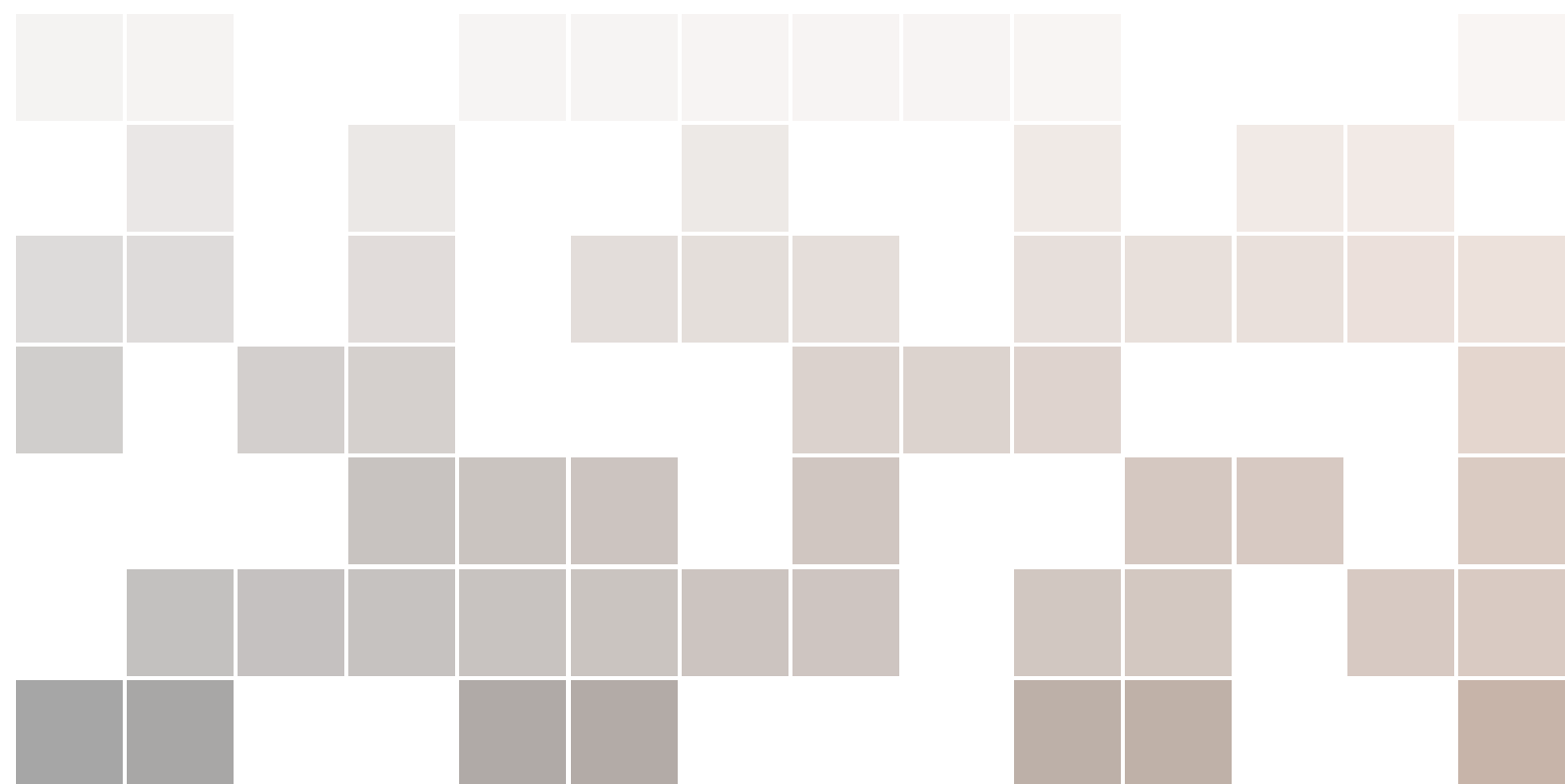


# Representation and Reasoning for Intelligent Systems

Stefan Klaus



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## Constraint Satisfaction Problem

### Basic terms about CSP:

Node Consistency

### Arc Consistency Algorithm(AC-3)

### Path consistency

### Backtracking

Improving backtracking efficiency

Forward checking

Arc consistency

### Structure

Tree-structure CSPs

Algorithm for tree-structured CSPs

Nearly tree-structured CSPs

### Local Search for CSPs

Min-Conflict Algorithms

# 1. Chapter 1:Constraint Satisfaction Problem

## 1.1 Constraint Satisfaction Problem

Constraint satisfaction problems(CSP) are mathematical problems defined as a set of objects whose state must satisfy a number of constraints or limitations. One example of a CSP is the game “Sudoku”

## 1.2 Basic terms about CSP:

- an assignment is to assign values to some or all variables
- an assignment that does not violate any constraints is called a consistent assignment. With values from domain  $D_i$
- A complete assignment is one in which each variable is assigned
- a partial assignment is one that assigns value to some of the variables

### Constraint graph

Binary CSP: each constraint relates at most two variables, e.g: WASA constraint graph: nodes are variables(e.g. region WA), arcs show constraints(e.g. WASA)

### Varieties of Variables

#### Discrete variables

- Finite Domains
- boolean CSPs, include: boolean satisfiability(NP - complete)
- Sudoku
- Infinite Domains(Integers, Strings, etc.)
- job scheduling, variables are start/end days for each job, need a constraint language, e.g.  
 $StartJob_1 + 5 \leq StarJob_3$

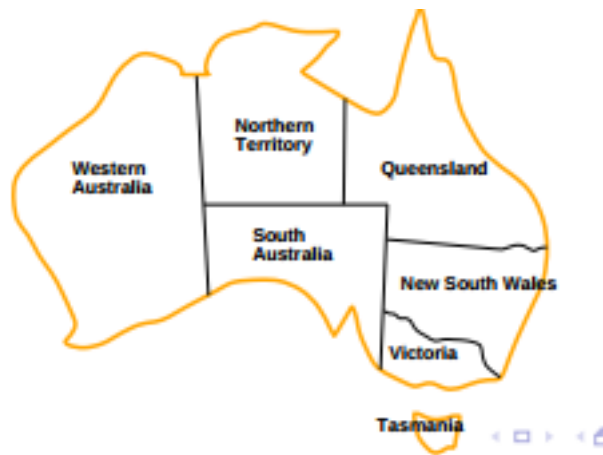
#### Continuous variables

- start /end times for Hubble Telescope observations
- Unary constraints involve a single variable
  - $SA \neq Green$

- binary constraints involve pairs of variables
  - $SA \neq WA$
- Higher-order constraints involve 3 or more variables
  - cryptarithmic column constraints
- Preferences(soft) constraints
  - red is better than green
  - CSPs with preference are often with optimization search algorithms constraints optimization problems

### 1.2.1 Node Consistency

If a node is node-consistent if all the value's domain satisfy the variable's unary constraints.



Example:

$D = \text{Red, Green, Blue}$

Variable  $X$

$X$  dislikes green, then  $X$  starts with  $D = \text{Red, Green, Blue}$ , and becomes node consistent after eliminating Green.  $X$  is node consistent with the reduced domain,  $D = \text{Red, Blue}$ .

### Arc Consistency

$X_i$  is arc-consistent with respect to another variables  $X_j$  if for every value in  $X_i$ 's current domain  $D_i$  there is one value in  $X_j$ 's domain  $D_j$  that satisfies the binary constraint on the arc  $(X_i, X_j)$

Example:

Given two variables  $X_i, X_j$  with values in  $0, 1, 2, \dots, 9$  and constraints  $(0, 0), (1, 1), (2, 4), (3, 9)$ .

To make  $X_i$  arc-consistent with respect to  $X_j$ , we reduce  $X_i$ 's domain to  $0, 1, 2, 3$ .

To make  $X_j$  arc-consistent with respect to  $X_i$ , we reduce  $X_j$ 's domain to  $0, 1, 4, 9$ .

### 1.3 Arc Consistency Algorithm(AC-3)

**function** AC-3(*csp*) **returns** false if an inconsistency is found and true otherwise

**inputs:** *csp*, a binary CSP with components ( $X, D, C$ )

**local variables:** *queue*, a queue of arcs, initially all the arcs in *csp*

```

while queue is not empty do
  ( $X_i, X_j$ )  $\leftarrow$  REMOVE-FIRST(queue)
  if REVISE(csp,  $X_i, X_j$ ) then
    if size of  $D_i = 0$  then return false
    for each  $X_k$  in  $X_i$ .NEIGHBORS -  $\{X_j\}$  do
      add ( $X_k, X_i$ ) to queue
return true

```

**function** REVISE(*csp*,  $X_i, X_j$ ) **returns** true iff we revise the domain of  $X_i$

*revised*  $\leftarrow$  false

**for each**  $x$  **in**  $D_i$  **do**

**if** no value  $y$  in  $D_j$  allows  $(x, y)$  to satisfy the constraint between  $X_i$  and  $X_j$  **then**

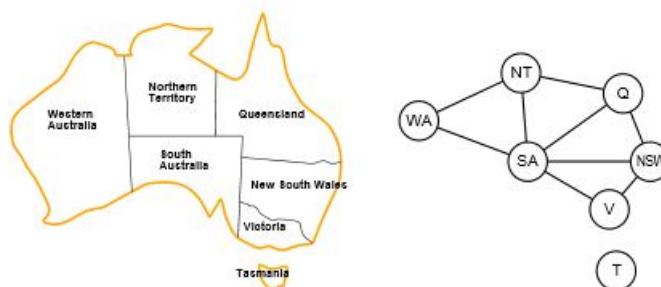
    delete  $x$  from  $D_i$

*revised*  $\leftarrow$  true

**return** *revised*

1. initially let a queue contain all arcs
2. remove an arc  $(X_i, X_j)$  from the queue and make the variable  $X_i$  arc-consistent to  $X_j$ 
  - (a) IF  $X_i$  domain  $D_i$  is unchanged, then check the next arc in the queue
  - (b) IF  $X_i$  's domain  $D_i$  is revised(smaller), then add all arcs  $(X_k, X_i)$  in the queue
  - (c) If  $X_i$  's domain  $D_i$  is empty, then CSP no solution
3. Keep checking all arcs in the queue until the queue is empty

### 1.4 Path consistency



A two variable set  $X_i, X_j$  is path consistency with respect to a third variable  $X_m$  if for every assignment  $X_i = a, X_j = b$  consistent with the constraints on  $X_i, X_j$ , where is an assignment to  $X_m$ , that satisfies the constraints on  $X_i, X_m$  and  $X_m, X_j$

Example:

Can we color the Australia map with two colors?

Make the set WA, SA path consistent with respect to NT?

Assignments: WA = blue, SA = red or WA =blue,SA=red

But no assignment exists for NT

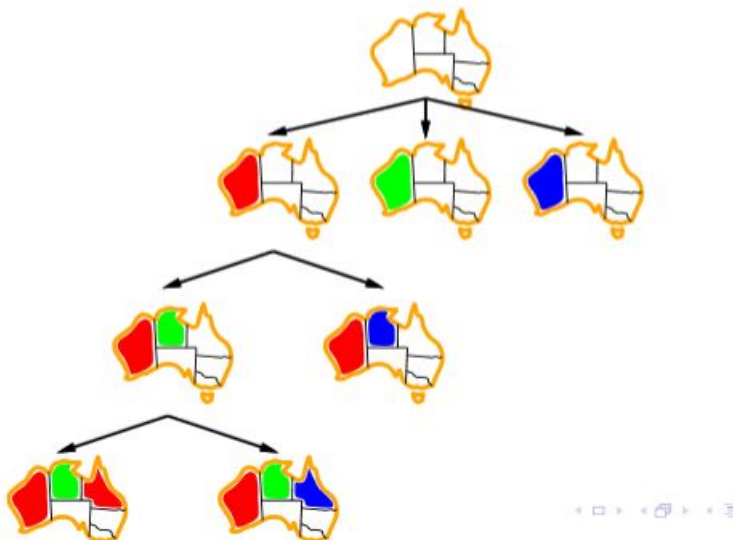
### Constraint propagation

- constraint propagation is a specific type of inference
  - use the constraints to reduce the number of legal values for a variable, which in turn can reduce the legal values for another variable, and so on
- node consistency
- arc consistency
- path consistency
- k-consistency: k variables involved
- Global consistency

### Limits

- Indeed AC-3 works for the easiest Sudoku puzzles
- slightly harder ones can be solved by PC-2, but at a greater computational cost: there are 255,960 different path constraints to consider in a Sudoku puzzle
- To solve the hardest puzzles and to make efficient progress, we will have to be more clever

## 1.5 Backtracking



1. Select an unassigned value
2. assign values
3. Depth-first search
4. If an inconsistency is detected, then BACKTRACK returns failure, causing the previous call to try another value

Backtracking search is a depth-first search for CSPs

- choose values for one variable at a time
- backtrack when a variables has no legal left to assign

Backtracking search is the basic uninformed algorithm for CSP. Can solve n-queens for  $n \approx 25$ .



```

function BACKTRACKING-SEARCH(csp) returns a solution, or failure
  return BACKTRACK({ }, csp)

function BACKTRACK(assignment, csp) returns a solution, or failure
  if assignment is complete then return assignment
  var ← SELECT-UNASSIGNED-VARIABLE(csp)
  for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
    if value is consistent with assignment then
      add { var = value } to assignment
      inferences ← INFERENCE(csp, var, value)
      if inferences ≠ failure then
        add inferences to assignment
        result ← BACKTRACK(assignment, csp)
        if result ≠ failure then
          return result
      remove { var = value } and inferences from assignment
  return failure

```

### 1.5.1 Improving backtracking efficiency

General-purpose methods can give huge gains in speed:

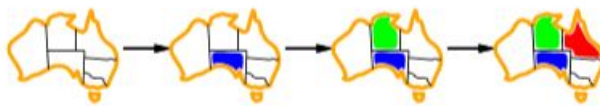
1. which variable should be assigned next?
2. in what order should values be tried?
3. can we detect inevitable failure early?
4. Can we take advantage of problem structure?

#### Minimum remaining values

Minimum remaining values (MRV): choose the variable with the fewest legal values.

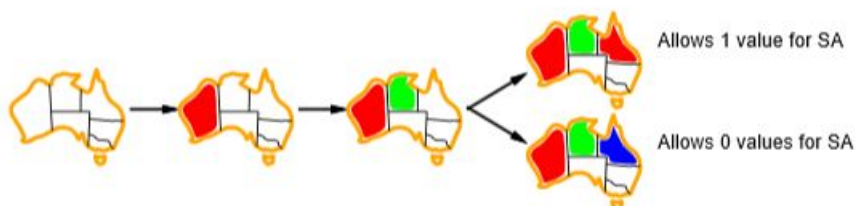
#### Degree heuristic

- Tie-breaker among MRV variables
- Degree heuristic: choose the variable with the most constraints on remaining variables



#### Least constraining value

Given a variable, choose the least constraining value: the one that rules out the fewest values in the remaining variables.

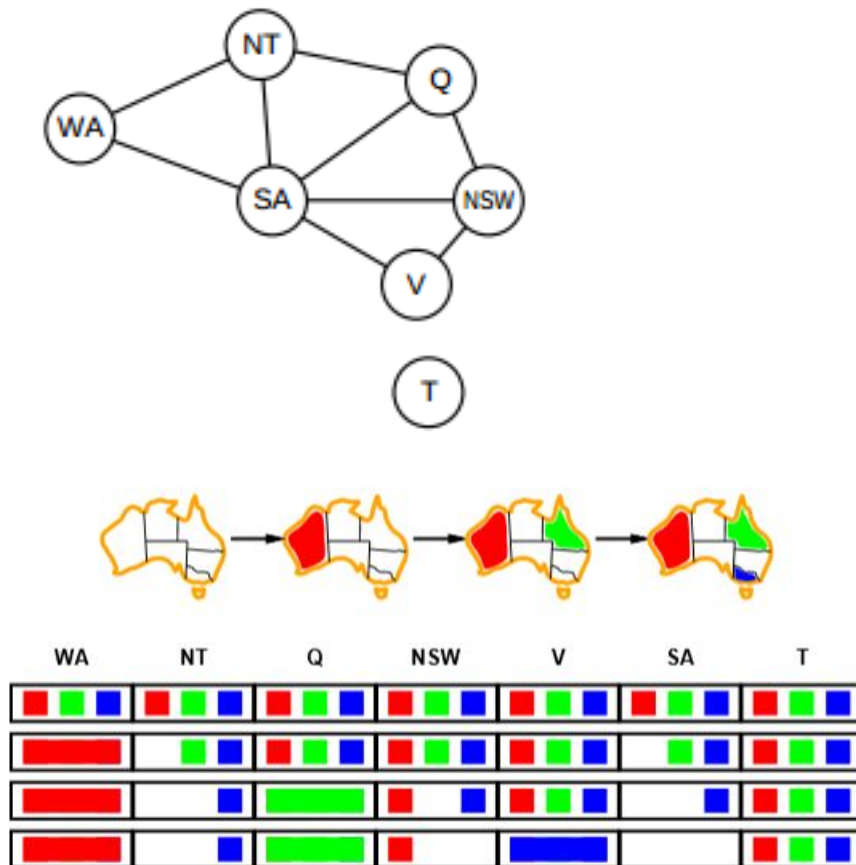


these heuristics makes 1000 queens feasible.

Combining

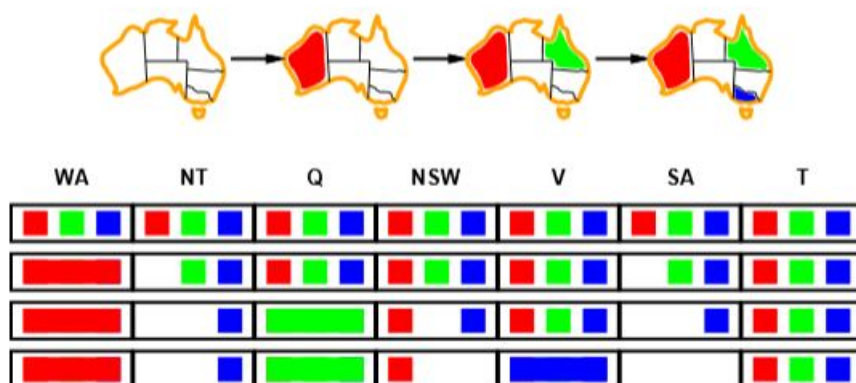
### 1.5.2 Forward checking

Idea: Keep track of remaining legal values for unassigned variables.  
Terminates search when any variable has no legal values.



#### Constraint propagation

Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:



NT and SA cannot both be blue!

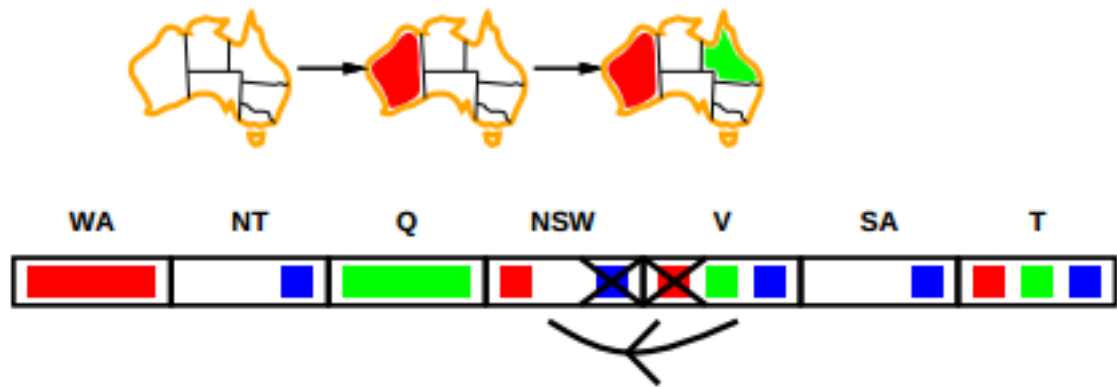
Constraint propagation repeatedly enforces constraints locally.

### 1.5.3 Arc consistency

Simplest form of propagation makes each arc consistent.

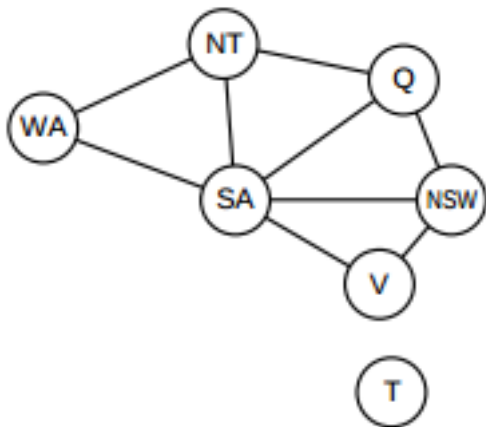
$X \rightarrow Y$  is consistent if for every value  $x$  of  $X$  there is some allowed  $y$

If  $X$  loses a value, neighbours need to be rechecked.



Arc consistency detects failure earlier than *forward checking*. Can be run as a predecessor or after each assignment.

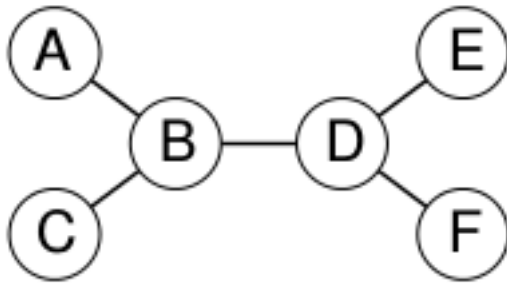
## 1.6 Structure



Tasmania and mainland Australia are independent subsections which can be identified as connected components of constraint graph.

- Suppose each subproblem has a  $c$  variable out of  $n$  total
- Worst-case solution cost is  $n/c * d^c$  linear in  $n$
- E.g.  $n = 80, d = 2, c = 20$ 
  - $2^{80} = 4$  billion years at 10 million nodes/sec
  - $2 * 2^{20} = 0.4$  seconds at 10 million nodes/sec

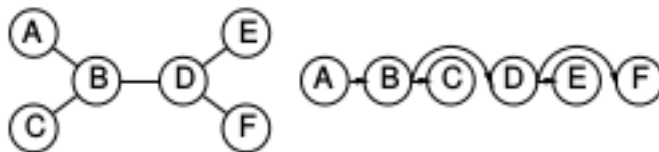
### 1.6.1 Tree-structure CSPs



- Theorem: if the constraint graph has no loops, the CSP can be solved in  $O(nd^2)$  time
- Compare to general CSPs, where worst-case time is  $O(d^n)$
- This property also applies to logical and probabilistic reasoning: an important example of the relation between syntactic restrictions and the complexity of reasoning

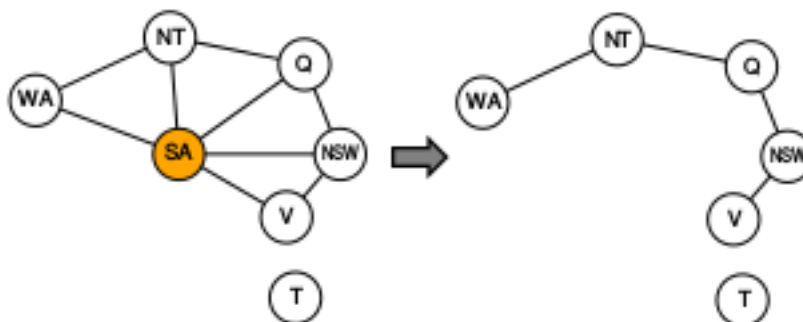
### 1.6.2 Algorithm for tree-structured CSPs

1. Choose a variable as root, order variables from root to leaves such that every node's parent precedes it in the ordering
2. For  $j$  from  $n$  down to 2, apply *RemoveInconsistent*(*Parent*( $X_j$ ),  $x_j$ )
3. For  $j$  from 1 to  $n$ , assign  $X_j$  consistently with *Parent*( $X_j$ )



### 1.6.3 Nearly tree-structured CSPs

- Conditioning: instantiate a variable, prune its neighbours domains
- Cutset conditioning: instantiate (in all ways) a set of variables such that the remaining constraint graph is a tree
- Cutset size  $c \Rightarrow \text{runtime } O(d^c * (n - c)d^2)$ , very fast for small  $c$



- Choose a subset  $S$  from  $VARIABLE[csp]$  such that the constraint graph becomes a tree after removal of  $S$
- For each possible assignment to the variables in  $S$  satisfies all constraint on  $S$ 
  - remove from the domains of the remaining variables any values that are inconsistent with the assignment of  $S$
  - If the remaining CSP has solution, then return it together the assignment to  $S$

## 1.7 Local Search for CSPs

- Local search, e.g. hill-climbing, simulated annealing for CSP
  - typically start with a "complete" state, i.e. all variables assigned to values, but may violated constraints
  - then search changes the value of one variable at each time for violated constraints
- Variable selection: randomly select any conflicted variable
- Value selection by min-conflicts heuristics:
  - choose value that violates the fewest constraints i.e. hillclimb with  $h(n)$  = total number of violated constraints

### 1.7.1 Min-Conflict Algorithms

**function** MIN-CONFLICTS(*csp*, *max\_steps*) **returns** a solution or failure

**inputs:** *csp*, a constraint satisfaction problem

*max\_steps*, the number of steps allowed before giving up

*current*  $\leftarrow$  an initial complete assignment for *csp*

**for** *i* = 1 to *max\_steps* **do**

**if** *current* is a solution for *csp* **then return** *current*

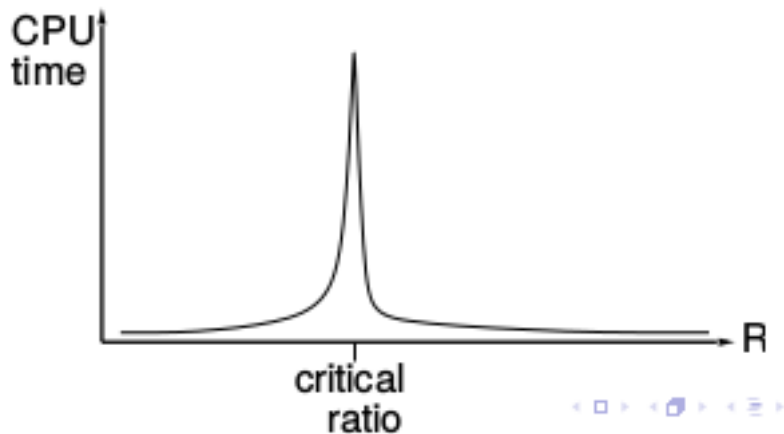
*var*  $\leftarrow$  a randomly chosen conflicted variable from *csp*.VARIABLES

*value*  $\leftarrow$  the value *v* for *var* that minimizes CONFLICTS(*var*, *v*, *current*, *csp*)

  set *var* = *value* in *current*

**return** failure

- Given random initial state, can solve *n*-queens in almost constant time for arbitrary *n* with high probability (e.g.  $n = 10000000$ )
- The same to be true for any randomly-generated CSP *except* in a narrow range of the ratio  $R = \frac{\text{number of constraints}}{\text{number of variables}}$





## Uncertainty

Probability for handling uncertainty

## Probability

Event

Random variables

Probability Distribution

Prior probability

Joint Probability distribution

Conditional probability

Chain rule

## 2. Chapter 2:Uncertainty

### 2.1 Uncertainty

A purely logical approach may not work very well for statements which include multiple uncertain factors(e.g. Road accident on your way to the airport? Road work? Flooding? Nazi Zombies?

A purely logical approach would state: " $A_8$  will get me there on time."

Considering uncertain factors this would change to:"If there's no accident on the bridge, and it does not rain, and my tires remain intact etc, THEN  $A_8$  will get me there on time"

Reasons for that:

- Failure to enumerate exceptions, qualifications etc.
- No complete theory for the domain
- Lack of relevant facts, initial conditions and so on

#### 2.1.1 Probability for handling uncertainty

Probabilistic provides a way of summarizing the uncertainty.

An example for that would be: conditional probabilities can be used to represent:

- Given the available evidence,  $A_8$  will get me there on time with probability 0.8
- Given the available evidence,  $A_{10}$  will get me there on time with probability 0.9
- Given the available evidence,  $A_{12}$  will get me there on time with probability 0.99

Condition	Result	Probability
Given the available evidence	$A_8$	0.9
Given the available evidence	$A_{10}$	0.99
Given the available evidence	$A_{12}$	0.999

Table 2.1: Table representation of the different plans

Probability theory is a main tool for dealing with degrees of belief.



**Making decisions**

Suppose given the following statements:

$$\begin{aligned} P(A_8 \text{ gets me there on time} \mid \text{Condition}) &= 0.9 \\ P(A_{10} \text{ gets me there on time} \mid \text{Condition}) &= 0.99 \\ P(A_{12} \text{ gets me there on time} \mid \text{Condition}) &= 0.999 \\ P(A_{24} \text{ gets me there on time} \mid \text{Condition}) &= 0.9999 \end{aligned}$$

Given that, what actions to choose?

- Depends on preferences, e.g. the length of the wait at the airport

Utility theory is used to represent and infer preferences.

Decision theory = utility theory + probability theory

**2.2 Probability**

Subjective or Bayesian probability:

- Probabilities relate propositions to one's own state of knowledge, e.g.  $P(A_8 \mid \text{noreportedaccidents}) = 0.9$
- But might be learned from past experience from past experiences of similar situations
- Probabilities of propositions change with new evidence: e.g.  $P(A_8 \mid \text{noreportedaccidents, leaveat5am}) = 0.95$

Sample point:

A set  $\Omega$  - the sample space:  $\omega \in \Omega$  is a sample point or atomic event, e.g. 6 possible rolls of a dice.

A probability model/space is a sample space with assigning a probability for every  $\omega \in \Omega$

- $P(1) = P(2) = P(3) = P(4) = P(5) = P(6) = 1/6$
- Property:  $0 \leq P(\omega) \leq 1$  for every  $\omega \in \Omega$ ,  $\sum_{\omega \in \Omega} P(\omega) = 1$

**2.2.1 Event**

An event  $A$  is any subset of  $\Omega$ .

$$P(A) = \sum_{\omega \in A} P(\omega) \quad (2.1)$$

- An event is 'dice roll is less than 4'
- The probability of the event happening is  $P(\text{diceroll} < 4) = P(1) + P(2) + P(3) = 1/2$

In AI's language, the sets are described by propositions:

- $\phi$  is "dice roll is less than 4"
- $P(\phi) = \sum_{\omega \in \phi} P(\omega)$

**2.2.2 Random variables**

A random variable  $X : \Omega \rightarrow R$  is a function from sample points to some range, e.g., the reals or Boolean.

Let  $X(\omega)$  be a Boolean variable to represent whether a dicing result  $\omega$  is odd, then:



$X(1) = true$   
 $X(2) = False$

But usually written in short *Odd*  $P(Odd)$

### 2.2.3 Probability Distribution

For a random variable  $X$  taking values from  $x_1, \dots, x_k$  probability distribution  $P(X = x_i)$  is the probability of  $X$  taking the value of  $x_i$ :

$$\begin{aligned}
 P(odd = true) &= P(1) + P(3) + P(5) \\
 &= 1/6 + 1/6 + 1/6 \\
 &= 1/2 \\
 P(Odd = false) &= P(2) + P(4) + P(6) \\
 &= 1/6 + 1/6 + 1/6 \\
 &= 1/2
 \end{aligned}$$

### 2.2.4 Prior probability

Prior or unconditional probabilities refer to degrees of belief in propositions in the absence of any other information

- $P(Cavity = true) = 0.1$
- $P(Weather = Sunny) = 0.72$

Probability distribution gives values for all possible probabilities:

$P(Weather) = \langle 0.72, 0.1, 0.08, 0.1 \rangle$  normalized, i.e. sums to 1.

$$\begin{aligned}
 P(Weather = sunny) &= 0.72 \\
 P(Weather = rain) &= 0.1 \\
 P(Weather = cloudy) &= 0.08 \\
 P(Weather = snow) &= 0.1
 \end{aligned}$$

### 2.2.5 Joint Probability distribution

Joint Probability distribution for a set of r.v.s gives the probability of every atomic event on those r.v.s (i.e. every sample point)

	Toothache		$\neg$ Toothache	
	catch	$\neg$ catch	catch	$\neq$ catch
cavity	0.108	0.012	0.072	0.008
$\neg$ cavity	0.016	0.064	0.144	0.576

### 2.2.6 Conditional probability

Conditional or posterior probabilities:

given some information, sometimes called evidence, the probability of an event happening under the evidence.

$$\begin{aligned}
& P(X_1, \dots, X_n) \\
&= P(X_1, \dots, X_{n-1})P(X_n|X_1, \dots, X_{n-1}) \\
&= P(X_1, \dots, X_{n-2})P(X_{n-1}|X_1, \dots, X_{n-2})P(X_n|X_1, \dots, X_{n-1}) \\
&= \dots \\
&= \prod_{i=1}^n P(X_i|X_1, \dots, X_{i-1})
\end{aligned}$$

- If a patient is observed to have toothache and no other information is yet available, then the probability of having cavity is 0.8
- $P(\text{cavity}|\text{toothache}) = 0.8$

$$\text{Toothache} = \text{true} \Rightarrow P(\text{cavity}|\text{toothache}) = 0.8 \quad (2.2)$$

If we know more facts e.g. cavity is also given, then we have:  
 $P(\text{cavity}|\text{toothache}, \text{cavity}) = 1$  The less specific belief *remains valid* after more evidence arrives, but is not always *useful*. New evidence may be irrelevant, allowing simplification, e.g.:

$$P(\text{cavity}|\text{toothache}, \text{dice} = 1) = P(\text{cavity}|\text{toothache}) = 0.8 \quad (2.3)$$

This kind of inference, sanctioned by domain knowledge, is crucial.

**Theorem 2.2.1 — Definition of conditional probability.**

$$P(a|b) = \frac{P(a \cap b)}{P(b)} \text{ if } P(b) \neq 0 \quad (2.4)$$

When the example used so far is applied to this theorem we will get this:

$$P(\text{cavity}|\text{toothache}) = \frac{P(\text{cavity}, \text{toothache})}{P(\text{toothache})} \quad (2.5)$$

If the product rule is applied, it gives an alternative formulation:

$$P(a \cap b) = P(a|b)P(b) = P(b|a)P(a) \quad (2.6)$$

A general version holds for whole distributions, e.g.:

$$P(\text{weather}, \text{cavity}) = P(\text{weather}|\text{cavity})P(\text{cavity}) \quad (2.7)$$

### 2.2.7 Chain rule

Chain rule is derived by successive application of product rule:

### 3. Presenting Information

#### 3.1 Table

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table 3.1: Table caption

#### 3.2 Figure

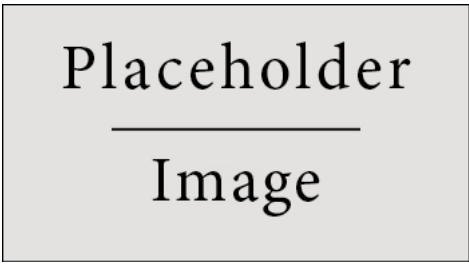


Figure 3.1: Figure caption



## 4. Chapter 7:Case-Based Reasoning

### 4.1 Case-Based Reasoning

- Case law: made up of, and from, hundred and thousands of precedent cases
- Principle: cases with similar facts should be treated in similar ways
- In cases where the parties disagree on what the law is: looking to past precedential decisions of relevant courts
- If a similar dispute has been resolved in the past: following the reasoning used in the prior decision
- If the current dispute is fundamentally distinct from all previous cases: creating new
- CBR: analogous to human experts solving a problem through employing their relevant past experience
  - exemplar-based reasoning
  - instance-based reasoning
  - memory-based reasoning
  - case-based reasoning
  - analogy-based reasoning
- if the new problem has some novel aspects, aspects, then the solution to the new problem is added to the case base
- Different from diagnostic fault tree or rule-based system
  - memory-based problem-solving
  - reusing past experiences

Domains that CBR Works well:

- Broad but shallow domain
  - not a single tree, but a forest of small trees
  - a number of loosely connected problems that must be dealt with
  - need different kinds of expertise
- Experience, rather than theory, is the primary source of knowledge
  - Many past examples of problems that occur
  - rather than having a deep understanding of the domain
- solutions are reusable
  - old solution is useful for a new problem
  - if each problem is different, then there is little to be gained by trying to reuse past

solutions

## 4.2 Case-Based Reasoning System and 4R Cycle

- Input: new problem
- Output: a solution to the new problem
- case base
  - store cases(experience)

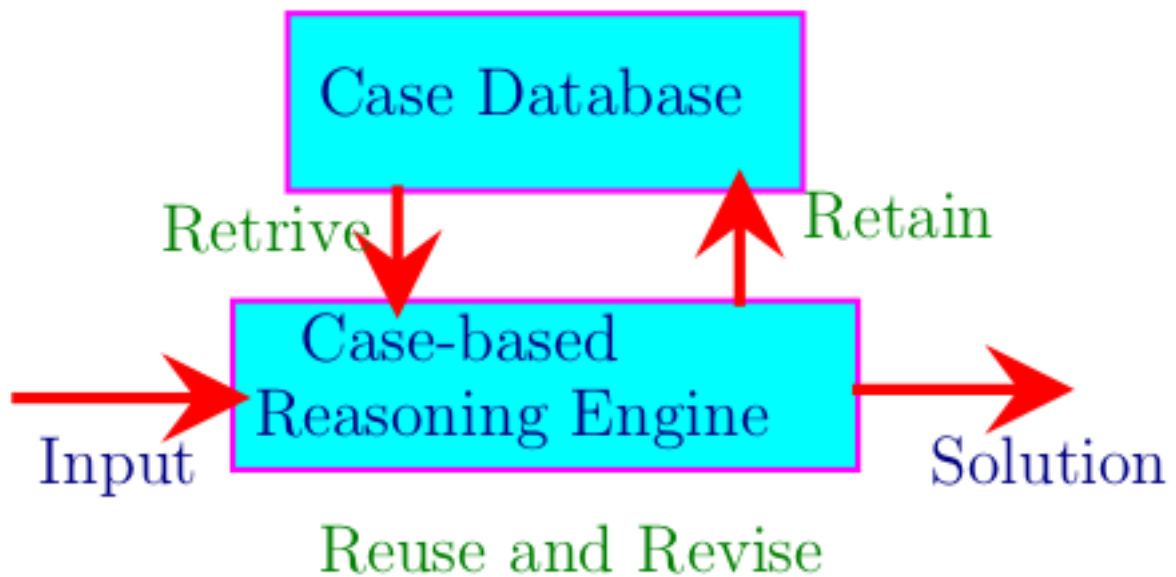


Figure 4.1: The Case-Based Reasoning System

### 4.2.1 4R Cycle

- Retrieve: relevant cases, match most similar cases, retrieve solutions from these cases
- Reuse: solutions in stored cases
- Revise: the retrieved solution(s) to reflect differences between new case and retrieved case(s)
- Retain: new cases into database

See figure 4.2 for visualisation.

#### New Problem vs Old Case

- Observations define a new problem
- Compare similarity of each feature
- Not all feature values may be known
- Some features may be more important
- New problem = case without a solution
- Similarity by weighted average

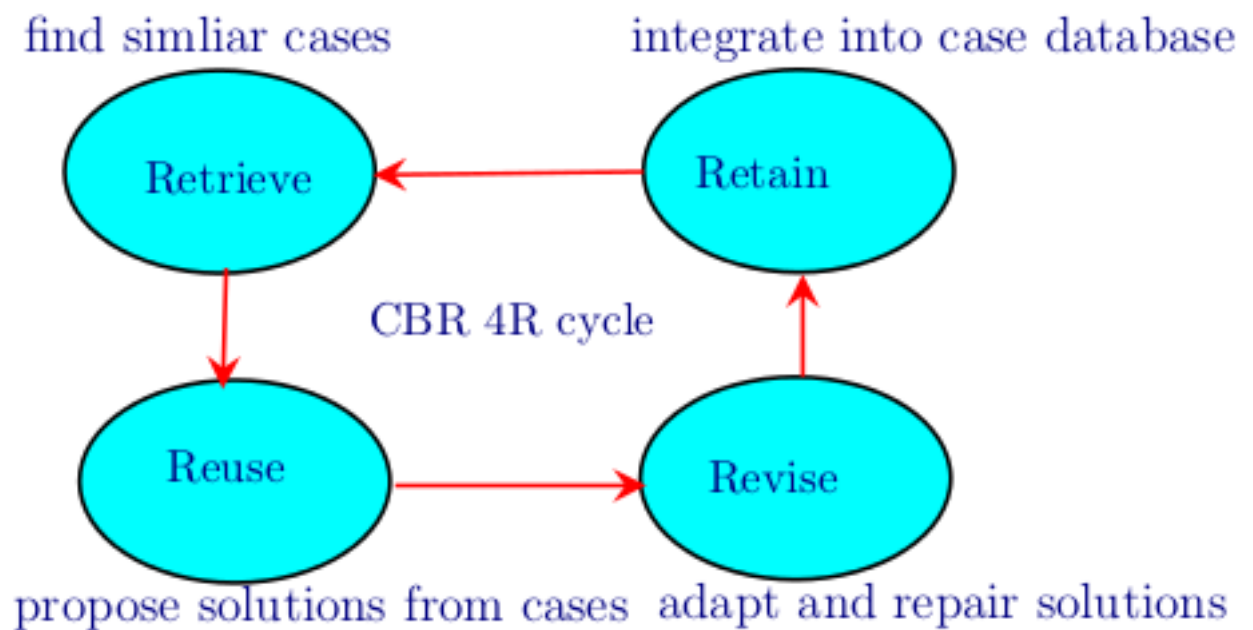


Figure 4.2: The Case-Based 4R cycle

### 4.3 Design Case-Based Reasoning System

#### 4.3.1 Case Representation

A case in diagnosis represents one diagnostic situation, include two parts:

1. Features
  - (a) symptoms
  - (b) failure
  - (c) feature values
  - (d) repair strategies
  - (e) test time and cost
2. Solutions
  - (a) cause of failure
  - (b) replace or repair fault unit

#### 4.3.2 Design Case database

- Dependent on the structure and content of its collection of cases
  - Deciding what to store in a case
  - Finding an appropriate structure for describing case contents
  - Deciding how the case memory should be organized and indexed for effective retrieval and reuse

#### 4.3.3 Retrieve: index

- Retrieve a case from case database
- Select indexes
  - Similar to books in library, index may help search cases in case database

**Match Case**

- Compare features and their value between the stored case and new problem
- Nearest-neighbour matching algorithm

**4.3.4 Retrieval: Ranking**

- Possibly more than one case is matched
- Among matched cases, ranking may be used to choose a case to reuse
- If a matched case cannot provide the solution to the problem, lower rank cases may be taken as the candidate for the problem
- Ranking value will depend on observation time and cost
  - Higher the rank → better solution (cheaper, faster, etc.)
  - Ranking Observation cost, observation time and case frequency need to be considered

**4.3.5 Reuse/Revive**

- Adapt/repair old solutions
- Different approaches
  - Substitution
  - Parameter adjustment (via specialized heuristics, e.g. Judge)
  - Local search (replacing fruits in a recipe)
  - Special purpose adaptation and repair
  - Model-based

**4.3.6 Retain: Store new cases and stop reasoning**

- Store all new cases
- Or store selected new cases (based on certain criteria?)
- The reasoning stops until a satisfied solution (from a solved case) is found
- or stop the reasoning procedure by the system





## Bibliography

**Books**

**Articles**





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