

# Constraint Satisfaction - II

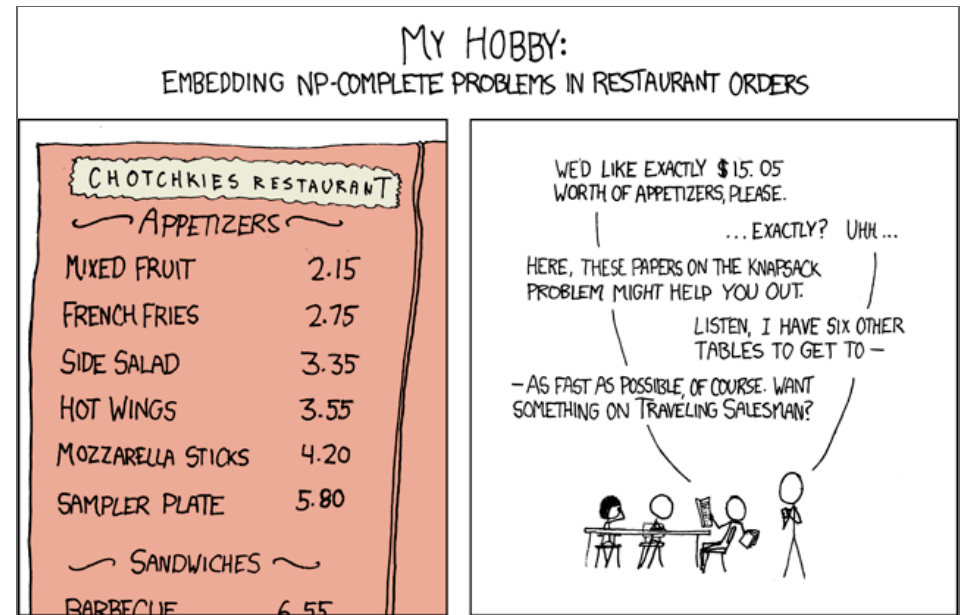
CS5491: Artificial Intelligence  
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Content Credits: **Prof. Wei**'s CS4486 Course  
and **Prof. Boddeti**'s AI Course

# TODAY

## Improvements to Backtracking Search:

- Filtering
- Ordering
- Problem Structure



XKCD

## Reading

- Today's Lecture: RN Chapter 6

# BACKTRACKING SEARCH

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# BACKTRACKING SEARCH

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Backtracking search is the basic uninformed algorithm for solving CSPs

Idea 1: One variable at a time

- Variable assignments are commutative, so fix ordering
- Problem is commutative if order of application of any given set of actions has no effect on outcome.
- i.e., [WA = red then NT = green] same as [NT = green then WA = red]
- Only need to consider assignments to a single variable at each step

Idea 2: Check constraints as you go

- i.e. consider only values which do not conflict with previous assignments
- Might have to do some computation to check the constraints
- "Incremental goal test"

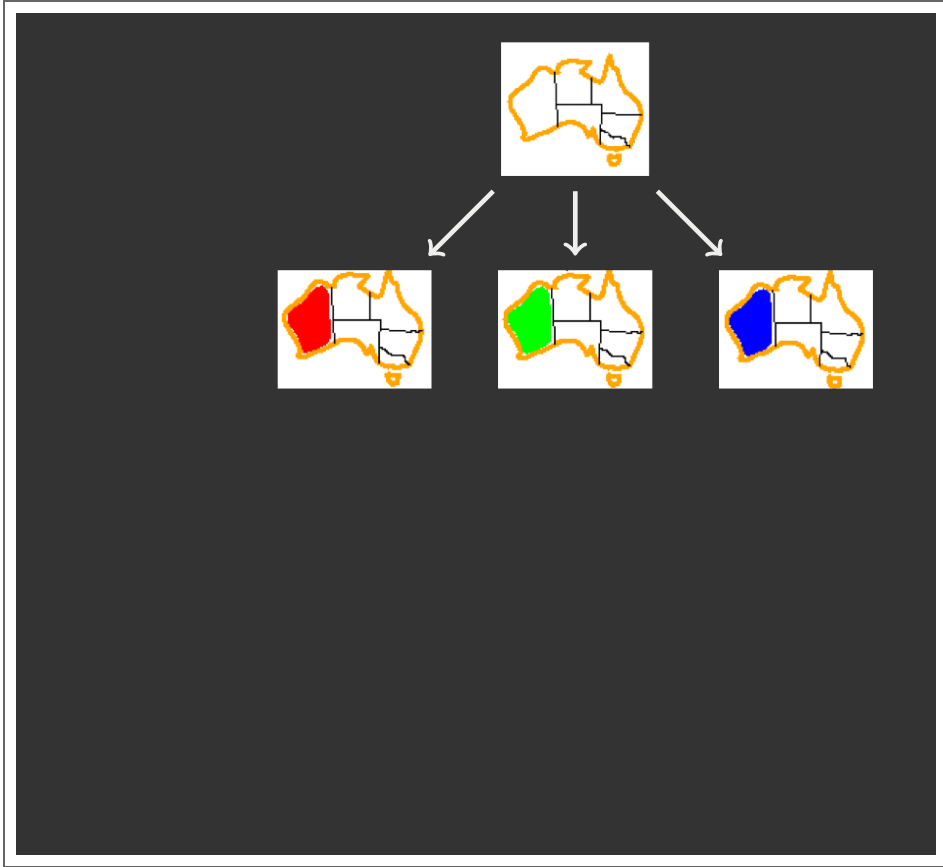
DFS with these two improvements is called backtracking search (not the best name)

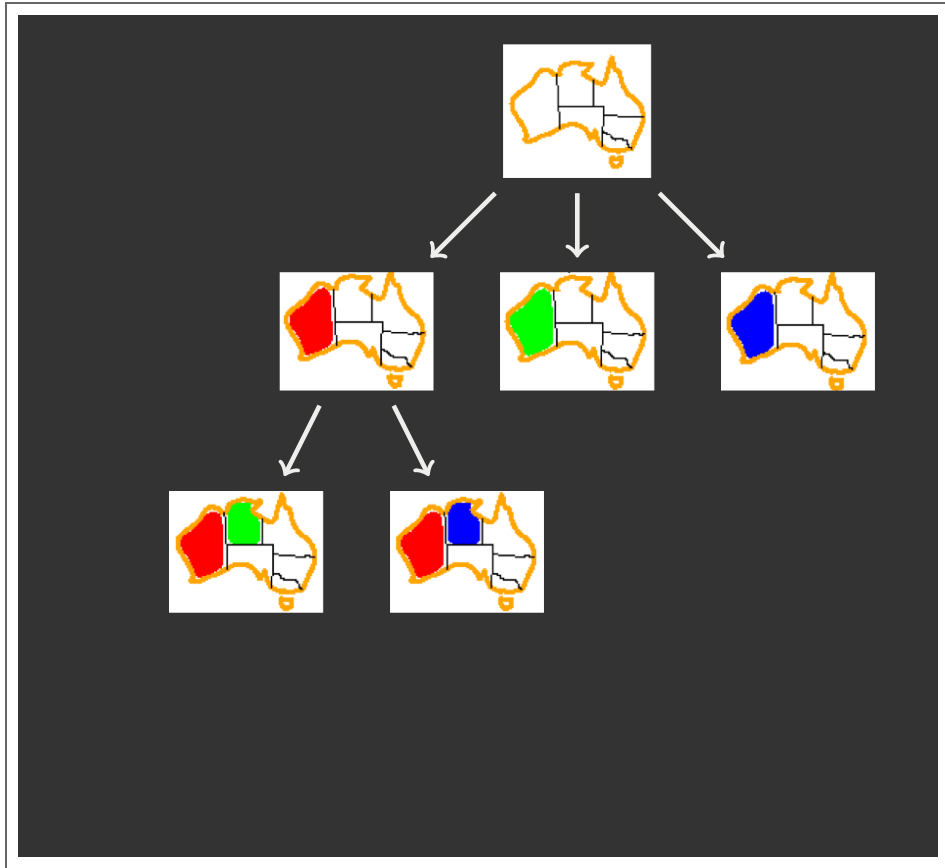
Can solve n-queens for  $n \approx 25$

# BACKTRACKING EXAMPLE

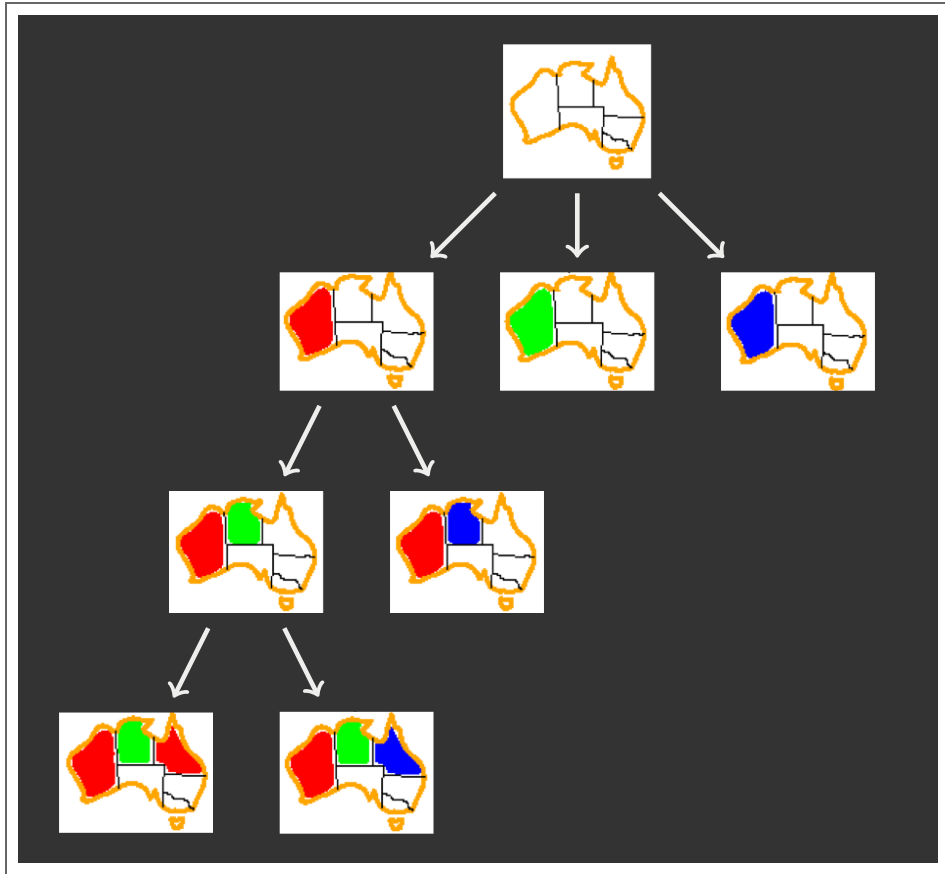
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# BACKTRACKING SEARCH

```
function BACKTRACKING-SEARCH(csp) returns solution/failure
  return RECURSIVE-BACKTRACKING({ }, csp)

function RECURSIVE-BACKTRACKING(assignment, csp) returns soln/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 given 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
```

- Backtracking = DFS + variable-ordering + fail-on-violation

# IMPROVING BACKTRACKING SEARCH

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General-purpose ideas give huge gains in speed

- Backtracking is an uninformed algorithm. So we don't expect it to be very effective for large problems. We know the informed search can improve the efficiency and effectiveness.

Ordering:

- Which variable should be assigned next?
- In what order should its values be tried?

Filtering: Can we detect inevitable failure early?

Structure: Can we exploit the problem structure?

# ORDERING

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## ORDERING: MINIMUM REMAINING VALUES

Variable Ordering: Minimum remaining values (MRV):

- Choose the variable with the fewest legal values left in its domain





Why min rather than max?

Also called "most constrained variable"

"Fail-fast" ordering

# ORDERING: LEAST CONSTRAINING VALUE

## Value Ordering: Least Constraining Value

- Given a choice of variable, choose the least constraining value
- i.e., the one that rules out the fewest values in the remaining variables



Why least rather than most?

Combining these ordering ideas makes 1000 queens feasible

# FILTERING

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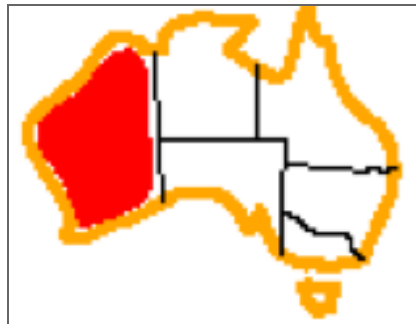


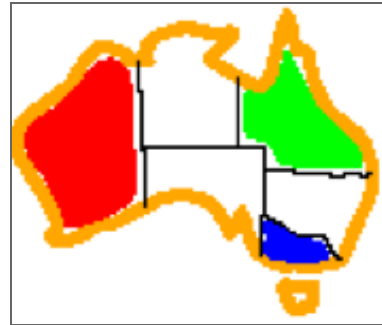
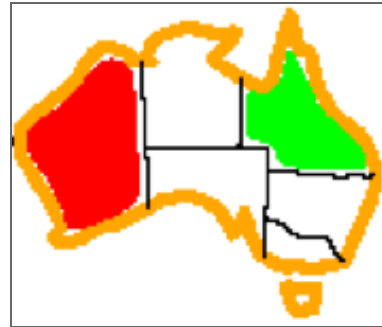
## FILTERING: FORWARD CHECKING

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Filtering: Keep track of domains for unassigned variables and cross off bad options.

Forward checking: Cross off values that violate a constraint when added to the existing assignment

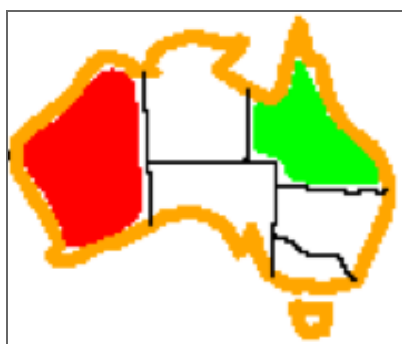




WA	NT	Q	NSW	V	SA	T
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## FILTERING: CONSTRAINT PROPAGATION

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



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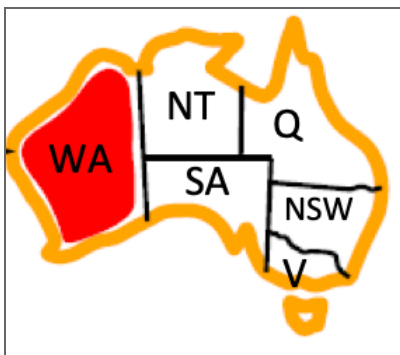
NT and SA cannot both be blue!

Why didn't we detect this yet?

**Constraint propagation:** reason from constraint to constraint

## CONSISTENCY OF A SINGLE ARC

An arc  $X \rightarrow Y$  is **consistent** iff for *every*  $x$  in the tail there is some  $y$  in the head which could be assigned without violating a constraint.



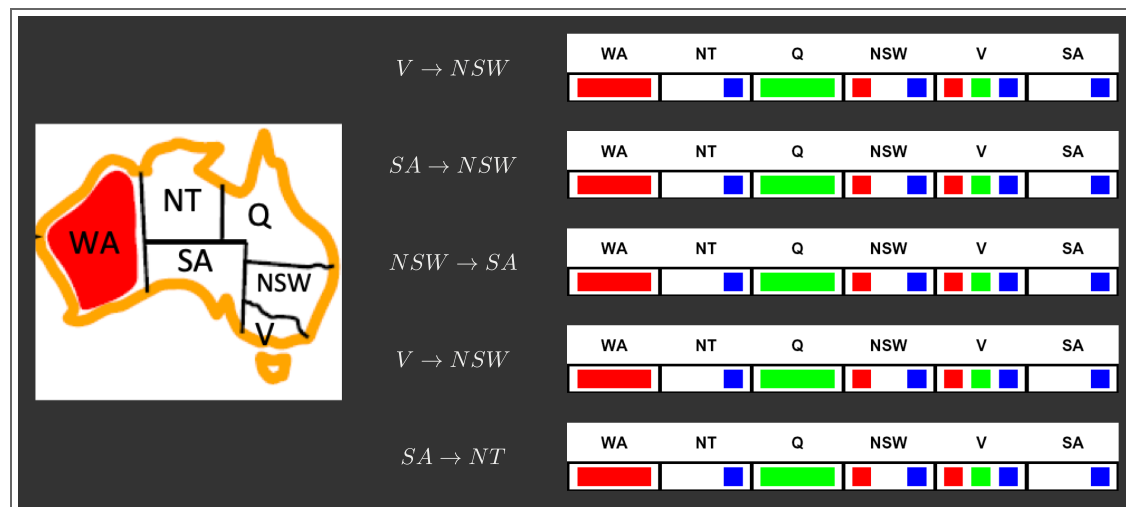
WA	NT	Q	NSW	V	SA
WA	NT	Q	NSW	V	SA
WA	NT	Q	NSW	V	SA

**Forward checking:** Enforcing consistency of arcs pointing to each new assignment.

**Delete from the tail !!**

# ARC CONSISTENCY OF AN ENTIRE CSP

A simple form of propagation makes sure all arcs are consistent:



Important: 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

What is the downside of enforcing arc consistency?

# ENFORCING ARC CONSISTENCY IN A CSP

```

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



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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
  
```

Runtime:  $\mathcal{O}(n^2 d^3)$ , can be reduced to  $\mathcal{O}(n^2 d^2)$

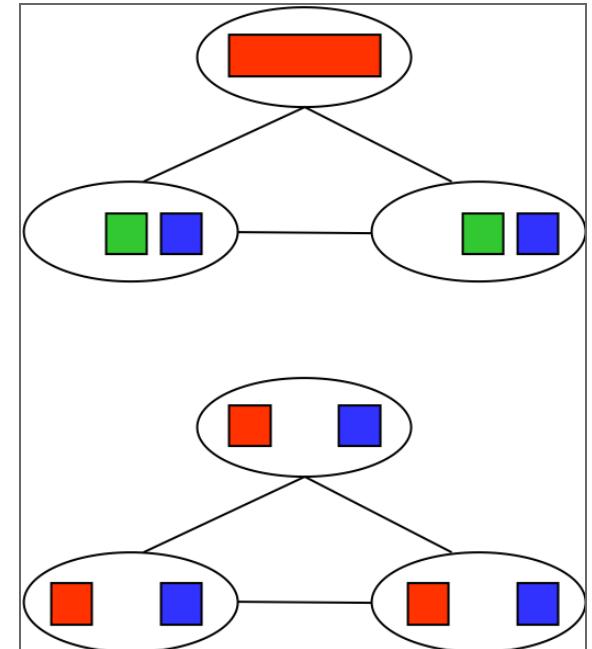
But detecting all possible future problems is NP-hard.

# LIMITATIONS OF 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 still runs inside a backtracking search.



# PROBLEM STRUCTURE

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# PROBLEM STRUCTURE

Real world problem can be decomposed into many subproblems.

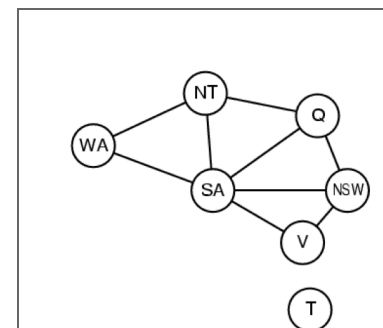
Extreme case: independent subproblems

- Tasmania and mainland are independent subproblems

Independent subproblems are identifiable as connected components of constraint graph

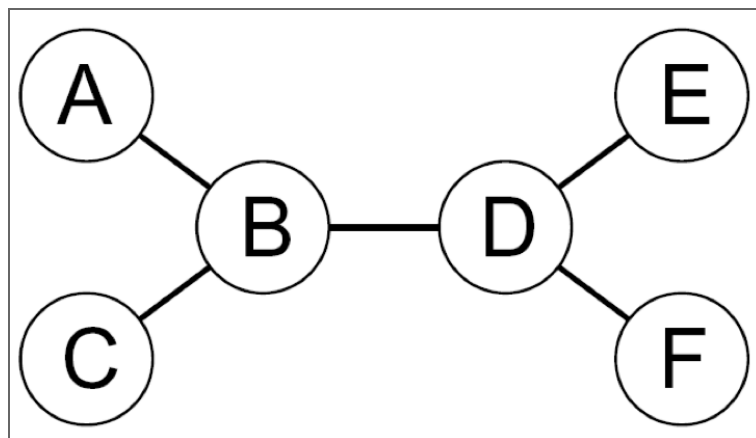
Suppose a graph of  $n$  variables can be broken into subproblems of only  $c$  variables:

- Worst-case solution cost is  $\mathcal{O}((n/c)(d^c))$ , linear in  $n$
- E.g.,  $n = 80, d = 2, c = 20$
- $2^{80} = 4$  billion years at 10 million nodes/sec
- $(4)(2^{20}) = 0.4$  seconds at 10 million nodes/sec



## PROBLEM STRUCTURE

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Theorem: if the constraint graph has no loops, the CSP can be solved in  $\mathcal{O}(nd^2)$  time

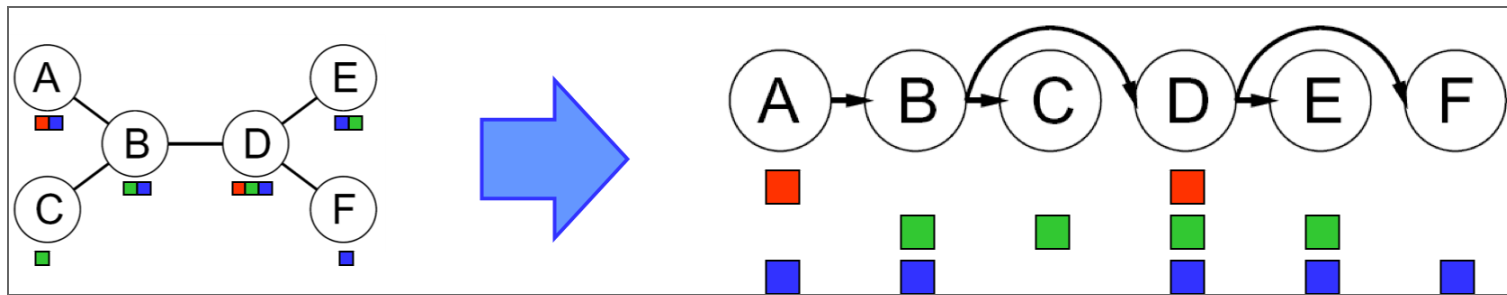
- Compare to general CSPs, where worst-case time is  $\mathcal{O}(d^n)$

This property also applies to probabilistic reasoning (later): an example of the relation between syntactic restrictions and the complexity of reasoning.

# PROBLEM STRUCTURE

Algorithm for tree-structured CSPs:

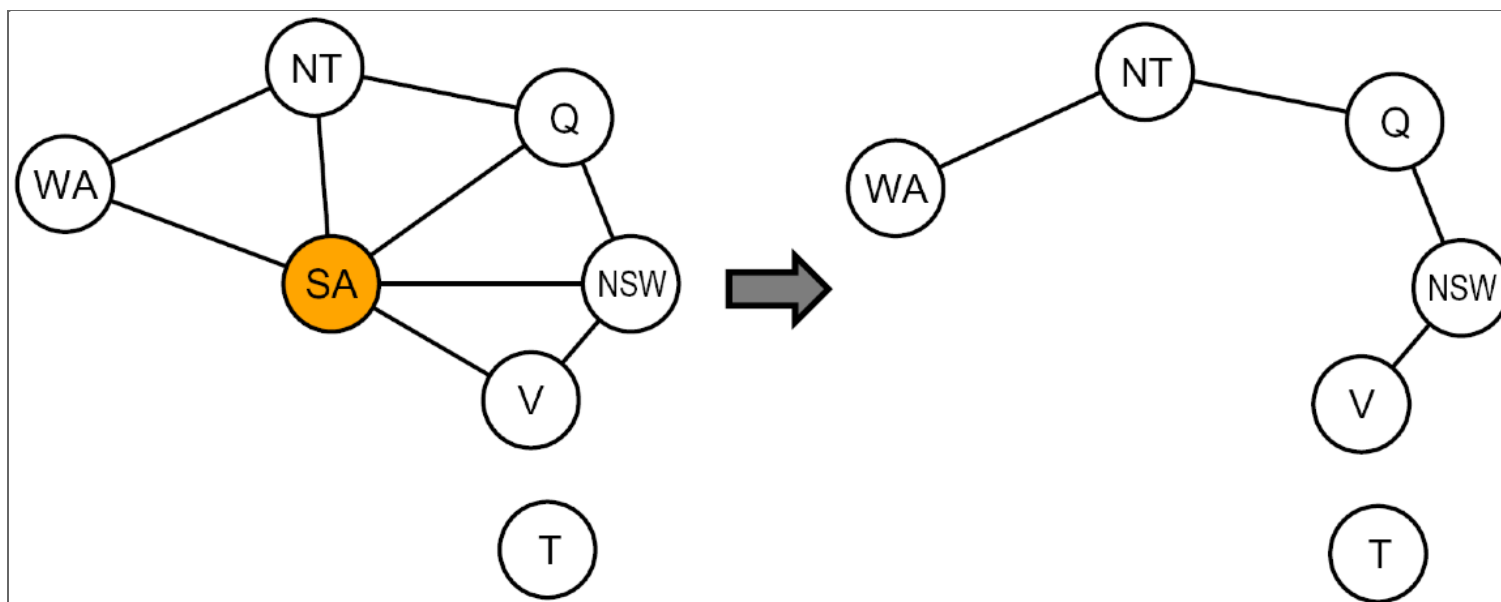
- Order: Choose a root variable, order variables so that parents precede children



- Remove backward: For  $i = n : 2$ , apply  $\text{RemoveInconsistent}(\text{Parent}(X_i), X_i)$
- Assign forward: For  $i = 1 : n$ , assign  $X_i$  consistently with  $\text{Parent}(X_i)$

Runtime:  $\mathcal{O}(nd^2)$

## PROBLEM 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  $\mathcal{O}((d^c)(n - c)d^2)$ , very fast for small  $c$ .

# Q & A



**XKCD**









## Speaker notes



Q & A

