CSE 40171: Artificial Intelligence



Constraint Satisfaction Problems: Inference and Backtracking Search

Homework #3 has been released It is due at 11:59PM on 10/9

In the regular state-space search algorithms, we could only do one thing:

Search

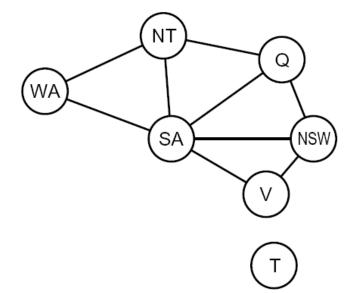
With CSPs, we can do two things:

- 1. Search
- 2. Use constraints to reduce the number of legal values for a variable

And this reduction can propagate to neighboring variables

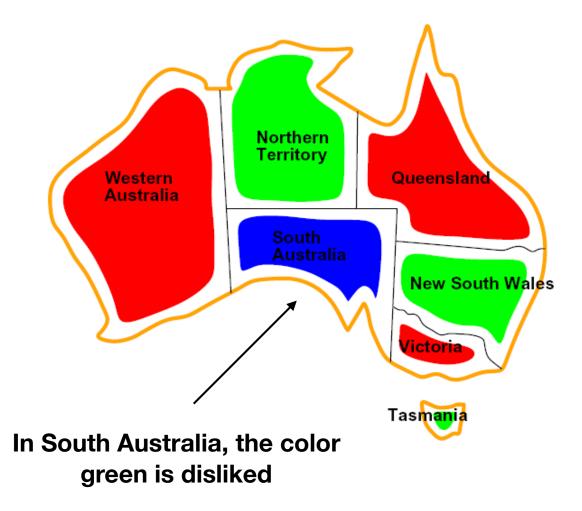
Local Consistency

Enforcing local consistency in each part of the graph causes inconsistent values to be eliminated throughout the graph



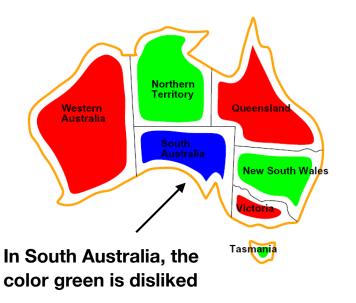
So where do we enforce it?

Vertex Consistency



Vertex Consistency

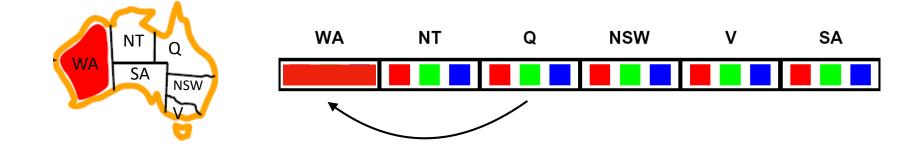
A single variable is **vertex-consistent** if all the values in its domain stratify its unary constraints



Starting Domain: {*red*, *green*, *blue*} Reduced Domain: {*red*, *blue*}

Edge Consistency

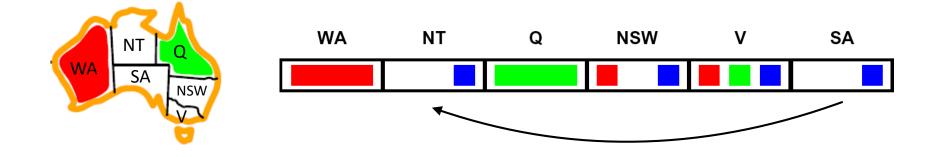
An edge $X \rightarrow Y$ is **consistent** iff for every x in the tail there is some y in the head which could be assigned without violating a constraint



Forward Checking: Enforcing consistency of edges pointing to each new assignment

Edge Consistency of an Entire CSP

A simple form of propagation makes sure **all** edges are consistent:



- Important: If X loses a value, neighbors of X need to be rechecked
- Edge consistency detects failure earlier than forward checking
- Can be run as a preprocessor or after each assignment
- What's the downside of enforcing edge consistency?

Remember: Delete from the tail!

Enforcing Edge Consistency in a CSP

function AC-3(*csp*) returns the CSP, possibly with reduced domains inputs: *csp*, a binary CSP with variables $\{X_1, X_2, \ldots, X_n\}$ local variables: *queue*, a queue of arcs, initially all the arcs in *csp* while *queue* is not empty do $(X_i, X_j) \leftarrow \text{REMOVE-FIRST}(queue)$

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

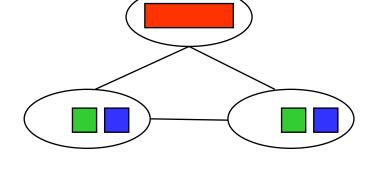
return removed
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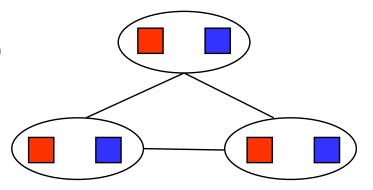
- Runtime: $O(n^2d^3)$, can be reduced to $O(n^2d^2)$
- ...but detecting all possible future problems is NP-hard why?

Limitations of Edge Consistency

After enforcing arc consistency:

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





What went wrong here?

Path Consistency

Tightens the binary constraints by using implicit constraints that are inferred by looking at triples of variables



Let's color the map with two colors:

Make the set {*WA*, *SA*} path consistent with respect to *NT*

Two options: $\{WA = red, SA = blue\}$ and $\{WA = blue, SA = red\}$

What do we assign to *NT*?

K-consistency

Let's generalize the notion of consistency:

A CSP is *K*-consistent if, for any set of k - 1 variables, and for any consistent assignment to those variables, a consistent value can always be assigned to any *k*th variable.

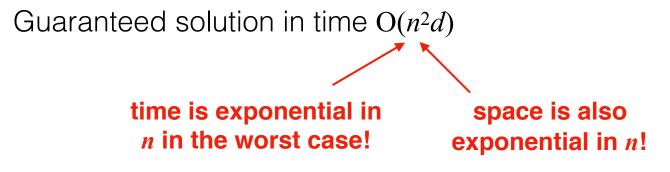
1-consistency? vertex consistency
2-consistency? edge consistency
3-consistency? path consistency

K-consistency

A CSP is strongly *K*-consistent if it is also (k-1)-consistent, (k-2)-consistent, all the way down to 1-consistent.

Assume we have a CSP with *n* nodes and want to make it strongly *n*-consistent:

For each variable X_i , we only need to search through the *d* values in the domain to find a value consistent with X_1, \ldots, X_{i-1} .



Global Constraints

The *Alldiff* constraint states that all variables involved must have distinct values

Inconsistency detector: if m variables are involved in the constraint, and if they have n possible district values, and m > n, then the constraint cannot be satisfied



Can we detect the inconsistency in the assignment {*WA* = *red*, *NSW* = *red*}?

Resource Constraints

We can also have an *Atmost* constraint, meaning no more than *n* resources can be assigned

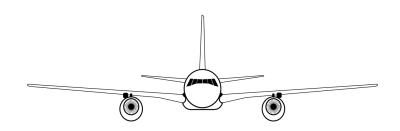
Scheduling Example:

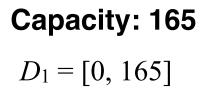
of personnel assigned to 4 tasks: P_1, \ldots, P_4

Constraint that no more than 10 people are assigned: Atmost $(10, P_1, P_2, P_3, P_4)$

If the domain of each variable is {2, 4, 5, 6}, is *Atmost* satisfied?

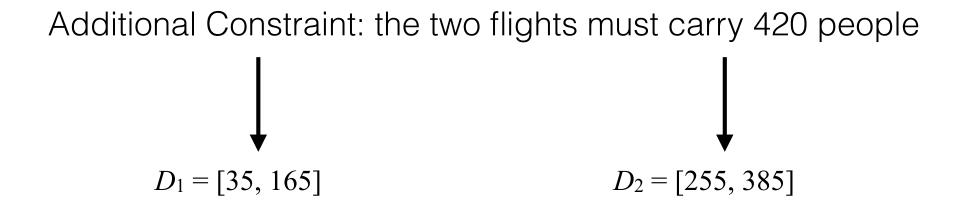
Bounds Propagation







Capacity: 385 $D_2 = [0, 385]$



Backtracking Search

Backtracking Search

Some problems, like Sudoku, can be solved by inference over constraints

• But this is not true for all problems

Backtracking search is the basic uninformed algorithm for solving CSPs

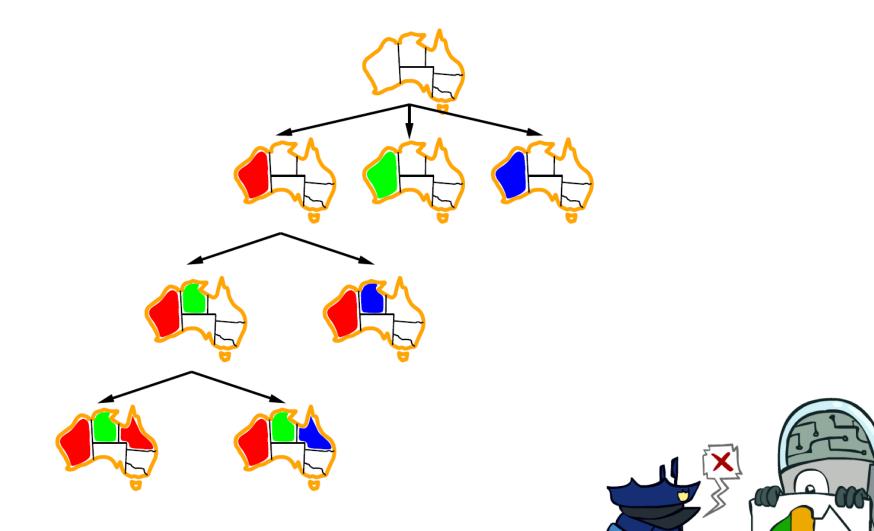
Idea 1: One variable at a time

- Variable assignments are commutative, so fix ordering
- For example, [*WA* = *red* then *NT* = *green*] is the 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

- For example, consider only values which do not conflict with previous assignments
- Might have to do some computation to check the constraints
- "Incremental goal test"

Backtracking Example



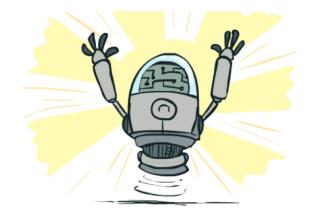
Backtracking Search

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 \begin{array}{l} \textbf{function BACKTRACKING-SEARCH}(csp) \ \textbf{returns solution/failure} \\ \textbf{return RECURSIVE-BACKTRACKING}(\{\ \}, csp) \\ \textbf{function RECURSIVE-BACKTRACKING}(assignment, csp) \ \textbf{returns soln/failure} \\ \textbf{if } assignment \ \textbf{is complete then return } assignment \\ var \leftarrow SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignment, csp) \\ \textbf{for each } value \ \textbf{in ORDER-DOMAIN-VALUES}(var, assignment, csp) \ \textbf{do} \\ \textbf{if } value \ \textbf{is consistent with } assignment \ \textbf{given CONSTRAINTS}[csp] \ \textbf{then} \\ & add \ \{var = value\} \ \textbf{to } assignment \\ result \leftarrow RECURSIVE-BACKTRACKING(assignment, csp) \\ & \textbf{if } result \neq failure \ \textbf{then return } result \\ remove \ \{var = value\} \ \textbf{from } assignment \\ return \ failure \end{aligned}
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Backtracking = DFS + variable-ordering + fail-on-violation

Improving Backtracking Search

- General-purpose ideas give huge gains in speed
- Filtering: Can we detect inevitable failure early?
- Ordering
 - Which variable should be assigned next?
 - In what order should its values be tried?
- Structure: Can we exploit the problem structure?



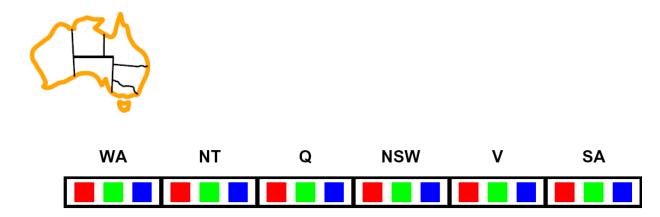
Filtering



Filtering: Forward Checking

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



Ordering



Ordering: Minimum Remaining Values

Variable Ordering: Minimum remaining values (MRV):

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

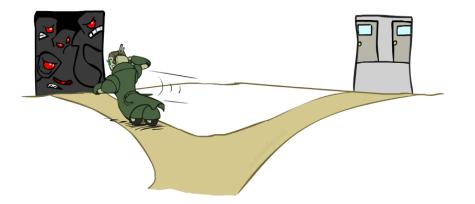


Ordering: Minimum Remaining Values

Why min rather than max?

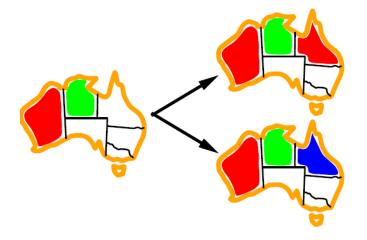
Also called "most constrained variable"

"Fail-fast" ordering



Ordering: Least Constraining Value

Value Ordering: Least Constraining Value



- Given a choice of variable, choose the least constraining value
- For example, the one that rules out the fewest values in the remaining variables
- Note that it may take some computation to determine this (e.g., rerunning filtering)

Ordering: Least Constraining Value

Why least rather than most?

 Combining these ordering ideas makes problems like 1000 queens feasible



Structure

- These solutions we've seen before:
 - Check the consistency of a single edge
 - Check the edge consistency of an entire CSP
 - The AC-3 algorithm!