## Search techniques in Constraint Programming

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## Outline

(1) Backtrack Search

- Variable Ordering
- Value Ordering (Branching)
- Restarts \& Randomization
(2) Discrepancy Search techniques


## Search Algorithms

- Tree Search
- Given a decision (a constraint) for example $x=v$, either:
$\star$ there exists a solution where $x=v$
$\star$ there exists a solution where $x \neq v$
$\star$ there is no solution
- Typical decisions (fix a value, split a domain, enforce a precedence, ...)
- Exploring both branches gives a complete algorithm
$\star$ In practice, it is often possible to detect inconsistencies after assigning only a few variables
$\star$ Before each decision, there is a propagation step to enforce local consistencies


## Variable Ordering

- The order in which variables are explored matters!
- During search, most of the time is spent in unsatisfiable sub-trees
- Detecting failure early (fail first)
- Start with variables that are most likely to "fail"
$\star$ Smallest domain size (less freedom, smaller branching factor)
* Maximum degree (most constrained variable)
$\star$ Minimum $\frac{\text { domain size }}{\text { degree }}$


## Coloring



## Lexicographic



## Lexicographic



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## Lexicographic



## Maximum Degree



## Maximum Degree



## Maximum Degree



## Maximum Degree



## Minimum Domain



## Minimum Domain



## Minimum Domain



## Minimum Domain



## Minimum Domain / Degree



## Minimum Domain / Degree



## Minimum Domain / Degree



## Minimum Domain / Degree



## Minimum Domain / Degree



## Minimum Domain / Degree



## Minimum Domain / Degree



## Weighted Degree Heuristic

- The weight of a constraint is initialised to 1
- When propagating, if a contradiction is detected on that constraint, its weight is increased by 1
- The weight of a variable is equal to the sum of the weights of its neighboring constraints

$$
\operatorname{weight}(x)=\sum_{c \text { s.t. } x \in \mathcal{X}(c)} \text { weight }(c)
$$

- Domain over weigthed degree:
- The variable that minimizes the ratio $\frac{\text { domain size }}{\text { weight }}$ is selected first


## Impact

- The impact $I(x, v)$ of a pair $(x, v)$ is initialised to 0
- The size of the search space of a network $\mathcal{P}=(\mathcal{X}, \mathcal{D}, \mathcal{C})$ is bounded by $\prod_{x \in \mathcal{X}}|\mathcal{D}(x)|$
- When the decision $x=v$ is succesful
- Let $b$ be the size of the search space of $\mathcal{P}=(\mathcal{X}, \mathcal{D}, \mathcal{C})$ (before the decision)
- Let $a$ be the size of the search space of $\mathcal{P}^{\prime}=\mathrm{AC}(\mathcal{X}, \mathcal{D}, \mathcal{C} \cup(x=v))$ (after the decision)
- The impact of this decision corresponds to the reduction of the search space: $\frac{b-a}{b}$
- The impact of $(x, v)$ is the average impact computed for all decisions $x=v$.
- The weight of a variable $x$ is $\sum_{v \in \mathcal{D}(x)} \frac{1}{T(x, v)}$, the variable with minimum weight is selected first


## Value Ordering

- Often considered less important than variable ordering
- Most of the search effort is spent in unsatisfiable subtrees
- Value ordering does not really matter in an unsatisfiable subtree since it must be fully explored
- In satisfaction problems:
- Choosing a satisfiable subtree when branching (promise: choose the least constrained value)
- In optimisation problems:
- Choosing the assignment that is likely to give the best objective value in order to get good upper bounds quickly


## Heavy Tail Behavior

- Given a collection of instances of a problem, we often observe a few exceptionally hard instances
- These instances are rare, but take exceptionally longer to solve
- Large impact on the mean runtime for a given set
- As opposed to normal distributions, the mean does not stabilize when the size of the sample grows
$\star$ When the sample grows, the mean runtime is skewed up
$\star$ Heavy tail behavior
- Not a characteristic of the instance, the same behavior behavior is observed if we run several times the same instance while varying some parameter of the solver
- For some combination instance / solver parameters, we get trapped into an exponential subtree


## Heavy Tail Behavior

- Randomization:
- Add some randomized parameter in variable or value selection (for instance to break ties)
- Given the same random seed the solver will explore the same tree, however it will never explore two identical subproblems in the same way
- Restarting:
- After a given limit $r$, for instance in number of explored nodes: restart from scratch
- Randomization + restarts eliminates the huge variance in solver performance
- And therefore reduces the mean runtime when a heavy tail behavior could be observed
- Which limit $r$ should we use?
- Geometric: $r_{i}=f^{i} b$

$$
\star b=100, f=2: 100,200,400,800, \ldots
$$

- Luby:

$$
\begin{aligned}
& \star \quad r_{i}=2^{i-1} b \text { if } i=2^{k}-1 \\
& \star \quad r_{i-2^{k-1}+1} b \text { if } 2^{k-1} \leq i \leq 2^{k}-1 \\
& \star \quad b=10: 10,10,20,10,10,20,40,10,10,20,10,10,20,40,80 \ldots
\end{aligned}
$$

## Outline

(1) Backtrack Search
(2) Discrepancy Search techniques

## Limits of heuristics

- Idea of Limited Discrepancy Search:
- A heuristic is never perfect
- But if we trust it, we want to search first as close as possible to the advised decisions.
- Idea of Depth Bounded Discrepency Search:
- Early choices are less informed
- A heuristic is generally less reliable at the top of the tree


## Limited Discrepancy Search



Depth-bounded discrepancy search


