Foundations of Artificial Intelligence D3. Constraint Satisfaction Problems: Backtracking

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Constraint Satisfaction Problems: Overview

Chapter overview: constraint satisfaction problems

- D1–D2. Introduction
- D3–D5. Basic Algorithms
 - D3. Backtracking
 - D4. Arc Consistency
 - D5. Path Consistency
- D6–D7. Problem Structure

CSP Algorithms

CSP Algorithms

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CSP Algorithms

In the following chapters, we consider algorithms for solving constraint networks.

basic concepts:

- search: check partial assignments systematically
- backtracking: discard inconsistent partial assignments
- inference: derive equivalent, but tighter constraints to reduce the size of the search space

Naive Backtracking

Naive Backtracking (= Without Inference)

```
function NaiveBacktracking(C, \alpha):
```

```
\langle V, \mathsf{dom}, (R_{uv}) \rangle := \mathcal{C}
if \alpha is inconsistent with \mathcal{C}:
```

return inconsistent

if α is a total assignment:

return α

select some variable v for which α is not defined

for each $d \in dom(v)$ in some order:

$$\alpha' := \alpha \cup \{ \mathsf{v} \mapsto \mathsf{d} \}$$

 $\alpha'' := \mathsf{NaiveBacktracking}(\mathcal{C}, \alpha')$

if $\alpha'' \neq \text{inconsistent}$:

return α''

return inconsistent

input: constraint network C and partial assignment α for C(first invocation: empty assignment $\alpha = \emptyset$) result: solution of \mathcal{C} or inconsistent

Running Example

Full Formal Model of Running Example

 $\mathcal{C} = \langle V, \mathsf{dom}, (R_{uv}) \rangle$ with

variables:

$$V = \{w, x, y, z\}$$

domains:

$$dom(w) = dom(y) = \{1, 2, 3, 4\}$$

 $dom(x) = dom(z) = \{1, 2, 3\}$

constraints:

$$\begin{split} R_{wx} &= \{\langle 2, 1 \rangle, \langle 4, 2 \rangle\} \\ R_{wz} &= \{\langle 1, 2 \rangle, \langle 1, 3 \rangle, \langle 2, 3 \rangle\} \\ R_{yz} &= \{\langle 2, 1 \rangle, \langle 3, 1 \rangle, \langle 3, 2 \rangle, \\ &\quad \langle 4, 1 \rangle, \langle 4, 2 \rangle, \langle 4, 3 \rangle\} \end{split}$$

W

X

Running Example: Search Tree

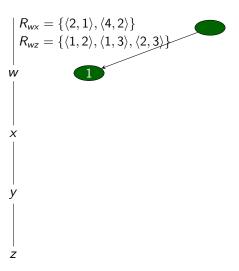
Naive Backtracking

$$R_{wx} = \{\langle 2, 1 \rangle, \langle 4, 2 \rangle\}$$

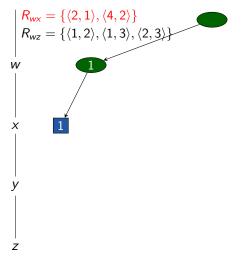
$$R_{wz} = \{\langle 1, 2 \rangle, \langle 1, 3 \rangle, \langle 2, 3 \rangle\}$$



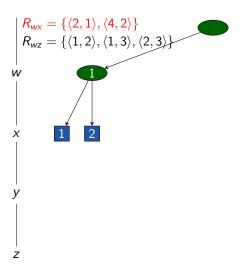
$$R_{yz} = \{ \langle 2, 1 \rangle, \langle 3, 1 \rangle, \langle 3, 2 \rangle, \\ \langle 4, 1 \rangle, \langle 4, 2 \rangle, \langle 4, 3 \rangle \}$$



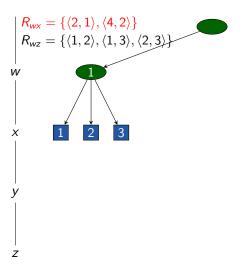
$$R_{yz} = \{ \langle 2, 1 \rangle, \langle 3, 1 \rangle, \langle 3, 2 \rangle, \\ \langle 4, 1 \rangle, \langle 4, 2 \rangle, \langle 4, 3 \rangle \}$$



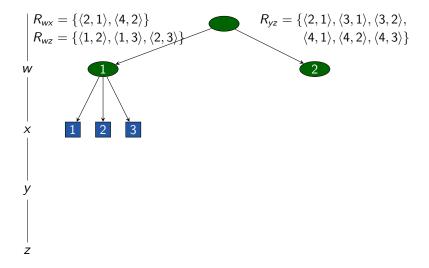
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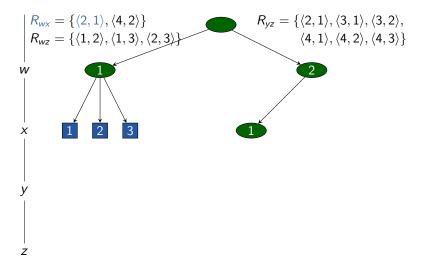


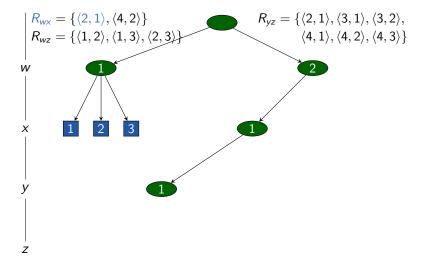
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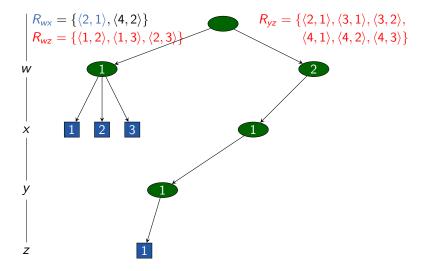


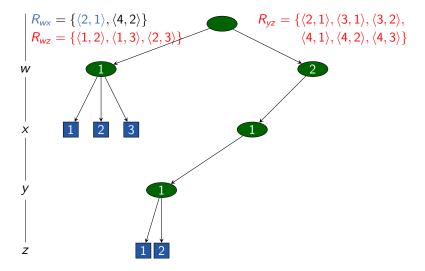
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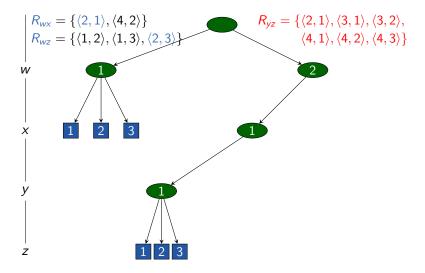


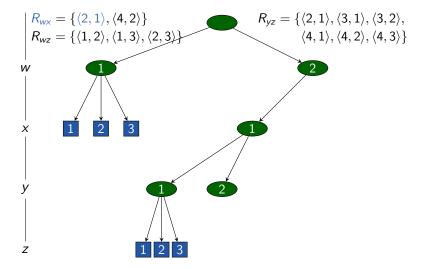


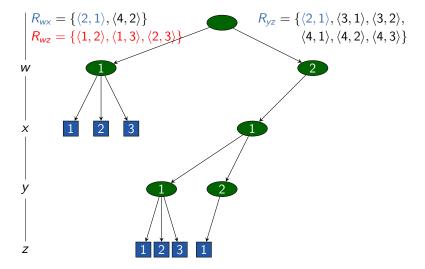


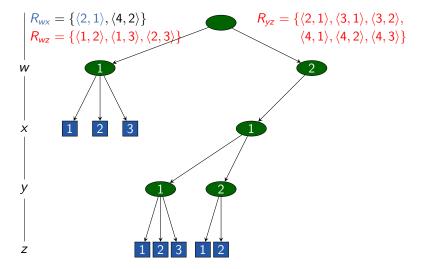


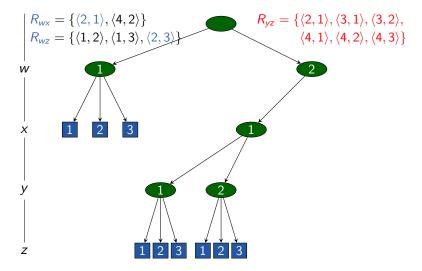




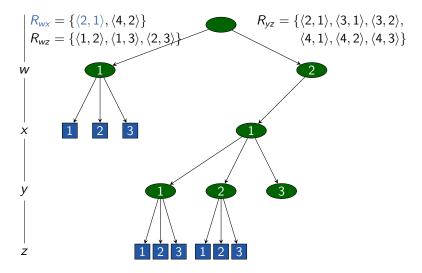


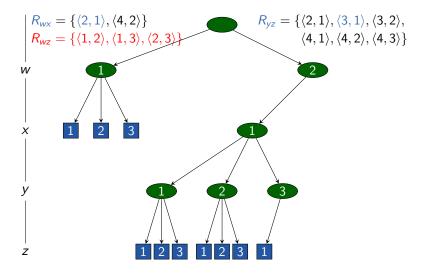


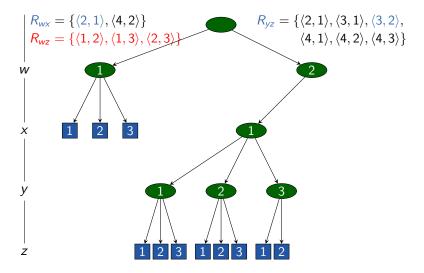


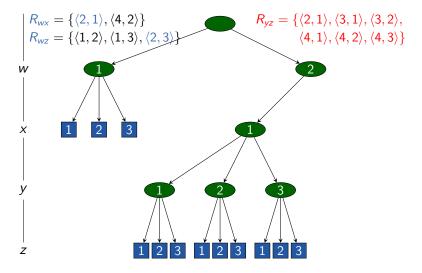


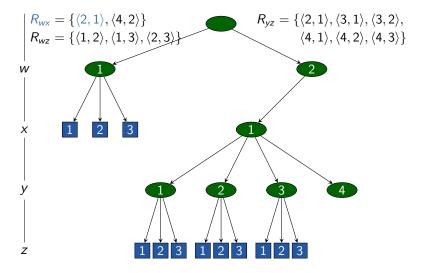
Naive Backtracking

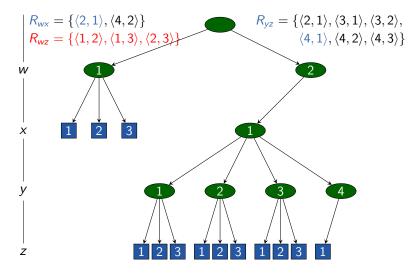


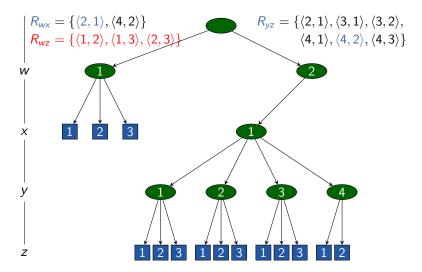


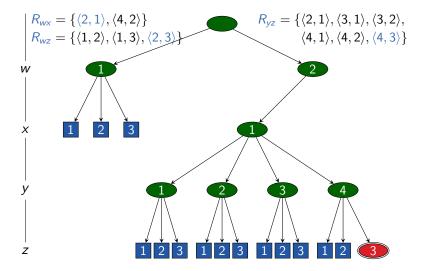












Is This a New Algorithm?

We have already seen this algorithm:

Backtracking corresponds to depth-first search (Chapter B8) with the following state space:

- states: partial assignments
- initial state: empty assignment ∅
- goal states: consistent total assignments
- actions: $assign_{v,d}$ assigns value $d \in dom(v)$ to variable v
- action costs: all 0 (all solutions are of equal quality)
- transitions:
 - for each non-total consistent assignment α , choose variable $v = \operatorname{select}(\alpha)$ that is unassigned in α
 - transition $\alpha \xrightarrow{assign_{v,d}} \alpha \cup \{v \mapsto d\}$ for each $d \in \text{dom}(v)$

Why Depth-First Search?

Depth-first search is particularly well-suited for CSPs:

- path length bounded (by the number of variables)
- solutions located at the same depth (lowest search layer)
- state space is directed tree, initial state is the root → no duplicates (Why?)

Hence none of the problematic cases for depth-first search occurs.

Naive backtracking often has to exhaustively explore similar search paths (i.e., partial assignments

Variable and Value Orders

 "Critical" variables are not recognized and hence considered for assignment (too) late.

that are identical except for a few variables).

- Decisions that necessarily lead to constraint violations are only recognized when all variables involved in the constraint have been assigned.
- → more intelligence by focusing on critical decisions and by inference of consequences of previous decisions

Variable and Value Orders

Naive Backtracking

function NaiveBacktracking(C, α):

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if $\alpha'' \neq \text{inconsistent}$:

return α''

return inconsistent

Variable Orders

- Backtracking does not specify in which order variables are considered for assignment.
- Such orders can strongly influence the search space size and hence the search performance.
 - → example: exercises

German: Variablenordnung

Variable and Value Orders

Value Orders

- Backtracking does not specify in which order the values of the selected variable v are considered.
- This is not as important because it does not matter in subtrees without a solution. (Why not?)
- If there is a solution in the subtree, then ideally a value that leads to a solution should be chosen. → prefer promising assignments

German: Werteordnung

Static vs. Dynamic Orders

we distinguish:

- static orders (fixed prior to search)
- dynamic orders (selected variable or value order depends on the search state)

comparison:

- dynamic orders obviously more powerful
- static orders → no computational overhead during search

The following ordering criteria can be used statically, but are more effective combined with inference (\rightsquigarrow later) and used dynamically.

Variable Orders

two common variable ordering criteria:

- minimum remaining values: prefer variables that have small domains
 - intuition: few subtrees → smaller tree
 - extreme case: only one value → forced assignment
- most constraining variable: prefer variables contained in many nontrivial constraints
 - intuition: constraints tested early
 - \leadsto inconsistencies recognized early \leadsto smaller tree

combination: use minimum remaining values criterion, then most constraining variable criterion to break ties

Value Orders

Definition (conflict)

Let $C = \langle V, \text{dom}, (R_{uv}) \rangle$ be a constraint network. For variables $v \neq v'$ and values $d \in \text{dom}(v)$, $d' \in \text{dom}(v')$, the assignment $v \mapsto d$ is in conflict with $v' \mapsto d'$ if $\langle d, d' \rangle \notin R_{vv'}$.

value ordering criterion for partial assignment α and selected variable ν :

 minimum conflicts: prefer values d ∈ dom(v) such that v → d causes as few conflicts as possible with variables that are unassigned in α

Summary

Summary: Backtracking

basic search algorithm for constraint networks: backtracking

- extends the (initially empty) partial assignment step by step until an inconsistency or a solution is found
- is a form of depth-first search
- depth-first search particularly well-suited because state space is directed tree and all solutions at same (known) depth

Summary: Variable and Value Orders

- Variable orders influence the performance of backtracking significantly.
 - goal: critical decisions as early as possible
- Value orders influence the performance of backtracking on solvable constraint networks significantly.
 - goal: most promising assignments first