

Domain Splitting, Local Search

CPSC 322 – CSP 4

Textbook §4.6, §4.8

February 4, 2011

Discussion of feedback

- Pace
 - 2 “fine”, 1 “could go faster”
 - 2: recap too long, 3: “sometimes rushed later (as a consequence)”
- Coloured card questions
 - Some more explanation would be good
 - More consistent: get everyone to vote”
- Which parts are most important?
 - Definitions + algorithms. Examples are for illustration
- Hard concepts:
 - Arc consistency: today + work in AIspace + practice exercise
 - Alternative formulation of CSP as graph search: after class

Discussion of feedback

- Midterm: review & sample questions?
 - Midterm date confirmed: Mon, Feb 28, 3pm (1 to 1.5 hours, TBD)
 - Sample midterm has been on WebCT for ~2 weeks
 - Topics: everything up to (including all of) CSP
 - The topic of its question 2 (Planning based on CSP) won't be on the midterm
 - Should we do a midterm review session?
- More explanation of practice exercises?
 - I'll show where they are in WebCT
 - If you have trouble with them, please come to office hours
- How will what we learn eventually be applied in making an intelligent agent?
 - Game AI: lots of search
 - Reasoning under constraints is core to making intelligent decisions
 - With CSPs, we're right in the middle of it!

Course Overview

Course Module

Environment

Deterministic

Stochastic

Representation

Reasoning
Technique

Problem Type

Constraint
Satisfaction

Arc
Consistency
Variables + Constraints
Search

Logic

Logics
Search

*Bayesian
Networks*

Variable
Elimination

Uncertainty

Sequential

Planning

STRIPS
Search

*Decision
Networks*

Variable
Elimination

Decision
Theory

We'll now
focus on CSP

Markov Processes

Value
Iteration

Lecture Overview



Arc consistency

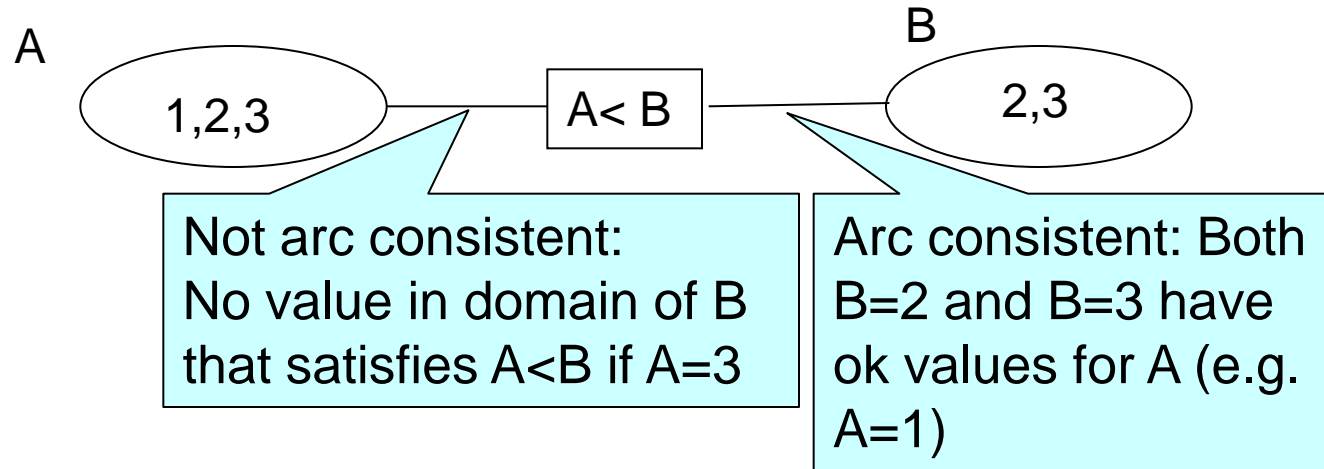
- Recap
 - Complexity analysis
 - Domain Splitting
- Intro to Local Search

Arc Consistency

Definition:

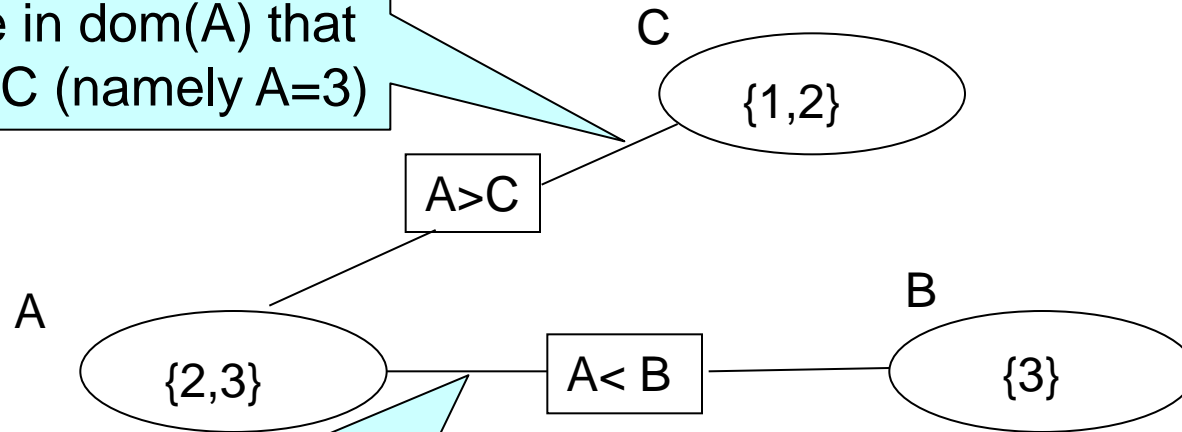
An arc $\langle x, r(x,y) \rangle$ is **arc consistent** if for each value x in $\text{dom}(X)$ there is some value y in $\text{dom}(Y)$ such that $r(x,y)$ is satisfied.

A network is arc consistent if all its arcs are arc consistent.



Arc Consistency

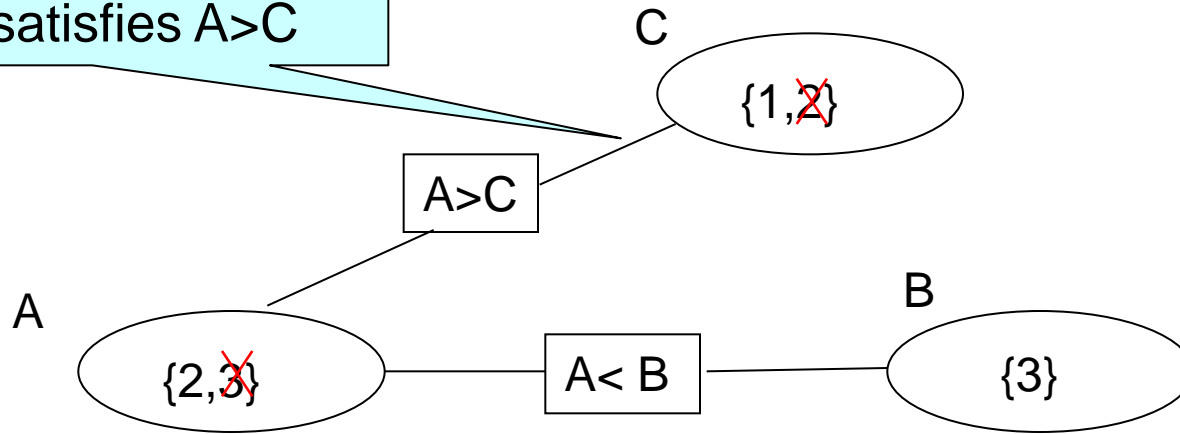
Arc consistent:
For each value in $\text{dom}(C)$,
there is one in $\text{dom}(A)$ that
satisfies $A > C$ (namely $A=3$)



Not arc consistent:
No value in domain of B
that satisfies $A < B$ if $A=3$

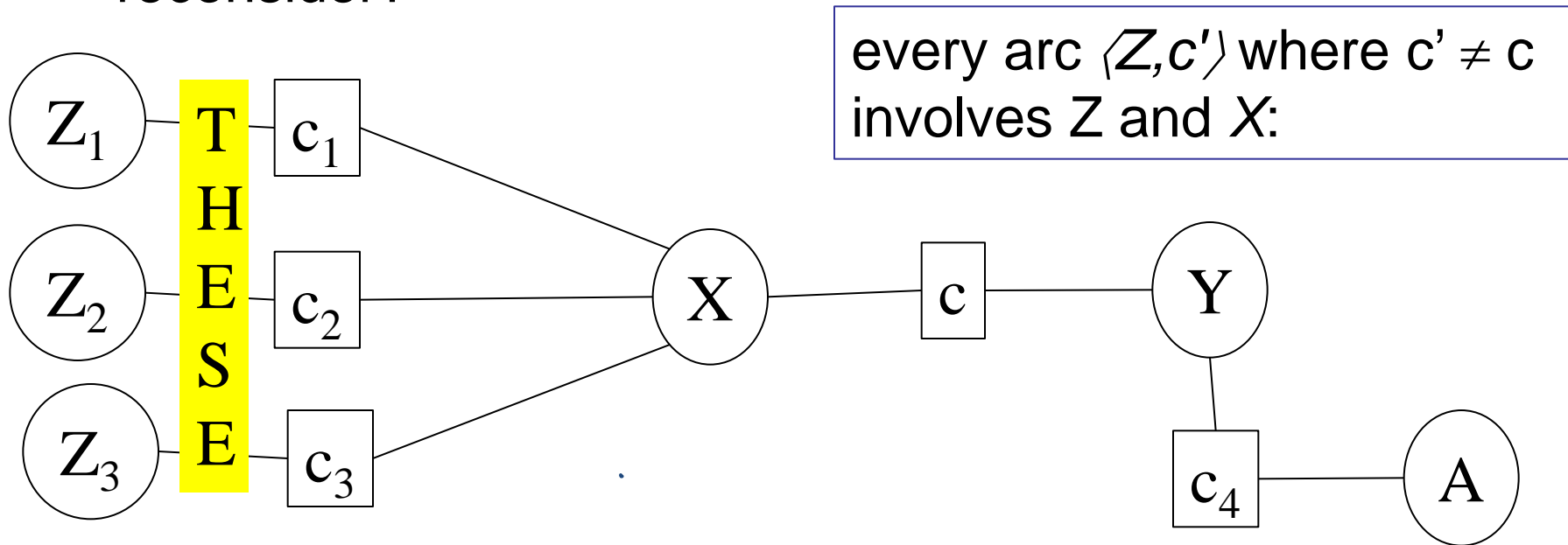
Arc Consistency

Not arc consistent anymore:
For $C=2$, there is no value in $\text{dom}(A)$ that satisfies $A > C$




Which arcs need to be reconsidered?

- When we reduce the domain of a variable X to make an arc $\langle X, c \rangle$ arc consistent, which arcs do we need to reconsider?



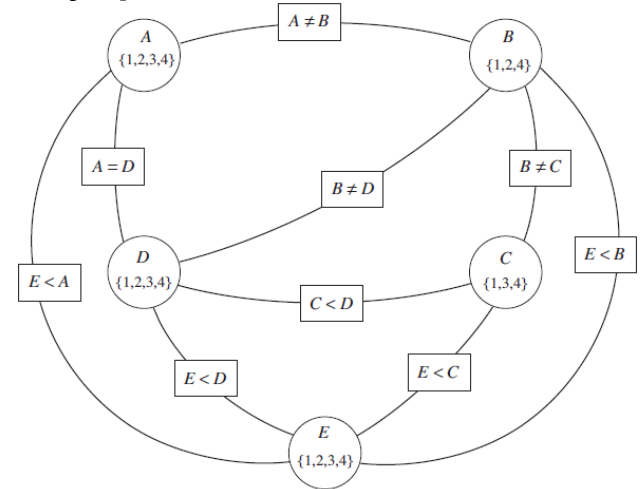
- You do not need to reconsider other arcs
 - If an arc $\langle X, c' \rangle$ was arc consistent before, it will still be arc consistent
 - Nothing changes for arcs of constraints not involving X

Lecture Overview


- Arc consistency
 - Recap
 -  Complexity analysis
 - Domain Splitting
- Intro to Local Search

Arc Consistency Algorithm: Complexity

- Worst-case complexity of arc consistency procedure on a problem with N variables
 - let d be the max size of a variable domain
 - let c be the number of constraints
- How often will we prune the domain of variable V ? $O(d)$ times
- How many arcs will be put on the ToDoArc list when pruning domain of variable V ?
 - $O(\text{degree of variable } V)$
 - In total, across all variables: sum of degrees of all variables = ...
 - $2 \cdot \text{number of constraints, i.e. } 2 \cdot c$
 - Together: we will only put $O(dc)$ arcs on the ToDoArc list
 - Checking consistency is $O(d^2)$ for each of them
- Overall complexity: $O(cd^3)$
- Compare to $O(d^N)$ of DFS!! Arc consistency is MUCH faster



Lecture Overview

- Arc consistency
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Can we have an arc consistent network with no solution?

YES

NO

- Example: vars A, B, C with domain $\{1, 2\}$ and constraints $A \neq B, B \neq C, A \neq C$
- Or see Alspace CSP applet Simple Problem 2

Domain splitting (or case analysis)

- Arc consistency ends: Some domains have more than one value → may or may not have a solution
 - A. Apply Depth-First Search with Pruning or
 - B. **Split the problem** in a number of disjoint cases:

CSP with $\text{dom}(X) = \{x_1, x_2, x_3, x_4\}$ becomes

CSP₁ with $\text{dom}(X) = \{x_1, x_2\}$ and

CSP₂ with $\text{dom}(X) = \{x_3, x_4\}$

- Solution to CSP is the **union** of solutions to CSP_i

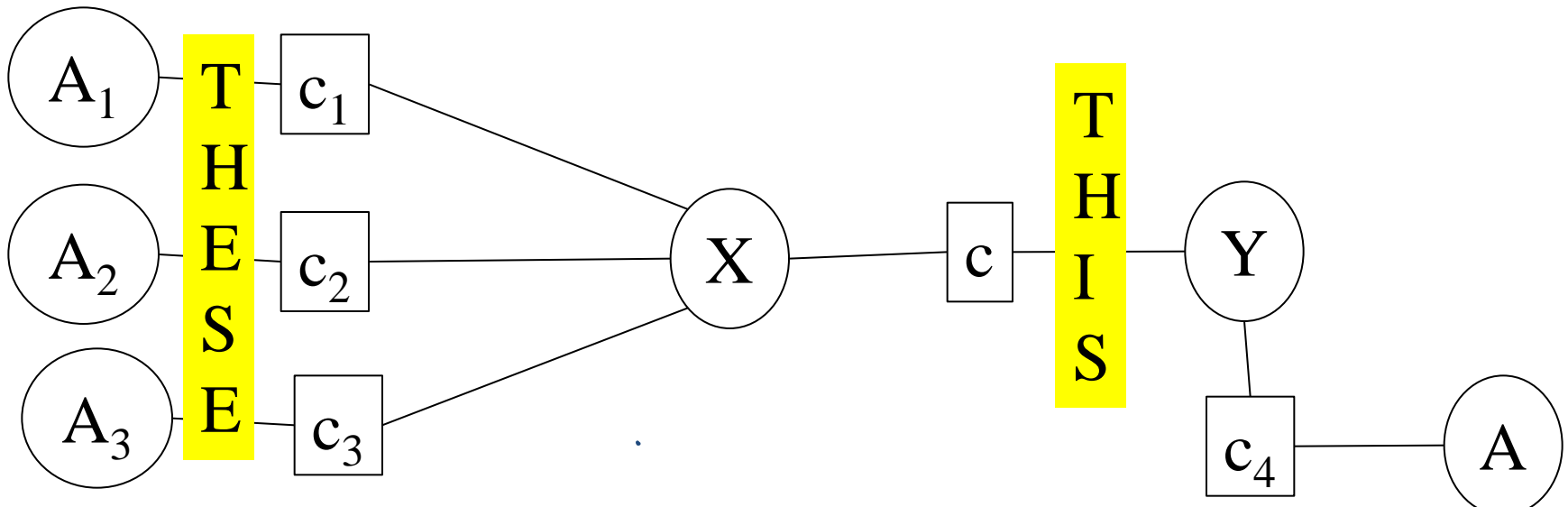
Domain splitting

- Each smaller CSP is easier to solve
 - Arc consistency might already solve it
- For each subCSP, which arcs have to be on the ToDoArcs list when we get the subCSP by splitting the domain of X?

arcs $\langle Z, r(Z,X) \rangle$

arcs $\langle Z, r(Z,X) \rangle$ and $\langle X, r(Z,X) \rangle$

All arcs



Domain splitting in action

- Trace it on “simple problem 2”



Searching by domain splitting

CSP, apply AC

If domains with multiple values

Split on one

CSP₁, apply AC

CSP_n, apply AC

If domains with multiple values

Split on one

If domains with multiple values.....Split on one

How many CSPs do we need to keep around at a time?

With depth m and b children at each split: $O(bm)$. It's a DFS

Learning Goals up to here

- Define/read/write/trace/debug the **arc consistency algorithm**. Compute its complexity and assess its possible outcomes
- Define/read/write/trace/debug **domain splitting** and its integration with arc consistency

Lecture Overview

- Arc consistency
 - Recap
 - Complexity analysis
 - Domain Splitting

 Intro to Local Search

Local Search: Why

- Solving a CSP is NP hard
 - Search space for many CSPs is huge
 - Exponential in the number of variables
 - Even arc consistency with domain splitting isn't enough
- Alternative: local search
 - Algorithms that often find a solution quickly
 - But that cannot prove that there is no solution
- **Useful method in practice**
 - Best available method for many **constraint satisfaction** and **constraint optimization** problems
 - Extremely general!
 - Works for problems other than CSPs
 - E.g. arc consistency only works for CSPs

Local Search

- **Idea:**
 - Consider the space of complete assignments of values to variables (all possible worlds)
 - Neighbours of a current node are similar variable assignments
 - Move from one node to another according to a function that scores how good each assignment is

1	8	1	4	8	3	4	3	5
7	9	3	6	2	8	1	4	7
4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5



2	8	1	4	8	3	4	3	5
7	9	3	6	2	8	1	4	7
4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5

Local Search Problem: Definition

Definition: A **local search problem** consists of a:

CSP: a set of variables, domains for these variables, and constraints on their joint values. A node in the search space will be a complete assignment to all of the variables.

Neighbour relation: an edge in the search space will exist when the neighbour relation holds between a pair of nodes.

Scoring function: this can be used to incorporate information about how many constraints are violated.

It can also incorporate information about the cost of the solution in an optimization context.

Example: Sudoku as a local search problem

CSP: usual Sudoku CSP

- One variable per cell; domains $\{1, \dots, 9\}$;
- Constraints:
each number occurs once per row, per column, and per 3x3 box

Neighbour relation: value of a single cell differs

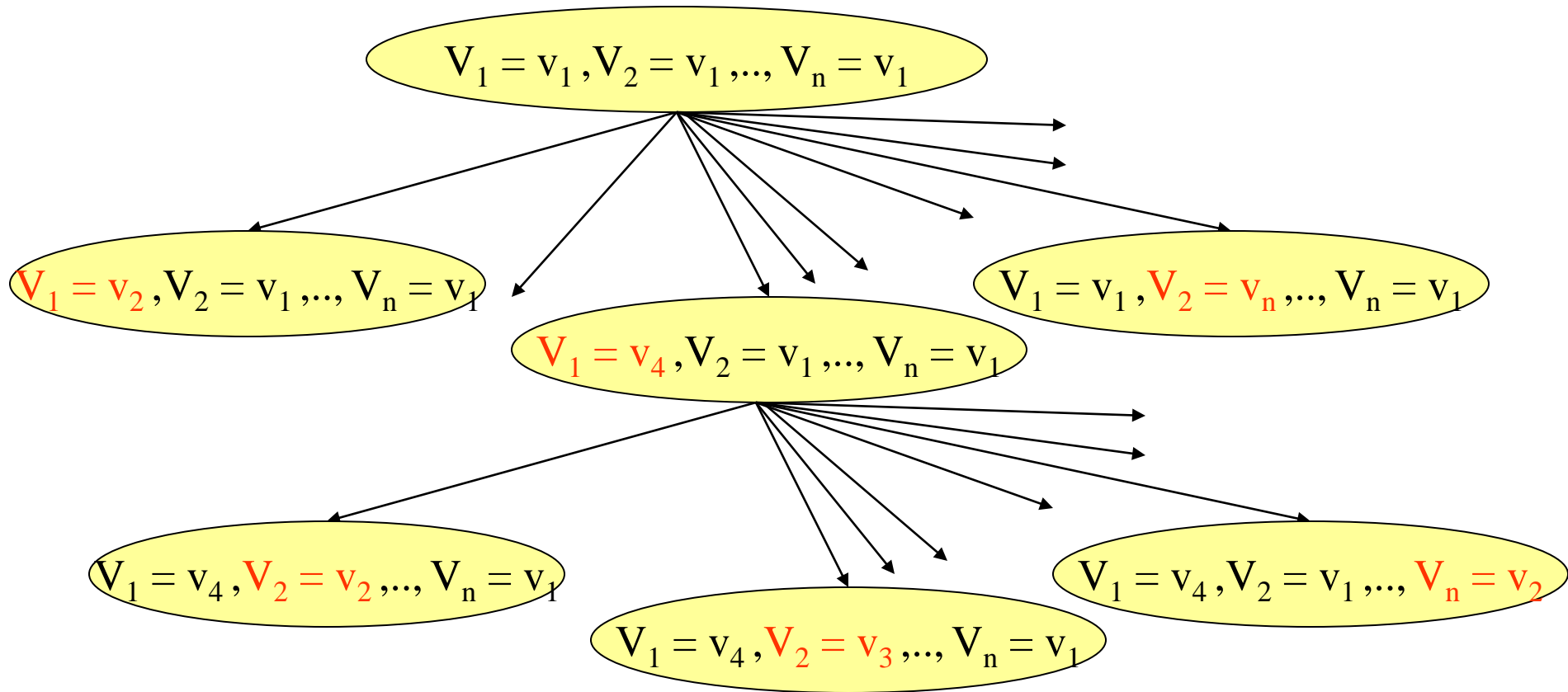
Scoring function: number of constraint violations

1	8	1	4	8	3	4	3	5
7	9	3	6	2	8	1	4	7
4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5



2	8	1	4	8	3	4	3	5
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4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5

Search Space



Only the current node is kept in memory at each step.

Very different from the search approaches we have seen so far!

Local search does NOT backtrack!

Example: Hill climbing for Sudoku

Assign random numbers
between 1 and 9 to blank
fields

	9	3	6	2	8	1	4	
	6						5	
	3			1			9	
	5		8		2		7	
	4			7			6	
	8						3	
	1	7	5	9	3	4	2	

Example: Hill climbing for Sudoku

Assign random numbers

between 1 and 9 to blank fields

Repeat

- For each cell & each number:
Evaluate how many constraint violations the assignment would yield
- Choose the cell and number that leads to the fewest violated constraints; **change it**

Until solved

1	8	1	4	8	3	4	3	5
7	9	3	6	2	8	1	4	7
4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5

Example: Hill climbing for Sudoku

Example for one local search step:

Reduces #constraint violations by 3:

- Two 1s in the first column
- Two 1s in the first row
- Two 1s in the top-left box

1	8	1	4	8	3	4	3	5
7	9	3	6	2	8	1	4	7
4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5



2	8	1	4	8	3	4	3	5
7	9	3	6	2	8	1	4	7
4	6	5	7	1	2	8	5	6
3	3	7	3	1	4	1	9	3
8	5	7	8	2	2	9	7	8
5	4	4	3	7	8	7	6	2
4	8	7	1	2	8	5	3	6
1	1	7	5	9	3	4	2	8
7	5	8	4	8	6	7	3	5

General Local Search Algorithm

```
1: Procedure Local-Search( $V, dom, C$ )
2:   Inputs
3:      $V$ : a set of variables
4:      $dom$ : a function such that  $dom(X)$  is the domain of variable  $X$ 
5:      $C$ : set of constraints to be satisfied Output
6:     complete assignment that satisfies the constraints
7:   Local
8:      $A[V]$  an array of values indexed by  $V$ 
9:   repeat
10:    for each variable  $X$  do
11:       $A[X] \leftarrow$  a random value in  $dom(X)$ ;
12:
13:    while (stopping criterion not met &  $A$  is not a satisfying assignment)
14:      Select a variable  $Y$  and a value  $V \in dom(Y)$ 
15:      Set  $A[Y] \leftarrow V$ 
16:
17:    if ( $A$  is a satisfying assignment) then
18:      return  $A$ 
19:
20:   until termination
```

You can be smart about selecting a variable and a new value for it: variable and value selection **heuristics**

Based on **local** information. E.g., for each neighbour, you can evaluate how many constraints are unsatisfied.

Hill climbing: select Y and V to minimize #unsatisfied constraints at each step

Learning Goals for local search (started)

- Implement **local search** for a CSP.
 - Implement different ways to **generate neighbors**
 - Implement **scoring functions** to solve a CSP by local search through either **greedy descent** or **hill-climbing**.
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- Assignment 1 is due on Monday
- Local search practice exercise is on WebCT
- Programming assignment (part of assignment #2) is available on WebCT (due Wednesday, Feb 23rd)
- Coming up: more local search, Section 4.8