

# Announcements

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- Project 1 is due **Friday, September 9, 11:59 PM PT**
  - Start soon if you haven't already! It's one of the longer projects.
- HW1 is due **Friday, September 9, 11:59 PM PT**

# CS 188: Artificial Intelligence

## Constraint Satisfaction Problems

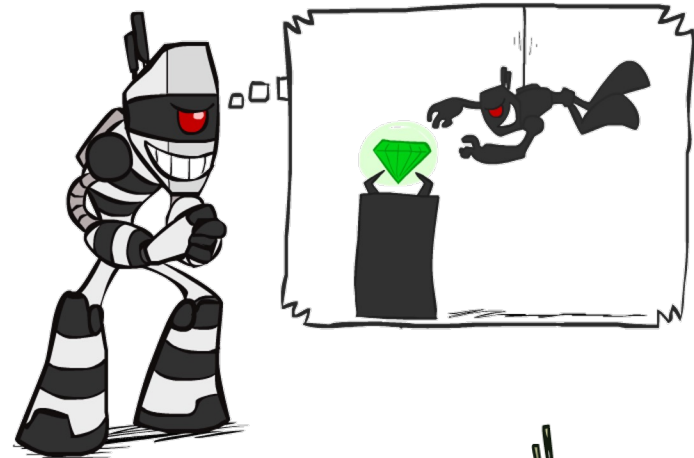


Fall 2022

University of California, Berkeley

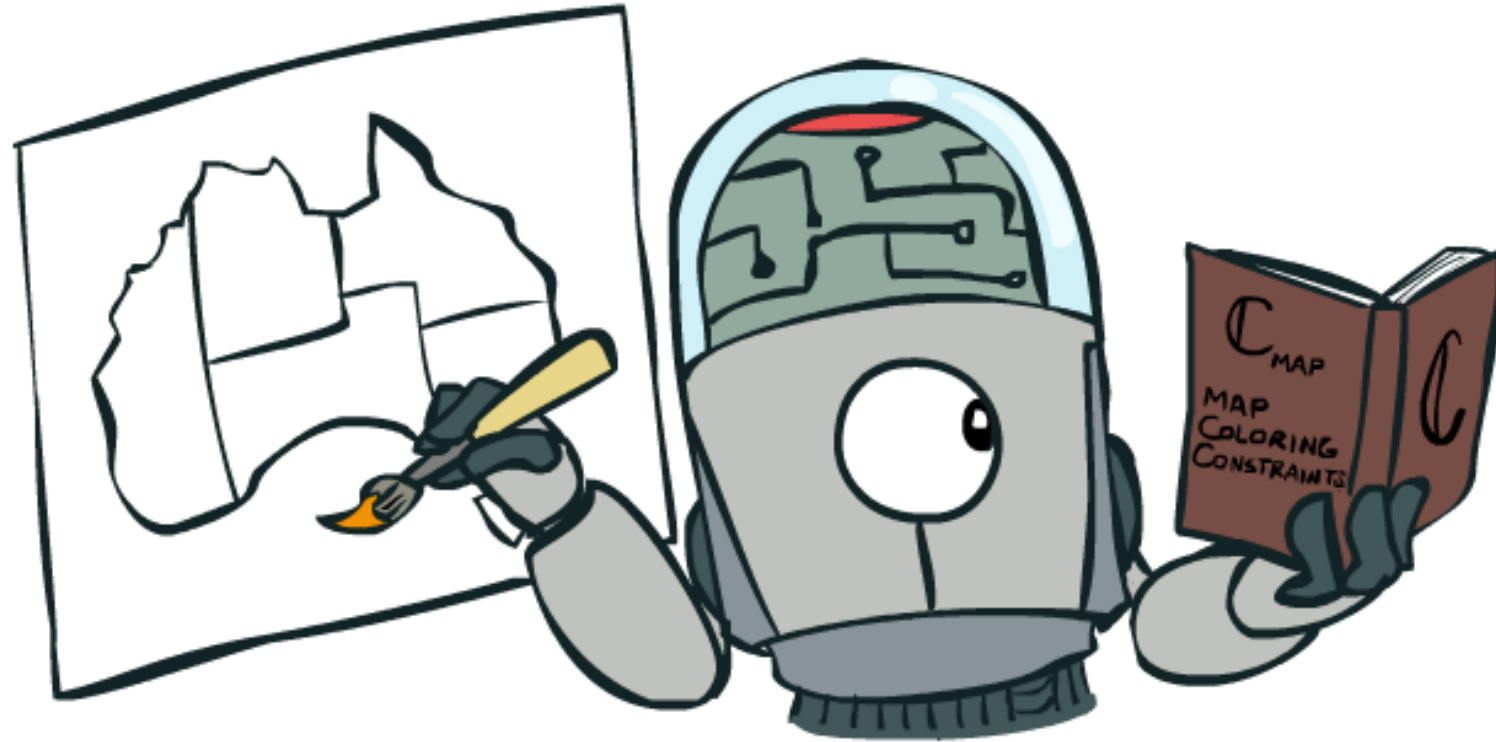
# What is Search For?

- Assumptions about the world: a single agent, deterministic actions, fully observed state, discrete state space
- Planning: sequences of actions
  - The path to the goal is the important thing
  - Paths have various costs, depths
  - Heuristics give problem-specific guidance
- Identification: assignments to variables
  - The goal itself is important, not the path
  - All paths at the same depth (for some formulations)
  - CSPs are a specialized class of identification problems



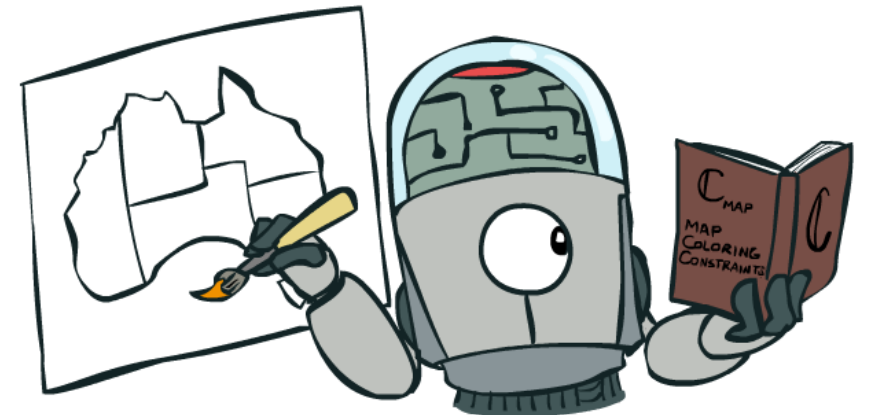
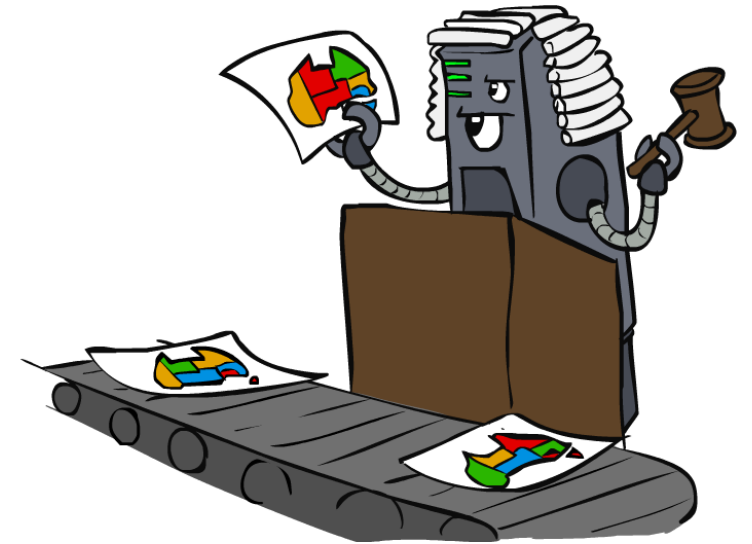
# Constraint Satisfaction Problems

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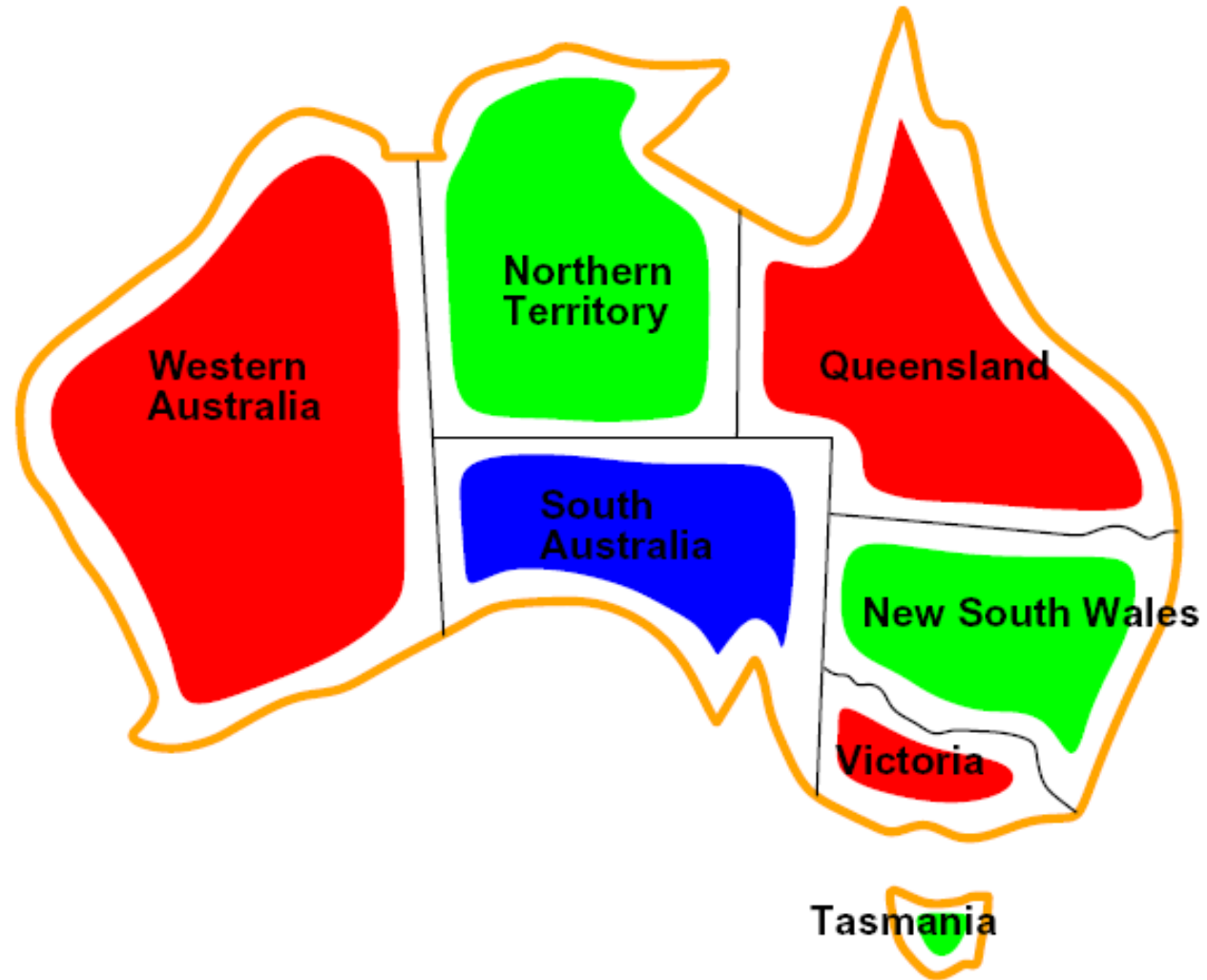


# Constraint Satisfaction Problems

- Standard search problems:
  - State is a “black box”: arbitrary data structure
  - Goal test can be any function over states
  - Successor function can also be anything
- Constraint satisfaction problems (CSPs):
  - A special subset of search problems
  - State is defined by **variables  $X_i$**  with values from a **domain  $D$**  (sometimes  $D$  depends on  $i$ )
  - Goal test is a **set of constraints** specifying allowable combinations of values for subsets of variables
- Simple example of a *formal representation language*
- Allows useful general-purpose algorithms with more power than standard search algorithms



# CSP Examples



# Example: Map Coloring

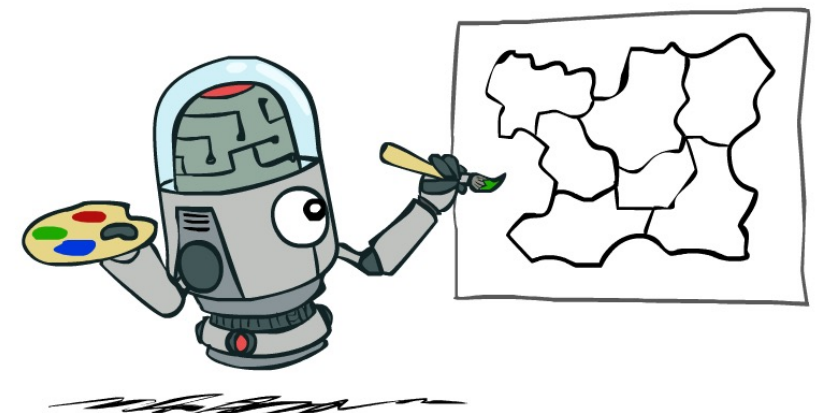
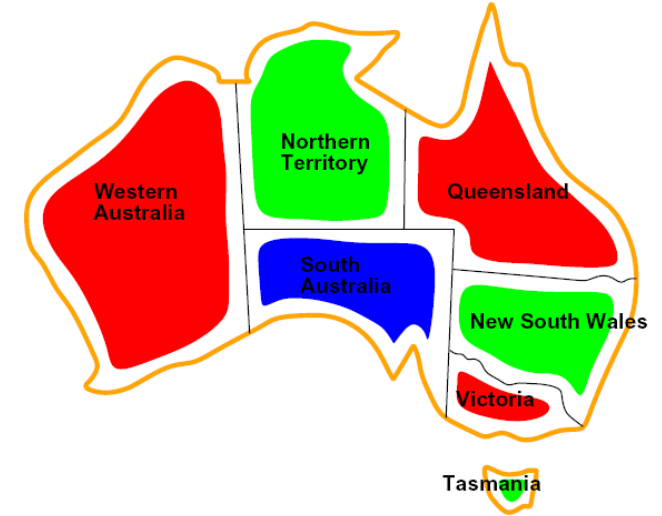
- Variables: WA, NT, Q, NSW, V, SA, T
- Domains:  $D = \{\text{red, green, blue}\}$
- Constraints: adjacent regions must have different colors

Implicit:  $WA \neq NT$

Explicit:  $(WA, NT) \in \{(\text{red, green}), (\text{red, blue}), \dots\}$

- Solutions are assignments satisfying all constraints, e.g.:

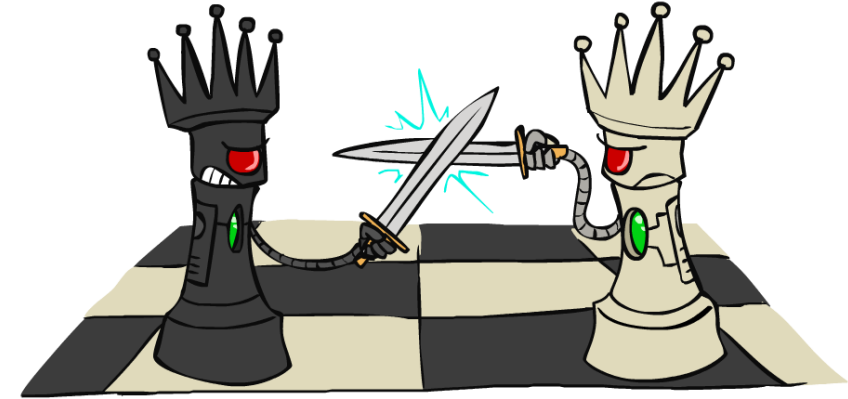
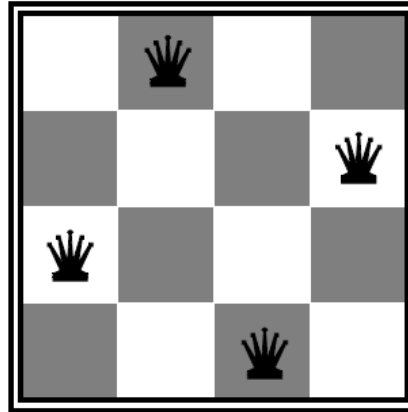
$\{WA=\text{red}, NT=\text{green}, Q=\text{red}, NSW=\text{green}, V=\text{red}, SA=\text{blue}, T=\text{green}\}$



# Example: N-Queens

- Formulation 1:

- Variables:  $X_{ij}$
- Domains:  $\{0, 1\}$
- Constraints



$$\forall i, j, k \quad (X_{ij}, X_{ik}) \in \{(0, 0), (0, 1), (1, 0)\}$$

$$\forall i, j, k \quad (X_{ij}, X_{kj}) \in \{(0, 0), (0, 1), (1, 0)\}$$

$$\forall i, j, k \quad (X_{ij}, X_{i+k, j+k}) \in \{(0, 0), (0, 1), (1, 0)\}$$

$$\forall i, j, k \quad (X_{ij}, X_{i+k, j-k}) \in \{(0, 0), (0, 1), (1, 0)\}$$

$$\sum_{i,j} X_{ij} = N$$



# Example: N-Queens

- Formulation 2:

- Variables:  $Q_k$

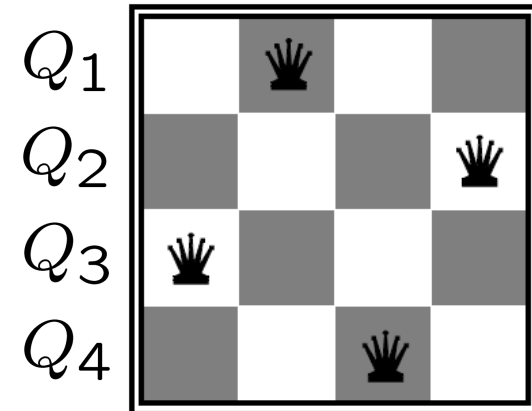
- Domains:  $\{1, 2, 3, \dots, N\}$

- Constraints:

Implicit:  $\forall i, j$  non-threatening( $Q_i, Q_j$ )

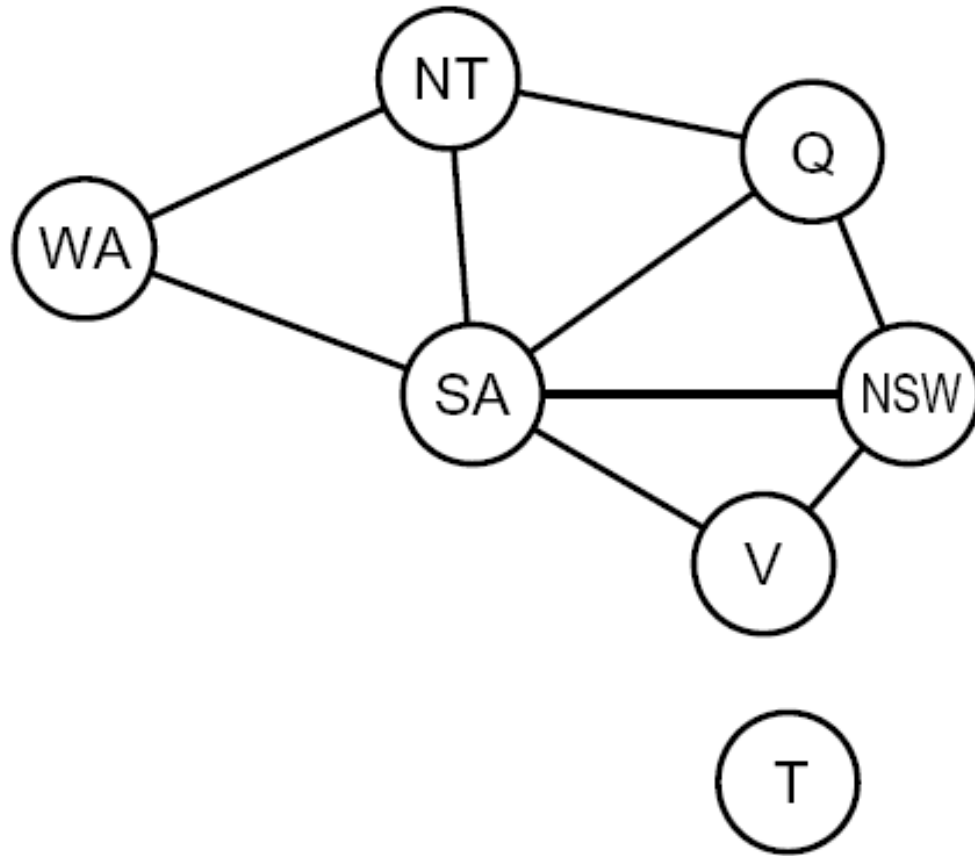
Explicit:  $(Q_1, Q_2) \in \{(1, 3), (1, 4), \dots\}$

...



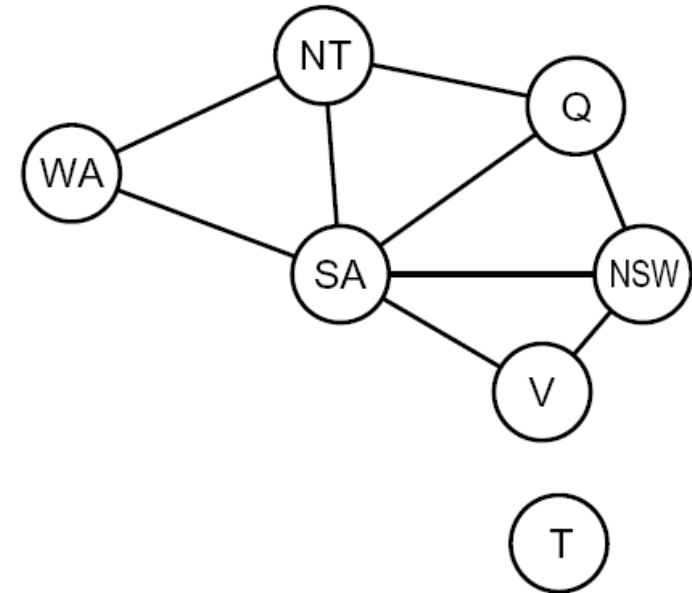
# Constraint Graphs

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# Constraint Graphs

- Binary CSP: each constraint relates (at most) two variables
- Binary constraint graph: nodes are variables, arcs show constraints
- General-purpose CSP algorithms use the graph structure to speed up search. E.g., Tasmania is an independent subproblem!



# Example: Cryptarithmic

- Variables:

$F T U W R O X_1 X_2 X_3$

- Domains:

$\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

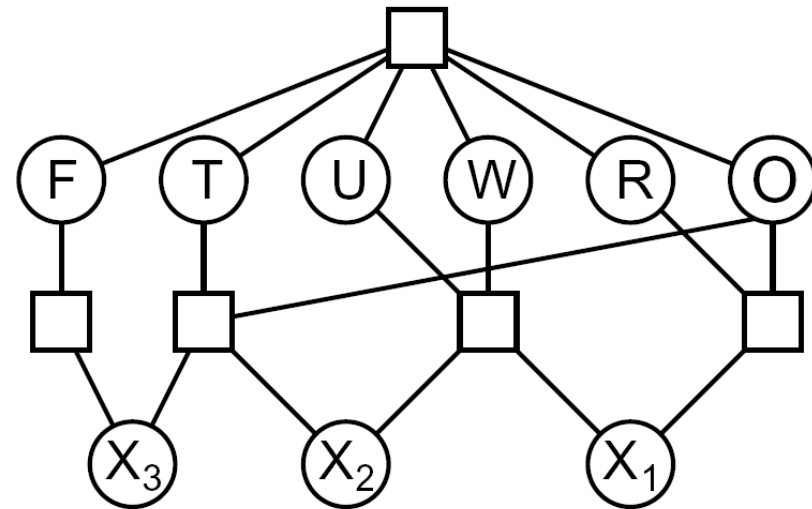
- Constraints:

$\text{alldiff}(F, T, U, W, R, O)$

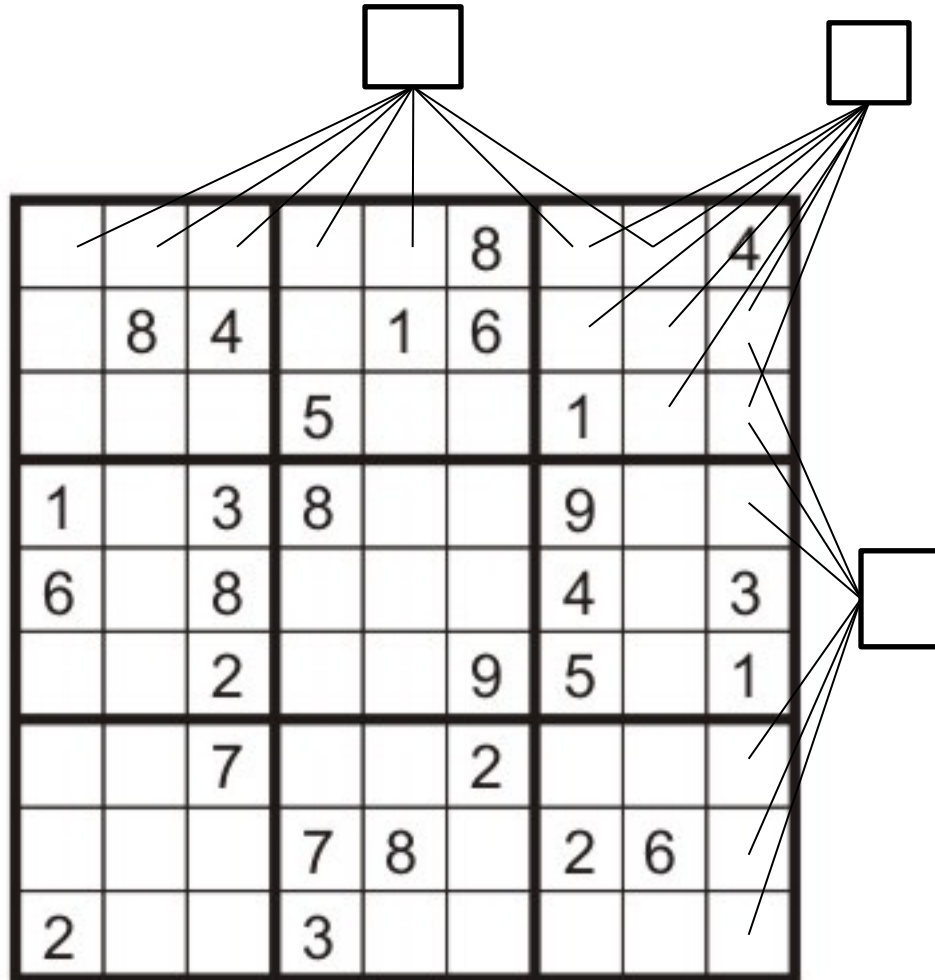
$O + O = R + 10 \cdot X_1$

...

$$\begin{array}{r} T W O \\ + T W O \\ \hline F O U R \end{array}$$



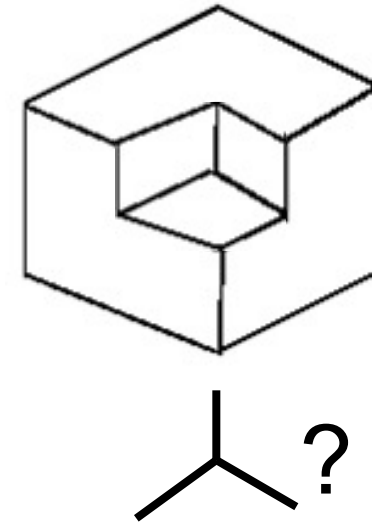
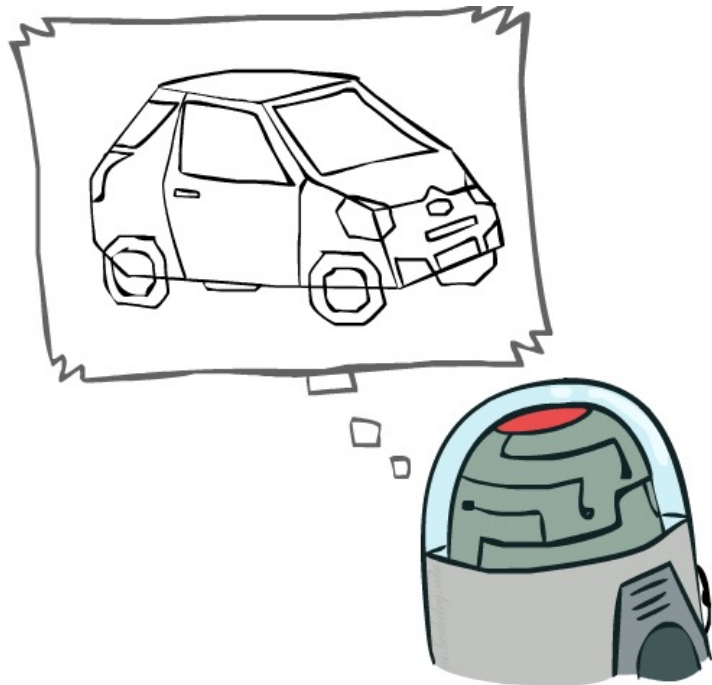
# Example: Sudoku



- Variables:
  - Each (open) square
- Domains:
  - $\{1,2,\dots,9\}$
- Constraints:
  - 9-way alldiff for each column
  - 9-way alldiff for each row
  - 9-way alldiff for each region
  - (or can have a bunch of pairwise inequality constraints)

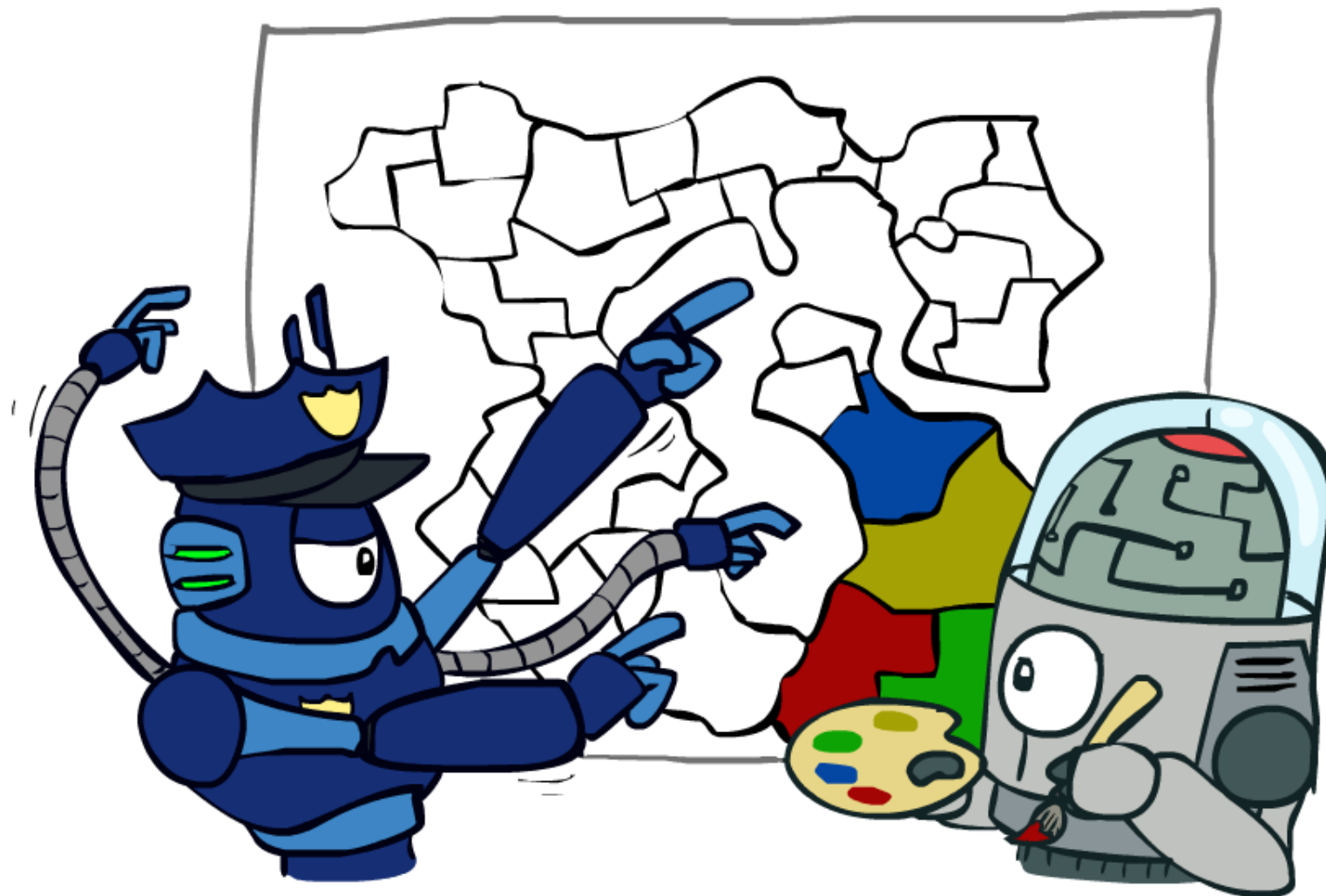
# Example: The Waltz Algorithm

- The Waltz algorithm is for interpreting line drawings of solid polyhedra as 3D objects
- An early example of an AI computation posed as a CSP



- Approach:
  - Each intersection is a variable
  - Adjacent intersections impose constraints on each other
  - Solutions are physically realizable 3D interpretations

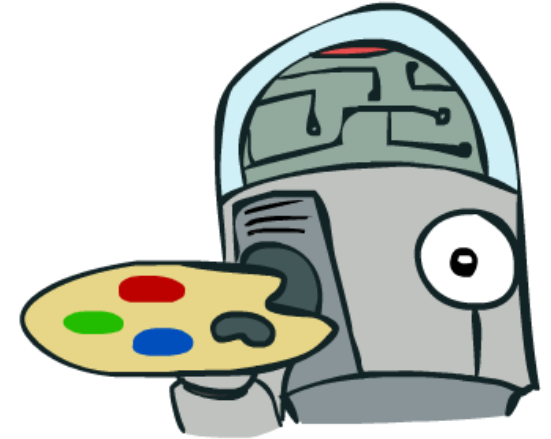
# Varieties of CSPs and Constraints



# Varieties of CSPs

- Discrete Variables

- Finite domains
  - Size  $d$  means  $O(d^n)$  complete assignments
  - E.g., Boolean CSPs, including Boolean satisfiability (NP-complete)
- Infinite domains (integers, strings, etc.)
  - E.g., job scheduling, variables are start/end times for each job
  - Linear constraints solvable, nonlinear undecidable



- Continuous variables

- E.g., start/end times for Hubble Telescope observations
- Linear constraints solvable in polynomial time by LP methods (see cs170 for a bit of this theory)





# Varieties of Constraints

- Varieties of Constraints

- Unary constraints involve a single variable (equivalent to reducing domains), e.g.:

$$SA \neq \text{green}$$

- Binary constraints involve pairs of variables, e.g.:

$$SA \neq WA$$

- Higher-order constraints involve 3 or more variables:  
e.g., cryptarithmic column constraints

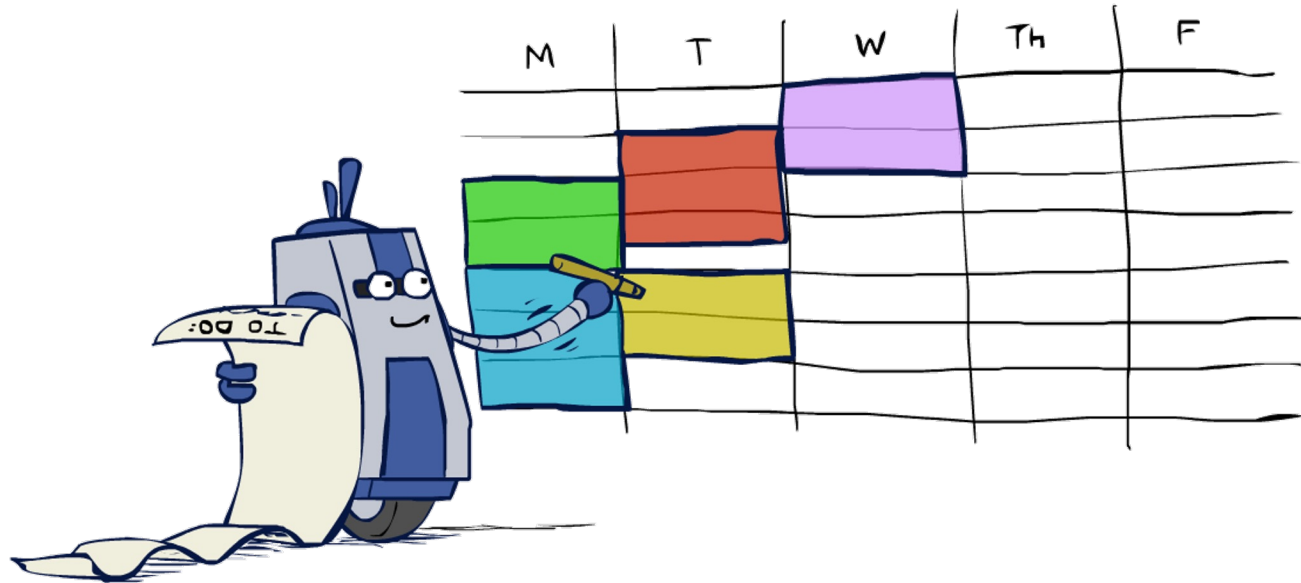
- Preferences (soft constraints):

- E.g., red is better than green
- Often representable by a cost for each variable assignment
- Gives constrained optimization problems
- (We'll ignore these until we get to Bayes' nets)



# Real-World CSPs

- Scheduling problems: e.g., when can we all meet?
- Timetabling problems: e.g., which class is offered when and where?
- Assignment problems: e.g., who teaches what class
- Hardware configuration
- Transportation scheduling
- Factory scheduling
- Circuit layout
- Fault diagnosis
- ... lots more!



- Many real-world problems involve real-valued variables...

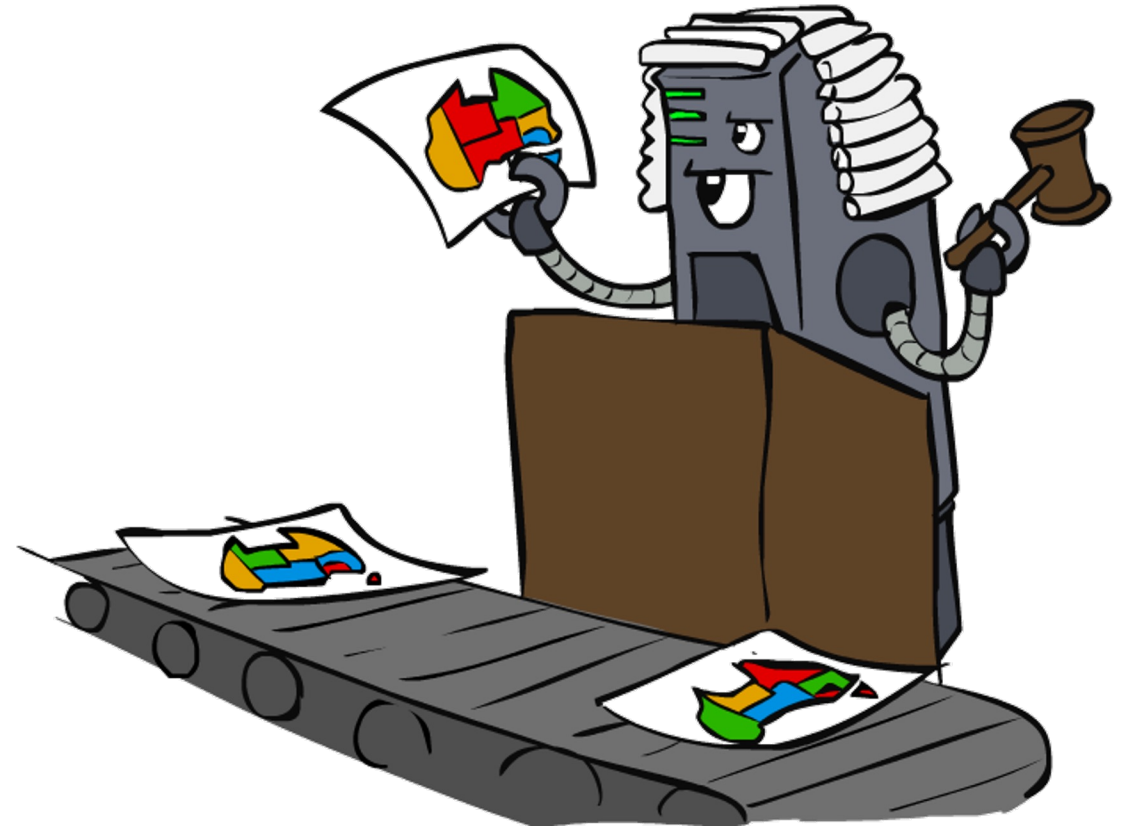
# Solving CSPs

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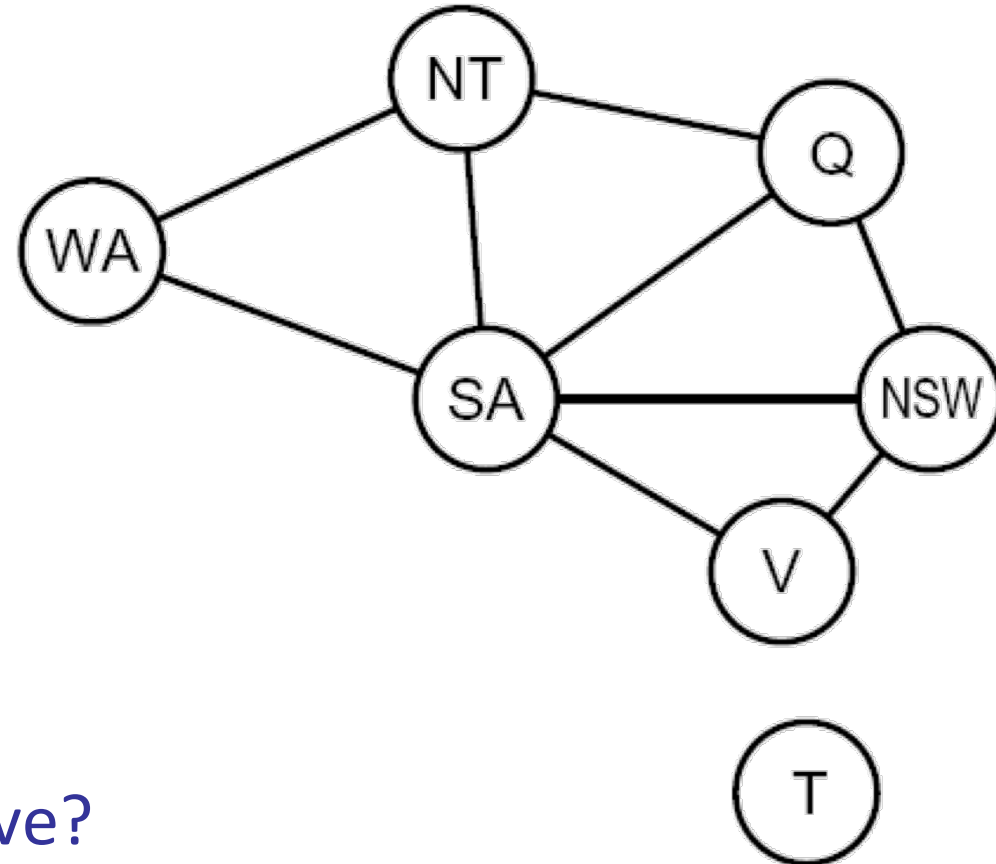
# Standard Search Formulation

- Standard search formulation of CSPs
- States defined by the values assigned so far (partial assignments)
  - Initial state: the empty assignment,  $\{\}$
  - Successor function: assign a value to an unassigned variable
  - Goal test: the current assignment is complete and satisfies all constraints
- We'll start with the straightforward, naïve approach, then improve it



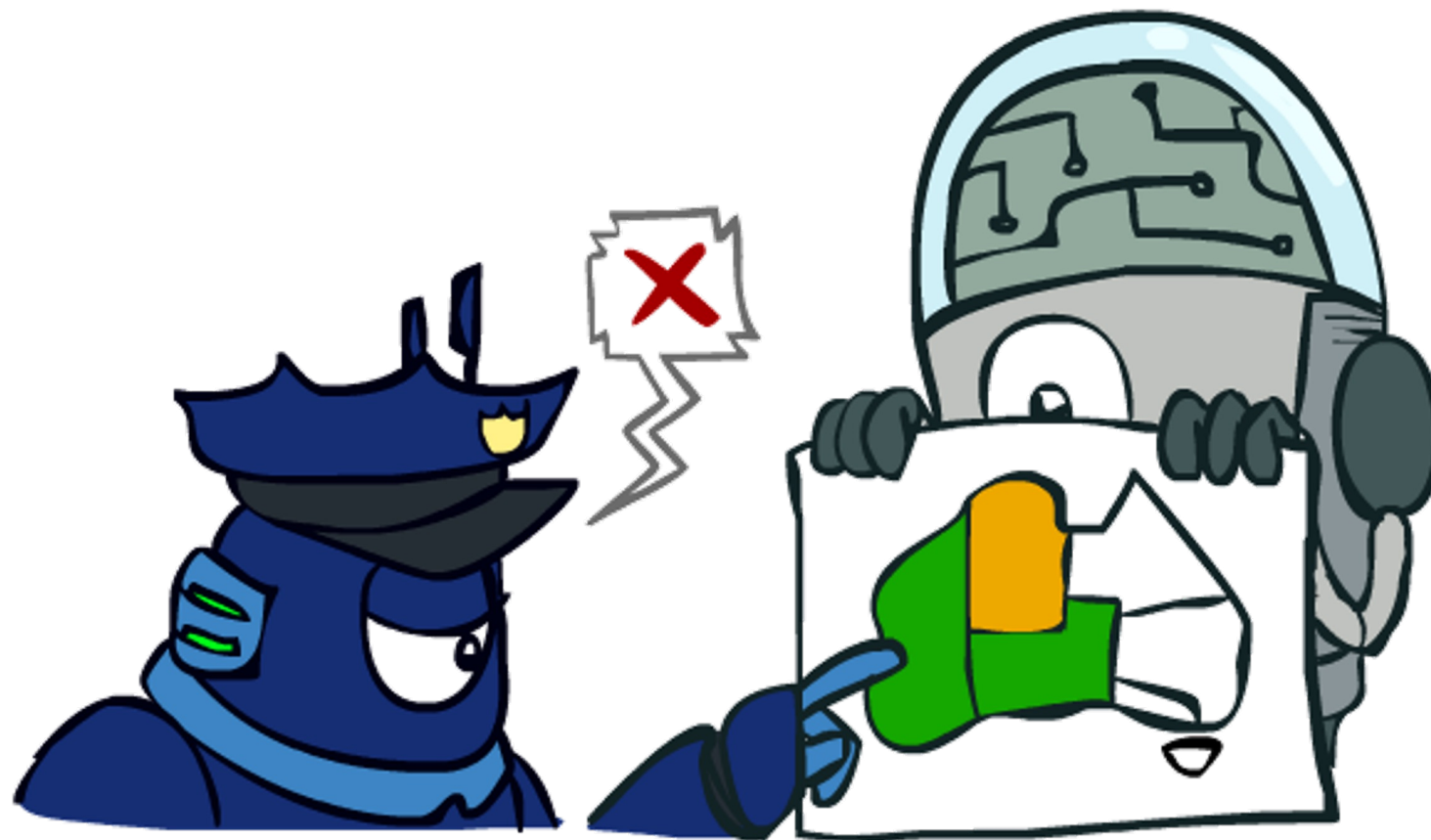
# Search Methods

- What would BFS do?
- What would DFS do?
- What problems does naïve search have?



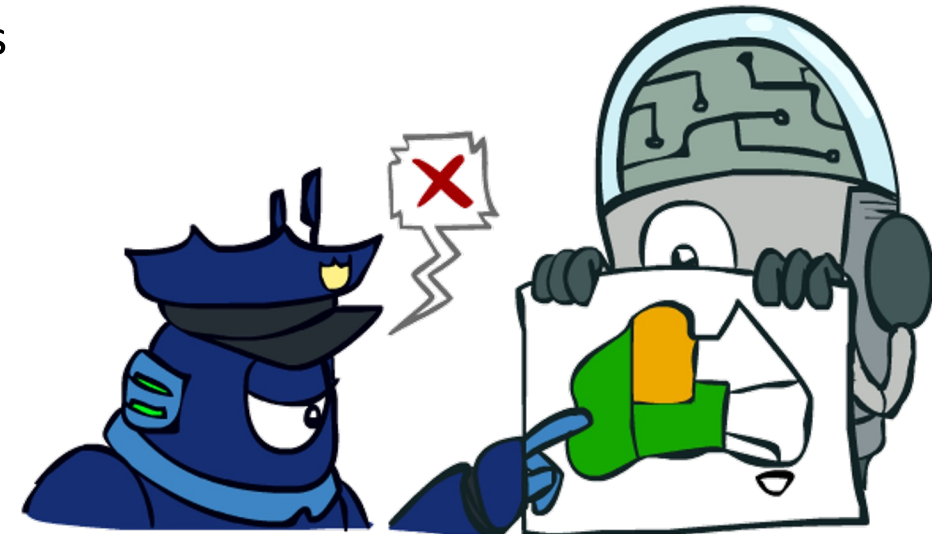
# Backtracking Search

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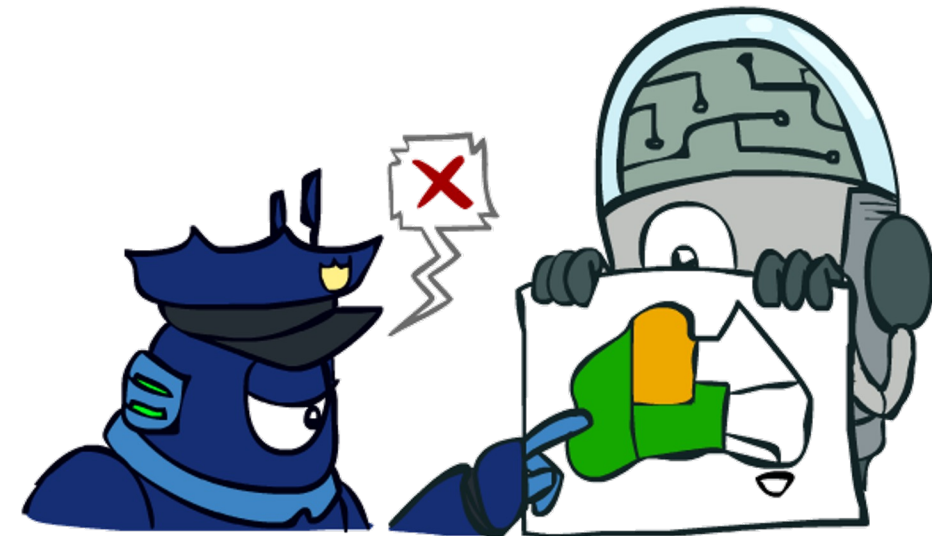
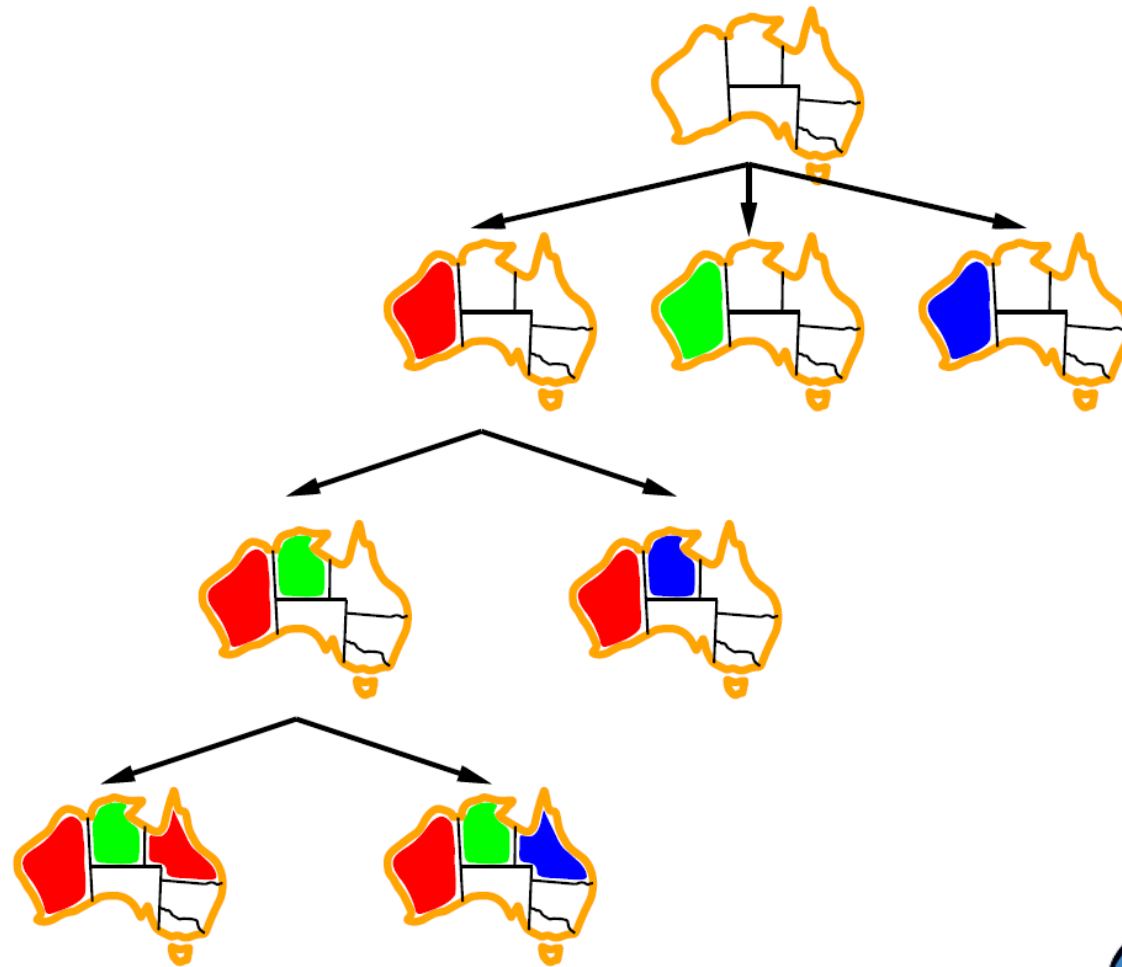


# Backtracking Search

- Backtracking search is the basic uninformed algorithm for solving CSPs
- Idea 1: One variable at a time
  - Variable assignments are commutative, so fix ordering
  - I.e., [WA = red then NT = green] same as [NT = green then WA = red]
  - Only need to consider assignments to a single variable at each step
- Idea 2: Check constraints as you go
  - I.e. consider only values which do not conflict with previous assignments
  - Might have to do some computation to check the constraints
  - “Incremental goal test”
- Depth-first search with these two improvements is called *backtracking search* (not the best name)
- Can solve n-queens for  $n \approx 25$



# Backtracking Example





# Backtracking Search

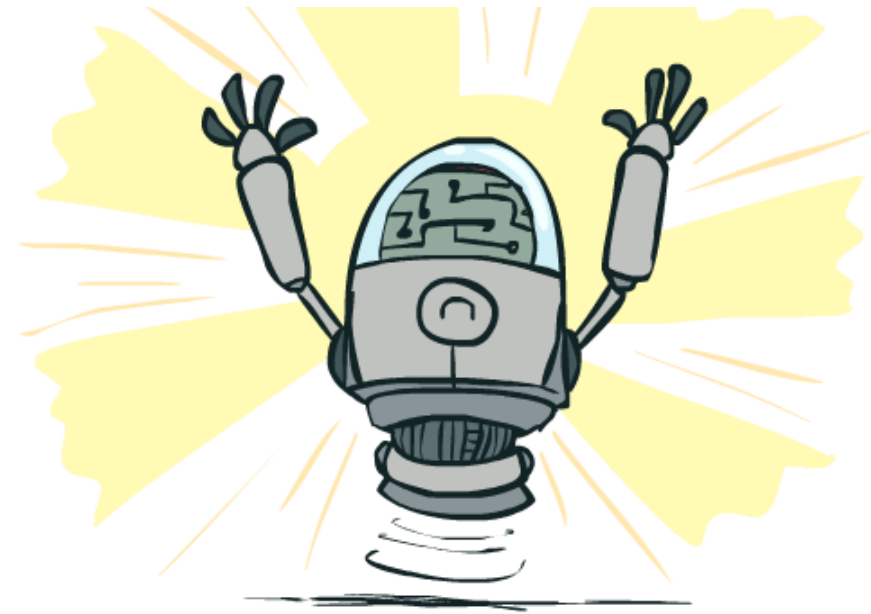
```
function BACKTRACKING-SEARCH(csp) returns solution/failure
  return RECURSIVE-BACKTRACKING({ }, csp)

function RECURSIVE-BACKTRACKING(assignment, csp) returns soln/failure
  if assignment is complete then return assignment
  var ← SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignment, csp)
  for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
    if value is consistent with assignment given CONSTRAINTS[csp] then
      add {var = value} to assignment
      result ← RECURSIVE-BACKTRACKING(assignment, csp)
      if result ≠ failure then return result
      remove {var = value} from assignment
  return failure
```

- Backtracking = DFS + variable-ordering + fail-on-violation
- What are the choice points?

# Improving Backtracking

- General-purpose ideas give huge gains in speed
- Ordering:
  - Which variable should be assigned next?
  - In what order should its values be tried?
- Filtering: Can we detect inevitable failure early?
- Structure: Can we exploit the problem structure?

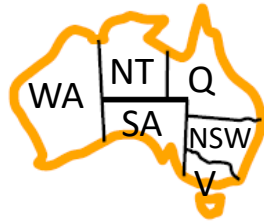


# Filtering



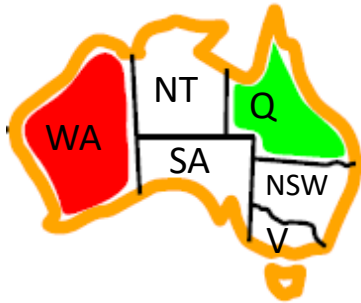
# Filtering: Forward Checking

- Filtering: Keep track of domains for unassigned variables and cross off bad options
- Forward checking: Cross off values that violate a constraint when added to the existing assignment



# Filtering: Constraint Propagation

- Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:

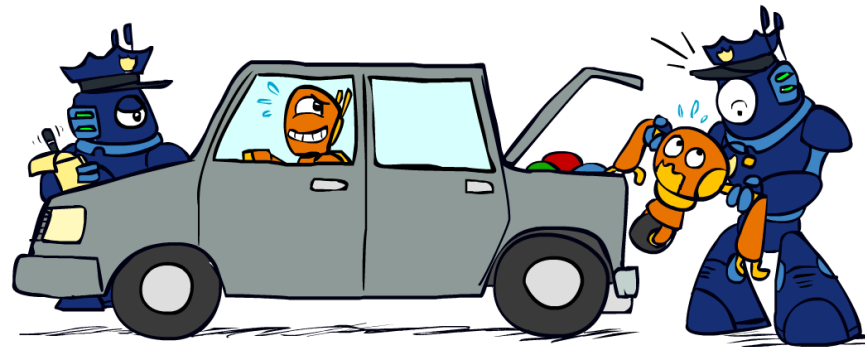
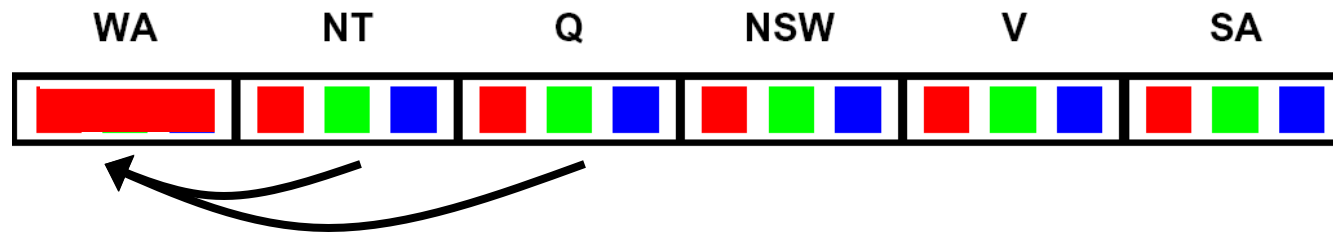
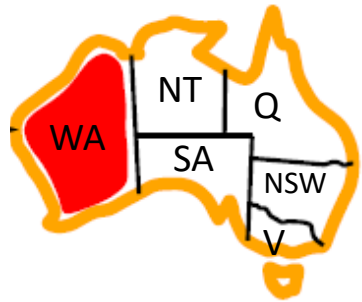


WA	NT	Q	NSW	V	SA
Red Green Blue	Red Green Blue	Red Green Blue	Red Green Blue	Red Green Blue	Red Green Blue
Red	Green Blue	Red Green Blue	Red Green Blue	Red Green Blue	Green Blue
Red	Blue	Green	Red Blue	Red Green Blue	Blue

- NT and SA cannot both be blue!
- Why didn't we detect this yet?
- Constraint propagation*: reason from constraint to constraint

# Consistency of A Single Arc

- An arc  $X \rightarrow Y$  is **consistent** iff for *every*  $x$  in the tail there is *some*  $y$  in the head which could be assigned without violating a constraint

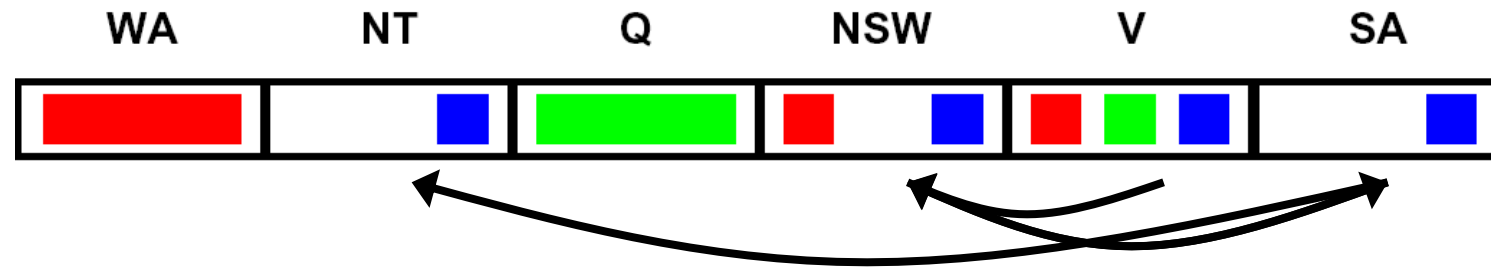
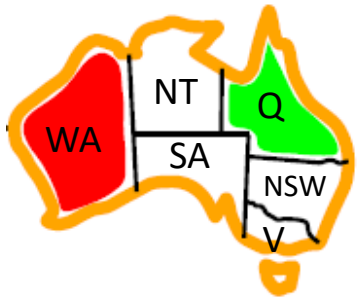


*Delete from the tail!*

- Forward checking: Enforcing consistency of arcs pointing to each new assignment

# Arc Consistency of an Entire CSP

- A simple form of propagation makes sure **all** arcs are consistent:



- Important: If X loses a value, neighbors of X need to be rechecked!
- Arc consistency detects failure earlier than forward checking
- Can be run as a preprocessor or after each assignment
- What's the downside of enforcing arc consistency?

*Remember:  
Delete from  
the tail!*

# Enforcing Arc Consistency in a CSP

```
function AC-3(csp) returns the CSP, possibly with reduced domains
inputs: csp, a binary CSP with variables  $\{X_1, X_2, \dots, X_n\}$ 
local variables: queue, a queue of arcs, initially all the arcs in csp

while queue is not empty do
     $(X_i, X_j) \leftarrow \text{REMOVE-FIRST}(\textit{queue})$ 
    if REMOVE-INCONSISTENT-VALUES( $X_i, X_j$ ) then
        for each  $X_k$  in NEIGHBORS[ $X_i$ ] do
            add  $(X_k, X_i)$  to queue

```

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```
function REMOVE-INCONSISTENT-VALUES( $X_i, X_j$ ) returns true iff succeeds
    removed  $\leftarrow$  false
    for each  $x$  in DOMAIN[ $X_i$ ] do
        if no value  $y$  in DOMAIN[ $X_j$ ] allows  $(x, y)$  to satisfy the constraint  $X_i \leftrightarrow X_j$ 
            then delete  $x$  from DOMAIN[ $X_i$ ]; removed  $\leftarrow$  true
    return removed

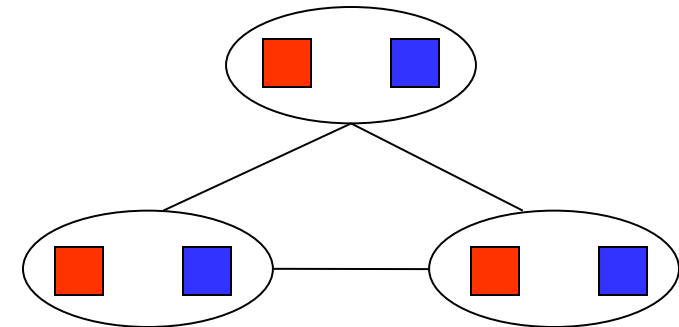
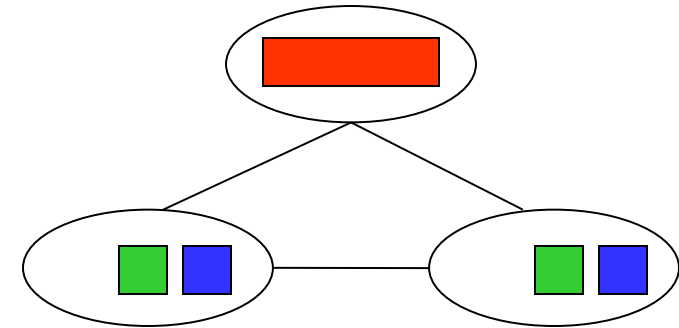
```

- Runtime:  $O(n^2d^3)$ , can be reduced to  $O(n^2d^2)$
- ... but detecting all possible future problems is NP-hard – why?



# Limitations of Arc Consistency

- After enforcing arc consistency:
  - Can have one solution left
  - Can have multiple solutions left
  - Can have no solutions left (and not know it)
- Arc consistency still runs inside a backtracking search!



*What went wrong here?*

[Demo: coloring -- forward checking]

[Demo: coloring -- arc consistency]

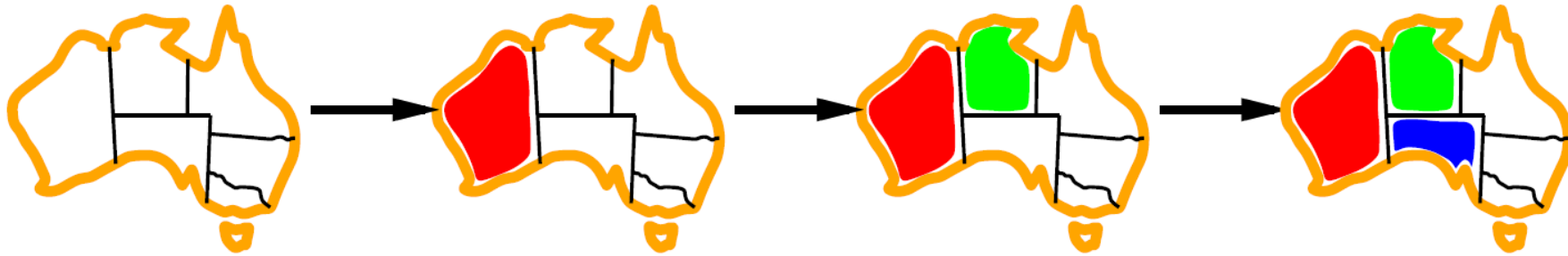
# Ordering

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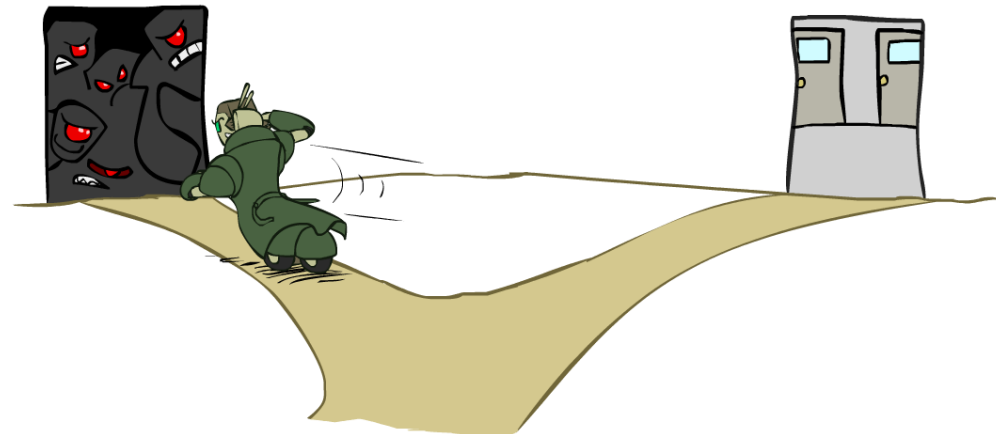


# Ordering: Minimum Remaining Values

- Variable Ordering: Minimum remaining values (MRV):
  - Choose the variable with the fewest legal left values in its domain

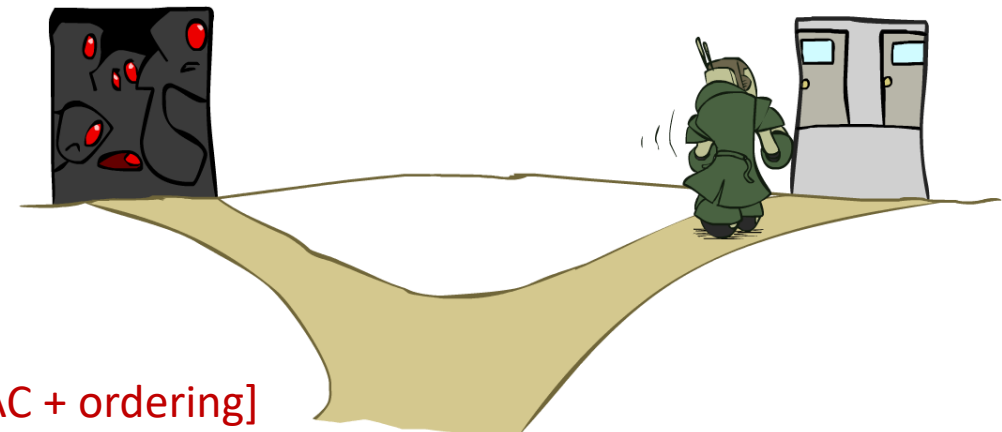
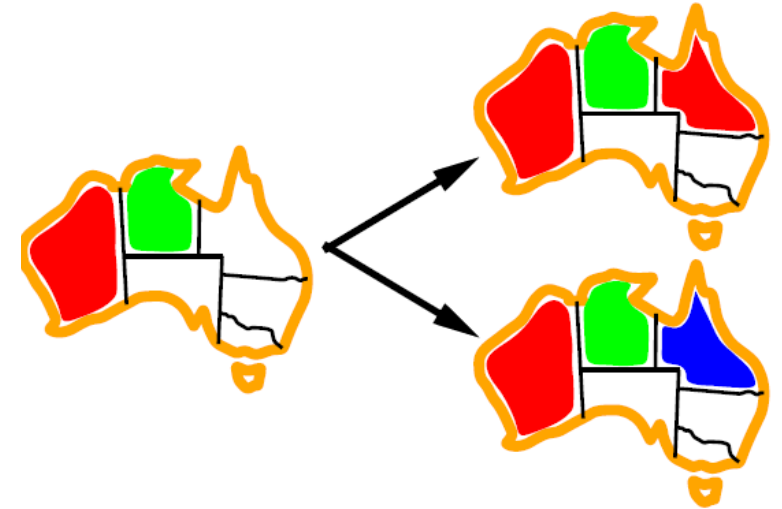


- Why min rather than max?
- Also called “most constrained variable”
- “Fail-fast” ordering



# Ordering: Least Constraining Value

- Value Ordering: Least Constraining Value
  - Given a choice of variable, choose the *least constraining value*
  - I.e., the one that rules out the fewest values in the remaining variables
  - Note that it may take some computation to determine this! (E.g., rerunning filtering)
- Why least rather than most?
- Combining these ordering ideas makes 1000 queens feasible



[Demo: coloring – backtracking + AC + ordering]