# Constraint Satisfaction Problem II

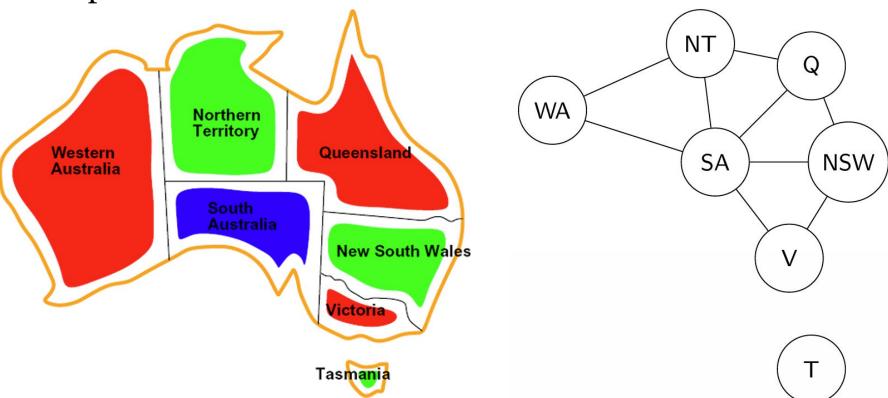
CSE 4617: Artificial Intelligence



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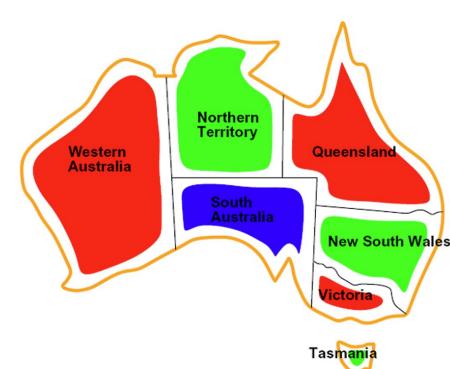


## Examples of CSPs

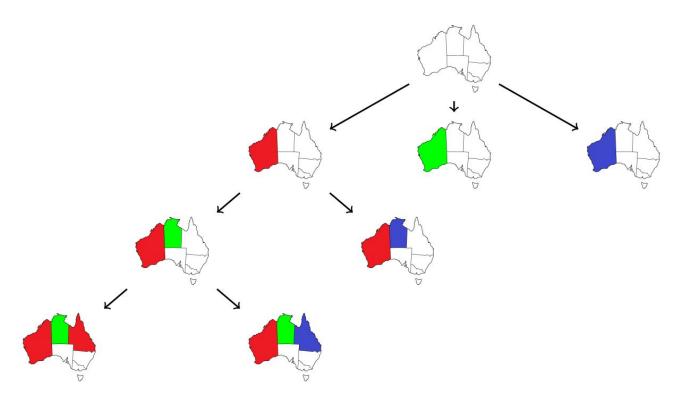


## Examples of CSPs

- Variables
  - o WA, NT, Q, NSW, V, SA, T
- Domains
  - $\circ$   $D = \{\text{red, green, blue}\}$
- Constraints → Adjacent regions must be different colored
  - $\supset$  Implicit: WA  $\neq$  NT, ...
  - Explicit: (WA, NT)  $\subseteq$  {(red, green), (red, blue), (blue, green), ...}
- Solution
  - An assignment of variables that satisfy all constraints



## Backtracking Search



## Backtracking Search

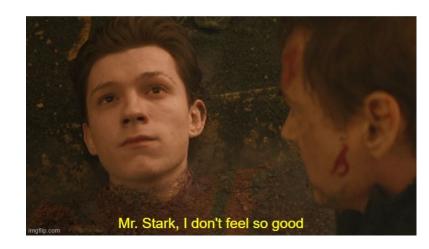
```
return RECURSIVE-BACKTRACKING ({}, csp)
RECURSIVE-BACKTRACKING (assignment, csp) → returns a solution or failure
   if assignment is complete then return assignment
    var ← SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignment, csp)
    for value in ORDER-DOMAIN-VALUE(var, assignment, csp):
        if value is consistent with assignment given CONSTRAINTS[csp]:
            then add {var = value} to assignment
            result ← RECURSIVE-BACKTRACKING (assignment, csp)
            if result is not failure then return result
            remove {var = value} from assignment
    return failure
```

BACKTRACKING-SEARCH  $(csp) \rightarrow returns$  a solution or failure

## How to Improve Backtracking Search

- Filtering
  - Limiting our choices for variable assignment
  - Detects an inevitable failure early
- Ordering
  - In what order should we assign variables
  - Does it actually matter?
- Structure
  - Can we exploit the structure of a problem?

Certain values as soon as arc consistency is checked

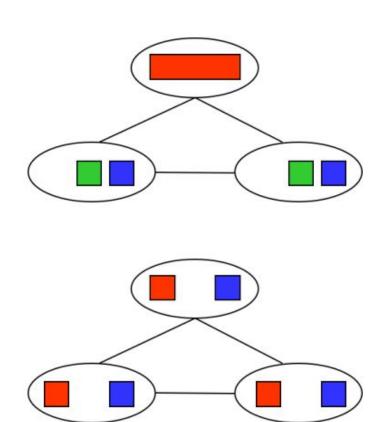


## Filtering: Arc Consistency

After enforcing arc consistency:

- Can have one solution left
- Can have multiple solutions left
- Can have no solutions left (and not know it)

Arc consistency only checks pairs :(



# k-Consistency

### k-Consistency

#### Increasing degrees of consistency:

- 1-Consistency → Each node's domain has a value which meets that node's unary constraints
- 2-Consistency → For each pair of nodes, any consistent assignment to one can be extended to the other → Arc Consistency
- k-Consistency  $\rightarrow$  For each k nodes, any consistent assignment to k-1<sup>th</sup> can be extended to the k<sup>th</sup> node
  - $\circ$  As the value of k increases, it gets more difficult to compute k-Consistency
- Strong k-Consistency  $\rightarrow$  Nodes are k 1, k 2, k 3, ..., 2, 1 consistent
- Strong n-consistency  $\rightarrow$  Can solve without backtracking !  $\rightarrow$  *n* is the number of variables

## Structure

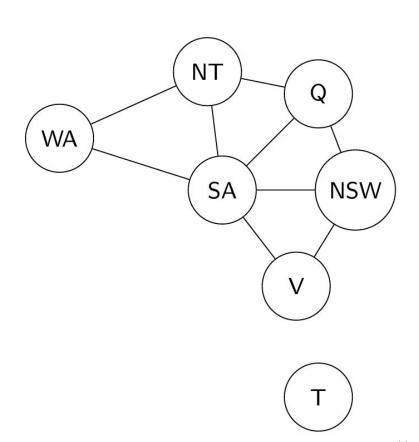
#### Structure

In this specific graph:

- There are 2 independent subproblems
- Independent subproblems are identifiable as connected components of constraint graph
  - How to detect independent subproblems?

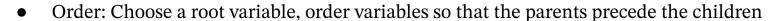
If a graph of *n* variables can be broken down into subproblems of only *c* variables:

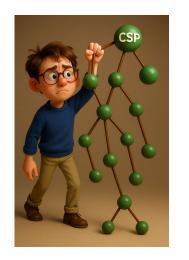
- The worst case solution cost is  $O((n/c)(d^c))$
- This is much better than the worst case of naive DFS which is  $O(d^n)$



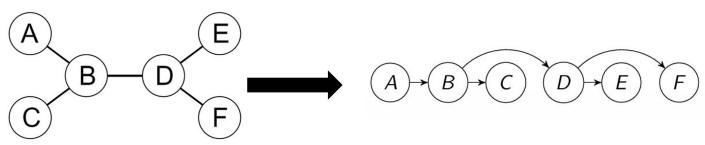
In most cases, encountered graphs have a tree-like structure

#### For tree-structured CSPs:





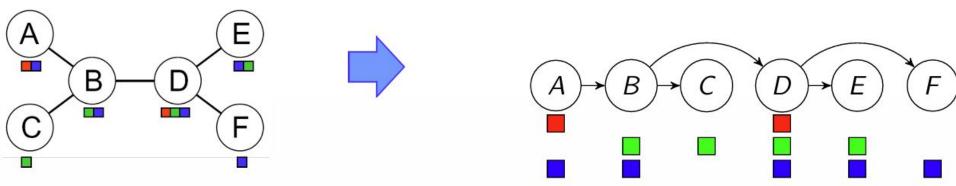
Use Topological Sort



Notice that it is now a DAG, even though the original graph wasn't

#### For tree-structured CSPs:

- Order: Choose a root variable, order variables so that the parents precede the children
- Remove Backward: Start from the rightmost node and keep going left as you remove inconsistent values from nodes to ensure consistency of the arcs
- Assign Forward: Assign values from left to right nodes by taking valid values from the domain



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#### Runtime: $O(nd^2)$

- Go from tail to head and then head to tail  $\rightarrow O(n)$
- Check pairs of values for consistency/assignment  $\rightarrow$  O( $d^2$ )

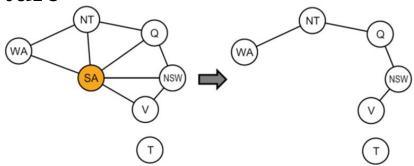
I can make a few claims about tree-structured CSPs:

- After a backward pass, all root-to-leaf arcs are consistent → Why?
  - $\circ$  Each  $X \to Y$  was made consistent at one point and Y's domain could not have been reduced thereafter
- If all root-to-leaf arcs are consistent, forward assignment will not backtrack
  - $\circ$  Arc consistency implies for X  $\to$  Y, for a consistent assignment of X so far, we have a consistent assignment of Y

Why doesn't this algorithm work with cycles in the constraint graph?

```
TREE-CSP-SOLVER (csp) \rightarrow returns a solution or failure
     X \leftarrow \text{set of variables}
     N \leftarrow \text{number of variables in } X
     root \leftarrow any random variable in X
     D ← domain of possible values
     X \leftarrow \text{TOPOLOGICAL-SORT}(X, root)
     for i in range(n \rightarrow 2):
          MAKE-ARC-CONSISTENT (PARENT (X_i), X_i)
          if no consistency then return failure
     for i in range(1 \rightarrow n):
          X_i \leftarrow \text{any consistent value from } D_i
          if no consistency then return failure
     return X
```

Improving Structure



- Conditioning → Instantiate a variable, prune its neighbors' domains
- Cutset conditioning → Instantiate (in all ways) a set of variables such that the remaining constraint graph is a tree

Cutset size *c* gives runtime  $O(d^c(n-c)d^2)$ :

- Total instantiations  $\rightarrow O(d^c)$
- Total remaining subproblems  $\rightarrow$  (n c)

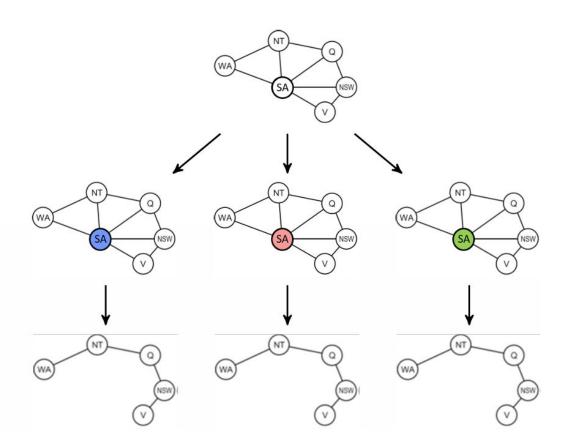
## **Cutset Conditioning**

Choose a cutset

Instantiate the cutset (all possible ways)

Compute residual CSP for each assignment

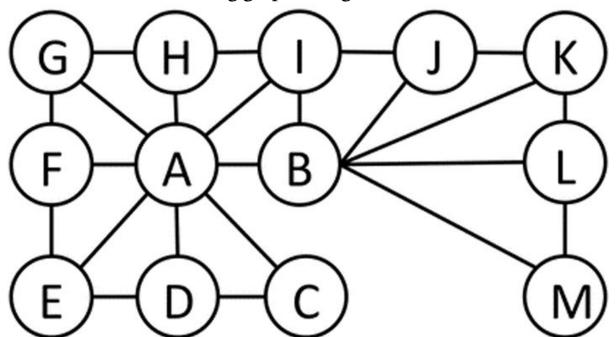
Solve the residual CSPs (tree structured)



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## **Cutset Conditioning**

Find the smallest cutset for the following graph that gives us a tree:



Local search methods typically work with "complete" states, i.e., all variables assigned

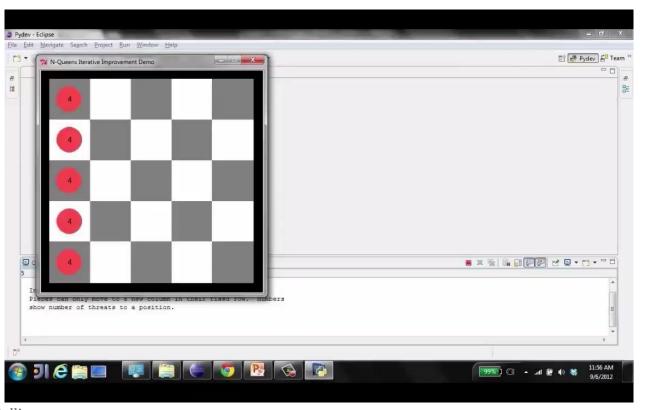
To apply the same idea to CSPs:

- Take an assignment with unsatisfied constraints
- Operators reassign variable values
- No need for fringe!

Keep randomly selecting any conflicted variable and set the value to the one with minimum conflicts





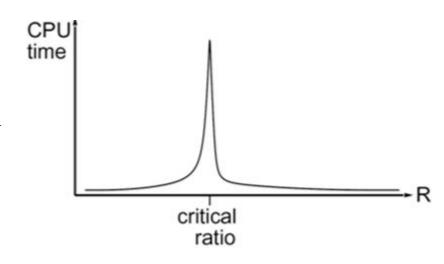


Given random initial state, can solve n-queens in almost constant time for arbitrary n with high probability

• Such as n = 10,000,000

The same appears to be true for any randomly-generated CSP except in a narrow range of the ratio

$$R = \frac{\text{number of constraints}}{\text{number of variables}}$$



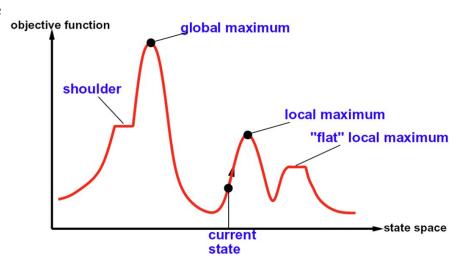
# Local Search

#### Local Search

- Tree search keeps unexplored alternatives on the fringe → This ensures completeness
- Local search improves a single option until you can't make it better → no fringe!

#### General idea:

- Randomly start
- Repeat: move to the best neighboring state
- If no neighbors better than current, quit
- Not complete
- Not optimal
- Very efficient in finding good-enough solutions



#### Additional Resources

- <u>Backtracking Search Simulator</u>
- What are Genetic Algorithms?
- A.I. Learns To Walk

# Thank you