Constraint-based Modeling and Algorithms for Decision-making — INF555

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Part I

Decision problems, optimization, complexity and modelling

Decision Problems

- Finite input
 - Words
 - Rational numbers
 - Images
 - Sounds
 - Programs
 - <u>ا ا</u>



• yes/no output

- providing an arbitrary solution is optional
- providing all solutions is another class: enumeration problem

Examples

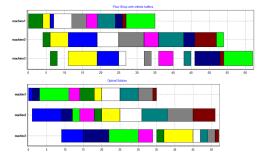
We will see during the class:

- Can we place N queens on a chessboard with no attack?
- Do we have enough rooms for the lectures? **assignment problem**
- Can we land in the next 20 mn a given set of flights arriving in Orly? **scheduling**
- Can we find a sequence of actions to achieve a given goal? **planning**

• ...

Other classical examples include **routing** (traveling salesman), **personnel staffing**, etc.

Optimization Problems



• Input: finite data same as before

• output: optimal cost

- single number, or
- vector of numbers for *multi-objective* optimization
- providing an arbitrary optimal solution is optional
- providing all solutions is another class: enumeration problem

- How many rooms are necessary to give the lectures?
- What is the time required to land a given set of flights arriving in Orly?
- How many flights from a given set of flights can land in the next 20min?

…

An optimization problem admits one **associated decision problem**: Is there a solution of given cost *k*?

Several optimization problems can be associated to a decision problem (choice of the inputs treated as objective function)

Mono-objective vs. Multi-objective optimization

The cost is always finite data

An *unique* rational number for mono-objective optimization.

- single optimization criterion
- possibly a robustness criterion w.r.t. perturbations
- the aggregation of multiple criteria representing a **trade-off**

Mono-objective vs. Multi-objective optimization

Some finite vector of rational numbers for multi-objective optimization

$$(f,g) < (f',g') \triangleq (f < f' \land g \leq g') \lor (f \leq f' \land g < g')$$

The optimal cost vectors max(f,g) not unique: **Pareto frontier** Computational Time-complexity Classes

An algorithm belongs to time-complexity class C if it requires **at most** C(n) elementary operations on a random access machine for an **input of size** n

A problem belongs to class *C* if there exists an algorithm in *C* to solve it

 $g(n) \in O(f(n)) \triangleq \exists k, n_0 \quad \forall n > n_0 \quad g(n) \le k \cdot f(n)$

Examples

O(1)constant time, independent of the input O(n)linear time $O(n \log n)$ best **possible** complexity for sorting $O(n^2)$ quadratic time **polynomial time**, i.e. $O(n^k)$ for some k P / PTIME $O(2^{n})$ exponential time, i.e. $O(k^n)$ for some k FXPTIMF $O(2^{2^n})$ Non-elem not bounded by a finite tower of exponentials $O(2^{2^{2^{\cdots}}})$

Non-deterministic Time-complexity

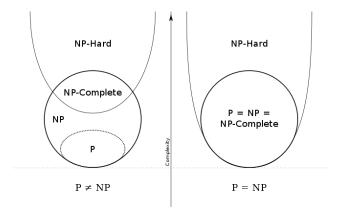
NP: class of languages recognized in polynomial time by a **non-deterministic** Turing machine ≡ decision problems with proofs **verifiable in PTIME**

E.g., disjunctive scheduling, timetabling, planning, ...

NP-complete: class of problems **in NP** that can encode in polynomial time **any other NP problem**, i.e., the *hardest* NP problems

E.g., boolean satisfiability, graph coloring, disjunctive scheduling, ...

NP-hard: class of problems *harder than NP*, i.e., they can encode in polynomial time any NP problem



E.g., *optimization problems* with NP-complete associated decision problem

Space-complexity Classes

An algorithm belongs to a space complexity class C if it requires **at most** C memory locations PSPACE: polynomial space, i.e., $O(n^k)$ for some k

Why do we have NP⊂PSPACE?

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Why do we have NP⊂PSPACE?

Iterative deepening!

Bounded backtracking with increasing depth dAt depth d, d binary choices to remember, O(d) space Computation of result at $O(n^k)$ depth: $O(n^k)$ space Time Complexity ≠ Size of the Search Space

Size of the solution domain: **bad upper bound for time-complexity**

Sorting n integers!n $O(n \log n)$ Placing n queens n^n or !n

Time Complexity ≠ Size of the Search Space

Size of the solution domain: **bad upper bound for time-complexity**

Sorting n integers!n $O(n \log n)$ Placing n queens n^n or !nO(1) analytic solutionFermat Theorem ∞ O(1) $\forall n \exists ?abc a^n + b^n = c^n$ \forall

Time Complexity ≠ Size of the Search Space

Size of the solution domain: **bad upper bound for time-complexity**

Sorting <i>n</i> integers	!n	$O(n \log n)$
Placing <i>n</i> queens	<i>nⁿ</i> or ! <i>n</i>	O(1) analytic solution
Fermat Theorem	∞	<i>O</i> (1)
$\forall n \exists ?abc \ a^n + b^n = c^n$		<i>n</i> >? 2 (A. Wiles 1994)

Separation results (like $P \neq NP$) are hard: need to quantify on all mathematical properties Theoretical Complexity only Bounds the Practical Complexity

Worst-case complexity ≠ **average** time-complexity (random inputs)

Can we solve NP-hard problems on very large instances?

Theoretical Complexity only Bounds the Practical Complexity

Worst-case complexity ≠ **average** time-complexity (random inputs)

Can we solve NP-hard problems on very large instances? **Yes!** But not on all (even small) instances (probably exponential)

Practical instances may happen to be easy

- Polynomial class
- Phase transition

- *Pathological examples* (exponential algorithm with polynomial empirical complexity)

Constraint Satisfaction Problems

Input: Finite set of Variables Corresponding Domains of values Finite set of Constraints Optional objective function

$$x_1, \dots, x_n$$

$$D_1, \dots, D_n$$

$$c_1, \dots, c_k$$

$$f(x_1, \dots, x_n) \in \mathbb{R}$$

Output:

Decision

Optimization

Solutions

$$\exists ?(x_1, \dots, x_n) \in D_1 \times \dots \times D_n$$

s.t. $c_1 \wedge \dots \wedge c_k$
$$\min_{c_1 \wedge \dots \wedge c_k} f(x_1, \dots, x_n)$$

$$\operatorname{argmin}_{c_1 \wedge \dots \wedge c_k} f(x_1, \dots, x_n)$$

N Queens on an $N\times N$ chessboard with no attack

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Variables:

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Variables: x_1, \dots, x_N (columns)

N Queens on an $N\times N$ chessboard with no attack

Variables: x_1, \dots, x_N (columns) Domains:

N Queens on an $N\times N$ chessboard with no attack

Variables: $x_1, ..., x_N$ (columns) Domains: $D_i = \{1, ..., N\}$ (lines)

N Queens on an $N\times N$ chessboard with no attack

```
Variables: x_1, ..., x_N (columns)
Domains: D_i = \{1, ..., N\} (lines)
Constraints:
```

N Queens on an $N\times N$ chessboard with no attack

Variables: $x_1, ..., x_N$ (columns) Domains: $D_i = \{1, ..., N\}$ (lines) Constraints: "not same line"

N Queens on an $N\times N$ chessboard with no attack

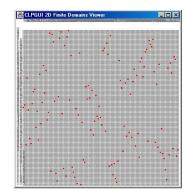
Variables: $x_1, ..., x_N$ (columns) Domains: $D_i = \{1, ..., N\}$ (lines) Constraints: "not same line" $\forall i < j x_i \neq x_j$

N Queens on an $N\times N$ chessboard with no attack

Variables: $x_1, ..., x_N$ (columns) Domains: $D_i = \{1, ..., N\}$ (lines) Constraints: "not same line" $\forall i < j x_i \neq x_j$ "not same diagonal" $\forall i < j x_i \neq x_j + i - j \land x_i \neq x_j - i + j$

N Queens on an $N \times N$ chessboard with no attack

Variables: $x_1, ..., x_N$ (columns) Domains: $D_i = \{1, ..., N\}$ (lines) Constraints: "not same line" $\forall i < j x_i \neq x_j$ "not same diagonal" $\forall i < j x_i \neq x_j + i - j \land x_i \neq x_j - i + j$



MiniZinc Constraint Modelling Language

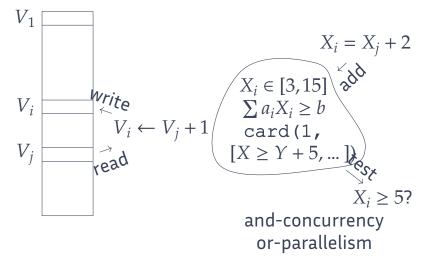
```
int: n;
array[1..n] of var 1..n: queens;
constraint forall (i, j in 1..n where i < j) (
    queens[i] != queens[j] /\
    queens[i] != queens[j] + j - i /\
    queens[i] != queens[j] + i - j
);
```

solve satisfy;

(Declarative) Programming as Modeling

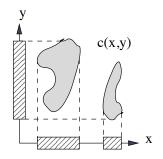
- 1940 Machine language
- **1954** Fortran: arithmetic expressions and control flow
- **1959** Lisp: functions over lists (Church's λ -calculus)
- 1960 Algol: algorithms
- 1970 C: for whole operating system
- 1972 Prolog: first-order logic
- 1975 Smalltalk: objects
- 1978 ML: typed functions
- 1984 Constraint Logic Programming
- 1990 Constraint programming libraries for C++
- 1991 Python
- 1996 Java: object-oriented threaded programming
- 2008 Zinc: solver-independent constraint language

Von Neumann vs. Constraint machine memory of values memory of constraints programming variables mathematical variables



Constraints are Domain Filtering Agents

for each constraint c_i for each variable x_j in c_i compute the projection P_{ij} of the solutions on x_j over-approximate if necessary $D_j \leftarrow D_j \cap P_{ij}$



communication through shared variables in \wedge

Or-branches: no communication, easy to parallelize And-concurrency: lots of comm., difficult to parallelize

Part II

MiniZinc, Jupyter and friends...

MiniZinc

Most of the course will use MiniZinc as programming/modelling language



MiniZinc ^{compile} FlatZinc high-level low-level

MiniZinc syntax

A MiniZinc program may contain parameters

int: i = 1; int j; j = 2;

Fixed value (named constants), of type int, float, bool or string

May be given in a separate *data* file (.dzn)

MiniZinc syntax

A MiniZinc program may contain decision variables

```
var int: u;
var 1..10: v;
```

Only int or float, given with an optional *domain* Parameters and variables can appear in **constraints** (using the usual arithmetic and Boolean relation operators)

constraint u = 18 * v + 42; constraint alldifferent([x, y, z]);

Additional MiniZinc Syntax

It is possible to define sets and arrays of objects

set of int: STUDENT = 0..n; % m[i] is the mark of student number i array[STUDENT] of var int: m;

Iterators over those structures are given

```
constraint exists(s in STUDENT)
 (m[s] = 20);
constraint forall(s in STUDENT)
 (m[s] <= 20);</pre>
```

Final Bits

At least one **solve** statement must appear in a MiniZinc model

```
solve satisfy;
solve maximize u+3*v;
solve minimize sum(i in STUDENT)(m[i]);
```

output takes a list of strings and displays them

Many other things (function or predicate definition, enums, comprehensions, etc.) \longrightarrow in TDs



Work will be done using Jupyter Notebooks

Assuming some basic knowledge of Python

Otherwise see: https://docs.python.org/3/ tutorial/introduction.html

Code editing will use a version of **VS Code** embedded in a browser. (vim and emacs are also provided)



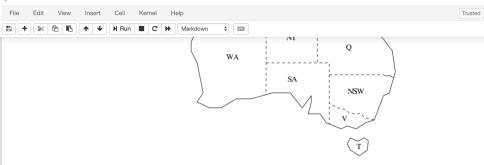
Files

Running Clusters

Select items to perform actions on them.

C code-server2.preview.11-vsc1.37.0-linux-x86_64		
□ □ Vimcat		
C 🖉 Australia.ipynb		
🕞 🛢 TD.ipynb		
□ □ aust.dzn		
□ □ aust.mzn		
□ □ aust.png		
□ □ aust_enum.mzn		
□ □ aust_opt.mzn		
□ □ aust_param.dzn		

Jupyter TD (unsaved changes)



A MiniZinc model is composed of

- variable declarations
- · constraints
- · a solve statement

Let us first have a look at a partial model (file aust.mzn) for coloring Australia such that two neighbor states have a different color.

As you see, the basic editor is not that great... You can instead open a terminal (from the launcher) and launch vi/emacs if you like.

We will have colorized output in the notebook through a shell command

In [1]: !vimcat.sh aust.mzn

```
% Colouring Australia using nc colours
int: nc;
var l..nc: wa; var l..nc: nt; var l..nc: sa; var l..nc: q;
var l..nc: nsw; var l..nc: v; var l..nc: t;
constraint wa != nt;
```

File Edit Selection View Go Debug Terminal Help

ne	Edit Selection view Go Debug Terminal	
Ð	EXPLORER	
	imes OPEN EDITORS	🕏 inf555.py >
Q	× 🌳 inf555.py	
\sim	-> JOVYAN [CODE-SERVER] 13 1日 ひ 自	
	> .cache	
مړ	> .conda	
	> .config	5 """ 6 <u>import</u> matplotlib.pyplot as plt
逐		
×.	> .empty	8 import numpy as np
	> .ipynb_checkpoints	
₽	> .ipython	10 from pymzn import (
	> .jupyter	11 Solver,
<u>Ż</u>	> .local	12 cbc,
	> .pylint.d	13 chuffed,
	> .vim	14 rebase_array,
	> code-server2.preview.11-vsc1.37.0-linux-x	15) 16 from pymzn import minizinc as minizn
	> Minizinc	16 from pymzn import minizinc as minizn 17
	> minizinc-mode	
		<pre>19 def minizinc(mzn, *dzn_files, include=".", **kwargs):</pre>
	> Picat	
	> vim-minizinc	21 return minizn(mzn, *dzn_files, include=include, **kwargs)
	> Vimcat	
	> work	
	.bash_logout	24 class PicatSatSolver(Solver): 25 """Solver instance for PicatSat."""
	.bashrc	
	≣ .emacs	27 def init (self):
	.profile	28 """Nothing special here."""
	≣ .viminfo	<pre>29 super()init(solverid='picat')</pre>
	≡ .wget-hsts	
	≡ aust_enum.mzn	<pre>31 def args(self, fzn_file, **kwargs):</pre>
		32 """Arguments for the CLI call."""
	≣ aust_opt.mzn	33 return ["picat", "fzn_picat_sat", fzn_file]



All will be run from **Docker** containers

Same environment for everyone

Do not forget to save your work! upload it to the Moodle at the end of the TD session (and later...)



Download Docker https://docs.docker.com/install/

Install Docker

9 Pull the image for the course

docker pull \
registry.gitlab.inria.fr/soliman/inf555

Windows Users

You might need Docker Toolbox (and not CE) if you are using Family Edition https://docs.docker.com/toolbox/ toolbox_install_windows/

You might need to use 192.168.99.100 instead of localhost for connecting to Jupyter

If all else fails, use VirtualBox to install an Ubuntu image and follow the instructions to install Docker there

TD1

Pull the missing files

```
docker pull \
registry.gitlab.inria.fr/soliman/inf555/td1
```

Run on **local port 8888** with the work directory of the container pointing to where you launch the command

docker run -p 8888:8888 -p 8080:8080 -v \
"\$PWD":/home/jovyan/work \
registry.gitlab.inria.fr/soliman/inf555/td1

You can now start the TD: http://localhost: 8888/notebooks/TD.ipynb