

Seminar on Constraint Programming

Talk 3

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Outline

- 1 Fundamental Concept Review
- 2 Local Consistencies Weaker than AC
 - Directional Arc Consistency
 - Forward Checking Consistency
 - Bound Consistency
- 3 Specific Constraints
 - Specific Propagators in Solvers
 - Modification to Constraints

Constraint Network

Definition

A **constraint network** $N(X, D, C)$ is composed of

- a finite sequence of **variables** $X = \{x_1, \dots, x_n\}$
- a **domain** D for all the variables in X
- a set of **constraints** $C = \{c_1, \dots, c_n\}$

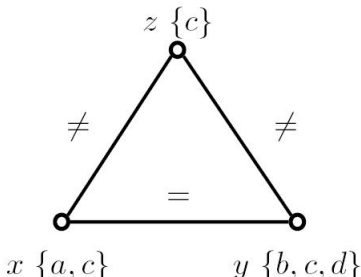
Example

Consider a constraint network:

$\{x, y, z\}$

$\langle x \in \{a, c\}, y \in \{b, c, d\}, z = c \rangle$

$\{x = y, y \neq z, x \neq z\}$



Motivation of Constraint Propagation

- The constraint satisfaction problem (CSP) is always NP-complete
- Exploring the whole space of instantiations of a given CSP is usually too expensive
- The idea behind constraint propagation is to make the searching space small
- That is, to make the constraint network of the given CSP tight

Implementation of Constraint Propagation

- We define and achieve all kinds of **local consistencies** by tightening the constraint network
- After achieving a certain local consistency, the **domain** of the CSP is tightened
- Then the solution of the given CSP can be find by looking for **global consistency** in the tightened network
- We say the constraint network $N(X, D, C)$ is **consistent** if there exists a solution

Different Methods of Constraint Propagation

Different local consistencies with different time complexities

- arc consistency AC3 on binary network $O(ed^3)$
- arc consistency AC4 AC6 AC2001 on binary network $O(ed^2)$
- stronger than AC: path consistency, k-consistency, triangle-based consistency, neighborhood inverse consistency. . .
- weaker than AC: directional arc consistency, forward checking consistency, bound consistency

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Basis

- GAC runs in $O(er^3 d^{r+1})$
- The time complexity is extremely large with respect to large r and d
- Directional arc consistency (DAC) is simpler to enforce than AC.

Definition

A binary network $N(X, D, C)$ is DAC according to ordering $o = (x_{k_1}, \dots, x_{k_n})$ on X , where (k_1, \dots, k_n) is a permutation of $(1, \dots, n)$, iff for all $c(x_i, x_j) \in C$, if $x_i <_o x_j$ then x_i is arc consistent on $c(x_i, x_j)$

Example 1 of DAC

Example

$X = \{x_1, x_2, x_3\}$, $D(x_1) = D(x_2) = \{1..5\}$, $D(x_3) = \{1..3\}$

$C = \{x_1 < x_2, x_2 = x_3, x_1 > x_3\}$

What will happen after enforcing the DAC?

What will happen after enforcing the AC?

Example 2 of DAC

Example

Consider the constraint network $\langle x < y; x \in [2..10], y \in [3..7] \rangle$

What will happen after enforcing the DAC?

What will happen after enforcing the AC?

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Basis

Definition

A network $N(X, D, C)$ is forward checking consistent according to the instantiation I on $Y, Y \subseteq X$, iff I is locally consistent and for all $x_i \in Y$, for all $x_j \in X \setminus Y$, for all $c(x_i, x_j) \in C$, x_j is arc consistent on $c(x_i, x_j)$.

Note

The difference between forward checking consistency and arc consistency is that the former only checks a single unassigned variable at time for consistency, while the second also checks pairs of unassigned variables for mutual consistency

Example

Example

$X = \{x_1, x_2, x_3\}$, $D(x_1) = D(x_2) = \{1..5\}$, $D(x_3) = \{1..3\}$

$C = \{x_1 < x_2, x_2 = x_3, x_1 > x_3\}$

What will happen after enforcing the FCC?

What will happen after enforcing the AC?

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Bound support

Definition

Given a network N , given a constraint c , a **bound support** τ on c is a tuple that satisfies c and such that for all $x_i \in X(c)$, $\min_D(x_i) \leq \tau[x_i] \leq \max_D(x_i)$.

Example

$D(x_1) = D(x_2) = \{1, 2\}, D(x_3) = D(x_4) = \{2, 3, 5, 6\}, D(x_5) = \{5\}, D(x_6) = \{3, \dots, 7\}$

$C = \text{alldifferent}(x_1, \dots, x_6)$

Amazingly, tuple **(1, 2, 4, 6, 5, 3)** is a bound support on C

Three kinds of bound consistency

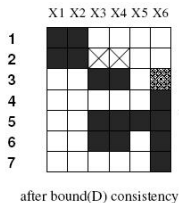
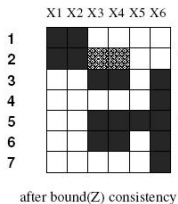
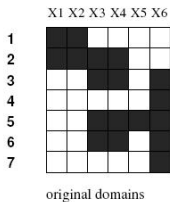
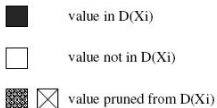
Definition

- A constraint c is **bound(Z) consistent** iff for all $x_i \in X(c)$, $(x_i, \min_D(X_i))$ and $(x_i, \max_D(X_i))$ belong to a bound support on c .
- A constraint c is **range consistent** iff for all $x_i \in X(c)$, for all $v_i \in D(x_i)$, (x_i, v_i) belongs to a bound support on c .
- A constraint c is **bound(D) consistent** iff for all $x_i \in X(c)$, $(x_i, \min_D(X_i))$ and $(x_i, \max_D(X_i))$ belong to a support on c .

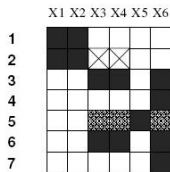
Example

$D(x_1) = D(x_2) = \{1, 2\}, D(x_3) = D(x_4) = \{2, 3, 5, 6\}, D(x_5) = \{5\}, D(x_6) = \{3, \dots, 7\}$
 $C = alldifferent(x_1, \dots, x_6)$

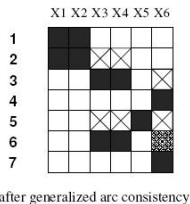
Example



after bound(D) consistency



after range consistency



after generalized arc consistency

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Constraint Propagator Design

Design Principle

Making the computational load as small as possible according to specific feature of the constraint network.

- All constraint solvers attach a specific propagation algorithm (e.g. AC3) to the specific types of constraints (e.g. arc consistency) they contain
- However, designing a constraint propagator is quite a flexible task
- More attention is paid on designing a propagator based on arithmetic constraints

Arithmetic Propagator Design based on AC3

We define the following 4 types of **events**

- RemValue: when a value v is removed from $D(x_i)$
- IncMin: when the minimum value of $D(x_i)$ increases
- DecMax: when the maximum value of $D(x_i)$ decreases
- Instantiate: when $D(x_i)$ becomes a singleton

Then the AC3 can be adapted like this:

Algorithm 3.10: AC3-like constraint propagation schema

```

function Constraint-Propag(in  $X$ : set): Boolean ;
  begin
  1   foreach  $c \in C$  do perform init-propag on  $c$  and update  $Q$  with relevant events;
  2   while  $Q \neq \emptyset$  do
  3     select and remove  $(x_i, c, x_j, Mtype)$  from  $Q$ ;
  4     if Revise $(x_i, c, (x_j, Mtype), Changes)$  then
  5       if  $D(x_i) = \emptyset$  then return false ;
  6       foreach  $c' \in \Gamma^C(x_i), Mtype \in Changes$  do
  7         foreach  $x_j \in X(c'), j \neq i$  do  $Q \leftarrow Q \cup \{(x_j, c', x_i, Mtype)\}$ ;
  8   return true ;
  end
  /*  $\Gamma^C(x_i)$  is the set of constraints with  $x_i$  in their scheme */
  
```

Example

Example

Let $x_1 \leq x_2$, with $D(x_1) = D(x_2) = \{1 \dots 100\}$

What will happen if we remove value 100 from $D(x_2)$?

What will happen if we remove 50 from $D(x_2)$?

```

function revise(inout  $x_i$ ; in  $c \equiv x_{k_1} \leq x_{k_2}$ ; in ( $x_j, Mtype$ ); out  $Changes$ ): Boolean ;
   $Changes \leftarrow \emptyset$ ;
  switch  $Mtype$  do
    case  $RemValue$ 
      nothing;
    case  $IncMin$ 
      if  $j = k_1$  then remove all  $v < min_D(x_j)$  from  $D(x_i)$ ;
    case  $DecMax$ 
      if  $j = k_2$  then remove all  $v > max_D(x_j)$  from  $D(x_i)$ ;
    case  $Instantiate$ 
      if  $j = k_1$  then remove all  $v < min_D(x_j)$  from  $D(x_i)$ ;
      else remove all  $v > max_D(x_j)$  from  $D(x_i)$ ;
   $Changes \leftarrow$  the types of changes performed on  $D(x_i)$ ;
  
```

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Motivation

- In general, the constraint propagation procedure replaces a given CSP by a simpler one, yet equivalent
- We discussed several techniques that made the **domain** of the network smaller
- The **constraints** can also become smaller using suitable methods

Example

Given a set of constraints $\{x < y, y < x\}$

After examining the constraints, we can find there is obviously no solution

This examination on constraints save us time

Classes of Specific Constraint: Global Constraint

Global constraint represents a class of constraints defined on it

Example

some global constraints

- *alldifferent*(x_1, x_2, \dots, x_n) is the class of constraints that are defined on any sequence of n variables such that $x_i \neq x_j$ for all $i \neq j$
- *NValue*($y, [x_1, x_2, \dots, x_n]$) is the class of constraints that are defined on any sequence of $n + 1$ variables, $n \geq 1$, such that $|\{x_i | 1 \leq i \leq n\}| = y$

Important Conclusions from Relevant Literature

- Some global constraints admit a decomposition that preserves GAC
- Sometimes even decomposing a global constraint is difficult.

Summary of this chapter

- We discussed different local consistencies and their features
- Different local consistencies are enforced by different propagation algorithms
- How to tighten the given domain and how to decompose the given constraint depend on specific problem