

# CSPs: Arc Consistency & Domain Splitting

Computer Science cpSC322, Lecture 13

*(Textbook Chpt 4.5, 4.6)*

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# Lecture Overview

- **Recap (CSP as search & Constraint Networks)**
- Arc Consistency Algorithm
- Domain splitting

# Standard Search vs. Specific R&R systems

## Constraint Satisfaction (Problems):

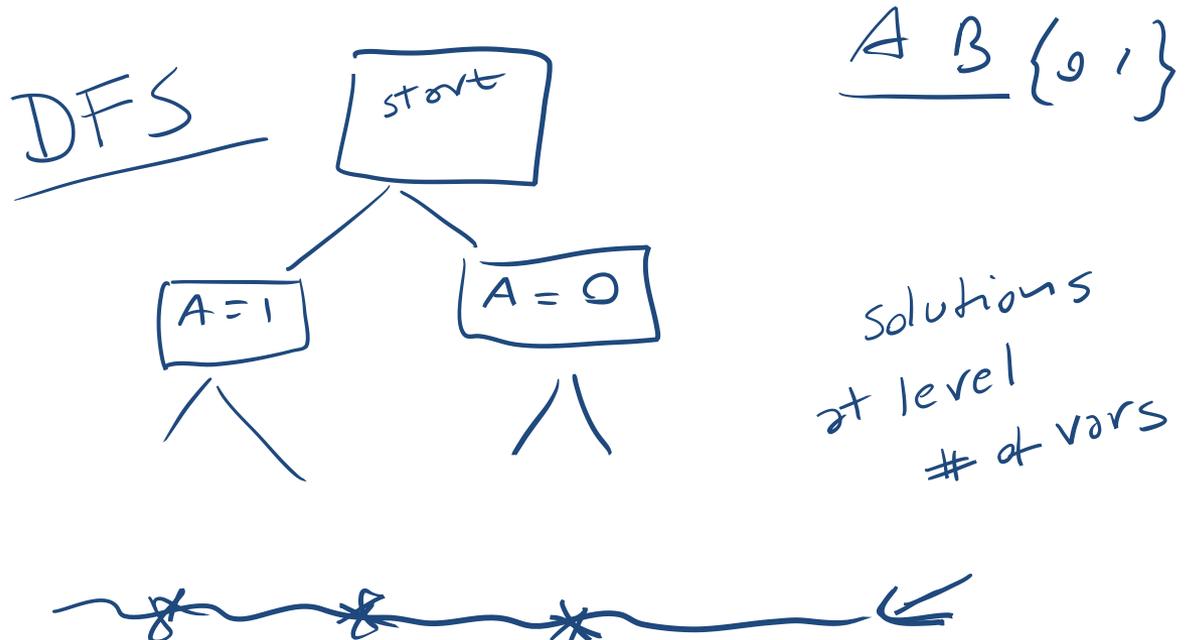
- **State:** assignments of values to a subset of the variables
- **Successor function:** assign values to a “free” variable
- **Goal test:** set of constraints
- **Solution:** possible world that satisfies the constraints
- **Heuristic function:** *none (all solutions at the same distance from start)*

### Planning :

- State
- Successor function
- Goal test
- Solution
- Heuristic function

### Query

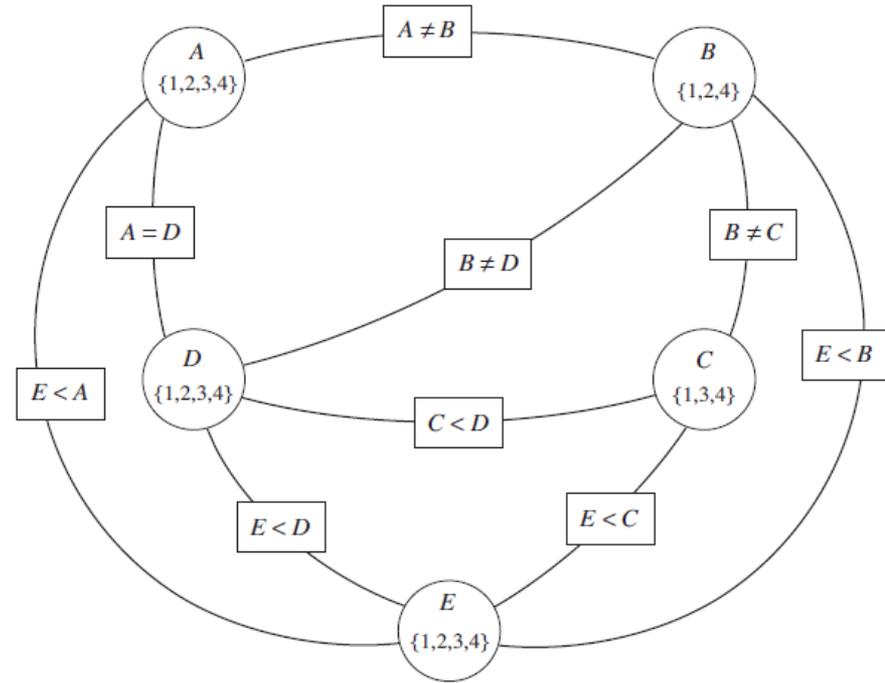
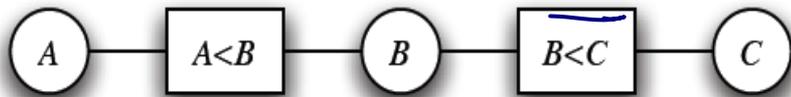
- State
- Successor function
- Goal test
- Solution
- Heuristic function



# Recap: We can do much better..

- Build a constraint network:

A B C      A < B      B <<<



- Enforce domain and arc consistency



# Lecture Overview

- Recap
- Arc Consistency Algorithm
  - Abstract strategy ←
  - Details
  - Complexity
  - Interpreting the output
- Domain Splitting

# Arc Consistency Algorithm: high level strategy

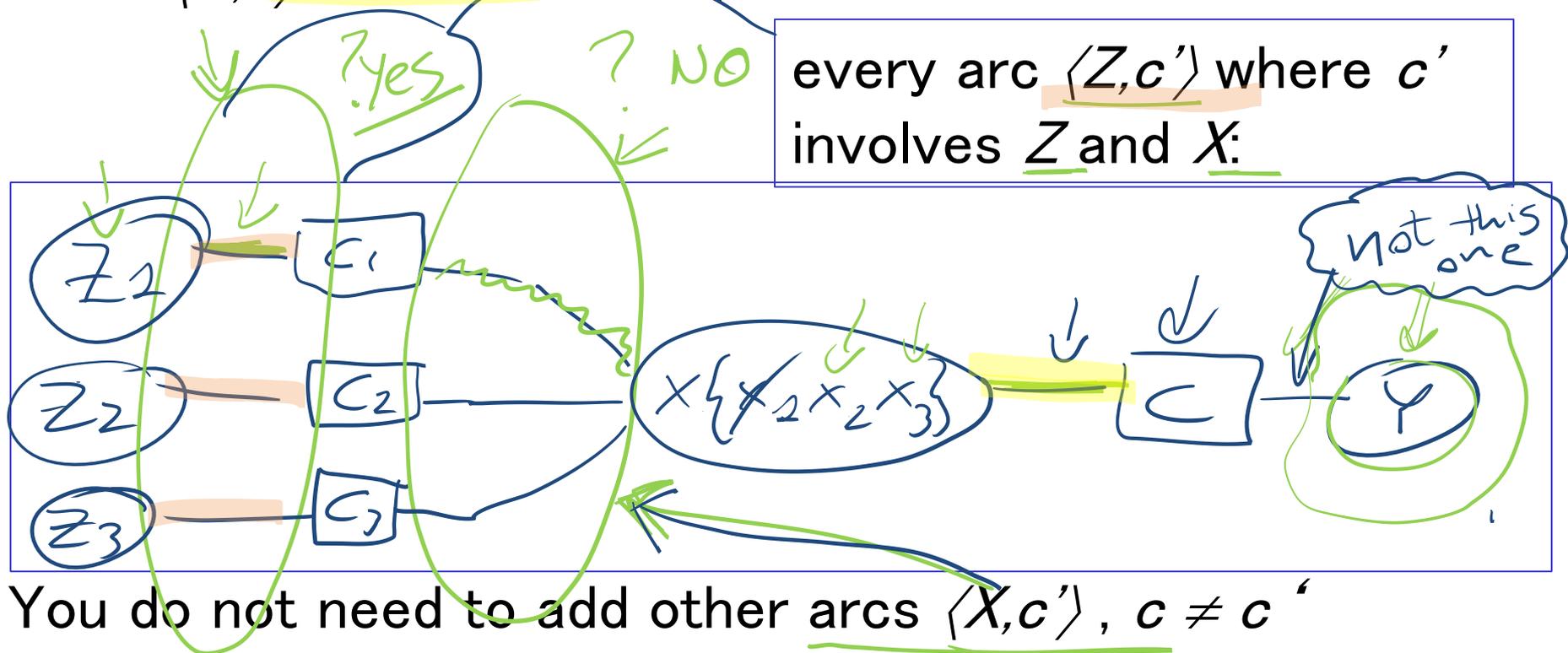
- Consider the arcs in turn, making each arc consistent.
- BUT, arcs may need to be revisited whenever...



- NOTE – Regardless of the order in which arcs are considered, we will terminate with the same result

# What arcs need to be revisited?

When we reduce the domain of a variable  $X$  to make an arc  $\langle X, c \rangle$  arc consistent, we add.....



You do not need to add other arcs  $\langle X, c' \rangle$ ,  $c \neq c'$

- If an arc  $\langle X, c \rangle$  was arc consistent before, it will still be arc consistent (in the "for all" we'll just check fewer values)

# ARC CONSISTENCY PSEUDO-CODE

TDA ← all arcs in Constraint Network

**WHILE** (TDA is not empty)

- select arc  $a$  from TDA

**IF** ( $a$  is not consistent) **THEN**

- make  $a$  consistent

- add arcs to TDA that  
may now be inconsistent

SEE PREVIOUS  
SLIDE

# Arc consistency algorithm (for binary constraints)

Procedure GAC(V,dom,C)

## Inputs

V: a set of variables

dom: a function such that dom(X) is the domain of variable X

C: set of constraints to be satisfied

## Output

arc-consistent domains for each variable

## Local

$D_X$  is a set of values for each variable X

TDA is a set of arcs

Scope of constraint  $c$  is the set of variables involved in that constraint

TDA:  
ToDoArcs,  
blue arcs  
in AIspace

```
1: for each variable X do
2:    $D_X \leftarrow \text{dom}(X)$ 
3:   TDA  $\leftarrow \{ \langle X, c \rangle \mid X \in V, c \in C \text{ and } X \in \text{scope}(c) \}$ 

4:   while (TDA  $\neq \{ \}$ )
5:     select  $\langle X, c \rangle \in \text{TDA}$ 
6:     TDA  $\leftarrow \text{TDA} \setminus \{ \langle X, c \rangle \}$ 
7:      $\text{ND}_X \leftarrow \{ x \mid x \in D_X \text{ and } \exists y \in D_Y \text{ s.t. } (x, y) \text{ satisfies } c \}$ 
8:     if ( $\text{ND}_X \neq D_X$ ) then
9:       TDA  $\leftarrow \text{TDA} \cup \{ \langle Z, c' \rangle \mid X \in \text{scope}(c'), c' \neq c, Z \in \text{scope}(c') \setminus \{ X \} \}$ 
10:       $D_X \leftarrow \text{ND}_X$ 

11:   return  $\{ D_X \mid X \text{ is a variable} \}$ 
```

$\text{ND}_X$ : values  $x$  for  $X$  for which there is a value for  $y$  supporting  $x$

X's domain changed:  
 $\Rightarrow$  arcs  $\langle Z, c' \rangle$  for variables  $Z$  sharing a constraint  $c'$  with  $X$  are added to TDA

If arc was inconsistent

Domain is reduced

# Arc Consistency Algorithm: Complexity

- Let's determine Worst-case complexity of this procedure (compare with DFS  $d^n$ )
  - let the max size of a variable domain be  $d$
  - let the number of variables be  $n$
  - The max number of binary constraints is ?

A.  $n * d$

B.  $d * d$

C.  $(n * (n-1)) / 2$

D.  $(n * d) / 2$



# Arc Consistency Algorithm: Complexity

- Let's determine Worst-case complexity of this procedure (compare with DFS)
  - let the max size of a variable domain be  $d$
  - let the number of variables be  $n$
- How many times the same arc can be inserted in the ToDoArc list?

A.  $n$

B.  $d$

C.  $n * d$

D.  $d^2$

iclicker.

- How many steps are involved in checking the consistency of an arc?

A.  $n^2$

B.  $d$

C.  $n * d$

D.  $d^2$

iclicker.

# Arc Consistency Algorithm: Complexity

- Let's determine Worst-case complexity of this procedure (compare with DFS  $d^n$ )
  - let the max size of a variable domain be  $d$
  - let the number of variables be  $n$
  - The max number of binary constraints is  $n(n-1)/2$

- How many times the same arc can be inserted in the ToDoArc list?



$d$

$$O(d^3 n^2)$$

- How many steps are involved in checking the consistency of an arc?  $d^2$

$$\{x_1 \dots x_d\} \quad \{y_1 \dots y_d\}$$

OVERALL COMPLEXITY

# Arc Consistency Algorithm: Interpreting Outcomes

- Three possible outcomes (when all arcs are arc consistent):

- One domain is empty → no sol
- Each domain has a single value → unique sol 
- Some domains have more than one value → may or may not be a solution

- in this case, arc consistency isn't enough to solve the problem: we need to perform search

see arc consistency (AC) practice exercise

# Lecture Overview

- Recap
- Arc Consistency
- Domain splitting

# Domain splitting (or case analysis)

- Arc consistency ends: Some domains have more than one value  $\rightarrow$  may or may not be a solution
  - A. Apply Depth-First Search with Pruning  $\leftarrow$
  - B. Split the problem in a number of (two) disjoint cases  $\leftarrow$

$$\begin{array}{l} \text{CSP} = \{X = \{x_1, x_2, x_3, x_4\} \dots\} \\ \swarrow \qquad \searrow \\ \text{CSP}_1 \{X = \{x_1, x_2\} \dots\} \qquad \text{CSP}_2 \{X = \{x_3, x_4\}\} \end{array}$$

- Set of all solution equals to...

$$\text{Sol}(\text{CSP}) = \bigcup_i \text{sol}(\text{CSP}_i)$$

## But what is the advantage?

By reducing  $\text{dom}(X)$  we may be able to... *run AC again*

- Simplify the problem using **arc consistency** ←

- No unique solution i.e., for at least one var, ←

$|\text{dom}(X)| > 1$

- **Split X** ←

- For all the splits ←

  - Restart arc consistency on arcs  $\langle Z, r(Z,X) \rangle$

*Initial TDA*

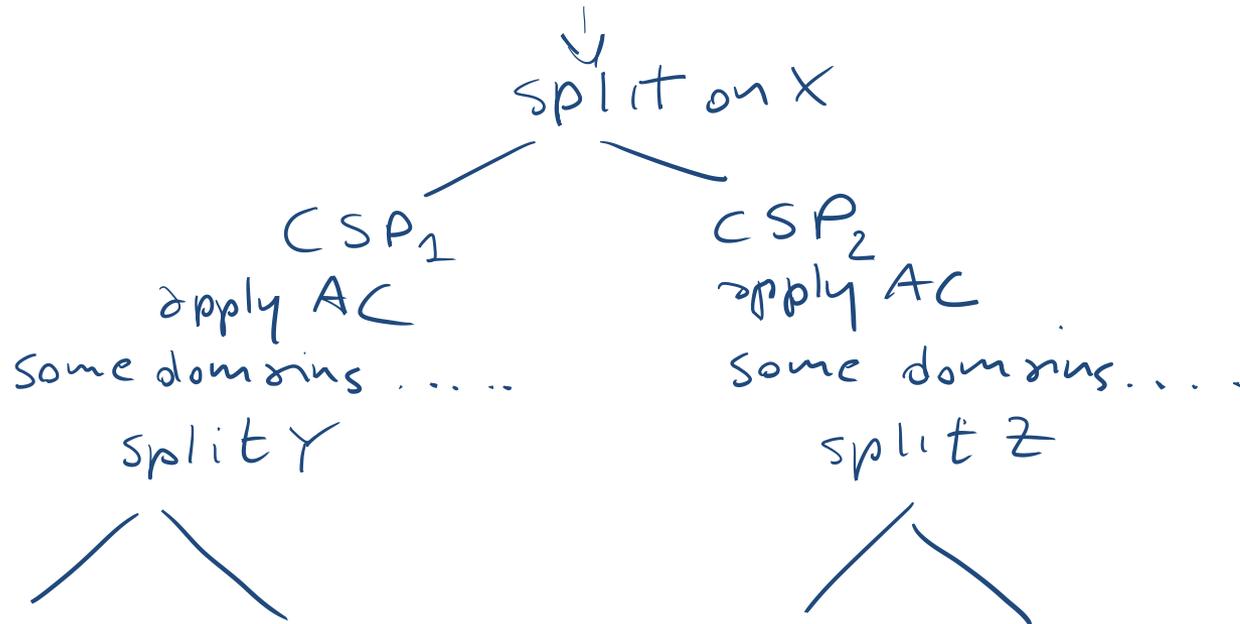
these are the ones that are possibly inconsistent

- Disadvantage ☹️: you need to keep all these CSPs around (vs. lean states of DFS)

# Searching by domain splitting

CSP; apply AC

some domains have multiple values

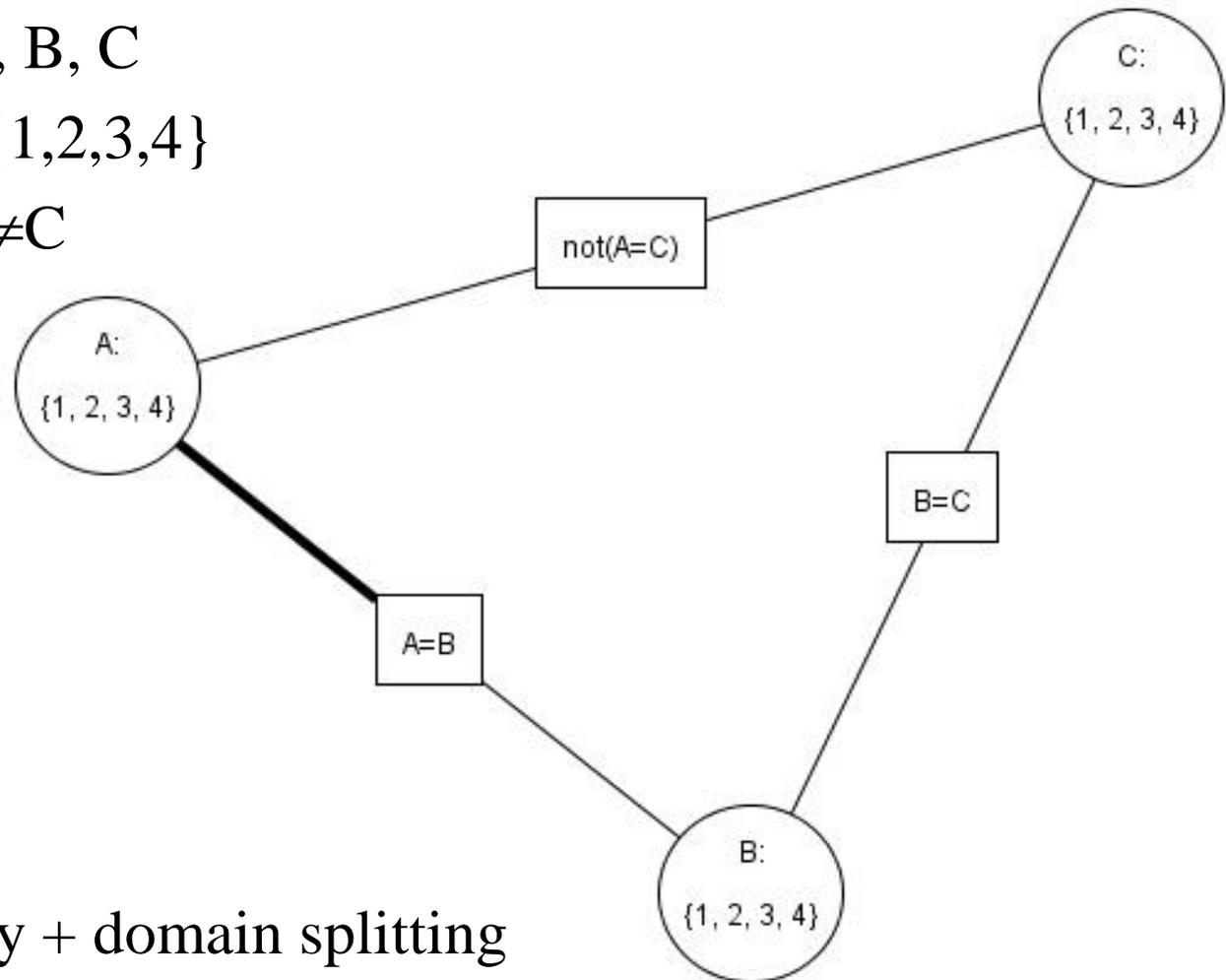


## More formally: Arc consistency with domain splitting as another formulation of CSP as search

- **Start state:** run AC on vector of original domains ( $\text{dom}(V_1), \dots, \text{dom}(V_n)$ )
- **States:** “remaining” domains ( $D(V_1), \dots, D(V_n)$ ) for the vars with  $D(V_i) \subseteq \text{dom}(V_i)$  for each  $V_i$
- **Successor function:**
  - split one of the domains + run arc consistency
- **Goal state:** vector of unary domains that satisfies all constraints
  - That is, only one value left for each variable
  - The assignment of each variable to its single value is a **model**
- **Solution:** that assignment

# Domain Splitting in Action:

- 3 variables: A, B, C
- Domains: all  $\{1,2,3,4\}$
- $A=B$ ,  $B=C$ ,  $A \neq C$



- Let's trace  
arc consistency + domain splitting  
for this network for "Simple Problem 2" in AIspace

# Learning Goals for today's class

## You can:

- 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

- **Work on CSP Practice Ex:**

- Exercise 4.A: arc consistency
- Exercise 4.B: constraint satisfaction problems
- 

## Next Class (Chpt. 4.8)

- **Local search:**
- Many search spaces for CSPs are simply too big for systematic search (but solutions are densely distributed).
  - Keep only the current state (or a few)
  - Use very little memory / often find reasonable solution
- ... **Local search for CSPs**

# K-ary vs. binary constraints

- **Not a topic for this course** but if you are curious about it...
- Wikipedia example clarifies basic idea...
- [http://en.wikipedia.org/wiki/Constraint\\_satisfaction\\_dual\\_problem](http://en.wikipedia.org/wiki/Constraint_satisfaction_dual_problem)
- The **dual problem** is a reformulation of a constraint satisfaction problem expressing each constraint of the original problem as a variable. Dual problems only contain binary constraints, and are therefore solvable by algorithms tailored for such problems.
- See also: **hidden transformations**