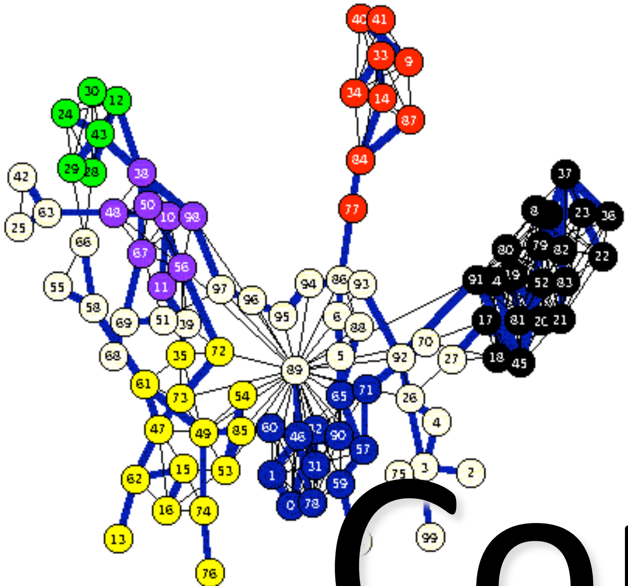


# Constraint Satisfaction

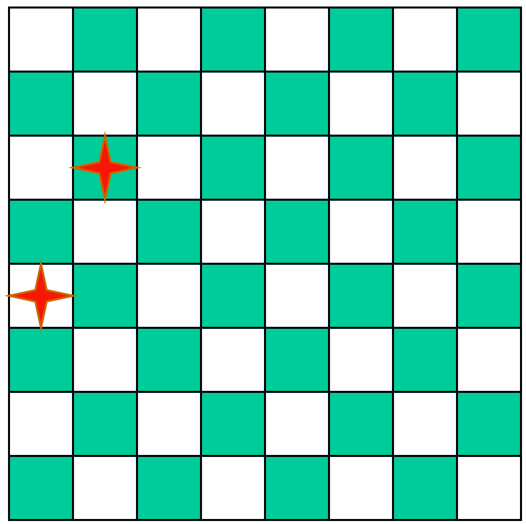
**Russell & Norvig Ch. 6**

# Overview

- Constraint satisfaction is a powerful problem-solving paradigm
  - Problem: set of variables to which we must assign values satisfying problem-specific constraints
  - Constraint programming, constraint satisfaction problems (CSPs), constraint logic programming…
- Algorithms for CSPs
  - Backtracking (systematic search)
  - Constraint propagation (k-consistency)
  - Variable and value ordering heuristics
  - Backjumping and dependency-directed backtracking

# Motivating example: 8 Queens

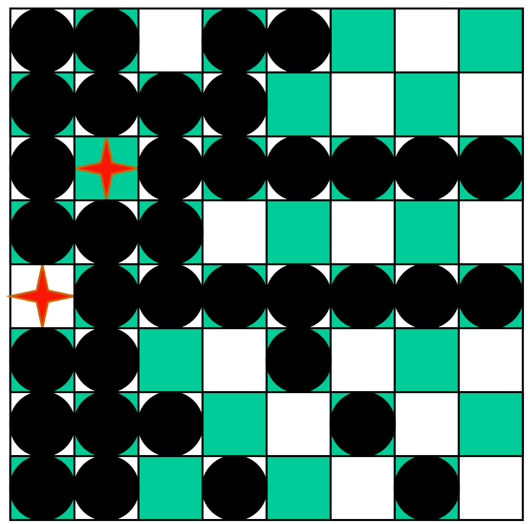
Place 8 queens on a chess board such
That none is attacking another.



Generate-and-test, with no
redundancies → “only” $8^8$ combinations

8**8 is 16,777,216

# Motivating example: 8-Queens



After placing these two queens, it's trivial to mark the squares we can no longer use

# What more do we need for 8 queens?

- Not just a successor function and goal test
- But also
  - a means to propagate constraints imposed by one queen on others
  - an early failure test

→ Explicit representation of constraints and constraint manipulation algorithms

# Informal definition of CSP

- **CSP** (Constraint Satisfaction Problem), given

  (1) finite set of variables

  (2) each with domain of possible values (often finite)

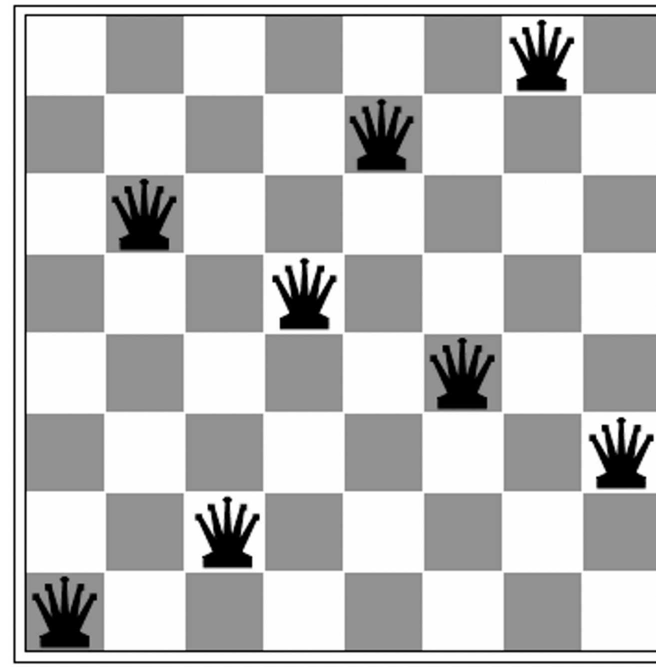
  (3) set of constraints limiting values variables can take

- **Solution:** assignment of a value to each variable such that all constraints are satisfied

- **Possible tasks:** decide if solution exists, find a solution, find all solutions, find *best solution* according to some metric (objective function)

# Example: 8-Queens Problem

- What are the variables?
- What are the variables domains, i.e., sets of possible values
- What are the constraints between (pairs of) variables?

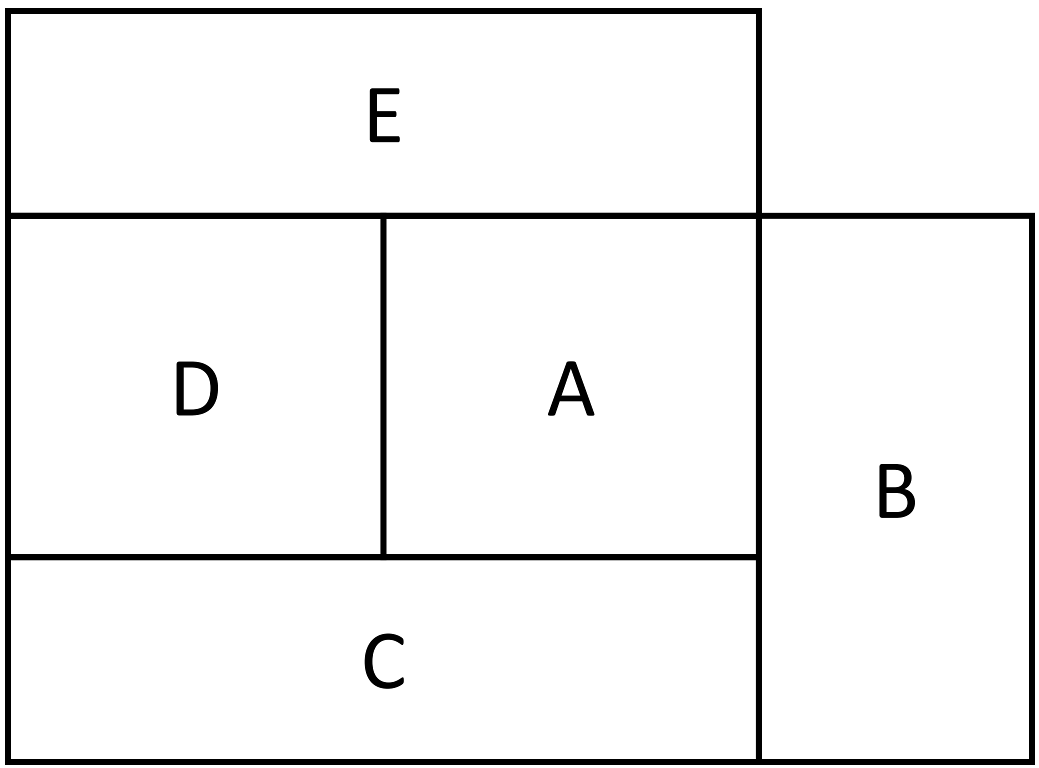


# Example: 8-Queens Problem

- Eight variables Qi, i = 1..8 where Qi is the row number of queen in column i
- Domain for each variable {1,2,…,8}
- Constraints are of the forms:
  - No queens on same row
    Qi = k ➔ Qj $\neq$ k  for j = 1..8, j$\neq$i
  - No queens on same diagonal
    Qi=rowi, Qj=rowj ➔ |i-j| $\neq$ |rowi-rowj| for j = 1..8, j$\neq$i

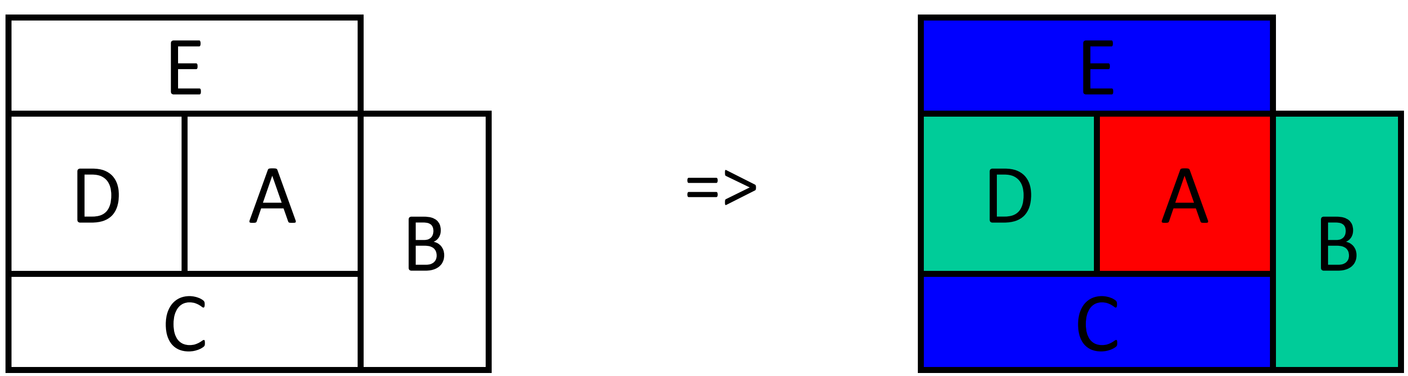
# Example: Map coloring

Color this map using three colors (red, green, blue) such that no two adjacent regions have the same color



# Map coloring

- Variables: A, B, C, D, E all of domain RGB
- Domains: RGB = {red, green, blue}
- Constraints: A≠B, A≠C, A≠E, A≠D, B≠C, C≠D, D≠E
- A solution: A=red, B=green, C=blue, D=green, E=blue



# Brute Force methods

- Finding a solution by a brute force search is easy
  - Generate and test is a *weak method*
  - Just generate potential combinations and test each
- Potentially very inefficient
  - With n variables where each can have one of 3 values, there are $3^n$ possible solutions to check
- There are ~190 countries in the world, which we can color using four colors
- $4^{190}$ is a big number!

```
solve(A,B,C,D,E) :-
  color(A),
  color(B),
  color(C),
  color(D),
  color(E),
  not(A=B),
  not(A=B),
  not(B=C),
  not(A=C),
  not(C=D),
  not(A=E),
  not(C=D).

color(red).
color(green).
color(blue).
```

generate

test

4**190 is 2462625387274654950767440006258975862817483704404090416746768337765357610718575663213391640930307227550414249394176L

# Example: SATisfiability

- Given a set of logic propositions containing variables, find an assignment of the variables to {false, true} that satisfies them
- For example, the two clauses:
  - $(A \lor B \lor \neg C) \land (\neg A \lor D)$
  - equivalent to $(C \to A) \lor (B \land D \to A)$

  are satisfied by

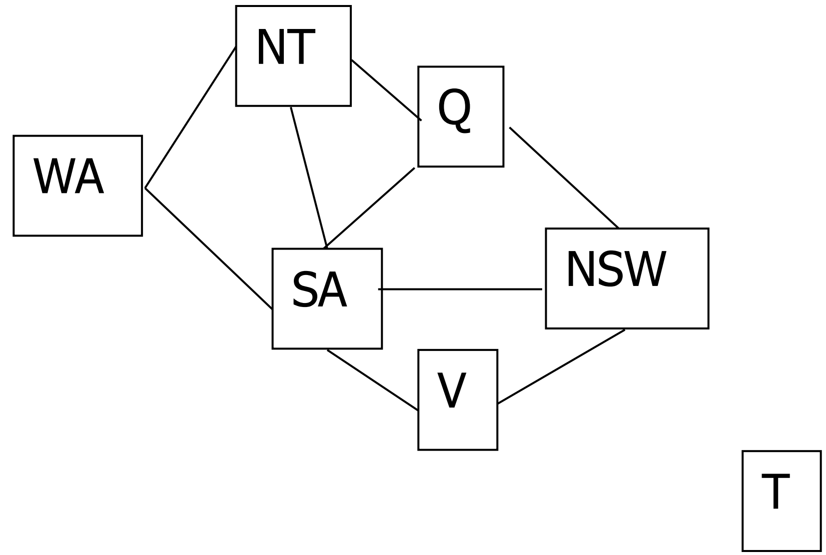
  $A$ = false, $B$ = true, $C$ = false, $D$ = false
- Satisfiability known to be NP-complete
- $\Rightarrow$ worst case, solving CSP problems requires exponential time

# Real-world problems

CSPs are a good match for many practical problems that arise in the real world

- Scheduling
- Temporal reasoning
- Building design
- Planning
- Optimization/satisfaction
- Vision
- Graph layout
- Network management
- Natural language processing
- Molecular biology / genomics
- VLSI design

# Running example: coloring Australia

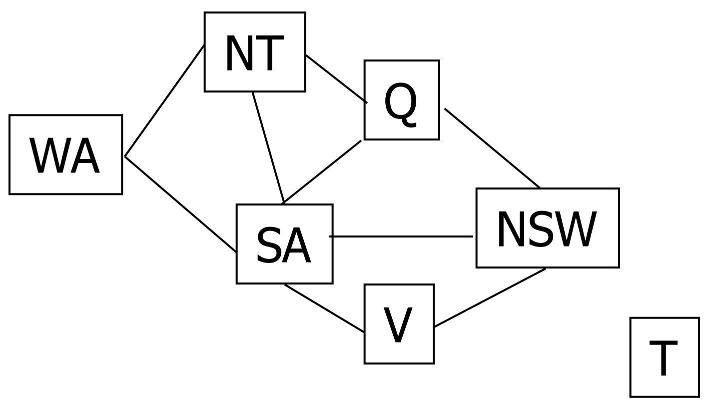



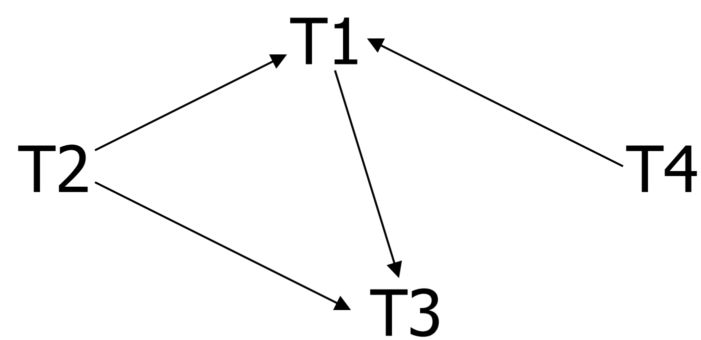

- Seven variables: {WA, NT, SA, Q, NSW, V, T}
- Each variable has same domain: {red, green, blue}
- No two adjacent variables can have same value:

WA≠NT, WA≠SA, NT≠SA, NT≠Q, SA≠Q, SA≠NSW, SA≠V,Q≠NSW, NSW≠V

# Unary & binary constraints most common

Binary constraints




- Two variables are adjacent or neighbors if connected by an edge or an arc
- Possible to rewrite problems with higher-order constraints as ones with just binary constraints

# Formal definition of a CN

- Instantiations
  - An instantiation of a subset of variables S is an assignment of a value (in its domain) to each variable in S
  - An instantiation is legal iff it violates no constraints
- A solution is a legal instantiation of all variables in the network

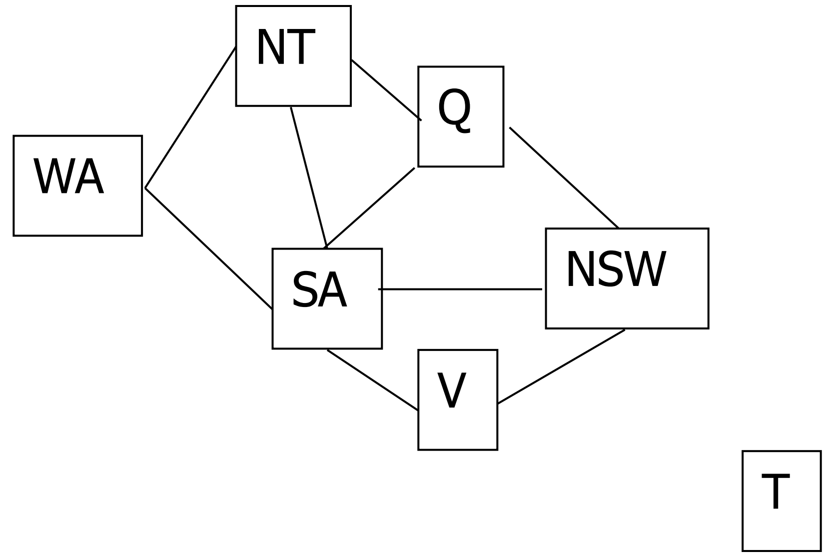
# Typical tasks for CSP

- Possible solution related tasks:
  - Does a solution exist?
  - Find one solution
  - Find all solutions
  - Given a metric on solutions, find best one
  - Given a partial instantiation, do any of above
- Transform the constraint network into an equivalent one that's easier to solve

# Binary CSP

- A binary CSP is a CSP where all constraints are binary or unary
- Any non-binary CSP can be converted into a binary CSP by introducing additional variables
- A binary CSP can be represented as a constraint graph, with a node for each variable and an arc between two nodes iff there's a constraint involving them
  - Unary constraints appear as self-referential arcs

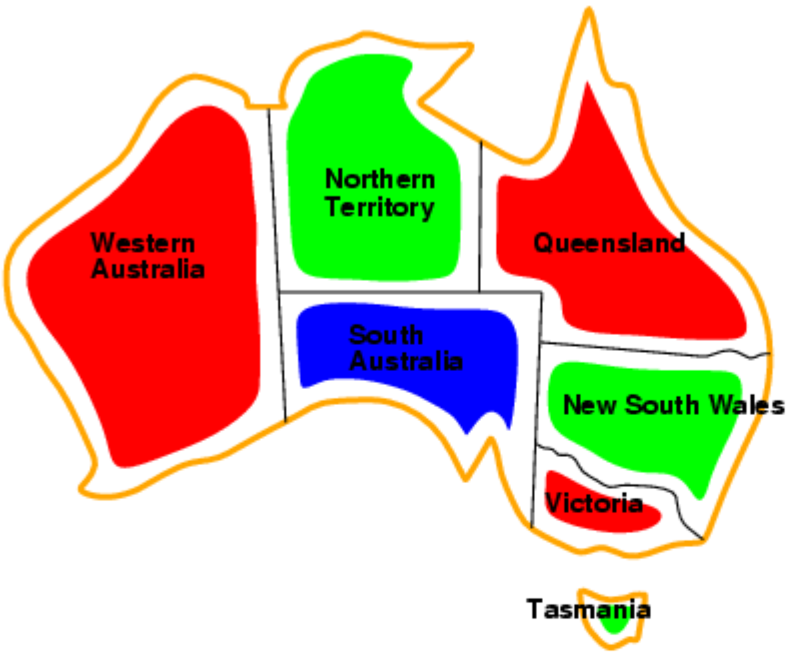
# Running example: coloring Australia

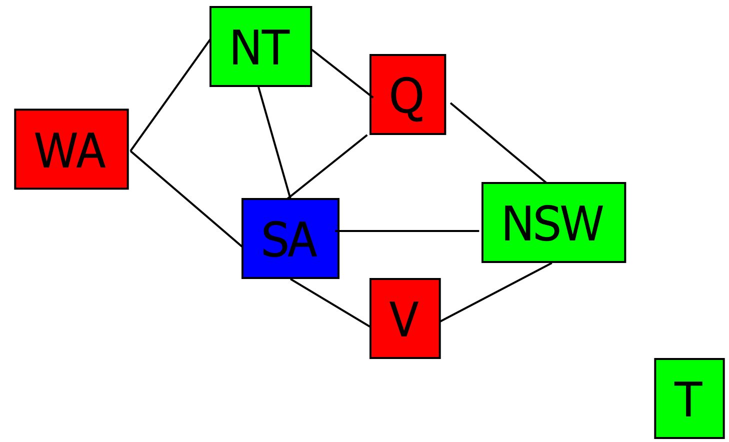




- Seven variables: {WA, NT, SA, Q, NSW, V, T}
- Each variable has same domain: {red, green, blue}
- No two adjacent variables can have same value:

WA≠NT, WA≠SA, NT≠SA, NT≠Q, SA≠Q, SA≠NSW, SA≠V,Q≠NSW, NSW≠V

# A running example: coloring Australia

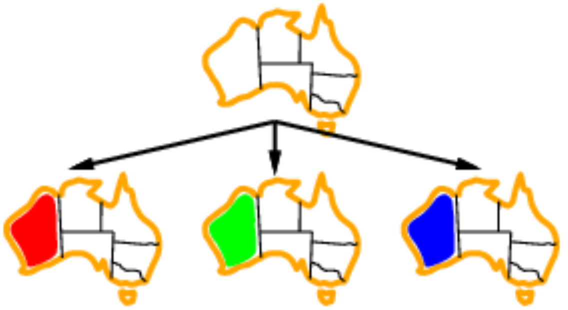


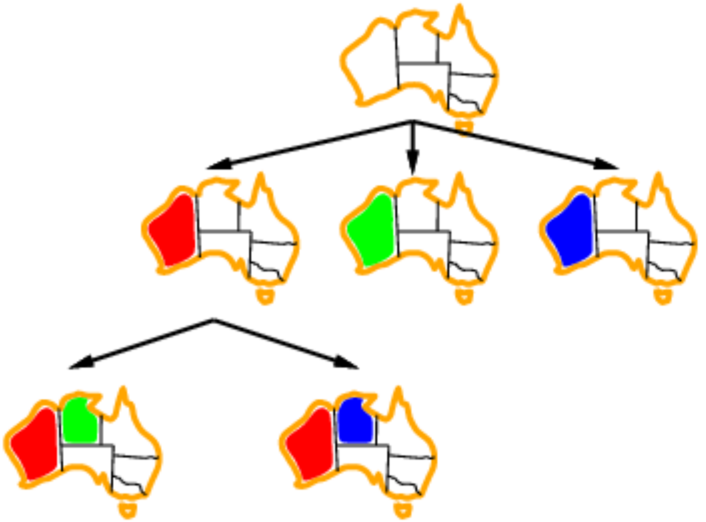

- Solutions: complete & consistent assignments
- Here is one of several solutions
- For generality, constraints can be expressed as relations, e.g., describe WA ≠ NT as {(red,green), (red,blue), (green,red), (green,blue), (blue,red),(blue,green)}

# Backtracking example

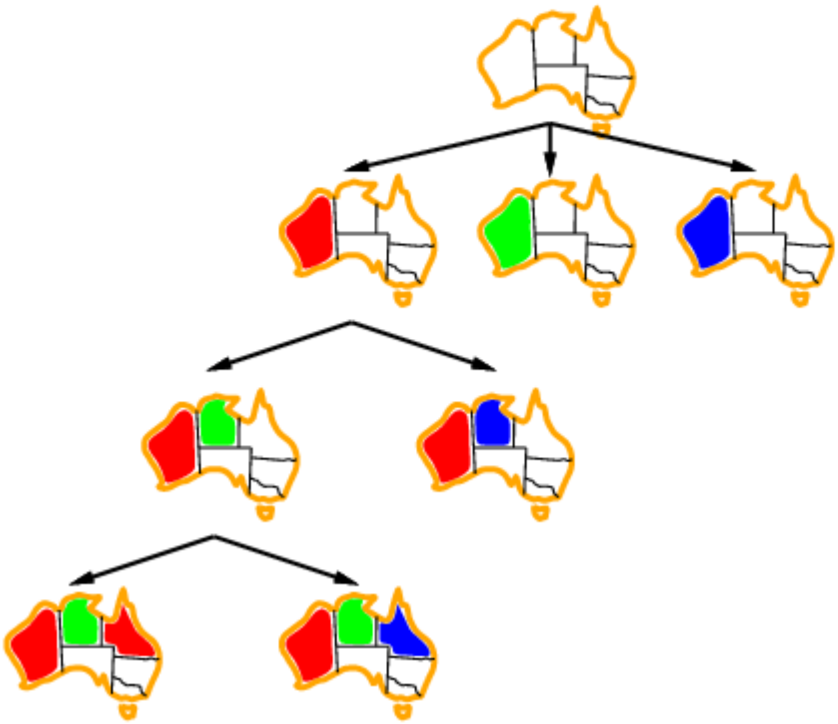
# Backtracking example



# Backtracking example



# Backtracking example



## Basic backtracking algorithm

CSP-backtracking(PartialAssignment a)

- If a is complete then return a
- X ← select an unassigned variable
- D ← select an ordering for the domain of X
- For each value v in D do

  If v consistent with a then

    - Add (X=v) to a
    - result ← CSP-BACKTRACKING(a)
    - If result ≠ failure then return result
    - Remove (X= v) from a
- Return failure

Start with CSP-BACKTRACKING({})

Note: depth first search; can solve n-queens problems for n ~ 25

# Problems with Backtracking

- Thrashing: keep repeating the same failed variable assignments
- Things that can help avoid this:
  - Consistency checking
  - Intelligent backtracking schemes
- Inefficiency: can explore areas of the search space that aren’t likely to succeed
  - Variable ordering can help

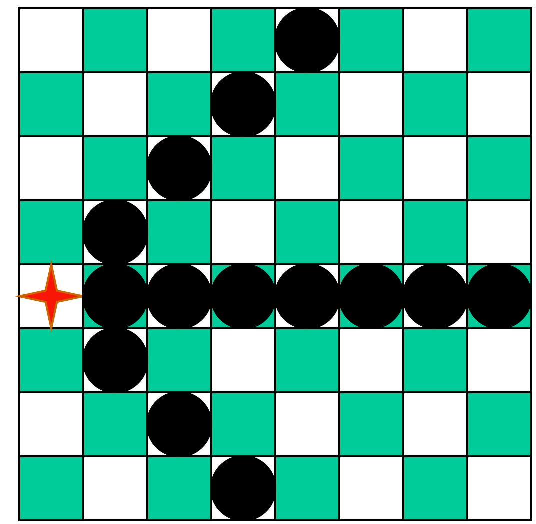
# Improving backtracking efficiency

Here are some standard techniques to improve the efficiency of backtracking

- Can we detect inevitable failure early?
- Which variable should be assigned next?
- In what order should its values be tried?

# Forward Checking

After variable X is assigned to value v, examine each unassigned variable Y connected to X by a constraint and delete values from Y's domain inconsistent with v

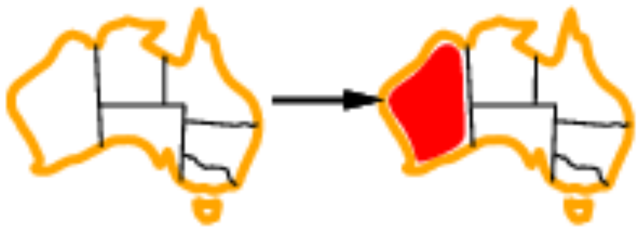


Using forward checking and backward checking roughly doubles the size of N-queens problems that can be practically solved

# Forward checking

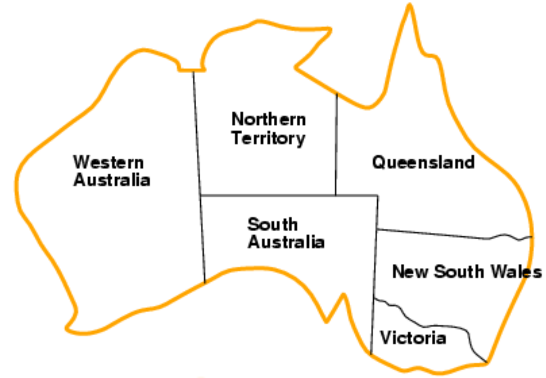

- Keep track of remaining legal values for unassigned variables
- Terminate search when any variable has no legal values

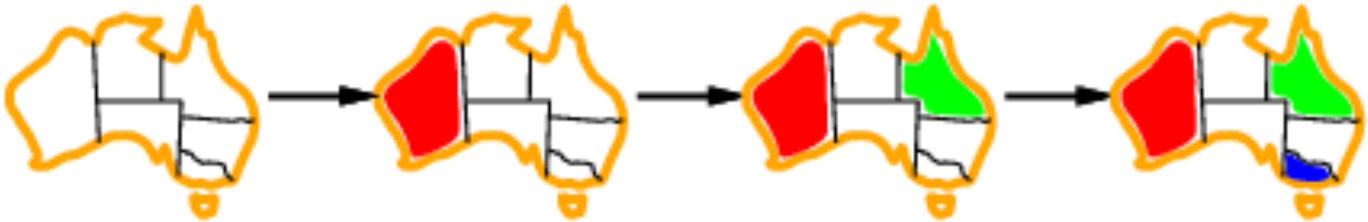

# Forward checking



# Forward checking


# Forward checking

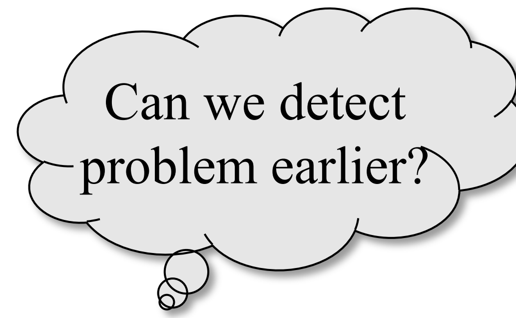



SA (South Australia) domain is empty!

# Constraint propagation


- Forward checking propagates info. from assigned to unassigned variables, but doesn't provide early detection for all failures
- NT and SA cannot both be blue!

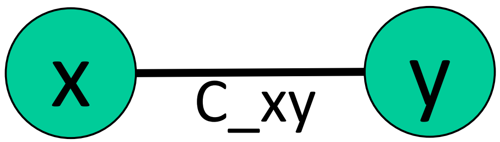



# Definition: Arc consistency

- A constraint C_xy is arc consistent w.r.t. x if for each value v of x there is an allowed value of y
- Similarly define C_xy as arc consistent w.r.t. y
- Binary CSP is arc consistent iff every constraint C_xy is arc consistent w.r.t. x as well as y
- When a CSP is not arc consistent, we can make it arc consistent by using the AC3 algorithm
  - Also called "enforcing arc consistency"

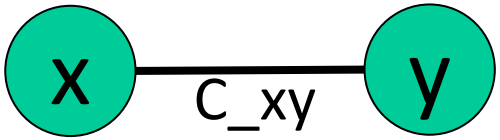
# Arc Consistency Example 1

- Domains
  - D_x = {1, 2, 3}
  - D_y = {3, 4, 5, 6}




- Constraint
  - Note: for finite domains, we can represent a constraint as an set of legal value pairs
  - C_xy = {(1,3), (1,5), (3,3), (3,6)}
- C_xy isn't arc consistent w.r.t. x or y. By enforcing arc consistency, we get reduced domains
  - D'_x = {1, 3}
  - D'_y={3, 5, 6}

# Arc Consistency Example 2




- Domains
  - D_x = {1, 2, 3}
  - D_y = {1, 2, 3}
- Constraint
  - C_xy = `lambda v1,v2: v1 < v2`
- C_xy not arc consistent w.r.t. x or y; enforcing arc consistency, we get reduced domains:
  - D'_x = {1, 2}
  - D’_y = {2, 3}

# Aside: Python lambda expressions

Previous slide expressed constraint between two variables as an *anonymous* Python function of two arguments

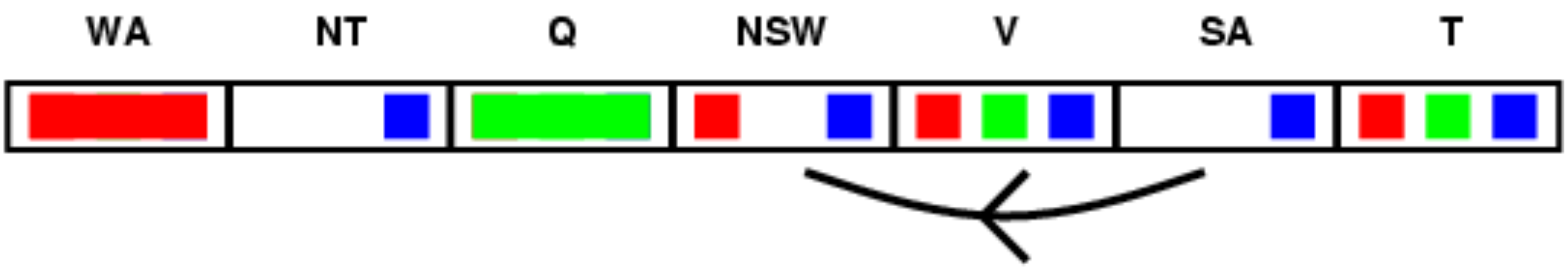
```
lambda v1,v2: v1 < v2
```

```
>>> f = lambda v1,v2: v1 < v2
>>> f
<function <lambda> at
0x10fcf21e0>
>>> f(100,200)
True
>>> f(200,100)
False
```

*Python uses lambda after Alonzo Church's [lambda calculus] from the 1930s*

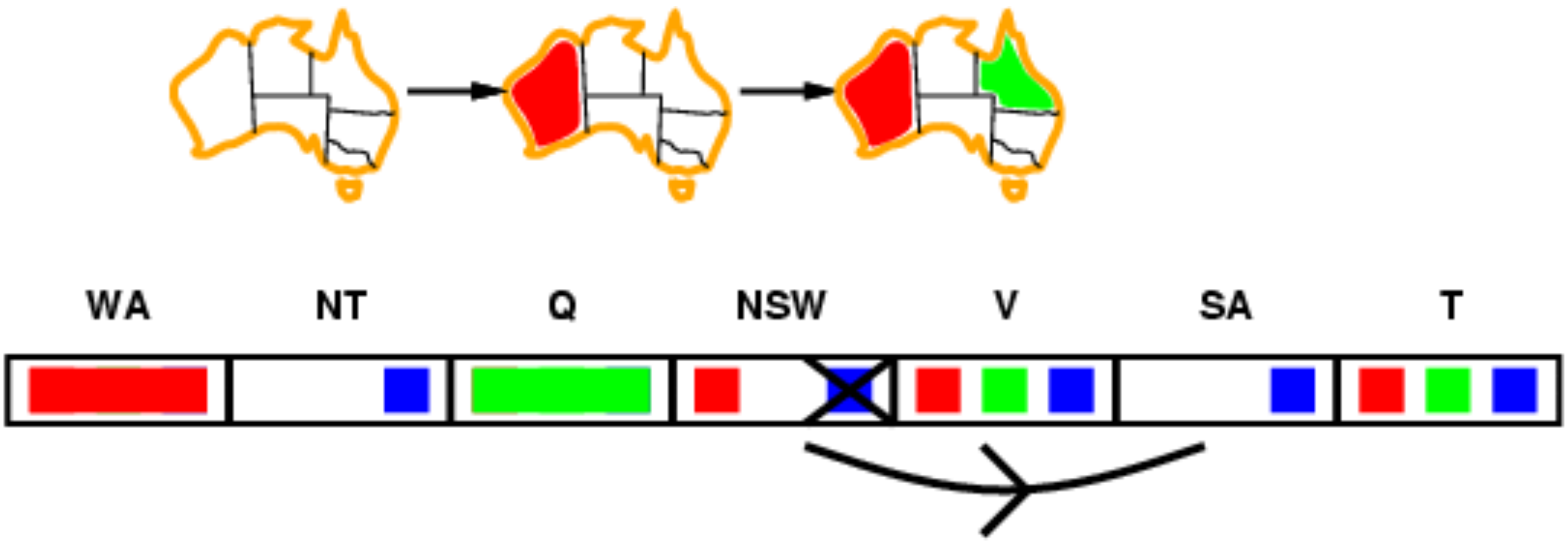
# Arc consistency


- Simplest form of propagation makes each arc consistent
- X $\rightarrow$ Y is consistent iff for every value $x_i$ of X there is some allowed value $y_j$ in Y

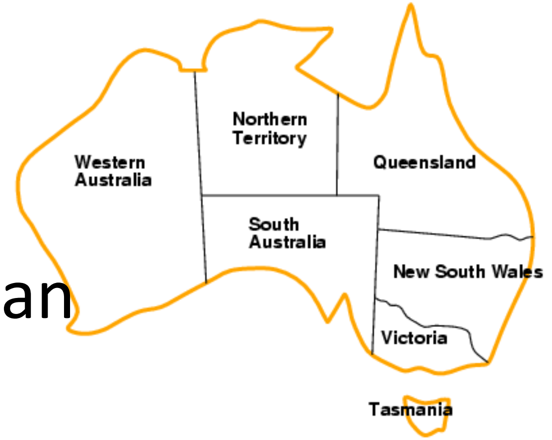


# Arc consistency

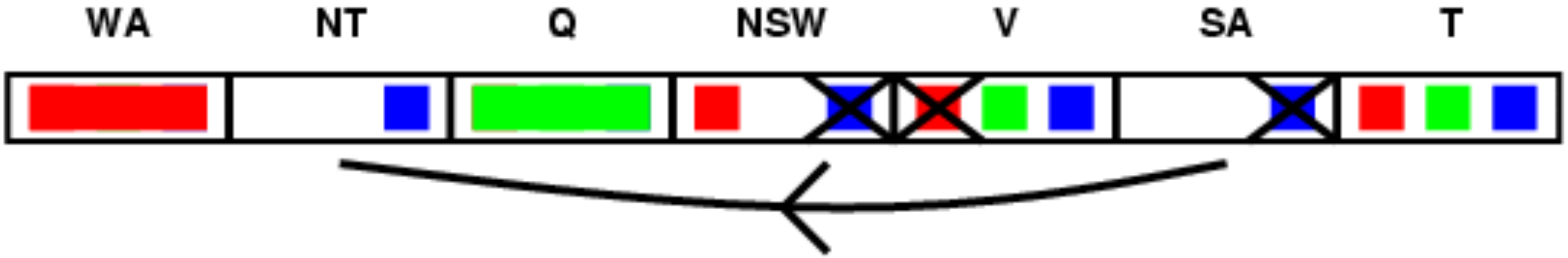

- Simplest form of propagation makes each arc consistent
- X → Y is consistent iff for every value $x_i$ of X there is some allowed value $y_j$ in Y



# Arc consistency




- Arc consistency detects failure earlier than simple forward checking
- WA=red and Q=green is quickly recognized as a **deadend**, i.e. an impossible partial instantiation
- The arc consistency algorithm can be run as a preprocessor or after each assignment



# General CP for Binary Constraints

```
Algorithm AC3
contradiction ← false
Q ← stack of all variables
 while Q is not empty and not contradiction do
   X ← UNSTACK(Q)
   For every variable Y adjacent to X do
      If REMOVE-ARC-INCONSISTENCIES(X,Y)
         If domain(Y) is non-empty then STACK(Y,Q)
         else return false
```

# Complexity of AC3

- e = number of constraints (edges)
- d = number of values per variable
- Each variable is inserted in queue up to d times
- REMOVE-ARC-INCONSISTENCY takes $O(d^2)$ time
- CP takes $O(ed^3)$ time

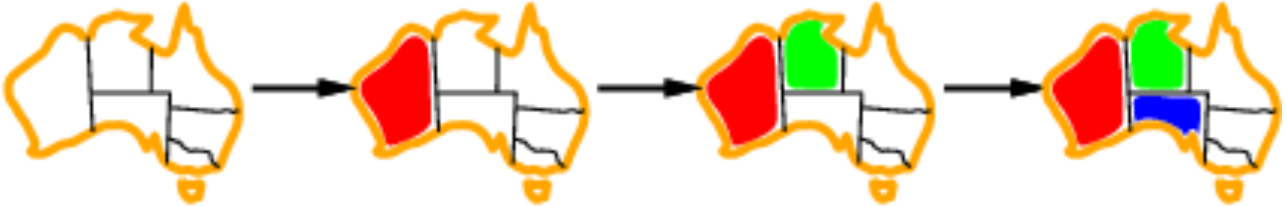
# Improving backtracking efficiency

- Some standard techniques to improve the efficiency of backtracking
  - Can we detect inevitable failure early?
  - Which variable should be assigned next?
  - In what order should its values be tried?
- Combining constraint propagation with these heuristics makes 1000-queen puzzles feasible

# Most constrained variable

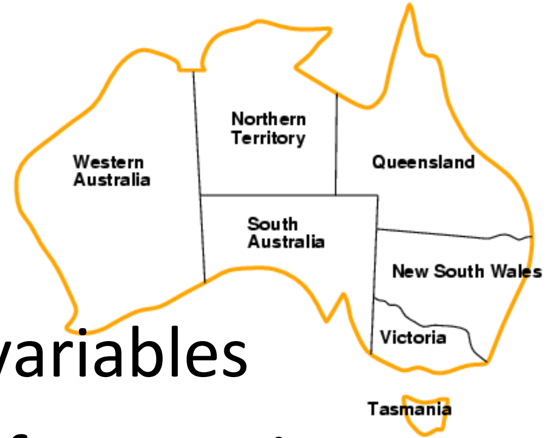

- Most constrained variable:

  choose the variable with the fewest legal values

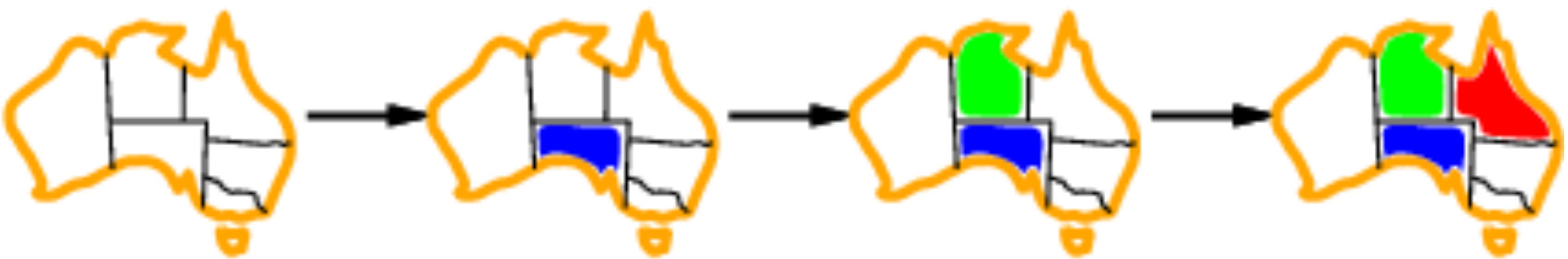


- a.k.a. minimum remaining values (MRV) heuristic
- After assigning value to WA, both NT and SA have only two values in their domains
  - choose one of them rather than Q, NSW, V or T

# Most constraining variable

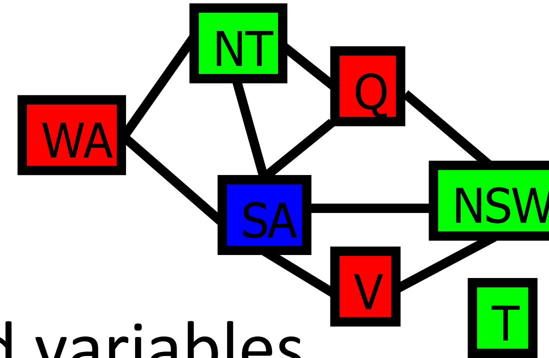



- Tie-breaker among most constrained variables
- Choose variable involved in largest # of constraints on remaining variables

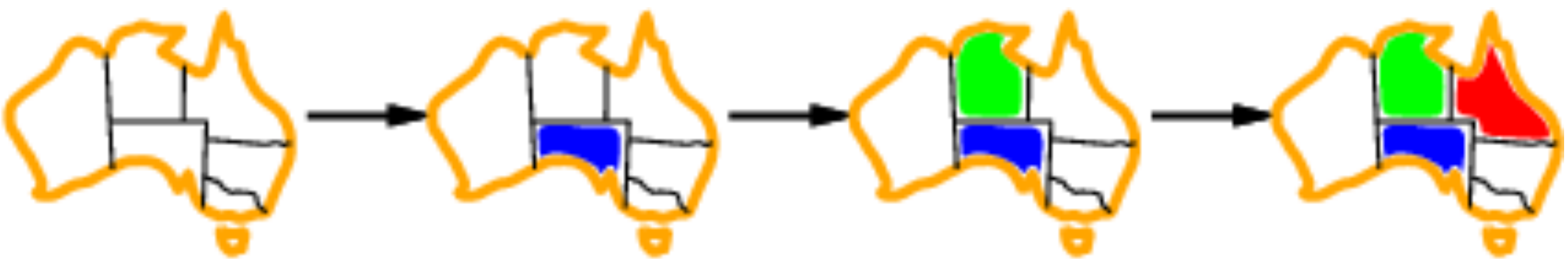


- After assigning SA to be blue, WA, NT, Q, NSW and V all have just two values left.
- WA and V have only one constraint on remaining variables and T none, so choose one of NT, Q & NSW

# Most constraining variable



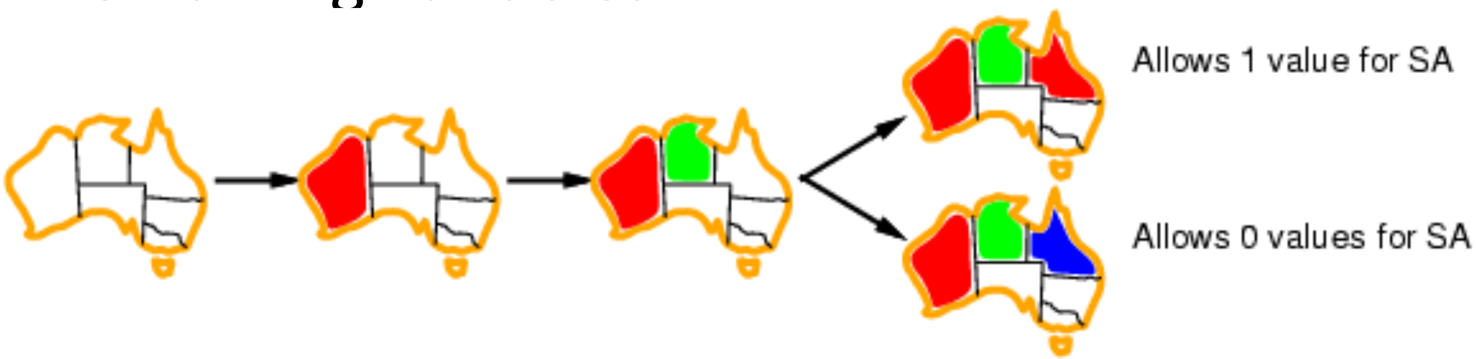

- Tie-breaker among most constrained variables
- Choose variable involved in largest # of constraints on remaining variables



- After assigning SA to be blue, WA, NT, Q, NSW and V all have just two values left.
- WA and V have only one constraint on remaining variables and T none, so choose one of NT, Q & NSW

# Least constraining value

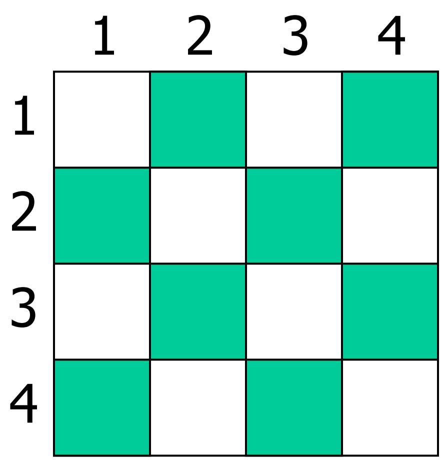
- Given a variable, choose least constraining value:
  - the one that rules out the fewest values in the remaining variables

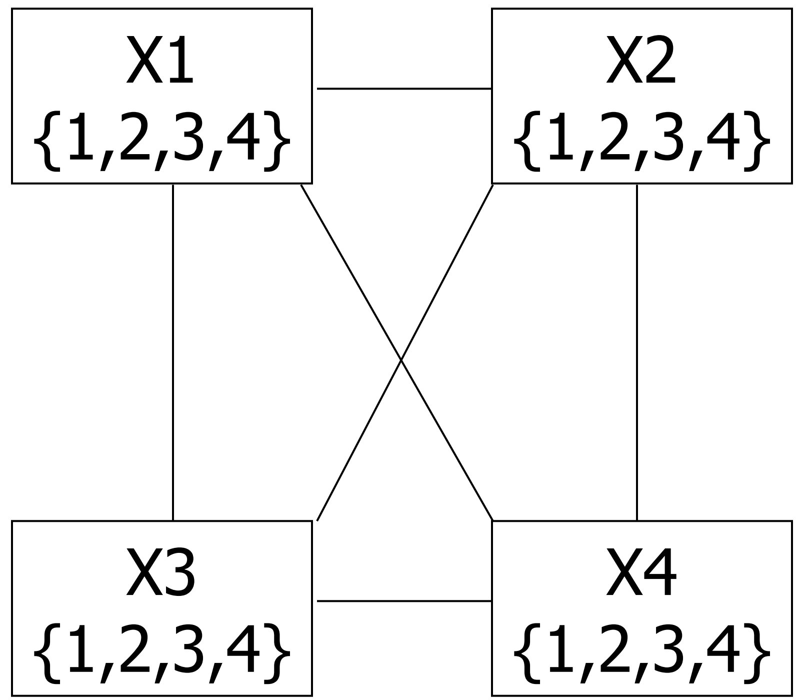



- Combining these heuristics makes 1000 queens feasible
- What’s an intuitive explanation for this?

# Is AC3 Alone Sufficient?

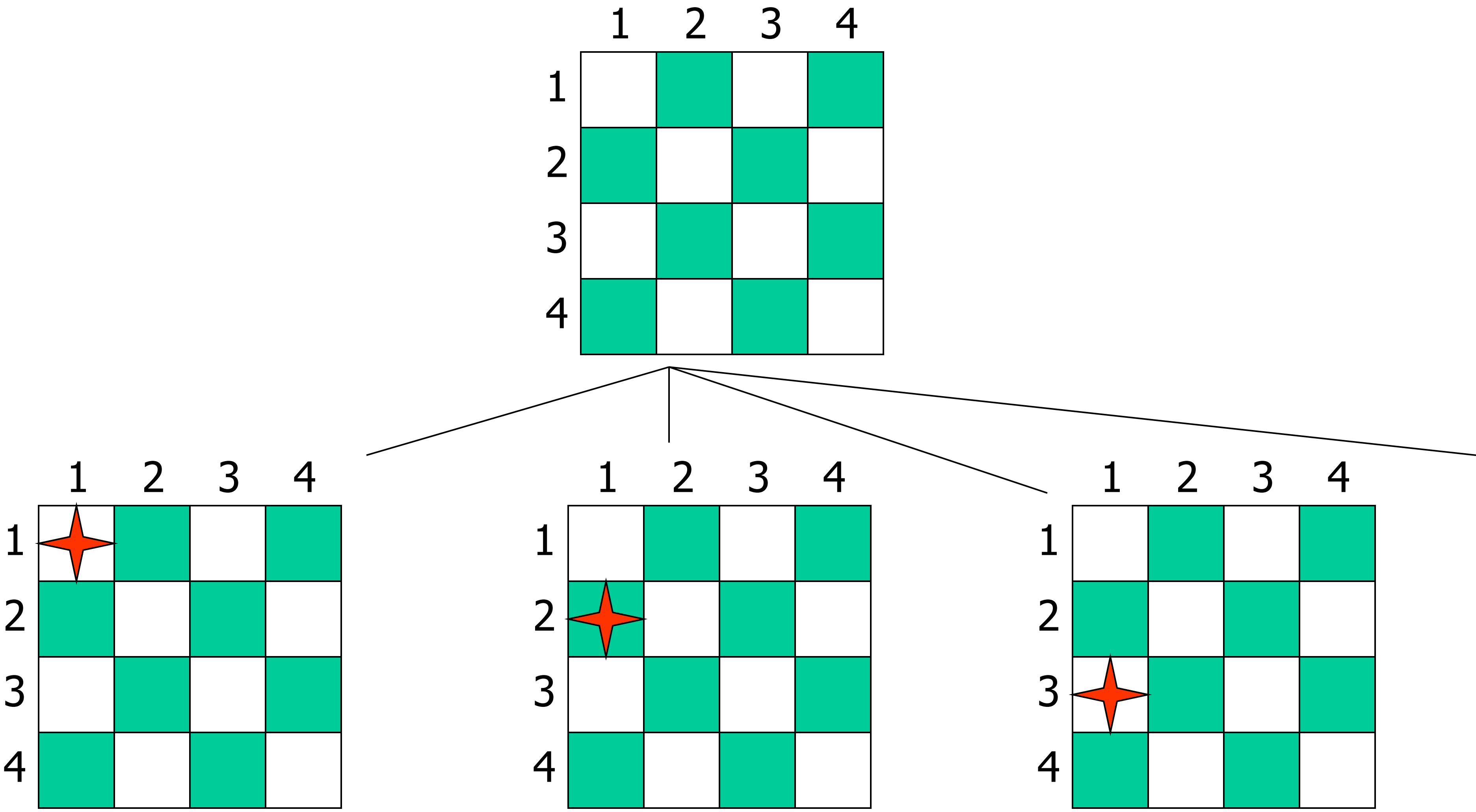
Consider the four queens problem



# Solving a CSP still requires search

- Search:
  - can find good solutions, but must examine non-solutions along the way
- Constraint Propagation:
  - can rule out non-solutions, but this is not the same as finding solutions
- Interweave constraint propagation & search:
  - perform constraint propagation at each search step


1 2 3 4
1
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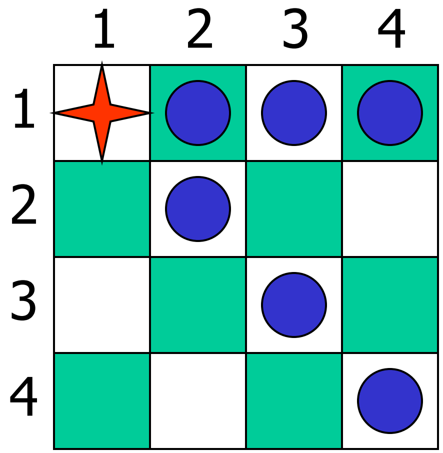
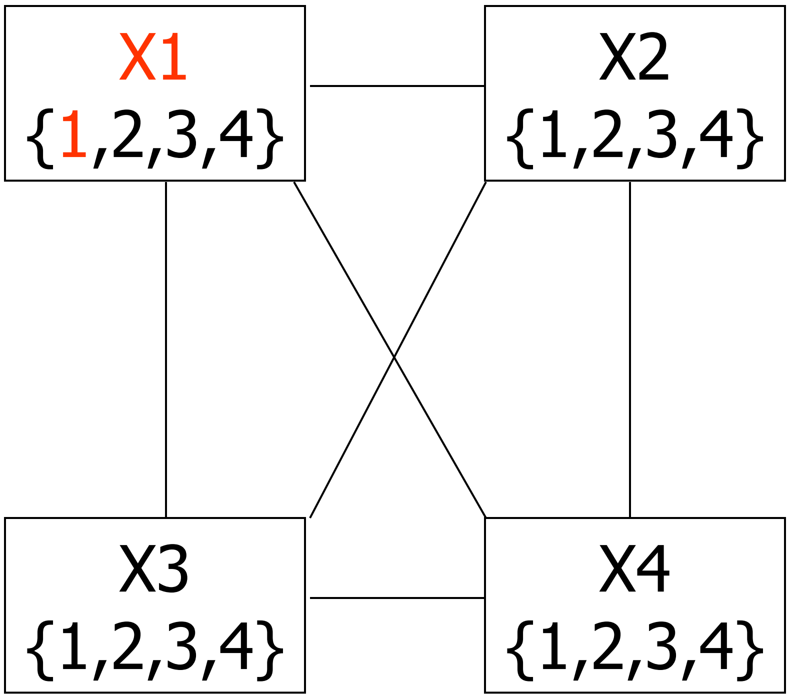
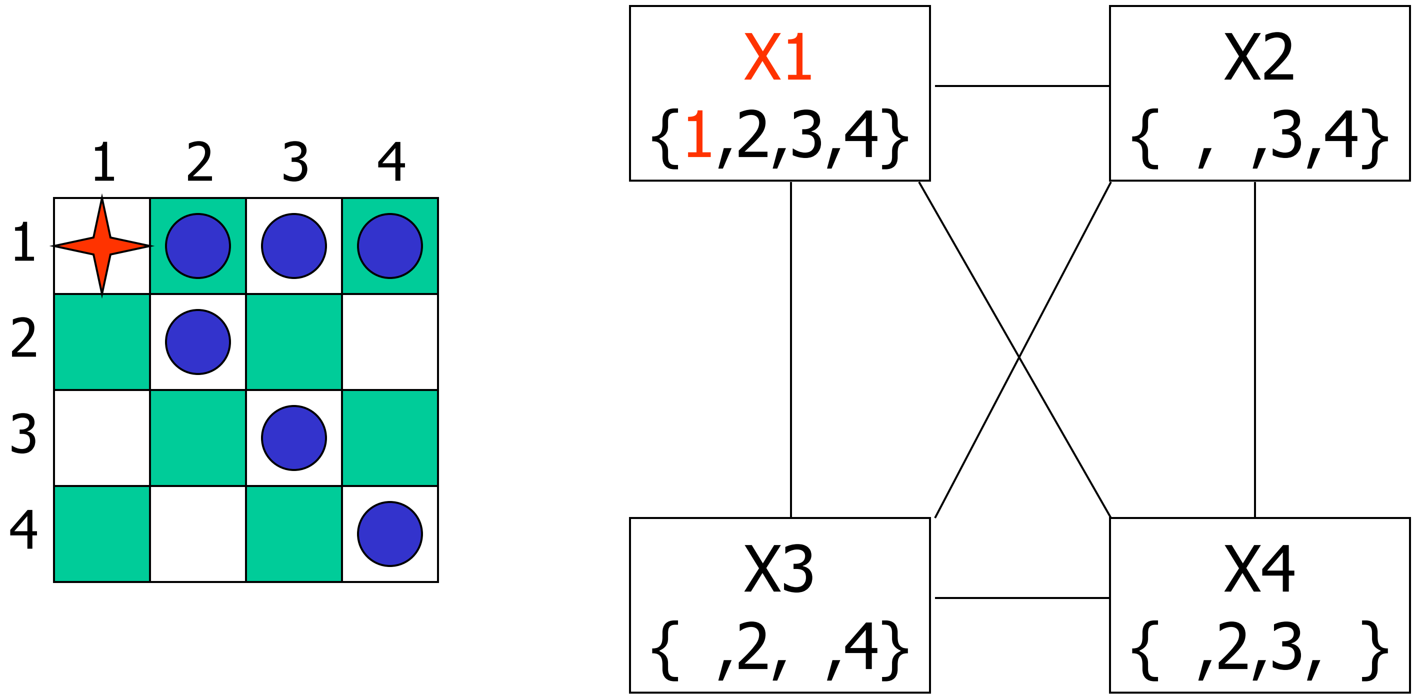
# 4-Queens Problem

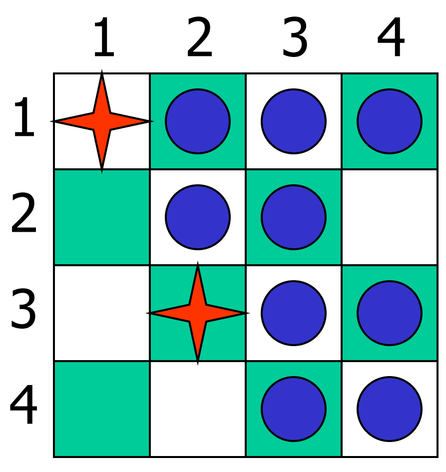


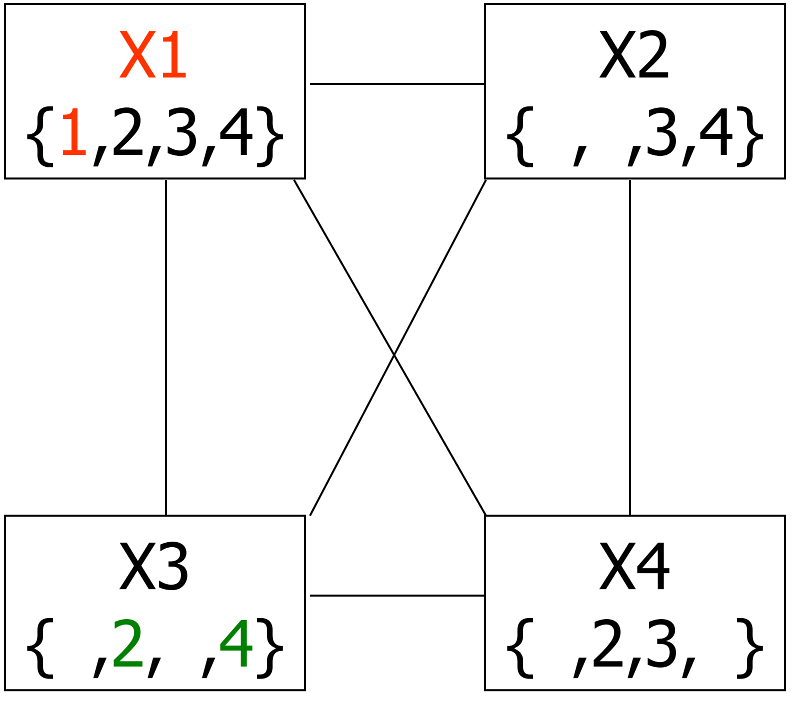



# 4-Queens Problem



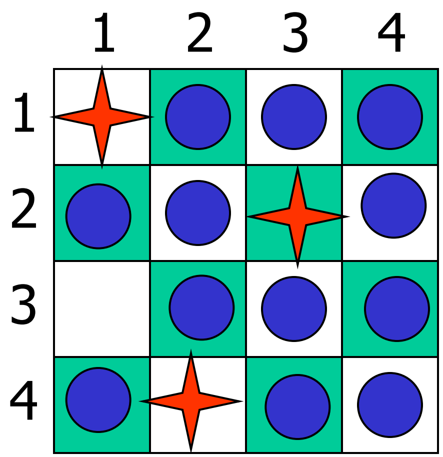
# 4-Queens Problem

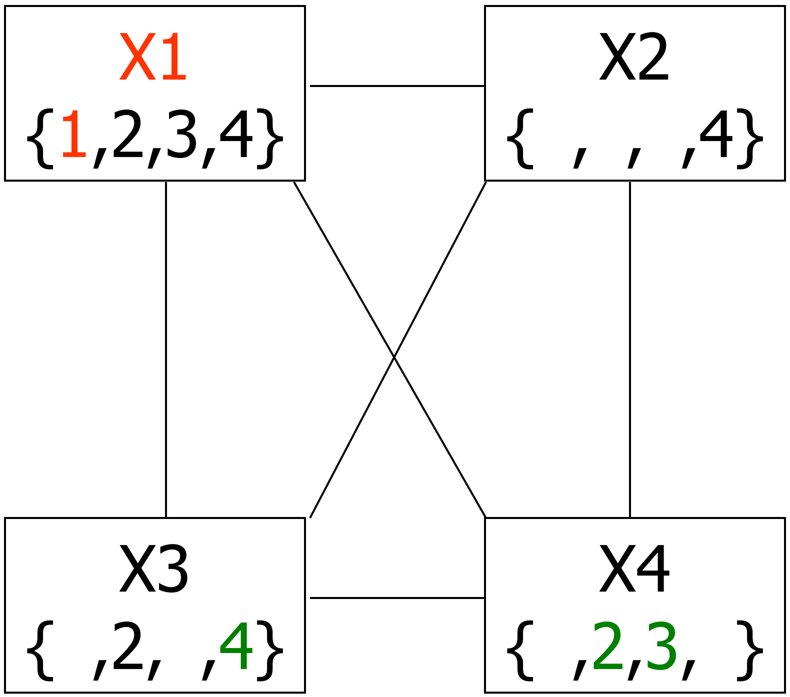



**X2=3 eliminates { X3=2, X3=3, X3=4 }**
**⇒ inconsistent!**

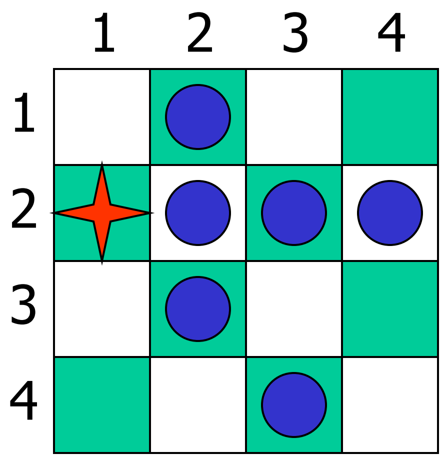
# 4-Queens Problem

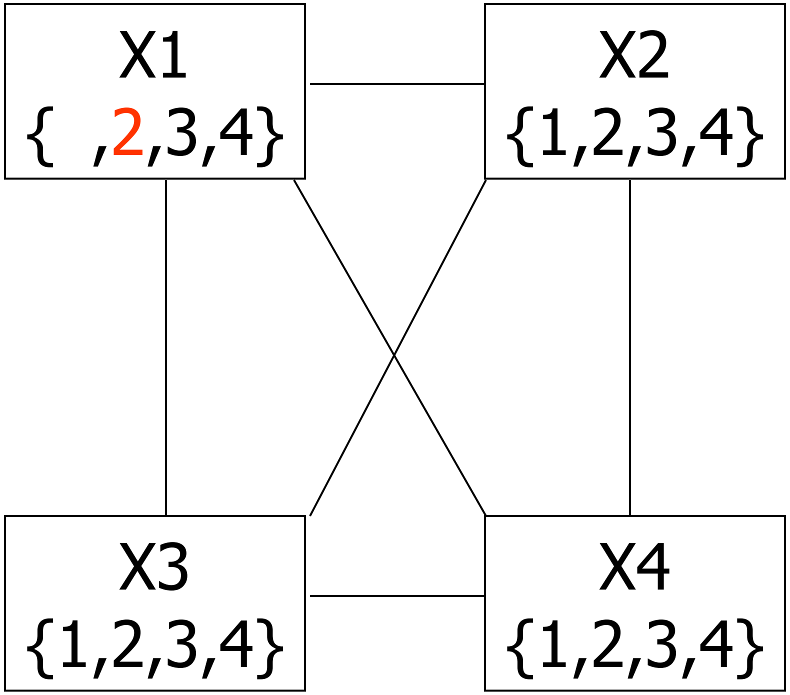



**X2=4 ⇒ X3=2, which eliminates { X4=2, X4=3}**
**⇒ inconsistent!**

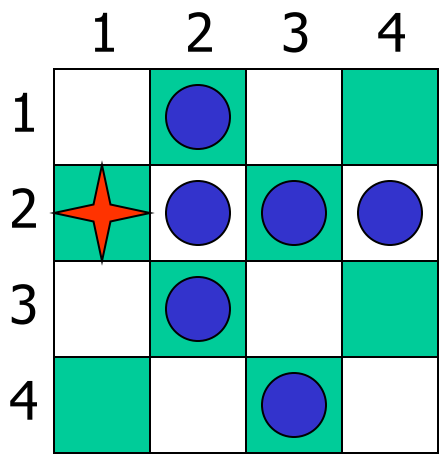
# 4-Queens Problem

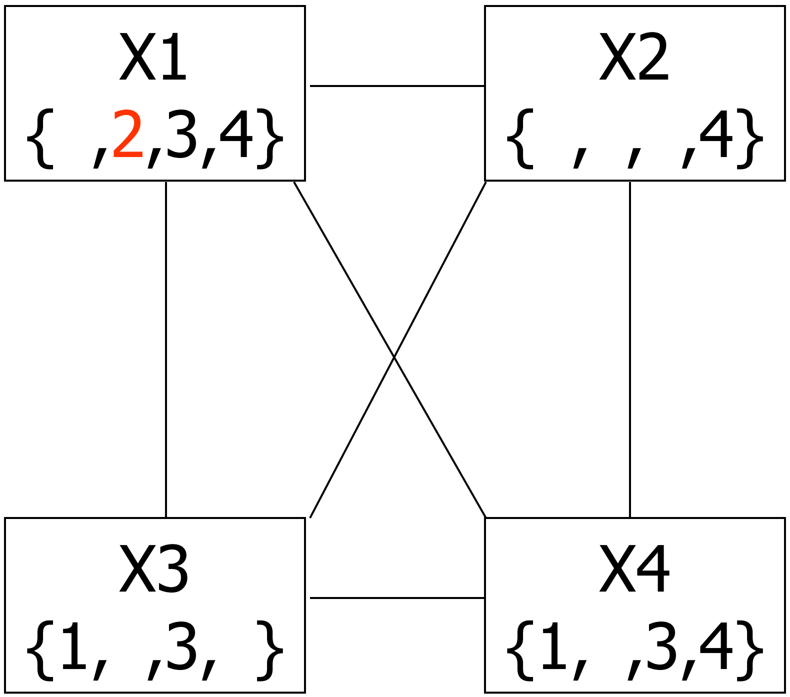



**X1 can't be 1, let's try 2**

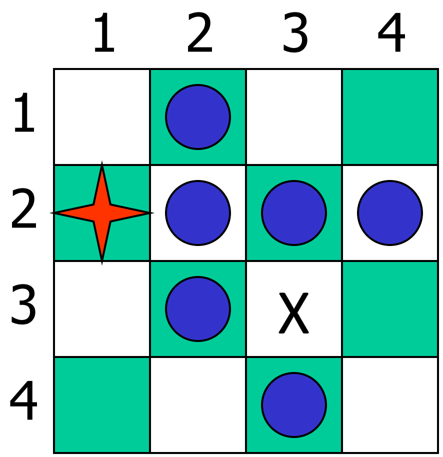
# 4-Queens Problem

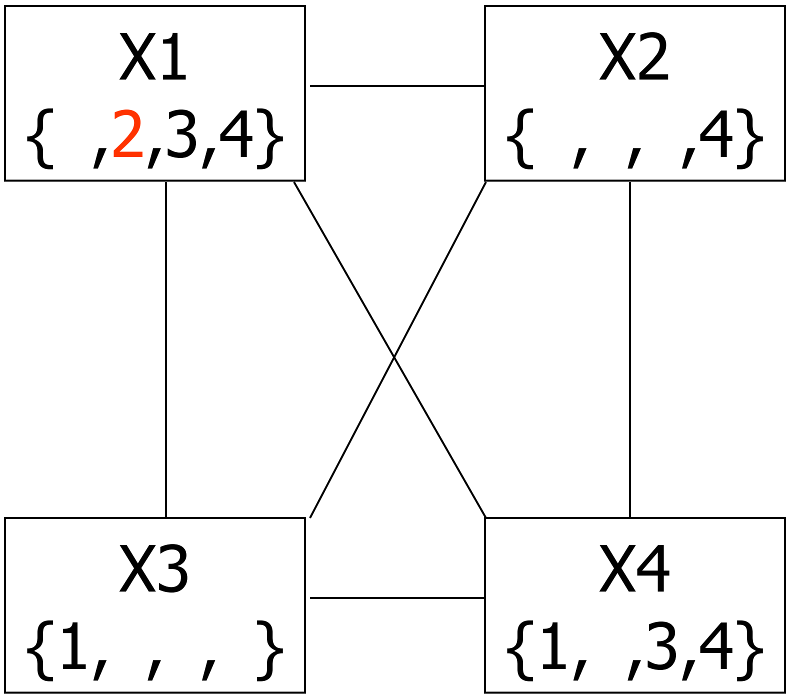


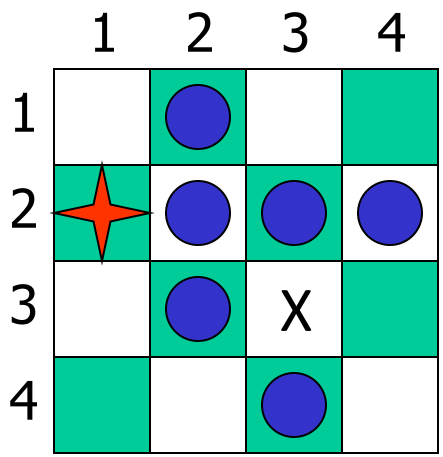

Can we eliminate any other values?

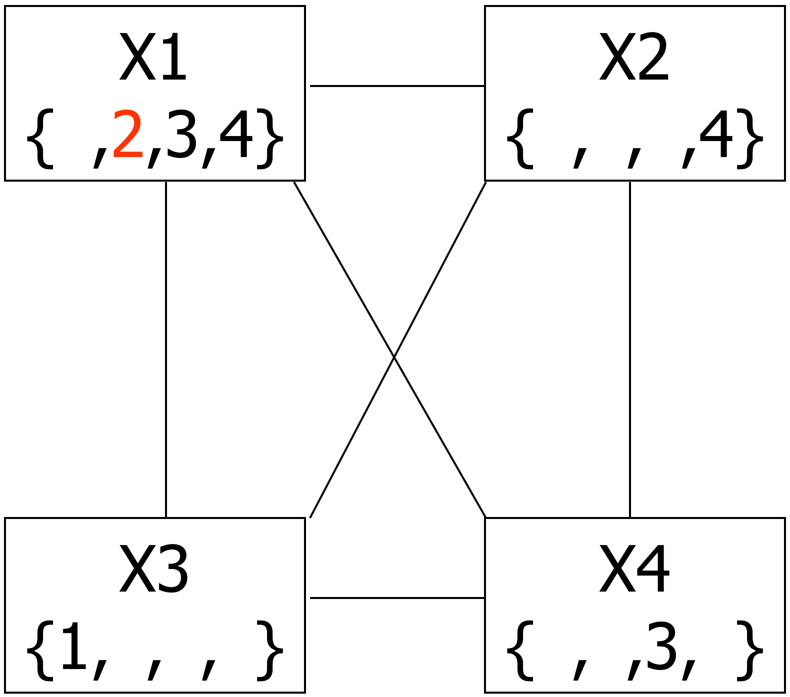
# 4-Queens Problem



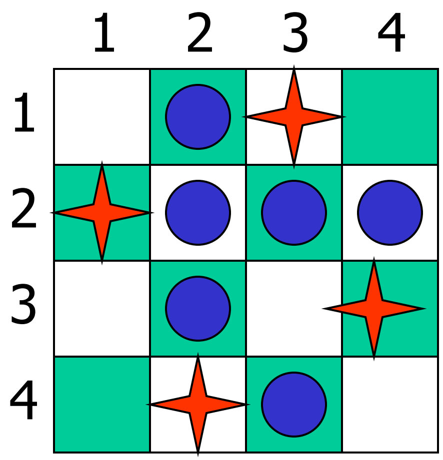
# 4-Queens Problem

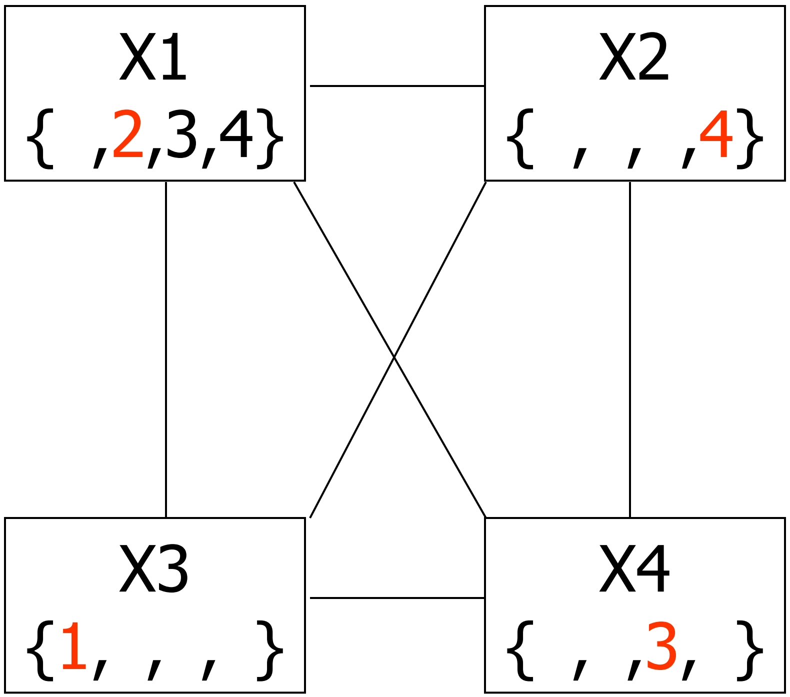



**Arc constancy eliminates x3=3 because it's not consistent with X2's remaining values**

# 4-Queens Problem




**There is only one solution with X1=2**

# Sudoku

- Digit placement puzzle on 9x9 grid with unique answer
- Given an initial partially filled grid, fill remaining squares with a digit between 1 and 9
- Each column, row, and nine 3 × 3 sub-grids must contain all nine digits

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| A | | | 3 | | 2 | | 6 | | |
| B | 9 | | | 3 | | 5 | | | 1 |
| C | | | 1 | 8 | | 6 | 4 | | |
| D | | | 8 | 1 | | 2 | 9 | | |
| E | 7 | | | | | | | | 8 |
| F | | | 6 | 7 | | 8 | 2 | | |
| G | | | 2 | 6 | | 9 | 5 | | |
| H | 8 | | | 2 | | 3 | | | 9 |
| I | | | 5 | | 1 | | 3 | | |

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 4 | 8 | 3 | 9 | 2 | 1 | 6 | 5 | 7 |
| B | 9 | 6 | 7 | 3 | 4 | 5 | 8 | 2 | 1 |
| C | 2 | 5 | 1 | 8 | 7 | 6 | 4 | 9 | 3 |
| D | 5 | 4 | 8 | 1 | 3 | 2 | 9 | 7 | 6 |
| E | 7 | 2 | 9 | 5 | 6 | 4 | 1 | 3 | 8 |
| F | 1 | 3 | 6 | 7 | 9 | 8 | 2 | 4 | 5 |
| G | 3 | 7 | 2 | 6 | 8 | 9 | 5 | 1 | 4 |
| H | 8 | 1 | 4 | 2 | 5 | 3 | 7 | 6 | 9 |
| I | 6 | 9 | 5 | 4 | 1 | 7 | 3 | 8 | 2 |

- Some initial configurations are easy to solve and others very difficult

# Sudoku Example

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| A | | | 3 | | 2 | | 6 | | |
| B | 9 | | | 3 | | 5 | | | 1 |
| C | | | 1 | 8 | | 6 | 4 | | |
| D | | | 8 | 1 | | 2 | 9 | | |
| E | 7 | | | | | | | | 8 |
| F | | | 6 | 7 | | 8 | 2 | | |
| G | | | 2 | 6 | | 9 | 5 | | |
| H | 8 | | | 2 | | 3 | | | 9 |
| I | | | 5 | | 1 | | 3 | | |

*initial problem*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 4 | 8 | 3 | 9 | 2 | 1 | 6 | 5 | 7 |
| B | 9 | 6 | 7 | 3 | 4 | 5 | 8 | 2 | 1 |
| C | 2 | 5 | 1 | 8 | 7 | 6 | 4 | 9 | 3 |
| D | 5 | 4 | 8 | 1 | 3 | 2 | 9 | 7 | 6 |
| E | 7 | 2 | 9 | 5 | 6 | 4 | 1 | 3 | 8 |
| F | 1 | 3 | 6 | 7 | 9 | 8 | 2 | 4 | 5 |
| G | 3 | 7 | 2 | 6 | 8 | 9 | 5 | 1 | 4 |
| H | 8 | 1 | 4 | 2 | 5 | 3 | 7 | 6 | 9 |
| I | 6 | 9 | 5 | 4 | 1 | 7 | 3 | 8 | 2 |

*a solution*

How can we set this up as a CSP?

```python
def sudoku(initValue):
    p = Problem()
    # Define a variable for each cell: 11,12,13...21,22,23...98,99
    for i in range(1, 10) :
        p.addVariables(range(i*10+1, i*10+10), range(1, 10))
    # Each row has different values
    for i in range(1, 10) :
        p.addConstraint(AllDifferentConstraint(), range(i*10+1, i*10+10))
    # Each column has different values
    for i in range(1, 10) :
        p.addConstraint(AllDifferentConstraint(), range(10+i, 100+i, 10))
    # Each 3x3 box has different values
    p.addConstraint(AllDifferentConstraint(), [11,12,13,21,22,23,31,32,33])
    p.addConstraint(AllDifferentConstraint(), [41,42,43,51,52,53,61,62,63])
    p.addConstraint(AllDifferentConstraint(), [71,72,73,81,82,83,91,92,93])

    p.addConstraint(AllDifferentConstraint(), [14,15,16,24,25,26,34,35,36])
    p.addConstraint(AllDifferentConstraint(), [44,45,46,54,55,56,64,65,66])
    p.addConstraint(AllDifferentConstraint(), [74,75,76,84,85,86,94,95,96])

    p.addConstraint(AllDifferentConstraint(), [17,18,19,27,28,29,37,38,39])
    p.addConstraint(AllDifferentConstraint(), [47,48,49,57,58,59,67,68,69])
    p.addConstraint(AllDifferentConstraint(), [77,78,79,87,88,89,97,98,99])

    # add unary constraints for cells with initial non-zero values
    for i in range(1, 10) :
        for j in range(1, 10):
            value = initValue[i-1][j-1]
            if value:
                p.addConstraint(lambda var, val=value: var == val, (i*10+j,))
    return p.getSolution()
```

```python
# Sample problems
easy = [
  [0,9,0,7,0,0,8,6,0],
  [0,3,1,0,0,5,0,2,0],
  [8,0,6,0,0,0,0,0,0],
  [0,0,7,0,5,0,0,0,6],
  [0,0,0,3,0,7,0,0,0],
  [5,0,0,0,1,0,7,0,0],
  [0,0,0,0,0,0,1,0,9],
  [0,2,0,6,0,0,0,5,0],
  [0,5,4,0,0,8,0,7,0]]

hard = [
  [0,0,3,0,0,0,4,0,0],
  [0,0,0,0,7,0,0,0,0],
  [5,0,0,4,0,6,0,0,2],
  [0,0,4,0,0,0,8,0,0],
  [0,9,0,0,3,0,0,2,0],
  [0,0,7,0,0,0,5,0,0],
  [6,0,0,5,0,2,0,0,1],
  [0,0,0,0,9,0,0,0,0],
  [0,0,9,0,0,0,3,0,0]]

very_hard = [
  [0,0,0,0,0,0,0,0,0],
  [0,0,9,0,6,0,3,0,0],
  [0,7,0,3,0,4,0,9,0],
  [0,0,7,2,0,8,6,0,0],
  [0,4,0,0,0,0,0,7,0],
  [0,0,2,1,0,6,5,0,0],
  [0,1,0,9,0,5,0,4,0],
  [0,0,8,0,2,0,7,0,0],
  [0,0,0,0,0,0,0,0,0]]
```

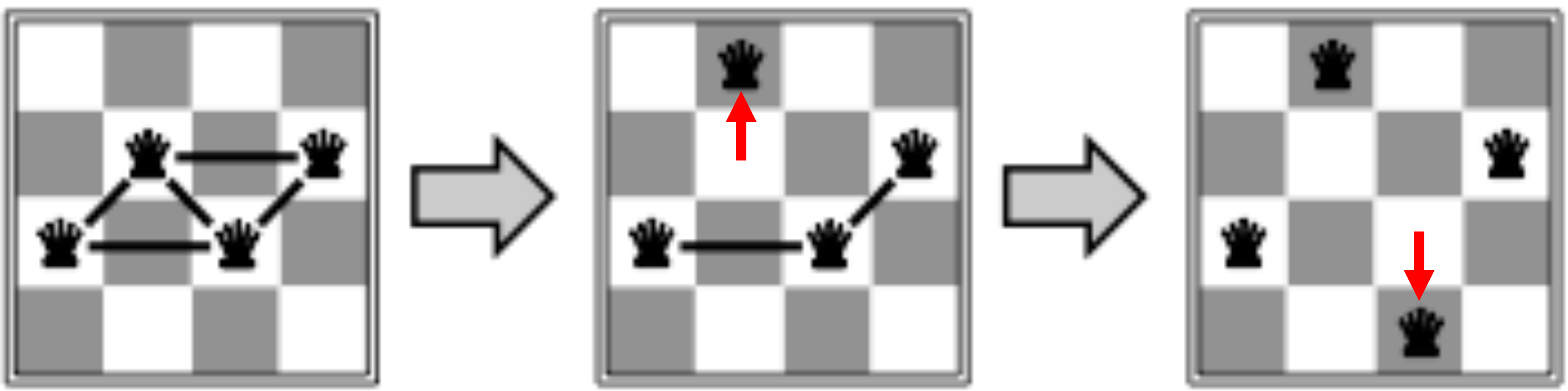
# Local search for constraint problems

- Remember local search?
- There’s a version of local search for CSP problems
- Basic idea:
  - generate a random “solution”
  - Use metric of “number of conflicts”
  - Modifying solution by reassigning one variable at a time to decrease metric until solution found or no modification improves it
- Has all features and problems of local search

  like….?

# Min Conflict Example

- **States:** 4 Queens, 1 per column
- **Operators:** Move a queen in its column
- **Goal test:** No attacks
- **Evaluation metric:** Total number of attacks



How many conflicts does each state have?

# Basic Local Search Algorithm

Assign one domain value $d_i$ to each variable $v_i$

while no solution & not stuck & not timed out:

    bestCost $\leftarrow \infty$;    bestList $\leftarrow$ [ ];

    for each variable $v_i$ | Cost(Value($v_i$)) > 0

        for each domain value $d_i$ of $v_i$

            if Cost($d_i$) < bestCost

                bestCost $\leftarrow$ Cost($d_i$); bestList $\leftarrow$ [$d_i$];

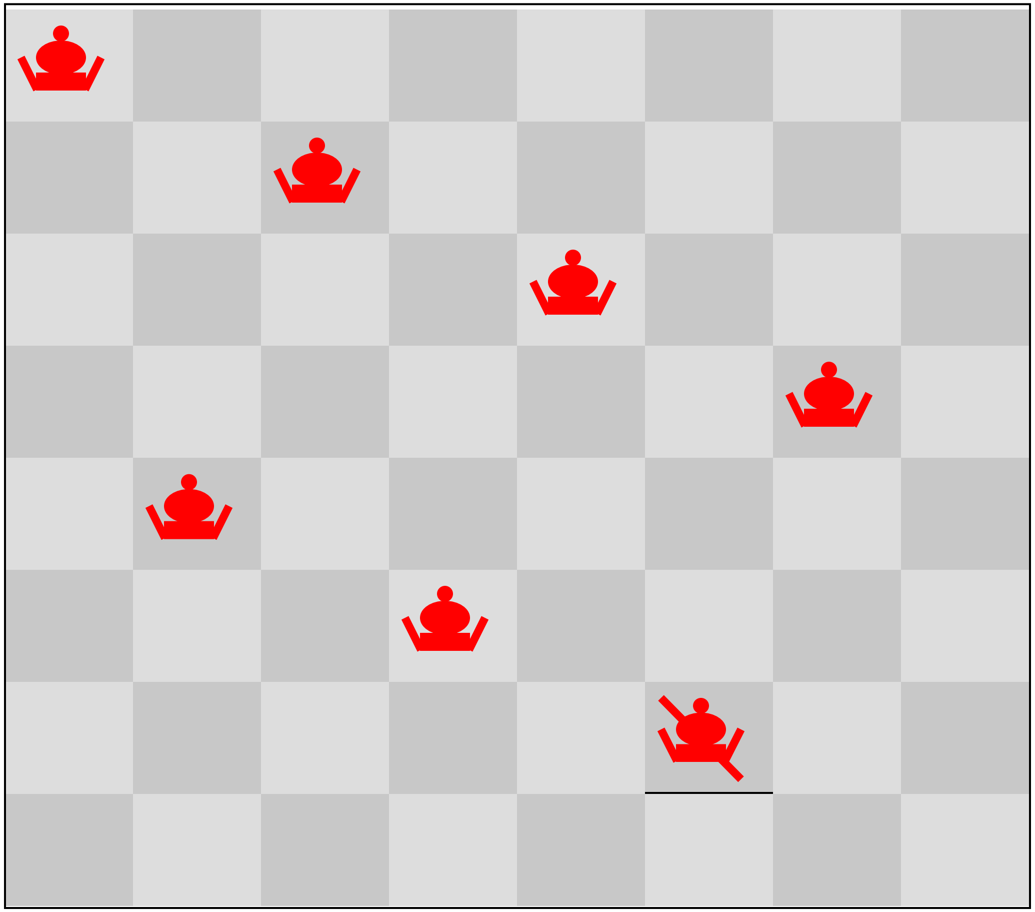
            else if Cost($d_i$) = bestCost

                bestList $\leftarrow$ bestList $\cup$ $d_i$

    Take a randomly selected move from bestList

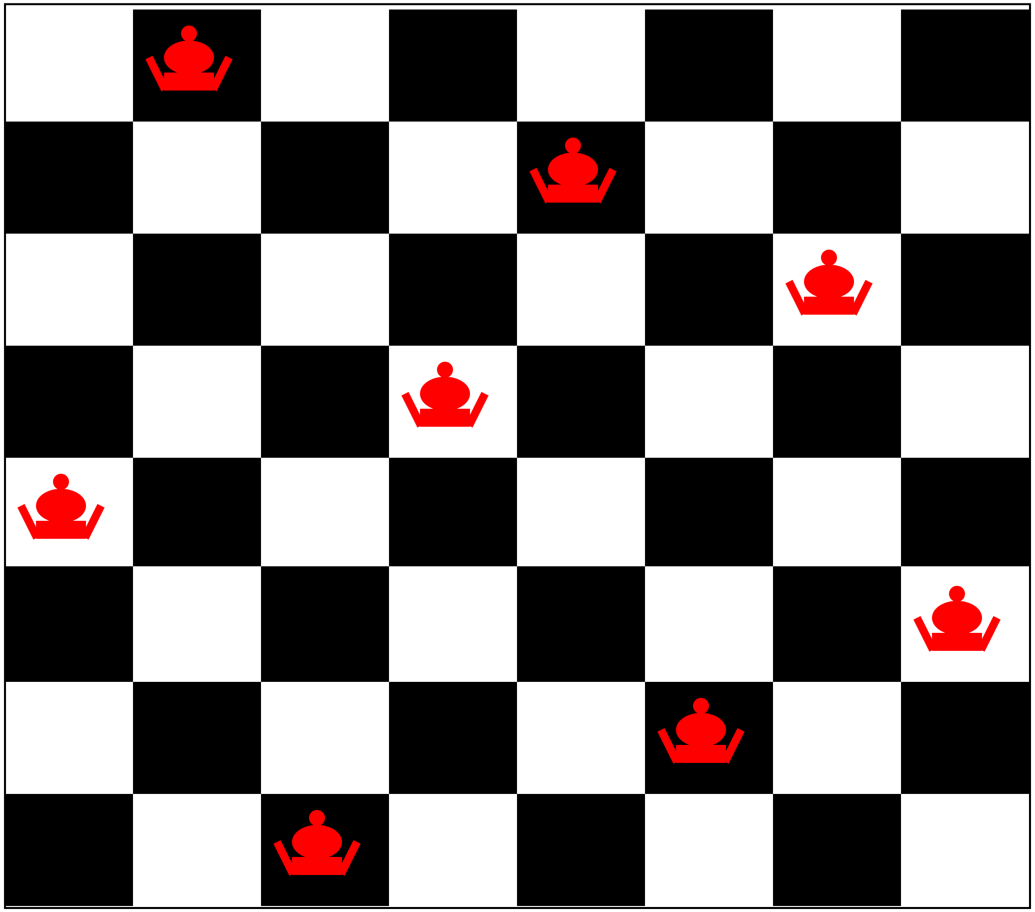
# Eight Queens using Backtracking

Undo move
for Queen 7
and so on...

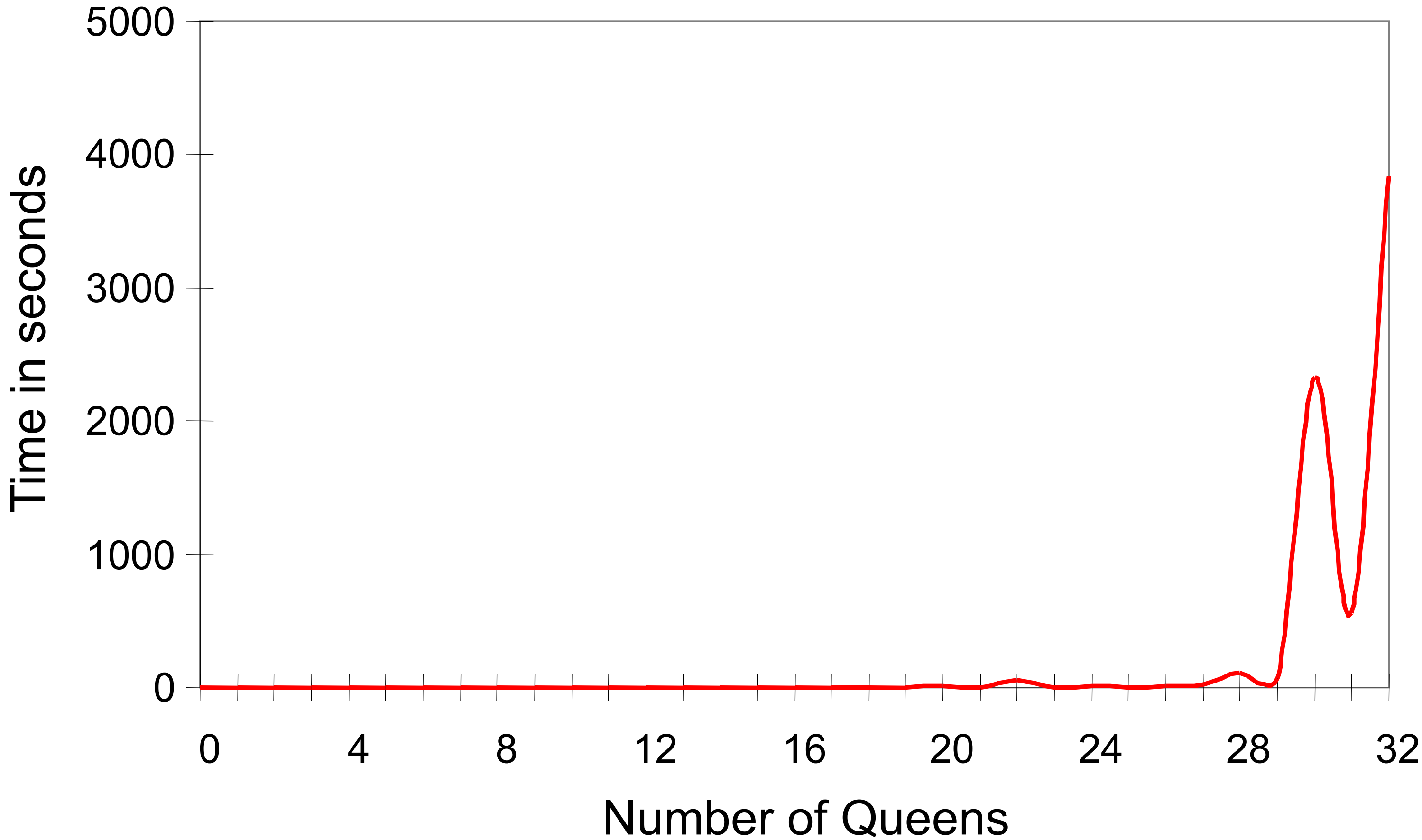


# Eight Queens using Local Search

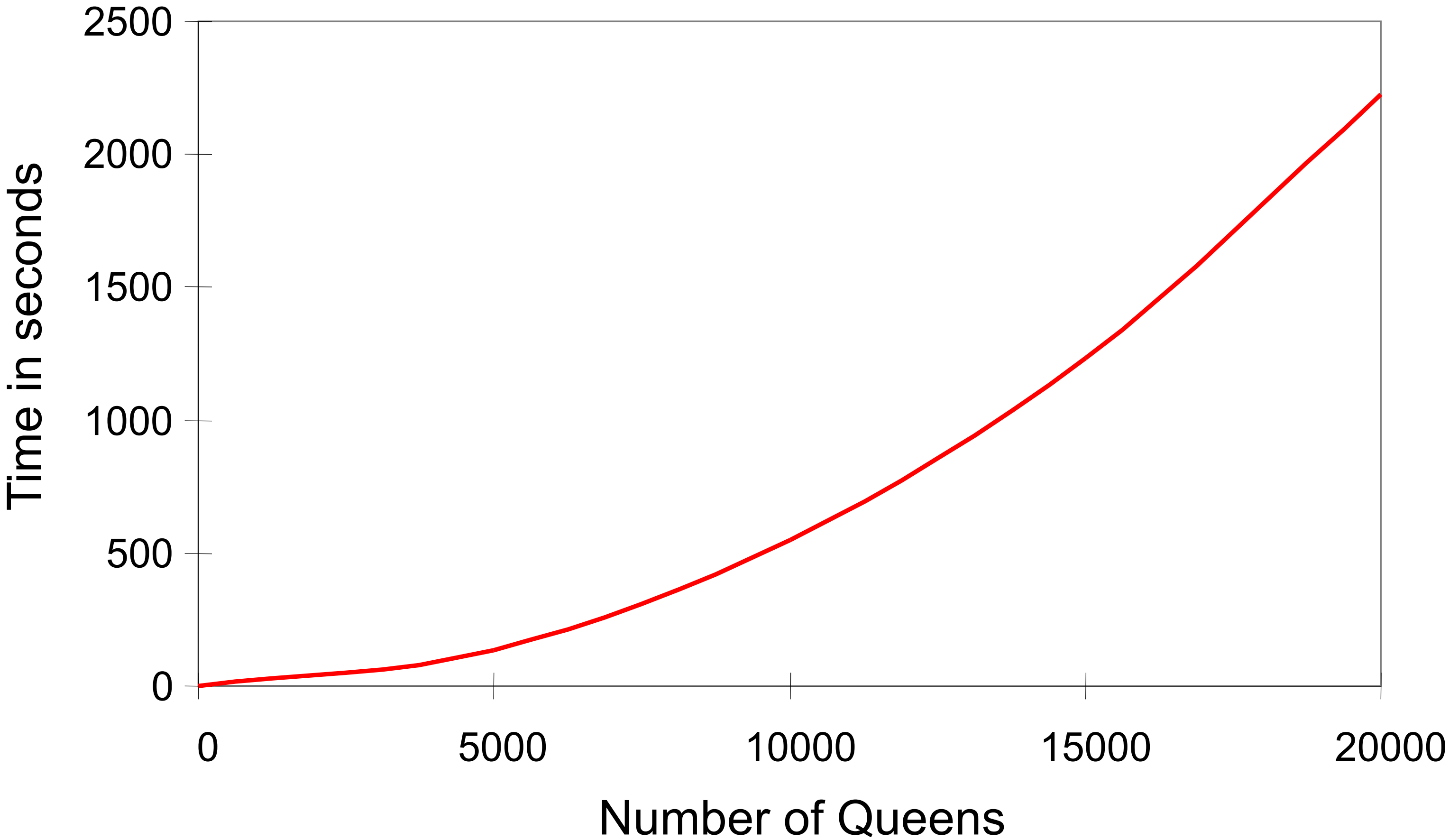
Answer Found



# Backtracking Performance



# Local Search Performance

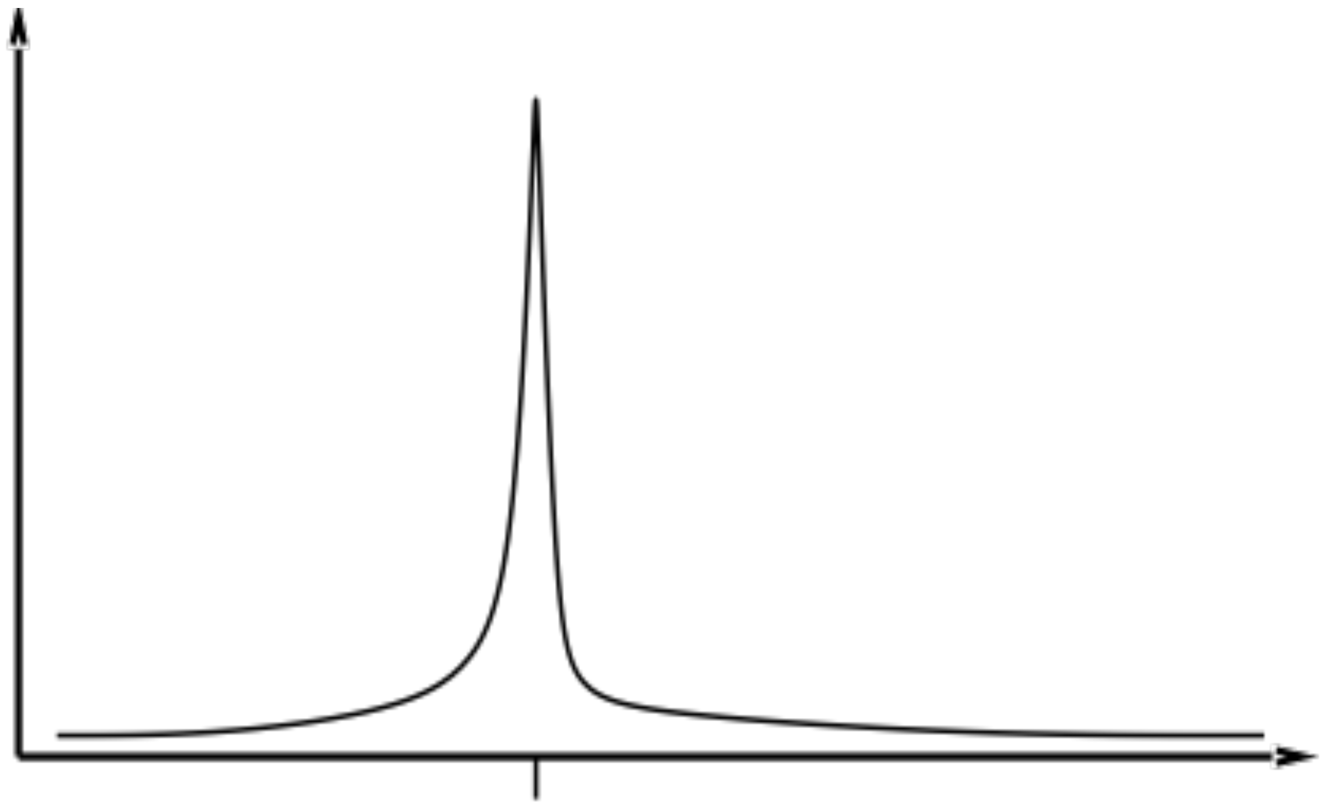


# Min Conflict Performance

- Performance depends on quality and informativeness of initial assignment; inversely related to distance to solution
- Min Conflict often has astounding performance
- Can solve arbitrary size (i.e., millions) N-Queens problems in constant time
- Appears to hold for arbitrary CSPs with the caveat…

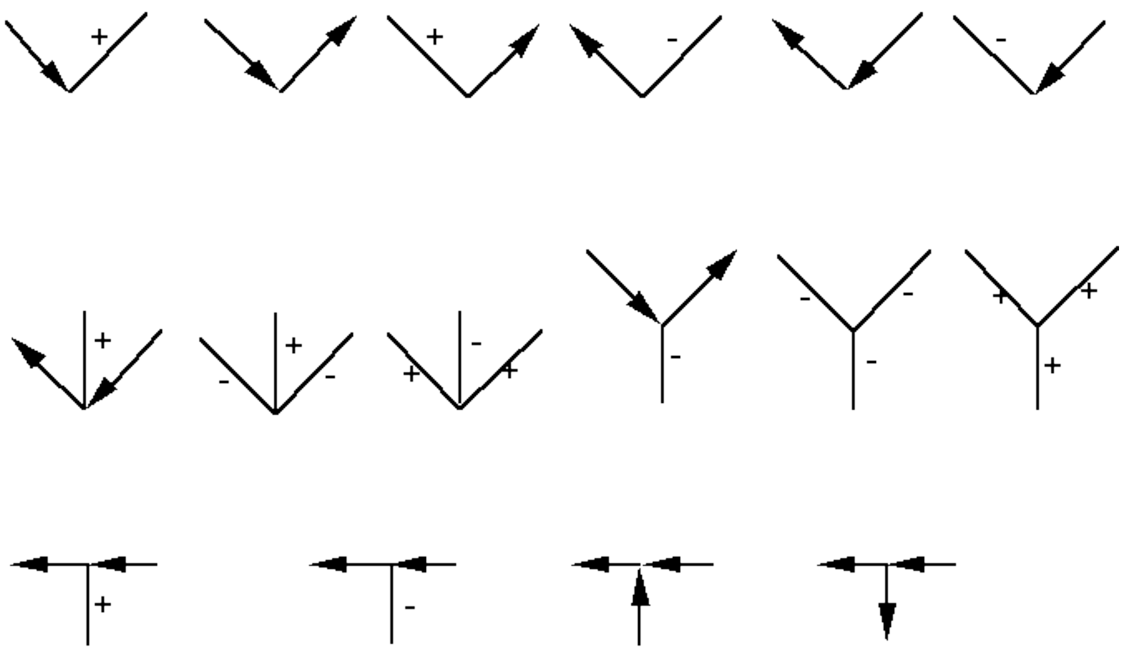
# Min Conflict Performance

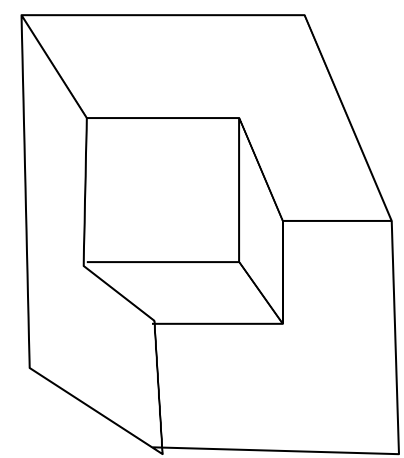
Except in a certain critical range of the ratio constraints to variables.



# Famous example: labeling line drawings

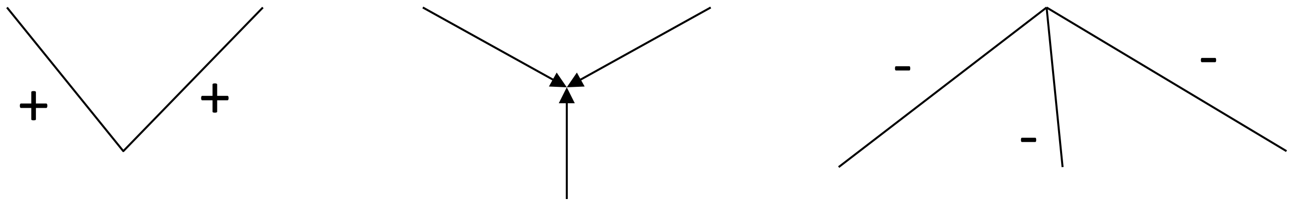
- [Waltz](#) labeling algorithm, earliest AI CSP application (1972)
  - Convex interior lines labeled as +
  - Concave interior lines labeled as –
  - Boundary lines labeled as with background to left
- 208 labeling possible labelings, but only 18 are legal





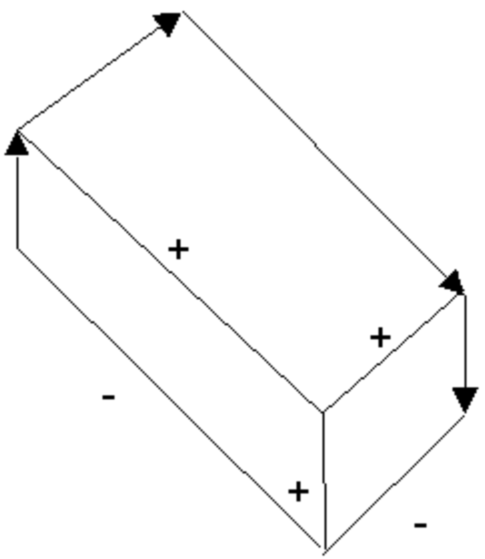
# Labeling line drawings II

Here are some illegal labelings

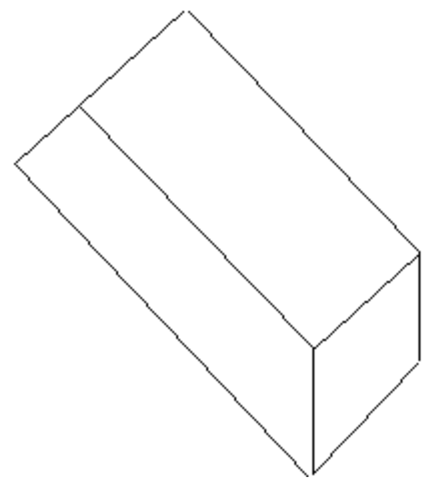


# Labeling line drawings

Waltz labeling algorithm: propagate constraints repeatedly until a solution is found



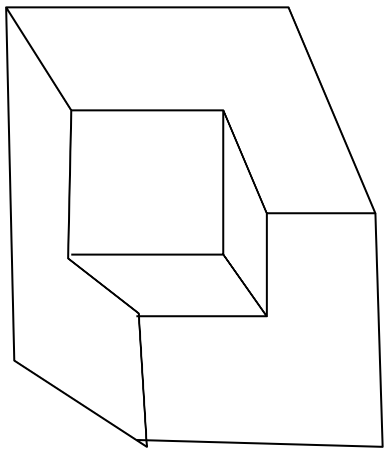

solution for one labeling problem



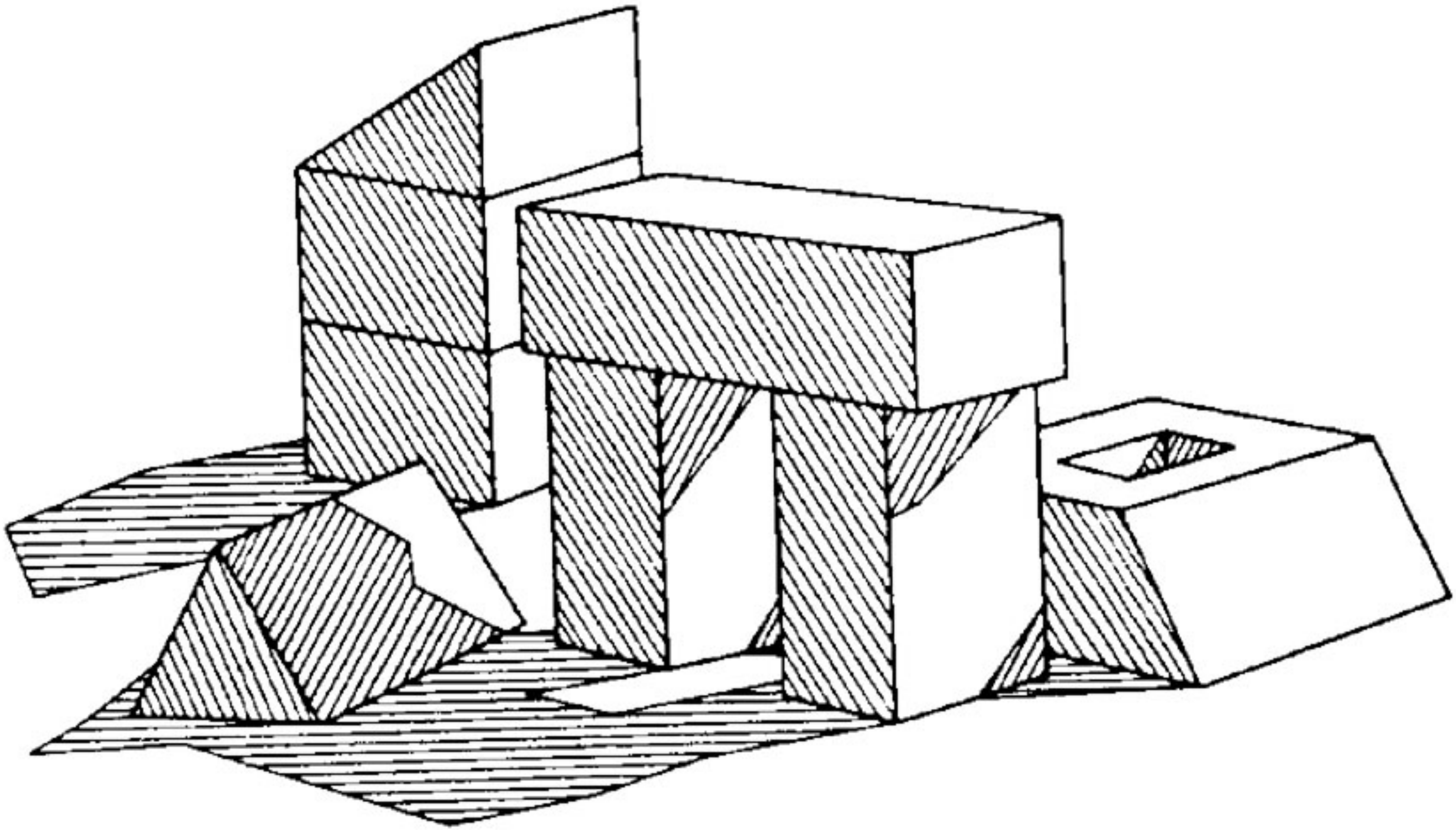
labeling problem with no solution

# Labeling line drawings

This line drawing is ambiguous, with two interpretations



# Shadows add complexity



CSP was able to label scenes where some of the lines were caused by shadows

# Challenges for constraint reasoning

- What if not all constraints can be satisfied?
  - Hard vs. soft constraints vs. preferences
  - Degree of constraint satisfaction
  - Cost of violating constraints
- What if constraints are of different forms?
  - Symbolic constraints
  - Logical constraints
  - Numerical constraints [constraint solving]
  - Temporal constraints
  - Mixed constraints

# Challenges for constraint reasoning

- What if constraints are represented intentionally?
  - Cost of evaluating constraints (time, memory, resources)
- What if constraints, variables, and/or values change over time?
  - Dynamic constraint networks
  - Temporal constraint networks
  - Constraint repair
- What if multiple agents or systems are involved in constraint satisfaction?
  - Distributed CSPs
  - Localization techniques