

# HUST

**ĐẠI HỌC BÁCH KHOA HÀ NỘI**

HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY

ONE LOVE. ONE FUTURE.





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# Introduction to Constraint Programming

Almost slides from the course CP given by  
Pascal Van Hentenryck & Yves Deville

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- ❑ A first challenge
- ❑ Constraint Satisfaction Problem
- ❑ Constraint Programming
- ❑ Examples with Or-Tools

# Sudoku

- Fill the empty cells with numbers in {1,..,9}
- Constraint** : each number only appears **once** in each
  - Row
  - Column
  - Region

easy

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

hard

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



# Sudoku

easy

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

hard

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

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

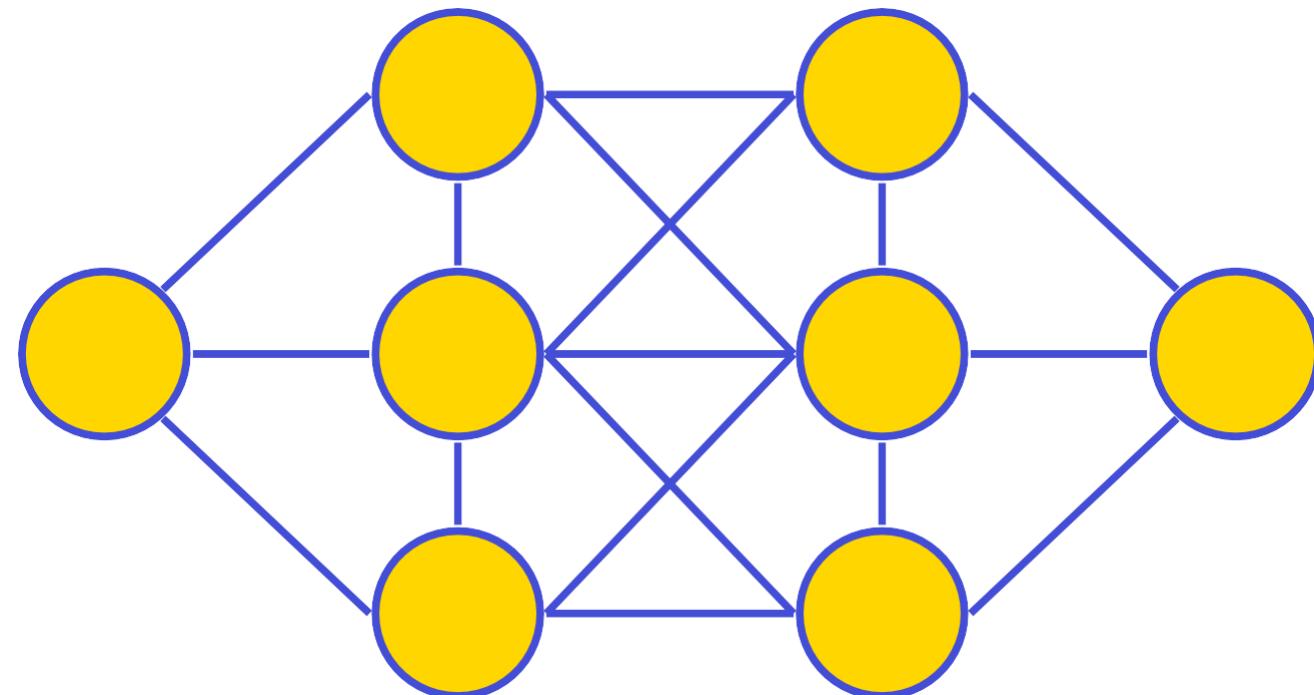
5	9	6	1	4	7	3	8	2
3	2	8	5	9	6	4	1	7
4	1	7	8	3	2	5	9	6
2	7	1	3	8	9	6	5	4
6	4	5	2	7	1	9	3	8
8	3	9	6	5	4	2	7	1
9	6	2	7	1	3	8	4	5
1	8	4	9	6	5	7	2	3
7	5	3	4	2	8	1	6	9

- Sudoku is a (very) simple example of Constraint Satisfaction Problem (CSP)
  - A set of **variables**, defined over **domains**
  - A set of **constraints** over the variables
- What is a solution?
  - A **solution** is an **assignment** of values to the variables
  - does not violate any constraint

# A challenge from T. Walsh

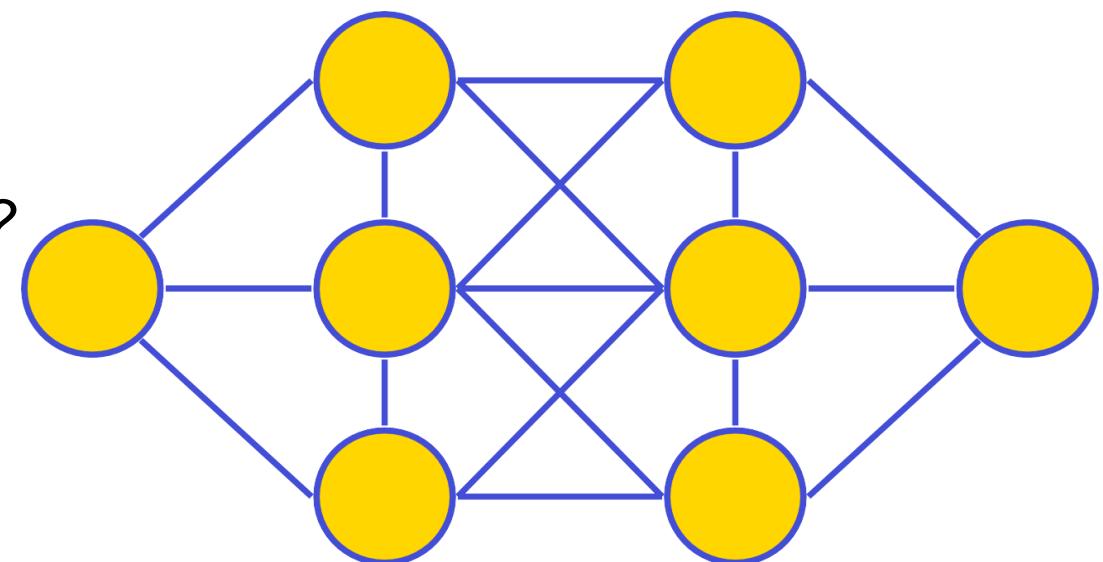
- Place numbers 1 through 8 on nodes
  - Each number appears exactly once
  - No connected nodes have consecutive number

How long  
will you take ?



- This is an example of a **Constraint Satisfaction Problem** (CSP)
  - A set of variables defined over domains
  - A set of constraints over the variables
- It can be solved by **Constraint Programming**

*How did you solved this problem manually ?  
Which techniques did you used ?*



- ❑ A first challenge
- ❑ Constraint Satisfaction Problem
- ❑ Constraint Programming
- ❑ Examples with Or-Tools

# Constraint Optimization Problem

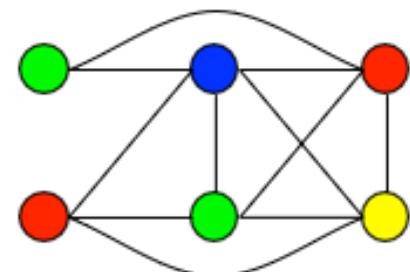
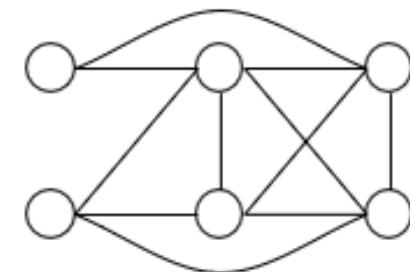
- Constraint Satisfaction Problem (CSP)
  - A set of **variables**, defined over finite **domains**
  - A set of **constraints** over the variables
- Solution
  - A **solution** is a **assignment** of values to the variables
  - No violation of constraint
- Constraint Optimization Problem (COP)
  - Add an **objective** function
  - Find a solution maximizing the objective function

Many CSP / COP are complex and challenging (NP-hard)



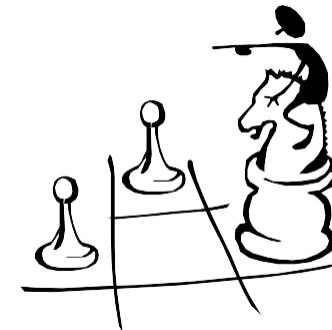
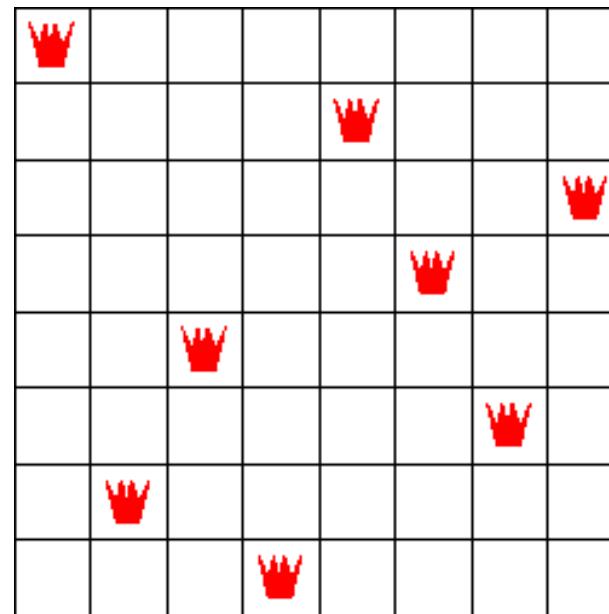
# A simple example

- **CSP** : Graph Coloring with 4 colors
  - Graph  $G=(V,E)$
  - Decision variables
    - $\text{color}[v] \quad v \in V$
  - Domain of variables : {red,blue,green,yellow}
  - Constraints
    - $\forall (v,w) \in E : \text{color}[v] \neq \text{color}[w]$
- **COP** : minimize the used colors



# Example : N-queens

- How to place 8 queens on a 8x8 board such that they do not attack each other
- A solution



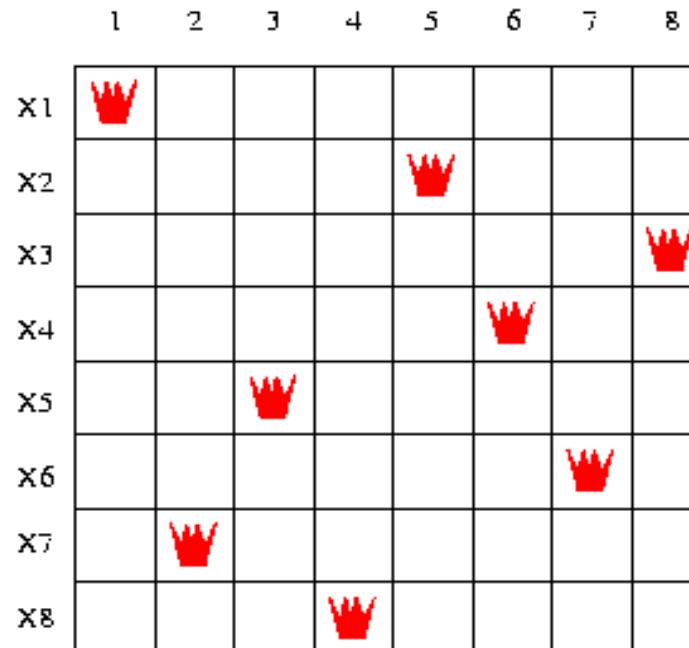
# N-queens as a CSP

- **Variables**

- $X_i$  : position (column) of the queen on row  $i$  ( $1 \leq i \leq 8$ )

- **Domains**

- Domain of  $X_i$  :
  - $\{1,2,3,4,5,6,7,8\}$



# N-queens as a CSP

- **Constraints**

- Two queens cannot be on the same column

- $X_i \neq X_j$

- Two queens cannot be on the same diagonal

- $X_i - X_j \neq i - j$     $X_i - X_j \neq j - i$

- **8-queens**

- 8 variables

- 84 constraints

$X_1 \neq X_2, X_1 \neq X_3, X_1 \neq X_4, X_1 \neq X_5, X_2 \neq X_3, X_2 \neq X_4, X_2 \neq X_5, X_3 \neq X_4, X_3 \neq X_5, X_4 \neq X_5, \dots$

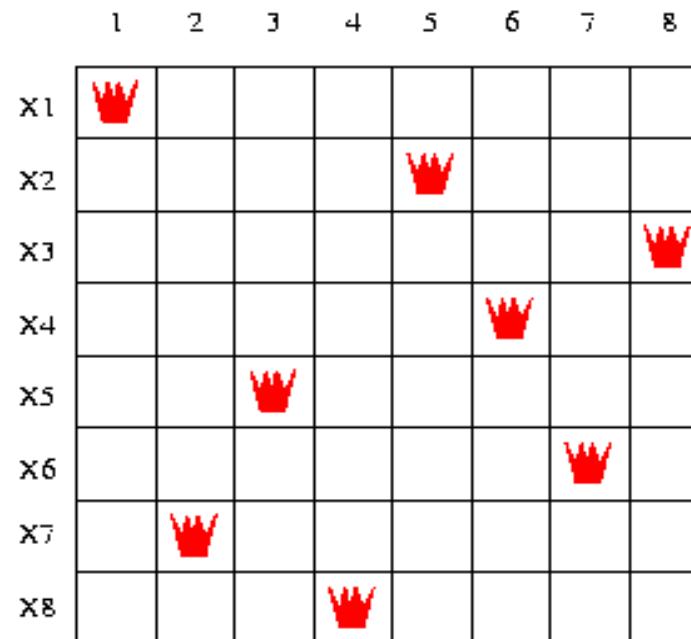
$X_1 - X_2 \neq -1, X_1 - X_2 \neq 1, X_1 - X_3 \neq -2, X_1 - X_3 \neq 2, X_1 - X_4 \neq -3, X_1 - X_4 \neq 3, X_1 - X_5 \neq -4, X_1 - X_5 \neq 4, X_2 - X_3 \neq -1, X_2 - X_3 \neq 1, X_2 - X_4 \neq -2, X_2 - X_4 \neq 2, X_2 - X_5 \neq -3, X_2 - X_5 \neq 3, X_3 - X_4 \neq -1, X_3 - X_4 \neq 1, X_2 - X_5 \neq -2, X_2 - X_5 \neq 2, X_3 - X_5 \neq -2, X_3 - X_5 \neq 2, X_4 - X_5 \neq -1, X_4 - X_5 \neq 1, \dots$



# N-queens as a CSP

- $X_i$  : position of the queen on row i

- $X_1 = 1$
- $X_2 = 5$
- $X_3 = 8$
- $X_4 = 6$
- $X_5 = 3$
- $X_6 = 7$
- $X_7 = 2$
- $X_8 = 4$



# Constraints

- Constraints as basic computational elements
  - $2X + 3Y \leq 17$        $X^2 - Y^3 = 17$
- Constraints appear naturally in :
  - artificial intelligence
  - operational research
  - combinatorial optimization
  - graphics, visualisation
  - concurrency
  - databases
  - hardware design, verification
  - ...



# Who does optimization ?

- Microsoft (1st largest software company)
- SAP (2nd largest software company)
- Oracle (3rd largest software company)
  - Supply chain management
- IBM (of course)
- Siebel, PeopleSoft
  - Personal management
- UPS
  - Dispatching
- Google, IBM, Carmen systems, Fair Isaac



- Computational Complexity
  - NP-Hard or worse (at least **exponential**)
  - No reasonable approximation
- *Yet, it is important to solve them*
- The best specific algorithms
  - tough to design and implement
  - experimental



# Solving Paradigms

- **Mathematical Programming** : *IP, MIP, column generation, SDP, ...*
- **Dynamic Programming**
- **Local Search** : tabu search, simulated annealing, genetic algorithms, evolutionary algorithms...
- Greedy algorithms, Ant Colony Optimization, greedy randomized, ...
- **Constraint Programming**
- ...



# Solving Paradigms

Paradigms can usually be classified according to two criteria

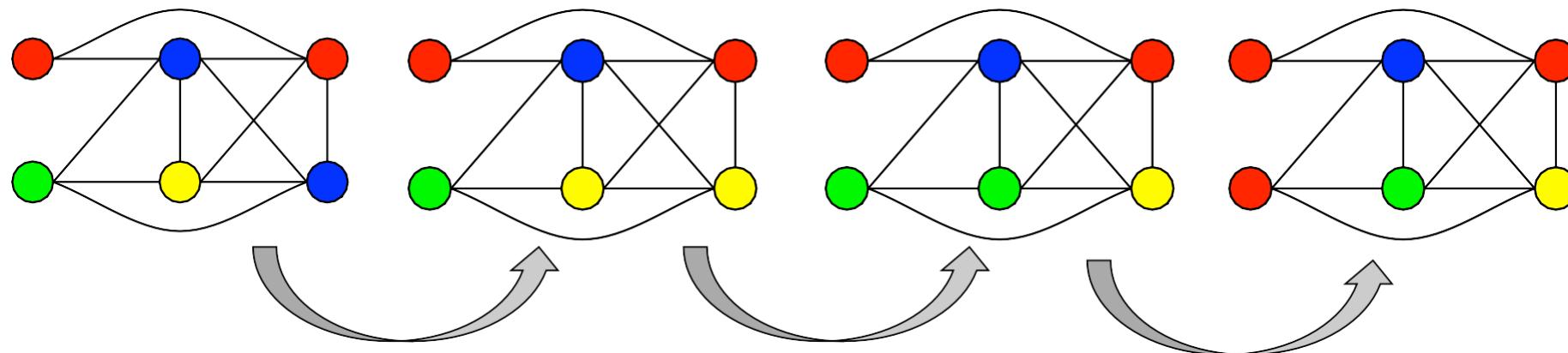
- **Perturbative** vs **constructive**
- **Systematic** vs **incomplete**



# Perturbative vs Constructive

## ■ Perturbative approaches

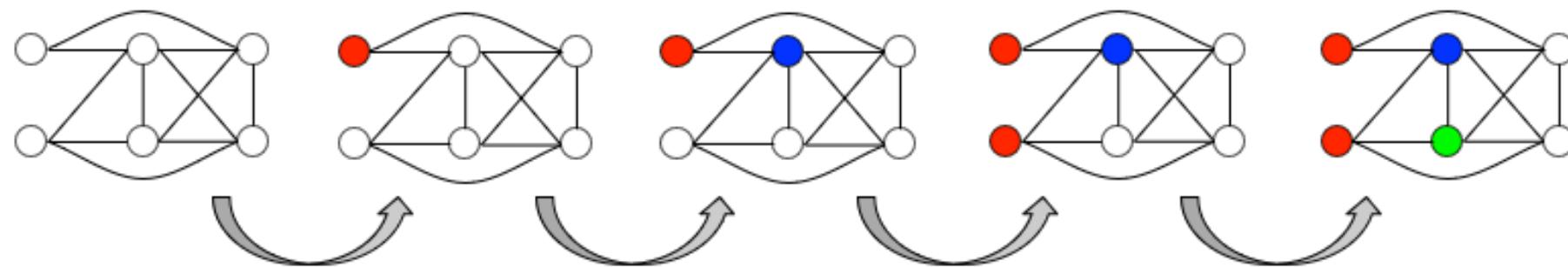
- A candidate solution is a complete solution (a value is assigned to each variable)
- Generation of a new solution by modifications, perturbation of an existing one
- Search is performed on the succession of candidate solutions



# Perturbative vs Constructive

## ■ **Constructive** approaches

- A candidate solution is partial (some variables are not assigned)
- A partial candidate solution is progressively extended, constructed



- **Systematic** approaches
  - Systematic exploration of the search space
  - Completeness
    - CSP : find an *exact* solution
    - COP : find the *best* solution, (+ proof of optimality)
    - If no solution, proof of non existence
  - Computationally expensive

- **Incomplete** approaches
  - Exploration based on a neighborhood function
  - Incomplete
    - CSP: find an *approximation* of a solution
    - COP: find a *good* solution
    - No guarantee to find the (best) solution
  - Computationally less expensive

# Paradigms

	Systematic	Incomplete
Pertubative	<ul style="list-style-type: none"><li>■ Simplex</li><li>■ Systematic local search</li></ul>	<ul style="list-style-type: none"><li>■ Local search</li><li>■ Evolutionary algo.</li></ul>
Constructive	<ul style="list-style-type: none"><li>■ Dynamic Programming</li><li>■ Branch &amp; Bound</li><li>■ <b>Constraint Programming</b></li></ul>	<ul style="list-style-type: none"><li>■ Greedy</li><li>■ Ant Colony Optimizatio</li><li>■ GRASP</li></ul>



- ❑ A first challenge
- ❑ Constraint Satisfaction Problem
- ❑ **Constraint Programming**
  - What is CP ?
  - Constraints and propagation
  - Modeling
  - Searching
  - Global constraint
  - Computation domain
- Examples with Or-Tools

# Constraint programming

- A field at the intersection of
  - Artificial intelligence
  - Operational research
- A framework for solving CSP



Solution process

=

Model + Search

- The model
  - what the solutions are and their quality
- The search
  - how to find the solutions

- **Constraint Programming**
  - *Modeling with Constraints*
  - Systematic and constructive paradigm
  - Computation based on **branch & propagate**
- **Constraint-Based Local Search**
  - *Modeling with Constraints*
  - Incomplete and perturbative paradigm
  - Computation based on **neighborhood**

- Iterations of two steps

- **Propagation**

- reducing the domains of the variables
- uses constraints to detect impossible values of variables
- solve a relaxation of the problem

- **Branch** (also called **Search**)

- Decompose into subproblems
- nondeterministic choices (e.g., giving a value for a variable)
- automatic support for backtracking

# Constraint Programming

- Began in 1980s from AI world
  - Prolog III (Marseilles, France)
  - CLP(R) (Melbourne & IBM)
  - CHIP (ECRC, Germany)
- Active research area
  - Specialized conferences (CP, CP-AI-OR, ...)
  - Journal (Constraints, CP Letters)
  - Commercial products

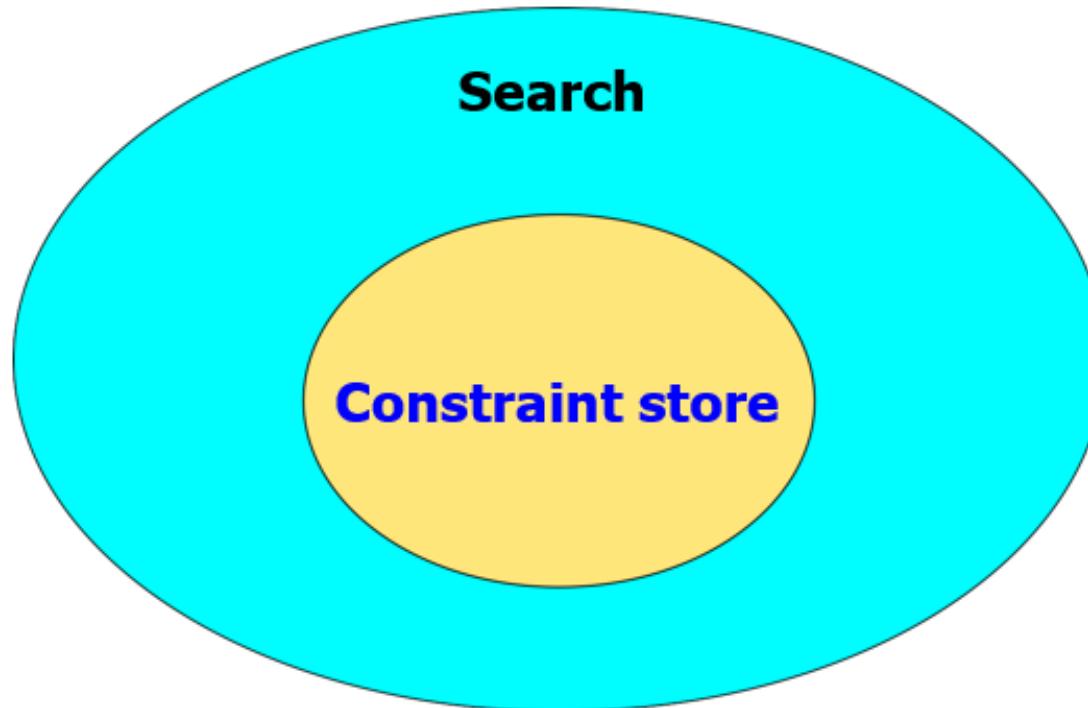


# The CP Language

- A rich constraint language
  - Arithmetic, higher-order, logical constraints
  - Global constraints for natural substructures
- Specification of a search procedure
  - Definition of search tree to explore
  - Specification of exploration strategy
- Separation of concerns
  - Constraints and search are separated



# Computational Model



Constraint propagation techniques are related to specific **computation domains**

- Finite domains
- Finite sets
- Boolean
- Interval
- Reals
- Graphs
- ...

- ❑ A first challenge
- ❑ Constraint Satisfaction Problem
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# What is a constraint ?

- Numerical inequalities and equations
- Combinatorial / global constraints
  - natural subproblems arising of many applications
  - e.g. a set of activities A cannot overlap in time
- Logical/threshold combinations of these
- ...



# Constraints

- Powerful modelling tool
  - Numerical constraints
    - $x = y + 2z$ ,  $x \neq y - 2$ ,  $x \leq y - z$ ,  $|x-y| \neq 2$ , ...
  - Symbolic Constraints
    - $\text{cost} = \sum_{i \in R} \text{price[rack}[i]\text{]}$
    - Composed constraints
      - $\sum_{1 \leq i \leq k} (x[i]=y) \leq k$  (at most k occurrences of y in x[])
      - $\text{load}[j] = \sum_{i \in Obj} (\text{bin}[i]=j).\text{w}[i]$  (load of bin j in bin packing)
  - Global constraints
    - `alldifferent( x[1..n] )`
    - `knapsack( x[1..n], weigh[1..n], cap )`
    - Grammar constraints, scheduling constraints, ...



# Propagation

## Why propagation ?

- Exhaustive search of a solution: exponential time

## Objectives of propagation

- Reduce the search space
- Find an equivalent CSP to the original one with *smaller domains* of variables

## Techniques

- Consider the constraints *locally*
- **Consistency techniques**
  - Domain Consistency : consider each possible value in the domain
  - Bound Consistency : only considers the bounds of the domains
  - Other consistencies



- Domain Consistency
  - The holy grail
- A constraint is **domain-consistent** if,
  - for every variable  $x$  and every value in the domain of  $x$ ,
  - there exist values in the domains of the other variables
  - such that the constraint is satisfied for these values

# Domain consistency

$$X \geq Y + 2$$

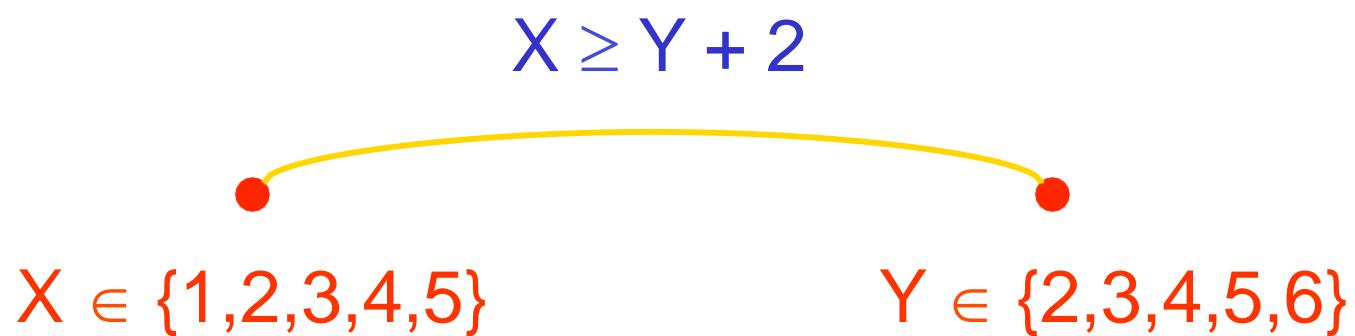
$$X \in \{1,2,3,4,5\}$$

$$Y \in \{2,3,4,5,6\}$$

- remove any values from the domain of X for which there is no value in the domain of Y that satisfies the constraint (and vice versa)



# Domain consistency



- remove any values from the domain of X for which there is no value in the domain of Y that satisfies the constraint (and vice versa)

# Domain consistency

$$X \geq Y + 2$$

$$X \in \{4,5\}$$

$$Y \in \{2,3\}$$

- This constraint is now domain consistent
- Possible objective : make *all* constraints domain consistent
- Should be done *efficiently*

*Consistency does not solve the CSP !*



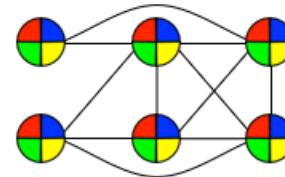
# Bound Consistency

- Achieving domain consistency can be computationally expensive
- Bound consistency is a weaker form of consistency
  - a domain is approximated by an interval  $[\min D(x), \max D(x)]$
  - only verify that the bounds of the domain are in a solution of the constraint

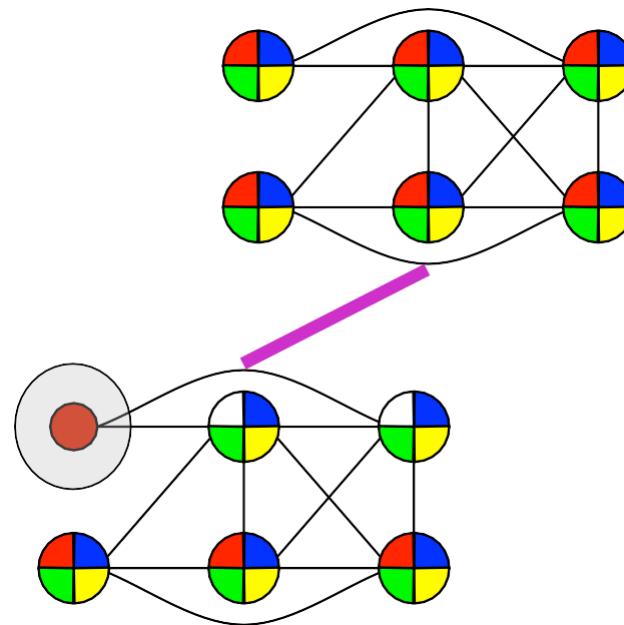


- Specialized to each constraint type
  - $x + y + z = 10$
  - $x \in \{0,1,2,3,4\}$ ,  $y \in \{1,2,4\}$ ,  $z \in \{1,2,4\}$
- Domain consistency (AC) gives
  - $x \in \{2,4\}$ ,  $y \in \{2,4\}$ ,  $z \in \{2,4\}$
  - expensive to compute ( $O(d^3)$ )
- Bound consistency (BC) gives
  - $x \in \{2,3,4\}$ ,  $y \in \{2,4\}$ ,  $z \in \{2,4\}$
  - can be computed very efficiently ( $O(1)$ )

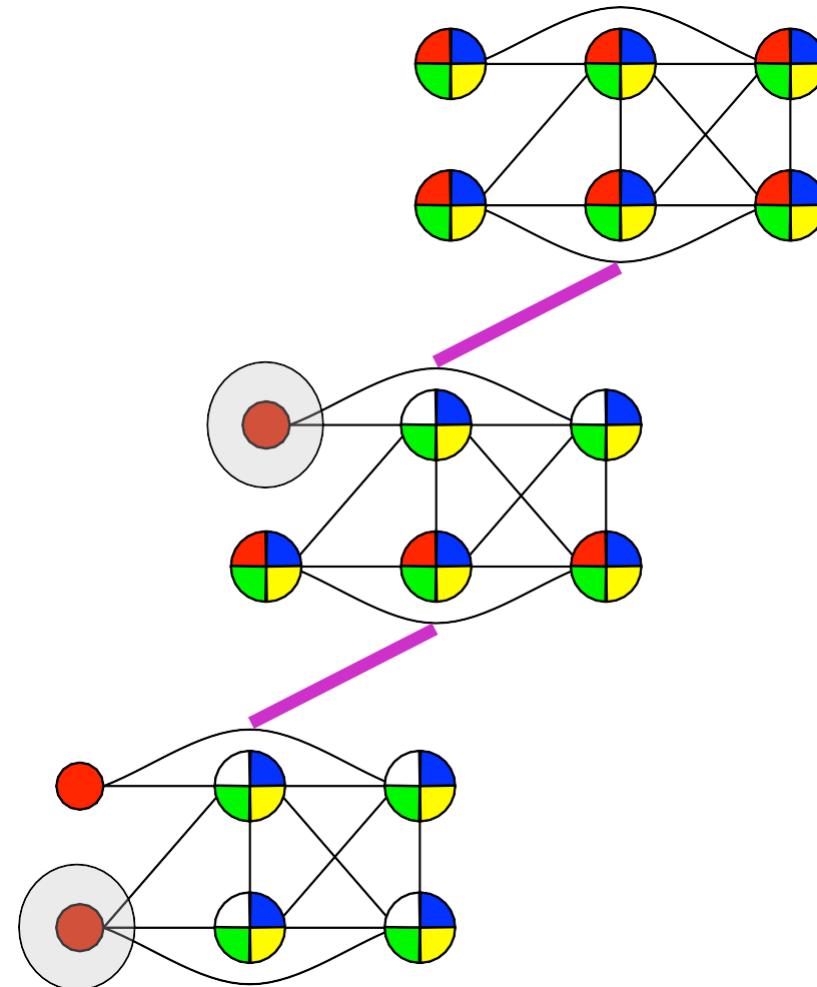
# Graph Coloring CP



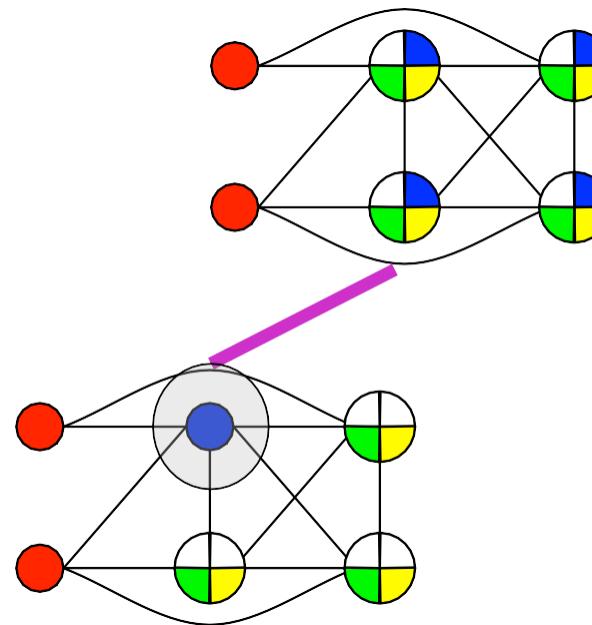
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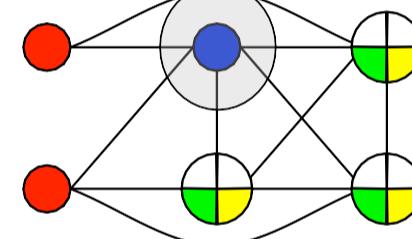
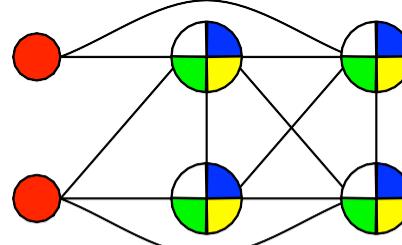
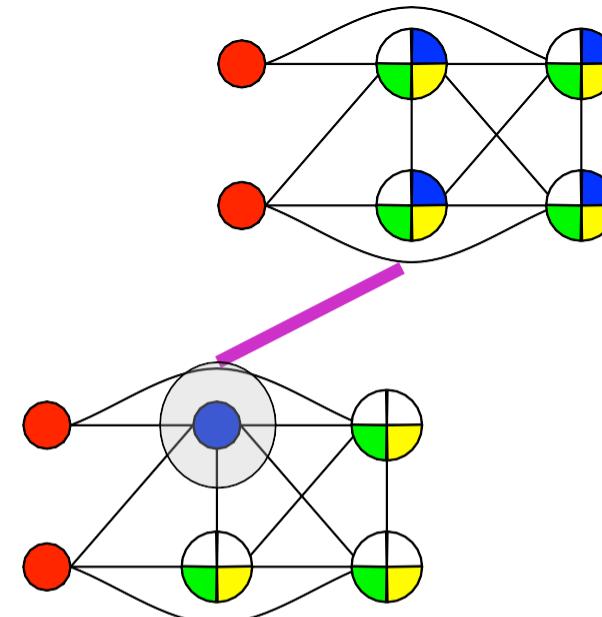
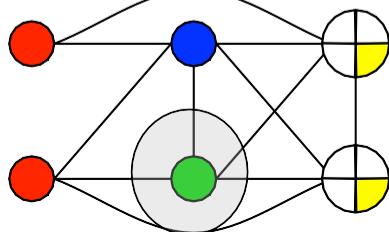
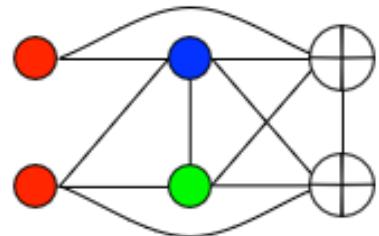
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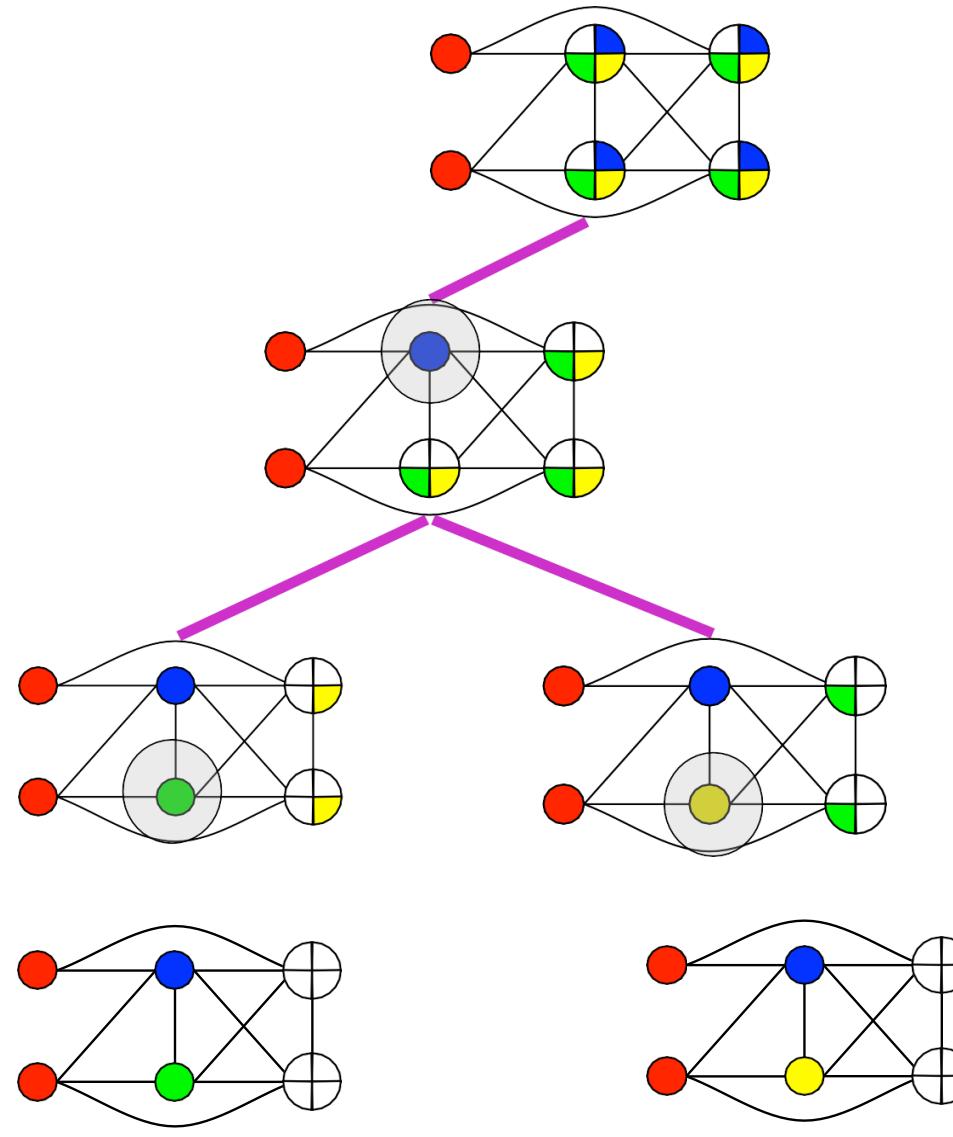
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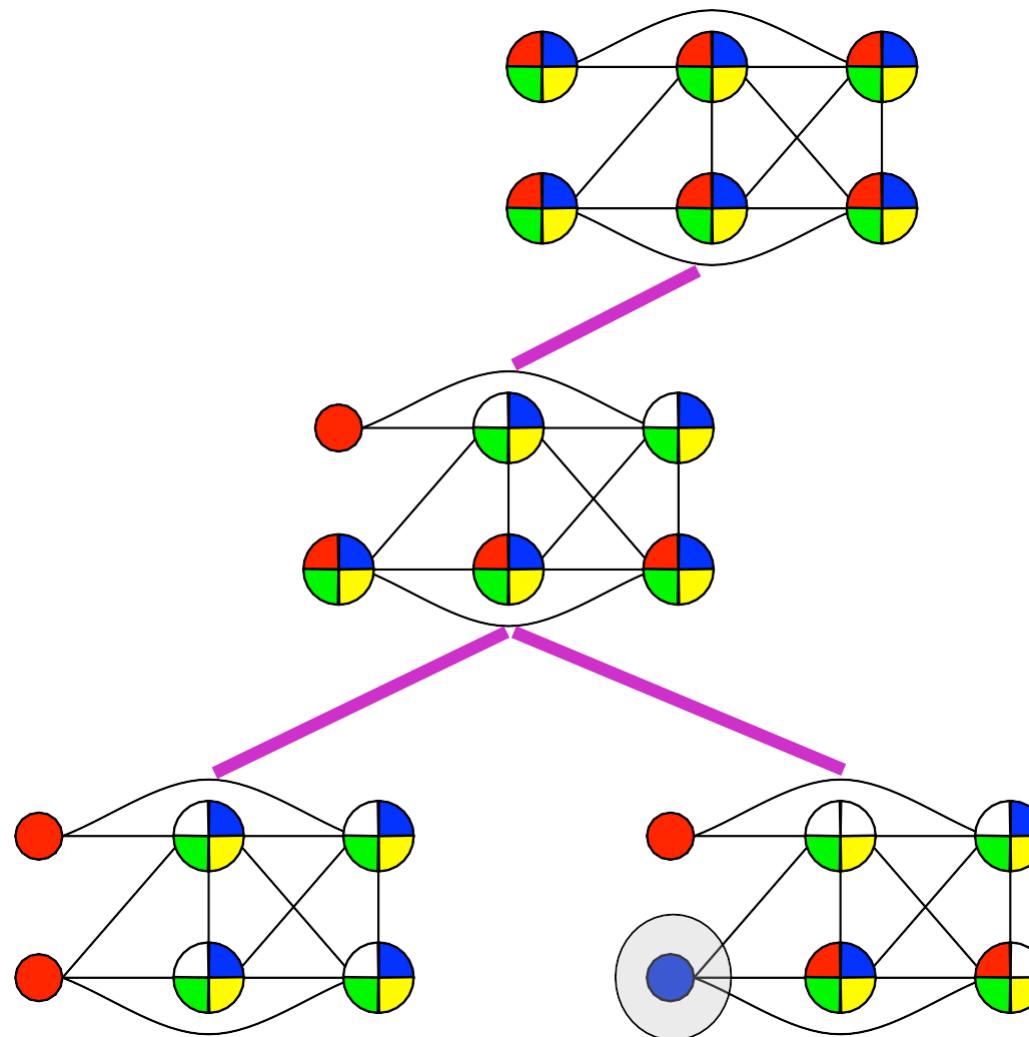
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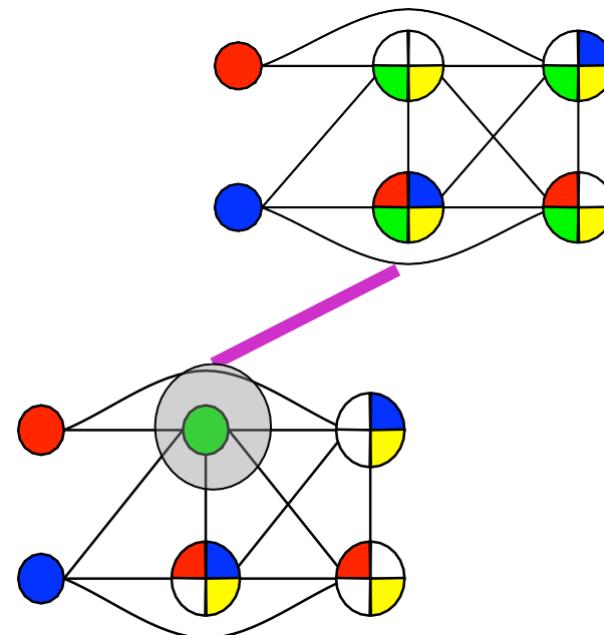
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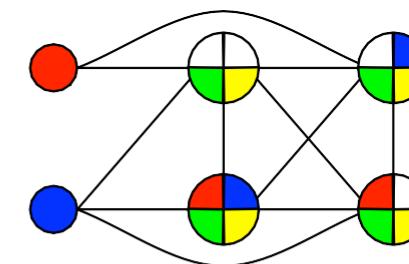
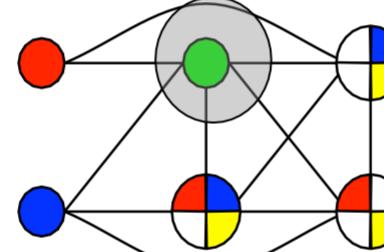
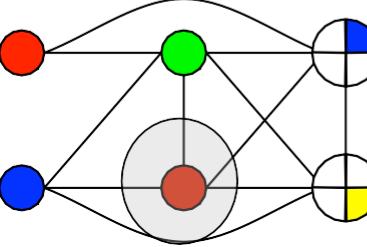
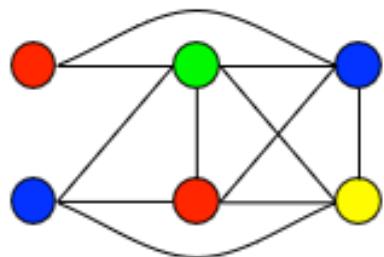
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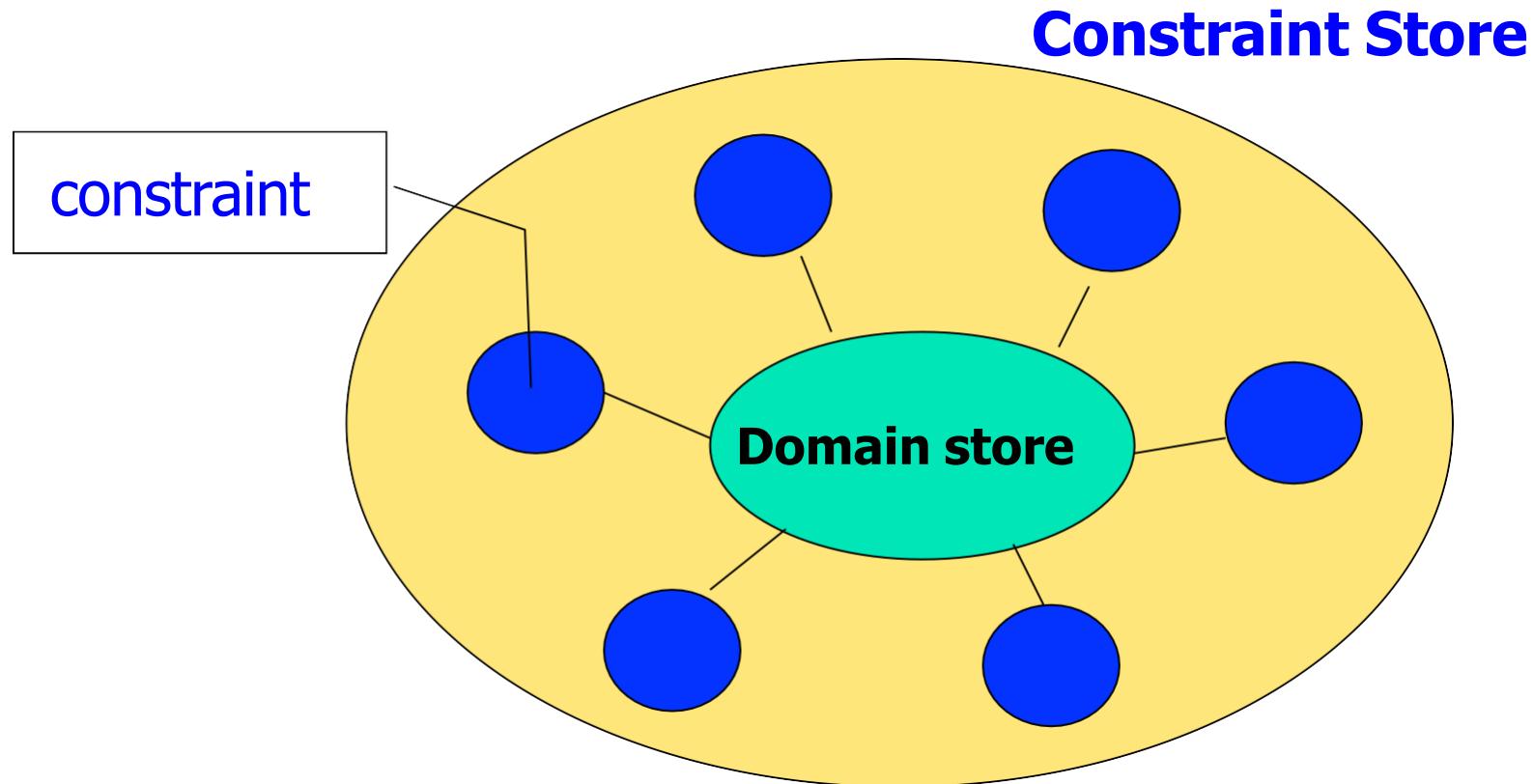
# Graph Coloring CP



# Graph Coloring CP



# Computational Model



## ■ Domain store

- For each variable: what is the set of possible values?
- If empty for any variable, then infeasible
- If singleton for all variables, then solution

## ■ Constraints

- Capture interesting and well studied substructures
- Need to
  - **Check Feasibility :** Determine if constraint is feasible wrt the domain store
  - **Prune :** remove “impossible” values from the domains

- General (fixpoint) algorithm is

repeat

    select a constraint c

    if c is infeasible wrt the domain store

        return infeasible

    else

        apply pruning algorithm of c

until no value can be removed

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Solution process

=

Model + Search

- The model
  - what the solutions are and their quality
- The search
  - how to find the solutions



# Example : SEND + MORE = MONEY

- Replace each letter by a different digit so that

$$\begin{array}{r} \text{SEND} \\ + \text{MORE} \\ \hline \text{MONEY} \end{array}$$

is a correct sum.

- Unique solution:

$$\begin{array}{r} 9567 \\ + 1085 \\ \hline 10652 \end{array}$$

- Variables: S, E, N, D, M, O, R, Y
- Domains:
  - [1::9] for S, M,
  - [0::9] for E, N, D, O, R, Y .



# Example : SEND + MORE = MONEY

- 1 equality constraint

- $$\begin{aligned} & 1000 S + 100 E + 10 N + D + \\ & 1000 M + 100 O + 10 R + E \\ & = 10000 M + 1000 O + 100 N + 10 E + Y \end{aligned}$$

$$\begin{array}{r} \text{S E N D} \\ + \text{M O R E} \\ \hline \text{M O N E Y} \end{array}$$
$$\begin{aligned} & S * 1000 + E * 100 + N * 10 + D \\ & + M * 1000 + O * 100 + R * 10 + E \\ & = M * 10000 + O * 1000 + N * 100 + E * 10 + Y \end{aligned}$$

# Example : SEND + MORE = MONEY

- **Or** 5 equality constraints.

- Use carry variables  $C_1, \dots, C_4 \in [0..1]$
- $D + E = 10 C_1 + Y$
- $C_1 + N + R = 10 C_2 + E$
- $C_2 + E + O = 10 C_3 + N$
- $C_3 + S + M = 10 C_4 + O$
- $C_4 = M$

$$\begin{array}{r} & C_4 & C_3 & C_2 & C_1 \\ & S & E & N & D \\ + & M & O & R & E \\ \hline & M & O & N & E & Y \end{array}$$

$$C_1 + N + R = E + 10 * C_2$$

# Example : SEND + MORE = MONEY

- 28 disequality constraints.
  - $x \neq y$  for  $x, y \in \{S;E;N;D;M;O;R;Y\}$
- **Or** a single constraint for disequalities.
  - For variables  $x_1, \dots, x_n$  with domains  $D_1, \dots, D_n$  :  $\text{all\_different}(x_1, \dots, x_n) := \{(d_1, \dots, d_n) \mid d_i \neq d_j \text{ for } i \neq j\}$
  - Use  $\text{all\_different}(S, E, N, D, M, O, R, Y)$
- **Or** modeling it as an IP problem.
  - For  $x, y \in \{S;E;N;D;M;O;R;Y\}$  transform  $x \neq y$  to
    - $x - y \leq 10 - 11 z_{xy}$
    - $y - x \leq 11 z_{xy} - 1$
  - where  $z_{xy} \in [0..1]$ ;  $z_{xy}=1 \Rightarrow x < y$ 
    - **Disadvantage**: 28 new variables.



- ❑ A first challenge
- ❑ Constraint Satisfaction Problem
- ❑ **Constraint Programming**
  - What is CP ?
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  - **Searching**
  - Global constraint
  - Computation domain
- Examples with Or-Tools

- Once constraint propagation is done, apply the search method

Choose a variable  $x$  with non-singleton domain  $(d_1, d_2, \dots d_i)$

For each **d** in  $(d_1, d_2, \dots d_i)$   
try to solve the problem with the additional constraint  **$x=d$**

Solution process

=

Model + Search

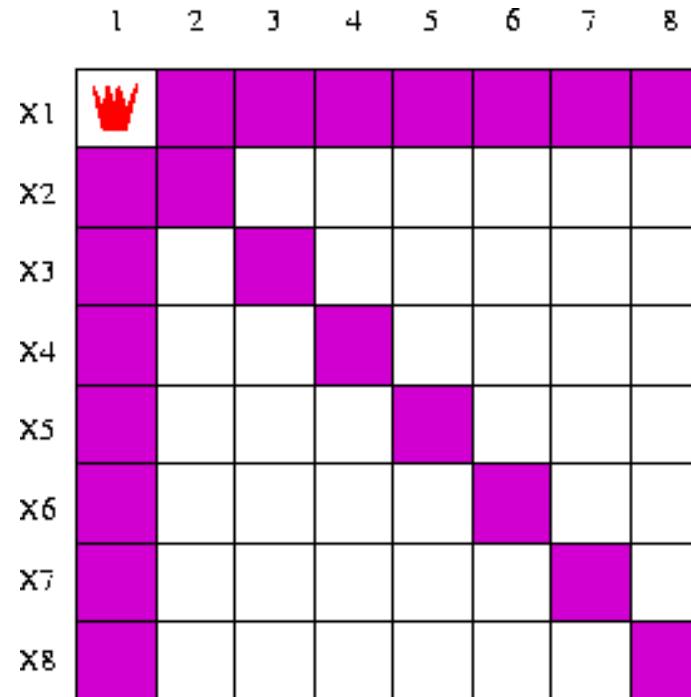
- The search
  - nondeterministic program + exploration strategy
  - **exploration strategy:** DFS, LDS, BFS, ...

# The Queen Problem

Assuming domain consistency

Propagation of  
 $\text{queen}[1] \leftrightarrow \text{queen}[2]$   
 $\text{queen}[1] \leftrightarrow \text{queen}[3]$   
...  
 $\text{queen}[1] \leftrightarrow \text{queen}[8]$

Propagation of  
 $\text{queen}[1]+1 \leftrightarrow \text{queen}[2]+2$   
 $\text{queen}[1]+1 \leftrightarrow \text{queen}[3]+3$   
...  
 $\text{queen}[1]+1 \leftrightarrow \text{queen}[8]+8$

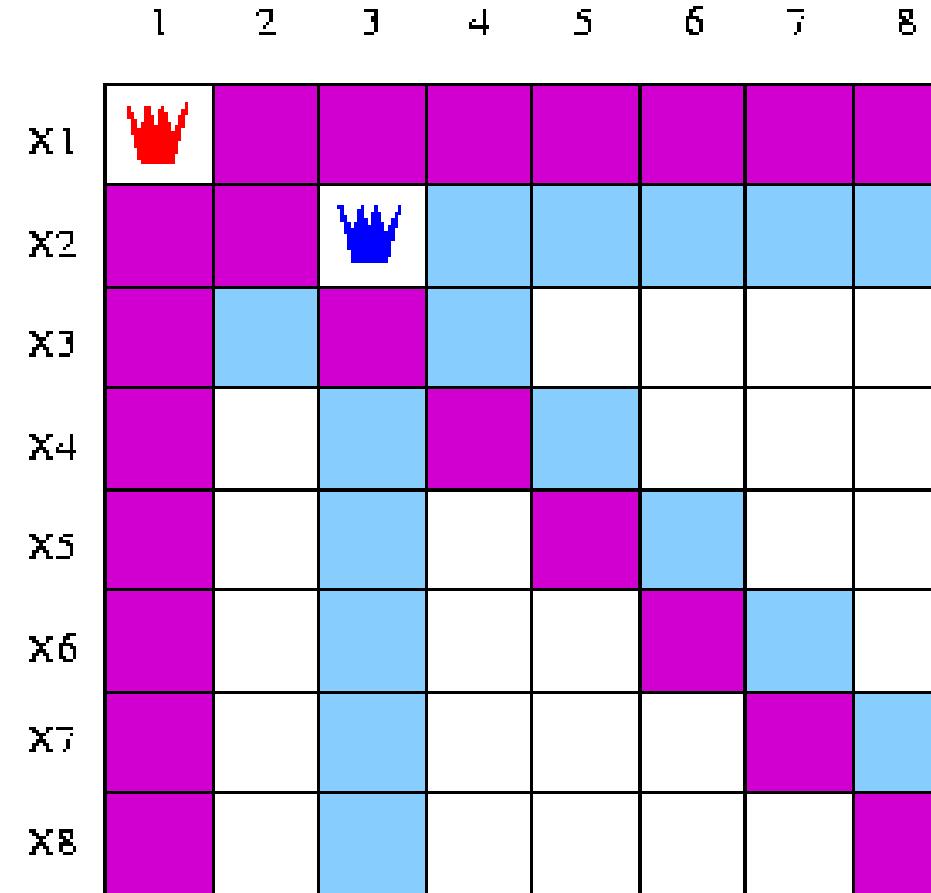


Consequence of  
 $\text{queen}[1]=1$

No more pruning  
Place another queen  
Questions

Which one ?  
On which tile ?

# The Queen Problem



# The Queen Problem

	1	2	3	4	5	6	7	8
X1	👑							
X2			👑					
X3					👑			
X4								
X5								
X6								
X7								
X8								

## Search Procedure

=

Nondeterministic Program + Exploration Strategy

- Nondeterministic program
  - specify (implicitly) an **and-or tree**
- Exploration strategy
  - specify **how to explore the tree**

# Content

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# Global Constraints

- Recognize some combinatorial substructures arising in many practical applications
  - **alldifferent** is a fundamental building block
  - many others (as we will see)
- Make modeling easier and more natural
  - Declarative
  - Compositionality



# The alldifferent Constraint

- Most well-known global constraint.
  - $\text{alldifferent}(x, y, z)$
- states that  $x$ ,  $y$ , and  $z$  take on different values.
  - $x=2, y=1, z=3$  would be ok,
  - but not  $x=1, y=3, z=1$
- Why does it prune more than  $x \neq y$ ,  $y \neq z$ ,  $x \neq z$  ?
- Very useful in many resource allocation, time tabling, sport scheduling problems

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# Computation domains

- Propagators are associated to constraints and their underlying **computation domain**
- Basic computation domain : **finite domains**
- A set of constraints and their associated propagators (over a computation domain), is called a **constraint solver**
- Some possibilities to combine different computation domains (i.e. different solvers) within a CSP
- **Constraint programming engine** = constraint solvers + search



# Computation domains

- Finite domains
- Linear real (rational) arithmetics
- Boolean
- Finite sets
- Terms
- Reals
- Intervals
- Graphs
- ...



- ❑ A first challenge
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## Example 1

- **Biến**
  - $X = \{X_0, X_1, X_2, X_3, X_4\}$
- **Miền giá trị**
  - $X_0, X_1, X_2, X_3, X_4 \in \{1, 2, 3, 4, 5\}$
- **Ràng buộc**
  - C1:  $X_2 + 3 \neq X_1$
  - C2:  $X_3 \leq X_4$
  - C3:  $X_2 + X_3 = X_0 + 1$
  - C4:  $X_4 \leq 3$
  - C5:  $X_1 + X_4 = 7$
  - C6:  $X_2 = 1 \Rightarrow X_4 \neq 2$



# Solution

```
from ortools.sat.python import cp_model

model = cp_model.CpModel()

x0 = model.NewIntVar(1, 5, 'x0')
x1 = model.NewIntVar(1, 5, 'x1')
x2 = model.NewIntVar(1, 5, 'x2')
x3 = model.NewIntVar(1, 5, 'x3')
x4 = model.NewIntVar(1, 5, 'x4')

model.Add(x2 + 3 != x1)
model.Add(x3 <= x4)
model.Add(x2 + x3 == x0 + 1)
model.Add(x4 <= 3)
model.Add(x1 + x4 == 7)

b = model.NewBoolVar('b')
model.Add(x2 == 1).OnlyEnforceIf(b)
model.Add(x2 != 1).OnlyEnforceIf(b.Not())
model.Add(x4 != 2).OnlyEnforceIf(b)

solver = cp_model.CpSolver()
status = solver.Solve(model)

if status == cp_model.OPTIMAL:
    print('Maximum of objective function: %i' % solver.ObjectiveValue())
    print()
    print('x0 value: ', solver.Value(x0))
    print('x1 value: ', solver.Value(x1))
    print('x2 value: ', solver.Value(x2))
    print('x3 value: ', solver.Value(x3))
    print('x4 value: ', solver.Value(x4))
```



## Example 2: CP + IS + FUN = TRUE

```
def CPIsFunSat():
    """Solve the CP+IS+FUN==TRUE cryptarithm."""
    # Constraint programming engine
    model = cp_model.CpModel()

    base = 10

    c = model.NewIntVar(1, base - 1, 'C')
    p = model.NewIntVar(0, base - 1, 'P')
    i = model.NewIntVar(1, base - 1, 'I')
    s = model.NewIntVar(0, base - 1, 'S')
    f = model.NewIntVar(1, base - 1, 'F')
    u = model.NewIntVar(0, base - 1, 'U')
    n = model.NewIntVar(0, base - 1, 'N')
    t = model.NewIntVar(1, base - 1, 'T')
    r = model.NewIntVar(0, base - 1, 'R')
    e = model.NewIntVar(0, base - 1, 'E')

    # We need to group variables in a list to use the constraint AllDifferent.
    letters = [c, p, i, s, f, u, n, t, r, e]
```



## Example 2: CP + IS + FUN = TRUE

```
# Verify that we have enough digits.
assert base >= len(letters)

# Define constraints.
model.AddAllDifferent(letters)

# CP + IS + FUN = TRUE
model.Add(c * base + p * base + i * base + s * base * base + f * base * base * base + u * base +
          n == t * base * base * base + r * base * base * base + u * base + e)

### Solve model.
solver = cp_model.CpSolver()
solution_printer = VarArraySolutionPrinter(letters)

# Enumerate all solutions.
solver.parameters.enumerate_all_solutions = True
# Solve.
status = solver.Solve(model, solution_printer)

print()
print('Statistics')
print(' - status      : %s' % solver.StatusName(status))
print(' - conflicts   : %i' % solver.NumConflicts())
print(' - branches    : %i' % solver.NumBranches())
print(' - wall time   : %f s' % solver.WallTime())
print(' - solutions found : %i' % solution_printer.solution_count())
```



## Example 2: CP + IS + FUN = TRUE

```
class VarArraySolutionPrinter(cp_model.CpSolverSolutionCallback):
    """Print intermediate solutions."""

    def __init__(self, variables):
        cp_model.CpSolverSolutionCallback.__init__(self)
        self.__variables = variables
        self.__solution_count = 0

    def on_solution_callback(self):
        self.__solution_count += 1
        for v in self.__variables:
            print('%s=%i' % (v, self.Value(v)), end=' ')
        print()

    def solution_count(self):
        return self.__solution_count
```



## Example 3: N-Queen problem

```
def main(board_size):
    model = cp_model.CpModel()
    # Creates the variables.
    # The array index is the column, and the value is the row.
    queens = [model.NewIntVar(0, board_size - 1, 'x%i' % i)
              for i in range(board_size)]
    # Creates the constraints.
    # The following sets the constraint that all queens are in different rows.
    model.AddAllDifferent(queens)

    # Note: all queens must be in different columns because the indices
    # of queens are all different.
```



## Example 3: N-Queen problem

```
# The following sets the constraint that no two queens can be on
# the same diagonal.
for i in range(board_size):
    # Note: is not used in the inner loop.
    diag1 = []
    diag2 = []
    for j in range(board_size):
        # Create variable array for queens(j) + j.
        q1 = model.NewIntVar(0, 2 * board_size, 'diag1_%i' % i)
        diag1.append(q1)
        model.Add(q1 == queens[j] + j)
        # Create variable array for queens(j) - j.
        q2 = model.NewIntVar(-board_size, board_size, 'diag2_%i' % i)
        diag2.append(q2)
        model.Add(q2 == queens[j] - j)
    model.AddAllDifferent(diag1)
    model.AddAllDifferent(diag2)
```



# Example 3: N-Queen problem

```
### Solve model.  
solver = cp_model.CpSolver()  
solution_printer = SolutionPrinter(queens)  
status = solver.SearchForAllSolutions(model, solution_printer)  
print()  
print('Solutions found : %i' % solution_printer.SolutionCount())  
  
class SolutionPrinter(cp_model.CpSolverSolutionCallback):  
    """Print intermediate solutions."""  
  
    def __init__(self, variables):  
        cp_model.CpSolverSolutionCallback.__init__(self)  
        self._variables = variables  
        self._solution_count = 0  
  
    def OnSolutionCallback(self):  
        self._solution_count += 1  
        for v in self._variables:  
            print('%s = %i' % (v, self.Value(v)), end = ' ')  
        print()  
  
    def SolutionCount(self):  
        return self._solution_count
```



## Example 4: Bài toán Phân bổ môn học

- Có  $N$  môn học  $1, 2, \dots, N$  cần được phân bổ vào  $P$  học kỳ  $1, 2, \dots, P$
- Mỗi môn học  $i$  có số tín chỉ là  $credit(i)$
- $L = \{(i, j)\}$ : tập các cặp môn học  $(i, j)$  trong điều kiện tiên quyết (môn  $i$  phải được xếp và học kỳ trước học kỳ của môn  $j$ )
- Cho trước các hằng số  $\alpha, \beta, \lambda, \gamma$ . Hãy tìm cách xếp  $N$  môn học vào  $P$  học kỳ sao cho
  - Tổng số môn học trong mỗi học kỳ phải lớn hơn hoặc bằng  $\alpha$  và nhỏ hơn hoặc bằng  $\beta$
  - Tổng số tín chỉ các môn học trong mỗi học kỳ phải lớn hơn hoặc bằng  $\lambda$  và nhỏ hơn hoặc bằng  $\gamma$



## Example 4: Bài toán Phân bổ môn học

Môn	1	2	3	4	5	6	7	8	9	10	11	12
Số tín chỉ	2	1	2	1	3	2	1	3	2	3	1	3

$3 \leq$  Số môn học mỗi học kỳ  $\leq 3$

$5 \leq$  Số tín chỉ các môn học mỗi học kỳ  $\leq 7$

Phương án  
phân bổ

Học kỳ	1	2	3	4
Danh sách môn	2, 5, 3	1, 6, 10	4, 7, 8	9, 11, 12

2	1
6	9
5	6
5	8
4	11
6	12
2	7
3	10
5	7
8	11
4	12

## Example 4: Bài toán Phân bổ môn học

- Biên
  - $X[p,i] = 1$ : môn i được phân vào học kỳ p
  - $D(X[p,i]) = \{0,1\}$
- Ràng buộc
  - $X[q,i] = 1 \rightarrow X[p,j] = 0, (i,j) \in L, 1 \leq p \leq q \leq P$
  - $\sum_{p=1}^P X[p,i] = 1$ , với mọi  $i = 1, 2, \dots, N$
  - $\alpha \leq \sum_{i=1}^N X[p,i] \leq \beta$ , với mọi  $p = 1, 2, \dots, P$
  - $\lambda \leq \sum_{i=1}^N X[p,i] credit(i) \leq \gamma$ , với mọi  $p = 1, 2, \dots, P$

## Example 4: Bài toán Phân bổ môn học

```
N = 12
P = 4
credits = [2, 1, 2, 1, 3, 2, 1, 3, 2, 3, 1, 3]

orderCourseLst = [(0, 1), (1, 2)]

alpha = 3
beta = 3
lamb = 5
gamma = 7

model = cp_model.CpModel()

# Khai báo biến x[i,j] = 1 nếu môn học j được phân vào kỳ p
x = []
for i in range(P):
    t = []
    for j in range(N):
        t.append(model.NewIntVar(0, 1, 'x[' + str(i) + "," + str(j) + "]"))
    x.append(t)
```



## Example 4: Bài toán Phân bổ môn học

```
#Ràng buộc: Mỗi môn học chỉ được phân vào duy nhất 1 kỳ  
for j in range(N):  
    model.Add(sum(x[i][j] for i in range(P)) == 1)
```

```
#Ràng buộc: Số lượng môn học trong một kỳ phải nằm trong [alpha, beta]  
for i in range(P):  
    model.Add(sum(x[i][j] for j in range(N)) >= alpha)  
    model.Add(sum(x[i][j] for j in range(N)) <= beta)
```

```
#Ràng buộc: Số tín chỉ trong một kỳ phải nằm trong [lambda, gamma]  
for i in range(P):  
    model.Add(sum(x[i][j]*credits[j] for j in range(N)) >= lamb)  
    model.Add(sum(x[i][j]*credits[j] for j in range(N)) <= gamma)
```



## Example 4: Bài toán Phân bổ môn học

```
#Ràng buộc: Thứ tự các môn học
for item in orderCourseLst:
    i = item[0]
    j = item[1]

    for q in range(P):
        for p in range(q+1):

            b = model.NewBoolVar('b')
            model.Add(x[q][i] == 1).OnlyEnforceIf(b)
            model.Add(x[q][i] != 1).OnlyEnforceIf(b.Not())
            model.Add(x[p][j] == 0).OnlyEnforceIf(b)
```



## Example 4: Bài toán Phân bổ môn học

```
### Solve model.  
solver = cp_model.CpSolver()  
status = solver.Solve(model)  
  
if status == cp_model.OPTIMAL or status == cp_model.FEASIBLE:  
    print(f'Total cost = {solver.ObjectiveValue()}')  
    print()  
    for i in range(P):  
        for j in range(N):  
            if solver.BooleanValue(x[i][j]):  
                print(  
                    f'Môn học {j} được phân cho kỳ {i}')  
else:  
    print('No solution found.')
```





**HUST**

**THANK YOU !**