Intelligent Systems Programming

Lecture 8: Constraint Programming

Today's Program

- [10:00-10:50]
 - Constraint Satisfaction Problems (CSPs)
 - Constraint Propagation
 - Backtracking
- [11:00-12:00]
 - Variable and value selection
 - Forward Checking
 - Maintaining arc consistency (MAC) algorithm
 - Global constraints
 - Modern constraint propagation systems

Constraint Satisfaction Problems (CSPs)

	1	2	3	4	5	6	7	8	9
Α			3		2		6		
В	9			3		5			1
С			1	8		6	4		
D			8	1		2	9		
Е	7								8
F			6	7		8	2		
G			2	6		9	5		
Н	8			2		3			9
1			5		1		3		

Container Vessel Slot Planning



Definition of CSPs

A CSP is a triple <*X*,*D*,*C*>, where:

 $X = \{X_1, ..., X_n\}$ is a finite set of variables.

 $D = \{D_1, ..., D_n\}$ is a set of domains of possible values for each variable, where $D_i = \{v_1, ..., v_{ki}\}$

 $C = \{C_1, ..., C_m\}$ is a set of constraints, where $C_i = \langle \text{scope}, \text{ relation} \rangle$

e.g. $X_1 \in \{A, B\}, X_2 \in \{A, B\}$

Implicit constraint representation: $\langle (X_1, X_2), X_1 \neq X_2 \rangle$

Explicit constraint representation: $\langle (X_1, X_2), [(A,B), (B,A)] \rangle$

Typical short notation: $X_1 \neq X_2$

CSP Solutions

- Partial Assignment: Values assigned to only some of the variables.
- Complete Assignment: Each variable has a value assigned.
- Consistent Assignment: Each constraint, where all variables in its scope are assigned, is satisfied.
- Solution: Complete consistent assignment.

Types of Constraints

Different Arity

Unary constraints involve a single variable.

$$-$$
 e.g. *X* ≠ 12

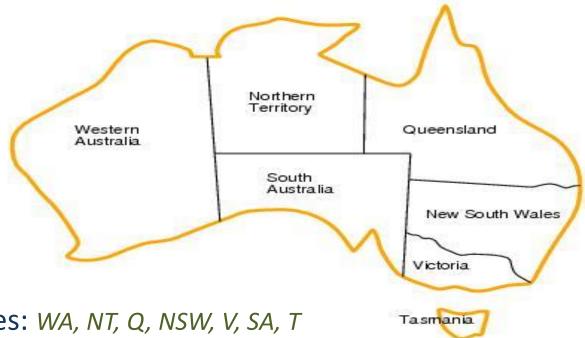
Binary constraints involve pairs of variables.

```
- e.g. X > Y, P = MIB \land C = Black
```

- Global constraints involve arbitrary number of variables.
 - e.g. AllDifferent

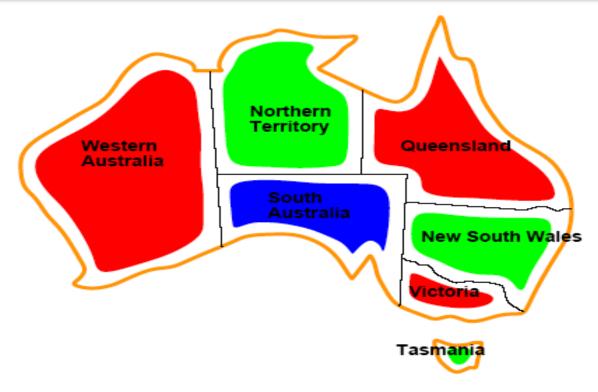
This lecture: all* algorithms assume binary constraints

CSP Example: Map Coloring



- Variables: WA, NT, Q, NSW, V, SA, T
- Domains: *D_i* = {*red, green, blue*}
- Constraints: adjacent regions must have different colors.

CSP Example: Map Coloring

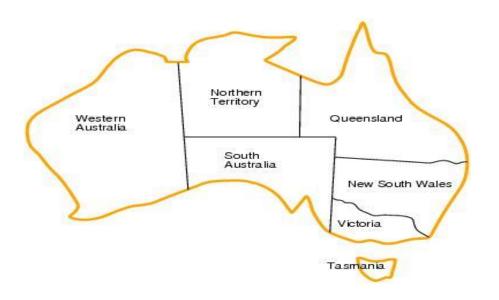


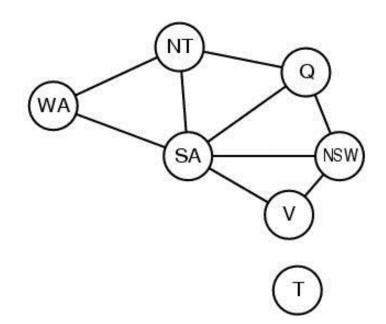
Solutions are assignments satisfying all constraints, e.g.

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

Constraint Graph Representation of CSP

- Nodes are variables
- Edges are binary constraints





Constraint Propagation (Rule Inference)

CSPs are solved combining search and constraint propagation

Constraint Propagation

• Node consistency: for every value v_i of variable X, all unary constraints of X are satisfied.

Example

```
SA \in \{red, green, blue\}, SA \neq \{green\}

SA \in \{red, blue\}
```

• Arc consistency: for every $X \rightarrow Y$ arc, every value v_i in X has a support value u_i in Y.

Arc Consistency Examples

- 1) $SA \in \{red, green, blue\}, NT \in \{blue\}, SA \neq NT \\ SA \rightarrow NT \text{ arc-consistent: } SA \in \{red, green\}$
- 2) $X,Y \in \{0,1,...,9\}, Y=X^2$
 - $X \to Y \text{ arc-consistent} : X \in \{0, 1, 2, 3\}, Y \in \{0, 1, ..., 9\}$
 - $Y \to X$ arc-consistent: $X \in \{0, 1, ..., 9\}$, $Y \in \{0, 1, 4, 9\}$
- 3) $SA \in \{red, green, blue\}$, $WA \in \{red, green, blue\}$, $SA \neq WA$ $SA \rightarrow WA / WA \rightarrow SA$ arc-consistent: can we prune any values?

Arc Consistency Algorithm AC-3

```
function AC-3(csp) returns false if an inconsistency is found and true otherwise (+ updated CSP)
  inputs: csp, a binary CSP with components (X, D, C)
  local variables: queue, a queue of arcs, initially all the arcs in csp
  while queue is not empty do
                                                                  Obs: two arcs for
     (X_i, X_i) \leftarrow \text{REMOVE-FIRST}(queue)
                                                                  each binary
    if REVISE(csp, X_i, X_j) then
                                                                  constraint!
       if size of D_i = 0 then return false
       for each X_k in X_i. NEIGHBORS - \{X_i\} do
         add (X_k, X_i) to queue
  return true
function REVISE(csp, X_i, X_j) returns true iff we revise the domain of X_i
  revised \leftarrow false
  for each x in D_i do
    if no value y in D_i allows (x,y) to satisfy the constraint between X_i and X_j then
       delete x from D_i
       revised \leftarrow true
  return revised
```

Complexity of AC-3

Assume

- n variables,
- at most d values in domains
- *c* binary constraints

Observations

- An arc can at most be added to Q d times
- An arc can be revised in d^2
- Thus, worst case runtime is $O(cd^3)$

CSP Solving

Search in CSP

- Inference is not enough
- Apply depth-first search:
 - State: Partial assignment
 - Action: var = value
- Complexity
 - Branching factor b at the top level is nd
 - -b = (n-l)d at depth *l*, hence $n!d^n$ leaves
 - But only dⁿ complete assignments?!

Backtracking Search

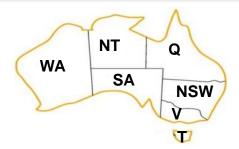
Insight:

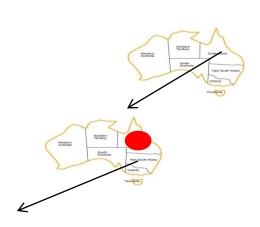
- If we assign the first *k* variables to values, it does not matter in what order we did it in.
- Thus, after choosing which variable to assign in a node, do not change it.

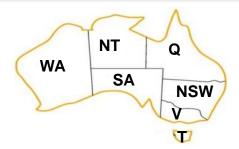
Backtracking Algorithm:

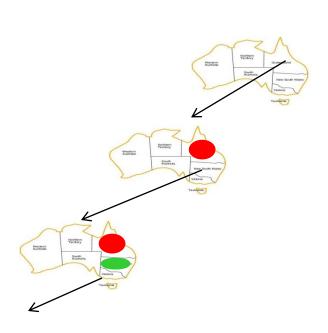
- Choose values for one variable at the time.
- Backtrack when a variable has no legal values left.

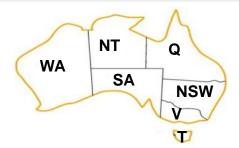


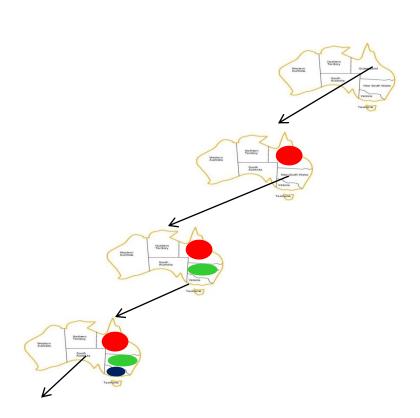


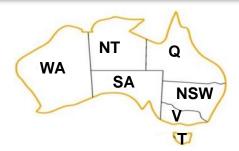


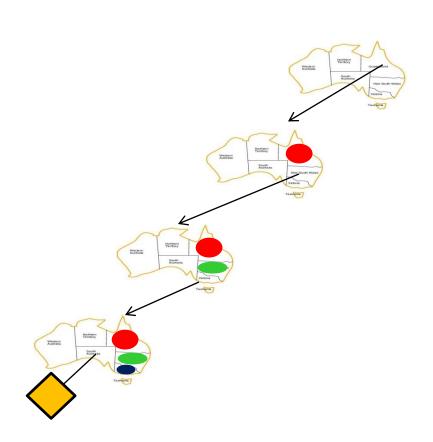


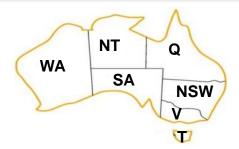


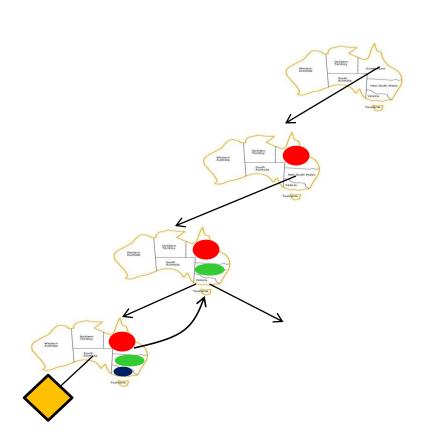


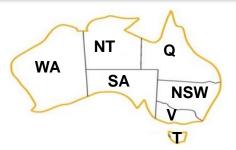


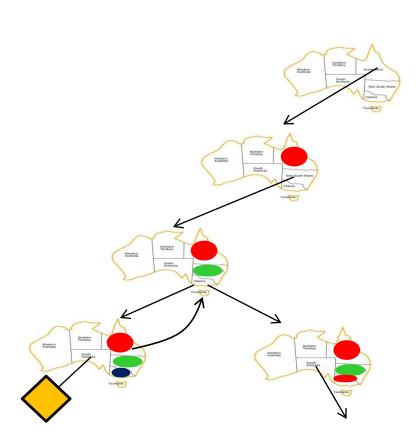


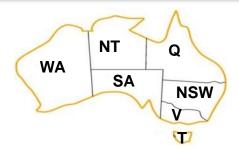


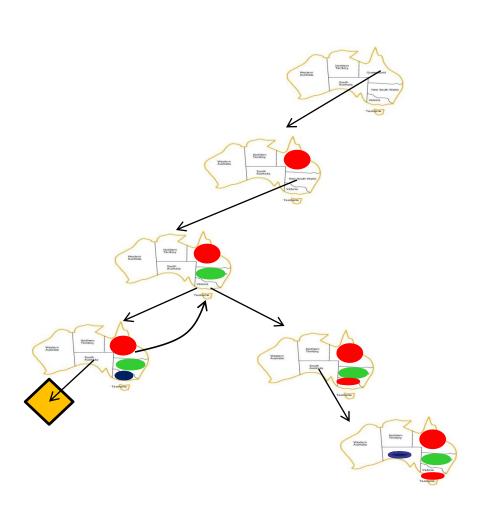


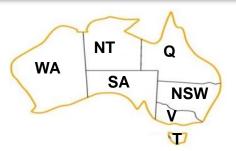










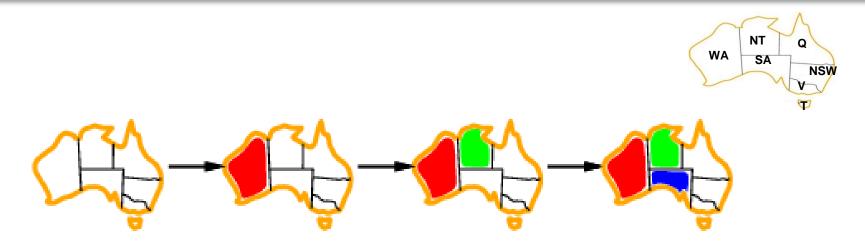




Backtracking Algorithm

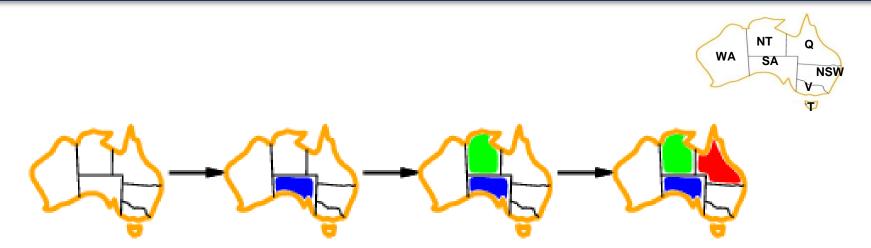
```
function BACKTRACKING-SEARCH(csp) returns a solution, or failure
  return BACKTRACK({ }, csp)
function BACKTRACK(assignment, csp) returns a solution, or failure
  if assignment is complete then return assignment
  var \leftarrow SELECT-UNASSIGNED-VARIABLE(csp)
  for each value in ORDER-DOMAIN-VALUES(var, 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
```

Select-Unassigned-Variable



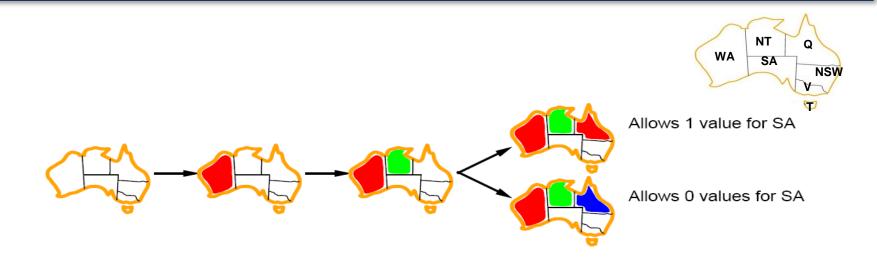
- Minimum remaining values (MRV)
- Rule: choose variable with the fewest legal values

Select-Unassigned-Variable

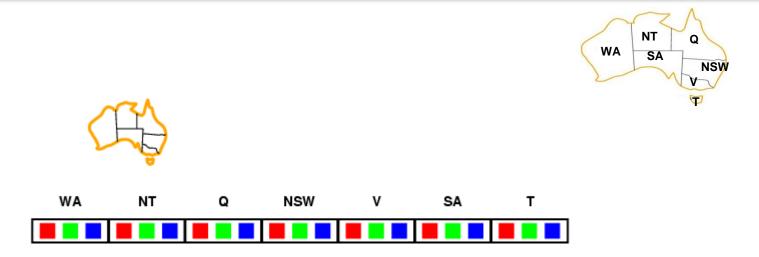


- Degree heuristic
- Rule: select variable that is involved in the largest number of constraints on other unassigned variables.
- Degree heuristic is very useful as a tie breaker

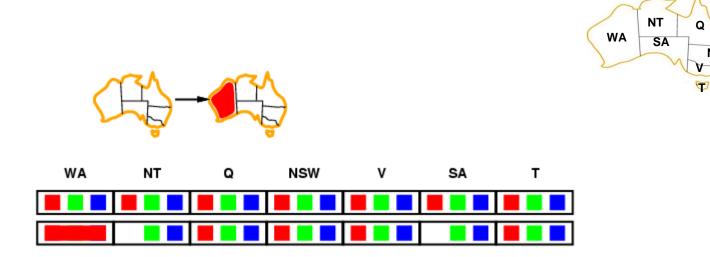
Order-Domain-Values



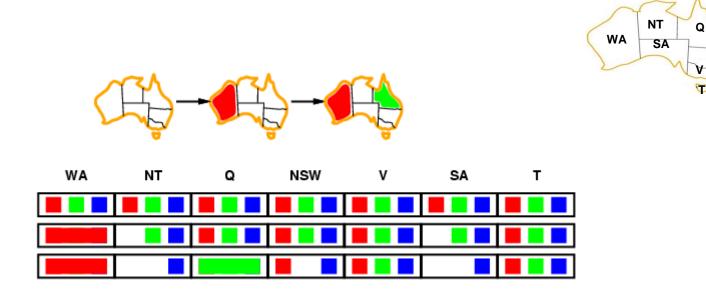
- Least constraining value heuristic
- Rule: given a variable choose the least constraining value i.e., the one that leaves the maximum flexibility for subsequent variable assignments.



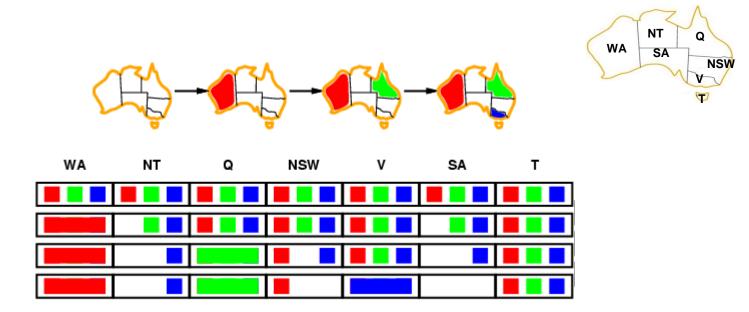
- Forward checking: Whenever a value v is assigned to a variable X_i , make all variables consistent with this assignment.
- Terminates search when any variable has no legal values.



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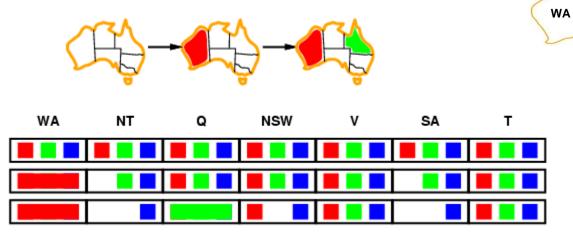


- Forward checking: Whenever a value v is assigned to a variable X_i , make all variables consistent with this assignment.
- Terminates search when any variable has no legal values.

Forward Checking Algorithm

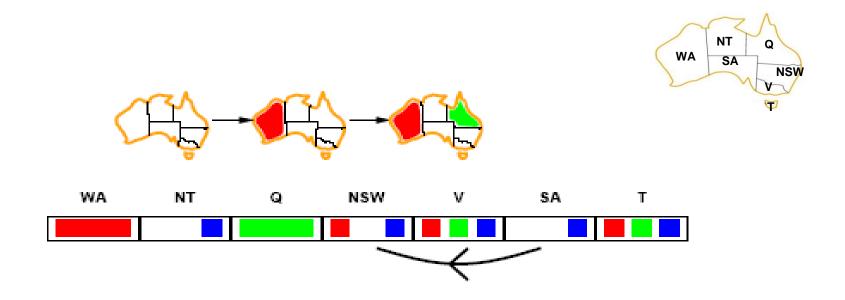
function FORWARD-CHECKING-SEARCH(csp) **returns** a solution or failure **return** RECURSIVE-FORWARD-CHECKING({ },csp) **function** RECURSIVE-FORWARD-CHECKING(assignment, csp) **returns** a solution or failure **if** assigment is complete **then return** assigment $var \leftarrow SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignent, csp)$ for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do if value is consistent with assignment do add{*var=value*} to *assigment inferences* ← remove all domain values of remaining variables inconsistent with {var = value} **if** *inferences* ≠ *failure* **then** add inferences to assignent and update csp result←RECURSIVE-FORWARD-CHECKING(assigment, csp) if result#failure then result result remove {var=value} and inferences from assignment and csp return failure

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



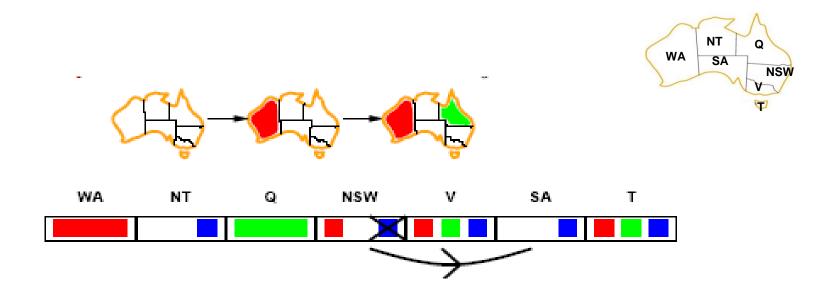
NT and SA cannot both be blue!

Arc Consistency



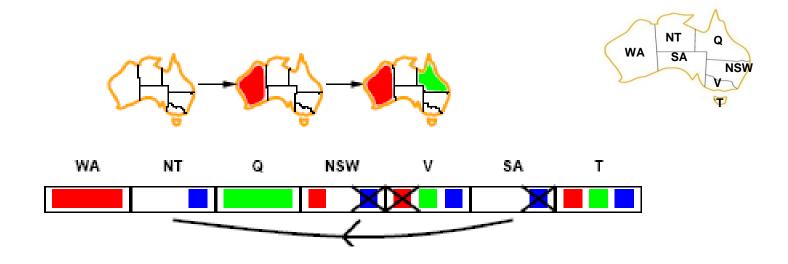
X → Y is consistent iff for every value u_i of X there is some allowed v_i value in Y

Arc Consistency



X → Y is consistent iff for every value u_i of X there is some allowed v_i value in Y

Arc Consistency



- $X \rightarrow Y$ is consistent iff for every value u_i of X there is some allowed v_i value in Y.
- Arc consistency detects failure earlier than FC

MAC

```
function MAC-SEARCH(csp) returns a solution or failure
 run AC-3(csp)
 return RECURSIVE-MAC(\{\},csp)
function RECURSIVE-MAC(assignment,csp) returns a solution or failure
 if assigment is complete then return assigment
  var \leftarrow SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignent, csp)
  for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
   if value is consisten with assignment do
    add{var=value} to assigment
    inferences \leftarrow AC-3(csp)
    if inferences ≠ failure then
     add inferences to assignent and update csp
     result←RECURSIVE-MAC(assigment, csp)
     if result≠failure then
       result result
     remove {var=value} and inferences from assignment and csp
 return failure
```

Global Constraints

Definition

Depends on arbitrary number of variables

Generalized Arc Consistency (GAC)

- For each value in domain of X_i , there exists a valid assignment for all the remaining variables in the constraint
- $x,y,z \in \{1,2,3\}, [x > y \land y = z]: \{(3,2,2),(3,1,1),(2,1,1)\}$ GAC: $x \in \{2,3\}, y \in \{1,2\}, z \in \{1,2\}$

Alldifferent

• All different: all $X_i \in \text{scope}$ of constraint are assigned to different values.

e.g.
$$X_1,..., X_4 \in \{0, 1, 2, 3, 4\}$$
 Alldiff (X_1, X_2, X_3, X_4)

$$X_1=0, X_2=1, X_3=2, X_4=3$$

$$X_1=0, X_2=1, X_3=1, X_4=2$$
 X

 How to represent Alldifferent with binary ≠ constraints?

Simple approximation to AllDiff GAC

1. If #values < #vars then return failure

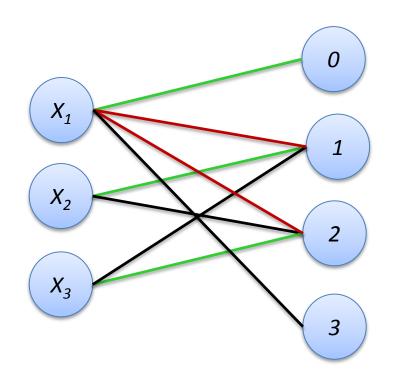
$$X_1=0, X_2\in\{1, 2\}, X_3\in\{1, 2\}, X_4=3$$

 $X_1\in\{1, 2\}, X_2\in\{1, 2\}, X_3\in\{1, 2\}, X_4=3$ \times

- 2. Remove all vars with singleton domains
- 3. Remove singleton values from remaining domains
- 4. Goto 1

Fast Computation of AllDiff GAC

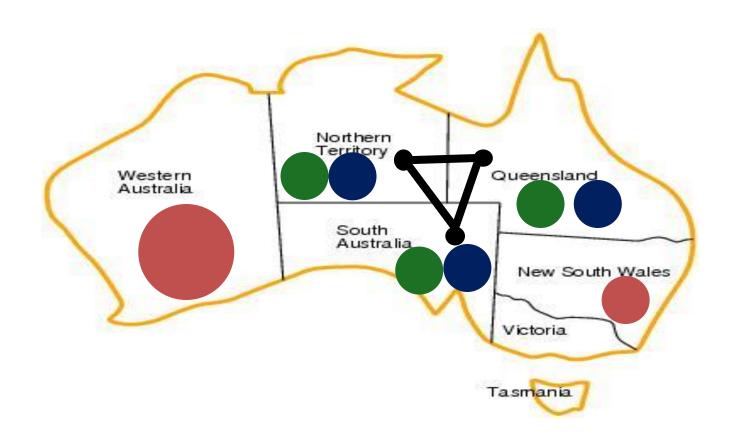
- GAC = Find all max matchings in a bipartite graph e.g. $X_1 \in \{0, 1, 2, 3\}, X_2 \in \{1, 2\}, X_3 \in \{1, 2\}$



Can be shown to be possible in $O(d\sqrt{n})$

Where AC-3 on $O(d^2)$ not equal constraints takes $O(d^5)$

AllDiff Stronger than binary constraints



Inconsistency detected by AllDiff GAC, but not by AC-3!

Constraint propagation systems

World's best 08-12 **Gecode** (link on ISP learnit page)

- Constraint Store
- Propagators
- Propagator Loop
- Search

Constraint store

$$x \in \{3,4,5\}$$
 $y \in \{3,4,5\}$

Maps variables to possible values

Constraint store

finite domains

$$x \in \{3,4,5\}$$
 $y \in \{3,4,5\}$

- Maps variables to possible values
- Others: finite sets, continuous domains, trees, ...

Constraints and Propagators

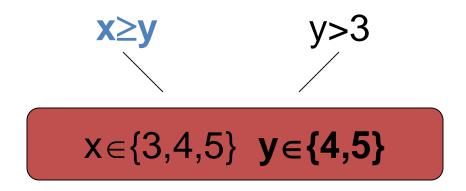
- Extensive use of global constraints
- Propagators implement constraints!
 - prune values in conflict with constraint

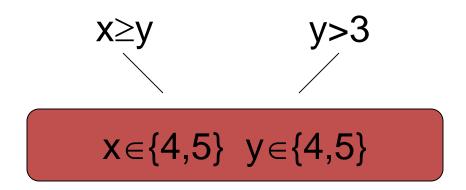
Constraint propagation drives propagators for several constraints

$$x \ge y$$
 $y > 3$ $x \in \{3,4,5\}$ $y \in \{3,4,5\}$

$$x \ge y$$
 $y > 3$ $x \in \{3,4,5\}$ $y \in \{3,4,5\}$

$$x \ge y$$
 $y > 3$ $x \in \{3,4,5\}$ $y \in \{4,5\}$





- Amplify store by constraint propagation
- Disappear when done (subsumed, entailed)
 - no more propagation possible

$$x \ge y$$
 $x \in \{4,5\} \quad y \in \{4,5\}$

- Amplify store by constraint propagation
- Disappear when done (subsumed, entailed)
 - no more propagation possible

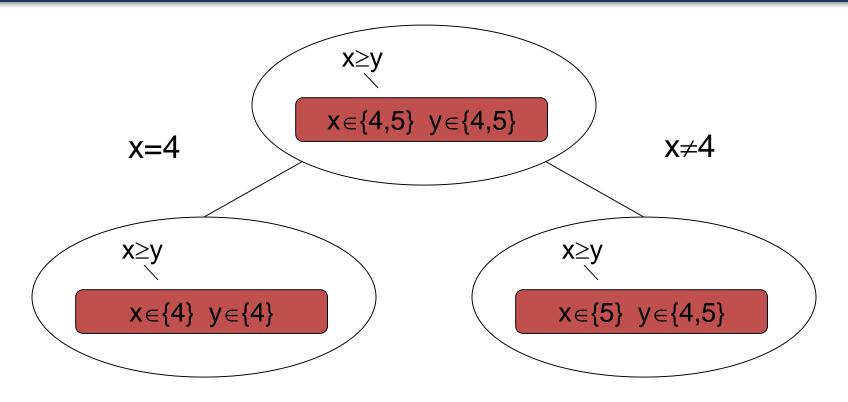
Propagation loop

```
function PROPAGATE(csp)
   Q \leftarrow \{c_1, c_2, ..., c_n\}
                                       // Queue of propagators from csp
   while Q \neq \{\} do
     c \leftarrow \text{REMOVE-FIRST}(Q)
     \mathsf{EXECUTE}(c) // run propagator, prune domains of variables
      if any domain in csp is empty then
          return false
     for each X_i \in SCOPE(c) s.t. D_i was narrowed do
        ADD(GET-PROPS(X_i) - c) to Q //Add new propagators
     end for
   end while
                                                // Fixed point reached!!
 return true
```

Search

- Propagation alone is not enough!
- Search: Explore search tree for solutions (Backtracking)
- Branching: Select variable and value (define search tree)
 - Minimum remaining values
 - Degree
 - Least constraining value

Search: Branching



- Create subproblems with additional information
- Enable further constraint propagation

Constraint propagation systems

- Each node in the search tree has different information.
- Constraint store and propagators are encapsulated in a Space.
- Manipulate spaces: Copy, add new constraints, ask for solutions, etc.

Search algorithm

```
function SEARCH(csp) returns solution or failure csp \leftarrow PROPAGATE(csp)
if csp is failure then return failure
if csp is solved then return SOL(csp)
csp' \leftarrow csp
ADD(csp', BRANCH(csp',1))
csp'' \leftarrow csp
ADD(csp'', BRANCH(csp'',2))
solution \leftarrow SEARCH(csp'')
if solution is valid then return solution
else return SEARCH(csp'')
```

function BRANCH(*csp*, *nbranch*) **return** the constraint representing the *nbranch* according to variable and value heuristic selection.