

# **DECISION MAKING WITH CONSTRAINT PROGRAMMING**

**2023/2024**

**Second cycle degree/two year  
Master in Computer Science  
Dept of Computer Science and  
Engineering (DISI)  
University of Bologna**



# Course Info

- **Lecturer**

- Zeynep KIZILTAN (associate professor in AI and optimization).
- Email: [zeynep.kiziltan@unibo.it](mailto:zeynep.kiziltan@unibo.it)
- Appointment at Teams, upon request by email.

- **Content**

- Fundamentals of Constraint Programming (CP), a general-purpose AI-based approach to **combinatorial decision making**.

- **Prerequisites**

- Basic computer science such as discrete mathematics, logic, algorithms and data structures, programming.
- Prior knowledge on AI is not necessary.

# Course Info

- **Timetable:** September 18 – December 5
  - 5 + 5 weeks
    - No lecture during the weeks of October 23 and 30.
  - Monday 11:00 – 13:00 (Aula Bombelli)
  - Tuesday 14:00 – 16:00 (Aula E1)
- **Lectures**
  - Theory and practice via programming exercises using personal laptops.
  - Lecture timing (please vote later in Virtuale):
    - A: Start on time, finish 10 mins before?
    - B: Start 10 mins later, finish on time?

# Course Info

- **Teaching Tools**

- Virtuale platform

- Distribution of the course material (lecture slides, exercises, lecture recordings, resources, etc).
    - Communication between the students and the lecturer.
    - Discussion of anything related to the course.
    - Working on programming exercises **interactively**.
    - Exchange of feedback.
    - Participation to polls and informal quiz.

# Course Info

- **Teaching Tools**

- Virtuale platform

- Participate now!

- Enrollment: study programme and password (230901).

- Add a profile photo for fast recognition.

- Check your UniBo email **frequently!**

- Check the course syllabus to program yourselves.

- Activate notifications.

- Material will be available before the lectures.

- Take a look at them in advance.

# Course Info

- **Exam**

- Programming exercises.
  - To complete and submit following the exercise sessions.
    - Interactively with the lecturer via Virtuale.
    - Try and complete each one before the next exercise session.
  - **First deadline for completion:** November 1 (the first two exercises)
  - **Final deadline for completion:** December 19 (all the exercises)
- Oral exam on the course contents.
  - January/February for those completed the exercises in December.
  - At a later time for those completed after December and by September.
  - Is not granted otherwise, need to repeat the course next year.
- Final grade in equal parts.

# Course Info

- **Programming Tool**

- **MiniZinc**

- a modeling language with interfaces to several CP (and other) solvers (<https://www.minizinc.org/>),
    - by Monash University in collaboration with Data61 and the University of Melbourne.
    - Free and well-documented.
    - Download it and start getting familiar with it.

# Course Info

- **Tips**

- Theory lectures are important to understand the practice and for the oral exam.
- Practical sessions are important to correctly complete the exercises and for the oral exam.
- Participation and engagement are vital!
  - Ask questions, don't be shy 😊
  - Follow the Virtuale page!
  - Use the forum for discussions and exchange of knowledge, rather than sending emails to the lecturer.
  - Answer questions, don't be humble 😊
  - Submit exercises on time, long before the deadlines to for modifications and resubmissions.



# Course Info

- **FAQ**

- Can I follow the course via the video recordings?
  - Sure, if necessary (health, work, uncancellable appointment etc) for some lectures.
  - Not recommended if you cannot participate at all.
    - Remember that you cannot get engaged 😞
- I graduate in October, can I catch up?
  - Yes! Follow the Virtuale page.
- I graduate in December, can I catch up?
  - No! Please take the course next year.

# Introduce Yourself

- Send a message to the discussion forum under the topic “Hello!”.
  - Name & surname.
  - Exchange student or not.
  - Degree programme & year.
  - Bachelor background.
  - Followed the course previously?
  - Prior knowledge and experience with Mathematical Programming & CP.
  - Any particular situation? Especially for exchange students.

# Introduction

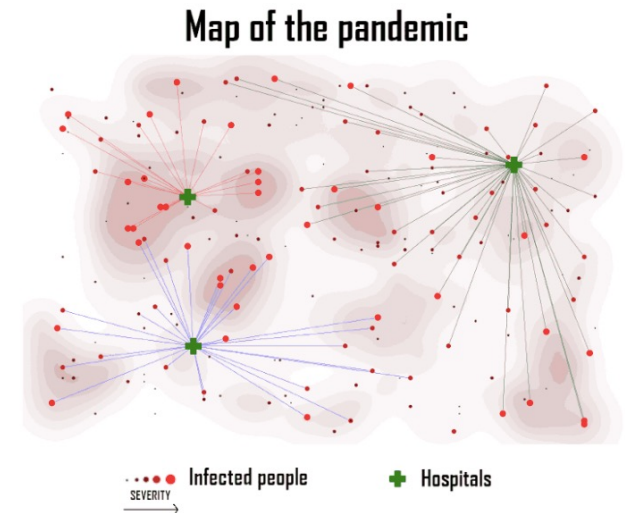
- Combinatorial Decision Making.
- Why with Constraint Programming (CP)?
- Overview of CP.
- Examples from MiniZinc.

# Combinatorial Decision Making

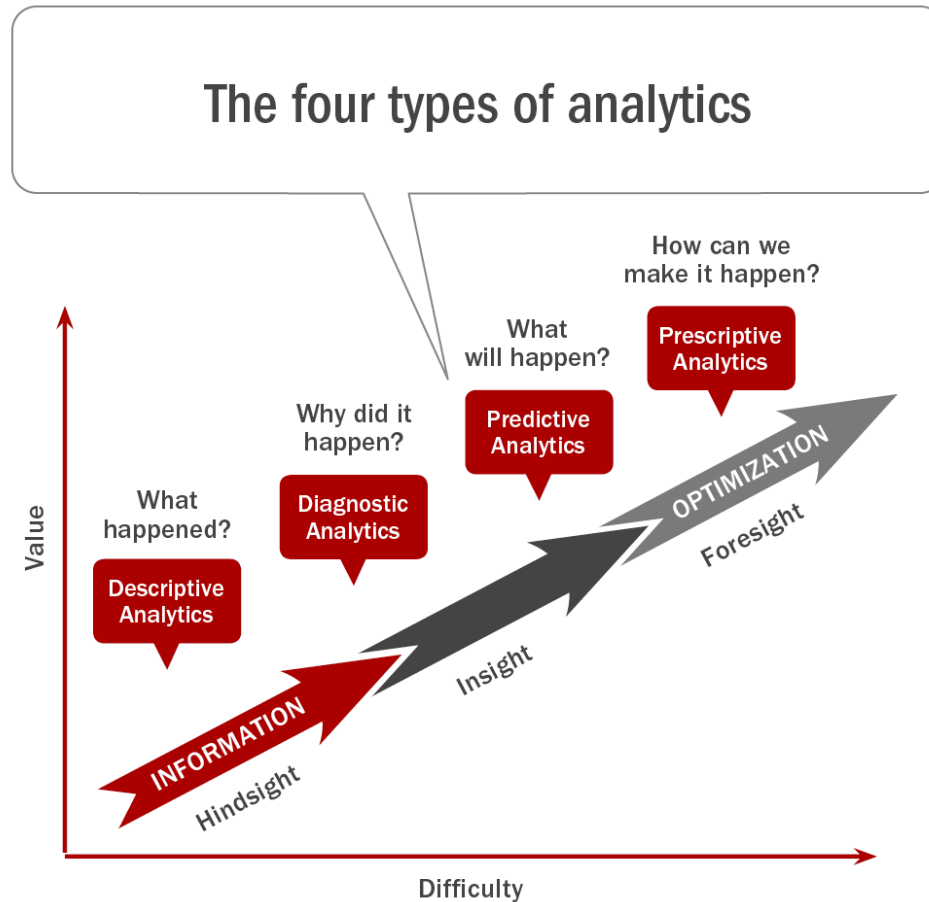
- Decision making within many combinations of possibilities subject to **restrictions = constraints**.
  - Any solution (that meets all constraints).
  - Optimal solution (best solution according to an objective).
- Can appear under different names, e.g.,
  - **combinatorial optimization**.
  - **constraint satisfaction/optimization**.
- Common in our daily lives, business, industry and science.

# Hospitalization during the Pandemic

- Assign infected people to hospitals according to:
  - severity of illness,
  - patient age,
  - patient location,
  - hospital capacity,
  - hospital equipment, etc.
- An approach like neural networks is not suitable:
  - no historical data for training,
  - data cleaning and consolidation is time consuming,
  - a variety of architectures would need to be tested with lengthy training sessions.

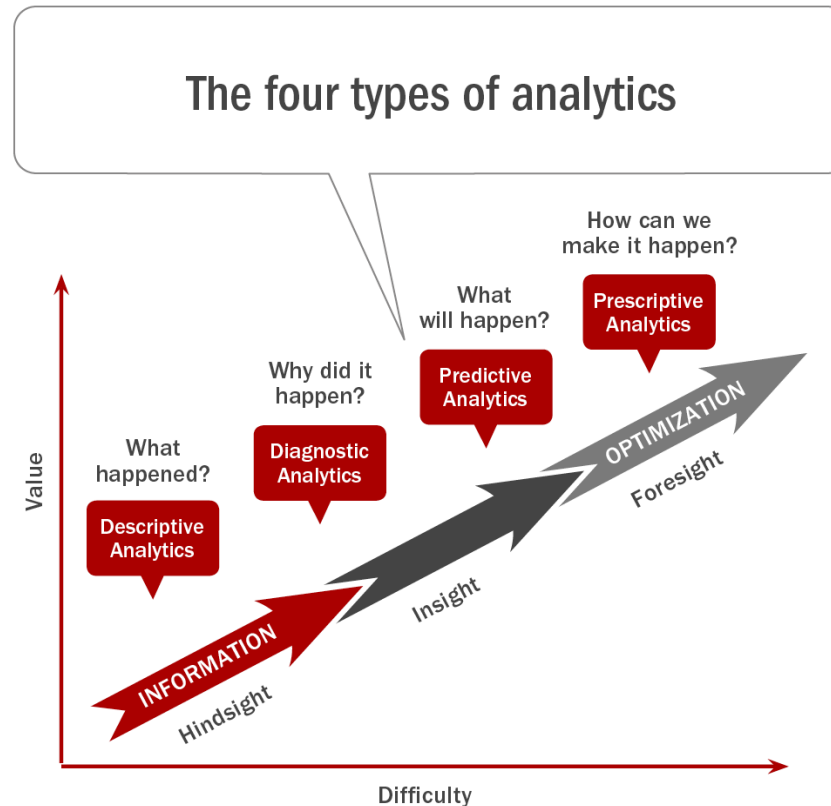


# Data Analytics



# Data Analytics

- AI is not just for machine learning, but also for decision support.



# Combinatorial Decision Making

- Properties
  - Computationally difficult (NP-hard in general).
  - Can only be solved by **intelligent search**.
  - Experimental in nature.
  - Finding good/optimal solutions can save time, \$ and reduce environmental impact.
- Many solution techniques
  - Integer Linear Programming (ILP).
  - Boolean SATisfiability, SAT Modulo Theories (SMT).
  - Heuristic search methods (HS).
  - **Constraint Programming (CP)**.



# Popularity of Constraint Programming

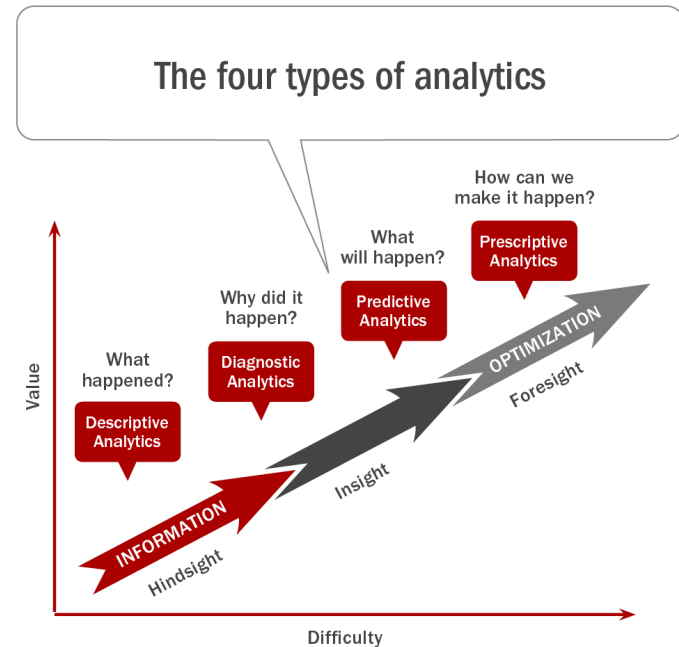
- An important and growing area of AI.
  - Universities, research centers and companies (such as IBM, Google) around the world contribute to the advancement of the state-of-the-art.
  - Many companies are applying CP successfully.
    - Including IBM, Google, Ericsson, Siemens, Renault, Oracle, Sap, Intel, Tacton.
- Technology of choice in logistics, scheduling, planning...
- **A useful asset on the job market!**

# Example: Covid-19 Test Scheduling

- Ocado Retail Ltd, one of the world's biggest online-only grocery retail businesses.
- Employs over 15K people, many of them performing frontline roles such as packing in the warehouses, delivering orders, providing customer service in the call centers etc.
- With the pandemic, the company decided to test all frontline employees on a weekly basis, which required scheduling the employees at each site subject to various constraints.
  - Proved difficult to solve manually.
- Data Science team developed a CP-based solution, which was successfully used to schedule up to 3,500 employees across 4 sites ([IFORS news, vol. 15, number 4, December 2020](#))

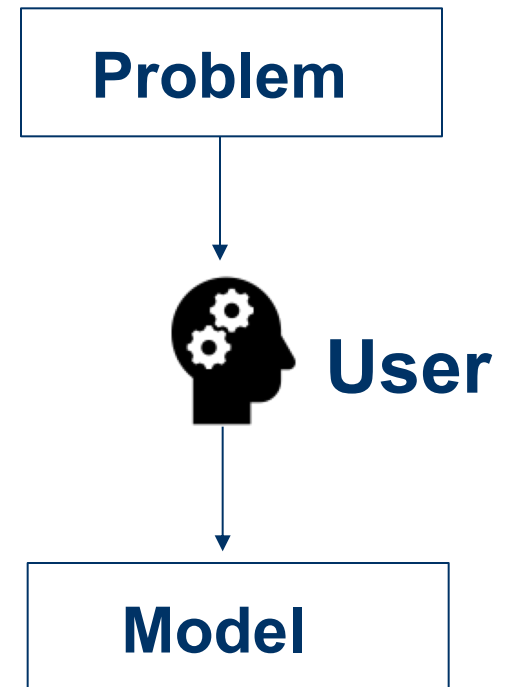
# Example: London Bike Hiring

- AI is not just for machine learning, but also for decision support.
  - IBM® ILOG® CPLEX® Optimization Studio for London bike hiring scheme
  - ML to forecast and predict the movements of bikes, customer demand, customer behavior, maintenance time of bikes, ...
  - Combinatorial optimization to decide how to move bikes to the stations in the best possible way and how many bikes to leave in each station.



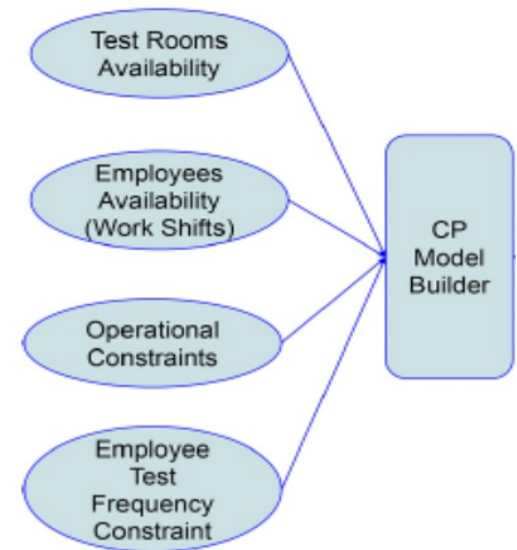
# What is Constraint Programming?

- A **declarative programming paradigm** for stating and solving combinatorial optimization problems.
  - User **models** a decision problem by formalizing:
    - **the unknowns** of the decision → **decision variables** ( $X_i$ ).
    - **possible values** for unknowns → **domains** ( $D(X_i) = \{v_j\}$ ).
    - **relations** between the unknowns → **constraints** ( $r(X_i, X_j)$ ).



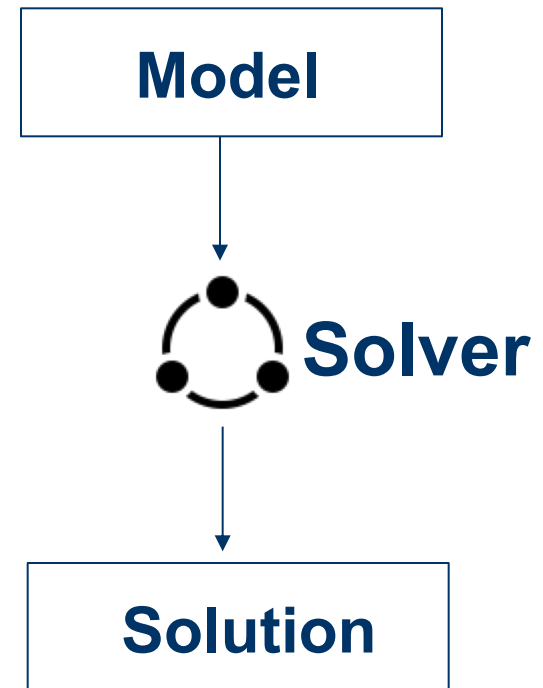
# Covid-19 Test Scheduling

- When and where to test each employee?
- Availability Constraints
  - Testing room, tester, and employee availabilities.
- Frequency constraints
  - The spacing between tests performed on the same employee should be within given bounds.
- Operational constraints
  - Each employee should be tested within their working shift.
  - Only a limited share of employees from the same work area should be scheduled for a test on the same day.

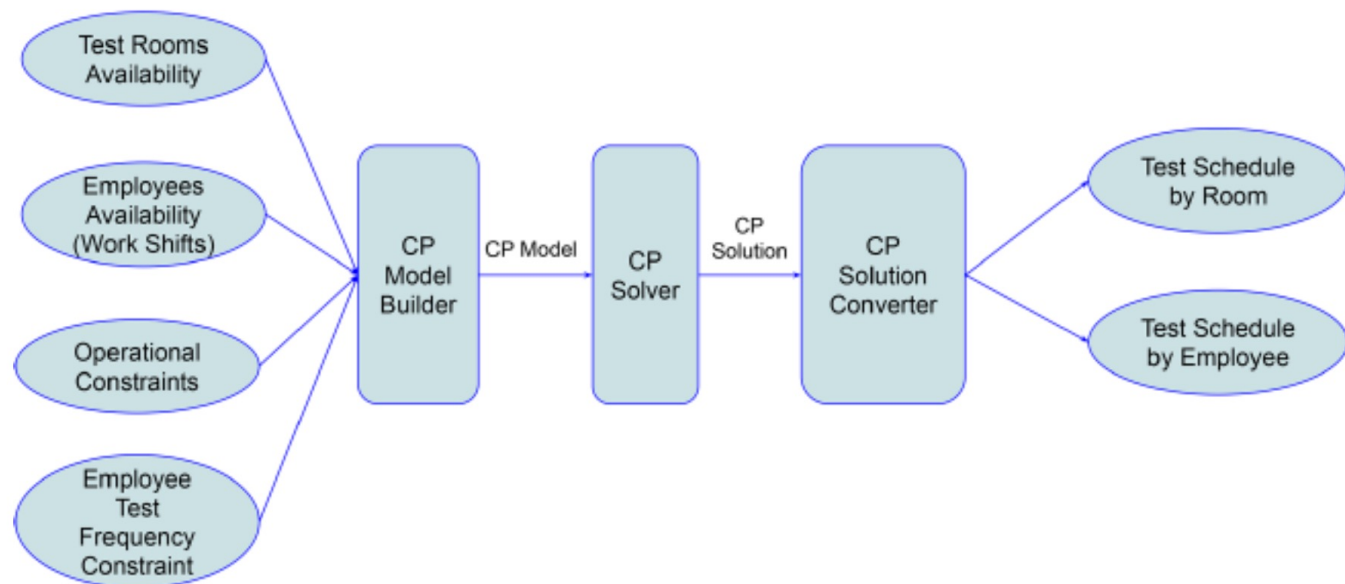


# What is Constraint Programming?

- A **declarative programming paradigm** for stating and solving combinatorial optimization problems.
  - A constraint **solver** finds a solution to the model (or proves that no solution exists) by assigning a value to every variable ( $X_i \leftarrow v_j$ ) via a **search algorithm**.



# Covid-19 Test Scheduling



# Why Constraint Programming?

- Sounds like Integer Linear Programming.
- CP provides **a rich language for expressing constraints and defining search procedures.**
  - Easy modelling.
    - Fast prototyping with a variety of constraints.
    - Easy to maintain programs.
    - Extensibility.
  - Easy control of search.
    - Experimentation with advanced search strategies.



# Why Constraint Programming?

- Main focus on **constraints** and **feasibility**.
  - Constraints → reductions in the search space.
  - Of interest on tightly constrained problems.
  - More constraints mean more domain reductions, making the problem easier to solve.

# Orthogonal and Complementary Approaches to Combinatorial Optimization

## ● ILP

- Modeling with linear inequalities.
- Numerical calculations.
- Focus on objective function and optimality.
  - Bounding → elimination of suboptimal assignments.
- Exploits global structure.
  - Relaxations, cutting planes, and duality theory.

## ● CP

- Rich language for modeling and search procedures.
- Logical processing.
- Focus on constraints and feasibility.
  - Propagation → elimination of infeasible assignments.
- Exploits local structure.
  - Domain reductions based on individual constraints.

# Strengths of CP

- Success on irregular problems!
  - Timetabling, sequencing, scheduling allocation, rostering, etc.
  - Contain messy constraints non-linear in nature.
  - Contain multiple disjunctions which result in poor information returned by a linear relaxation of the problem.

# Weaknesses and Opportunities of CP

- Optimality
  - **CP**: no special focus on objective function and optimality 😞
  - **ILP**: scales up on loosely constrained optimization problems.
  - **HS**: is effective in finding quickly good-quality solutions.
- Best optimality approaches are often hybrids of CP, ILP and HS.
  - CP is a suitable framework for hybridization 😊

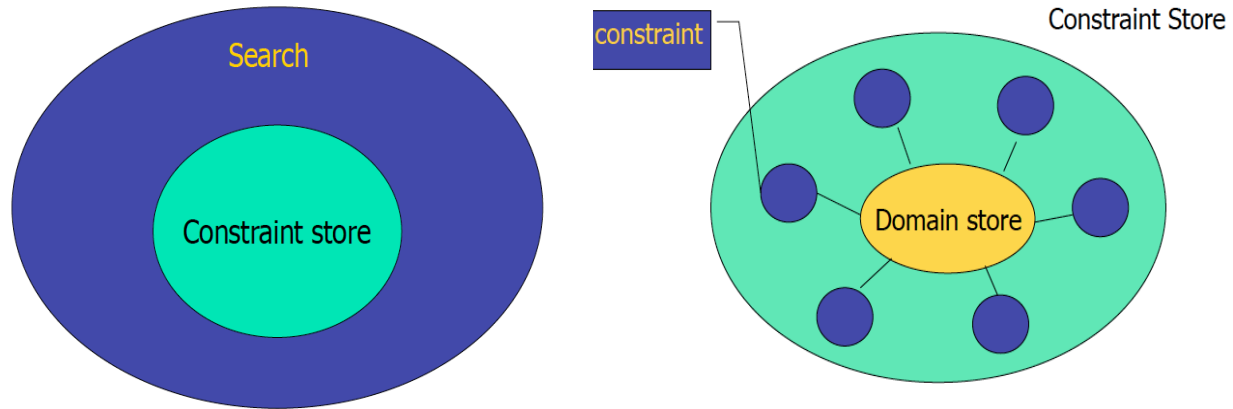
# Overview of CP



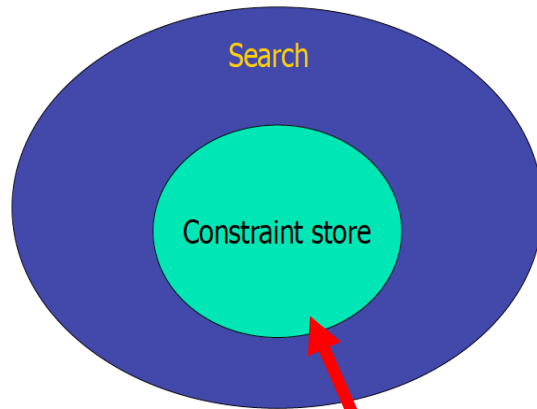
# Constraint Solver

- Enumerates all possible variable-value combinations via a **systematic backtracking tree search**.
  - Guesses a value for each variable.
- During search, examines the constraints to **remove incompatible values** from the domains of the **future (unexplored) variables**, via **propagation**.
  - Shrinks the domains of the future variables.

# Constraint Programming

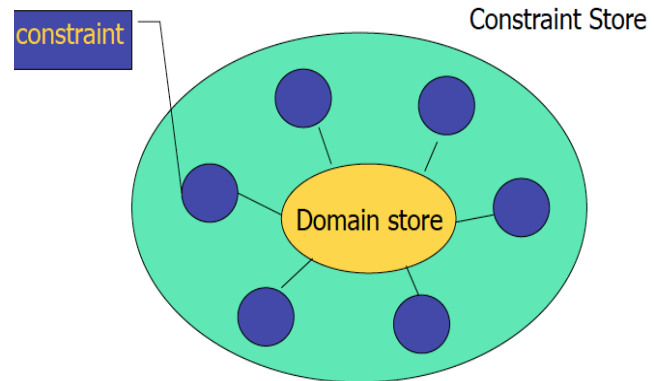


# Constraint Programming



**Modelling**

User expresses the problem

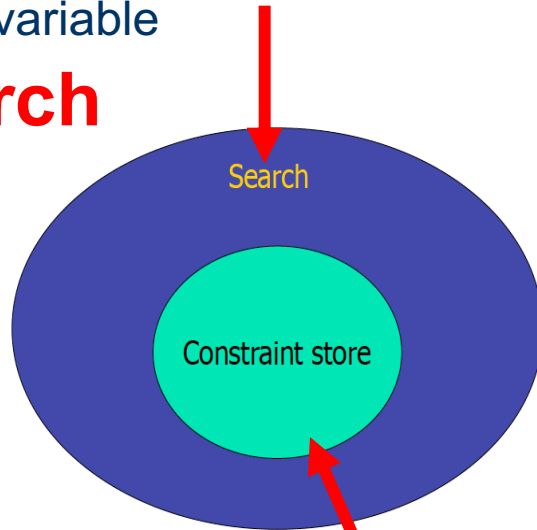




# Constraint Programming

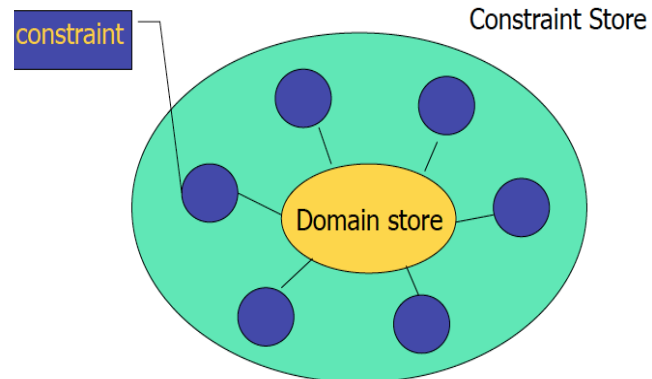
Solver uses a backtracking tree search algorithm to guess a value for each variable

**Search**



**Modelling**

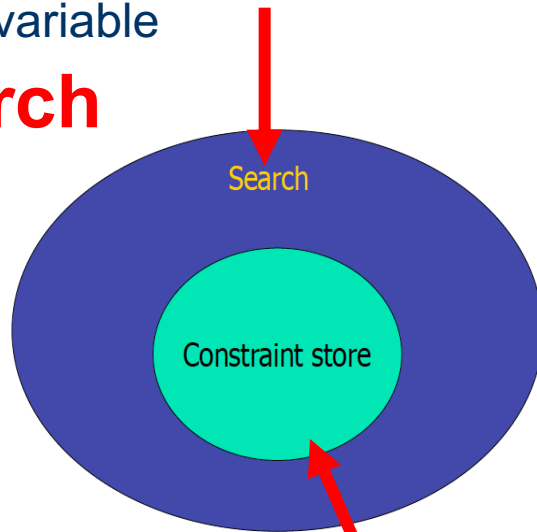
User expresses the problem



# Constraint Programming

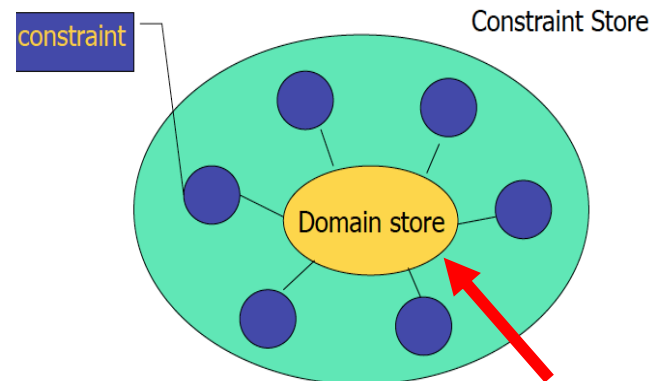
Solver uses a backtracking tree search algorithm to guess a value for each variable

**Search**



**Modelling**

User expresses the problem



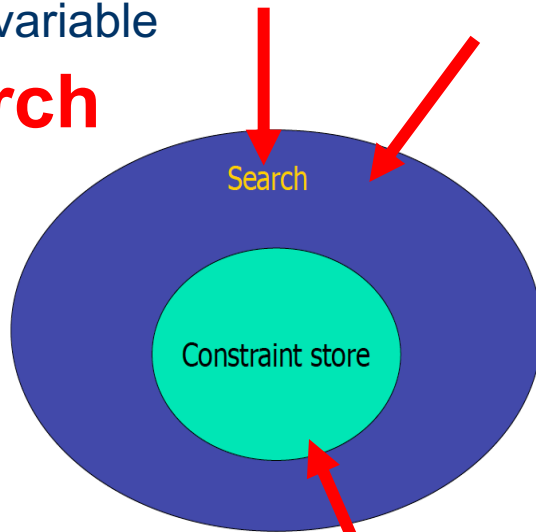
**Propagation**

Solver uses algorithms to examine each constraint to reduce the domains of the future variables

# Constraint Programming

Solver uses a backtracking tree search algorithm to guess a value for each variable

**Search**

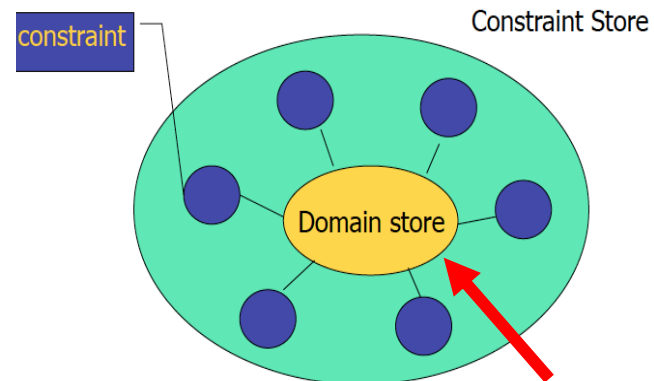


**Modelling**

User expresses the problem

Solver exploits the current search state and problem specific knowledge to guide the search

**Search heuristics**



**Propagation**

Solver uses algorithms to examine each constraint to reduce the domains of the future variables

# Dual Role of a Model

- Captures combinatorial substructures.
- Enables solver to reduce the search space.
  - Constraints act as propagation algorithms.
  - Variables' domains act as communication mechanism.

# Search and Propagation

- Search decisions and propagation are interleaved.

Propagation



$$X_i \leftarrow v_j$$



Propagation



$$X_i \leftarrow v_j$$



Propagation

# Expectation from CP

- Declarative programming
  - The user **declaratively models** the problem.
  - An underlying solver returns a solution with its **default search**.

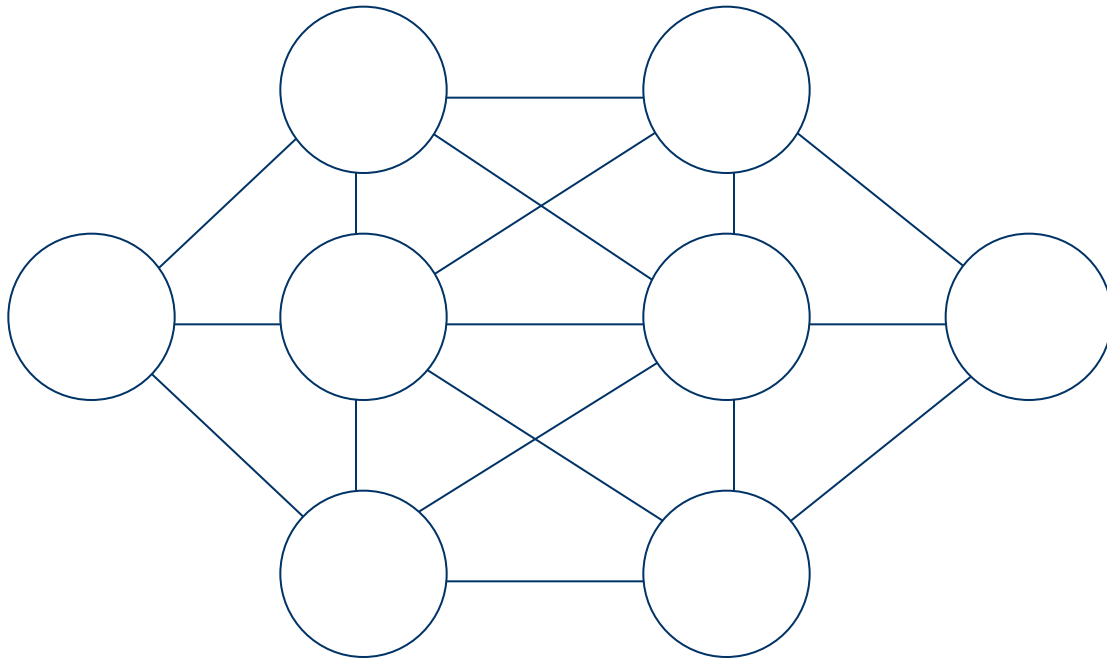


# Reality in CP

- Modelling is critical!
  - The user often has to use **advanced modelling techniques for strong propagation.**
- Default search of the solver is usually not enough!
  - The user often has to **program the search strategy** (search algorithm, search heuristics,...)



# A Puzzle

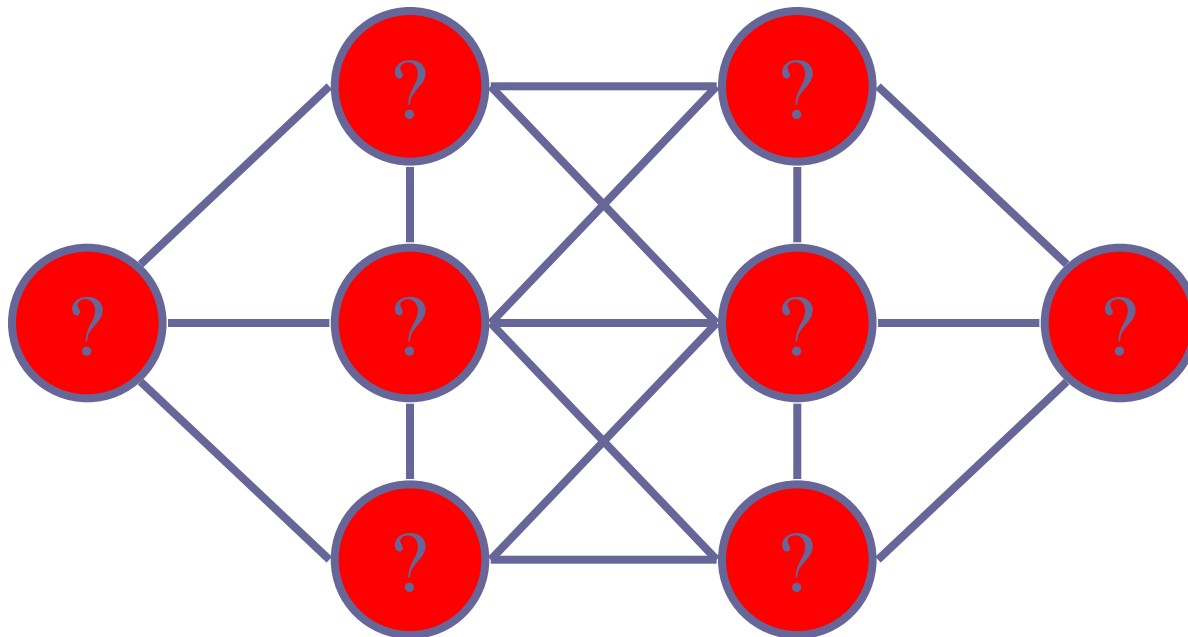


Place a different number in each node (1 to 8) such that adjacent nodes cannot take consecutive numbers



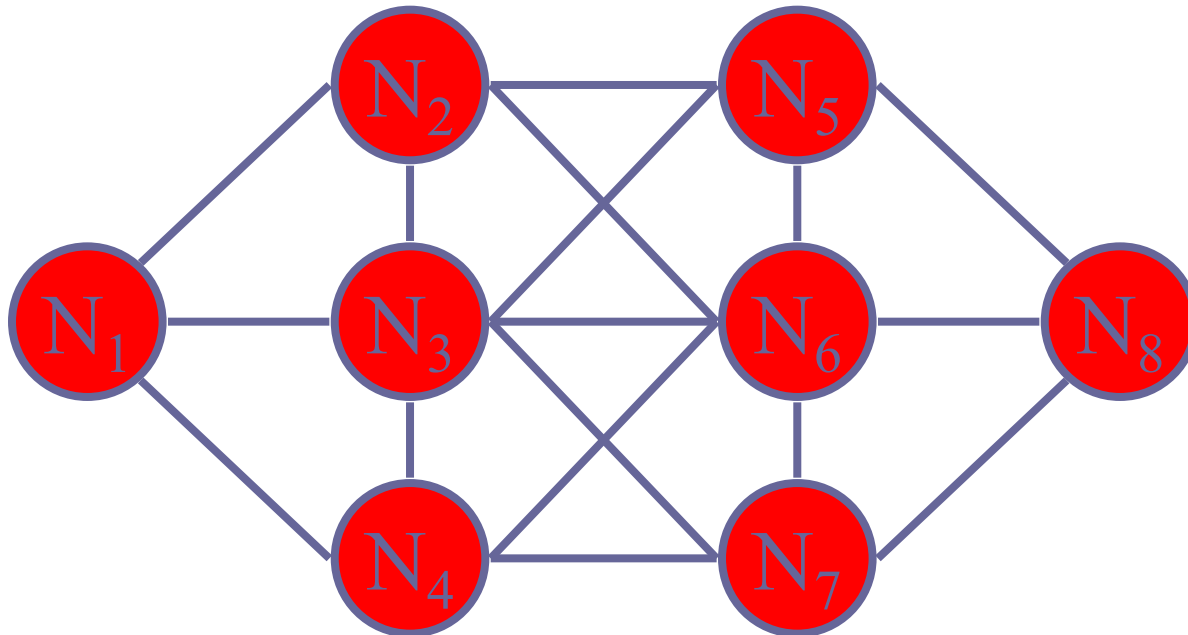
# A Puzzle

- Place numbers 1 through 8 on nodes, s.t.:
  - each number appears exactly once;
  - no connected nodes have consecutive numbers.



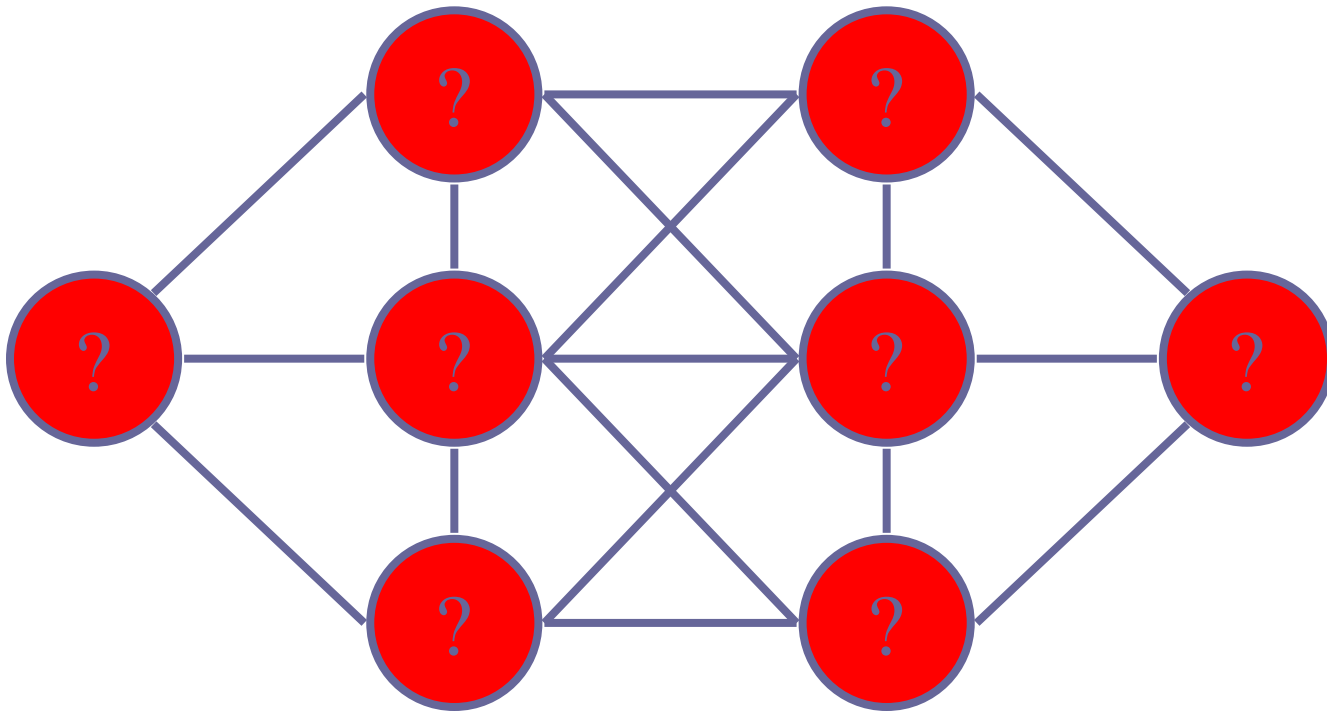
# Modelling

- Variables:  $N_1 \dots N_8$  that represent the nodes
- Domains: the set of values  $\{1, 2, 3, 4, 5, 6, 7, 8\}$  that  $N_1 \dots N_8$  can take
- Constraints: for all  $i < j$  s.t.  $N_i$  and  $N_j$  are adjacent  $|N_i - N_j| > 1$   
for all  $i < j$   $N_i \neq N_j$



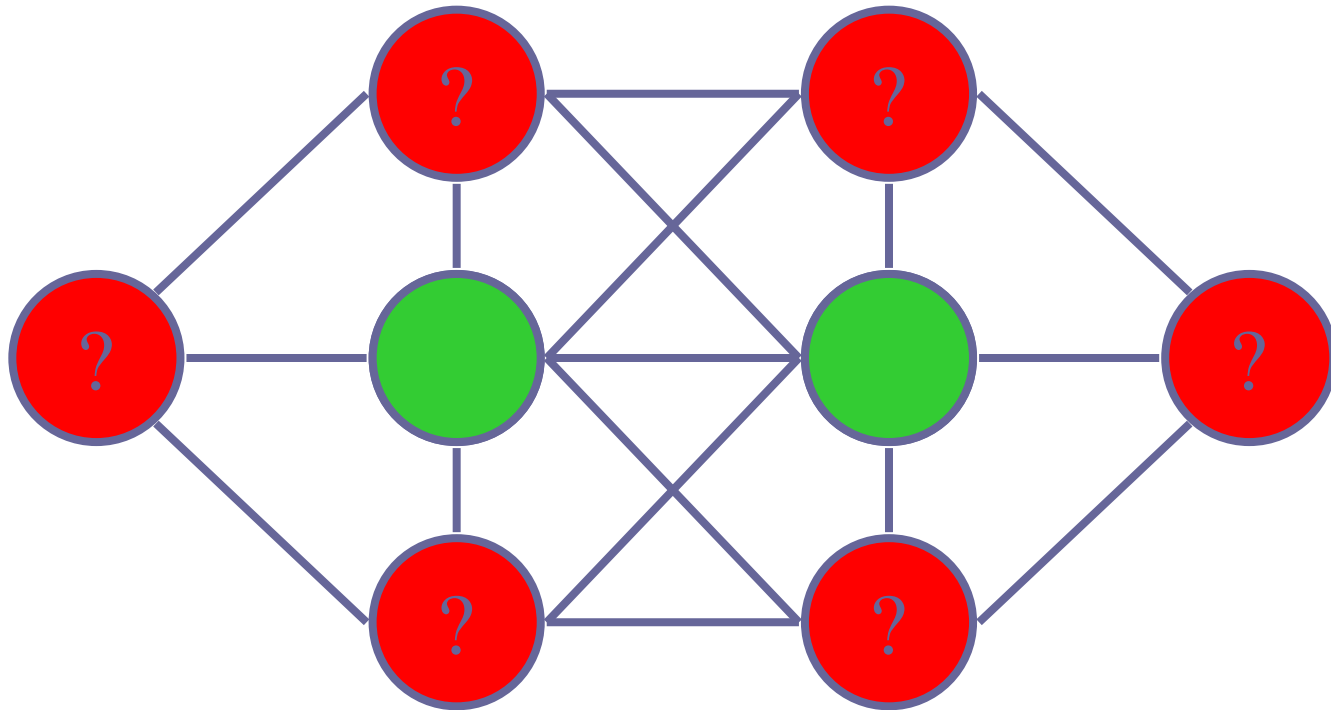
# Backtracking Search + Heuristics

- Guess a value for a variable!



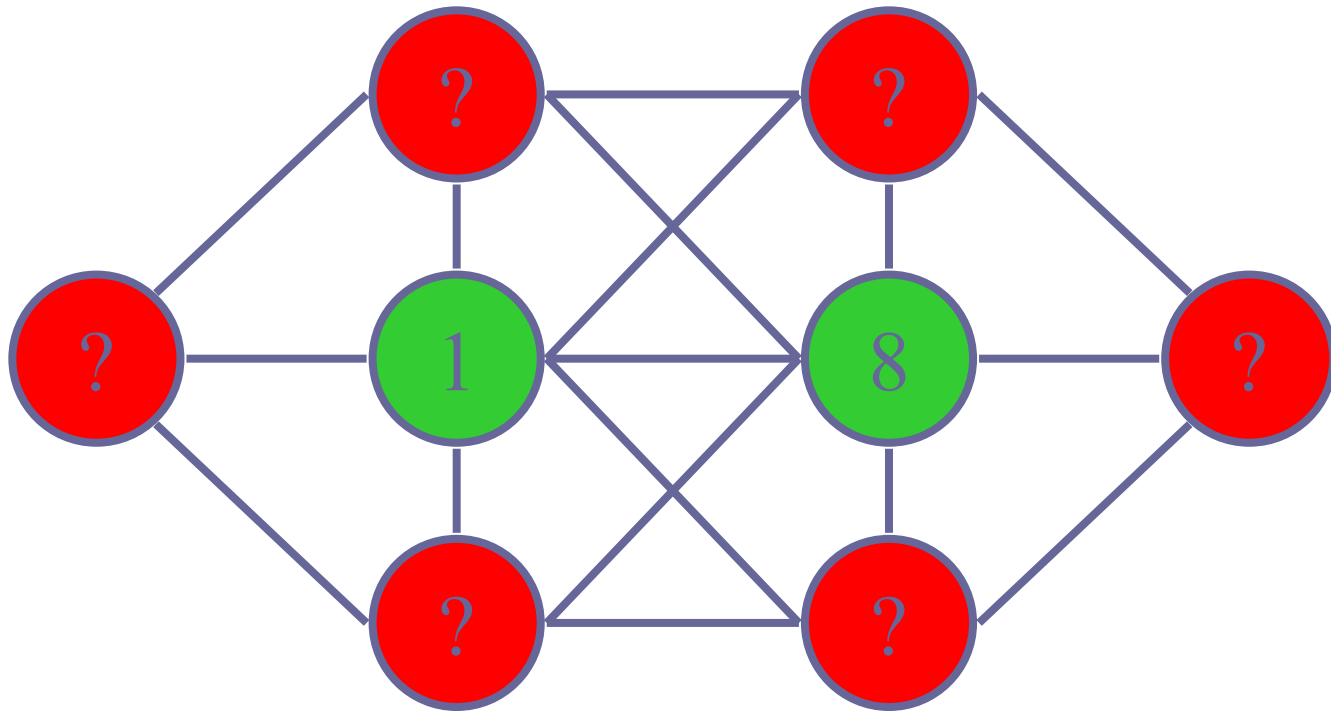
# Backtracking Search + Heuristics

- Guess a value for a variable!
  - We start with the hardest variables.



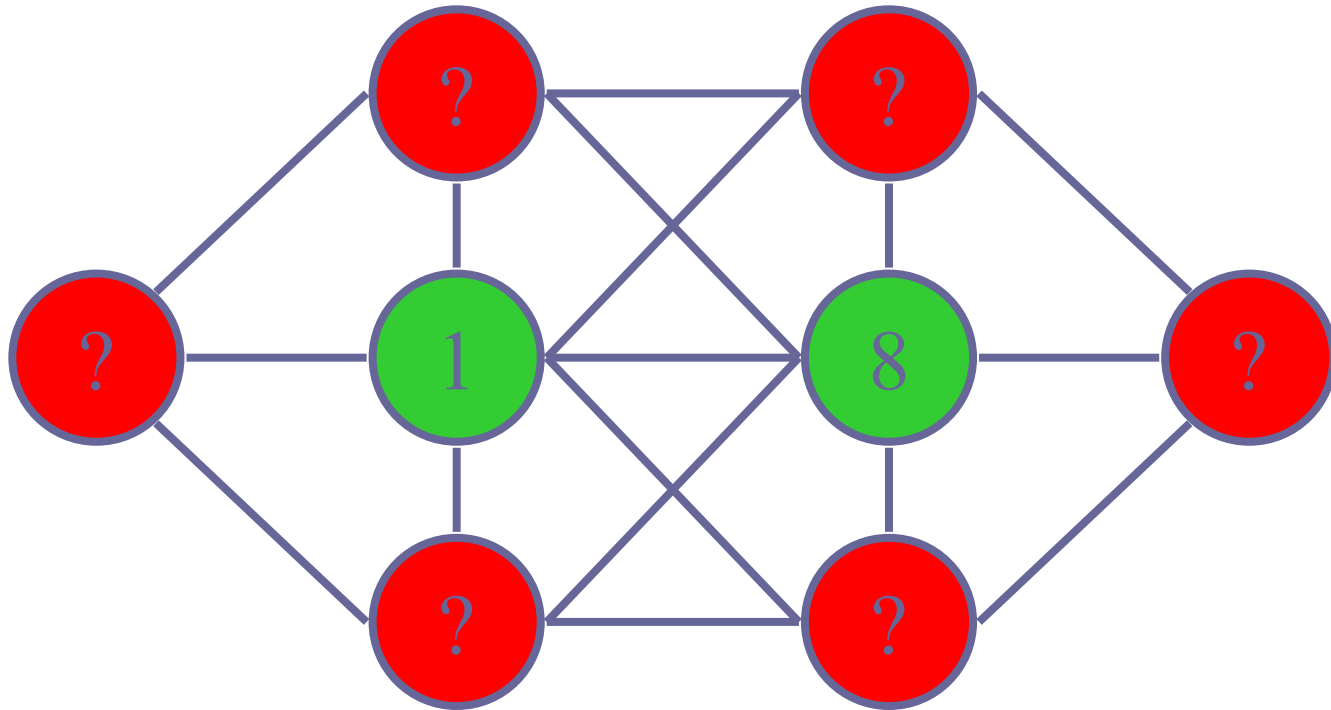
# Backtracking Search + Heuristics

- Guess a value for a variable!
  - We assign them the safest values.

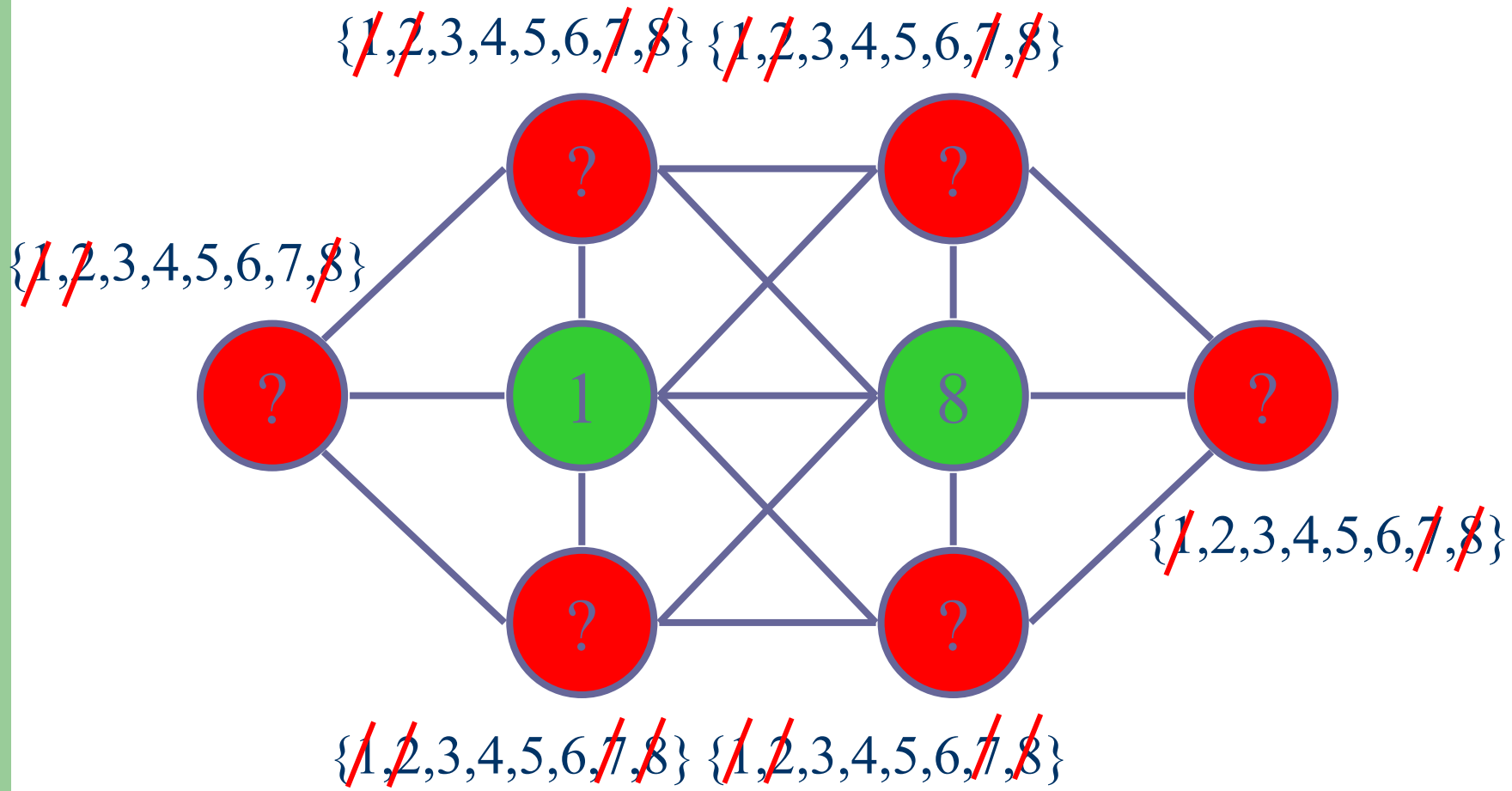


# Propagation

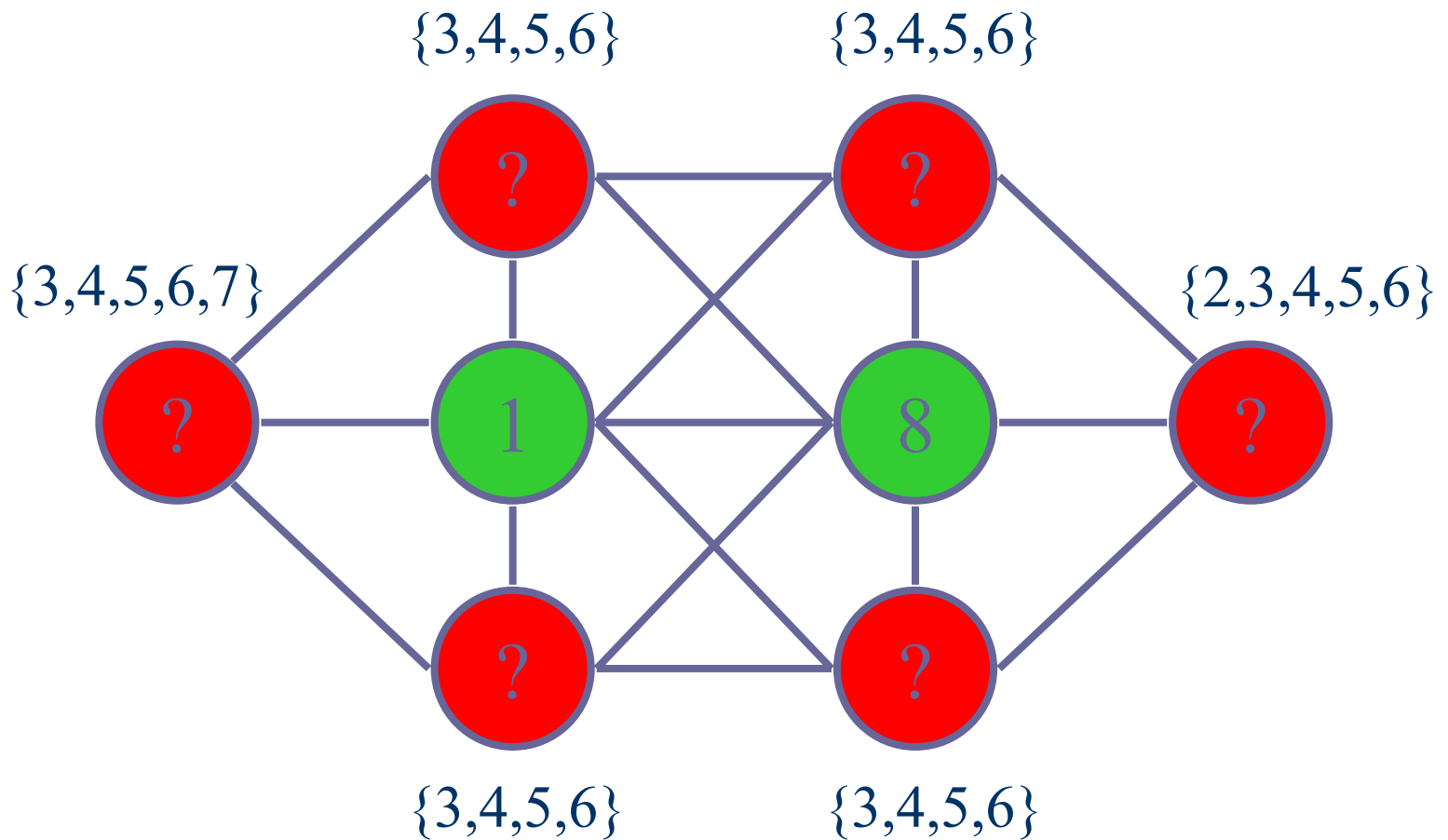
- We now examine the constraints.



# Propagation



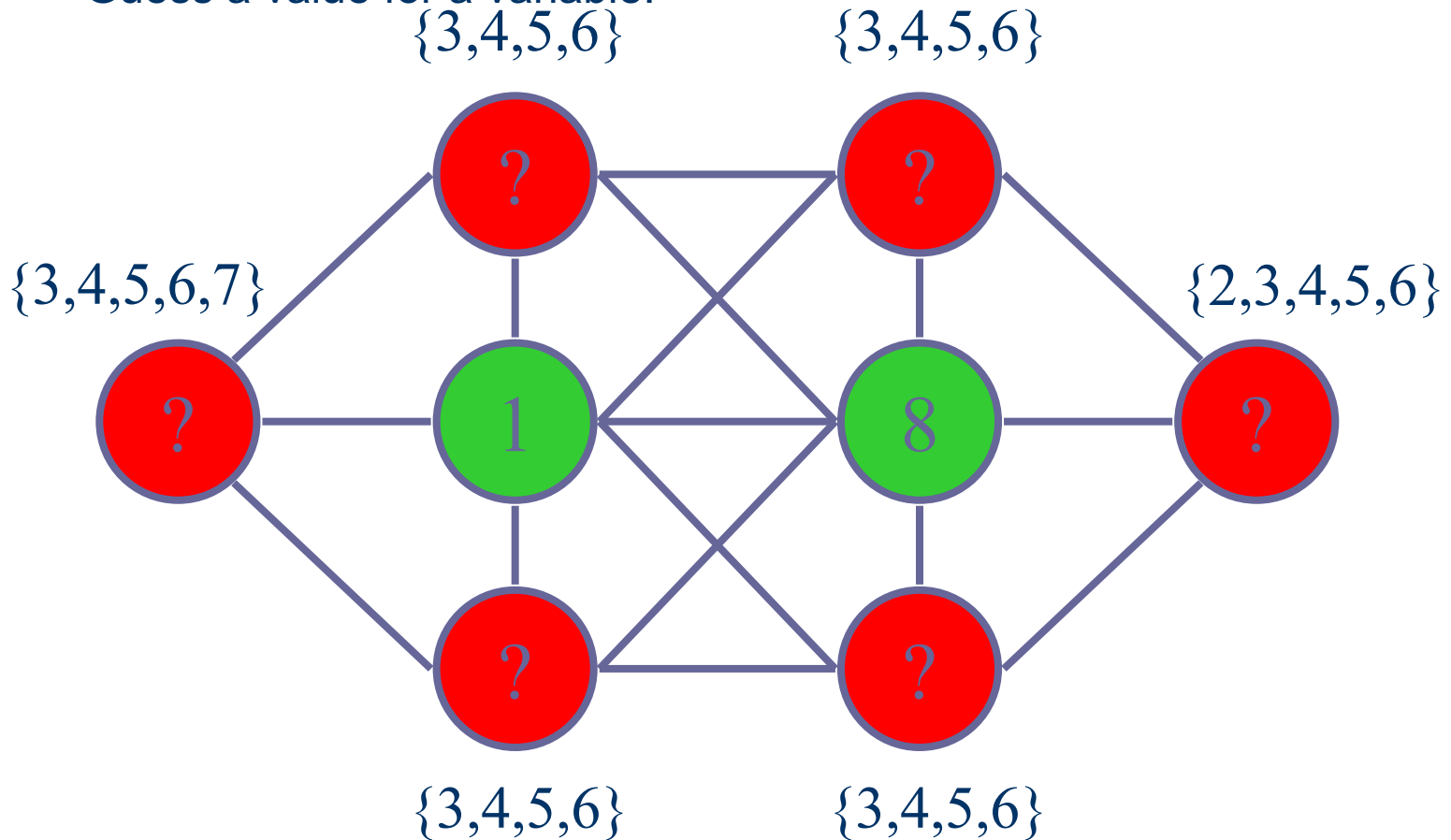
# Propagation





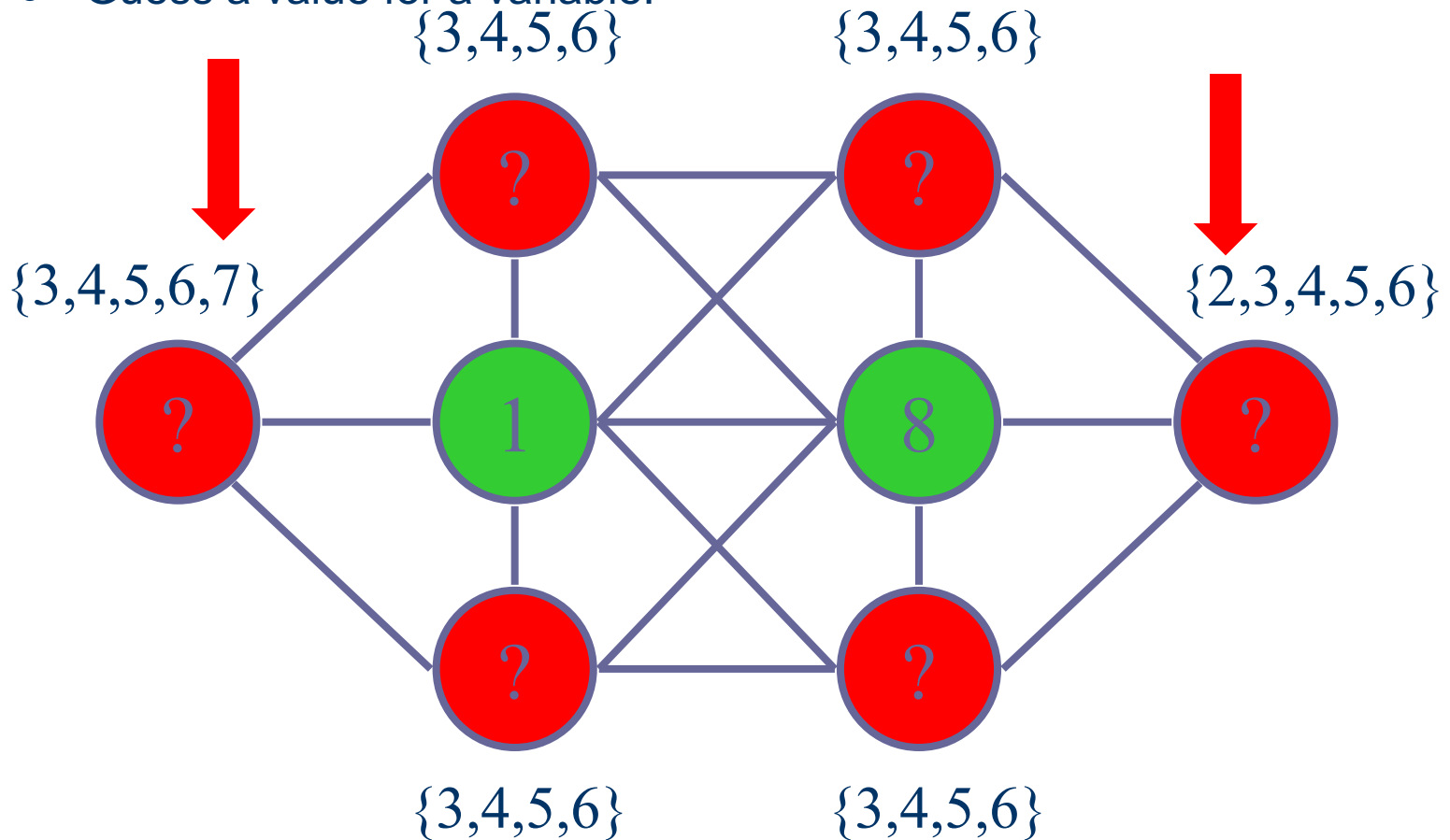
# Backtracking Search + Heuristics

- Guess a value for a variable!

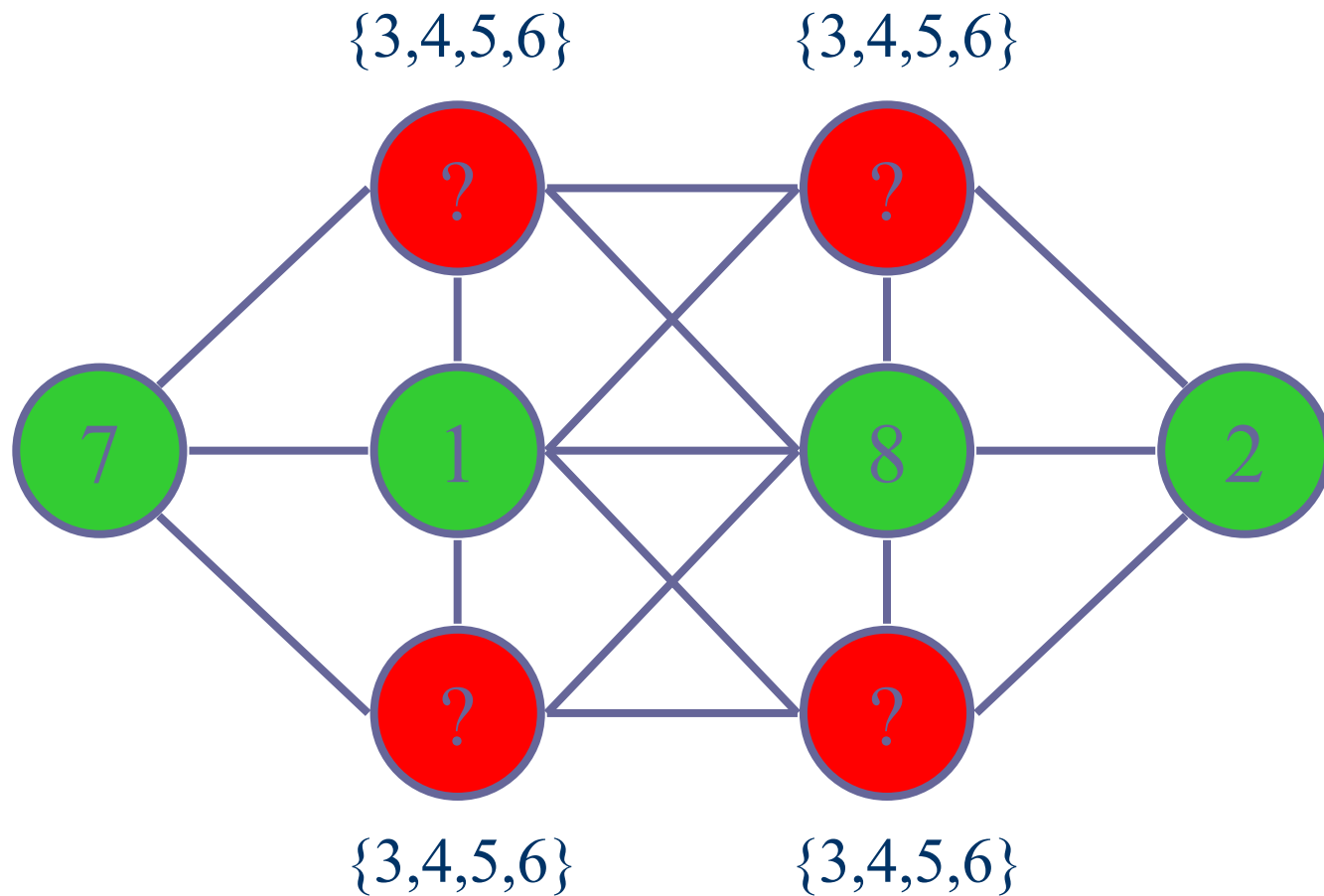


# Backtracking Search + Heuristics

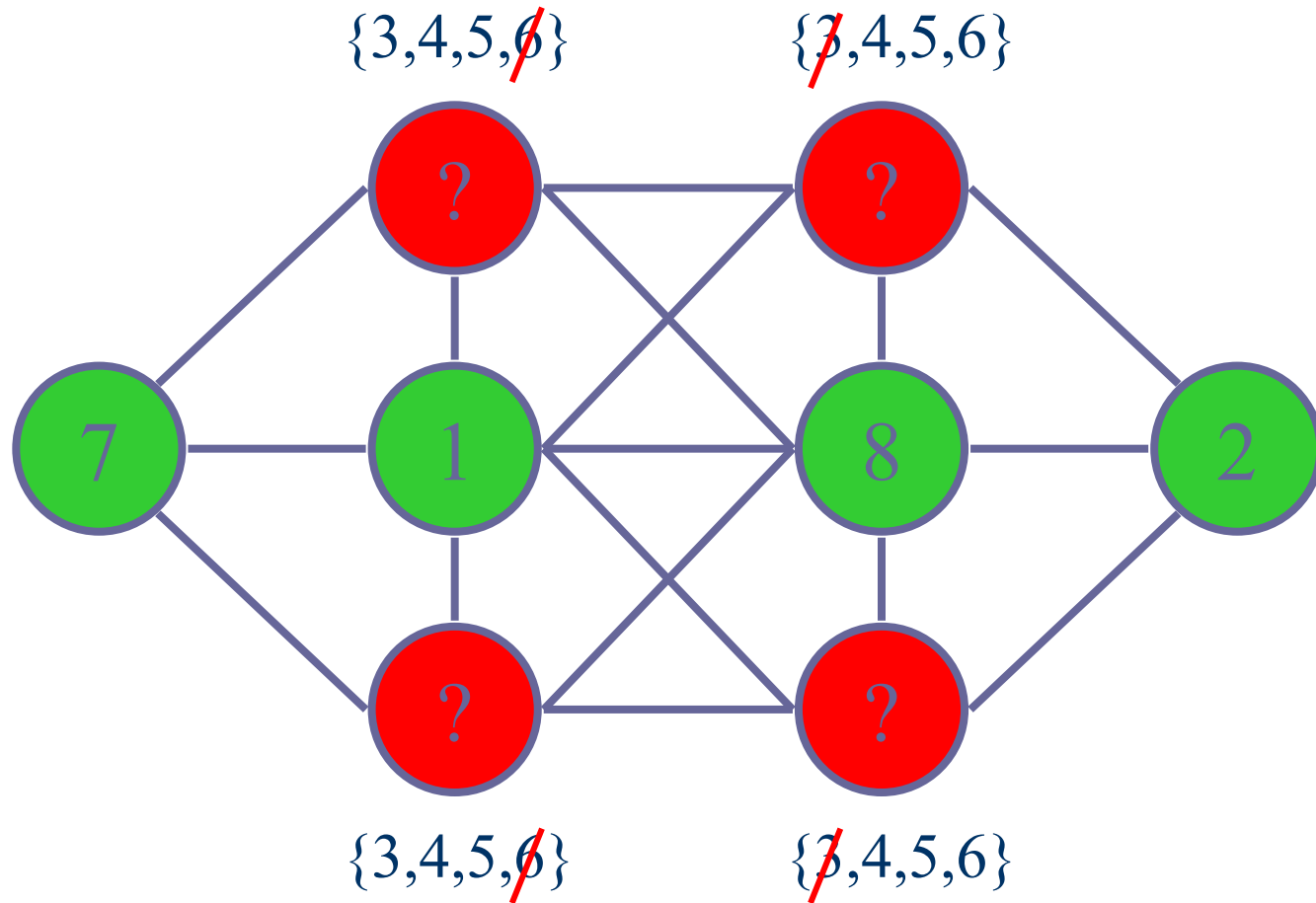
- Guess a value for a variable!



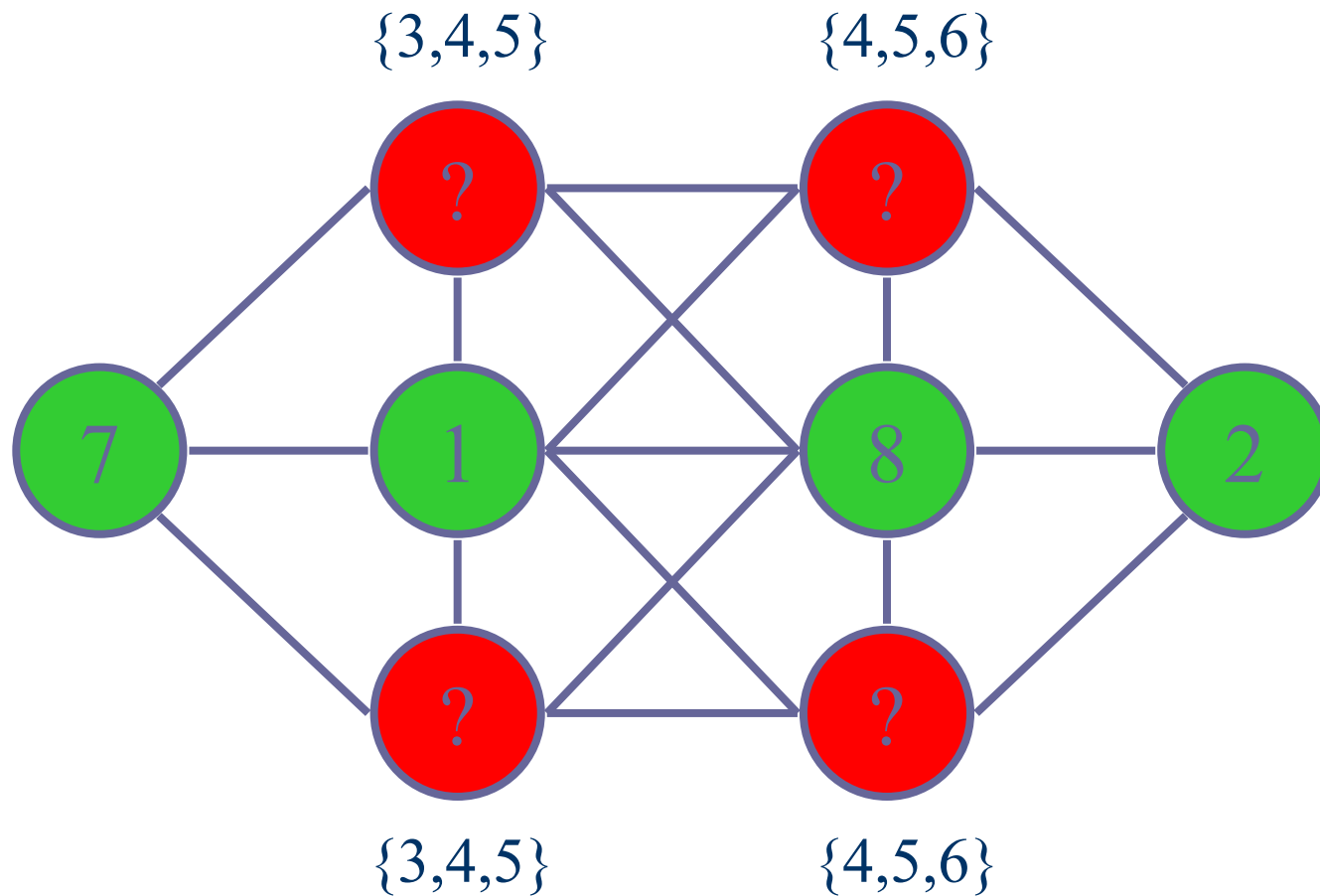
# Backtracking Search + Heuristics



# Propagation

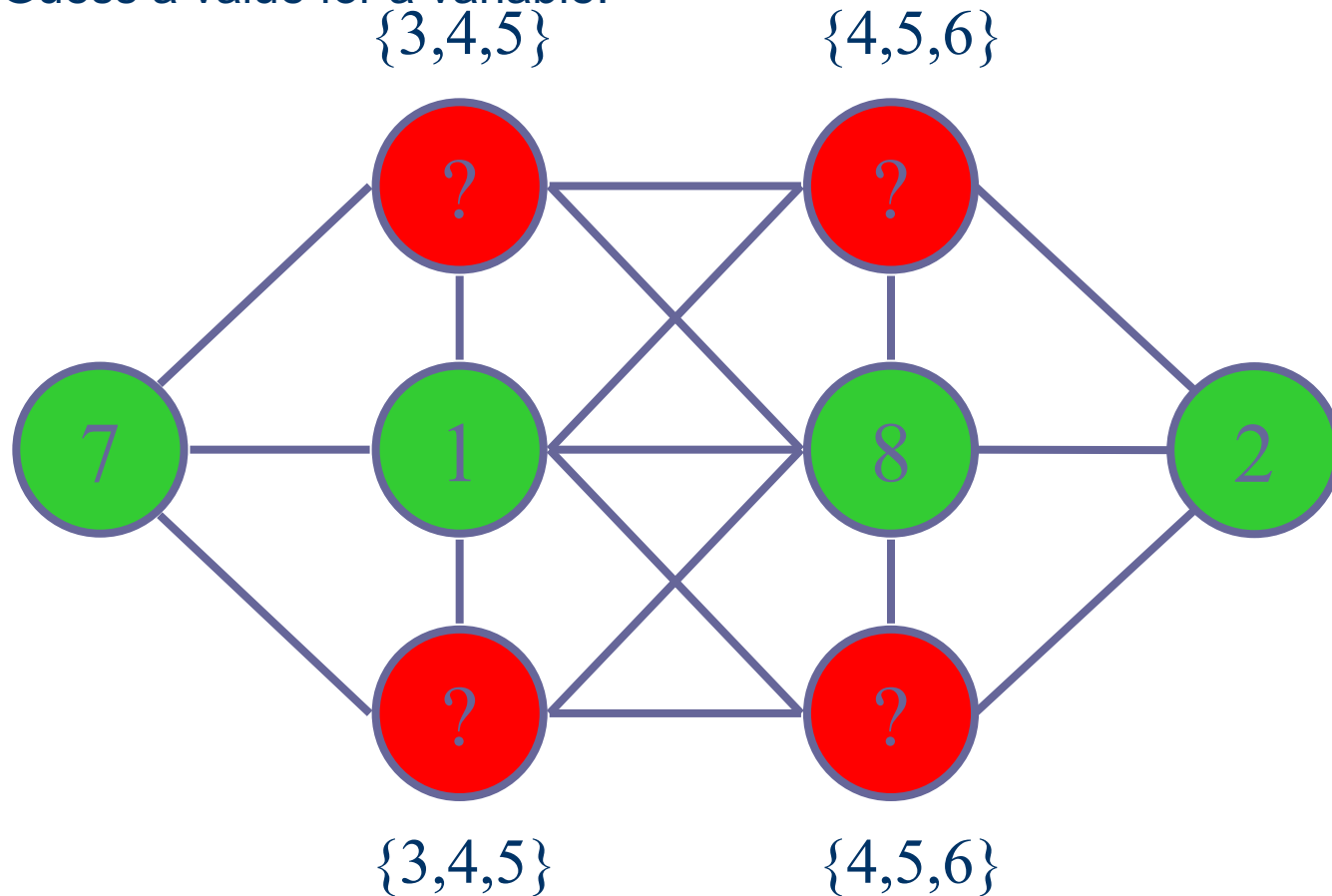


# Propagation

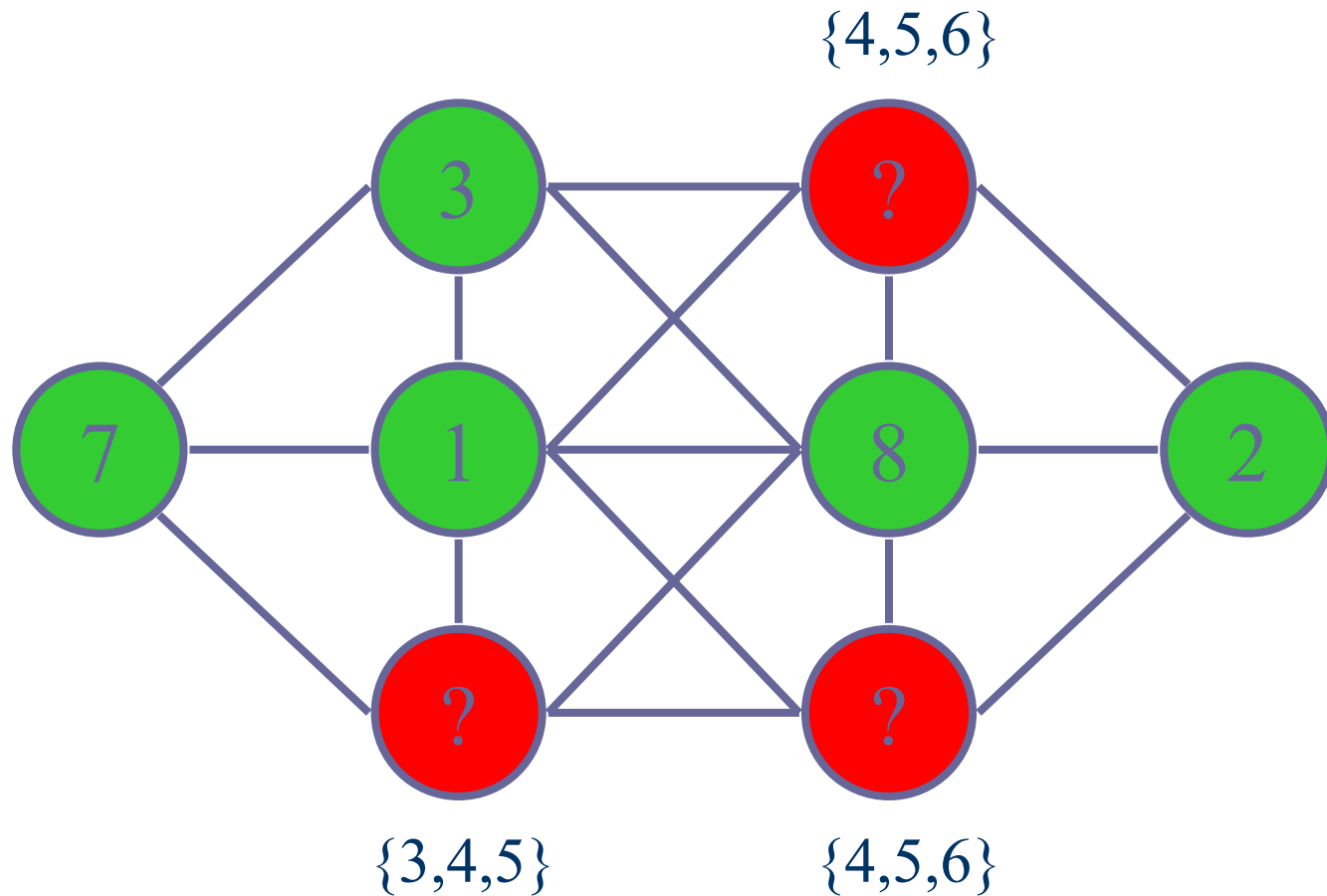


# Backtracking Search + Heuristics

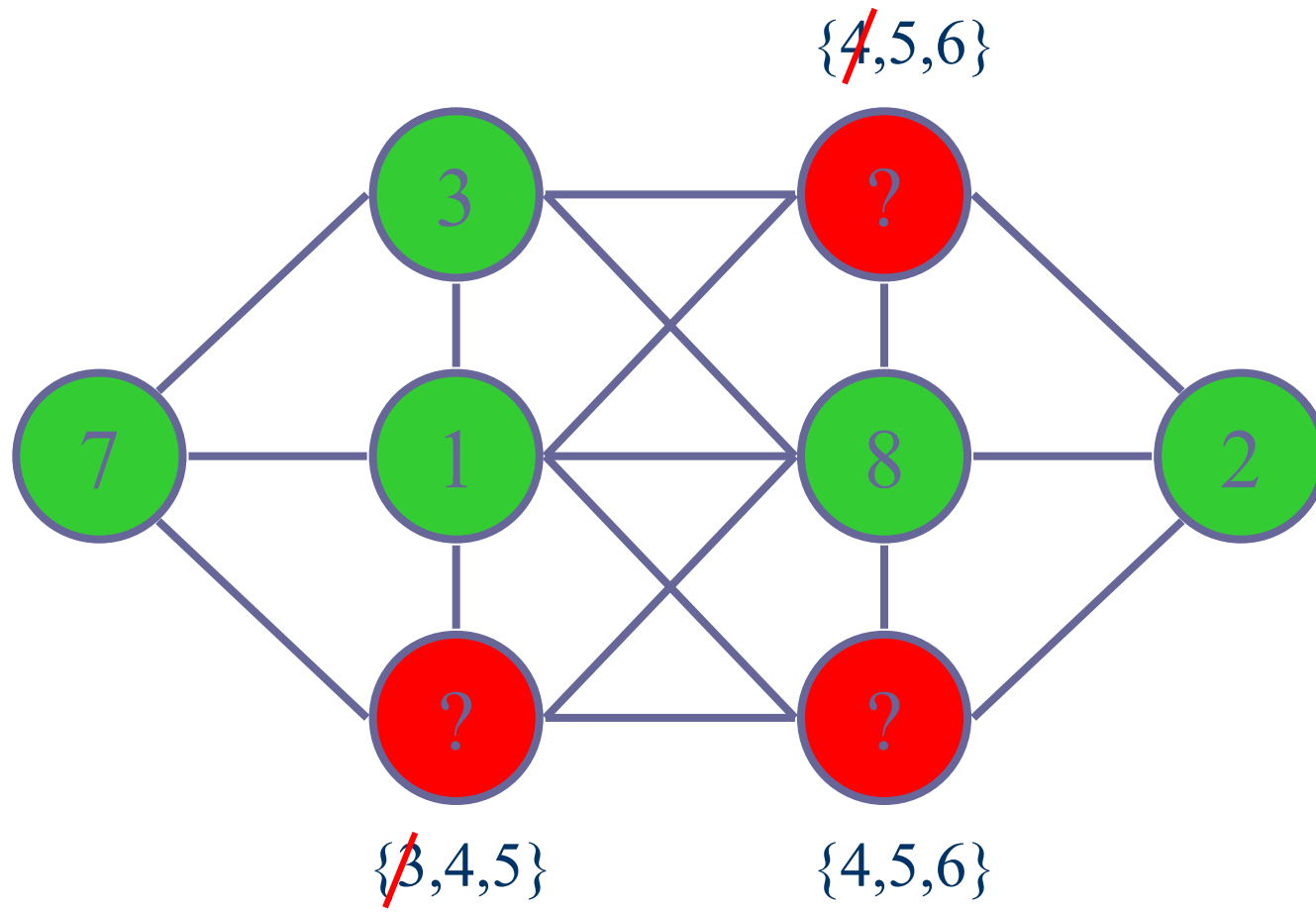
- Guess a value for a variable!



# Backtracking Search + Heuristics

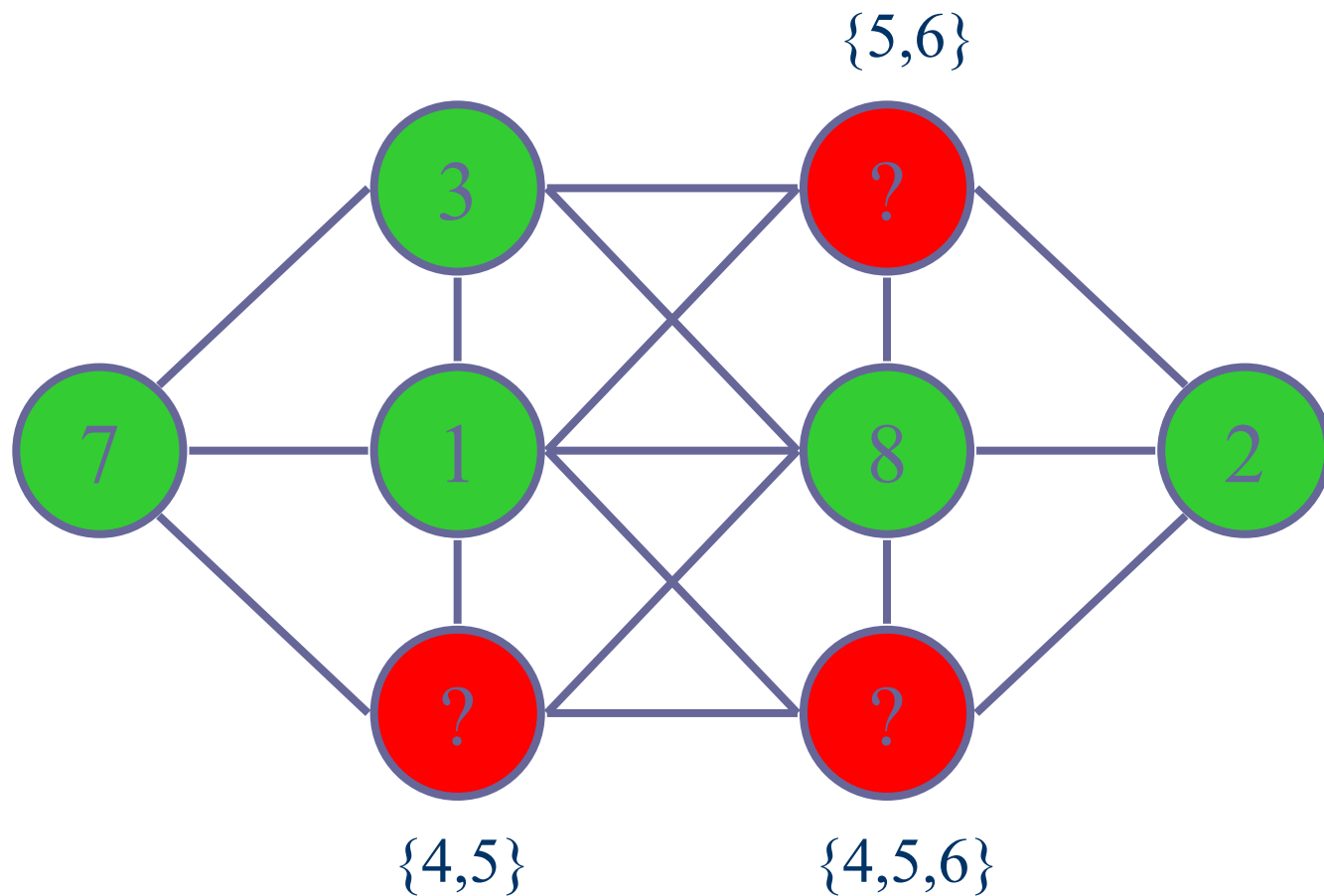


# Propagation



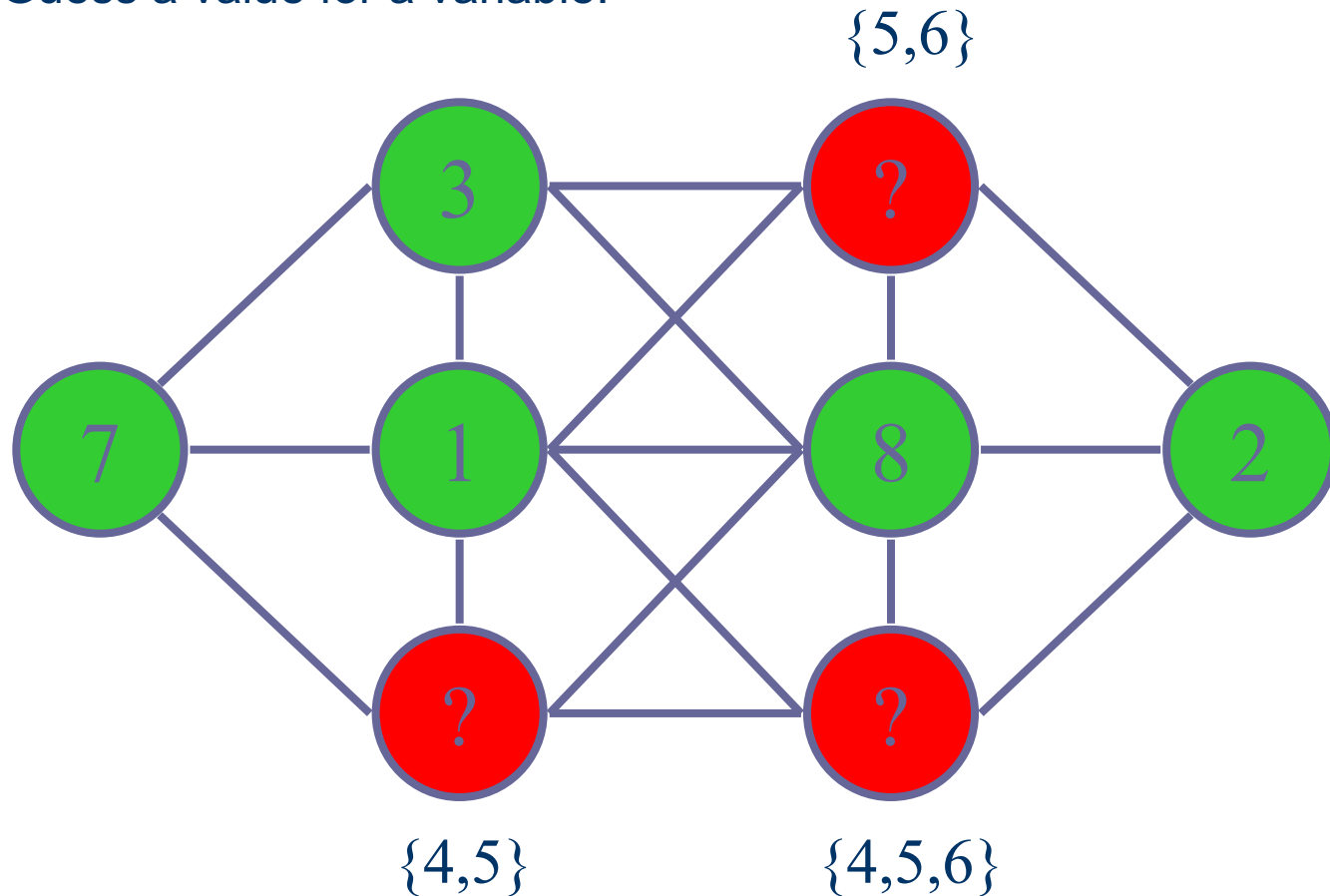


# Propagation

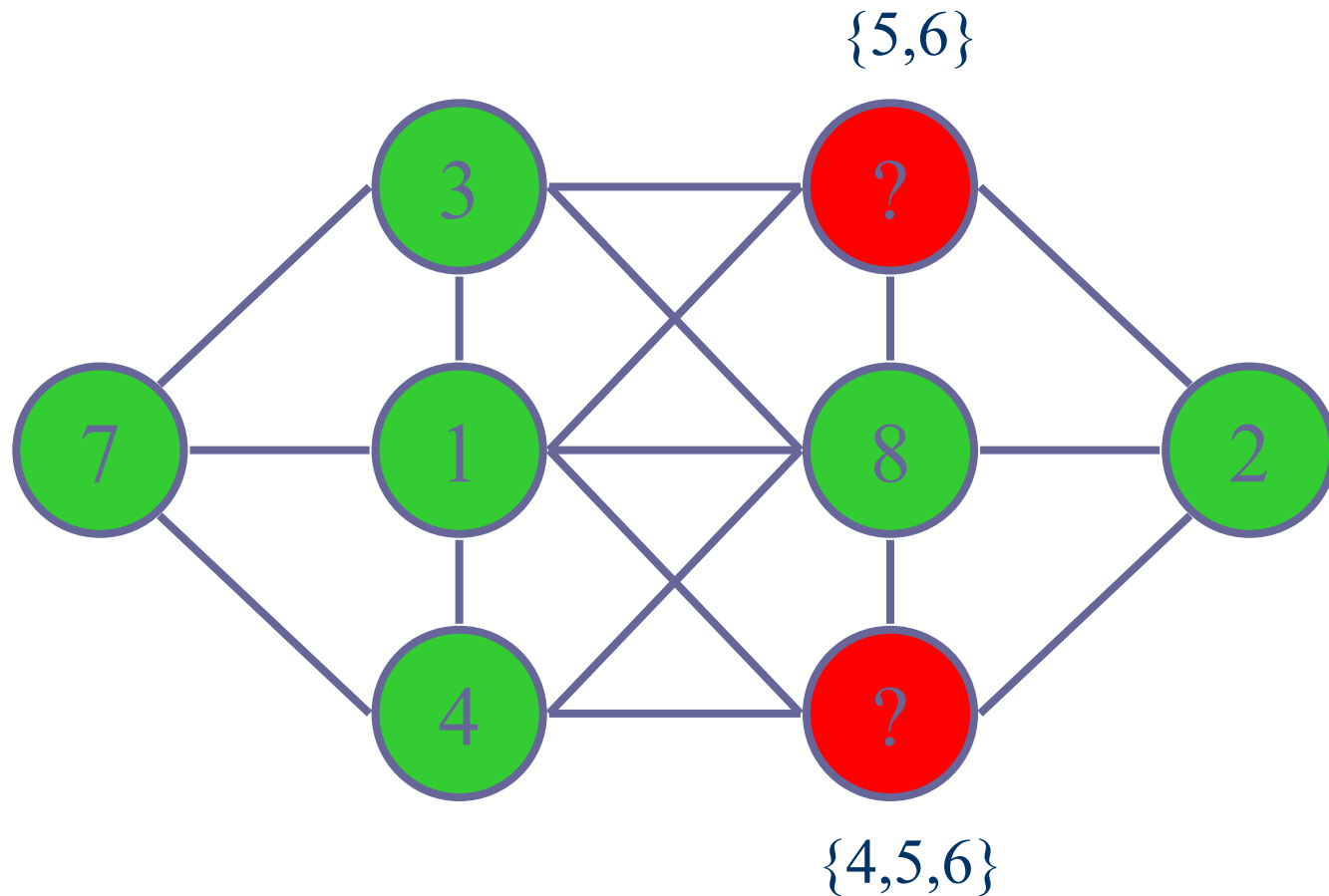


# Backtracking Search + Heuristics

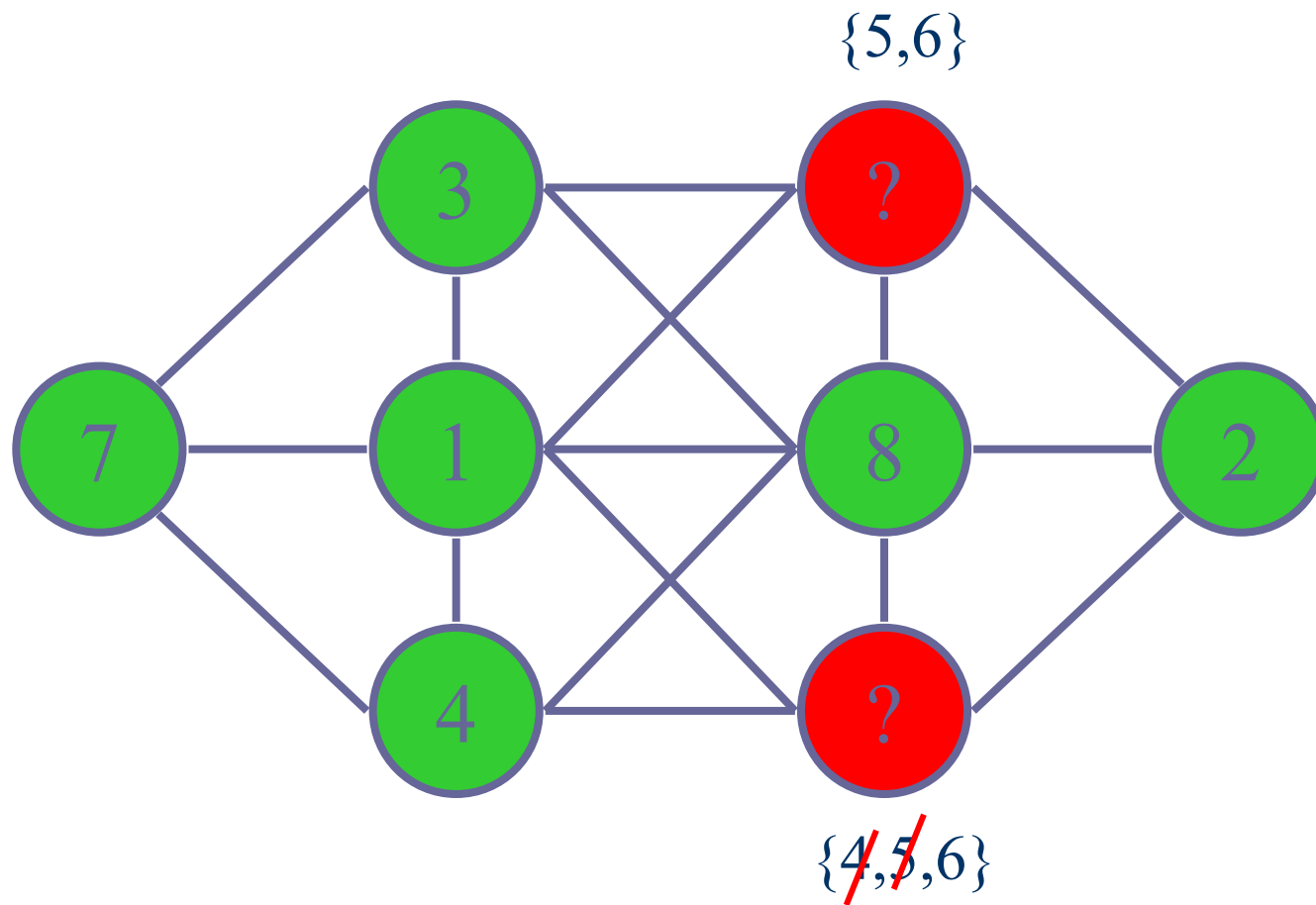
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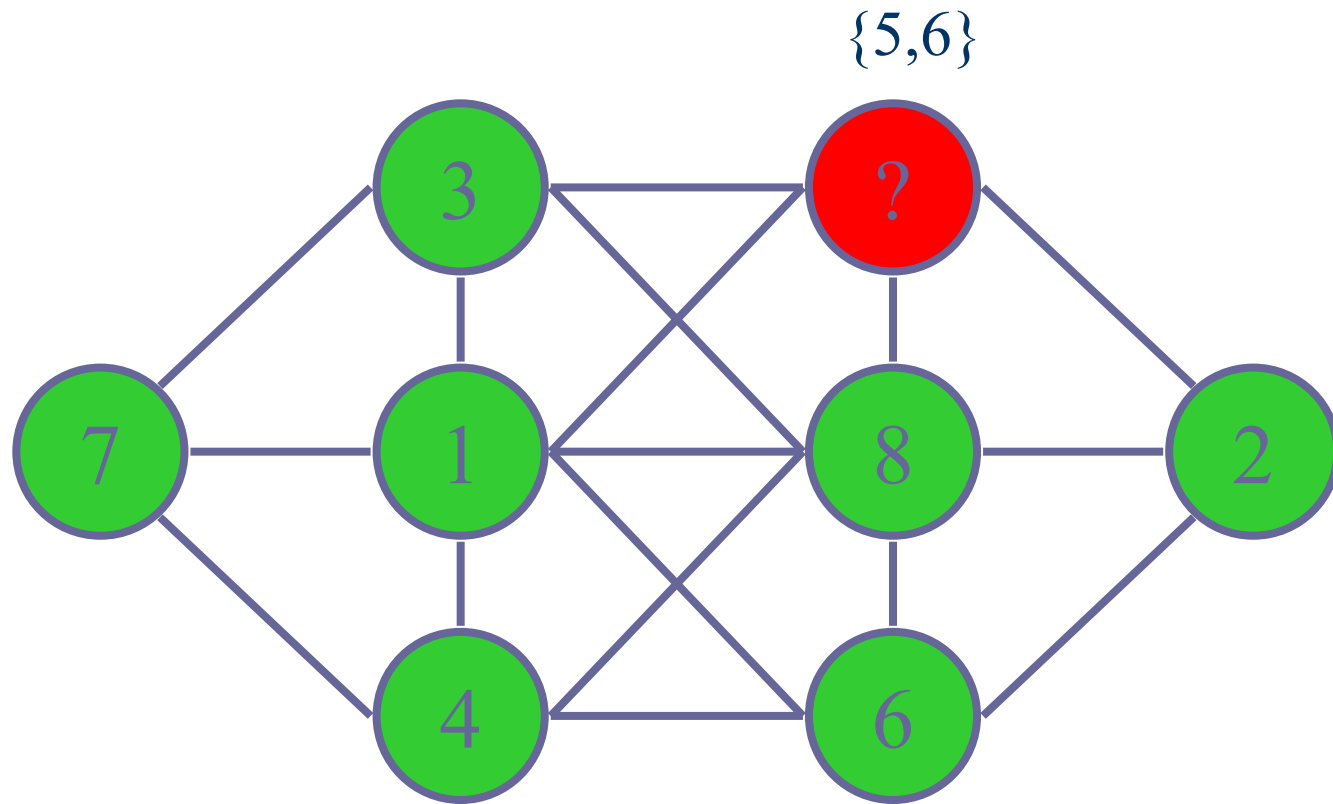
# Backtracking Search + Heuristics



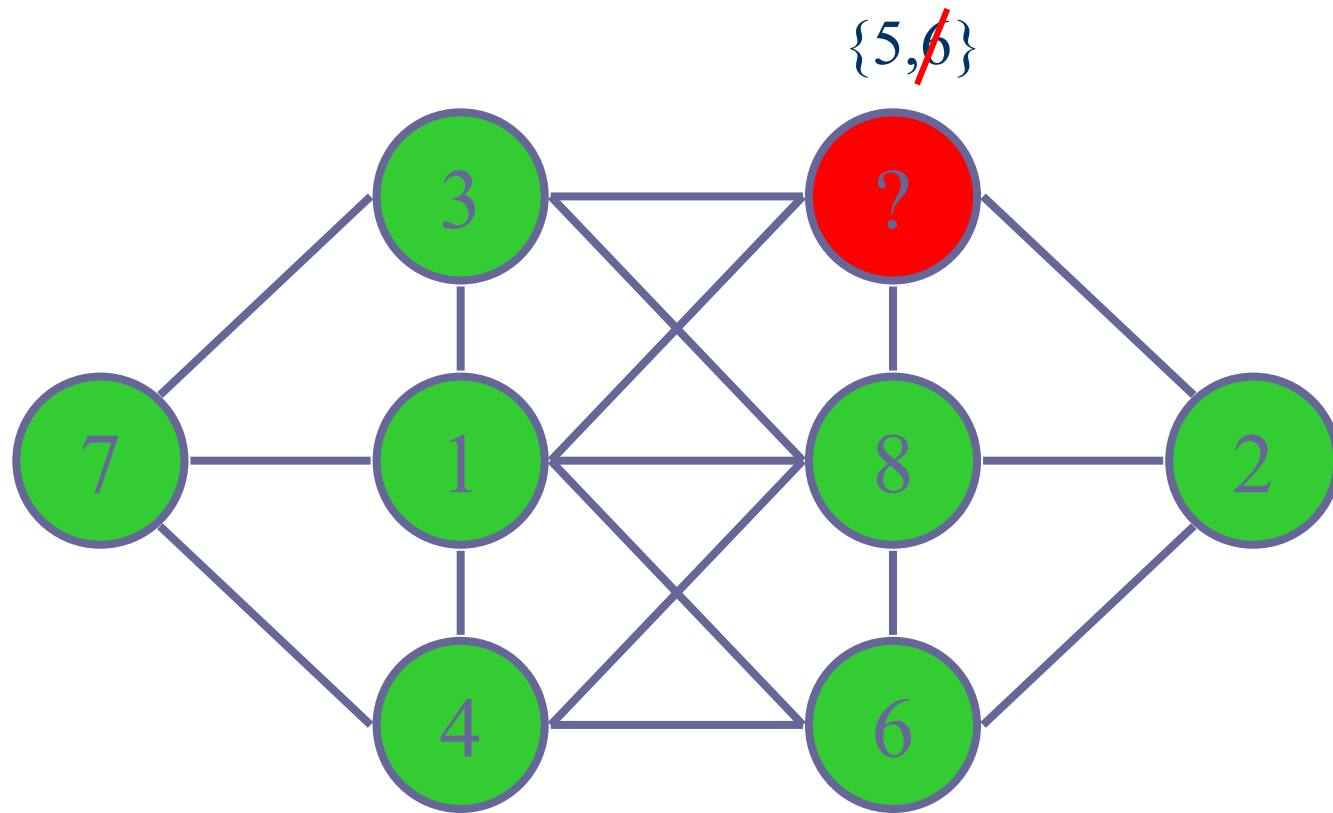
# Propagation



# Propagation

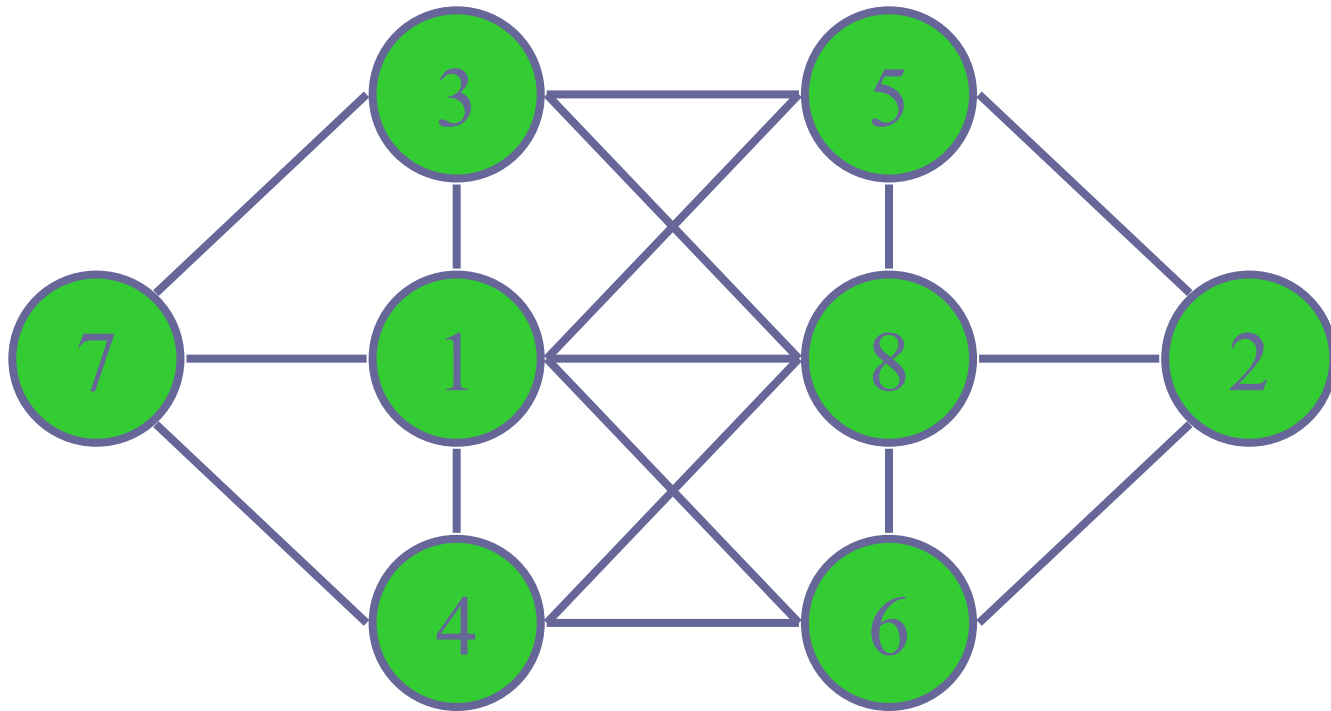


# Propagation

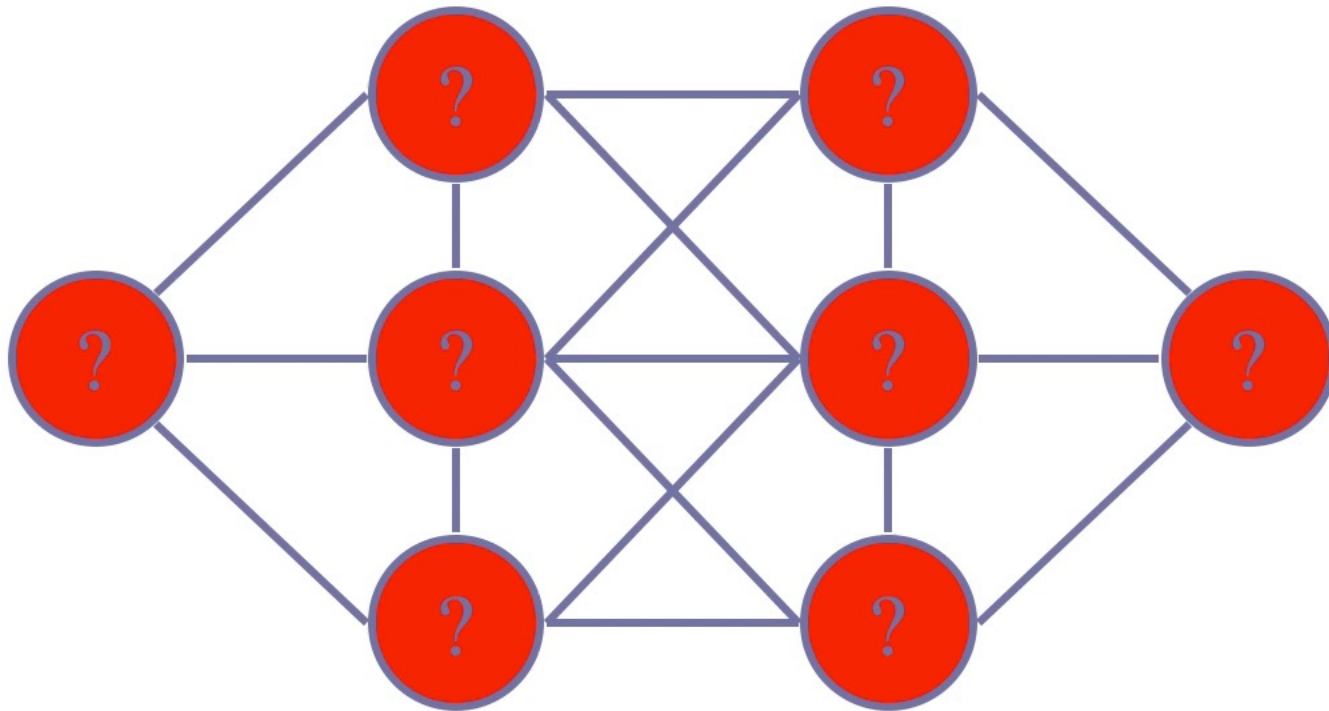


# Solution

- 8 guesses, without any backtracking!



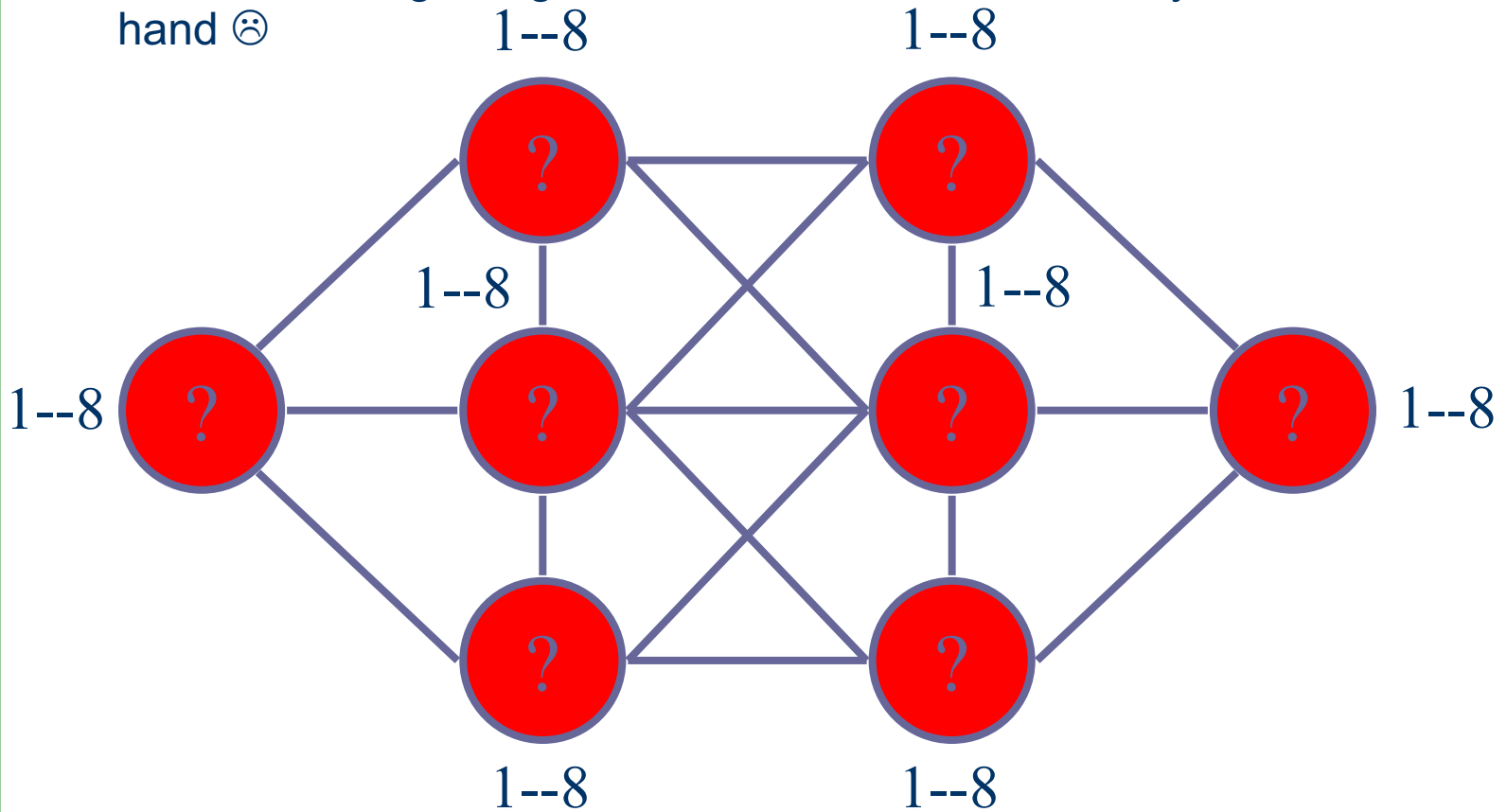
# Backtracking Search without Heuristics





# Backtracking

- Back to the beginning after 45 backtracks without any solution at hand 😞

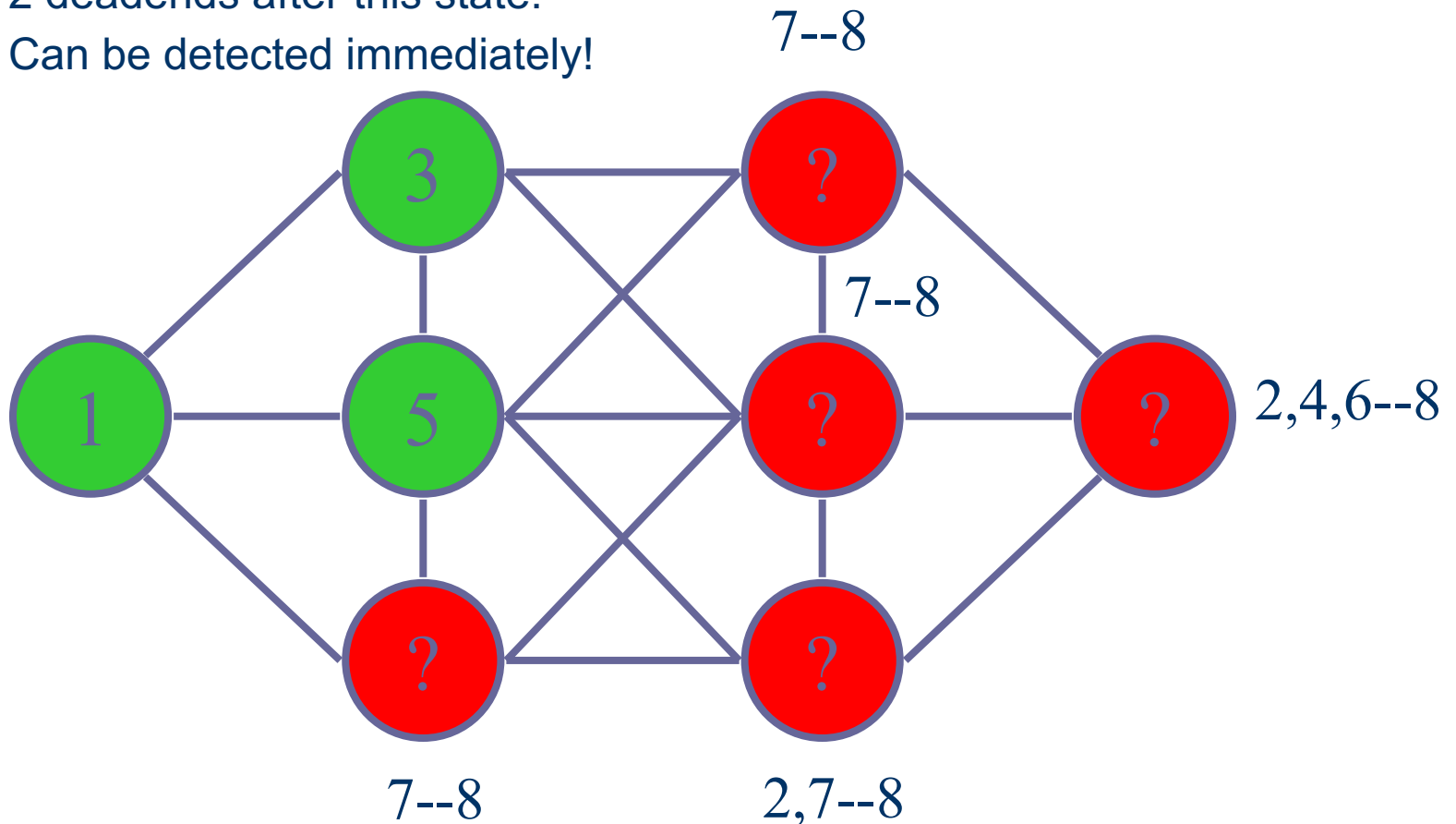


# What's going on?

- Bad choice of variables, bad assignment of values.
  - Good heuristic choice is very important!
- Good heuristics are always possible?
  - Yes and no 🤔
- What can we do then?
  - Apply stronger form of propagation during search!

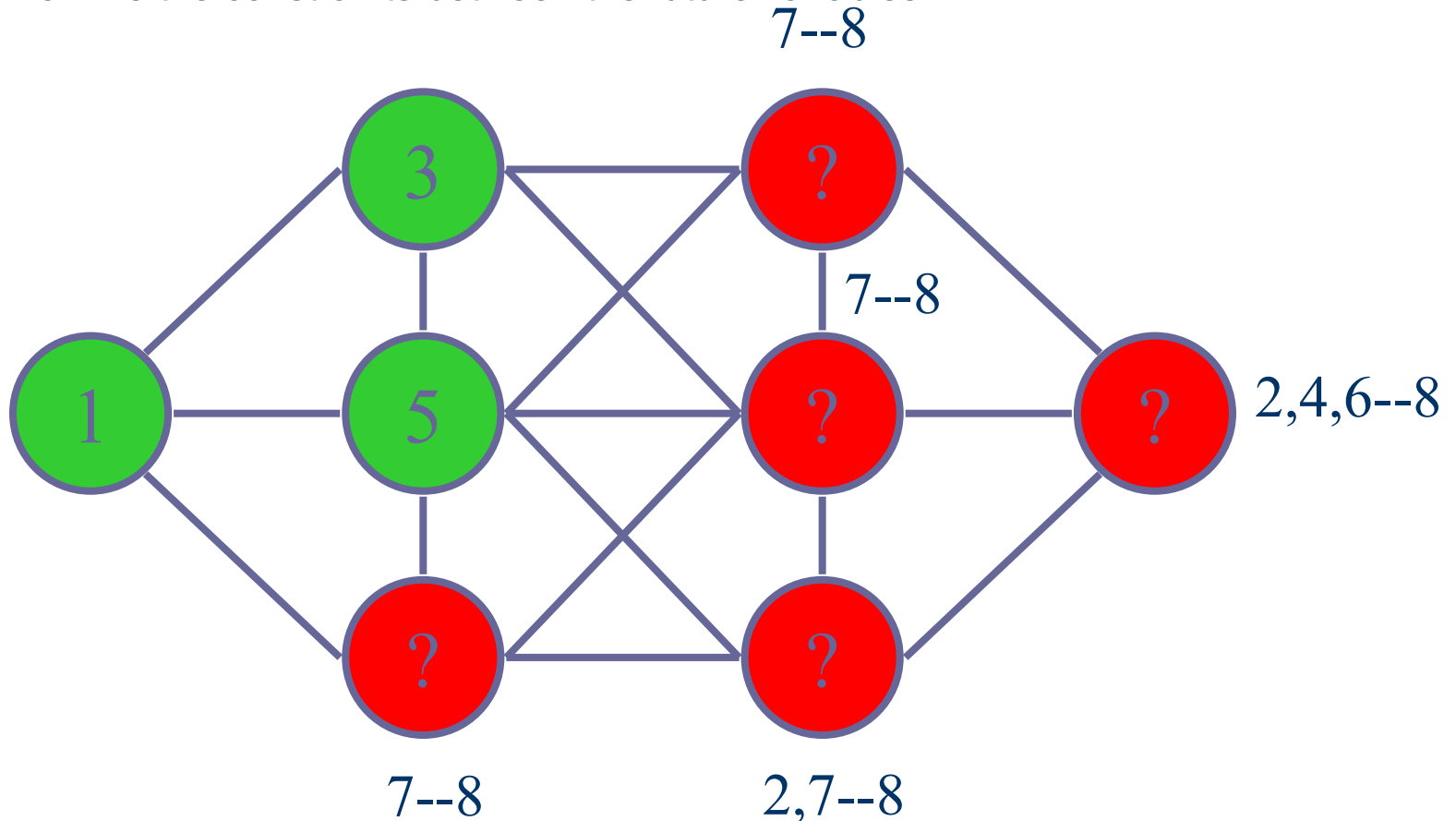
# A State During Search

- 2 deadends after this state.
- Can be detected immediately!



# A State During Search

- Examine the constraints between the future variables.

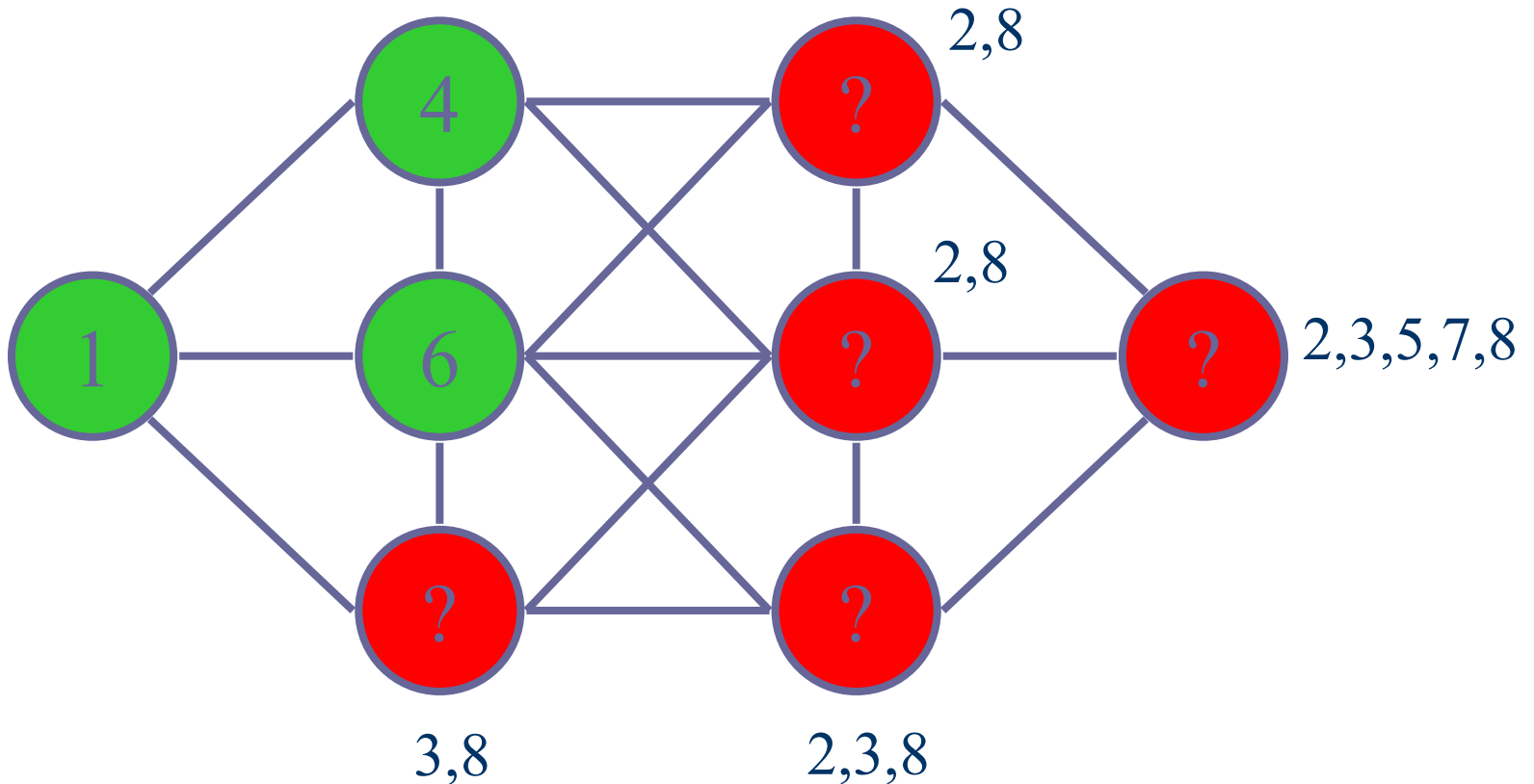


# What's going on?

- Bad choice of variables, bad assignment of values.
  - Good heuristic choice is very important!
- Good heuristics are always possible?
  - Yes and no 🙄
- What can we do then?
  - Apply stronger form of propagation during search!
- Is that all?
  - Better modelling can result in stronger form of propagation.

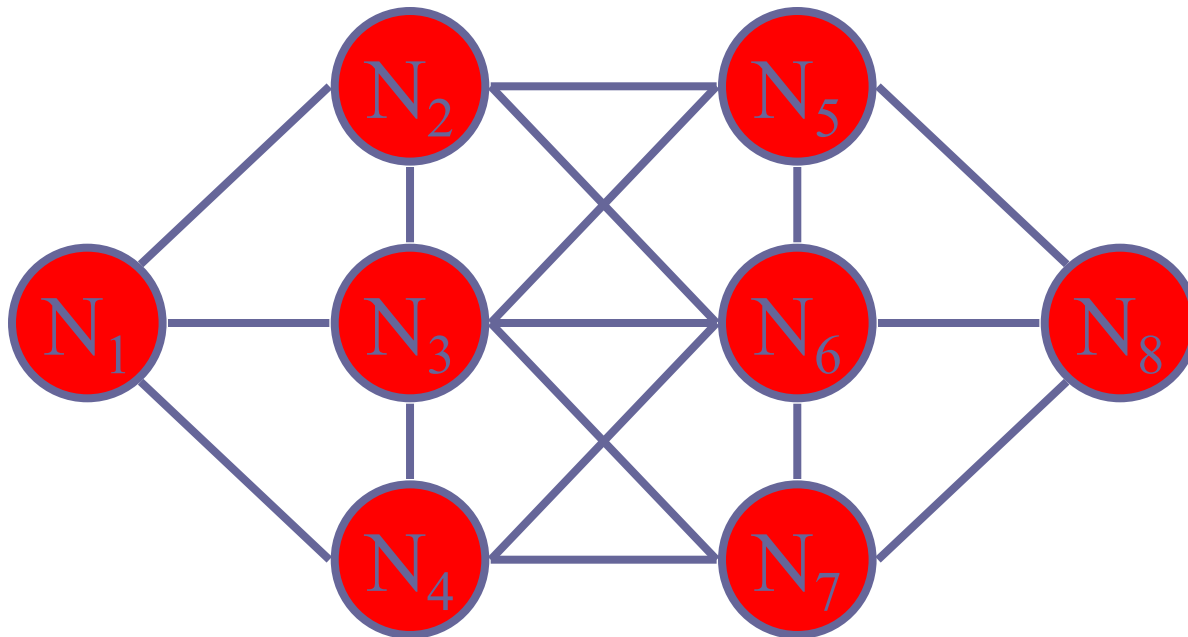
# Another State

- Cannot detect the inconsistency of  $N_3 = 6$ .
  - Future variables are fine wrt the constraints.



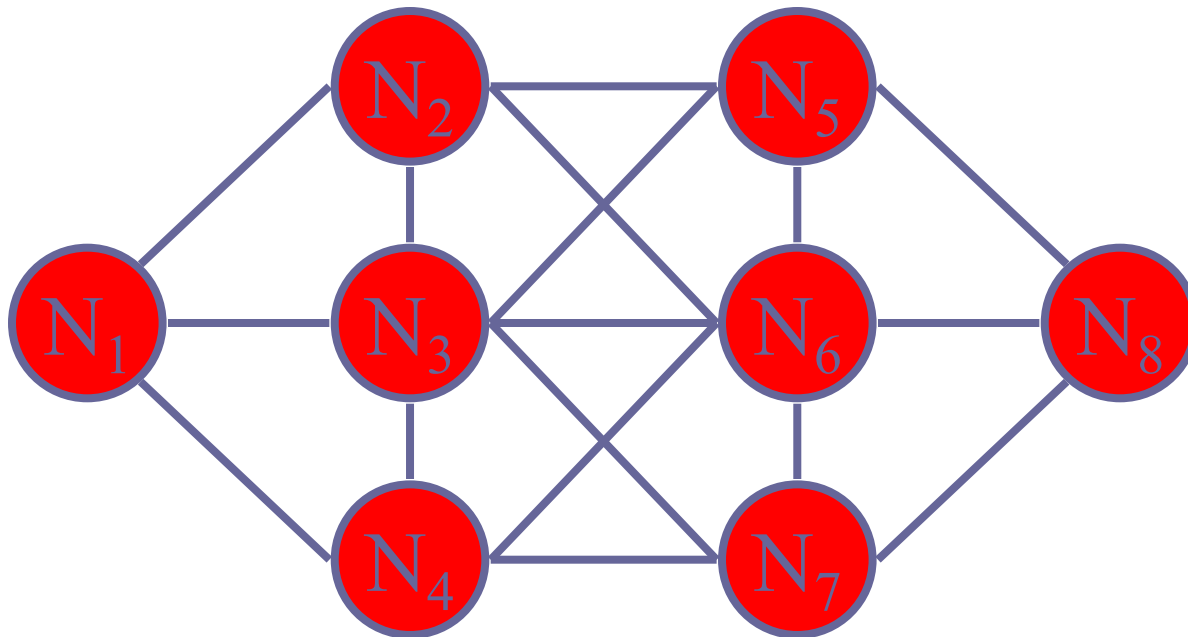
# Initial Model

- Constraints:
  - for all  $i < j$  s.t.  $N_i$  and  $N_j$  are adjacent  $|N_i - N_j| > 1$
  - for all  $i < j$   $N_i \neq N_j$



# Better Model

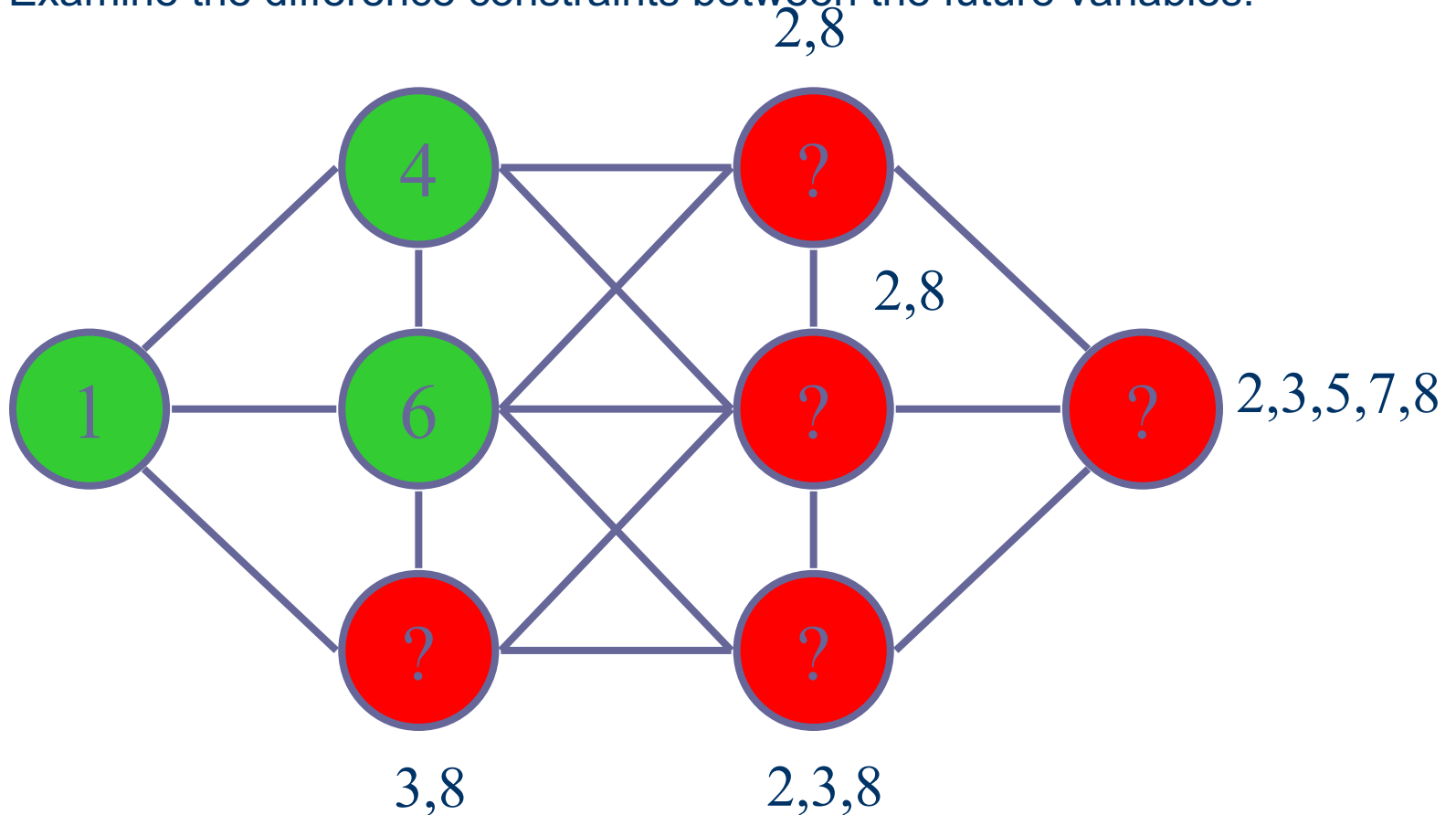
- Constraints:
  - for all  $i < j$  s.t.  $N_i$  and  $N_j$  are adjacent  $|N_i - N_j| > 1$
  - **alldifferent**( $[N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8]$ )





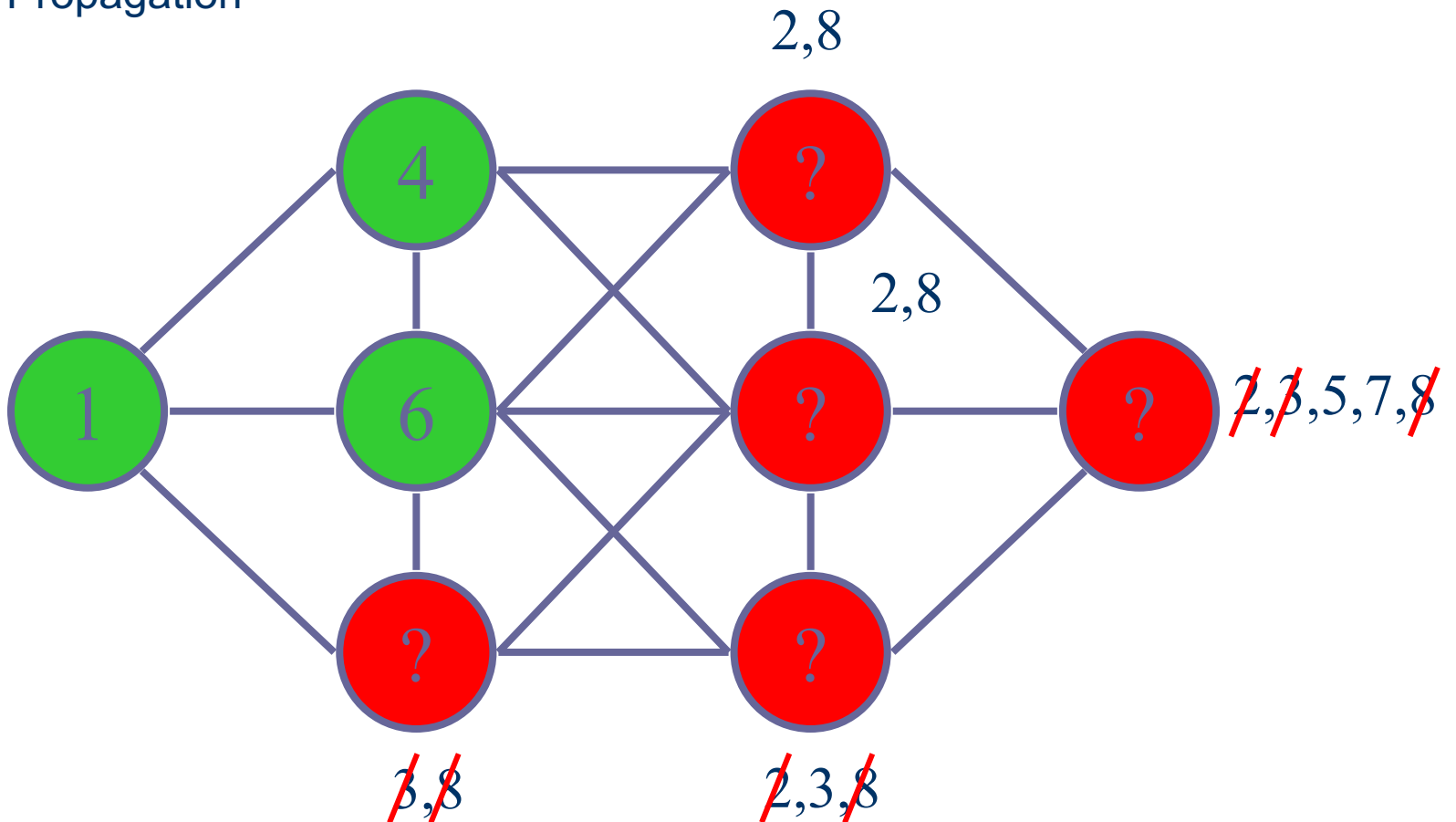
# Another State

- Examine the difference constraints between the future variables.



# Another State

- Propagation



# Constraint Programming

- For an efficient CP solving, we need:
  - effective propagation algorithms;
  - a model with effectively propagating constraints;
  - effective search algorithm and heuristics.
- **Attention!**
  - Intelligent reasoning comes with a cost.
  - Need a good balance.

# Constraint Programming

- Declarative programming, as in **ILP**:
  - the user models the problem;
  - an underlying search-based solver returns a solution.
- Computer programming:
  - the user needs to program a strategy to search for a solution:
    - search algorithm, heuristics, ...
  - otherwise, solving process can be inefficient.

# Examples from MiniZinc



# Map Coloring

- What is the minimum number of colors needed to color the map?



# Map Coloring

```
1 % number of colours available
2 int: nc = 6;
3
4 % variables mapping states to colours
5 var 1..nc: wa; var 1..nc: nt;
6 var 1..nc: sa; var 1..nc: q;
7 var 1..nc: nsw; var 1..nc: v;
8 var 1..nc: t;
9
10 % adjacent states have different
11 % colours
12
13 constraint wa != nt;
14 constraint wa != sa;
15 constraint nt != sa;
16 constraint nt != q;
17 constraint sa != q;
18 constraint sa != nsw;
19 constraint sa != v;
20 constraint q != nsw;
21 constraint nsw != v;
22
23 % minimize the total number of colours used
24 solve minimize max([wa,nt,sa,q,nsw,v,t]);
```



Data



Variables & domains



Constraints



Search & objective

# Crypto Arithmetic

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

$$\begin{array}{r} \text{MINI} \\ + \text{ZINC} \\ \hline = \text{ROCKZ} \end{array}$$



# SEND + MORE = MONEY

```
1 include "alldifferent.mzn";
2
3 %variables for the digits
4 var 1..9: S;
5 var 0..9: E;
6 var 0..9: N;
7 var 0..9: D;
8 var 1..9: M;
9 var 0..9: O;
10 var 0..9: R;
11 var 0..9: Y;
12
13 constraint          1000 * S + 100 * E + 10 * N + D
14                   + 1000 * M + 100 * O + 10 * R + E
15   = 10000 * M + 1000 * O + 100 * N + 10 * E + Y;
16
17 constraint alldifferent([S,E,N,D,M,O,R,Y]);
18
19 solve satisfy;
20
21 output ["  \ (S)\ (E)\ (N)\ (D)\n",
22         "+  \ (M)\ (O)\ (R)\ (E)\n",
23         "= \ (M)\ (O)\ (N)\ (E)\ (Y)\n"];
24
```



Variables  
& domains



Constraints



Search

# SEND + MORE = MONEY

```
1 include "alldifferent.mzn";
2
3 %variables for the digits
4 var 1..9: S;
5 var 0..9: E;
6 var 0..9: N;
7 var 0..9: D;
8 var 1..9: M;
9 var 0..9: O;
10 var 0..9: R;
11 var 0..9: Y;
12
13 constraint
14     1000 * S + 100 * E + 10 * N + D
15     + 1000 * M + 100 * O + 10 * R + E
16     = 10000 * M + 1000 * O + 100 * N + 10 * E + Y;
17 constraint alldifferent([S,E,N,D,M,O,R,Y]);
18
19 solve satisfy;
20
21 output ["  \ (S)\ (E)\ (N)\ (D)\ \n",
22         "+  \ (M)\ (O)\ (R)\ (E)\ \n",
23         "= \ (M)\ (O)\ (N)\ (E)\ (Y)\ \n"];
24
```

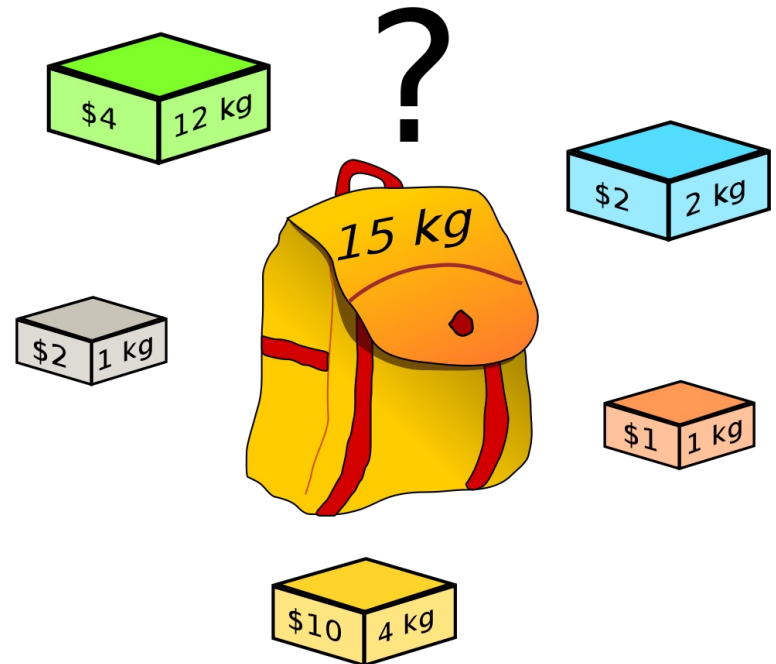
← Variables  
& domains

← Constraints

← Search

# Knapsack

- Given items, each with a weight and a value, determine which item and how many of it to pack in your knapsack without exceeding its capacity while maximizing your profit?



# Knapsack

```
1 enum ITEM; %a set of items to pack
2 int: capacity; %knapsack capacity
3
4 array[ITEM] of int: profits; %item profits
5 array[ITEM] of int: weights; %item weights
6
7 array[ITEM] of var 0..1: knapsack; % a Bool. variable
8                               % for each item
9 var int: totalProfit; %objective function
10
11 constraint sum (i in ITEM) (weights[i]*knapsack[i]) <= capacity;
12 constraint totalProfit = sum (i in ITEM) (profits[i]*knapsack[i]);
13
14 solve maximize totalProfit;
15
16 output ["knapsack = \(knapsack)\n", "Total Profit = ", show(totalProfit)];
```



Data



Variables  
& domains



Cons.ts



Search &  
objective

# Knapsack

```
1 enum ITEM; %a set of items to pack
2 int: capacity; %knapsack capacity
3
4 array[ITEM] of int: profits; %item profits
5 array[ITEM] of int: weights; %item weights
6
7 array[ITEM] of var 0..1: knapsack; % a Bool. variable
8                               % for each item
9 var int: totalProfit; %objective function
10
11 constraint sum (i in ITEM) (weights[i]*knapsack[i]) <= capacity;
12 constraint totalProfit = sum (i in ITEM) (profits[i]*knapsack[i]);
13
14 solve maximize totalProfit;
15
16 output ["knapsack = \(knapsack)\n", "Total Profit = ", show(totalProfit)];
```



Data



Variables  
& domains



Cons.ts



Search &  
objective

# Task Assignment

```
1 int: n;  
2 set of int: WORK = 1..n;  
3 int: m;  
4 set of int: TASK = 1..m;  
5 array[WORK, TASK] of int: profit;  
6  
7 array[WORK] of var TASK: x;  
8 array[WORK] of var int: px =  
9     [ profit[w, x[w]] | w in WORK ];  
10 var int: obj = sum(w in WORK)(px[w]);  
11  
12 include "alldifferent.mzn";  
13 constraint alldifferent(x);  
14  
15 ann: varselect = largest;  
16 ann: valselect = indomain;  
17  
18 solve :: int_search(px, varselect, valselect, complete)  
19         maximize obj;  
20  
21 output ["obj = \(obj); x = \(x);\n"];
```



Data



Variables  
& domains



Constraints



Search &  
objective

# Task Assignment

```
1 int: n;  
2 set of int: WORK = 1..n;  
3 int: m;  
4 set of int: TASK = 1..m;  
5 array[WORK, TASK] of int: profit;  
6  
7 array[WORK] of var TASK: x;  
8 array[WORK] of var int: px =  
9     [ profit[w, x[w]] | w in WORK ];  
10 var int: obj = sum(w in WORK)(px[w]);  
11  
12 include "alldifferent.mzn";  
13 constraint alldifferent(x);  
14  
15 ann: vartype x = largest;  
16 ann: vartype px = indomain;  
17  
18 solve :: int_search(px, vartype x, vartype px, complete)  
19         maximize obj;  
20  
21 output ["obj = \({obj}\); x = \({x}\); \n"];
```



Data



Variables  
& domains



Constraints



Search &  
objective