

Intelligent Autonomous Agents and Cognitive Robotics

Topic 3: Constraint Satisfaction Problems

Slides partly from Hwee Tou Ng's
Chapter 5 of AIMA

Outline

- Constraint Satisfaction Problems (CSP)
- Backtracking search for CSPs
- Multi-Agents → distributed backtracking

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 **variables** X_i ($i=1..n$) with
 - ♦ **values** from **domain** D_i
 - ♦ **goal test** is a set of **constraints** C_m ($m=1..z$) 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

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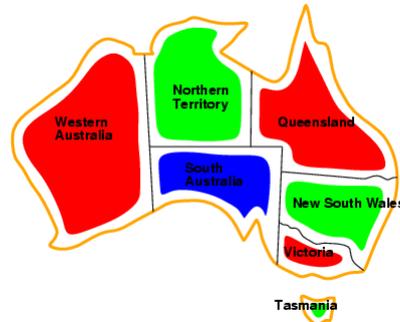
Visual example: Map-Coloring



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

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Example: Map-Coloring

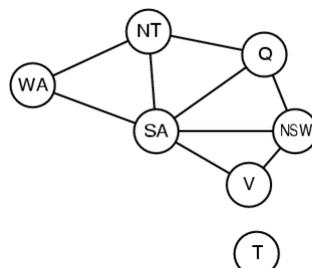


- **Solutions** are **complete** and **consistent** assignments, e.g.,
 - ♦ WA = red, NT = green, Q = red, NSW = green, V = red, SA = blue, T = green

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Constraint graph

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



General-purpose CSP algorithms use the graph structure to speed up search. E.g., Tasmania is an independent sub problem!

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Varieties of CSPs

- Discrete variables
 - ♦ finite domains:
 - n variables, domain size $d \rightarrow O(d^n)$ complete assignments
 - e.g., n-queens problem
 - ♦ 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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Varieties of constraints

- **Unary** constraints involve a single variable,
 - ♦ 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

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Real-world CSPs

- Assignment problems
 - ♦ e.g., who teaches what class
- Timetabling problems
 - ♦ e.g., which class is offered when and where; preferences
- Hardware configuration
- Transportation scheduling
- Factory scheduling

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Constraint propagation

- In CSP an algorithm can do
 - ♦ Constraint propagation = inference
 - ♦ Search
 - ♦ Intertwined or as preprocessing
- The key idea is to create *local* consistency

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Node consistency

- A variable is node-consistent if all the values satisfy the unary constraints
- Infer the values that are legal for a variable,
 - ♦ e.g. if South Australia does not like green, eliminate it {red, blue}
 - ♦ e.g. don't want to teach at 8 pm

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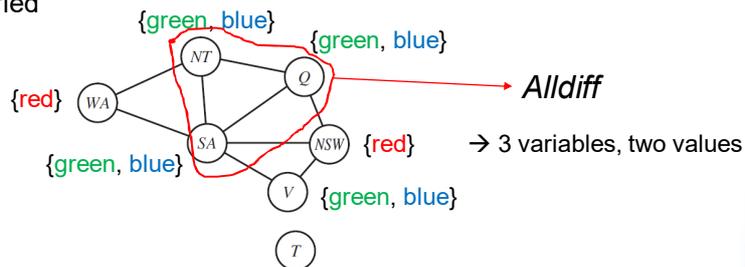
Global Constraints

- *Alldiff* (many algorithms)
 - ♦ Idea: If m variables have n values and $m > n \rightarrow$ can not be satisfied
 - Remove any variable with singleton domain and propagate this into other domains. Repeat as long as there are singleton domains.
 - If an empty domain is produced or $m > n$, then an inconsistency has been detected

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Global Constraints

- *Alldiff* (many algorithms)
 - ♦ Idea: If m variables have n values and $m > n \rightarrow$ can not be satisfied



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Resource Constraints

- Resource constraints: *Atmost*
We can detect an inconsistency simply by checking the sum of the minimum values of the current domains:
 $Atmost(10, P1, P2, P3, P4)$ persons for tasks.
 - ♦ Each variable has domain $\{3, 4, 5, 6\}$
→ can not be satisfied
 - ♦ Each variable has domain $\{2, 3, 4, 5, 6\}$
→ delete 5 and 6

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Resource Constraints

- Bounds propagation/bounds consistent
 - ♦ In complex problems often not possible to enumerate domain values
 - ♦ Constraints:
 - Plane capacities for $F1=[0, 165]$, $F2[0, 385]$
 - Constraint: $F1+F2 = 420$

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Resource Constraints

- Bounds propagation/bounds consistent
 - ♦ In complex problems often not possible to enumerate domain values
 - ♦ Constraints:
 - Plane capacities for $F1=[0, 165]$, $F2[0, 385]$
 - Constraint: $F1+F2 = 420$

$\rightarrow F1[35, 165] \text{ and } F2[255, 385]$
 - ♦ We say that a CSP is **bounds consistent** if for every variable X , and for both the lower-bound and upper-bound values of X , there exists some value of Y that satisfies the constraint between X and Y for every variable Y . (Often used in praxis)

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Standard search formulation

Let's start with the straightforward approach, then fix it

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
1. Every solution appears at depth n with n variables
→ use depth-first search
 2. Path is irrelevant
 3. At the root we have n variables and d values $b = nd$
 4. At depth l we have $b = (n - l)d$
 5. All combinations $n! \cdot d^n$ leaves

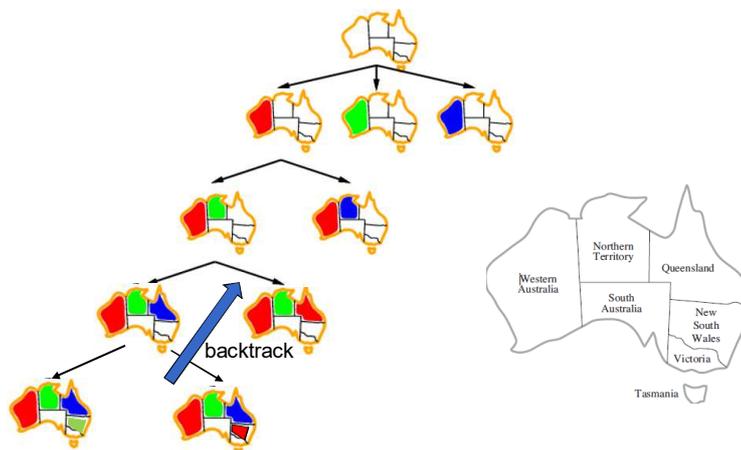
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Backtracking search

- Variable assignments are **commutative**
[WA = red then NT = green] same as [NT = green then WA = red]
- Only need to consider assignments to a single variable at each node
→ $b = d$ branching factor, n variables → d^n leaves
- Depth-first search for CSPs with single-variable assignments is called **backtracking** search
- Backtracking search is the basic uninformed algorithm for CSPs

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Backtracking example



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Backtracking search

function BACKTRACKING-SEARCH(*csp*) **returns** a solution, or failure
return BACKTRACK($\{\}$, *csp*)

function BACKTRACK(*assignment*, *csp*) **returns** a solution, or failure

if *assignment* is complete **then return** *assignment*

var \leftarrow SELECT-UNASSIGNED-VARIABLE(*csp*)

for each *value* in ORDER-DOMAIN-VALUES(*var*, *assignment*, *csp*) **do**

if *value* is consistent with *assignment* **then**

 add {*var* = *value*} to *assignment*

inferences \leftarrow INFERENCE(*csp*, *var*, *value*)

if *inferences* \neq failure **then**

 add *inferences* to *assignment*

result \leftarrow BACKTRACK(*assignment*, *csp*)

if *result* \neq failure **then**

return *result*

 remove {*var* = *value*} and *inferences* from *assignment*

return failure

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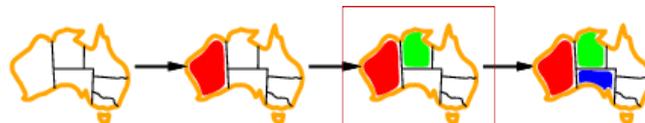
Improving backtracking efficiency

- **General-purpose** methods can give huge gains in speed:
 - ♦ Which variable should be assigned next
SELECT-UNASSIGNED-VARIABLE?
 - ♦ In what order should its values be tried
ORDER-DOMAIN-VALUES?
 - ♦ What inferences should be performed at each step in
the search INFERENCE?
 - ♦ 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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Most constrained variable

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

What about the first state

MRV does not help in the first state

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Degree heuristic

- Tie-breaker among most constrained variables:
Degree heuristic
- Most constraining variable:
 - ♦ choose the variable with the most constraints on remaining variables
 - ♦ used together with MRV



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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 *Queensland is selected*



- Combining these heuristics makes 1000 queens feasible

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Inference: Forward checking

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

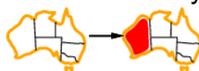


WA = red

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Inference: Forward checking

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



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



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Inference: Forward checking

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



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



Q = green

Victoria = blue

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Inference: Forward checking

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



Victoria = blue

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Forward checking

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



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

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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 of Y
- Constraint $Y=X^2$ and domain $\{0,1,..9\}$. Can write the constraint as
 $[(X, Y), \{(0, 0), (1, 1), (2, 4), (3, 9)\}]$
 Can reduce the domains
 $X = \{0, 1, 2, 3\}$
 $Y = \{0, 1, 4, 9\}$
- What about $(SA \neq WA)$ and domain $\{\text{red, green, blue}\}$
 $[(SA, WA),$
 $\{(\text{red}, \text{green}), (\text{red}, \text{blue}), (\text{green}, \text{red}), (\text{green}, \text{blue}), (\text{blue}, \text{red}),$
 $(\text{blue}, \text{green})\}]$



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Arc consistency algorithm AC-3

```

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

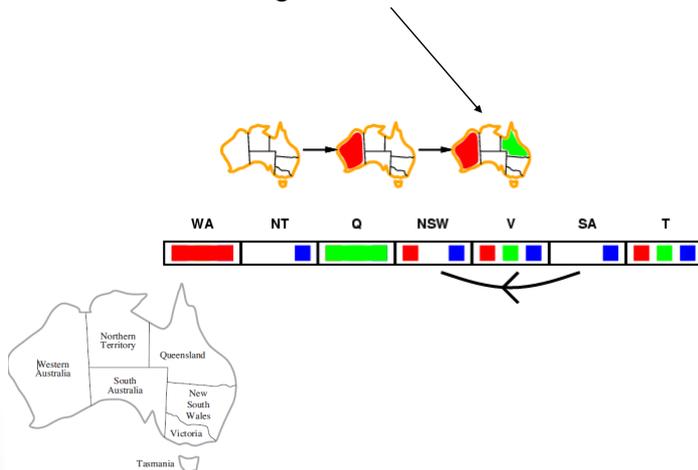
function REMOVE-INCONSISTENT-VALUES( $X_i, X_j$ ) returns true iff succeeds
  removed  $\leftarrow$  false
  for each  $x$  in DOMAIN[ $X_i$ ] do
    if no value  $y$  in DOMAIN[ $X_j$ ] allows  $(x,y)$  to satisfy the constraint  $X_i \leftrightarrow X_j$ 
      then delete  $x$  from DOMAIN[ $X_i$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

- Time complexity: $O(cd^3)$

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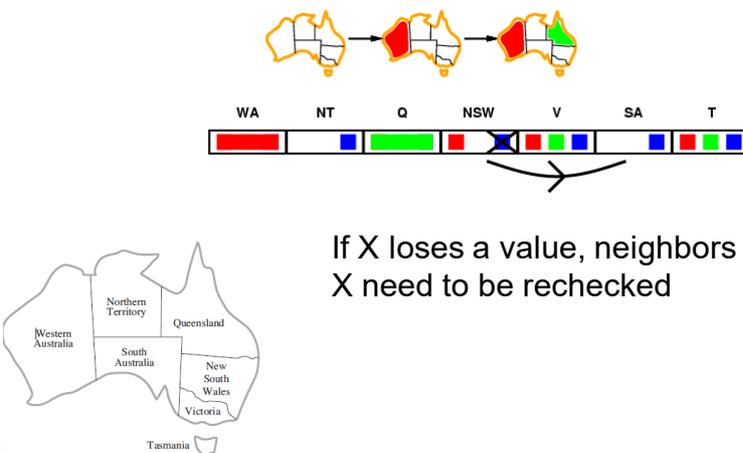
Arc consistency

- Assume we begin in state



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Arc consistency



If X loses a value, neighbors of X need to be rechecked

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Arc consistency

The diagram shows three maps of Australia illustrating the process of arc consistency. The first map shows all regions (WA, NT, Q, NSW, V, SA, T) with their initial color sets. The second map shows that the color red is removed from the NSW node because it is not compatible with its neighbors. The third map shows that the color green is also removed from the NSW node because it is not compatible with its neighbors. The constraint graph below shows the color sets for each node: WA (red), NT (blue), Q (green), NSW (red, blue, green), V (red, blue, green), SA (blue), and T (red, green, blue). An arrow points from the NSW node to the V node, indicating a constraint between them.

- If X loses a value, neighbors of X need to be rechecked

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Arc consistency

The diagram shows three maps of Australia illustrating the process of arc consistency. The first map shows all regions (WA, NT, Q, NSW, V, SA, T) with their initial color sets. The second map shows that the color red is removed from the NSW node because it is not compatible with its neighbors. The third map shows that the color green is also removed from the NSW node because it is not compatible with its neighbors. The constraint graph below shows the color sets for each node: WA (red), NT (blue), Q (green), NSW (red, blue, green), V (red, blue, green), SA (blue), and T (red, green, blue). An arrow points from the NSW node to the V node, indicating a constraint between them.

- If X loses a value, neighbors of X need to be rechecked
- Is run as a preprocessor
- Can also be modified to work with backtracking
 - ♦ On assignment put only (X_i, X_j) in the queue

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Path consistency

- $\{X_i, X_j\}$ is path consistent with respect to X_m if for every consistent assignment there is an for X_m that is consistent. $\{X_i, X_m\}$ and $\{X_m, X_j\}$.
See the CSP graph for detecting paths
- Could also be extended to K-Consistency

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Multi-Agents CSP

- Also called distributed CSP
 - ♦ Variable and domain definition as before
 - ♦ Each agent owns a variable (many can be mapped to one)
 - ♦ Agents decides on value with relative autonomy
 - ♦ Has no global view on all dependencies
 - ♦ BUT! Can communicate with his neighbors in the constraint graph
- Many algorithms!! We only sketch one important algorithm

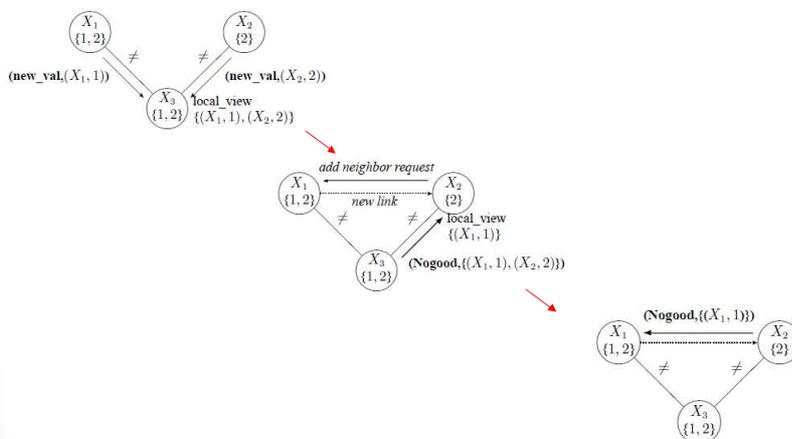
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Multi-Agents CSP: Asynchronous Backtracking

- The algorithm makes an ordering on agents and assigns them priority numbers. All agents set their initial value concurrently
- a higher-priority agent j informs all lower-priority agents k_i of its assignment if connected in constraint graph
- lower-priority agent k evaluates the shared C_{jk} constraint with its own assignment
 - ♦ if constraints are satisfied with the current assignment \rightarrow no action
 - ♦ otherwise, agent k looks for a different value consistent with choice of agent j
 - ♦ if such a consistent value exists \rightarrow agent j adopts this value and informs other low-priority agents
 - ♦ if such a consistent value does not exist, agent j updates *NoGood list* and sends the message to agent j and seek for a value that is consistent with all connected higher priority agents
 - ♦ j receives a NoGood mentioning i it is not connected with j ; j asks i to set up a link

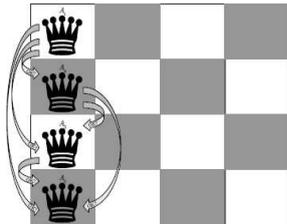
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Adding edges



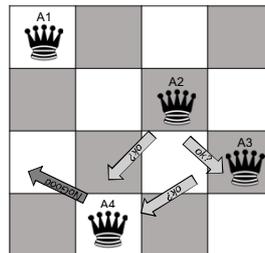
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Example: 4-Queens



- A1 knows no position
- A2 knows A1
- A3 knows A2 and A1
- A4 knows all positions

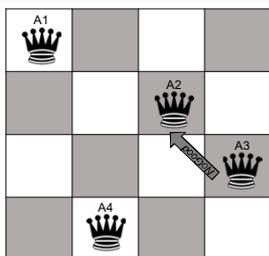
Based on local information each queen checks where to move or to resolve conflicts with upper queen. Afterwards do nothing, send "OK?" or "NoGood" messages.



NoGood: $A1=1$ and $A2=1 \rightarrow A3 \neq 1$

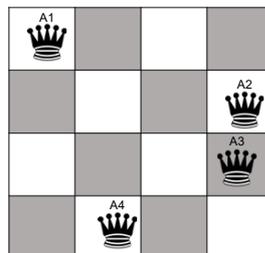
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Example: 4-Queens



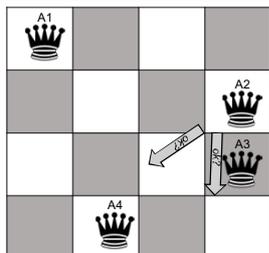
NoGood: $A1=1 \rightarrow A2 \neq 3$

Only A3 is active

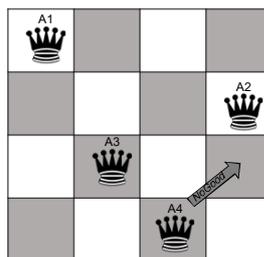


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Example: 4-Queens

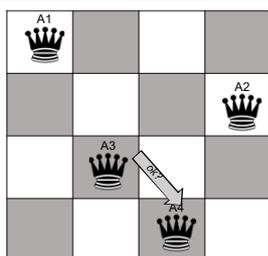


*A4 sends a NoGood message:
 $A1=1$ and $A2=4 \rightarrow A3 \neq 4$ (no
 longer valid)
 and moves.*

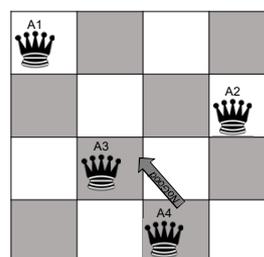


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Example: 4-Queens

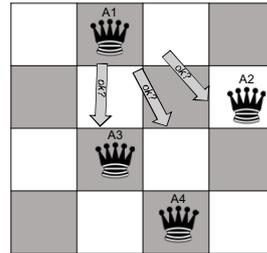
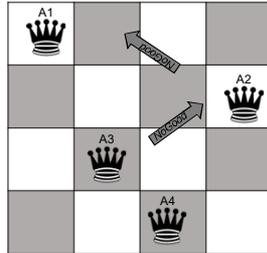


*A4 sends a NoGood message:
 $A1=1$ and $A2=4 \rightarrow A3 \neq 2$
 and does not move, no conflict.*



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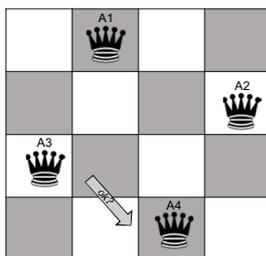
Example: 4-Queens



A3 has no option \rightarrow NoGood: $A1=1 \rightarrow A2 \neq 4$,
 A2 had a former NoGood message from A3 not to stay in 3
 \rightarrow send NoGood: $A1 \neq 1$

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Example: 4-Queens



No conflict for any queen \rightarrow solved

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