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# Backtracking Search Algorithms

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# General Idea

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- Backtracking Search Algorithms are complete search methods: given sufficient time and space, they are guaranteed to find a solution if one exists.
- The search proceeds by building up a solution little by little, and when a deadend is discovered, the algorithm *backtracks* to a point where the deadend could have been avoided.

# Overview of the Presentation

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- Branching strategies: what the branches of the search are like.
- Constraint Propagation: how to reduce the search space *as the search progresses*.
- Nogoods: how to characterize deadends.
- Backjumping: how to backtrack to a point where all was not lost.

# Preliminaries

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- A constraint satisfaction problem (CSP) consists of a set of variables  $X = \{x_1, \dots, x_n\}$ ; a set of values  $D = \{a_1, \dots, a_d\}$ , where each variable  $x_i \in X$  has an associated finite domain  $dom(x_i) \subseteq D$  of possible values; and a collection of constraints.
- A constraint  $C$  is a relation — a set of tuples — over some set of variables, denoted  $vars(C)$ .
- A solution to a CSP is an assignment of a value to each variable that satisfies all the constraints.

# 6-queens running example

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- A variable for each column of the board  $\{x_1, \dots, x_6\}$ , each with domain  $dom(x_i) = \{1, \dots, 6\}$ .
- Assigning a value  $j$  to a variable  $x_i$  means placing a queen in row  $j$ , column  $i$ .
- For  $1 \leq i < j \leq 6$  there is a constraint  $C_{ij}$ , given by  $(x_i \neq x_j) \wedge (|i - j| \neq |x_i - x_j|)$ .

# Search Trees

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- A (chronological) backtracking search resembles depth-first traversal of a search tree, which is generated as the search progresses.
- The method of extending a node of the tree is called *branching strategy*.
- A node in the search tree is a *deadend* if it does not lead to a solution.
- (whiteboard example of the naive backtracking algorithm for the 6-queens problem)

# Branching Strategies

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- In the naive BT, a node  $p = \{x_1 = a_1, \dots, x_j = a_j\}$  was extended by selecting an uninstantiated variable  $x$  and adding a branch to a new node  $p \cup \{x = a\}$  for each  $a \in \text{dom}(x)$ .
- More generally, a node  $p = \{b_1, \dots, b_j\}$  is a set of *branching constraints*, where  $b_i, i \leq j$  is the branching constraint *posted* at level  $i$ . A node  $p$  is extended by adding the branches to nodes  $p \cup \{b_{j+1}^1\}, \dots, p \cup \{b_{j+1}^k\}$ . The branching constraints have to be mutually exclusive and exhaustive.
- This presentation considers only unary branching constraints.

# Branching Strategies (continued)

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The three most common branching strategies are:

- *Enumeration or d-way branching*: A branch is generated for each value in the domain of an uninstantiated variable  $x$ . (see the naive BT)

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- *Domain splitting*: Given an uninstantiated  $x$ , the domain of  $x$  is split into sub-domains. For example, if  $\text{dom}(x) = \{1, 2, 3, 4\}$ , constraints  $x \leq 2$  and  $x > 2$  could be posted.

# Constraint Propagation in BT

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Motivation and intuition:

- As we have learnt in the previous presentations, CP can dramatically reduce the search space of a CSP.
- In the worst case (when no solution exists), backtracking algorithms have to go through the entire search space, so such reduction would be welcome.
- Each time a branching constraint is posted, applying constraint propagation may reduce the domains of still uninstantiated variables, which simplifies the subproblem. Furthermore, if some domain becomes empty, we have come to a deadend and may backtrack.

# Maintaining Arc Consistency

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- Arc Consistency: Given a constraint  $C$ , a value  $a \in \text{dom}(x)$  for a variable  $x \in \text{vars}(C)$  is said to have a *support* in  $C$  if there exists a tuple  $t \in C$  such that  $a = t[x]$  and  $t[y] \in \text{dom}(y)$  for every  $y \in \text{vars}(C)$ . A constraint  $C$  is said to be *arc consistent* if for each  $x \in \text{vars}(C)$ , each value  $a \in \text{dom}(x)$  has a support in  $C$ .

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- (whiteboard example for the 6-queens problem)

# The Cost of Constraint Propagation

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- While CP may simplify the subproblem, it adds the extra cost of running the CP algorithm.
- One way to reduce the extra cost is to only apply CP to certain constraints
  - Forward Checking (FC) maintains arc consistency only on constraints with one uninstantiated variable (whiteboard example).

# Nogoods

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- A Nogood is a set of branching constraints that is not consistent with any solution.
- For example, in the 6-queens problem,  $\{x_1 = 2, x_2 = 5\}$  is a nogood, because it is not contained in any solution.
  - After this has been discovered somehow, a new constraint  $(x_1 \neq 2 \vee x_2 \neq 5)$  can be added.
  - $(x_1 \neq 2 \vee x_2 \neq 5)$  is called an *implied constraint*, because it does not affect the set of solutions to the CSP.

# Discovering Nogoods

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- *Jumpback nogood*: Let  $p = \{b_1, \dots, b_j\}$  be a deadend node in the search tree, where  $b_i$  is the branching constraint posted at level  $i$  in the search tree. In the case where no constraint propagation is performed, jumpback nogood for  $p$ ,  $J(p)$ , is defined recursively as follows:

# Jumpback definition

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1.  $p$  is a leaf node. Let  $C$  be a constraint that is not consistent with  $p$ :

$$J(p) = \{b_i \mid vars(b_i) \cap vars(C) \neq \emptyset, 1 \leq i \leq j\}.$$

2.  $p$  is not a leaf node. Let  $\{b_{j+1}^1, \dots, b_{j+1}^k\}$  be all the possible extensions of  $p$  attempted by the branching strategy, each of which has failed:

$$J(p) = \bigcup_{i=1}^k (J(p \cup \{b_{j+1}^i\}) \setminus \{b_{j+1}^i\}).$$

# Jumpback example

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Consider node

$p = \{x_1 = 2, x_2 = 5, x_3 = 3, x_4 = 1, x_5 = 4\}$  in the 6-queens search tree. All attempts to expand the node on  $x_6$  will fail, so we get the following:

$$\begin{aligned} J(p) &= \bigcup_{k=1}^6 (J(p \cup \{x_6 = k\}) \setminus \{x_6 = k\}) \\ &= \{x_2 = 5\} \cup \dots \cup \{x_3 = 3\} \\ &= \{x_1 = 2, x_2 = 5, x_3 = 3, x_5 = 4\} \end{aligned}$$

Notice that it matters which constraint is chosen at the leaf nodes! Also, there is no  $x_4$  in  $J(p)$ !

# Eliminating explanation

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- An eliminating explanation is a constraint that is sufficient to account for the removal of a value from a domain.
- *Eliminating explanation*: Let  $p = \{b_1, \dots, b_j\}$  be a node in the search tree and  $a \in \text{dom}(x)$  be a value that is removed from the domain of a variable  $x$  by constraint propagation at node  $p$ . Eliminating explanation  $\text{expl}(x \neq a)$  is a subset of  $p$  such that  $\text{expl}(x \neq a) \cup \{x = a\}$  is a nogood.
- In the 6-queens, when  $p = \{x_1 = 2, x_2 = 5\}$ ,  $\text{expl}(x_6 \neq 1) = \{x_2 = 5\}$ .

# Jumpbacks with CP

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Eliminating explanations allow us to generalize the definition of jumpback nogoods to deadends found by constraint propagation:

1.  $p$  is a leaf node.

$$J(p) = \bigcup_{a \in \text{dom}(x)} \text{expl}(x \neq a)$$

2.  $p$  is not a leaf node. Same as before.

# Non-Chronological Backtracking

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- Upon discovering a deadend, the standard backtracking algorithms retract the most recently posted constraint.
- If the most recent constraint does not bear responsibility for the deadend, it is more efficient to retract further back in history.
- Let  $J(p) \subseteq p$  be a nogood at  $p$ . Backjump point is the largest  $i$  such that  $b_i \in J(p)$ . (whiteboard example of  $p = \{x_1 = 2, x_2 = 5, x_3 = 3, x_4 = 1\}$ )

# Partial Order Backtracking

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- Partial order backtracking is an even more “relaxed” way of backtracking: it does not care about the order in which branching constraints have been posted, but creates an order of its own based on discovered nogoods.
- Notice that a nogood  $((x_1 = a_1), \dots, (x_j = a_j))$  can be written as
$$((x_1 = a_1) \wedge \dots \wedge (x_{j-1} = a_{j-1})) \Rightarrow (x_j \neq a_j).$$
- Now such a nogood induces order
$$(x_j = a_j) \geq (x_1 = a_1), \dots, (x_j = a_j) \geq (x_{j-1} = a_{j-1}).$$

# Partial Order Continued

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- When backtracking, a maximal branching constraint should be chosen. If not possible and a non-maximal  $(x = a)$  has to be chosen, then the ordering relation has to be relaxed wherever  $(x = a)$  appears.
- It is not clear to me how to choose a branching constraint of a nogood to be the right side of the equation. I guess it is simply arbitrary.
- If time is not up, an example of a method to compute eliminating explanations.