

# Topic 5: Search<sup>1</sup>

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



# 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
  - ...



# Outline

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Branching

Exploration

**1** Branching

**2** Exploration



# Outline

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Branching

Exploration

**1** Branching

2 Exploration



## Definition (Brancher)

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

- **Contraction:**  $\forall i : s_i \preceq s$ . (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** is  $\text{Propagate}(P, P, s_0)$ .
- Node  $\langle R, s \rangle$  has the  $n$  nodes  $\text{Propagate}(R \cup R_i, R_i, s)$  as **children**, where  $b(R, s) = \langle R_1, \dots, R_n \rangle$  with  $n \neq 1$ ; it is a **leaf** if  $s = \emptyset$  (**failed** node) or  $n = 0$  (**solved** node).



## Definition (Variable selection strategies)

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** ( $= |\{p \in R \mid v \in \text{var}(p)\}|$ ) in  $R$ .
- **AFCmin**: Select **a** variable unfixed by  $s$  with the smallest accumulated failure count.
- ...

Ties are broken under any combination of these strategies.

See Topic 9 for selection strategies for set variables.



## Definition (Value selection strategies)

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

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

We assume domains are ordered.

## Definition (Decisions, or guesses)

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  $\{v = d_1\}, \dots, \{v = d_n\}$ .
- ...

See Topic 9 for selection strategies for set variables.



# First-Fail Brancher

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Branching

Exploration

## 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  $\langle \rangle$ 
```



# Outline

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Branching

Exploration

1 Branching

2 **Exploration**



## 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

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## 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.