

Previously ...



Characteristics of intelligent systems



- Possess one or more of these:
 - Capability to extract and store **knowledge**
 - Human like **reasoning** process
- Knowledge representation and reasoning:
 - Logic-based
 - Rule-based expert systems
 - Constraint Satisfaction and Optimisation Problems
- Recent trend (**LLMs** & Multimodal Foundation Models - **MFMs**):
 - More sophisticated interaction with the user through:
 - natural language understanding
 - speech recognition and synthesis
 - image analysis & synthesis

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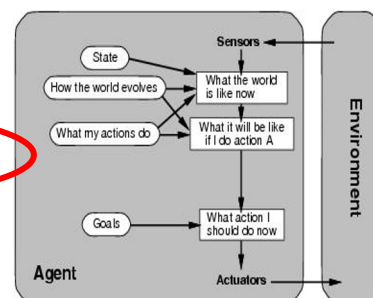
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Previously ...



Agent types; goal-based

- The agent needs a goal to know which situations are *desirable*.
 - Things become difficult when long sequences of actions are required to find the goal
- Typically investigated in **search** and **planning** research.
- Major difference: future is taken into account
- Is more flexible since knowledge is represented explicitly and can be manipulated.



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Outline



Problem-solving agents

- A kind of goal-based agent
 - Problem formulation
 - Example problems
 - Standard **SEARCH** algorithms

Constraint Satisfaction Problems (CSP)

- Search where the path does not matter
- Backtracking search (BTS) algorithm
 - Methods for improving backtracking efficiency
- Local search algorithms

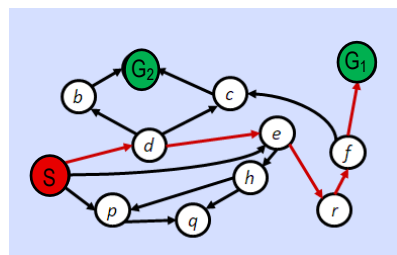


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Standard Search vs CSP



- General state space search:
 - ☐ Standard search problem: Search in a state space
- **State** is a “black box” – any **data structure** that support three problem-specific requirements:
 - ☐ **Goal** test: At which state can the problem be considered “SOLVED”?
 - ☐ Successor function (aka. **Transition model**): from a state, which neighbour states can be transitioned to?
 - ☐ (if applicable) heuristic function $h(S)$: is there a way to **estimate** the cheapest cost to get to a goal state from the state S ?



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Example: 8-puzzle



7	2	4
5		6
8	3	1

Start State

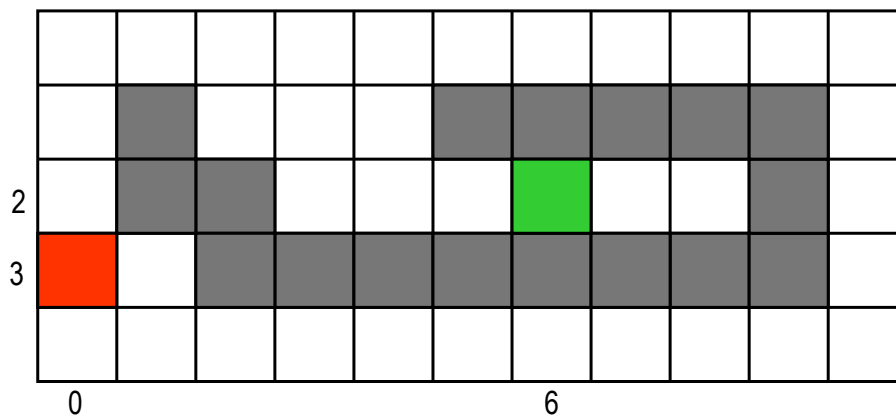
	1	2
3	4	5
6	7	8

Goal State



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Example: Robot Navigation



 Start state
[0,3]

 Goal state
[6,2]



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Single-state problem formulation



A **problem** is defined by four items:

1. **initial state** e.g., $[0, 3]$
 2. **Transition model** or **successor function** $S(x)$ = set of action–state pairs
 - e.g., $S([0,3]) = \{<UP, [0, 2]>, <DOWN, [0, 4]>, <RIGHT, [1, 3]>\}$
 3. **goal test**, can be
 - **explicit**, e.g., $x = [6, 2]$
 - **implicit**, e.g., $Checkmate(x)$
 4. **path cost** (additive)
 - e.g., sum of distances, number of actions executed, etc.
 - $c(x,a,y)$ is the **step cost**, assumed to be ≥ 0
- A **solution** is a sequence of actions leading from the initial state to a goal state



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Simple tree search example

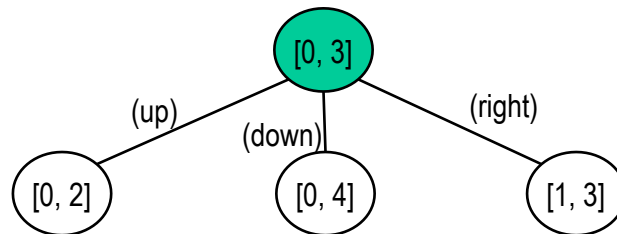


$[0, 3]$

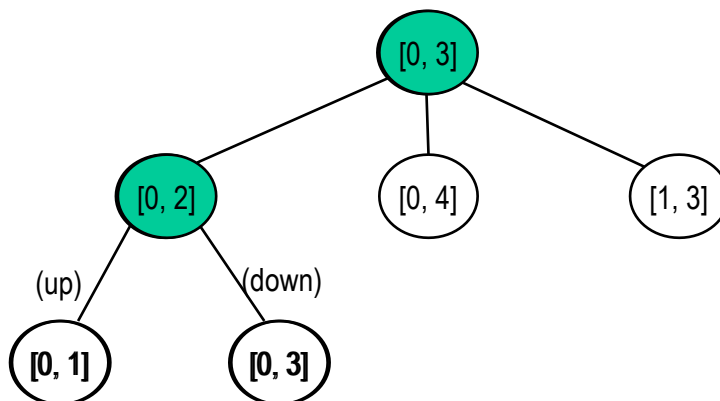


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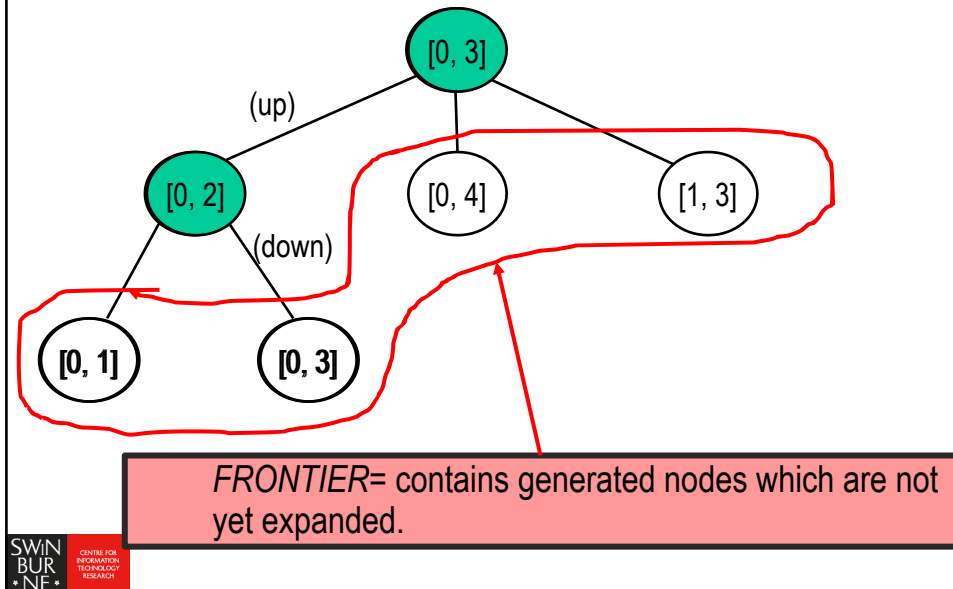
Simple tree search example



Simple tree search example



What is the *FRONTIER*?



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Search where the path doesn't matter



- So far, we looked at problems where the path was the solution
 - ☐ Traveling on a graph
 - ☐ Eights puzzle
- However, in many problems, we just want to find a goal state
 - ☐ Doesn't matter how we get there

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Queens puzzle



- Place eight queens on a chessboard so that no two attack each other

				Q			
		Q					
Q							
						Q	
	Q						
							Q
				Q			
			Q				



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Sudoku



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

- Each row, column and “major block” must be all different
- “Well posed” if it has unique solution: **27 constraints**



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Constraint satisfaction problems (CSPs)



- Standard search problem:
 - **state** is a "black box" – any data structure that supports successor function, heuristic function, and goal test
- CSP:
 - **state** is defined by a sequence of values x_i from domain D_i
 - **goal test** is a function that checks if a combination of values for all variables is a solution. Note: Choosing the "right" representation can be challenging
 - Simple example of a **formal representation language**
 - Allows useful **general-purpose** algorithms with more power than standard search algorithms



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Example: Variables, domains & Constraints



- **Crossword Puzzle:**
 - **Variables** are words that have to be filled in
 - **Domains** (of the variables) are the English words of correct length
 - (binary) **constraints**: words have the same letters at cells where they intersect
- **Crossword 2:**
 - **Variables** are cells (individual squares)
 - **Domain** (of all variables) is the English alphabet
 - (k-ary) **constraints**: sequences of letters that form the valid English words from the dictionary

D	E	S	E	R	V	E	S	U	M	U	P
R	T	A	D	I	P	A	R				
I	R	O	N	I	N	G	I	S	S	U	E
F	O	N		Y	E	N	C	E			
T	A	P	E		T		A	G	O	M	
				S	N	O	R	K	E	L	
S				D	I	V	O			T	
M	A	R			P	O	L	E	C	A	T
O			E	A	U		N		F	I	R
C			C		N	I	P		M		D
K	H	A	K	I		E	D	I	T	I	O
E	N		S	A	E		S	L		C	
D	I	T	C	H		R	E	S	T	Y	L

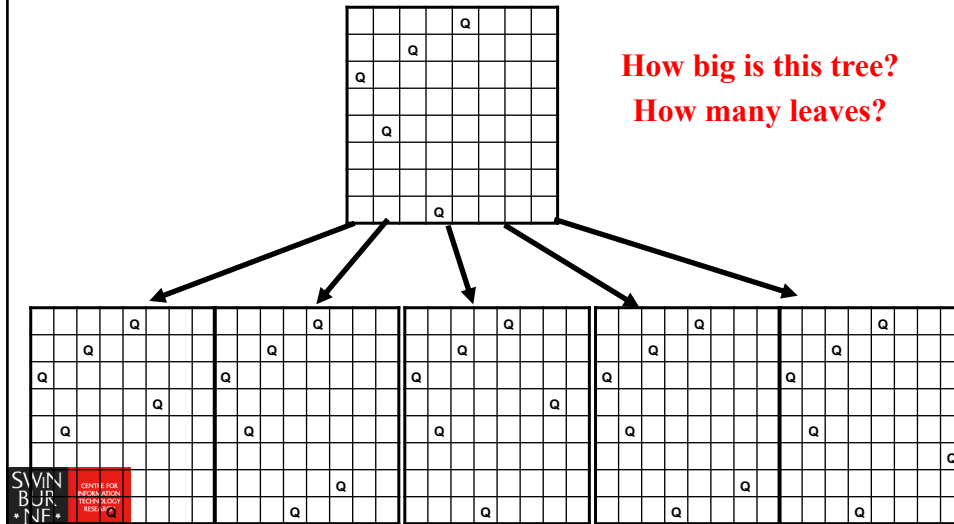


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Search formulation of the queens puzzle



- **Successors:** all valid ways of placing additional queen on the board; **goal:** eight queens placed

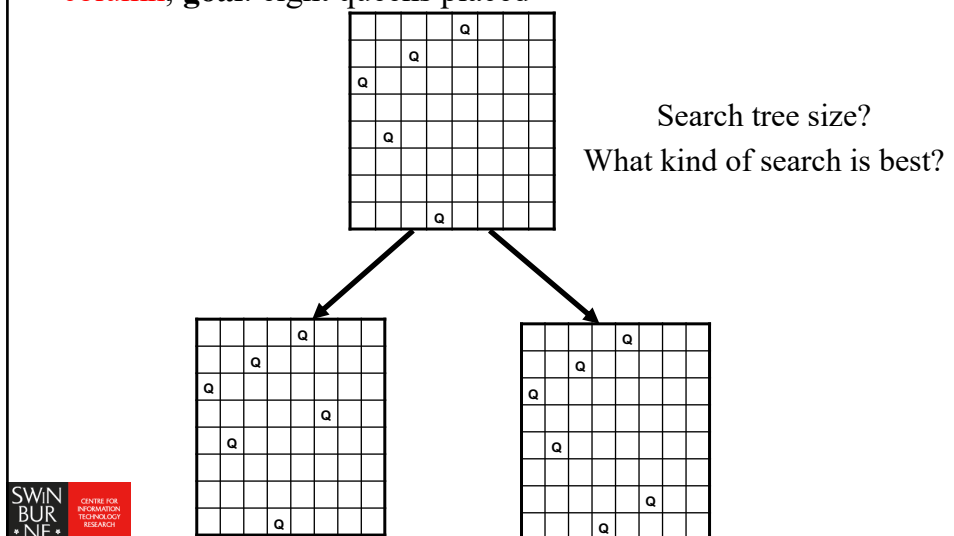


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Search formulation of the queens puzzle



- **Successors:** all valid ways of placing a queen **in the next column**; **goal:** eight queens placed



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Example: Map-Coloring

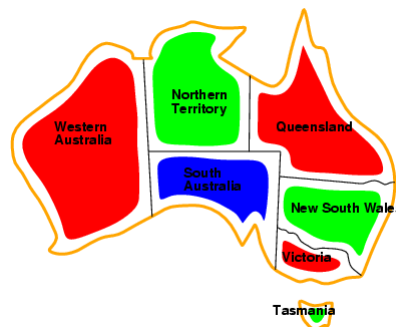


- **Variables** WA, NT, Q, NSW, V, SA, T
- **Domains** $D_i = \{\text{red, green, blue}\}$
- **Constraints**: adjacent regions must have different colors
 - e.g., **Implicit**: $WA \neq NT$ (aka. **Intensional representation**), or
 - **Explicit**: (WA, NT) in $\{(\text{red, green}), (\text{red, blue}), (\text{green, red}), (\text{green, blue}), (\text{blue, red}), (\text{blue, green})\}$ (aka. **Extensional representation**)



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Example: Map-Coloring



- **Solutions** are **complete** and **consistent** assignments,
e.g., $WA = \text{red}, NT = \text{green}, Q = \text{red}, NSW = \text{green}, V = \text{red},$
 $SA = \text{blue}, T = \text{green}$

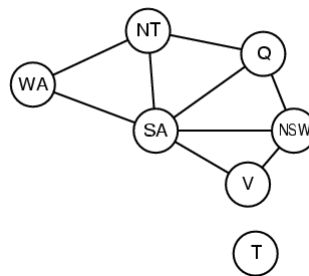


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Constraint graph



- **Binary CSP:** each constraint relates two variables
- **Constraint graph:** nodes are variables, arcs are constraints
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Varieties of CSPs



- **Discrete variables**
 - finite domains:
 - n variables, domain size $d \rightarrow O(d^n)$ complete assignments
 - e.g., Boolean CSPs, incl. ~Boolean satisfiability (NP-complete)
 - infinite domains:
 - integers, strings, etc.
 - e.g., job scheduling, variables are start/end days for each job
 - need a constraint language, e.g., $StartJob_1 + 5 \leq StartJob_3$
- **Continuous variables**
 - e.g., start/end times for Hubble Space Telescope observations
 - linear constraints solvable in polynomial time by linear programming



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Real-world CSPs



- Staff assignment problems
 - e.g., who teaches what unit, which software developer does what tasks
- Timetabling problems
 - e.g., which class is offered when and where?
- Transportation scheduling
- Factory scheduling
- Notice that **many real-world problems involve real-valued variables**
-



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Standard search formulation (quick analysis)



States are defined by the values assigned so far

- **Initial state:** the empty assignment { }
- **Successor function:** assign a value to an unassigned variable that does not conflict with current assignment
 - fail if no legal assignments
- **Goal test:** the current assignment is complete
- Would search methods based on BFS work well?
 - **Short answer is NO.**
 - **Large branching factor** -> Memory consumption alone is a barrier
 - Most of the time, we only need one solution!



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Standard search formulation (incremental)



States are defined by the values assigned so far

- **Initial state:** the empty assignment { }
- **Successor function:** assign a value to an unassigned variable that does not conflict with current assignment
→ fail if no legal assignments
- **Goal test:** the current assignment is complete
- Let's start with the straightforward approach, then fix it
 - This is the same for all CSPs
 - Every solution appears at depth n with n variables
→ use depth-first search
 - Path is irrelevant, so can also use complete-state formulation



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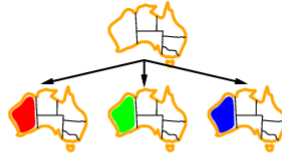
Backtracking example



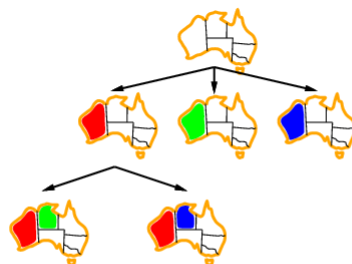
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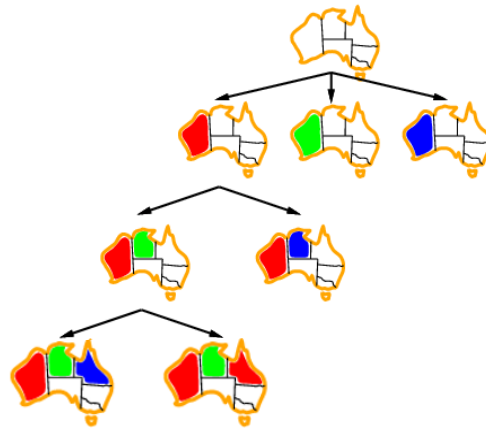
Backtracking example



Backtracking example



Backtracking example



Backtracking search



```

function BACKTRACKING-SEARCH(csp) returns a solution, or failure
  return RECURSIVE-BACKTRACKING({}, csp)

function RECURSIVE-BACKTRACKING(assignment, csp) returns a solution, or
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 according to 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 search



- Depth-first search for CSPs with single-variable assignments is called **backtracking** search
 - Backtracking is the idea that, as you go depth-first down a branch of the search tree and you try to find an assignment for the next variable that does not violate any constraint but you can't then you have to backtrack (from that current branch) to get to another branch
- Backtracking search is the basic **uninformed** algorithm for CSPs
- Can solve n -queens for $n \approx 25$
-

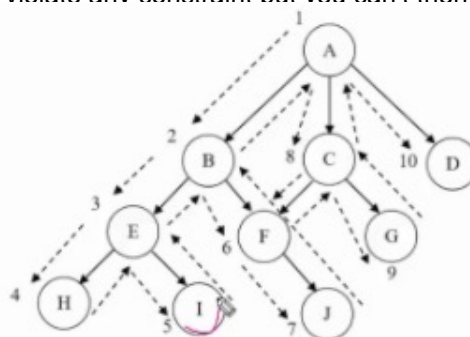


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- Backtracking search CSPs
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-



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Backtracking search



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QUESTION: Can our search be **better informed**??



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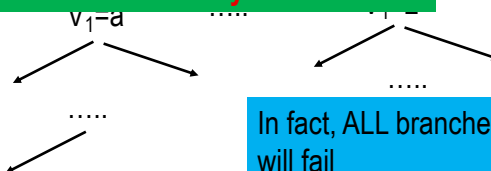
Example: Need better ordering of variables



- 100 variables V_1, \dots, V_{100} with large domains (hundreds of values)
- 3 variables V_{101} with domain $D_{101} = \{\text{red}\}$, V_{102} with domain $D_{102} = \{\text{red}, \text{blue}\}$, and V_{103} with domain $D_{103} = \{\text{blue}\}$ and the two constraints $V_{101} \neq V_{102}$ and $V_{102} \neq V_{103}$.

Lesson learnt:

"If you are going to fail on a branch,
fail early."



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Improving backtracking efficiency



- **General-purpose** methods can give huge gains in speed (i.e. search in a smart way, **not** in an uninformed manner):

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



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Most constrained variable



- Most constrained variable:
choose the variable with the fewest legal values



- a.k.a. **minimum remaining values (MRV)** heuristic

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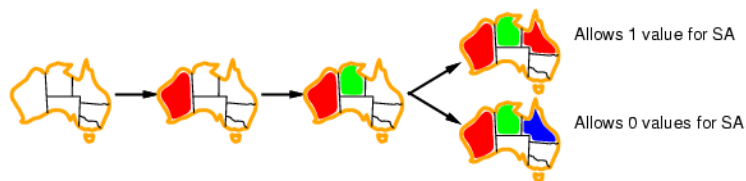


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Least constraining value



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



- Combining these heuristics makes 1000 queens feasible

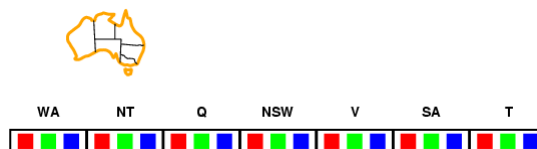


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Forward checking



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



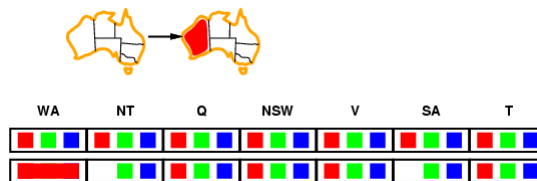
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Forward checking



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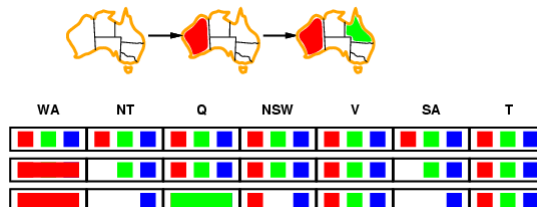


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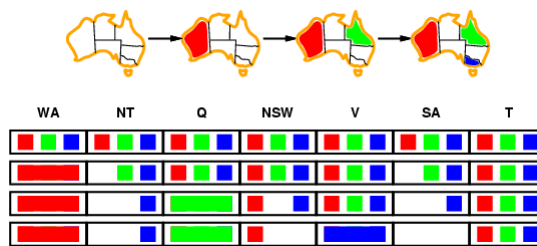


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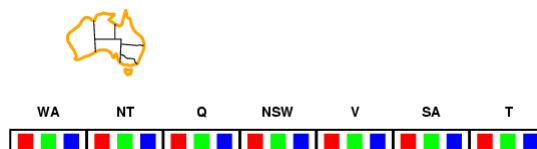


Constraint propagation



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

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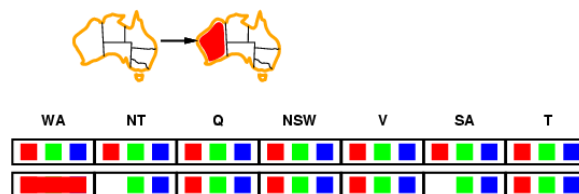


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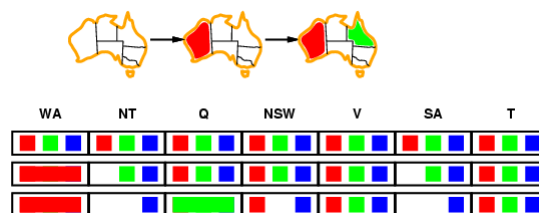


Constraint propagation



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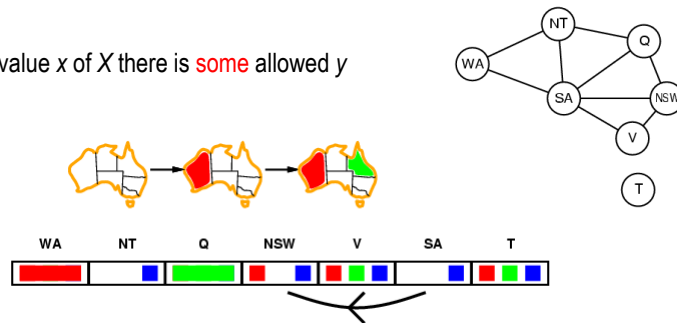


- NT and SA cannot both be blue!
- **Constraint propagation** repeatedly enforces constraints locally

Arc consistency



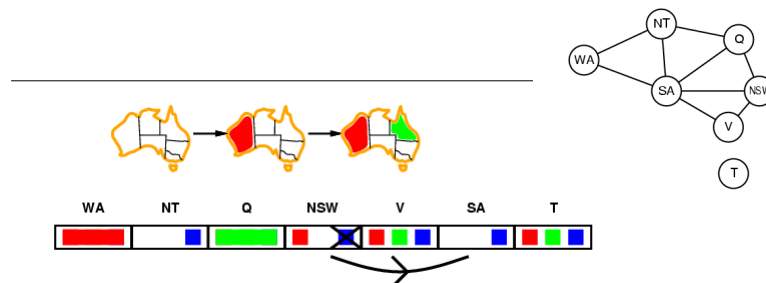
- Simplest form of propagation makes each arc **consistent**
- $X \rightarrow Y$ is consistent iff
 - for **every** value x of X there is **some** allowed y



Arc consistency



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- $X \rightarrow Y$ is consistent iff
 - for **every** value x of X there is **some** allowed y



Local search for CSPs



- Hill-climbing, simulated annealing typically work with "complete" states, i.e., all variables assigned
- To apply to CSPs:
 - ☐ allow states with unsatisfied constraints
 - ☐ operators **reassign** variable values
- Variable selection: randomly select any conflicted variable
- Value selection by **min-conflicts** heuristic:
 - ☐ choose value that violates the fewest constraints
 - ☐ i.e., hill-climb with $h(n)$ = total number of violated constraints
 - ☐



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Summary



- CSPs are a special kind of problem:
 - ☐ states defined by values of a fixed set of variables
 - ☐ goal test defined by constraints on variable values
- Backtracking = depth-first search with one variable assigned per node
- Variable ordering and value selection heuristics help significantly
- Forward checking prevents assignments that guarantee later failure
- Constraint propagation (e.g., arc consistency) does additional work to constrain values and detect inconsistencies
- Iterative min-conflicts is usually effective in practice



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