# Chapter 5: Constraint Satisfaction Problems

Source A: Foundations of Artificial Intelligence by J. Boedecker, W. Burgard, F. Hutter, B. Nebel (Uni. Freiburg)

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- What are CSPs?
- Backtracking Search for CSPs
- CSP Heuristics
- Constraint Propagation
- Problem Structure

#### Constraint Satisfaction Problems

- A Constraint Satisfaction Problems (CSP) is given by
  - a set of variables x<sub>1</sub>, x<sub>2</sub>, ..., x<sub>n</sub>,
  - an associated set of value domains  $dom_1, dom_2, ..., dom_n$ , and
  - a set of constraints. i.e., relations, over the variables.
- An assignment of values to variables that satisfies all constraints is a solution of such a CSP.
- In CSPs viewed as search problems, states are explicitly represented as variable assignments. CSP search algorithms take advantage of this structure.
- The main idea is to exploit the constraints to eliminate large portions of search space.
- Formal representation language with associated general inference algorithms

#### Example: Map-Coloring



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

Values: red,green,blue

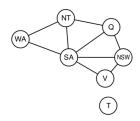
 $\bullet$  Constraints: adjacent regions must have different colors, e.g.,  $NSW \neq V$ 

#### One Solution



- Solution assignment:
  - $\bullet \ \ \mathsf{WA} = \mathsf{red}, \mathsf{NT} = \mathsf{green}, \mathsf{Q} = \mathsf{red}, \mathsf{NSW} = \mathsf{green}, \mathsf{V} = \mathsf{red}, \mathsf{SA} = \mathsf{blue}, \mathsf{T} = \mathsf{green}$

#### Constraint Graph



- a constraint graph can be used to visualize binary constraints
- for higher order constraints, hyper-graph representations might be used
- $\bullet \ \mathsf{Nodes} = \mathsf{variables}, \ \mathsf{arcs} = \mathsf{constraints} \\$

#### Note

Our problem is three-colorability for a planar graph

#### **Variations**

- Binary, ternary, or even higher arity (e.g., ALL DIFFERENT)
- Finite domains (d values)  $\to d^n$  possible variable assignments
- Infinite domains (reals, integers)
  - linear constraints (each variable occurs only in linear form): solvable (in P if real)
  - nonlinear constraints: unsolvable

#### **Applications**

- Timetabling (classes, rooms, times)
- Configuration (hardware, cars, . . . )
- Spreadsheets
- Scheduling
- Floor planning
- Frequency assignments
- Sudoku
- ..

#### Backtracking Search over Assignments

- Assign values to variables step by step (order does not matter)
- Consider only one variable per search node!
- DFS (Deep First Search) with single-variable assignments is called backtracking search
- ullet Can solve n-queens for n pprox 25

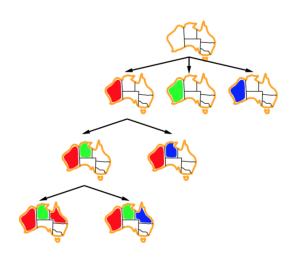
#### Algorithm

```
\label{eq:continuous} \begin{tabular}{ll} function BACKTRACKING-SEARCH(csp) returns a solution, or failure \\ return BACKTRACK(\{empty \ variable \ assignment\}, \ csp) \end{tabular}
```

```
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 
FACKTRACK(assignment,csp)
if result 
failure then
return result
remove var = value and inferences from assignment
return failure
```

- ORDER-DOMAIN-VALUES: Im Prinzip geht jede Ordnung
- INFERENCE: Eine Funktion andere mögliche Zuordnungen ausschließt bzw. festlegt (später mehr)

#### Example



# Improving Efficiency: CSP Heuristics & Pruning Techniques

- Variable ordering: Which one to assign first?
- Value ordering: Which value to try first?
- Try to detect failures early on
- Try to exploit problem structure
- ullet o Note: all this is not problem-specific!

#### Variable Ordering: Most constrained first

- Most constrained variable:
  - ullet choose the variable with the fewest remaining legal values o reduces branching factor!



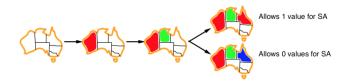
#### Variable Ordering: Most Constraining Variable First

- Break ties among variables with the same number of remaining legal values:
  - choose variable with the most constraints on remaining unassigned variables
  - ullet ightarrow reduces branching factor in the next steps



#### Value Ordering: Least Constraining Value First

- Given a variable,
  - choose first a value that rules out the fewest values in the remaining unassigned variables
  - ullet We want to find an assignment that satisfies the constraints (of course, this does not help if the given problem is unsatisfiable.)

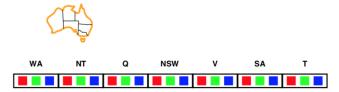


#### Rule out Failures early on: Forward Checking

- Whenever a value is assigned to a variable, values that are now illegal for other variables are removed
- Implements what the ordering heuristics implicitly compute
- WA = red, then NT cannot become red
- If all values are removed for one variable, we can stop!

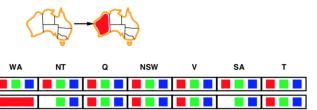
# Forward Checking (1)

- Keep track of remaining values
- Stop if all have been removed



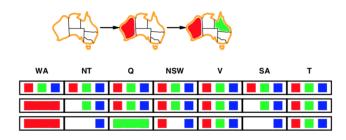
# Forward Checking (2)

- Keep track of remaining values
- Stop if all have been removed



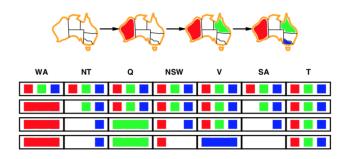
# Forward Checking (3)

- Keep track of remaining values
- Stop if all have been removed



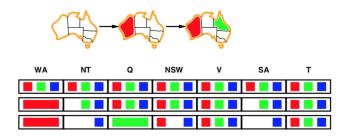
# Forward Checking (4)

- Keep track of remaining values
- Stop if all have been removed



#### Forward Checking: Sometimes it Misses Something

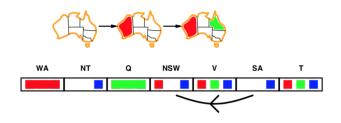
- Forward Checking propagates information from assigned to unassigned variables
- However, there is no propagation between unassigned variables



#### **Arc Consistency**

- ullet A directed arc X o Y is "consistent" iff
  - for every value x of X, there exists a value y of Y, such that (x, y) satisfies the constraint between X and Y
- Remove values from the domain of X to enforce arc-consistency
- Arc consistency detects failures earlier
- Can be used as preprocessing technique or as a propagation step during backtracking

#### Arc Consistency Example



- enforcing Arc-Consistency between SA and NSW implies to remove blue from NSW
- enforcing Arc-Consistency between SA and NT, leaves no possible variable assignment in NSW.

#### AC-3 Algorithm

One example of an algorithm that enforces Arc-Consistency

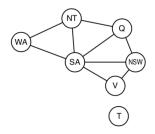
```
function AC-3(csp) returns false if an inconsistency is found and true otherwise inputs: csp, a binary CSP with components (X, D, C) local variables: queue, a queue of arcs, initially all the arcs in csp while queue is not empty do (X_i, X_j) \leftarrow \texttt{REMOVE-FIRST}(\texttt{queue}) \\ \text{if REVISE}(csp, X_i, X_j) \text{ then} \\ \text{if size of } D_i = 0 \text{ then return false} \\ \text{for each } X_k \text{ in } X_i.NEIGHBORS - \{X_j\} \text{ do} \\ \text{add}(X_k, X_i) \text{ to queue} \\ \text{return true}
```

```
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
```

#### Properties of AC-3

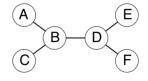
- ullet AC-3 runs in  $O(d^3n^2)$  time, with n being the number of nodes and d being the maximal number of elements in a domain
  - good! only polynomial!
- Of course, AC-3 does not detect all inconsistencies (which is an NP-hard problem)

# Problem Structure (1)



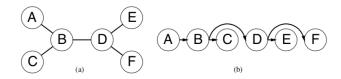
- CSP has two independent components
- Identifiable as connected components of constraint graph
- Can reduce the search space dramatically
  - One example here: T can be solved alone

# Problem Structure (2): Tree-structured CSPs



- $\bullet$  If the CSP graph is a tree, then it can be solved in  $O(nd^2)$  (general CSPs need in the worst case  $O(d^n)).$
- Idea: Pick root, order nodes, apply arc consistency from leaves to root, and assign values starting at root.

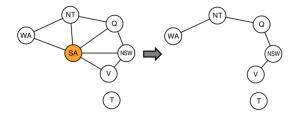
#### Problem Structure (2): Tree-structured CSPs



- Pick any variable as root; choose an ordering such that each variable appears after its parent in the tree.
- Apply arc-consistency to  $(x_i, x_k)$  when  $x_i$  is the parent of  $x_k$  for all k = n down to 2 (any tree with n nodes has n-1 arcs and per arc  $d^2$  comparisons are needed, which results in a complexity of  $O(nd^2)$ ).
  - We start from the bottom (i.e F): First arc-consistency between F-D, i.e. remove values at D, then move upwards... at the end we know, that all possible assignments which are left, lead to a solution
- ullet Now we can start at  $x_1$  assigning values from the remaining domains without creating any conflict in one sweep through the tree!
- This algorithm is linear in n.

#### Problem Structure (3): Almost Tree-structured

 Idea: Reduce the graph structure to a tree by fixing values in a reasonably chosen subset



 Instantiate a variable and prune values in neighboring variables is called "Conditioning"

#### Problem Structure (4): Almost Tree-structured

#### Algorithm Cutset Conditioning:

- Choose a subset S of the CSPs variables such that the constraint graph becomes a tree after removal of S. The set S is called a **cycle cutset**.
- $\bullet$  For each possible assignment of variables in S that satisfies all constraints on S
  - remove from the domains of the remaining variables any values that are inconsistent with the assignments for S, and
  - $\bullet$  if the remaining CSP has a solution, return it together with the assignment for S



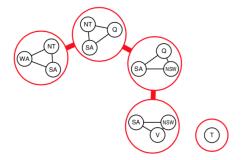
#### Note

Finding the smallest cycle cutset is NP hard, but several efficient approximation algorithms are known.

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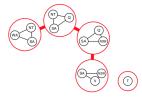
#### Another Method: Tree Decomposition (1/3)

- Decompose the problem into a set of connected sub-problems, where two sub-problems are connected when they share a constraint
- Solve the sub-problems independently and then combine the solutions



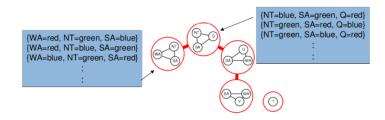
#### Another Method: Tree Decomposition (2/3)

- A tree decomposition must satisfy the following conditions:
  - Every variable of the original problem appears in at least one sub-problem
  - Every constraint appears in at least one sub-problem
  - If a variable appears in two sub-problems, it must appear in all sub-problems on the path between the two sub-problems
  - The connections form a tree



# Another Method: Tree Decomposition (3/3)

- Consider sub-problems as new mega-variables, which have values defined by the solutions to the sub-problems
- Use technique for tree-structured CSP to find an overall solution (constraint is to have identical values for the same variable)



#### Tree Width

- ullet The aim is to make the subproblems as small as possible. The tree width w of a tree decomposition is the size of largest sub-problem minus 1
- Tree width of a graph is minimal tree width over all possible tree decompositions
- If a graph has tree width w and we know a tree decomposition with that width, we can solve the problem in  $O(nd^{w+1})$
- Unfortunately, finding a tree decomposition with minimal tree width is NP-hard. However, there are heuristic methods that work well in practice.

#### Example: Bavarian Map-Coloring Problem (1/2)



- Constraints: Make Bavarians happy
- So-Called Al-Hard Problem: solution requires true intelligence

# Example: Bavarian Map-Coloring Problem (2/2)

• One possible starting point (might be already sufficient)



#### Summary and Outlook

- CSPs are a special kind of search problem:
  - states are value assignments
  - · goal test is defined by constraints
- Backtracking = DFS with one variable assigned per node. Other intelligent backtracking techniques possible
- Variable/value ordering heuristics can help dramatically Constraint propagation prunes the search space
- Path-consistency is a constraint propagation technique for triples of variables
- Tree structure of CSP graph simplifies problem significantly
- Cutset conditioning and tree decomposition are two ways to transform part of the problem into a tree
- CSPs can also be solved using local search