

# Topic 15: Search<sup>1</sup>

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Course 1DL441:  
Combinatorial Optimisation and Constraint Programming,  
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Modelling for Combinatorial Optimisation

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<sup>1</sup>Based partly on material by Christian Schulte and Yves Deville



# Outline

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Branching

Exploration

Dynamic  
Symmetry  
Breaking

## 1. Branching

## 2. Exploration

## 3. Dynamic Symmetry Breaking



# Search = Branching + Exploration

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- **Branching** describes how to **define** the search tree.
- **Exploration** describes how to **explore** the search tree:
  - first solution
  - all solutions
  - best solution: via branch-and-bound
  - depth-first
  - breadth-first
  - multi-start
  - ...



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## Definition (Brancher)

A **brancher**  $b$  satisfies the following conditions, when  $b(R, s) = \langle R_1, \dots, R_c \rangle \wedge \forall i. \text{Propagate}(R \cup R_i, R_i, s) = \langle \_, s_i \rangle$ :

■ **Contraction:**  $\forall i : s_i \not\preceq s$ . (Hence a finite search tree.)

■ **No solutions lost or duplicated:**  $\forall \sigma \in s : \exists ! i : \sigma \in s_i$ .

where propagator set  $R_i$  is called the  $i^{\text{th}}$  **decision** or **guess**.

## Definition (Branch & propagate search tree)

Let  $\langle V, U, P, b \rangle$  be a model extended with a brancher  $b$ .  
The **search tree** is as follows, for  $s_0 = \{v \mapsto U \mid v \in V\}$ :

- The **root** node is  $\text{Propagate}(P, P, s_0)$ .
- Node  $\langle R, s \rangle$  has the  $c$  nodes  $\text{Propagate}(R \cup R_i, R_i, s)$  as **children**, where  $b(R, s) = \langle R_1, \dots, R_c \rangle$  with  $c \neq 1$ ; it is a **leaf** if  $s = \emptyset$  (**failed** node) or  $c = 0$  (**solved** node).



## Definition (Variable selection strategy)

A brancher  $b(R, s)$  **selects a variable**, based on either the **current** store  $s$ , or the **current** set  $R$  of propagators, or both (**dynamic** selection); or neither (**static** selection); or also the previously visited nodes (**adaptive** selection):

- **Next**: Select the next variable by order in the model
- **Random**: Randomly select a variable unfixed by  $s$
- **SizeMin**: Select an unfixed var with smallest dom in  $s$
- **DegreeMax**: Select a variable  $v$  unfixed by  $s$  with the largest **degree** in  $R$  ( $= |\{p \in R \mid v \in \text{var}(p)\}|$ )
- **AFCmin**: Select a variable unfixed by  $s$  with the smallest accumulated failure count
- ...

Ties are broken under any combination of these strategies.



## Definition (Value selection strategy)

Further,  $b(R, s)$  **selects values** for the chosen variable  $v$ :

- Select the minimum:  $\underline{m} = \min(s(v))$
- Select the middle:  $\dot{m} = \left\lfloor \frac{\min(s(v)) + \max(s(v))}{2} \right\rfloor$
- Select all the values of  $s(v) = \{d_1, \dots, d_n\}$
- ...

We assume domains are ordered.

## Definition (Decision, or guess)

Finally,  $b(R, s)$  builds **decisions**, which are propagator sets:

- **ValMin**: Branch left on  $\{v = \underline{m}\}$  and right on  $\{v \neq \underline{m}\}$
- **SplitMin**: Branch left on  $\{v \leq \dot{m}\}$  and right on  $\{v > \dot{m}\}$
- **ValuesMin**: Branch left-right on  $\{v = d_1\}, \dots, \{v = d_n\}$
- ...





# Set Variables (Reminder)

## Definition

A **set (decision) variable** takes an integer set as value, and has a set of integer sets as domain. For its domain to be finite, a set variable must be a subset of a finite set  $\Sigma$ .

CP solvers over-approximate the domain of a set variable  $S$  by a pair  $\langle \ell, u \rangle$  of finite sets, denoting the set of all sets  $\sigma$  such that  $\ell \subseteq \sigma \subseteq u \subseteq \Sigma$ :

- $\ell$  is the **current** set of **mandatory** elements of  $S$ ;
- $u \setminus \ell$  is the **current** set of **optional** elements of  $S$ .

## Example

The domain of a set var represented as  $\langle \{1\}, \{1, 2, 3, 4\} \rangle$  has the sets  $\{1\}$ ,  $\{1, 2\}$ ,  $\{1, 3\}$ ,  $\{1, 4\}$ ,  $\{1, 2, 3\}$ ,  $\{1, 2, 4\}$ ,  $\{1, 3, 4\}$ , and  $\{1, 2, 3, 4\}$ . Removing  $\{1, 2, 3\}$  is impossible!



Strategies for the selection of a set variable  $S \doteq \langle \ell, u \rangle$ :

- **SizeMin**: Select a set variable with smallest  $|u \setminus \ell|$
- **MinMax**: Select a set variable with largest  $\min(u \setminus \ell)$
- ...

Strategies for the selection of an **optional** element of  $S$ :

- Select the minimum:  $\underline{m} = \min(u \setminus \ell)$
- Select the median  $\dot{m}$  of  $u \setminus \ell$
- Select a random element  $r$  of  $u \setminus \ell$
- ...

Branching decisions on inclusion and exclusion:

- **MinInc**: Branch left on  $\{\underline{m} \in S\}$  and right on  $\{\underline{m} \notin S\}$
- **RndExc**: Branch left on  $\{r \notin S\}$  and right on  $\{r \in S\}$
- ...



# First-Fail Brancher

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## Example (SizeMin $\times$ Random + ValMin)

```
function  $b(R, s)$   
if  $\exists v : |s(v)| > 1$  then  
    pick random  $v$   
        such that  $|s(v)| > 1$  and  $|s(v)|$  is smallest  
    return  $\langle \{p_{v=\min(s(v))}\}, \{p_{v \neq \min(s(v))}\} \rangle$   
else  
    return  $\langle \rangle$ 
```



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## Example (Depth-first first-sol'n search, bin. branching)

For  $\langle V, U, P, b \rangle$  call  $\text{DFE}(P, P, s_0, b)$ , which is defined as follows:

```
function DFE( $R, Q, s, b$ )  
   $\langle R', s' \rangle := \text{Propagate}(R, Q, s)$   
  if  $s' = \emptyset$  then                                     // failed node  
    return  $s'$   
  else                                                  //  $s'$  is not necessarily a solution store  
     $B := b(R', s')$   
    if  $B = \langle \rangle$  then  
      return  $s'$                                          // solved node:  $s'$  is a solution store!  
    else  
      let  $B = \langle R_1, R_2 \rangle$   
       $s'' := \text{DFE}(R' \cup R_1, R_1, s', b)$   
      if  $s'' = \emptyset$  then                               // failed node  
        return  $\text{DFE}(R' \cup R_2, R_2, s', b)$            // backtrack  
      else  
        return  $s''$                                      // solved node:  $s''$  is a solution store!
```



# State Restoration Upon Backtracking

## Approaches:

- **Trailing:** Remember changes and undo them.
  - ☞ Most common approach, but difficult to implement, and difficult to combine with concurrency.
- **Batch recomputation:** Recompute state from the root.
  - ☞ Problem-independent memory usage, but slow.
- **Copying** (or **cloning**): Store an additional copy.
  - ☞ Easy to implement, and easy to combine with concurrency or parallelism, but too costly in memory.

Gecode uses a hybrid of copying and batch recomputation, called **adaptive recomputation**, which remembers a copy on the path from the root.



# Diversification

## Example (Multistart Exploration)

Perform several searches, sequentially or in parallel, especially in order to benefit from randomisation in branching strategies or from adaptive branching strategies:

- Stop each search (especially in sequential multistart) at some **cutoff**, say on the execution time, the number of visited nodes, or the number of failed nodes. Under the chosen cutoffs, the search may be incomplete.
- Specified as a sequence of  $\langle b, e, c \rangle$  triples, each with a brancher  $b$ , exploration  $e$ , and cutoff  $c$ . Example:

$$\left[ \begin{array}{l} \langle \text{SizeMin} \times \text{DegreeMax} + \text{ValMin}, DFE, 1000 \text{ fails} \rangle, \\ \langle \text{AFCmin} \times \text{Random} + \text{Random}, DFE, +\infty \text{ hours} \rangle \end{array} \right]$$

One can also solve a COP as a sequence of CSPs.



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# Dynamic Symmetry Breaking (DSB)

## Definition

**DSB** = the elimination of symmetric solutions by **search**.

## Classification:

- Via the addition of constraints by the search procedure.
- Via a problem-specific search procedure.

## Benefit:

No interference with dynamic variable and value selection strategies, especially problem-specific ones!



# State of the Art

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Two dual approaches, with large bodies of research:

- **Symmetry breaking during search** (SBDS, ...): after reaching a leaf (failed or solved node) in the search tree, add constraints preventing its symmetric nodes from being visited in the **future**.
- **Symmetry breaking by dominance detection** (SBDD, GCF, ...): before expanding a node, check whether a symmetric node thereof has been visited in the **past**.

The SBD\* schemes are general and may take exponential time or space if there are exponentially many symmetries (and they are beyond the scope of this topic). Hence:

- **Dynamic structural symmetry breaking**: exploit the combinatorial structure of a problem for designing a symmetry-free search procedure (in SBDD style).



# Full Value Symmetry

## Example (Map colouring: symmetry-free search)

Given a partial colouring using  $u$  colours, only  $u + 1$  colours need to be considered for the next country  $c$ :

- Colour  $c$  with one of the  $u$  already used colours.
- Colour  $c$  with an arbitrary unused colour, if any left.

In practice: The already used colours are the first  $u$  colours, say  $0, \dots, u - 1$ , so that the new colour to be considered is  $u$ . This breaks all the  $n!$  value symmetries in **constant time and constant space** overhead at every node explored! We say that it takes **constant amortised time & space**.

## Applications (Van Hentenryck [& Michel]):

- Scene allocation (*INFORMS J. of Computing*, 2002)
- Steel mill slab design (*CPAIOR 2008*)



# Partial Value Symmetry (*IJCAI 2003*)

Example (Partial value symmetry; often in instances)

Weekdays vs weekend days; same-size boats.

## Clustering:

Let  $D = D_1 \cup D_2 \cup \dots \cup D_m$  be the domain of the variables, where the values in each set  $D_i$  are fully interchangeable (full value sym for  $m = 1$ ): cluster the variables for each  $D_i$ .

## Search procedure at constant amortised time & space:

In each set  $D_i$ , only the values already used and **one** so far unused value need to be tried.

## Application (Michel, ..., Van Hentenryck, *CPAIOR'08*):

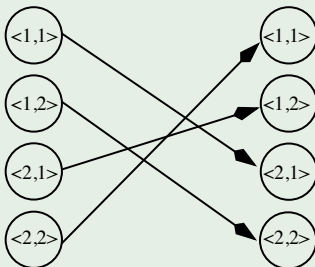
- Eventually-serialisable data service deployment



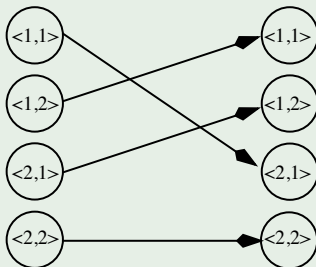
# Wreath Value Symmetry (IJCAI 2003)

## Example (Wreath value symmetry)

Schedule meetings in (day, room) pairs,  
where the days are interchangeable,  
and the rooms are interchangeable within each day:



Wreath permutation



**Not** a wreath permutation!



## Clustering:

Let  $D = D_1 \times D_2$  be the domain of the pairs of variables, where the values in each set  $D_i$  are fully interchangeable (full value symmetry for  $|D_2| = 1$ ): one cluster for  $D_1$ , and  $m$  clusters for  $D_2$  when  $m$  values of  $D_1$  are used, with variable clustering as for full value symmetry.

## Search procedure at constant amortised time & space:

- 1 For the first value component, in set  $D_1$ , only the values already used and **one** so far unused value need to be tried. Let  $d_1 \in D_1$  be the chosen value.
- 2 For the second value component, in set  $D_2$ , only the values already used with  $d_1$  and **one** so far unused value need to be tried.



## Selected Other Results

Consider a combinatorial problem with  $n$  decision variables over a domain of  $k$  values:

- **Generalisation to any value symmetry:**

- group equivalence (GE) trees

- (Roney-Dougal *et al.*, *ECAI 2004*)

- ☞  $O(n^4)$  time overhead at every node explored.

- **Partial variable symmetry + partial value symmetry**

- (Sellmann & Van Hentenryck, *IJCAI 2005*)

- ☞  $O(k^{2.5} + n \cdot k)$  time at every node explored.

- ☞ Coinage of the term **structural symmetry breaking**.

- ☞ Can be specialised for full variable symmetry only.



# Tractability: State of the Art

		variable symmetry				
		none	full	partial	wreath	
value symmetry	none		P <b>P</b>	P <b>P</b>	P <b>P</b>	scalar problem <b>set problem</b>
	full	P <b>P</b>	P <b>NP</b>	P <b>NP</b>	NP <b>NP</b>	scalar problem <b>set problem</b>
	partial	P <b>P</b>	P <b>NP</b>	P <b>NP</b>	NP <b>NP</b>	scalar problem <b>set problem</b>
	wreath	P <b>P</b>	P <b>NP</b>	P <b>NP</b>	NP <b>NP</b>	scalar problem <b>set problem</b>
	any	P				scalar problem <b>set problem</b>

P: All symmetric sub-trees can be eliminated with a polynomial time & space overhead at every node explored.

NP: Dominance-detection schemes (in SBDD style) are NP-hard.





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