailing. The propagation engine deals with seven priority levels and manage either fine or coarse grain events which enables to get efficient incremental constraint propagators.

The search algorithm relies on three components *Propagate, Learn and Move* depicted in [8]. Such a generic search algorithm is then instantiated to DFS, LNS [14], LDS [7], DDS [15] or HBFS [1].

The search process can also be greatly improved by various built-in search strategies such as Dom/WDeg [2] and CACD variant [16], ABS [10], Failure-based searches [9], BIVS [5], first-fail [6], etc., and by creating a problem-adapted search strategy.

One can solve a problem in many ways : checking satisfaction, finding one or all solutions, optimizing one or more objectives and solving on one or more thread, or simply propagating. The search process itself is observable and extensible.

3 The code and the dev team

Structurally, `Choco solver` is made of 573 Java classes which represents roughly 53k source code lines. The source code is hosted on GitHub under a BSD 4-clause licence. The project is mainly developed and maintained by Charles Prud'homme and Jean-Guillaume Fages, they can count on attentive contributors. Tutorials, Javadoc and a user guide can be referred to, as long as a Google group.

References

[1] David Allouche, Simon De Givry, Georgios KATSIRELOS, Thomas Schiex, and Matthias Zytnicki. Anytime hybrid best-first search with tree decom-

position for weighted CSP. In *CP 2015 - 21st International Conference on Principles and Practice of Constraint Programming*, page 17 p., Cork, Ireland, August 2015.

[2] Frédéric Boussemart, Fred Hemery, Christophe Lecoutre, and Lakhdar Sais. Boosting systematic search by weighting constraints. In *Proceedings of the 16th Eureopean Conference on Artificial Intelligence, ECAI'2004, including Prestigious Applicants of Intelligent Systems, PAIS 2004, Valencia, Spain, August 22-27, 2004*, pages 146–150, 2004.

[3] Gilles Chabert. Ibex 2.2.0, June 2017.

[4] Jean-Guillaume Fages, Gilles Chabert, and Charles Prud'Homme. Combining finite and continuous solvers Towards a simpler solver maintenance. In *The 19th International Conference on Principles and Practice of Constraint Programming*, page TRICS'13 Workshop: Techniques foR Implementing Constraint programming Systems, Uppsala, Sweden, September 2013.

[5] Jean-Guillaume Fages and Charles Prud'Homme. Making the first solution good! In *ICTAI 2017 29th IEEE International Conference on Tools with Artificial Intelligence*, Boston, MA, United States, November 2017.

[6] Robert M. Haralick and Gordon L. Elliott. Increasing tree search efficiency for constraint satisfaction problems. In *Proceedings of the 6th International Joint Conference on Artificial Intelligence - Volume 1*, IJCAI'79, pages 356–364, San Francisco, CA, USA, 1979. Morgan Kaufmann Publishers Inc.

[7] William D. Harvey and Matthew L. Ginsberg. Limited discrepancy search. In *Proceedings of the 14th International Joint Conference on Artificial Intelligence - Volume 1*, IJCAI'95, pages 607–613, San Francisco, CA, USA, 1995. Morgan Kaufmann Publishers Inc.

[8] Narendra Jussien and Olivier Lhomme. Unifying search algorithms for csp. Research report RR0203, EMN, 2002.

[9] Hongbo Li, Minghao Yin, and Zhanshan Li. Failure based variable ordering heuristics for solving csps (short paper). In Laurent D. Michel, editor, *27th International Conference on Principles and Practice of Constraint Programming, CP 2021, Montpellier, France (Virtual Conference), October 25-29, 2021*, volume 210 of *LIPIcs*, pages 9:1–9:10. Schloss Dagstuhl - Leibniz-Zentrum für Informatik, 2021.

[10] Laurent Michel and Pascal Van Hentenryck. Activity-based search for black-box constraint programming solvers. In Nicolas Beldiceanu, Narendra Jussien, and Éric Pinson, editors, *Integration of AI and OR Techniques in Contraint Programming for Combinatorial Optimzation Problems*, pages 228–243, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg.

[11] Franqis Laburthe. Choco: implementing a cp kernel. In *Proceedings of Techniques foR Implementing Constraint programming Systems (TRICS'00)*, pages 118–133, 2000.

[12] Charles Prud'homme, Jean-Guillaume Fages, and Xavier Lorca. *Choco Documentation*. TASC, LS2N CNRS UMR 6241, COSLING S.A.S., 2017.

[13] Christian Schulte and Guido Tack. Views and iterators for generic constraint implementations. In Peter van Beek, editor, *Principles and Practice of Constraint Programming - CP 2005, 11th International Conference, CP 2005, Sitges, Spain, October 1-5, 2005, Proceedings*, volume 3709 of *Lecture Notes in Computer Science*, pages 817–821. Springer, 2005.

[14] Paul Shaw. Using constraint programming and local search methods to solve vehicle routing problems. In Michael J. Maher and Jean-Francois Puget, editors, *Principles and Practice of Constraint Programming - CP98, 4th International Conference, Pisa, Italy, October 26-30, 1998, Proceedings*, volume 1520 of *Lecture Notes in Computer Science*, pages 417–431. Springer, 1998.

[15] Toby Walsh. Depth-bounded discrepancy search. In *In Proceedings of IJCAI-97*, pages 1388–1393, 1997.

[16] Hugues Wattez, Christophe Lecoutre, Anastasia Paparrizou, and Sébastien Tabary. Refining constraint weighting. In *31st IEEE International Conference on Tools with Artificial Intelligence, ICTAI 2019, Portland, OR, USA, November 4-6, 2019*, pages 71–77. IEEE, 2019.

CoSoCo 2.1

XCSP3 Competition 2022

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CoSoCo is a constraint solver written in C++.The main goal is to build a simple, but efficient constraint solver. Indeed, the main part of the solver contains less than 3,500 lines of code (including headers). CoSoCo will be available on github in september 2022. CoSoCo recognizes XCSP3 [2] by using the C++ parser that can be downloaded at https://github.com/xcsp3team/XCSP3-CPP-Parser. It can deal with all XCSP3 Core constraints. The part related to all constraint propagators contains around 5,500 lines of codes (including headers). This is the fourth participation of CoSoCo to XCSP competitions.

CoSoCo performs backtrack search, enforcing (generalized) arc consistency at each node (when possible). The main components are :

- *dom/wdeg* [1] as variable ordering heuristic;
- *lexico* as value ordering heuristic;
- lc(1), last-conflict reasoning with a collecting parameter k set to 1, as described in [4];
- a geometric restart policiy;
- a variable-oriented propagation scheme [5], where a queue Q records all variables with recently reduced domains (see Chapter 4 in [3]).
- The solution saving technque [6].

Acknowledgements

References

1. F. Boussemart, F. Hemery, C. Lecoutre, and L. Sais. Boosting systematic search by weighting constraints. In *Proceedings of ECAI'04*, pages 146–150, 2004.
2. F. Boussemart, C. Lecoutre, and C. Piette. XCSP3: an integrated format for benchmarking combinatorial constrained problems. *CoRR*, abs/1611.03398, 2016.
3. C. Lecoutre. *Constraint networks: techniques and algorithms*. ISTE/Wiley, 2009.
4. C. Lecoutre, L. Sais, S. Tabary, and V. Vidal. Reasonning from last conflict(s) in constraint programming. *Artificial Intelligence*, 173(18):1592–1614, 2009.
5. J.J. McGregor. Relational consistency algorithms and their application in finding subgraph and graph isomorphisms. *Information Sciences*, 19:229–250, 1979.
6. Julien Vion and Sylvain Piechowiak. Une simple heuristique pour rapprocher dfs et lns pour les cop. In *JFPC*, 2017.

Exchequer
Solving XCSP3 problems using `xcsp2c` and CBMC

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Version 1.0.1 – May 27, 2022

Exchequer is a solver for constraint satisfaction problems expressed in the XCSP3-Core format. This version is submitted to the Mini Solver track of the XCSP3 Competition 2022. Thus only a subset of XCSP3-Core is supported.

The solver works by translating an XCSP3 instance into a C program, which violates an assertion only if the values of the variables in the program give a solution to the instance. Then it uses the bounded model-checker CBMC [2] to attempt to verify absence of assertion violations. If CBMC finds an assertion violation, it reports back a counterexample trace, which Exchequer turns into an instance solution. If it finds no assertion violation, Exchequer reports that the instance is unsatisfiable.

CBMC itself works by translating a C program into a giant SAT instance, which it solves using a SAT solver. For the competition, we have used a version of CBMC built with the more modern SAT solver CaDiCaL [1] instead of the default MiniSat. This is slower on some easy problems, but tends to be faster on harder ones.

It is unlikely that Exchequer's approach will ever be better than a direct encoding in SAT. It was written primarily to demonstrate that its approach is feasible, and to see how much worse it is.

Exchequer's translation is quite naive. It can easily generate very large C files, for example, if the instance contains a large `extension` constraint that is used as a template. In this case, even if the instance is solved, most of the time is spent by CBMC generating the SAT instance, not running the SAT solver.

Encoding example. Consider the following XCSP3 example:

```
<instance format="XCSP3" type="CSP">
  <variables>
    <var id="x"> 1..10 </var>
    <var id="y"> 1..100 </var>
  </variables>
  <constraints>
    <intension>
      eq(y,mul(x,x))
    </intension>
  </constraints>
</instance>
```

Exchequer produces the following C encoding (with boilerplate header code omitted):

```
int main() {
    int32_t x;
    __CPROVER_assume(((x >= 1) && (x <= 10)));
    __CPROVER_printf("XCSP2C SOLUTION: x = %d", x);
    int32_t y;
    __CPROVER_assume(((y >= 1) && (y <= 100)));
    __CPROVER_printf("XCSP2C SOLUTION: y = %d", y);
    __CPROVER_assume((y == (x * x)));
#ifndef TARGET
    assert(0);
#endif
}
```

Implementation details. Exchequer is implemented as two Perl scripts: `xcsp2c.pl` performs the translation, while `exchequer.pl` is a wrapper that calls `xcsp2c.pl` and CBMC. Exchequer also uses XCSP3 Tools to validate solutions before returning them.

For constraint optimisation (COP) problems, Exchequer simply calls CBMC repeatedly, trying to find a solution incrementally better than the previous one each time. When a better solution cannot be found, we know this is the optimum. The actual value of the objective for each solution is calculated using XCSP3 Tools.

Usage. Download from https://gitlab.act.reading.ac.uk/ta918887/exchequer and run:

`perl DIR/tool/exchequer.pl --tmpdir=TMPDIR BENCHNAME`

where:

- `DIR` is the extracted release archive directory;

- `BENCHNAME` is the XML file encoding the XCSP3 instance;

- `TMPDIR` is the optional temporary directory to use.

If no temporary directory is given, Exchequer will use the directory containing the instance. In any case, it will write the following files:

- a `.c` file encoding the instance;

- a `.log` file recording the output from CBMC;

- a `.sol.xml` file containing the solution.

Licence. Exchequer, CaDiCaL and XCSP3 Tools are distributed under the MIT License. CBMC is distributed under a BSD-style 4-clause licence.

References

[1] Armin Biere, Katalin Fazekas, Mathias Fleury, and Maximillian Heisinger. CaDiCaL, Kissat, Paracooba, Plingeling and Treengeling entering the SAT Competition 2020. In *Proc. of SAT Competition 2020 – Solver and Benchmark Descriptions*, volume B-2020-1 of *Department of Computer Science Report Series B*, pages 51–53. University of Helsinki, 2020. https://helda.helsinki.fi/handle/10138/335114.

[2] Edmund M. Clarke, Daniel Kroening, and Flavio Lerda. A tool for checking ANSI-C programs. In *TACAS 2004*, volume 2988 of *Lecture Notes in Computer Science*, pages 168–176. Springer, 2004. https://doi.org/10.1007/978-3-540-24730-2_15.

Fun-sCOP

XCSP3 Competition 2022

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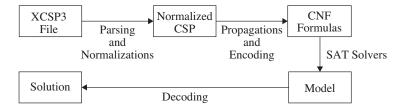
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1 Overview

Fun-sCOP is a SAT-based constraint programming system written in Scala, which
aims to be a re-implementation of Sugar [5] written in Java. Compared to the previ-
ous version named scop, Fun-sCOP equips the hybrid encoding integrating the order
and log encodings [3]. The following figure shows the framework of Fun-sCOP. We
explain each part of this framework in the remaining of this paper.

2 Parsing and Normalizations

Parsing is done by using the official tool XCSP3-Java-Tools [5]. Fun-sCOP accepts
constraints in the XCSP3-core language[6].

Normalizations are executed as follows:

– **Global Constraints** are decomposed into intensional constraints. We use extra pi-
geon hole constraints [5] for alldifferent constraints.
– **Extensional constraints** are translated into intensional constraints by using a vari-
ant of multi-valued decision diagrams. This is a difference to ones in Sugar.
– **Intensional Constraints** are normalized to be in the form of a conjunction of dis-
junctions of linear comparisons $\sum_i a_i x_i \geq k$ where a_i's are integer coefficients,
x_i's are integer variables and k is an integer constant. Tseitin transformation is used
to avoid the combinatorial explosion.

---

[5] https://github.com/xcsp3team/XCSP3-Java-Tools

[6] http://www.xcsp.org/specifications

3 Propagations and Encoding Methods

Constraint propagations are executed to the normalized CSP (clausal CSP, i.e., in the form of CNF over linear comparisons $\sum_i a_i x_i \geq k$) to remove redundant values, variables, and linear comparisons. It is done by using an AC3 like algorithm.

Encoding methods are as follows:

– **Order Encoding** [7, 6] is an encoding method using propositional variables $p_{x \geq d}$'s meaning $x \geq d$ for each domain value d of each integer variable x. To encode linear comparisons, Algorithm 1 of the literature [6] is used in Fun-sCOP.

– **Hybrid Encoding** [3] is an encoding method integrating the order and log encodings without channeling constraints. In the hybrid encoding, each variable is encoded by either the order encoding or the log encoding, and each constraint is encoded according to its variables' encoding. The degree of hybridization can be controlled by classifying the order-encoded and log-encoded variables. Fun-sCOP uses the criterion *domain product* to classify variables as same as in [3].

4 SAT Solvers

GlueMiniSat [2] is used for the order encoding. It is a winning solver in the SAT solver competitions, and the submitted version of GlueMiniSat uses a special propagator for the axiom clauses of the order encoding.

CaDiCaL [7] is used for the hybrid encoding. It is also a winning solver in the recent SAT solver competitions, and shows a good performance in our preliminary evaluation.

[7] https://github.com/arminbiere/cadical

References

1. Gotou, Y., Nabeshima, H.: ManyGlucose. In: Proceedings of SAT Competition 2018: Solver and Benchmark Descriptions, volume B-2018-1 of Department of Computer Science Series of Publications B, University of Helsinki. p. 27 (2018)
2. Nabeshima, H., Iwanuma, K., Inoue, K.: GlueMiniSat 2.2.8. In: Proceedings of SAT Competition 2014. pp. 35–36 (2014)
3. Soh, T., Banbara, M., Tamura, N.: Proposal and evaluation of hybrid encoding of CSP to SAT integrating order and log encodings. International Journal on Artificial Intelligence Tools 26(1), 1–29 (2017)
4. Soos, M., Nohl, K., Castelluccia, C.: Extending SAT solvers to cryptographic problems. In: Proceedings of the 12th International Conference on Theory and Applications of Satisfiability Testing (SAT 2009), LNCS 5584. pp. 244–257 (2009)
5. Tamura, N., Banbara, M.: Sugar: a CSP to SAT translator based on order encoding. In: Proceedings of the 2nd International CSP Solver Competition. pp. 65–69 (2008)
6. Tamura, N., Banbara, M., Soh, T.: PBSugar: Compiling pseudo-boolean constraints to SAT with order encoding. In: Proceedings of the 25th IEEE International Conference on Tools with Artificial Intelligence (ICTAI 2013). pp. 1020–1027 (Nov 2013)
7. Tamura, N., Taga, A., Kitagawa, S., Banbara, M.: Compiling finite linear CSP into SAT. Constraints 14(2), 254–272 (2009)

The Glasgow Constraint Solver

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Version of June 22nd, 2022

The Glasgow Constraint Solver is an open source constraint programming solver, developed in C++20. Currently it supports only integer variables, a few global constraints (all different, count, element, integer linear inequalities, table, min / max, n value), and simple backtracking with smallest domain first as a variable-ordering heuristic. It is not particularly optimised for performance. However, it has one unusual feature: it can produce proof logs for any problem that it can solve, allowing for independent verification of its results [1].

Licence. The Glasgow Constraint Solver is licensed under the MIT License

Code and documentation. Source code, installation instructions, and instructions on how to solve problems and verify solutions are all available on Github: https://github.com/ciaranm/glasgow-constraint-solver.

Acknowledgements

References

[1] Stephan Gocht, Ciaran McCreesh, and Jakob Nordström. An auditable constraint programming solver. In *Principles and Practice of Constraint Programming - 28th International Conference, CP*, 2022.

MiniCPBP
A Constraint Solver Propagating Beliefs

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June 2022

MiniCPBP is an open-source constraint solver used as a research platform by our team. It is developed in Java on top of MiniCP [3] and extends constraint propagation with belief propagation[4]. Among other things, it can use this extra information to guide search[1]. MiniCPBP features:

- integer variables, including 0/1 (Boolean) variables;

- many simple constraints (Abs, Or, Maximum, Minimum, $=$, $\neq$, $\leq$, $\times$) and, in most cases, their reification;

- several common global constraints (Element, Sum, AllDifferent, Cardinality, Table, Regular, Among/AtLeast/AtMost/Exactly, Circuit, Disjunctive, Cumulative);

- *dedicated weighted counting algorithms* for most of these constraints in order to propagate beliefs;

- *novel branching heuristics* exploiting the propagated beliefs about variable-value assignments (e.g. minEntropy, maxMarginal, maxMarginalStrength).

CP-based Belief Propagation

MiniCPBP implements a generalization of constraint propagation which, instead of simply propagating unsupported variable-value assignments, propagates beliefs about each possible variable-value assignment in the form of (marginal) probability distributions over each variable's domain. Such propagation is organized as synchronized message passing (iterated belief propagation). We illustrate this on a small example taken from [4]. Consider variables a, b, c and d with identical domains $\{1, 2, 3, 4\}$, and the following constraints :

i. $alldifferent(a, b, c)$

ii. $a + b + c + d = 7$

iii. $c \leq d$

This CSP has two solutions : $\langle a = 2, b = 3, c = 1, d = 1 \rangle$ and $\langle a = 3, b = 2, c = 1, d = 1 \rangle$. If we examine variable a, we observe that assignment $a = 2$ is present in one solution and that assignment $a = 3$ is present in the other one. There is no valid solution containing $a = 1$ or $a = 4$. Therefore its true marginal distribution is $\theta_a(1) = 0, \theta_a(2) = 1/2, \theta_a(3) = 1/2, \theta_a(4) = 0$. The true marginals for each variable are shown in Table 1 (top left).

	1	2	3	4			1	2	3	4
θ_a	0	.5	.5	0		θ_a	.25	.25	.25	.25
θ_b	0	.5	.5	0		θ_b	.25	.25	.25	.25
θ_c	1	0	0	0		θ_c	.25	.25	.25	.25
θ_d	1	0	0	0		θ_d	.25	.25	.25	.25

	1	2	3	4			1	2	3	4
θ_a	.50	.30	.15	.05		θ_a	.01	.52	.46	.01
θ_b	.50	.30	.15	.05		θ_b	.01	.52	.46	.01
θ_c	.62	.28	.09	.01		θ_c	.98	.02	.00	.00
θ_d	.29	.34	.26	.11		θ_d	.90	.10	.00	.00

Table 1: True marginals (top left); initial uniform marginals (top right), marginals after 1st iteration of BP (bottom left), and after 10th iteration (bottom right).

	1	2	3	4
θ_a^i	1/4	1/4	1/4	1/4
θ_a^{ii}	10/20	6/20	3/20	1/20
θ_b^i	1/4	1/4	1/4	1/4
θ_b^{ii}	10/20	6/20	3/20	1/20
θ_c^i	1/4	1/4	1/4	1/4
θ_c^{ii}	10/20	6/20	3/20	1/20
θ_c^{iii}	4/10	3/10	2/10	1/10
θ_d^{ii}	10/20	6/20	3/20	1/20
θ_d^{iii}	1/10	2/10	3/10	4/10

Table 2: Initial local marginals computed by each constraint. The superscript refers to the constraint whereas the subscript refers to the variable. Notice e.g. how constraints ii and iii initially give opposing beliefs for variable d.

CP-based Belief propagation starts from a uniform distribution for each variable x ($\theta_x(v) = 1/|D(x)| \quad \forall v \in D(x)$) which, as shown in Table 1, tries to converge to the true marginal distributions as iterations proceed. Each iteration adjusts a variable's marginals by taking the product of the local marginals computed at each constraint given the current marginals (this is where weighted counting comes in). For example the initial local marginals computed by each constraint (given uniform marginals) are shown in Table 2.

Entropy-based Branching

Because Belief Propagation allows us to approximate the marginal distribution for each variable of our model, we are also able to approximate the entropy of each variable. Entropy is a powerful expression of the knowledge we have about a variable: the lower its entropy, the more confident we are about which value it should take (e.g. a bound variable has zero entropy). Thus entropy is a powerful tool that we can exploit to make better branching decisions. We define the entropy $H(x)$ of variable x as

$$H(x) = - \sum_{v \in D(x)} \theta_x(v) log(\theta_x(v))$$

Branching heuristic *minEntropy* [2] selects the variable with the lowest entropy and the value with the highest marginal.

We can extend the concept of entropy to the whole model as the mean normalized entropy of its

variables:

$$\overline{H} = \frac{\sum_{x \in X} \frac{H(x)}{log(|D(x)|)}}{|X|}$$

The number of BP iterations we perform before each branching decision is decided dynamically based on how stable the model entropy has become [2].

Constraint Weights

In CP-based Belief Propagation by default all constraints are considered on an equal footing. However within a model the arity of constraints can vary significantly. A constraint with a considerably larger arity intuitively represents a larger part of the problem and thus should provide a more enlightened view of what a valid solution should be. We could therefore give more weight to the messages it sends. Let X denote the set of variables, C be the set of constraints, and $X(c)$ the scope of constraint c. We define the weight of c as

$$w_c = 1 + \frac{|X(c)| - min_{c' \in C}|X(c')|}{|X|},$$

which ranges between 1 and 2, and use it as an exponent on messages from constraints. A larger weight accentuates the extreme values among marginals.

Competition Entries

The two variants of our solver entered in this competition both branch according to minEntropy and stop BP iterations dynamically. They differ in that during BP one considers a constraint's weight as its arity. The code of MiniCPBP is available at https://github.com/PesantGilles/MiniCPBP

References

[1] B. Babaki, B. Omrani, and G. Pesant. Combinatorial Search in CP-Based Iterated Belief Propagation. In Helmut Simonis, editor, *Principles and Practice of Constraint Programming - 26th International Conference, CP 2020, Louvain-la-Neuve, Belgium, September 7-11, 2020, Proceedings*, volume 12333 of *Lecture Notes in Computer Science*, pages 21–36. Springer, 2020.

[2] A. Burlats and G. Pesant. Exploiting Model Entropy to Make Branching Decisions in Constraint Programming. In *CP'22 Doctoral Program*, 2022.

[3] L. Michel, P. Schaus, and P. Van Hentenryck. MiniCP: A Lightweight Solver for Constraint Programming. *Mathematical Programming Computation*, 13(1):133–184, 2021.

[4] G. Pesant. From Support Propagation to Belief Propagation in Constraint Programming. *J. Artif. Intell. Res.*, 66:123–150, 2019.

Mistral

Mistral **IS** a **T**errific **R**ecursive **A**cronym for a **L**ibrary

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August 2022

Abstract

Mistral is an open source constraint programming library written in C++ and available on GitHub. It implements a modelling API, however, it can also read instance files in XCSP3[1] or FlatZinc format. Moreover, it is fully interfaced with Numberjack [6] which provides a Python API for modelling and solving combinatorial optimization problems using several back-end solvers.

Solver Engine

The solver engine relies on standard mechanisms, using a priority constraint queue and a domain event stack to implement the propagation procedure. Moreover, it supports dynamic type change for variables: domains are initially implemented using intervals or Boolean types whenever possible, and can be changed to (bit)sets during search when a propagator requires it. The backtracking mechanism is implemented using a trail in a standard way.

Propagators

Several classic global constraints are implemented, such as LexOrdering [4], bound consistency propagator for AllDifferent [10] and Gcc [9]. Moreover, less standard constraints were implemented within the context of research articles on constraint propagation, such as the AtMostSeqCard constraint for car-sequencing [12] or a VertexCover constraint [3] to reason about cliques, independant set or vertex covers. Search Strategy The search heuristic used for the XCSP3 competition is based on *Last Conflict* [8], using a variant of *Weighted Degree* [2] as default strategy: in the case of failure raised by a propagator of a global constraint, an explanation of the conflict is computed and only the weight of the variables participating in the conflict is incremented. This heuristic is fully described in [7]. Moreover, given the next variable x to branch

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[1]Using Gilles Audemard's parser.

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on, the solver chooses the value that was assigned to x in the best solution found so far, if possible, or the minimum value in the domain of x otherwise.

Applications of Mistral

Mistral was used to implement a state-of-the-art method for disjunctive scheduling which improved several best known results on classic benchmarks [5]. More recently, some clause learning methods were implemented in Mistral, still improving the results on disjunctive scheduling [11] and car-sequencing problems [1]. These methods were not used within the context of the XCSP3 competition.

References

[1] Christian Artigues, Emmanuel Hebrard, Valentin Mayer-Eichberger, Mohamed Siala, and Toby Walsh. SAT and Hybrid Models of the Car Sequencing Problem. In *Integration of AI and OR Techniques in Constraint Programming (CPAIOR)*, pages 268–283, 2014.

[2] Frédéric Boussemart, Fred Hemery, Christophe Lecoutre, and Lakhdar Sais. Boosting Systematic Search by Weighting Constraints. In *Proceedings of the 16th European Conference on Artificial Intelligence (ECAI)*, pages 146–150, 2004.

[3] Clément Carbonnel and Emmanuel Hebrard. Propagation via Kernelization: The Vertex Cover Constraint. In *Principles and Practice of Constraint Programming (CP)*, pages 147–156, 2016.

[4] Alan M. Frisch, Brahim Hnich, Zeynep Kiziltan, Ian Miguel, and Toby Walsh. Propagation algorithms for lexicographic ordering constraints. *Artif. Intell.*, 170(10):803–834, 2006.

[5] Diarmuid Grimes and Emmanuel Hebrard. Solving Variants of the Job Shop Scheduling Problem Through Conflict-Directed Search. *INFORMS J. Comput.*, 27(2):268–284, 2015.

[6] Emmanuel Hebrard, Eoin O'Mahony, and Barry O'Sullivan. Constraint Programming and Combinatorial Optimisation in Numberjack. In *Integration of AI and OR Techniques in Constraint Programming (CPAIOR)*, pages 181–185, 2010.

[7] Emmanuel Hebrard and Mohamed Siala. Explanation-Based Weighted Degree. In *Integration of AI and OR Techniques in Constraint Programming (CPAIOR)*, pages 167–175, 2017.

[8] Christophe Lecoutre, Lakhdar Sais, Sébastien Tabary, and Vincent Vidal. Reasoning from last conflict(s) in constraint programming. *Artif. Intell.*, 173(18):1592–1614, 2009.

2

[9] Claude-Guy Quimper, Alexander Golynski, Alejandro López-Ortiz, and Peter van Beek. An Efficient Bounds Consistency Algorithm for the Global Cardinality Constraint. *Constraints An Int. J.*, 10(2):115–135, 2005.

[10] Claude-Guy Quimper, Peter van Beek, Alejandro López-Ortiz, Alexander Golynski, and Sayyed Bashir Sadjad. An Efficient Bounds Consistency Algorithm for the Global Cardinality Constraint. In *Principles and Practice of Constraint Programming (CP)*, pages 600–614, 2003.

[11] Mohamed Siala, Christian Artigues, and Emmanuel Hebrard. Two Clause Learning Approaches for Disjunctive Scheduling. In *Principles and Practice of Constraint Programming (CP)*, pages 393–402, 2015.

[12] Mohamed Siala, Emmanuel Hebrard, and Marie-José Huguet. An optimal arc consistency algorithm for a particular case of sequence constraint. *Constraints An Int. J.*, 19(1):30–56, 2014.

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Nacre
Nogood And Clause Reasoning Engine

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Version 1.0.6 – May, 2022

Nacre [3, 4] is a constraint solver written in C++. The main purpose of this solver is to experiment nogood recording (with a clause reasoning engine) in Constraint Programming (CP). In particular, the data structures of the solver have been carefully designed to play around nogoods and clauses.

Usage. You can compile and run Nacre using the following lines:

```
cd core && make -j

./nacre_mini_release <xcsp3_file> method [options]
```

with:

- <xcsp3_file>: a xcp3 file representing a CSP instance

- method: the method to use for solving the CSP instance. Possible values are:

  - -complete: Simple complete search
  - -incng: Complete search with Increasing Nogoods [6]
  - -nld: Complete search with Negative last-decision nogoods [5]
  - **-ca**: Hybrid solving with conflict analysis, SAT-based lazy explanations [1, 2]

- [options]: possible options to be used when running the solver (e.g. $-l100$ for Luby sequence where every terms is multiplied by 100 as restart policy; $-cm$ for competition verbose mode)

Competition. Nacre is enlisted in the **Minitrack - CSP** ; line used for the competition:

```
./nacre_mini_release BENCHNAME -ca -l100 -cm
```

Licence. Nacre is licensed under the GNU General Public License v3.0.

Code. Nacre code is available online at github.com/gglorian/Nacre[1].

---

[1] New official Nacre repository, forked from previous competition sources.

Acknowledgements

References

[1] Ian P. Gent, Ian Miguel, and Neil C. A. Moore. Lazy explanations for constraint propagators. In Manuel Carro and Ricardo Peña, editors, *Practical Aspects of Declarative Languages, 12th International Symposium, PADL 2010, Madrid, Spain, January 18-19, 2010. Proceedings*, volume 5937 of *Lecture Notes in Computer Science*, pages 217–233. Springer, 2010.

[2] Gael Glorian. *Hybridation de techniques d'apprentissage de clauses en programmation par contraintes*. Theses, Université d'Artois, December 2019.

[3] Gael Glorian. Nacre. In Christophe Lecoutre and Olivier Roussel, editors, *Proceedings of the 2018 XCSP3 Competition*, pages 85–85, 2019.

[4] Gael Glorian, Jean-Marie Lagniez, and Christophe Lecoutre. NACRE - A nogood and clause reasoning engine. In Elvira Albert and Laura Kovács, editors, *LPAR 2020: 23rd International Conference on Logic for Programming, Artificial Intelligence and Reasoning, Alicante, Spain, May 22-27, 2020*, volume 73 of *EPiC Series in Computing*, pages 249–259. EasyChair, 2020.

[5] Christophe Lecoutre, Lakhdar Sais, Sébastien Tabary, and Vincent Vidal. Recording and minimizing nogoods from restarts. *J. Satisf. Boolean Model. Comput.*, 1(3-4):147–167, 2007.

[6] Jimmy H. M. Lee, Christian Schulte, and Zichen Zhu. Increasing nogoods in restart-based search. In Dale Schuurmans and Michael P. Wellman, editors, *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, February 12-17, 2016, Phoenix, Arizona, USA*, pages 3426–3433. AAAI Press, 2016.

An XCSP3 Solver in Picat

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Abstract. This short paper gives an overview of the XCSP3 solver implemented in Picat. Picat provides several constraint modules, and the Picat XCSP3 solver uses the `sat` module. The XCSP3 solver mainly consists of a parser implemented in Picat, which converts constraints from XCSP3 format to Picat. The solver demonstrates the strengths of Picat, a logic-based language, in parsing, modeling, and encoding constraints into SAT. The solver submitted to the 2022 XCSP competition is based on the one that won the 2019 XCSP competition. The high performance of the solver also demonstrates the viability of using a SAT solver to solve general constraint satisfaction and optimization problems.

XCSP3

XCSP3 [1] is an XML-based domain specific language for describing constraint satisfaction and optimization problems (CSP). XCSP3 is positioned as an intermediate language for CSPs. It does not provide high-level constructs as seen in modeling languages. However, XCSP3 is significantly more complex than a canonical-form language, like FlatZinc [4]. A constraint can sometimes be described in either the standard format or simplified format. The advanced format, which is used by group and matrix constraints, allows more compact description of constraints.

Picat

Picat [10] is a simple, and yet powerful, logic-based multi-paradigm programming language. Picat is a Prolog-like rule-based language, in which predicates, functions, and actors are defined with pattern-matching rules. Picat incorporates many declarative language features for better productivity of software development, including explicit non-determinism, explicit unification, functions, list comprehensions, constraints, and tabling. Picat also provides imperative language constructs, such as assignments and loops, for programming everyday things. Picat provides facilities for solving combinatorial search problems, including a common interface with CP, SAT, MIP, and SMT solvers, tabling for dynamic programming, and a module for planning. Picat uses, in the XCSP3 solver, the SAT module, which generally performs better than the CP, MIP, and SMT modules on competition benchmarks.

Parsing

The availability of different formats in XCSP3 makes it a challenge to parse the XCSP3 language. A parser implemented in C++ by the XCSP3 designers has more than 10,000 lines of code. The entire Picat implementation of XCSP3 has about 2,000 lines of code, two-thirds of which is devoted to parsing and syntax-directed translation. As illustrated in the following example, Picat is well suited to parsing.

```
% E -> T E'
ex(Si,So) => term(Si,S1), ex_prime(S1,So).

% E' -> + T E' | - T E' | e
ex_prime(['+'|Si],So) =>
    term(Si,S1),
    ex_prime(S1,So).
ex_prime(['-'|Si],So) =>
    term(Si,S1),
    ex_prime(S1,So).
ex_prime(Si,So) => So = Si.
```

The parser follows the framework for translating context-free grammar into Prolog [5]: a non-terminal is encoded as a predicate that takes an input string (`Si`) and an output string (`So`), and when the predicate succeeds, the difference `Si-So` constitutes a string that matches the nonterminal. Unlike in Prolog, pattern-matching rules in Picat are fully indexed, which facilitates selecting right rules based on look-ahead tokens.

Modeling

It is well known that loops and list comprehensions are a necessity for modeling CSPs. The following Picat example illustrates the convenience of these language constructs for modeling.

```
post_constr(allDifferentMatrix(Matrix)) =>
    NRows = len(Matrix),
    NCols = len(Matrix[1]),
    foreach (I in 1..NRows)
        all_different(Matrix[I])
    end,
    foreach (J in 1..NCols)
        all_different([Matrix[I,J] : I in 1..NRows])
    end.
```

The `allDifferentMatrix(Matrix)` constraint takes a matrix that is represented as a two-dimensional array, and posts an `all_different` constraint for each row and each column of the matrix.

SAT Encoding

Picat adopts the log encoding [2] for domain variables. While log encoding had been perceived to be unsuited to arithmetic constraints due to its hindrance to propagation [3], we have shown that log encoding can be made competitive with optimizations [8]. There are hundreds of optimizations implemented in Picat, and they are described easily as pattern-matching rules in Picat. We have also shown that, with specialization, the binary adder encoding is not only compact, but

also generally more efficient than BDD encodings for PB constraints [9]. Picat adopts specialized decomposition algorithms for some of the global constraints, such as the circuit and reachability constraints [6, 7].

SAT Solving

Picat uses the kissat SAT solver.[1] For a satisfibility problem, Picat calls the SAT solver, and converts the SAT solution to a solution for the decision variables if the problem is satisfiable. For an optimization problem, Picat uses a branch-and-bound algorithm to find the best solution, and calls the SAT solver each time a domain bound of the objective variable is narrowed. The kissat generally outperforms the Maple solver, which is used in the Picat XCSP3 solver submitted to the 2019 competition.

References

1. Frederic Boussemart, Christophe Lecoutre, Gilles Audemard, and Cdric Piette. Xcsp3: An integrated format for benchmarking combinatorial constrained problems, 2016.
2. Kazuo Iwama and Shuichi Miyazaki. SAT-variable complexity of hard combinatorial problems. In *IFIP Congress (1)*, pages 253–258, 1994.
3. Donald Knuth. *The Art of Computer Programming, Volume 4, Fascicle 6: Satisfiability.* Addison-Wesley, 2015.
4. Nicholas Nethercote, Peter J. Stuckey, Ralph Becket, Sebastian Brand, Gregory J. Duck, and Guido Tack. MiniZinc: Towards a standard CP modelling language. In *CP*, pages 529–543, 2007.
5. Fernando C. N. Pereira and David H. D. Warren. Definite clause grammars for language analysis - A survey of the formalism and a comparison with augmented transition networks. *Artif. Intell.*, 13(3):231–278, 1980.
6. Neng-Fa Zhou. In pursuit of an efficient SAT encoding for the Hamiltonian cycle problem. In *CP*, pages 585–602, 2020.
7. Neng-Fa Zhou. Modeling and solving graph synthesis problems using SAT-encoded reachability constraints in Picat. In *Proceedings 37th International Conference on Logic Programming (Technical Communications)*, volume 345 of *EPTCS*, pages 165–178, 2021.
8. Neng-Fa Zhou and Håkan Kjellerstrand. Optimizing SAT encodings for arithmetic constraints. In *CP*, pages 671–686, 2017.
9. Neng-Fa Zhou and Håkan Kjellerstrand. Encoding PB constraints into SAT via binary adders and BDDs – revisited. In *Workshop on Experimental Evaluation of Algorithms for Solving Problems with Combinatorial Explosion RCRA*, 2018.
10. Neng-Fa Zhou, Håkan Kjellerstrand, and Jonathan Fruhman. *Constraint Solving and Planning with Picat.* Springer Briefs in Intelligent Systems. Springer, 2015.

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[1] https://github.com/arminbiere/kissat

RBO and miniRBO

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(mini)RBO (Restart Based Optimizer) is an open-source constraint solver for COP instances. It is written in C++ and implements a variant of the algorithm MAC+RST [3].

For the competition, we have made the following choices:

- The variable heuristic relies on Last Conflict [4] combined with a multi-armed bandit with 9 arms [1]. The i-th arm is based on CHS (for Conflict History Search [2]) with $\alpha = 0.1 * i$ and $\delta = 10^{-4}$.

- Solution-saving [5] combined with *lexico* is used as value ordering heuristic.

- Generalized arc-consistency is enforced by a propagation-based system exploiting events.

- (mini)RBO relies on restarts performed according to a geometric restart policy based on the number of conflicts with an initial cutoff set to 50 and an increasing factor set to 1.05,

(mini)RBO is able to handle all the constraints and objective functions used in the competition.

Licence.   (mini)RBO is licensed under the MIT License.

Code.   The source code is available on Github: https://github.com/Terrioux/BTD-RBO.

Command line.   (mini)RBO can be launched thanks to the following command line:

```
SOLVER TIMELIMIT BENCHNAME
```

where:

- `SOLVER` is the path to the executable BTD or miniBTD,

- `TIMELIMIT` is the number of seconds allowed for solving the instance,

- `BENCHNAME` is the name of the XML file representing the instance we want to solve.

References

[1] Mohamed Sami Cherif, Djamal Habet, and Cyril Terrioux. On the Refinement of Conflict History Search Through Multi-Armed Bandit. In *Proceedings of 32nd IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 264–271. IEEE, 2020.

[2] Djamal Habet and Cyril Terrioux. Conflict History Based Heuristic for Constraint Satisfaction Problem Solving. *J. Heuristics*, 27(6):951–990, 2021.

[3] C. Lecoutre, L. Saïs, S. Tabary, and V. Vidal. Recording and Minimizing Nogoods from Restarts. *JSAT*, 1(3-4):147–167, 2007.

[4] Christophe Lecoutre, Lakhdar Sais, Sébastien Tabary, and Vincent Vidal. Reasoning from last conflict(s) in constraint programming. *Artif. Intell.*, 173(18):1592–1614, 2009.

[5] Julien Vion and Sylvain Piechowiak. Une simple heuristique pour rapprocher DFS et LNS pour les COP. In *Actes des Journées Francophones de Programmations par Contraintes (JFPC)*, pages 39–45, 2017.

Sat4j-CSP-PB
A Pseudo-Boolean-Based Constraint Solver

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XCSP'22 - August 2022

`Sat4j-CSP-PB` is a CSP solver based on the pseudo-Boolean solver `Sat4j` [4].

1 Description of the solving approach

`Sat4j-CSP-PB` encodes the constraints it receives as pseudo-Boolean (PB) constraints of the form $\sum_{i=1}^{n} \alpha_i \ell_i \; \triangle \; \delta$, where n is a positive integer, the *weights* (or *coefficients*) α_i and the *degree* δ are integers, ℓ_i are literals and $\triangle \in \{<, \leq, =, \geq, >\}$. This allows to exploit the reasoning power of PB solvers based on the *cutting planes* proof system [2, 3, 5].

For some constraints, using a PB encoding is particularly convenient as it is more natural and more succinct than the clausal encodings that would be used by regular SAT solvers. This is particularly the case for the following constraints:

- `all-different`
- `cardinality`
- `count`
- `n-values`
- `sum`

As PB solvers are extensions of SAT solvers, we can also use clausal encodings for other constraints to encode, even though this often prevents PB solvers to benefit from the full inference power of the cutting planes proof system.

There are however some constraints that are not supported yet, and will lead the solver to output `s UNSUPPORTED` if one of the following features appears in the input instance:

- symbolic variables
- `bin packing`
- `circuit`
- `cumulative`
- `element` with matrices
- "smart" `extension`
- intension constraints using `pow`
- `mdd`
- `precedence`
- `regular`
- `stretch`

2 Variants of the underlying PB solver

`Sat4j-CSP-PB` uses one of the PB solvers implemented by `Sat4j` to solve the PB encoding used to represent the input problem. The variants submitted to the competition are:

- `sat4j-resolution`, which implements a resolution-based conflict analysis (PB constraints are lazily encoded as clauses during conflict analysis),
- `sat4j-cp`, which implements a cutting-planes-based conflict analysis,
- `sat4j-rs`, which implements a conflict analysis *à la* `RoundingSat` [1], and
- `sat4j-both`, which uses a portfolio of `sat4j-cp` and `sat4j-resolution`.

3 Running `Sat4j-CSP-PB`

`Sat4j-CSP-PB` is written in *Java 11* and uses the *Jigsaw* modular system. *Java 11* is thus required to compile and execute this solver. To compile `Sat4j-CSP-PB`, you may run the following command at the root of the project:

```
./gradlew csp
```

Then, you will be able to run the solver using the wrapper bash script provided along with the solver:

```
./exec/sat4j-csp.sh [options] <path/to/instance.xml>
```

where

- `<path/to/instance.xml>` is an XCSP3 file representing a CSP or COP instance, and
- `[options]` are the possible options to be used when running the solver.

4 License

`Sat4j-CSP-PB` is licensed under the GNU Lesser General Public License.

5 Code

The source code of `Sat4j-CSP-PB` is available on OW2's GitLab.

References

[1] Jan Elffers and Jakob Nordström. Divide and conquer: Towards faster pseudo-boolean solving. In *Proceedings of IJCAI 2018*, pages 1291–1299, 2018.

[2] Ralph E. Gomory. Outline of an algorithm for integer solutions to linear programs. *Bulletin of the American Mathematical Society*, pages 275–278, 1958.

[3] J. N. Hooker. Generalized resolution and cutting planes. *Annals of Operations Research*, 12(1):217–239, 1988.

[4] Daniel Le Berre and Anne Parrain. The SAT4J library, Release 2.2, System Description. *Journal on Satisfiability, Boolean Modeling and Computation*, 7:59–64, 2010.

[5] Jakob Nordström. On the Interplay Between Proof Complexity and SAT Solving. *ACM SIGLOG News*, 2(3):19–44, August 2015.

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toulbar2

An exact cost function network solver
Version 1.2 – July 11, 2022

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Introduction

toulbar2 is an open-source C++ solver for cost function networks (CFN). It is available at `https://github.com/toulbar2/toulbar2`, with an MIT license and a documentation describing its interfaces with C++ and python.

The constraints and objective function are factorized in local functions on discrete variables. Each function returns a cost for any assignment of its variables. Constraints are represented as functions with costs in $\{0, \top\}$ where $\top$ is an upper bound cost associated with forbidden assignments. toulbar2 looks for a non-forbidden assignment of all variables that minimizes the sum of all functions.

Using on the fly translation, toulbar2 can also directly solve optimization problems on other graphical models such as Maximum probability Explanation on Bayesian networks, and Maximum A Posteriori on Markov random fields [10]. It can also read partial weighted MaxSAT problems, (quadratic) pseudo-Boolean optimization problems as well as constrained satisfaction and optimization problems (COP in XCSP3 format).

toulbar2 provides and uses by default an *anytime* hybrid best-first branch-and-bound algorithm (HBFS) [1] that tries to quickly provide good solutions together with an upper bound on the gap between the cost of each solution and the (unknown) optimal cost. Thus, even when it is unable to prove optimality, it will bound the quality of the solution provided. It can also apply a variable neighborhood search algorithm exploiting a problem decomposition (UDGVNS) [15]. Both algorithms are complete (if enough CPU-time is given) and they can be run in parallel using OpenMPI [3, 15]. The variable ordering heuristic is *dom/wdeg* [4] combined with *last conflict* [12]. The value ordering heuristic exploits the last solution found if any [8] or else EDAC existential value [7]. EDAC is also used as soft local consistency during search to provide lower bounds and prune forbidden values [5]. A weaker relaxed version is used for pseudo-Boolean linear constraints [13]. Variable elimination is performed during search and restricted to variables with at most two neighbors [11]. More preprocessing techniques such as cost function decomposition [9] are done before search and pruning by dominance is also applied during search [6].

Beyond the service of providing optimal solutions, toulbar2 can also find a sequence of diverse solutions [16] or exhaustively enumerate solutions below a cost threshold and perform guaranteed approximate weighted counting of solutions. For stochastic graphical models, this means that toulbar2 will compute the partition function (or the normalizing constant). These problems being #P-complete, toulbar2 runtimes can quickly increase on such problems.

toulbar2 was originally developed by Toulouse (INRAE, MIAT) and Barcelona (UPC, IIIA-CSIC) teams, hence the name of the solver. Additional contributions by:

- Caen University, France (GREYC) and University of Oran, Algeria for (parallel) variable neighborhood search methods [15] ;

- The Chinese University of Hong Kong and Caen University, France (GREYC) for global cost functions [2] ;

- Marseille University, France (LSIS) for tree decomposition heuristics ;

- Ecole des Ponts ParisTech, France (CERMICS/LIGM) for INCOP local search solver [14] ;

- Artois University, France (CRIL) for the XCSP3 format reader of CSP and COP instances.

XCSP'2022 Competition Configuration Settings

For the XCSP'2022 competition, we used the following settings:

- For *COP sequential and mini COP* tracks, HBFS [1] was used with default settings ; command line:
  `DIR/toulbar2 -time=TIMELIMIT -seed=RANDOMSEED -v=-1 BENCHNAME`

- For *COP parallel* track, parallel HBFS [3] was used with the available number of cores and MPI compilation settings ; command line:
  `mpirun -n NBCORE DIR/toulbar2mpi -time=TIMELIMIT -seed=RANDOMSEED -v=-1 BENCHNAME`

- For *COP fast* track, UDGVNS [15] was used with a min-fill problem decomposition heuristic and merging clusters with their parent cluster if the ratio of separator variables is greater than 0.7 ; command line:
  `DIR/toulbar2 -time=TIMELIMIT -seed=RANDOMSEED -v=-1 BENCHNAME -vns -O=-3 -E`

Acknowledgements

References

[1] D Allouche, S de Givry, G Katsirelos, T Schiex, and M Zytnicki. Anytime Hybrid Best-First Search with Tree Decomposition for Weighted CSP. In *Proc. of CP-15*, pages 12–28, Cork, Ireland, 2015.

[2] David Allouche, Christian Bessière, Patrice Boizumault, Simon de Givry, Patricia Gutierrez, Jimmy H.M. Lee, Ka Lun Leung, Samir Loudni, Jean-Philippe Métivier, Thomas Schiex, and Yi Wu. Tractability-preserving transformations of global cost functions. *Artificial Intelligence*, 238:166–189, 2016.

[3] Abdelkader Beldjilali, Pierre Montalbano, David Allouche, George Katsirelos, and Simon de Givry. Parallel hybrid best-first search. In *Proc. of CP-22*, Haifa, Israel, 2022.

[4] F Boussemart, F Hemery, C Lecoutre, and L Sais. Boosting systematic search by weighting constraints. In *ECAI*, volume 16, page 146, 2004.

[5] M. Cooper, S. de Givry, M. Sanchez, T. Schiex, M. Zytnicki, and T. Werner. Soft arc consistency revisited. *Artificial Intelligence*, 174(7–8):449–478, 2010.

[6] S de Givry, S Prestwich, and B O'Sullivan. Dead-End Elimination for Weighted CSP. In *Proc. of CP-13*, pages 263–272, Uppsala, Sweden, 2013.

[7] S. de Givry, M. Zytnicki, F. Heras, and J. Larrosa. Existential arc consistency: Getting closer to full arc consistency in weighted csps. In *Proc. of IJCAI-05*, pages 84–89, Edinburgh, Scotland, 2005.

[8] E Demirovic, G Chu, and P J. Stuckey. Solution-based phase saving for CP: A value-selection heuristic to simulate local search behavior in complete solvers. In *Proc. of CP-18*, pages 99–108, Lille, France, 2018.

[9] A Favier, S de Givry, A Legarra, and T Schiex. Pairwise decomposition for combinatorial optimization in graphical models. In *Proc. of IJCAI-11*, Barcelona, Spain, 2011.

[10] D Koller and N Friedman. *Probabilistic graphical models: principles and techniques*. The MIT Press, 2009.

[11] J. Larrosa. Boosting search with variable elimination. In *Principles and Practice of Constraint Programming - CP 2000*, volume 1894 of *LNCS*, pages 291–305, Singapore, September 2000.

[12] C. Lecoutre, L Saïs, S. Tabary, and V. Vidal. Reasoning from last conflict(s) in constraint programming. *Artificial Intelligence*, 173:1592,1614, 2009.

[13] Pierre Montalbano, Simon de Givry, and George Katsirelos. Multiple-choice knapsack constraint in graphical models. In *Proc. of CP-AI-OR'2022*, Los Angeles, CA, 2022.

[14] B. Neveu and G. Trombettoni. INCOP: An Open Library for INcomplete Combinatorial OPtimization. In *Proc. of CP-03*, pages 909–913, Cork, Ireland, 2003.

[15] Abdelkader Ouali, David Allouche, Simon de Givry, Samir Loudni, Yahia Lebbah, Lakhdar Loukil, and Patrice Boizumault. Variable neighborhood search for graphical model energy minimization. *Artificial Intelligence*, 278(103194):22p., 2020.

[16] Manon Ruffini, Jelena Vucinic, Simon de Givry, George Katsirelos, Sophie Barbe, and Thomas Schiex. Guaranteed diversity and optimality in cost function network based computational protein design methods. *Algorithms*, 14(6):168, 2021.

Chapter 4

Results

In this chapter, rankings for the various tracks of the XCSP^3 Competition 2022 are given. Importantly, remember that you can find all detailed results, including all traces of solvers at http://www.cril.univ-artois.fr/XCSP22/.

4.1 Context

Remember that the tracks of the competition are given by Table 4.1 and Table 4.2.

Problem	Goal	Exploration	Timeout
CSP	one solution	sequential	40 minutes
COP	best solution	sequential	40 minutes
fast COP	best solution	sequential	4 minutes
// COP	best solution	parallel	40 minutes

Table 4.1: Standard Tracks.

Problem	Goal	Exploration	Timeout
MiniCSP	one solution	sequential	40 minutes
MiniCOP	best solution	sequential	40 minutes

Table 4.2: Mini-Solver Tracks.

Also, note that:

- the cluster was provided by CRIL and is composed of nodes with two quad-cores (Intel Xeon CPU E5-2637 v4 @ 3.50GHz, each equipped with 64 GiB RAM).

- Hyperthreading was disabled.

- Each solver was allocated a CPU and 64 GiB of RAM, independently from the tracks.

- Timeouts were set accordingly to the tracks through the tool `runsolver`:

  – sequential solvers in the fast COP track were allocated 4 min of CPU time and
    12 min of Wall Clock time,

  – other sequential solvers were allocated 40 min of CPU time and 120 min of Wall
    Clock time,

  – parallel solvers were allocated 160 min of CPU time and 120 min of Wall Clock time.

- The selection of instances for the Standard tracks was composed of 200 CSP instances
  and 250 COP instances.

- The selection of instances for the Mini-solver tracks was composed of 150 CSP instances
  and 158 COP instances.

About Scoring.   The number of points won by a solver S is decided as follows:

- for CSP, this is the number of times S is able to solve an instance, i.e., to decide the
  satisfiability of an instance (either exhibiting a solution, or indicating that the instance
  is unsatisfiable)

- for COP, this is, roughly speaking, the number of times S gives the best known result,
  compared to its competitors. More specifically, for each instance I:

  – if I is unsatisfiable, 1 point is won by S if S indicates that the instance I is unsat-
    isfiable, 0 otherwise,

  – if S provides a solution whose bound is less good than another one (found by another
    competing solver), 0 point is won by S,

  – if S provides an optimal solution, while indicating that it is indeed the optimality, 1
    point is won by S,

  – if S provides (a solution with) the best found bound among all competitors, this
    being possibly shared by some other solver(s), while indicating no information about
    optimality: 1 point is won by S if no other solver proved that this bound was optimal,
    0.5 otherwise.

Off-competition Solvers.   Some solvers were run while not officially entering the competi-
tion: we call them *off-competition* solvers. ACE is one of them because its author (C. Lecoutre)
conducted the selection of instances, which is a very strong bias (ACE_ABD was also consid-
ered as being off-competition of the main tracks to avoid any suspected collusion). Also, when
two variants (by the same competing team) of a same solver compete in a same track, only
the best one is ranked (and the second one considered as being off-competition). This is why
Fun-sCOP-glue was considered as off-competition in the CSP track.

4.2   Rankings

CSP

  1. Picat

  2. Fun-sCOP

  3. Choco

COP

1. Picat

2. CoSoCo

3. Mistral

Fast COP

1. CoSoCo

2. Picat

3. Mistral

// COP

1. Choco

2. toulbar2

Mini CSP

1. Exchequer

2. miniBTD

3. Sat4j-CSP-PB

Mini COP

1. Mistral

2. toulbar2

3. miniRBO

Bibliography

[1] R. Barták, N.-F. Zhou, R. Stern, E. Boyarski, and P. Surynek. Modeling and solving the multi-agent pathfinding problem in Picat. In *Proceedings of ICTAI'17*, pages 959–966, 2017.

[2] E. Bensana, M. Lemaitre, and G. Verfaillie. Earth observation satellite management. *Constraints*, 4(3):293–299, 1999.

[3] E. Bourreau and T. Benoist. Fast global filtering for eternity II. *Constraint Programming Letters*, 3:36–49, 2008.

[4] F. Boussemart, C. Lecoutre, G. Audemard, and C. Piette. *XCSP3: An Integrated Format for Benchmarking Combinatorial Constrained Problems*. Technical Report. v3.0.7 on CoRR, arXiv:1611.03398, 2016–2021. 242 pages.

[5] F. Boussemart, C. Lecoutre, G. Audemard, and C. Piette. *XCSP3-core: A Format for Representing Constraint Satisfaction/Optimization Problems*. Technical Report. v3.0.7 on CoRR, arXiv:2009.00514, 2020–2021. 106 pages.

[6] B. Cabon, S. de Givry, L. Lobjois, T. Schiex, and J.P. Warners. Radio Link Frequency Assignment. *Constraints*, 4(1):79–89, 1999.

[7] T. Guns, S. Nijssen, and L. De Raedt. Itemset mining: A constraint programming perspective. *Artificial Intelligence*, 175(12-13):1951–1983, 2011.

[8] C. Lecoutre and N. Szczepanski. *PyCSP3: Modeling Combinatorial Constrained Problems in Python*. Technical Report. v2.0 on CoRR, arXiv:2009.00326, 2020–2021. 144 pages.

[9] L. Libralesso, F. Delobel, P. Lafourcade, and C. Solnon. Automatic generation of declarative models for differential cryptanalysis. In *Proceedings of CP'21*, pages 40:1–40:18, 2021.

[10] J.-P. Métivier, P. Boizumault, and S. Loudni. Solving nurse rostering problems using soft global constraints. In *Proceedings of CP'09*, pages 73–87, 2009.

[11] G. Pesant, C.-G. Quimper, and A. Zanarini. Counting-based search: Branching heuristics for constraint satisfaction problems. *Journal of Artificial Intelligence Research*, 43:173–210, 2012.