

, 2022

## **Solving problems by Search**

**Goal-based Agents**

**Atomic-Factored-Structured**

**Dr. Bilal Hoteit**

# Introduction to Artificial Intelligence

## Table of contents

- **Constraint satisfaction problem**
- **Requirements: Linear Programming**

# Introduction to Artificial Intelligence

## Table of contents

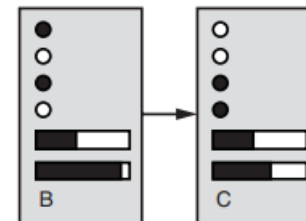
- **Requirements: Linear Programming**
- **Lecture 3 , p:67 - 73**
- **Src3 – production.py**

## Difference between Representations

- ❑ Atomic representation means a state representing single variable.
- ❑ Black box, no internal structure.



- ❑ Factored representation means a State consists of a vector of attribute values.
- ❑ Each state has several variables and may be each variable can have a set of values.



## Constraint Satisfaction problem

- ❑ So far, states are evaluated using either heuristics or goals.
- ❑ CSP = factored representation of the state.
- ❑ A state has several variables
- ❑ Each variable has a set of values
- ❑ CSP is finding a solution or no solution exists.
- ❑ CSP:
  - a.  $X$  is a set of variables,  $\{X_1, \dots, X_n\}$ .
  - b.  $D$  is a set of domains,  $\{D_1, \dots, D_n\}$ , one for each variable  $X$ .
    - $D_i = \{v_1, \dots, v_n\}$  for  $X_i$ .
  - c.  $C$  is a set of constraints specifying combinations of values?
    - $C_i = \{\text{scope}, \text{rel}\}$ .

## Constraint Satisfaction problem

a. Simulation go to word file in chapter seven folder.

**Simulation for back tracking algorithm:**

[Constraint Satisfaction: introduction - ...](#)

## Constraint Satisfaction problem formulation

### □ Example: Map Austria color

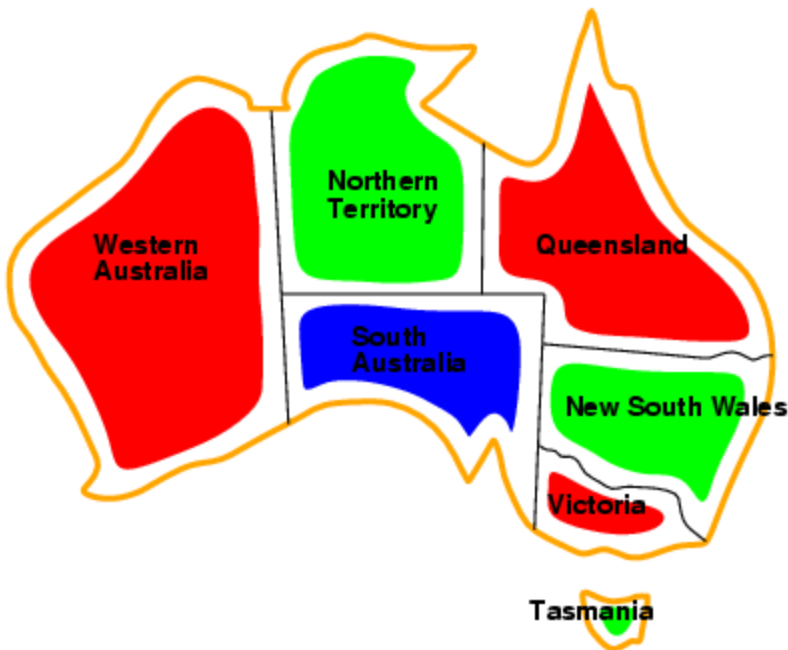


- Variables  $WA, NT, Q, NSW, V, SA, T$ .
- Domains  $D_i = \{\text{red}, \text{green}, \text{blue}\}$ .
- Constraints: adjacent regions must have different colors.

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

## Constraint Satisfaction problem formulation

### □ Example: Map Austria color



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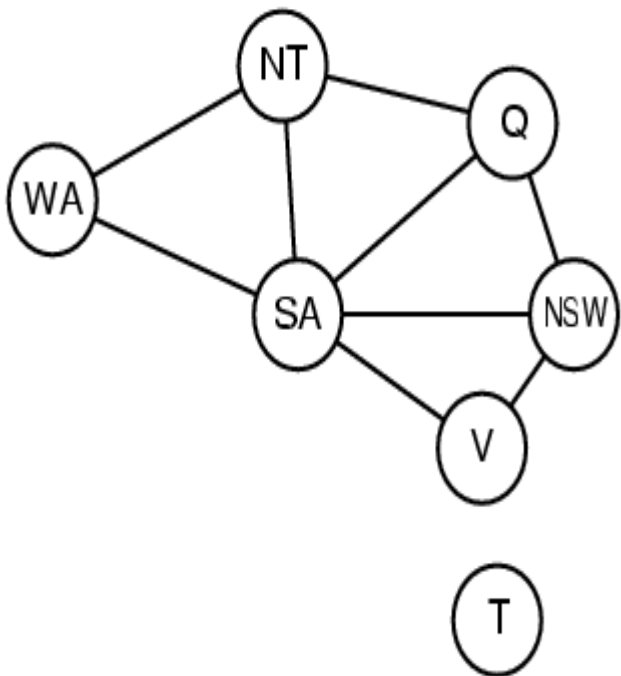
Solutions are complete and consistent assignments, e.g.,  $WA = \text{red}$ ,  $NT = \text{green}$ ,  $Q = \text{red}$ ,  $NSW = \text{green}$ ,  $V = \text{red}$ ,  $SA = \text{blue}$ ,  $T = \text{green}$ .



## Constraint Satisfaction problem formulation

### □ Example: Map Austria color

- Constraint graph: nodes are variables, arcs are 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.

## Constraint Satisfaction problem formulation

### □ Another Example.

#### Scheduling example...

- **Lecture 3 , p:74 - 157**

**Note: Node and ARC consistency**

**Note: Then back tracking algorithm**

**Code: back tracking algorithm demonstration**

**Src3 – scheduling0.py**

python-constraint

**Src3 – scheduling1.py**

## Constraint Satisfaction problem formulation

□ Inference (optimization)....

Scheduling example...

- Lecture 3 , p:158 - 184

**Note: Arc consistency**

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

**Then: Another problem simulation....**

## Constraint Satisfaction problem

### □ Back track algorithm

```
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
```

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Prerequisites  
Purpose  
AI définitions  
AI Types  
Trendings  
Confused

Context

1

## Constraint Satisfaction problem

❑ Back track algorithm simulation.



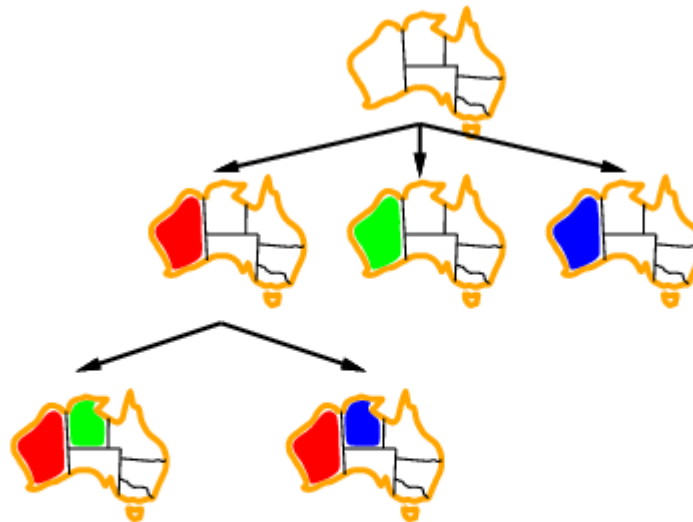
## Constraint Satisfaction problem

- Back track algorithm simulation.



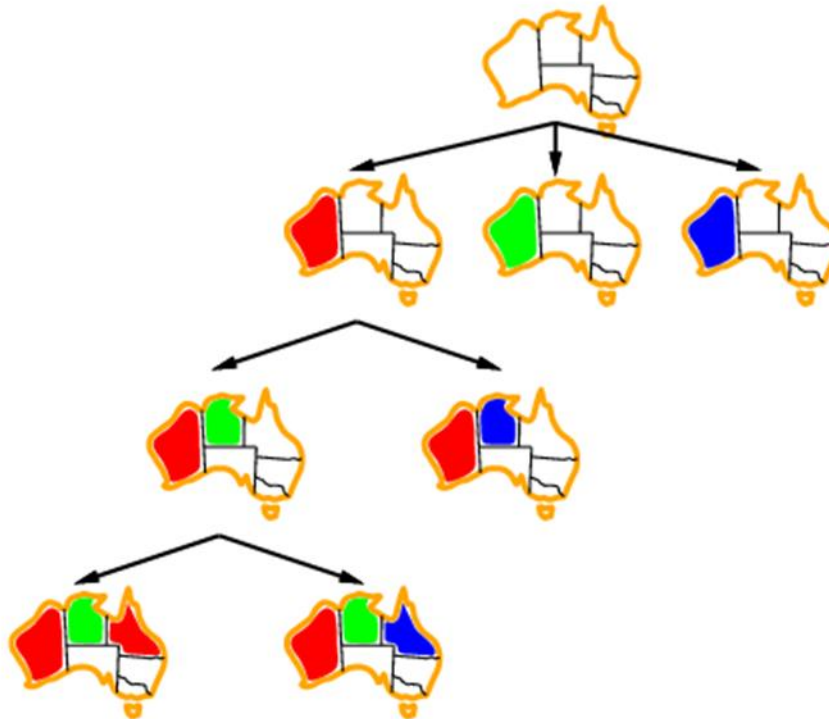
## Constraint Satisfaction problem

### □ Back track algorithm simulation.



## Constraint Satisfaction problem

### □ Back track algorithm simulation.





## Back track algorithm

- ❑ Improving backtracking efficiency
- ❑ General-purpose methods can give huge gains in speed:
  - Which variable should be assigned next?
  - In what order should its values be tried?
  - Can we detect inevitable failure early?

## Back track algorithm

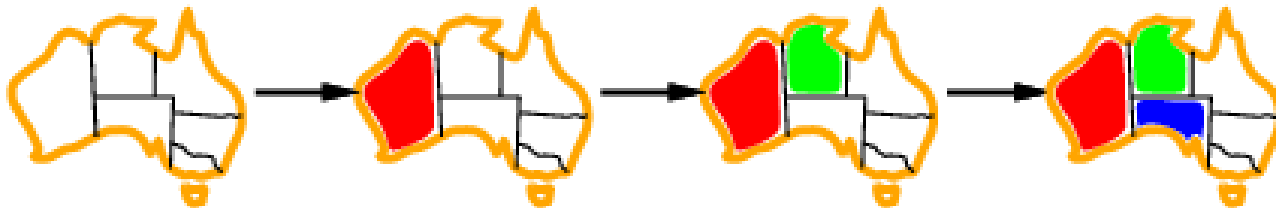
- ❑ Improving backtracking efficiency
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## Back track algorithm

### □ Improving backtracking efficiency

Most constrained variable:

choose the variable with the fewest legal values



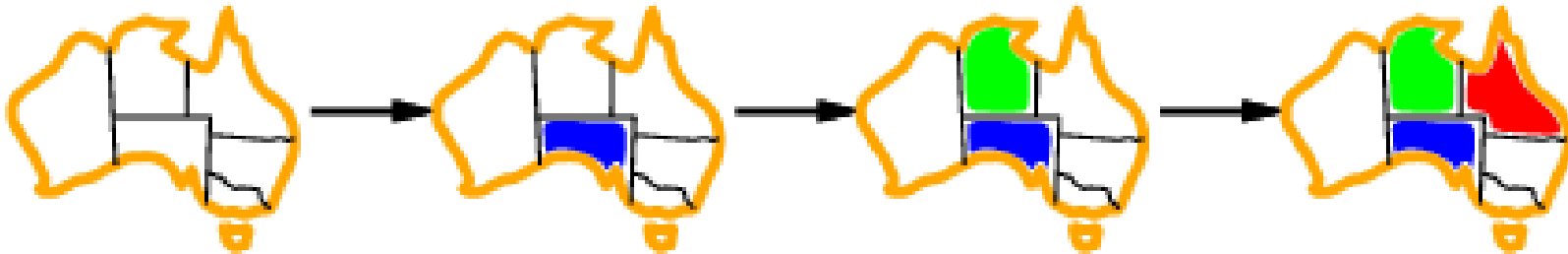
a.k.a. **minimum remaining values (MRV)** heuristic

## Back track algorithm

### □ Improving backtracking efficiency

Most constrained variable:

choose the variable with the fewest legal values



choose the variable with the most constraints on remaining variables

## Back track algorithm

### □ Improving backtracking efficiency

Least constraining value:

The one that rules out the fewest values in the remaining values



Combining these heuristics makes 1000 queens feasible.

## Back track algorithm

### □ Improving backtracking efficiency

```
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
```

## Back track algorithm

### □ Improving backtracking efficiency



**Idea:** Inference mechanisms (propagation using forward checking, or CS3)

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



## Back track algorithm

### □ Improving backtracking efficiency



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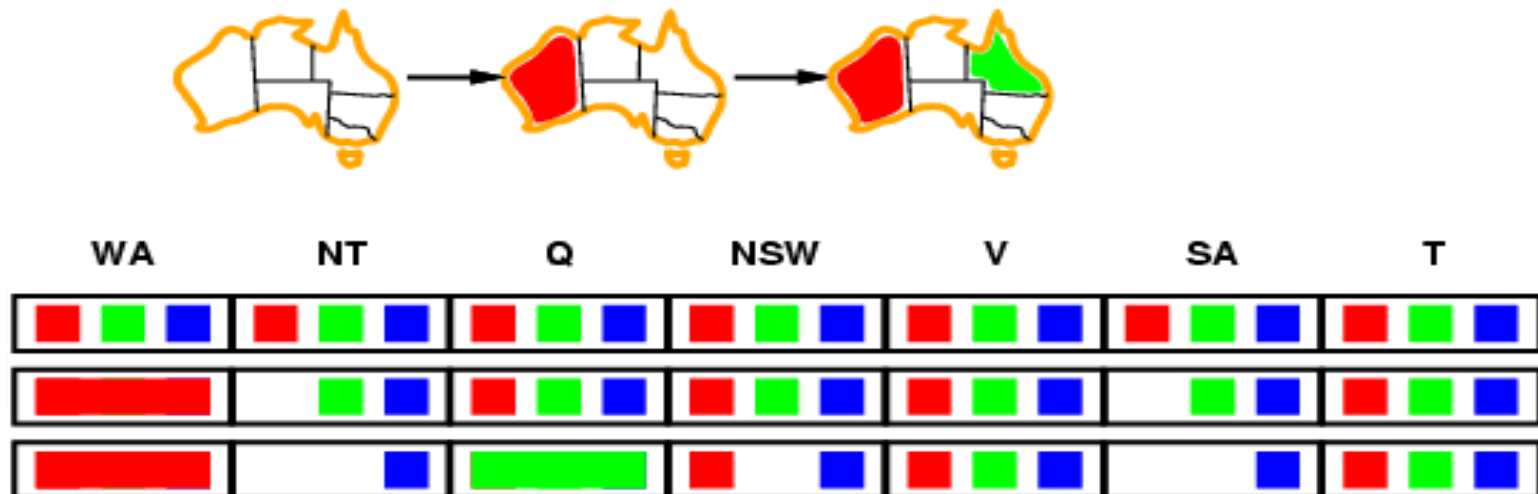
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### □ Improving backtracking efficiency



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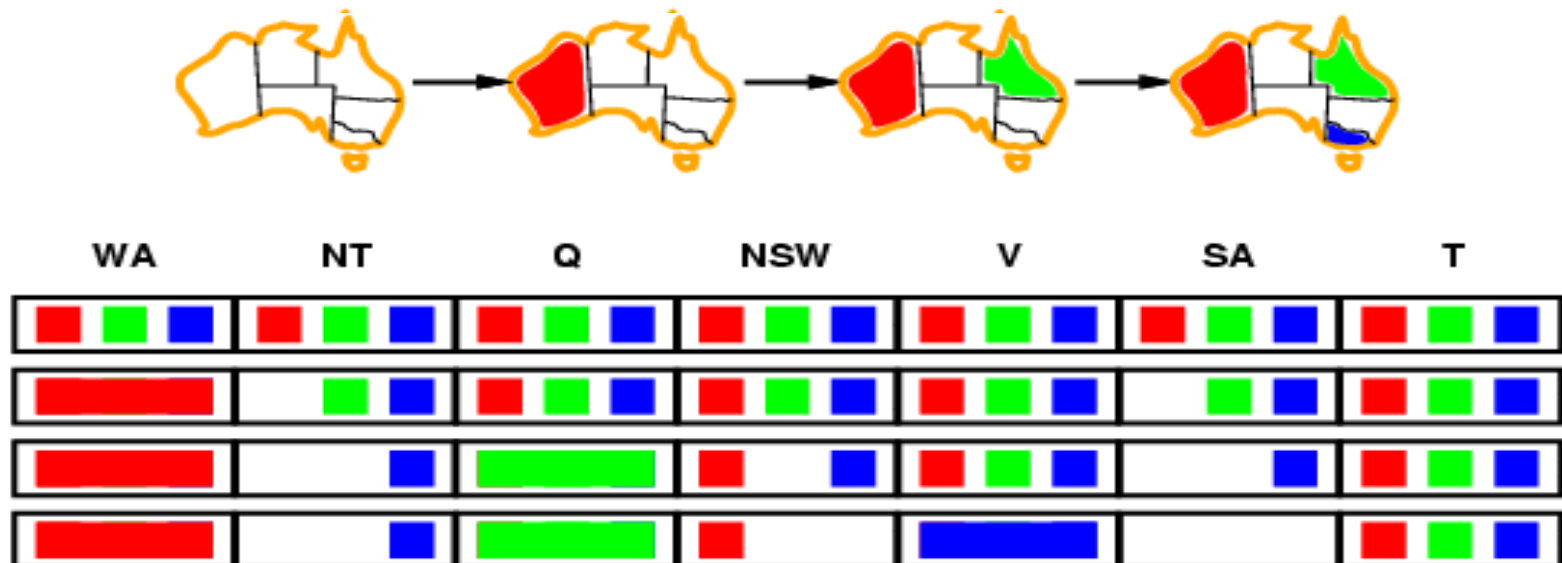
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## Back track algorithm

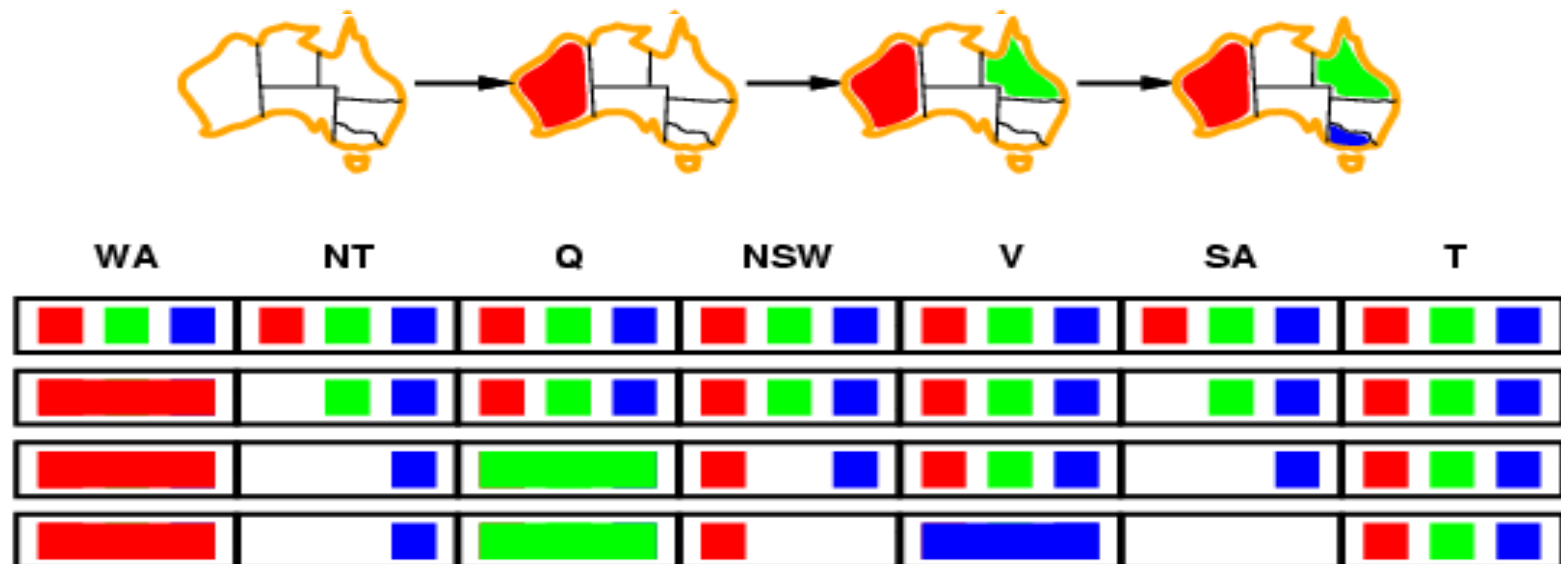
### □ Improving backtracking efficiency



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.



## Back track algorithm

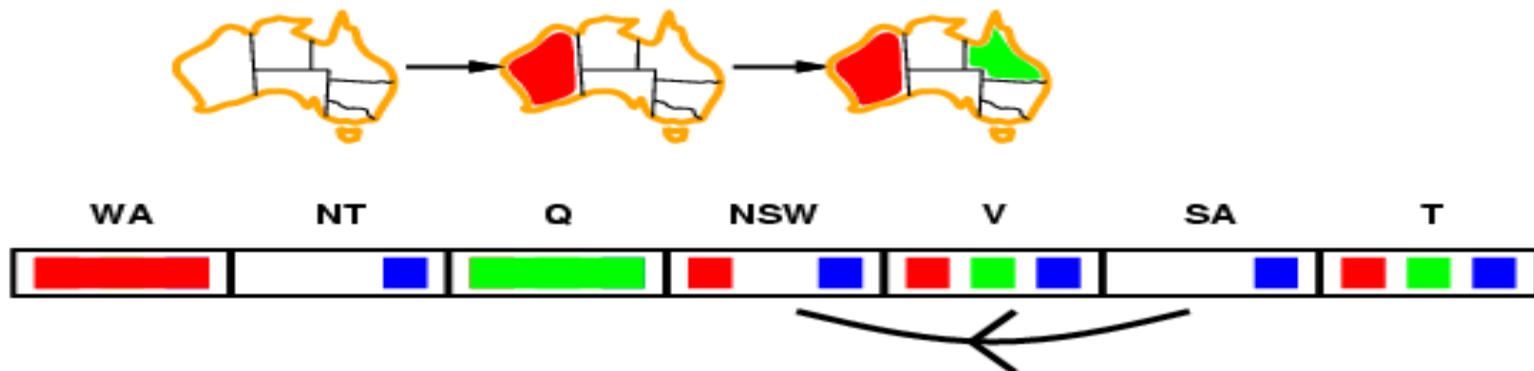
### □ Improving backtracking efficiency

**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  $y$



## Back track algorithm

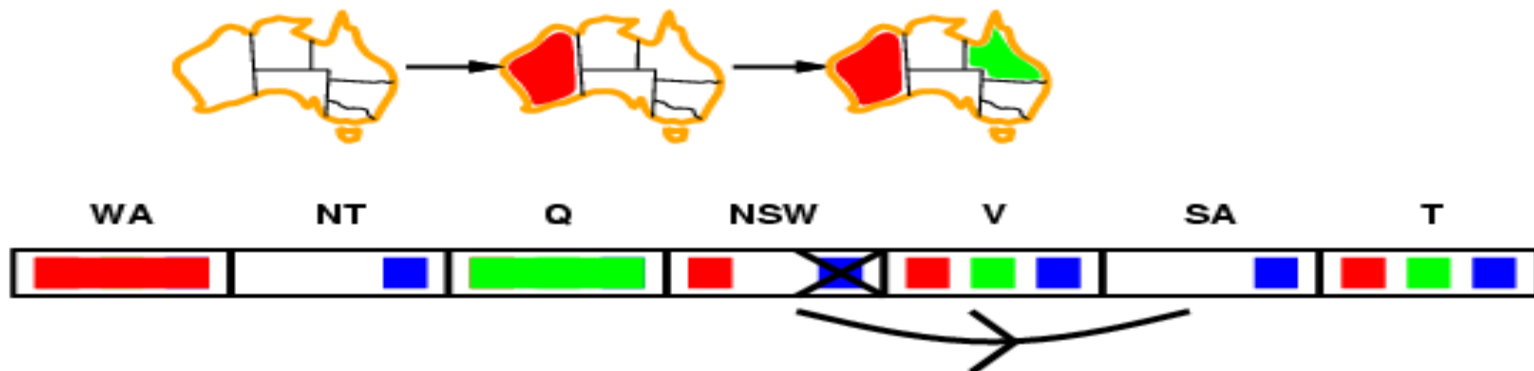
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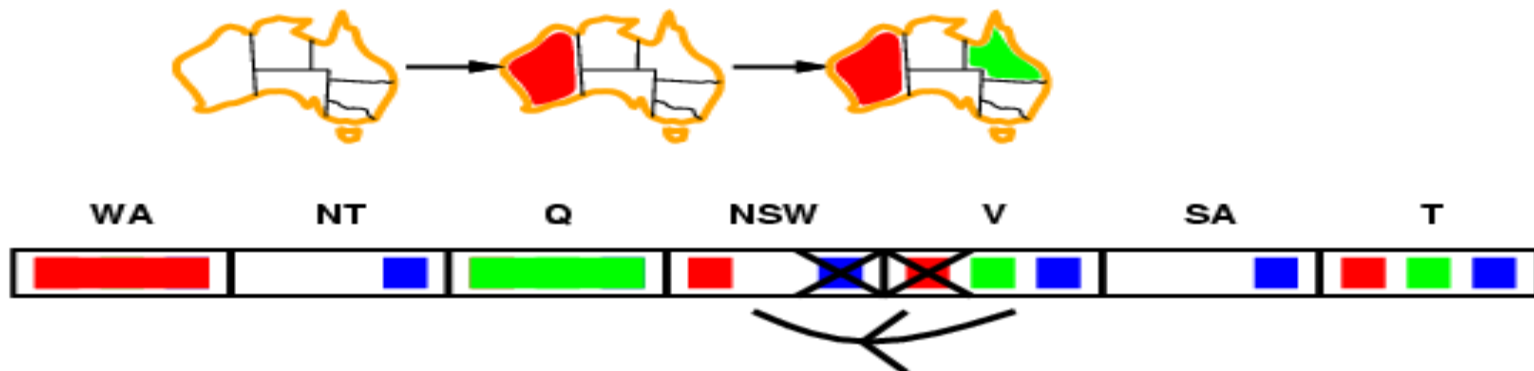
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If  $X$  loses a value, neighbors of  $X$  need to be rechecked

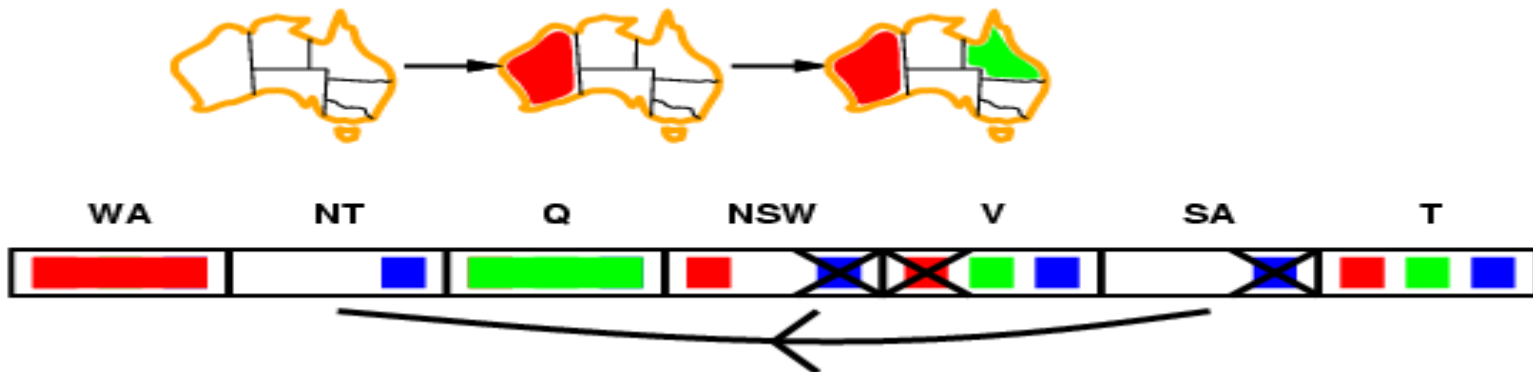
## Back track algorithm

### Improving backtracking efficiency

#### 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  $y$



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.



## 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 RM-INCONSISTENT-VALUES( $X_i, X_j$ ) then
      for each  $X_k$  in NEIGHBORS[ $X_i$ ] do
        add  $(X_k, X_i)$  to queue



---


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



## Local search for CSPs

- ❑ Hill-climbing, simulated annealing typically work with "complete" states, i.e., all variables assigned
- ❑ To apply to CSPs:
  - a. allow states with unsatisfied constraints.
  - b. operators reassign variable values.
- ❑ Variable selection: randomly select any conflicted variable
- ❑ Value selection by min-conflicts heuristic:
  - a. Choose value that violates the fewest constraints

**Thank you for your  
attention!**



**Questions?**