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# Features

# Basics

Features

▷ Basics

Satisficing Search

Optimization Search

- Consider problems where a solution is a single state (Sudoku, schedule).
- Instead of treating each state like a black box, one can reason about the *features* of a state.
- Each feature is mapped to a *variable*, which has a set of possible values, its *domain*.
- A *possible world* is an assignment of values to the variables. A valid possible world is a *model*.
- A *hard constraint* specifies valid combinations of values for, typically, a small subset of the variables.
- A *soft constraint* specifies the costs of different combinations of values.

# Constraint Satisfaction Problems

Features

Satisficing Search

▷ CSPs

GAC Algorithm

Example CSP

Domain Splitting

Optimization Search

- A Constraint Satisfaction Problems (CSP) consist of a set of variables, a domain for each variable, and a set of (hard) constraints.
- One way to solve CSPs is to use *arc consistency*.
  - Each variable  $X$  starts with all of its possible values.
  - A possible value  $x$  can be eliminated if arc inconsistent with a constraint  $c$ .
  - This means no combination of possible values allowed by  $c$  includes  $X = x$ .
- To solve CSPs, combine arc consistency with domain splitting, trying all values of a variable.

# Generalized Arc Consistency

Features

Satisficing Search

CSPs

▷ GAC Algorithm

Example CSP

Domain Splitting

Optimization Search

Procedure  $GAC(V, C, D)$

Inputs:  $V$ : a set of variables

$C$ : a set of constraints

$D_X$ : a set of values for each variable  $X$

Output: an arc-consistent  $D$

repeat until no more changes are made

for each constraint  $c \in C$

for each variable  $X$  used by  $c$

for each value  $x \in D_X$

if  $X = x$  is not valid for  $c$  and  $D$

remove  $x$  from  $D_X$

return  $D$

# Example CSP

Features

Satisficing Search

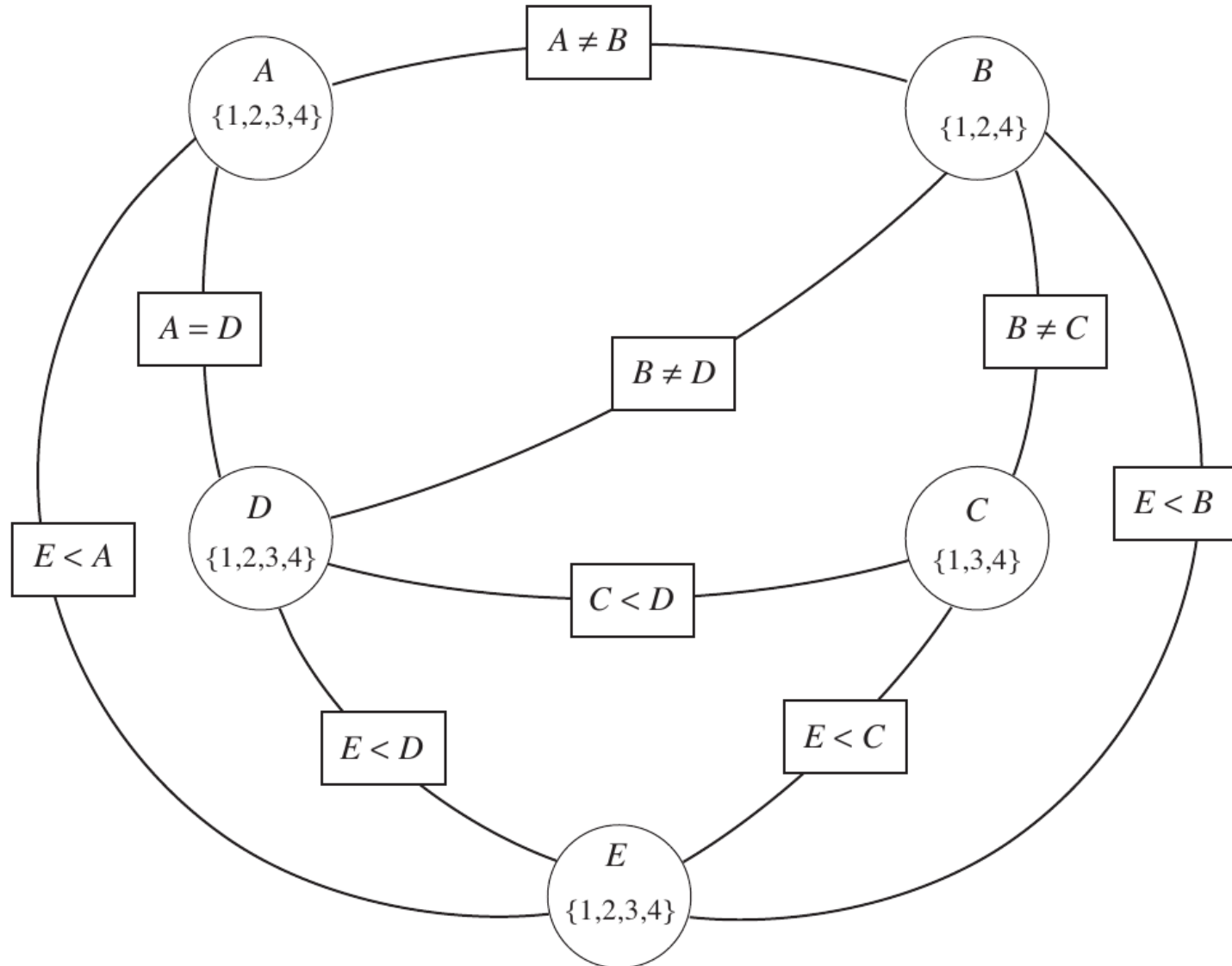
CSPs

GAC Algorithm

▷ Example CSP

Domain Splitting

Optimization Search



# Domain Splitting

Features

Satisficing Search

CSPs

GAC Algorithm

Example CSP

▷ Domain Splitting

Optimization Search

Procedure  $DS(V, C, D)$

Inputs:  $V$ : a set of variables

$C$ : a set of constraints

$D_X$ : a set of values for each variable  $X$

Output: null or a solution  $D'$

$D \leftarrow GAC(V, C, D)$

if some  $D_X = \emptyset$  return null

if every  $D_X$  has one value return  $D$

$X \leftarrow$  some variable where  $|D_X| > 1$

for each value  $x \in X$

$D' \leftarrow DS(V, C, \text{copy of } D \text{ with } D'_X = \{x\})$

if  $D' \neq \text{null}$  return  $D'$

return null

# Local Search

## Features

### Satisficing Search

### Optimization Search

#### ▷ Local Search

#### Iterative

#### Improvement

#### Local Optima

#### Randomization

#### Genetic Algorithms

Local search methods try to improve an assignment to the variables by taking a series of small steps. The goal is to to efficiently find good solutions.

Procedure *Local-Search*( $V, C$ )

Inputs:  $V$ : a set of variables

$C$ : a set of constraints

Output: a solution  $A$

$A \leftarrow$  an assignment of variables to values

while  $A$  does not satisfy  $C$

$A \leftarrow$  choose a “neighbor” of  $A$

return  $A$

# Iterative Improvement

Features

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Local Search

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Improvement

Local Optima

Randomization

Genetic Algorithms

- An *evaluation function* provides the value of each state.
  - For CSPs, one could use the number of constraints that are not satisfied.
- *Hill climbing* selects the best neighbor.
- For continuous variables, *gradient descent* changes all the variables based on partial derivatives.



# Local Optima

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The problem with iterative improvement is finding states that are locally optimal, but far from globally optimal.



# Randomization

Features

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▷ Randomization

Genetic Algorithms

Use *randomization* to avoid local optima.

- Random restart: repeatedly start local search with different assignments.
- Random walk: interleave random steps with improvement steps.
- Tabu list: avoid recently used variable-value assignments to try to avoid cycles.
- Simulated annealing: Start local search with mostly random steps and gradually increase the proportion of improvement steps.

# Genetic Algorithms

Features

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▷ Genetic Algorithms

Genetic algorithms is a popular local search method, inspired by natural selection.

- Population: Instead of storing one assignment (individual) at a time, store many individuals.
- Mutation: A new individual can be generated by random small steps from an old individual.
- Crossover: A new individual can be generated by combining the variable assignments of two old individuals.
- Random Selection: Select the new population using the evaluation function combined with some randomness.