

Informatics 2D · Agents and Reasoning · 2019/2020

# Lecture 8 · Smart Searching Using Constraints

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Based on slides by: Jacques Fleuriot, Michael Rovatsos, Michael Herrmann, Vaishak Belle

# Outline

- Constraint Satisfaction Problems (CSP)
- Backtracking search for CSP
- Efficiency matters

# Constraint Satisfaction Problems (CSP)

## Standard search problem

- A **state** is a *black box* – any data structure that supports a successor function, a heuristic function and a goal test.

## CSP

- A **state** is defined by a set of **variables**, each of which has a value.
- Solution: when each variable has a value that satisfies all its constraints.
- Allows useful *general-purpose* algorithms with more power than standard search algorithms.
- **Main idea**: eliminate large portions of the search space by identifying variable/value combinations that violate the constraints.

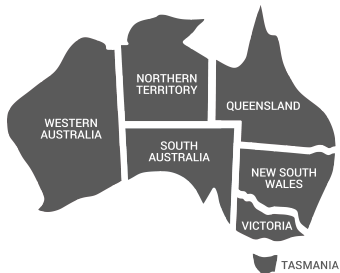
# Constraint Satisfaction Problems (CSP)

A CSP consists of:

- a set  $X = \{X_1, \dots, X_n\}$  of **variables**
- a set  $D = \{D_1, \dots, D_n\}$  of **domains**; each domain  $D_i$  is a set of possible values for variable  $X_i$
- a set  $C$  of **constraints** that specify accepted combinations of values.

A constraint  $c \in C$  consists of a **scope** – tuple of variables involved in the constraint – and a **relation** that defines the values that the variables can take.

## Example · Map-Colouring



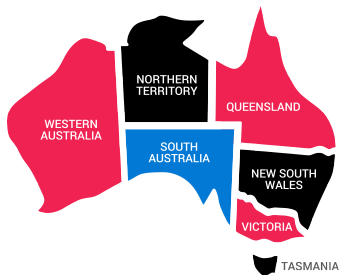
Variables: {WA, NT, Q, NSW, V, SA, T}

Domains:  $D_i = \{\text{red, black, blue}\}$

Constraints: adjacent regions must have different colours

- e.g. WA  $\neq$  NT or
- (WA, NT)  $\in \{(\text{red, black}), (\text{red, blue}), (\text{black, red}), (\text{black, blue}), (\text{blue, red}), (\text{blue, black})\}$

## Example · Map-Colouring



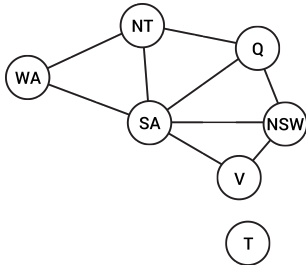
**Solutions** are complete and consistent assignments.

- e.g. WA  $\mapsto$  red, NT  $\mapsto$  black, Q  $\mapsto$  red, NSW  $\mapsto$  black, V  $\mapsto$  red, SA  $\mapsto$  blue, T  $\mapsto$  black.

# Constraint graph

## Binary CSP

- Each constraint relates two variables.
- **Constraint graph:**
  - nodes are variables
  - arcs (edges) represent constraints



# Varieties of CSP

## Discrete variables

- finite domains:
  - $n$  variables, domain size  $d$ ,  $O(d^n)$  complete assignments
  - e.g. Boolean CSPs, including Boolean satisfiability (NP-complete)
- infinite domains:
  - integers, strings, etc.
  - e.g. job scheduling
    - variables are start/end days for each job
    - we need a constraint language to express  $\text{StartJob}_1 + 5 \leq \text{StartJob}_3$

## Continuous variables

- e.g. start/end times for Hubble Space Telescope observations
- linear constraints solvable in polynomial time by linear programming



# Varieties of constraints

Unary constraints involve a single variable.

- e.g. SA  $\neq$  black

Binary constraints involve pairs of variables.

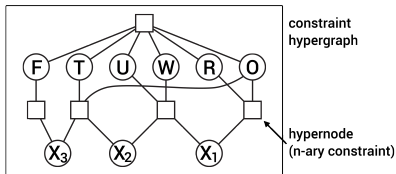
- e.g. SA  $\neq$  WA

Higher-order constraints involve 3 or more variables.

- e.g. crypt-arithmetic column constraints

Global constraints involve an arbitrary number of variables.

## Example · Crypt-arithmetic

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


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:  $\text{Alldiff}(F, T, U, W, R, O)$  ← global constraint

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

$$X_1 + W + W = U + 10 \cdot X_2$$

$$X_2 + T + T = O + 10 \cdot X_3$$

$$X_3 = F, \quad T \neq 0, \quad F \neq 0$$

# Real-world CSP

## Assignment problems

- e.g. who teaches what class

## Timetabling problems

- e.g. which class is offered when and where

## Transportation scheduling

## Factory scheduling

Many real-world problems involve real-valued variables.

## Standard search formulation (incremental)

*Let's start with the straightforward approach, then adapt 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 the current assignment  
→ *fail* if no legal assignments

**Goal test:** the current assignment is complete

- This is the same for all CSPs.
- For CSPs with  $n$  variables, any solution appears at depth  $n \Rightarrow$  use depth-first search.

# Backtracking search

- Variable assignments are **commutative**.
  - e.g. [WA  $\mapsto$  red then NT  $\mapsto$  black]  
is the same as  
[NT  $\mapsto$  black then WA  $\mapsto$  red]
- We only need to consider assignments to a single variable at each node. Thus,  $b = d$ , and there are  $d^n$  leaves.
- Depth-first search for CSPs with single-variable assignments is called **backtracking** search.
- Backtracking search: the basic uninformed algorithm for CSP.
- Can solve the  $n$ -queens problem for  $n \approx 25$ .

# 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 ← 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 ← INFERENCE(csp, var, value) ←  
    if inferences ≠ failure then  
      add inferences to assignment  
      result ← BACKTRACK(assignment, csp)  
      if result ≠ failure then  
        return result  
    remove {var = value} and inferences from assignment  
return failure
```

Optional; can be used to  
impose arc-consistency  
(more on this later)

## Backtracking example

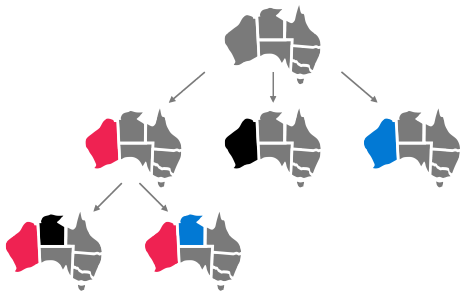


## Backtracking example

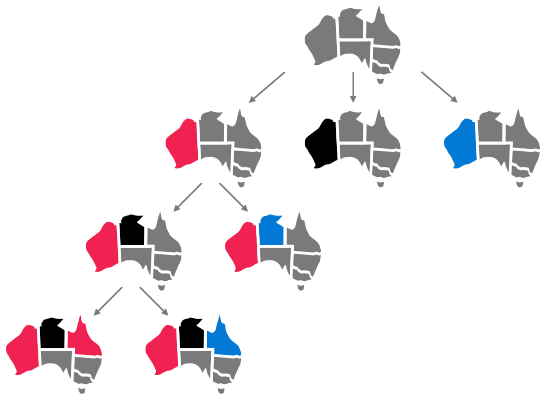




## Backtracking example



# Backtracking example



# Improving backtracking efficiency

General-purpose methods can give huge gains in speed.

Which **variable** should be assigned next?

- SELECT-UNASSIGNED-VARIABLE

Then, in what order should its **values** be tried?

- ORDER-DOMAIN-VALUES

What inferences should be performed at each search step?

- INFERENCE

Can we detect inevitable failure early?

# Most constrained variable

`var ← SELECT-UNASSIGNED-VARIABLE(csp)`

## Most constrained variable heuristic

- choose the variable with the fewest legal values
- a.k.a. minimum-remaining-values (MRV) heuristic



# Most constraining variable

Tie-breaker among most constrained variables.

## Most constraining variable heuristic

- choose the variable with the most constraints on remaining variables, thus reducing branching
- a.k.a. degree heuristic



# Least constraining value

## ORDER-DOMAIN-VALUES

Given a variable, choose the **least constraining value**

- the one that rules out the fewest values in the remaining variables



Combining these heuristics:  $n$ -queens feasible for  $n \approx 1000$ .

# Inference · Forward checking

## Idea

Keep track of remaining legal values for unassigned variables.  
Terminate the search when a variable has no more legal values.



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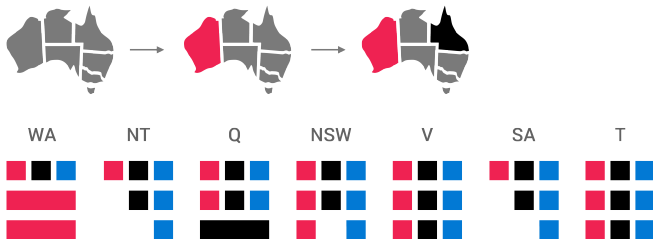




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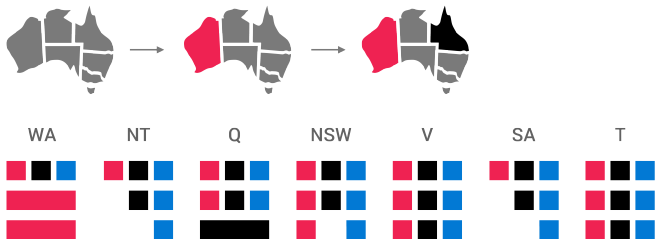
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## Constraint propagation

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



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  $x$  in the domain of  $X$

there is **some** allowed value  $y$  in the domain of  $Y$



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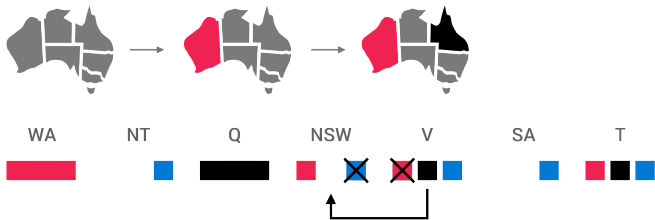
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If  $X$  loses a value, its neighbours need to be rechecked.

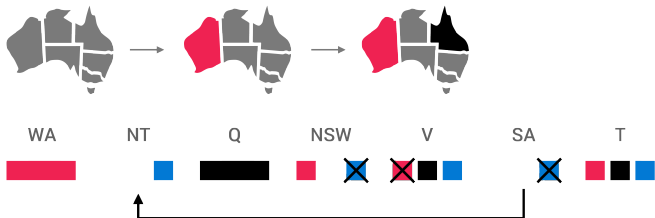
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If  $X$  loses a value, its neighbours need to be rechecked.

**Detects failure** earlier than forward checking.

Can be run as a preprocessor or after each assignment.

# Arc consistency algorithm · AC-3

```
function AC-3(csp) returns false if an inconsistency is found and true otherwise
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
  ( $X_i$ ,  $X_j$ )  $\leftarrow$  REMOVE-FIRST(queue)
  if REVISE(csp,  $X_i$ ,  $X_j$ ) then
    if size of  $D_i = 0$  then return false
    for each  $X_k$  in  $X_i$ .NEIGHBORS -  $\{X_j\}$  do
      add ( $X_k$ ,  $X_i$ ) to queue
  return true
```

← Make  $X_i$  arc-consistent with respect to  $X_j$   
← No consistent value left for  $X_i$  so fail  
← Since revision occurred, add all neighbours of  $X_j$  for consideration (or reconsideration)

---

```
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  $D_j$  allows ( $x, y$ ) to satisfy the constraint between  $X_i$  and  $X_j$  then
      delete  $x$  from  $D_i$ 
      revised  $\leftarrow$  true
  return revised
```

$d$  – maximum size of the domains

$c$  – number of binary constraints

Time complexity:  $O(cd^3)$

Space complexity:  $O(c)$



# Summary

In CSPs:

- 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.
- Forward checking prevents assignments that are certain to lead to later failure.
- Constraint propagation does additional work to limit values and detect inconsistencies.