Fundamentals of Artificial Intelligence
Chapter 06: **Constraint Satisfaction Problems**

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Outline

1. Constraint Satisfaction Problems (CSPs)
2. Search with CSPs
   - Inference: Constraint Propagation
   - Backtracking Search
3. Local Search with CSPs
4. Exploiting Structure of CSPs

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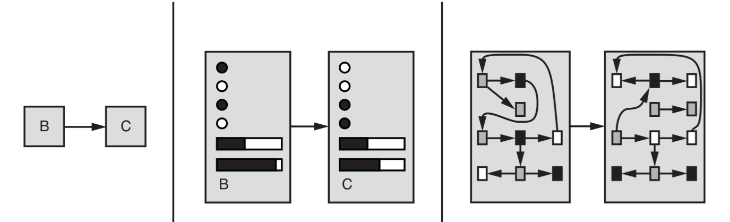
Recall: State Representations [Ch. 02]

Representations of states and transitions

- Three ways to represent states and transitions between them:
  - atomic: a state is a black box with no internal structure
  - factored: a state consists of a vector of attribute values
  - structured: a state includes objects, each of which may have attributes of its own as well as relationships to other objects
- increasing expressive power and computational complexity
- reality represented at different levels of abstraction



(a) Atomic (b) Factored (b) Structured

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Constraint Satisfaction Problems (CSPs): Generalities

Constraint Satisfaction Problems, CSPs (aka Constraint Satisfiability Problems)

- Search problem so far: Atomic representation of states
  - black box with no internal structure
  - goal test as set inclusion
- Henceforth: use a Factored representation of states
  - state is defined by a set of variables values from some domains
  - goal test is a set of constraints specifying allowable combinations of values for subsets of variables
    - a set of variable values is a goal iff the values verify all constraints
- CSP Search Algorithms
  - take advantage of the structure of states
  - use general-purpose heuristics rather than problem-specific ones
  - main idea: eliminate large portions of the search space all at once
    - identify variable/value combinations that violate the constraints

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CSPs: Definitions

CSPs

- A Constraint Satisfaction Problem is a tuple $\langle X, D, C \rangle$:
  - a set of variables $X \stackrel{\text{def}}{=} \{X_1, ..., X_n\}$
  - a set of (non-empty) domains $D \stackrel{\text{def}}{=} \{D_1, ..., D_n\}$, one for each X_i
  - a set of constraints $C \stackrel{\text{def}}{=} \{C_1, ..., C_m\}$
    - specify allowable combinations of values for the variables in X
- Each D_i is a set of allowable values $\{v_i, ..., v_k\}$ for variable X_i
- Each C_i is a pair $\langle scope, rel \rangle$
  - scope is a tuple of variables that participate in the constraint
  - rel is a relation defining the values that such variables can take
- A relation is
  - an explicit list of all tuples of values that satisfy the constraint (most often inconvenient), or
  - an abstract relation supporting two operations:
    - test if a tuple is a member of the relation
    - enumerate the members of the relation
- We need a language to express constraint relations!

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CSPs: Definitions [cont.]

States, Assignments and Solutions

- A state in a CSP is an assignment of values to some or all of the variables $\{X_i = v_{x_i}\}_i$ s.t $X_i \in X$ and $v_{x_i} \in D_i$
- An assignment is
  - complete (aka total) if every variable is assigned a value
  - incomplete (aka partial) if some variable is assigned a value
- An assignment that does not violate any constraints in the CSP is called a consistent or legal assignment
- A solution to a CSP is a consistent and complete assignment
- A CSP consists in finding one solution (or state there is none)
- Constraint Optimization Problems (COPs):
  CSPs requiring solutions that maximize/minimize an objective function

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Example: Sudoku

- 81 Variables: (each square) X_{ij}, $i = A, ..., I$; $j = 1...9$
- Domain: $\{1, 2, ..., 8, 9\}$
- Constraints:
  - $AllDiff(X_{i1}, ..., X_{i9})$ for each row i
  - $AllDiff(X_{Aj}, ..., X_{Ij})$ for each column j
  - $AllDiff(X_{A1}, ..., X_{A3}, X_{B1} ..., X_{C3})$ for each 3×3 square region

  (alternatively, a long list of pairwise inequality constraints: $X_{A1} \neq X_{A2}, X_{A1} \neq X_{A3}, ...$)
- Solution: total value assignment satisfying all the constraints: $X_{A1} = 4, X_{A2} = 8, X_{A3} = 3, ...$

	1	2	3	4	5	6	7	8	9
A			3		2		6		
B	9			3		5			1
C			1	8		6	4		
D			8	1		2	9		
E	7								8
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H	8	1	4	2	5	3	7	6	9
I	6	9	5	4	1	7	3	8	2

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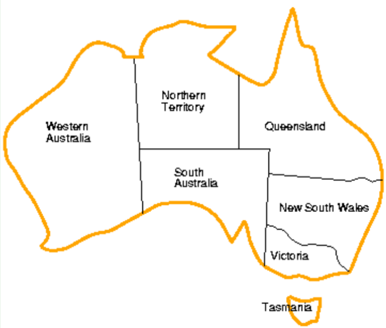
Example: Map-Coloring

- Variables WA, NT, Q, NSW, V, SA, T
- Domain $D_i = \{red, green, blue\}, \forall i$
- Constraints: adjacent regions must have different colours
  - e.g. (explicit enumeration): $\langle WA, NT \rangle \in \{\langle red, green \rangle, \langle red, blue \rangle, \}$
    or (implicit, if language allows it): $WA \neq NT$
- A solution: {WA=red,NT=green,Q=red,NSW=green,V=red,SA=blue,T=green}



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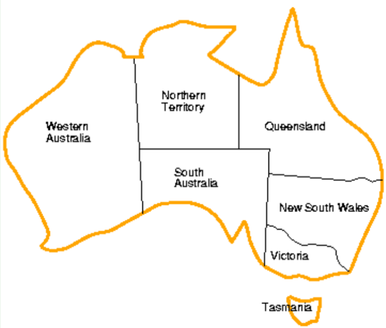

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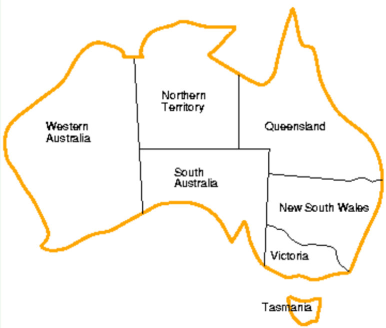

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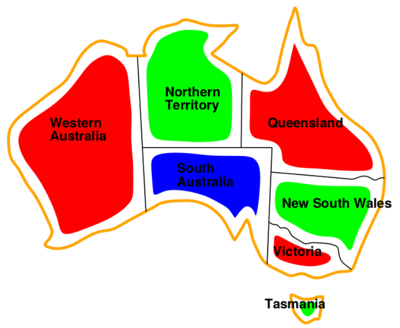

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Constraint Graphs

- Useful to visualize a CSP as a constraint graph (aka network)
  - the nodes of the graph correspond to variables of the problem
  - an edge connects any two variables that participate in a constraint
- CSP algorithms use the graph structure to speed up search
  - Ex: Tasmania is an independent subproblem!

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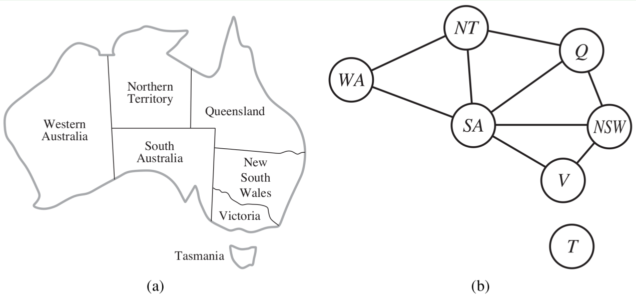
(a): map; (b) constraint graph



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Varieties of CSPs

- Discrete variables
  - Finite domains (ex: Booleans, bounded integers, lists of values)
    - domain size d $\Longrightarrow$ d^n complete assignments (candidate solutions)
    - e.g. Boolean CSPs, incl. Boolean satisfiability (NP-complete)
    - possible to define constraints by enumerating all combinations (although unpractical)
  - Infinite domains (ex: unbounded integers)
    - infinite domain size $\Longrightarrow$ infinite # of complete assignments
    - e.g. job scheduling: variables are start/end days for each job
    - need a constraint language (ex: $StartJob_1 + 5 \leq StartJob_3$)
    - linear constraints $\Longrightarrow$ solvable (but NP-Hard)
    - non-linear constraints $\Longrightarrow$ undecidable (ex: $x^n + y^n = z^n$, $n > 2$)
- Continuous variables (ex: reals, rationals)
  - linear constraints solvable in poly time by LP methods
  - non-linear constraints solvable (e.g. by Cylindrical Algebraic Decomposition) but dramatically hard

The same problem may have distinct formulations as CSP!

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The same problem may have distinct formulations as CSP!

Example: N-Queens

Formulation #1

- variables X_{ij}, $i, j = 1..N$ (there is a queen i position i, j)
- domains: $\{0, 1\}$ (false,true)
- constraints (explicit):
  - $\forall i, j, k \ \langle X_{ij}, X_{ik} \rangle \in \{\langle 0, 0 \rangle, \langle 1, 0 \rangle, \langle 0, 1 \rangle\}$ (row)
  - $\forall i, j, k \ \langle X_{ij}, X_{kj} \rangle \in \{\langle 0, 0 \rangle, \langle 1, 0 \rangle, \langle 0, 1 \rangle\}$ (column)
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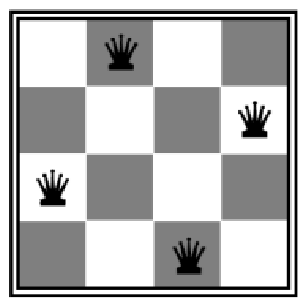
- explicit representation
- very inefficient



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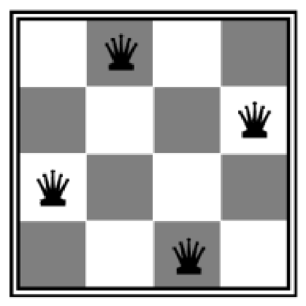

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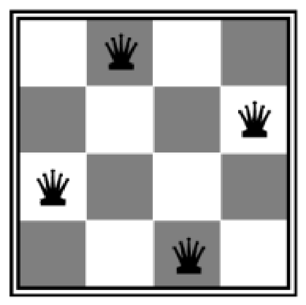

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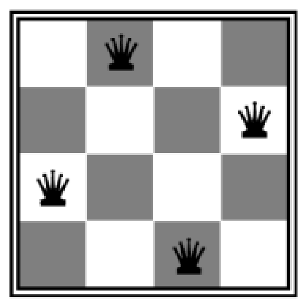

Example: N-Queens [cont.]

Formulation #2

- variables Q_k, $k = 1..N$ (row)
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- constraints (implicit): $Nonthreatening(Q_k, Q_{k'})$:
  - none (row)
  - $Q_i \neq Q_j$ (column)
  - $Q_i \neq Q_{j+k} + k$ (downward diagonal)
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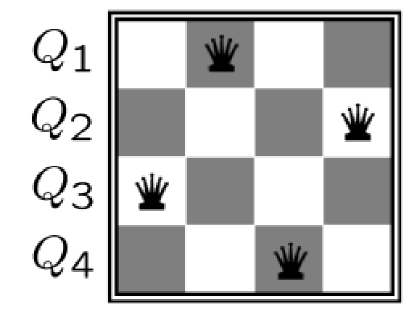

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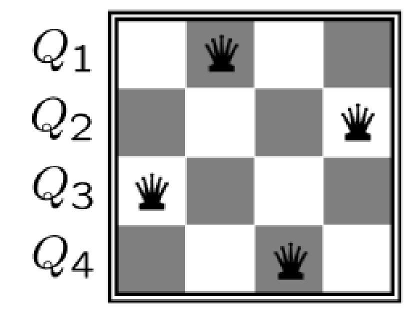

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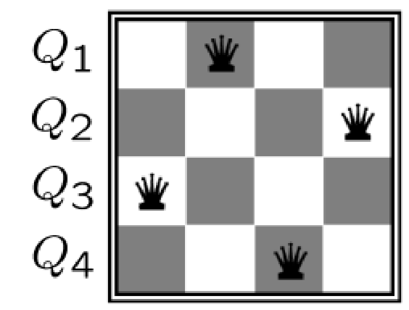

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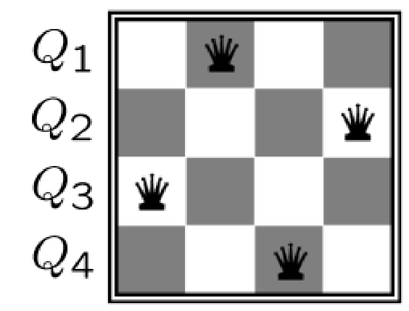

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Varieties of Constraints

- Unary constraints: involve one single variable
  - ex: $(SA \neq green)$
- Binary constraints: involve pairs of variables
  - ex: $(SA \neq WA)$
- Higher-order constraints: involve ≥ 3 variables
  - ex: cryptarithmetic column constraints
  - can be represented by constraint hypergraphs (hypernodes represent n-ary constraints, squares in cryptarithmetic example)
- Global constraints: involve an arbitrary number of variables
  - ex: $AllDiff(X_1, ..., X_k)$
  - note: maximum domain size $\geq k$, otherwise $AllDiff()$ unsatisfiable
  - compact, specialized routines for handling them
- Preference constraints (aka soft constraints): describe preferences between/among solutions
  - ex: "I'd rather WA in red than in blue or green"
  - can often be encoded as costs/rewards for variables/constraints:

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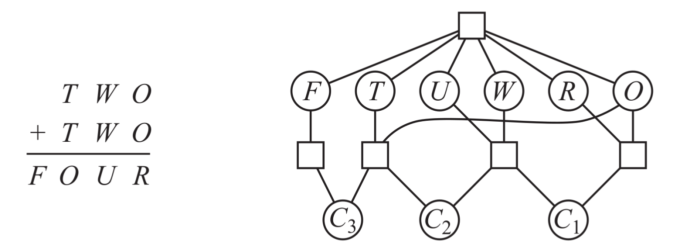
Example: Cryptarithmetic Puzzle

- Variables: F, T, U, W, R, O, plus C_1, C_2, C_3 (carry)
- Domains: $F, T, U, W, R, O \in \{0, 1, ..., 9\}$; $C_1, C_2, C_3 \in \{0, 1\}$
- Constraints: $\left\{ \begin{array}{l} AllDiff(F, T, U, W, R, O), \\ O + O = R + 10 \cdot C_1 \\ W + W + C_1 = U + 10 \cdot C_2 \\ T + T + C_2 = 10 \cdot C_3 + O \\ F = C_3, F \neq 0, T \neq 0 \end{array} \right\}$
- (one) solution: {F=1,T=7,U=2,W=1,R=8,O=4} (714+714=1428)



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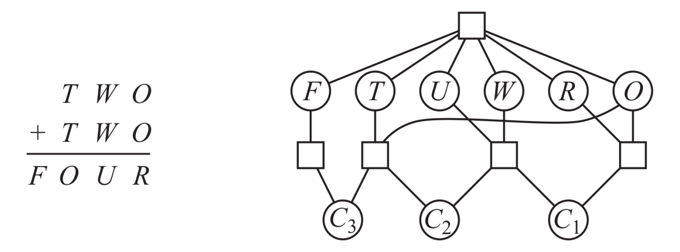

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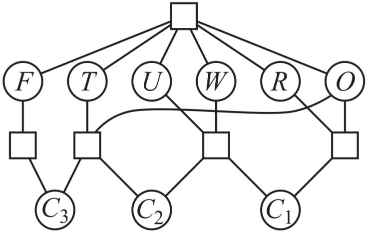

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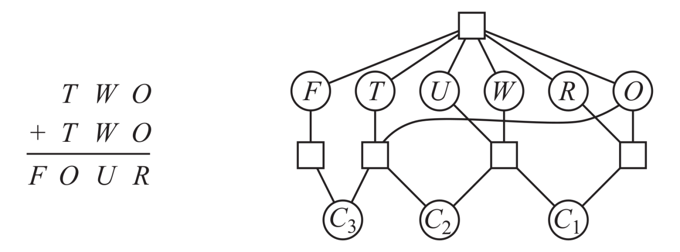

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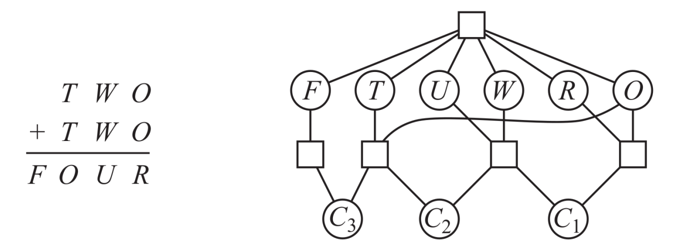

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Example: Job-Shop Scheduling

- Scheduling the assembling of a car requires several tasks
  - ex: installing axles, installing wheels, tightening nuts, put on hubcap, inspect
- Variables X_t (for each task t): starting times of the tasks
- Domain: (bounded) integers (time units)
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Remark

- k-ary constraints can be transformed into sets of binary constraints
  - hint: add enough auxiliary variables (see ex. 6.6 in AIMA book)

$\Longrightarrow$ often CSP solvers work with binary constraints only

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Real-World CSPs

- Task-Assignment problems
  - Ex: who teaches which class?
- Timetabling problems
  - Ex: which class is offered when and where?
- Hardware configuration
  - Ex: which component is placed where? with which connections?
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- many real-world problems involve real/rational-valued variables
- many real-world problems involve combinatorics and logic
- many real-world problems require optimization

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Outline

1 Constraint Satisfaction Problems (CSPs)

2 Search with CSPs
- Inference: Constraint Propagation
- Backtracking Search

3 Local Search with CSPs

4 Exploiting Structure of CSPs

Search & Constraint Propagation with CSPs

- In state-space search, an algorithm can only search
  - move from complete state to complete state,
- A CSPs interleaves search with constraint propagation:
  - search: pick a new variable assignment (and backtrack when needed)
    - does not move from complete state to complete state,
    - rather builds a complete state by progressively extending partial ones
  - constraint propagation (aka inference):
    - use the constraints to reduce the set of legal candidate values for a variable
    - forces next variable assignment when candidate values are reduced to one
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  $\Longrightarrow$ inconsistent values eliminated throughout the graph
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- X_i is node-consistent if all the values in the variable's domain satisfy its unary constraints
- A CSP is node-consistent if every variable is node-consistent
- Node-consistency propagation:
  remove all values from the domain D_i of X_i which violate unary constraints on X_i
  - ex: if the constraint $WA \neq green$ is added to map-coloring problem
    then WA domain $\{red, green, blue\}$ is reduced to $\{red, blue\}$
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  $\Longrightarrow$ ensure arcs from assigned to unassigned variables are arc consistent
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  - complexity: $O(|C| \cdot |D|^3)$ worst-case
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- Simplest form of propagation
- Idea: propagate information from assigned to unassigned variables
  - pick (novel) variable assignment
  - update remaining legal values for unassigned variables
- Does not provide early detection for all failures
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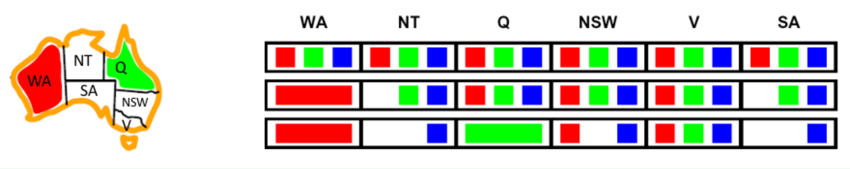
  - ex: SA single value is incompatible with NT single value

- Can we conclude anything?
  - NT and SA cannot both be blue!
- Why didn't we detect this inconsistency yet?



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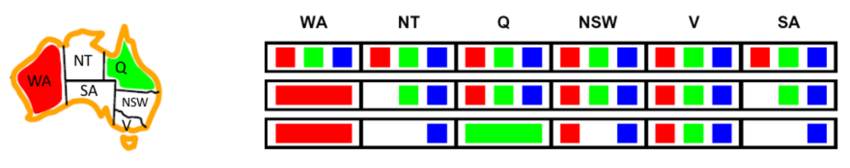

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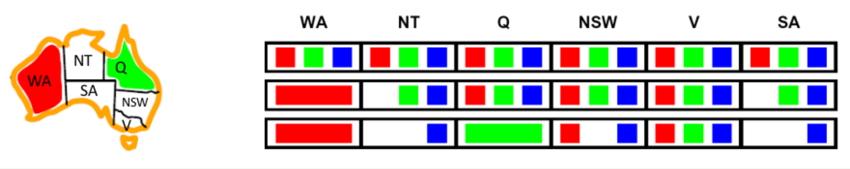

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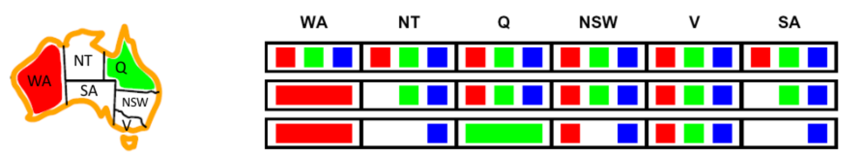

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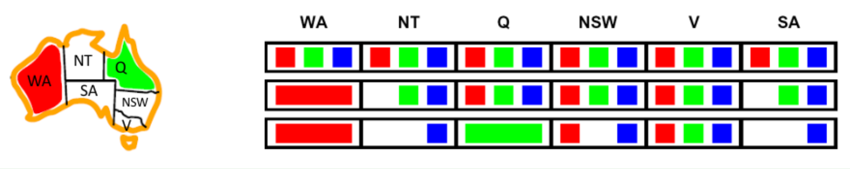

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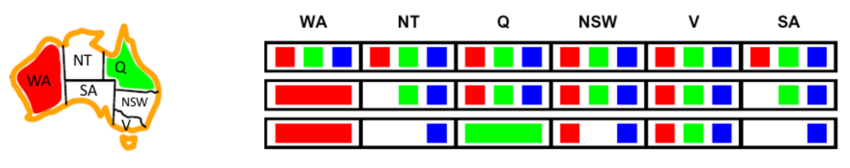

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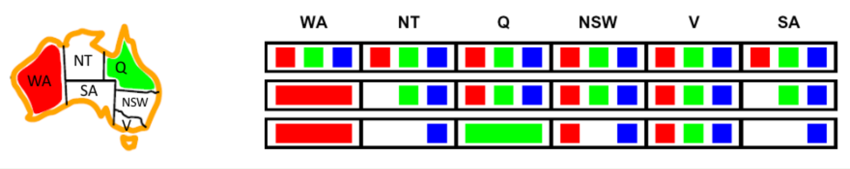

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The Arc-Consistency Propagation Algorithm AC-3

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**   // makes Xi arc-consistent wrt. Xj
      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*

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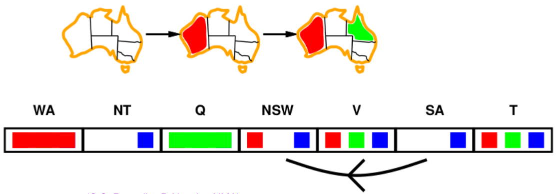
note: “queue” is LIFO $\Longrightarrow$ revises first the neighbours of revised vars

Arc-Consistency Propagation AC-3: Example

- Idea: If X loses a value, neighbors of X need to be rechecked
- Ex:
  - Revise(SA,NSW) $\Longrightarrow$ D_{SA} unchanged
  - ...
  - Revise(NSW,SA) $\Longrightarrow$ D_{NSW} revised
  - Revise(V,NSW) $\Longrightarrow$ D_V revised
  - ...
  - Revise(SA,NT) $\Longrightarrow$ D_{SA} revised
- Empty domain!

$\Longrightarrow$ Arc-consistency propagation detects failure earlier than forward checking



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Arc-Consistency Propagation AC-3: Example

- Idea: If X loses a value, neighbors of X need to be rechecked
- Ex:
  - Revise(SA,NSW) $\Longrightarrow$ D_{SA} unchanged
  - ...
  - Revise(NSW,SA) $\Longrightarrow$ D_{NSW} revised
  - Revise(V,NSW) $\Longrightarrow$ D_V revised
  - ...
  - Revise(SA,NT) $\Longrightarrow$ D_{SA} revised
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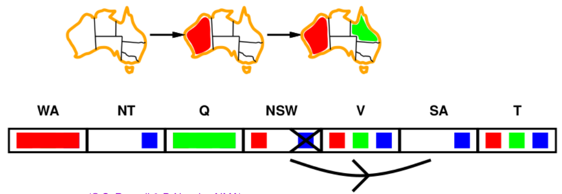

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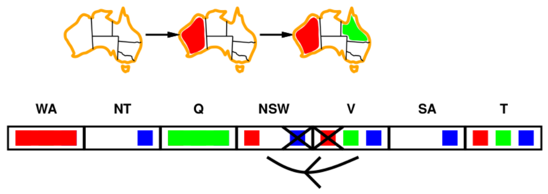

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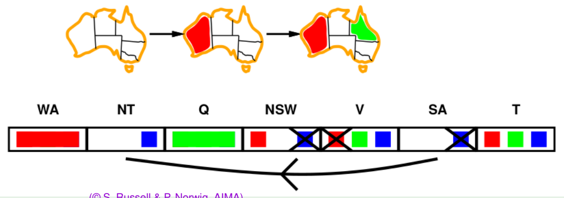

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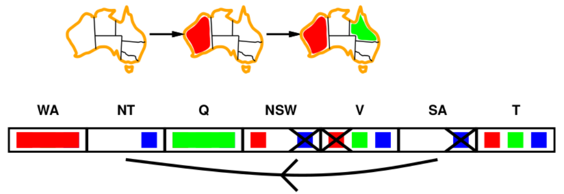

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Remark

Notice the differences between:

(a) an assigned variable X_i, with value v_j, and

(b) an unassigned variable X_i whose domain is reduced to a singleton $\{v_j\}$:

- With (b) X_i is not (yet) assigned the value v_j
  (although it will be likely assigned soon the value v_j by next search steps)
- With Forward Checking, (a) forces checking the domain of X_i's unassigned neighbours wrt. X_i, whereas (b) does not
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Example: Sudoku

(consider *AllDiff*() as a set of binary constraints)
Apply arc-consistency propagation:

- What about E6?
  - arc-consistency propagation on column 6: drop 2,3,5,6,8,9
  - arc-consistency propagation on square: drop 1,7 $\Longrightarrow$ Domain(E6)={4}
    (will be assigned to 4 at next search step, but triggers next propagations)
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	1	2	3	4	5	6	7	8	9
A			3		2		6		
B	9			3		5			1
C			1	8		6	4		
D			8	1		2	9		
E	7								8
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Path Consistency & K-Consistency

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A two-variable set $\{X_i, X_j\}$ is path-consistent wrt. a third variable X_m if,
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K-Consistency

- A CSP is k-consistent iff for any set of $k-1$ variables and for any consistent assignment to those variables, a consistent value can always be assigned to any other k-th variable
  - 1-consistency is node consistency
  - 2-consistency is arc consistency
  - 3-consistency is path consistency
- Algorithm for 3-consistency available: PC-2
  - generalization of AC-3
- Time and space complexity grow exponentially with k

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Arc vs. Path Consistency

- Can we say anything about X1?

  We can drop red & blue from D1

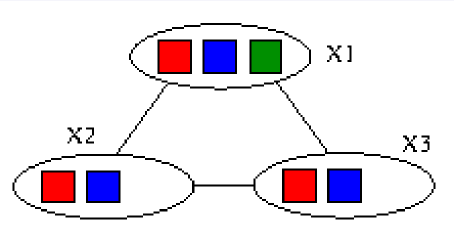
$\Longrightarrow$ Infers the assignment $C1 = \mathit{green}$

- Can arc-consistency propagation reveal it?

  NO!

- Can path-consistency propagation reveal it?

  YES!



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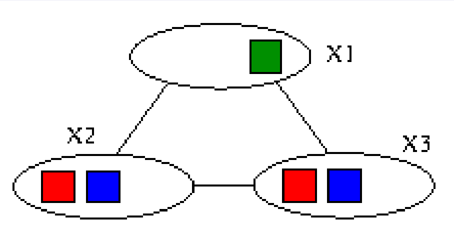

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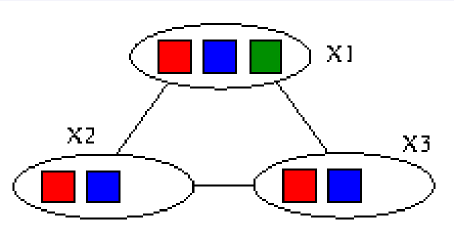

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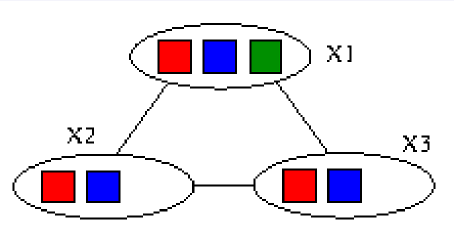

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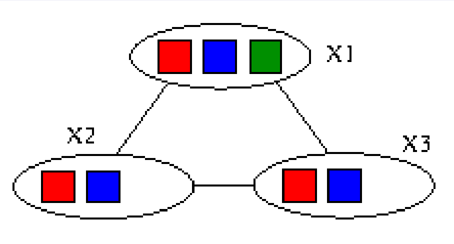

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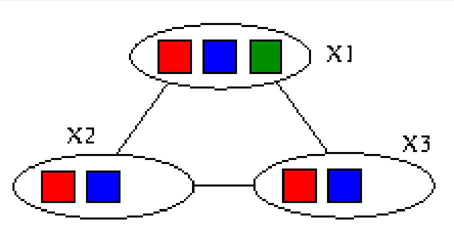

Arc vs. Path Consistency [cont.]

- Can we say anything?

  The triplet is inconsistent
- Can arc-consistency propagation reveal it?

  NO!
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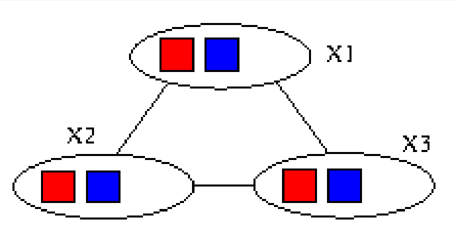

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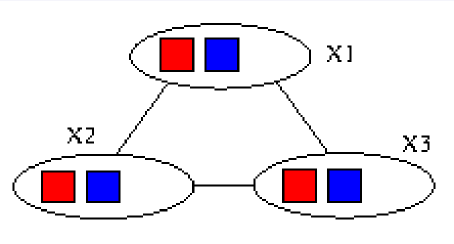

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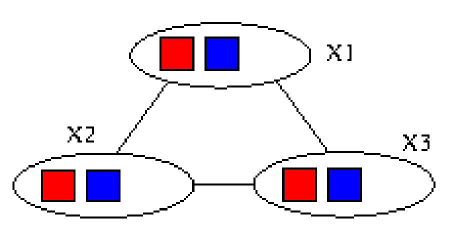

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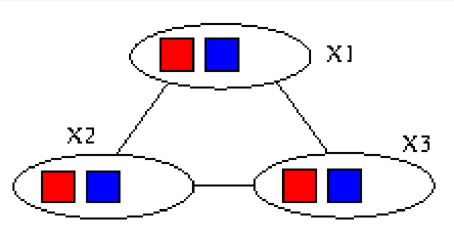

Arc vs. Path Consistency [cont.]

- Can we say anything?
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  NO!
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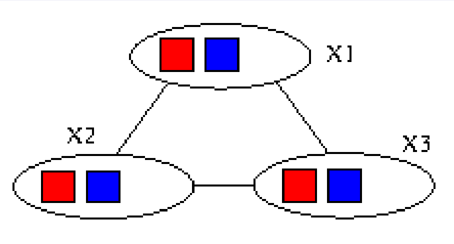

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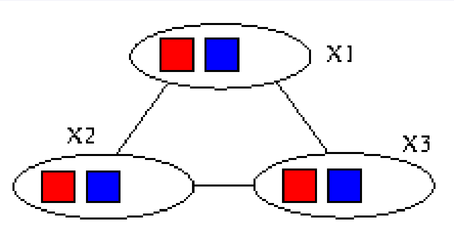

Outline

1. Constraint Satisfaction Problems (CSPs)
2. Search with CSPs
   - Inference: Constraint Propagation
   - Backtracking Search
3. Local Search with CSPs
4. Exploiting Structure of CSPs

Backtracking Search: Generalities

Backtracking Search

- Basic uninformed algorithm for solving CSPs
- Idea 1: Pick one variable at a time
  - variable assignments are commutative $\Longrightarrow$ fix an ordering
  - ex: $\{WA = red, NT = green\}$ same as $\{NT = green, WA = red\}$

  $\Longrightarrow$ can consider assignments to a single variable at each step
  - reasons on partial assignments
- Idea 2: Check constraints as long as you proceed
  - pick only values which do not conflict with previous assignments
  - requires some computation to check the constraints

  $\Longrightarrow$ "incremental goal test"
  - can detect if a partial assignments violate a goal
    $\Longrightarrow$ early detection of inconsistencies
- Backtracking search: DFS with the two above improvements

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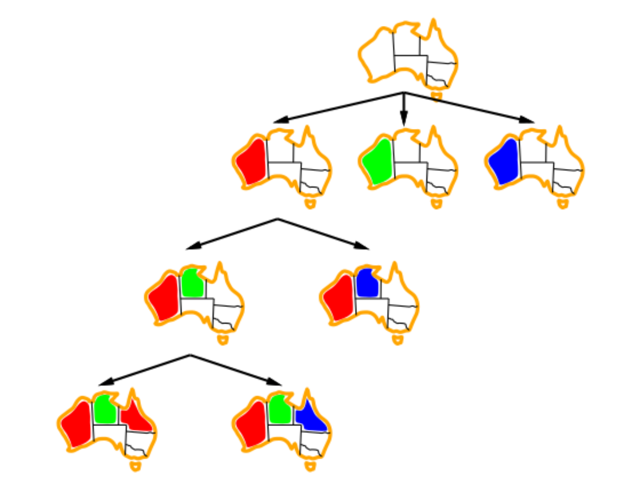
Backtracking Search: Example

(Part of) Search Tree for Map-Coloring



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Backtracking Search Algorithm

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** $assignment$
  $var \leftarrow$ 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 $assignment$
      $inferences \leftarrow$ INFERENCE(csp, var, $value$)
      if $inferences \neq failure$ **then**
        add $inferences$ to $assignment$
        $result \leftarrow$ BACKTRACK($assignment$, csp)
        if $result \neq failure$ **then**
          return $result$
inside first "if"
    remove $\{var = value\}$ and $inferences$ from $assignment$
  return $failure$

Backtracking Search Algorithm [cont.]

- General-purpose algorithm for generic CSPs
- The representation of CSPs is standardized
  $\Longrightarrow$ no need to provide a domain-specific initial state, action function, transition model, or goal test
- BACKTRACKING-SEARCH() keeps a single representation of a state
  - alters such representation rather than creating new ones
- We can add some sophistication to the unspecified functions:
  - SELECT-UNASSIGNED-VARIABLE(): which variable should be assigned next?
  - ORDER-DOMAIN-VALUES(): in what order should its values be tried?
  - INFERENCE(): what inferences should be performed at each step?
- We can also wonder: when an assignment violates a constraint
  - where should we backtrack s.t. to avoid usuless search?
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Variable Selection Heuristics

Minimum Remaining Values (MRV) heuristic

- Aka most constrained variable or fail-first heuristic
- MRV: Choose the variable with the fewest legal values

  $\Longrightarrow$ pick a variable that is most likely to cause a failure soon
- If X has no legal values left, MRV heuristic selects X

  $\Longrightarrow$ failure detected immediately
  - avoid pointless search through other variables
- (Otherwise) If X has one legal value left, MRV selects X

  $\Longrightarrow$ performs deterministic choices first!
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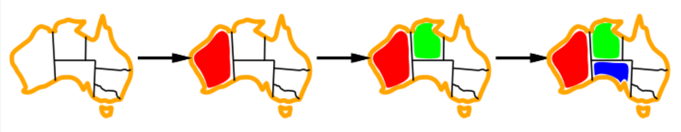

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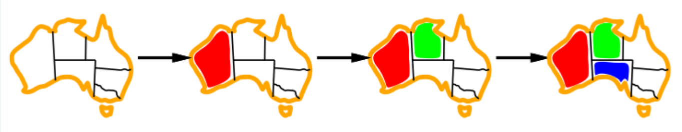

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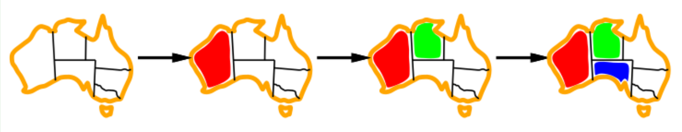

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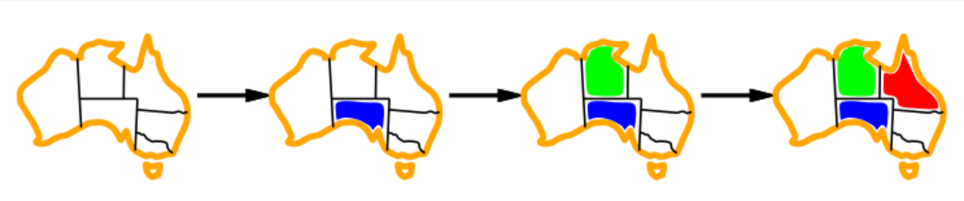

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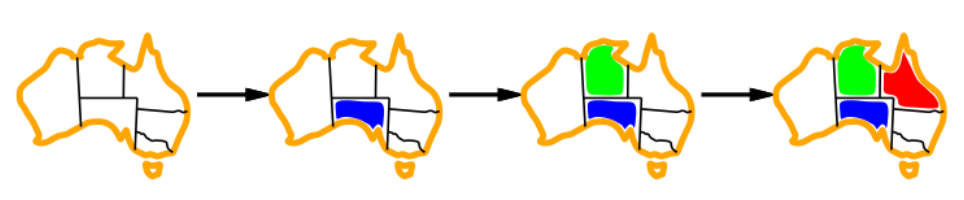

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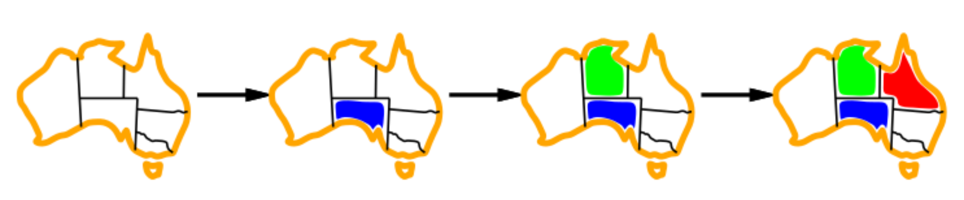

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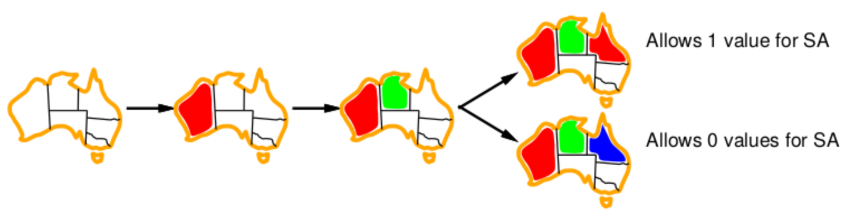

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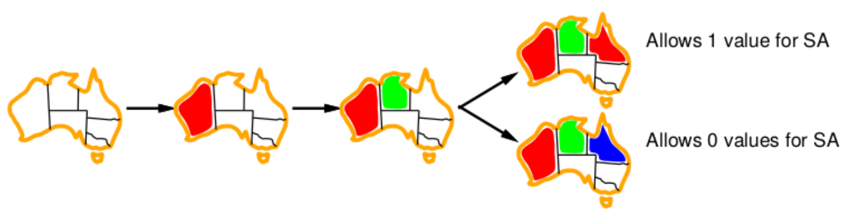

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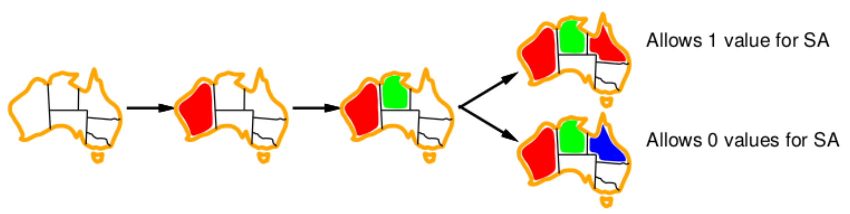

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Inference

Interleaving search and inference

- After a choice, infer new domain reductions on other variables
  - detect inconsistencies earlier
  - reduce search spaces
  - may produce unary domains (deterministic steps)
    $\Longrightarrow$ returned as assignments ("inferences")
- Tradeoff between effectiveness and efficiency
- Forward checking
  - cheap
  - ensures arc consistency of $\langle$*assigned*, *unassigned*$\rangle$ variable pairs only
- AC-3
  - more expensive
  - ensure arc consistency of all variable pairs
  - strategy (MAC):
    - after X_i is assigned, start AC-3 with only the arcs $\langle X_j, X_i \rangle$ s.t. X_j unassigned neighbour variables of X_i

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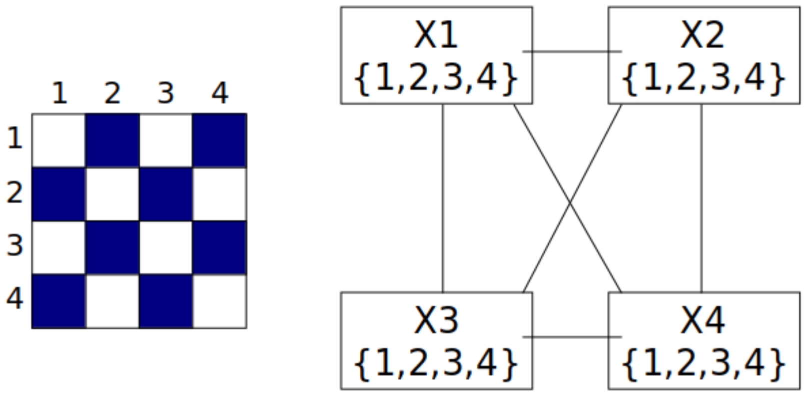
- Forward checking
  - cheap
  - ensures arc consistency of $\langle assigned, unassigned\rangle$ variable pairs only
- AC-3
  - more expensive
  - ensure arc consistency of all variable pairs
  - strategy (MAC):
    - after X_i is assigned, start AC-3 with only the arcs $\langle X_j, X_i\rangle$ s.t. X_j unassigned neighbour variables of X_i

    $\Longrightarrow$ much more effective than forward checking, more expensive

Backtracking with Forward Checking: Example

4-Queens



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...(after trying $X2 = 4$, $X3 = 2$, failing and backtracking) assign $X1 = 2$ ...

Backtracking with Forward Checking: Example

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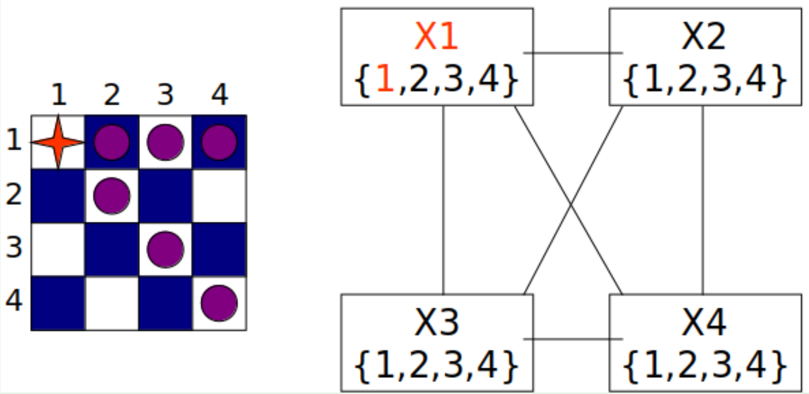

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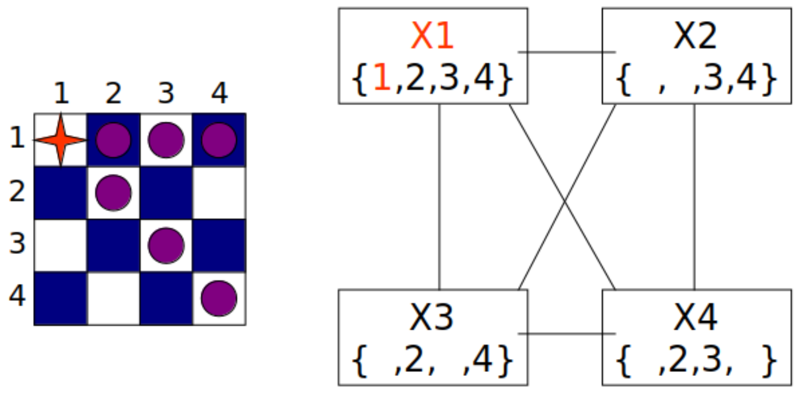

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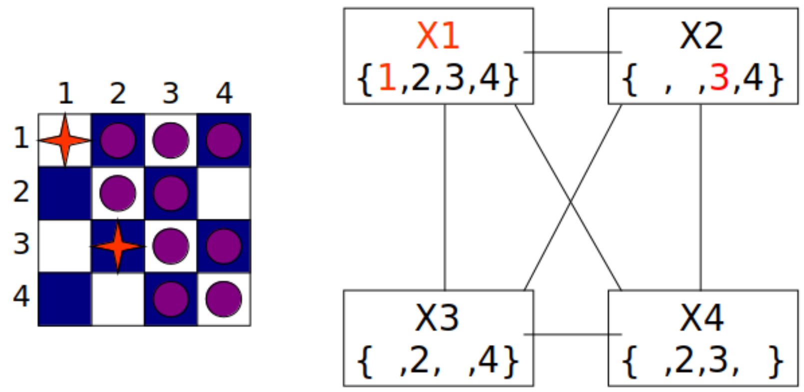

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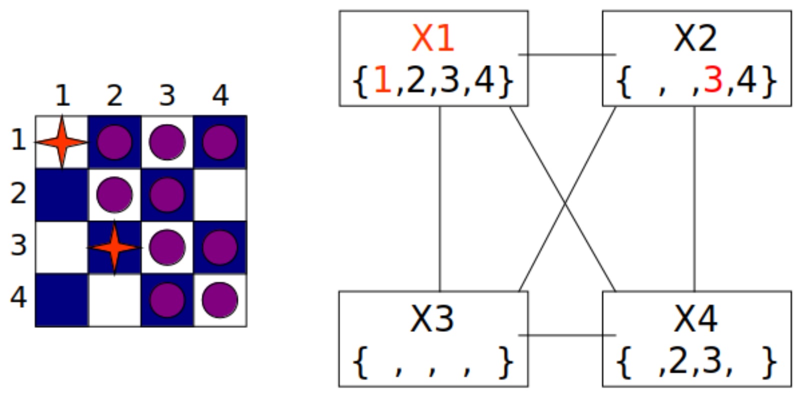

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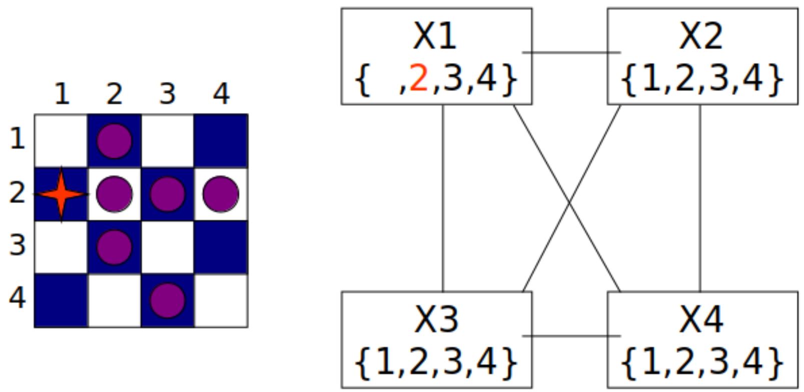

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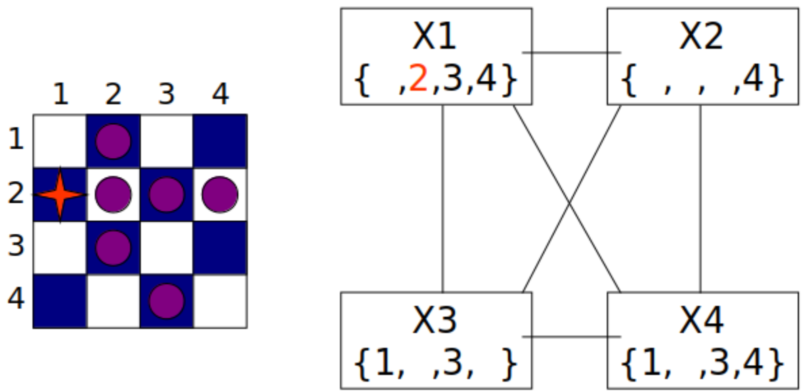

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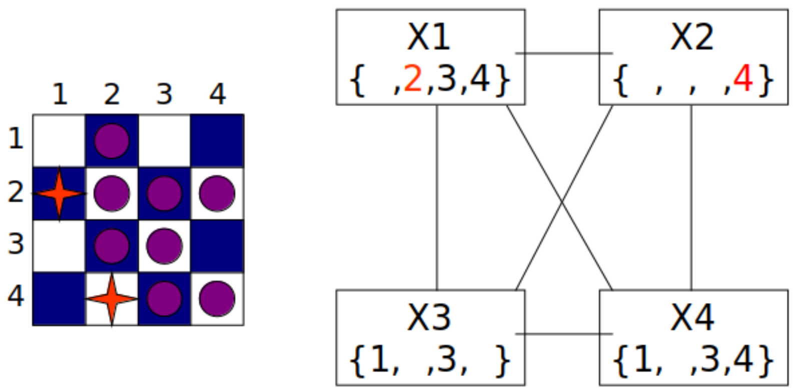

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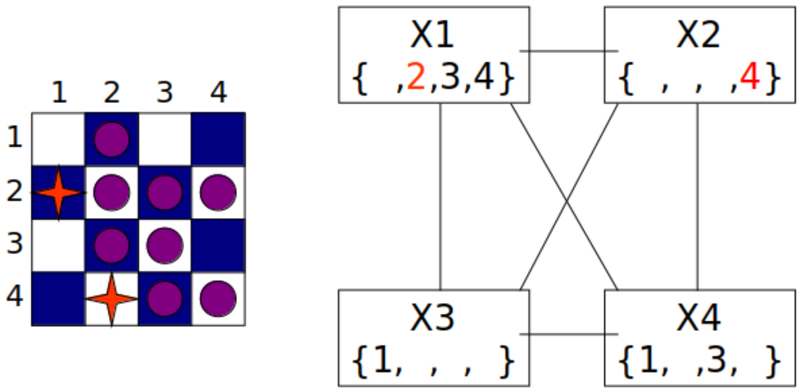

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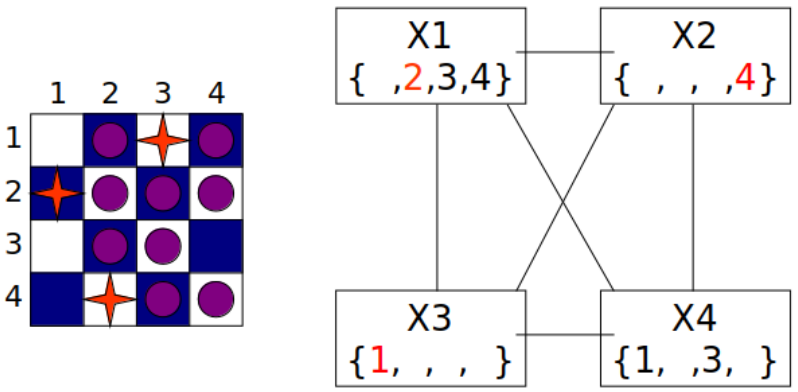

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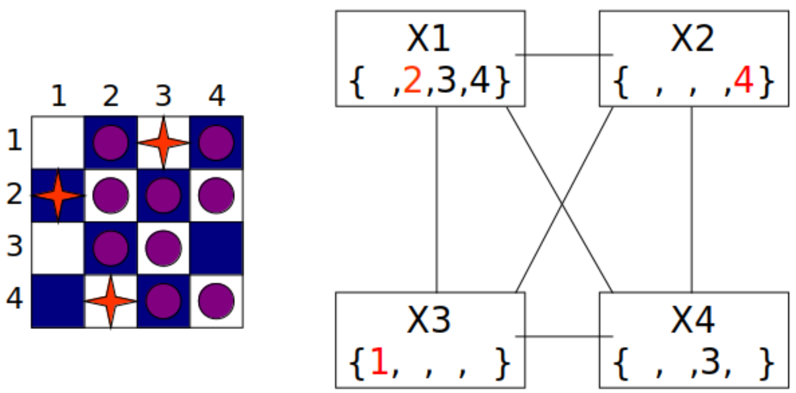

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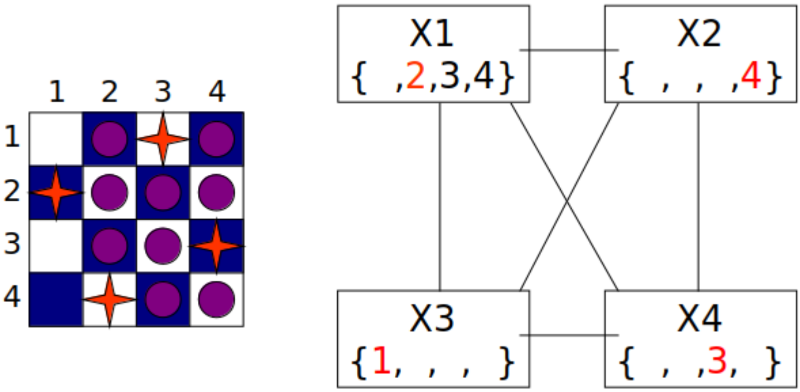

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Standard Chronological Backtracking

- When a branch fails (empty domain for variable X_i):
  1. back up to the preceding variable (who still has an untried value)
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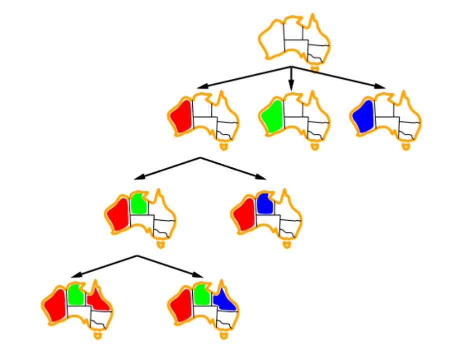
- Problem: lots of search wasted!



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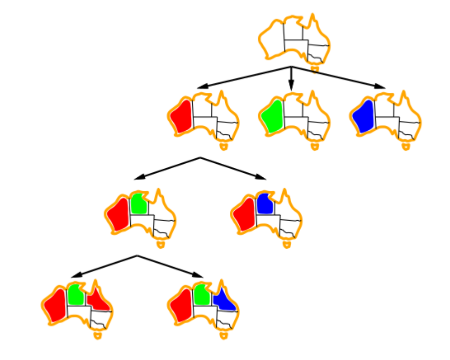

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Assume variable selection order: WA,NSW,T,NT,Q,V,SA

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(5)	$\stackrel{fc}{\Longrightarrow}$	$Q = b\ [b]$
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- backtrack to (5), pick $V = g \Longrightarrow$ (7) again
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$\Longrightarrow$ lots of useless search on *T* and *V* values

- source of inconsistency not identified: $\{WA = r, NSW = r\}$

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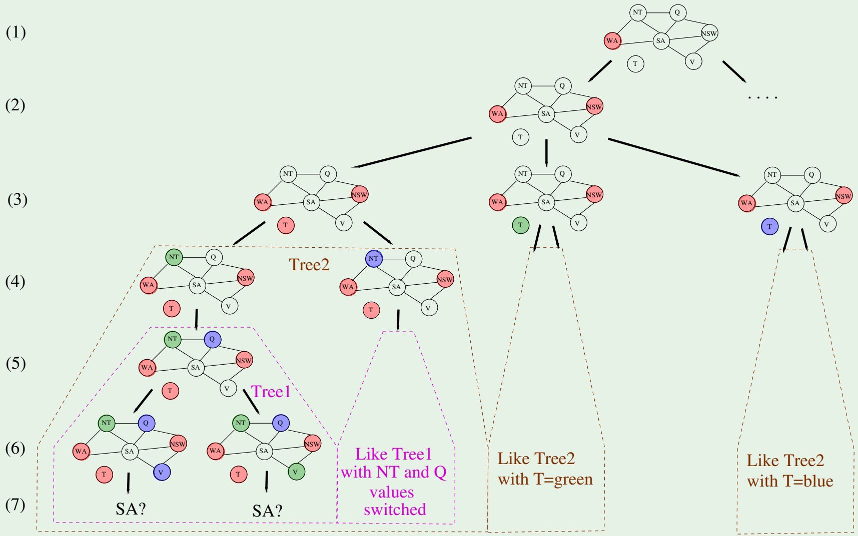
Standard Chronological Backtracking: Example [cont.]

Search Tree



Nogoods & Conflict Sets

- Nogood: subassignment which cannot be part of any solution
  - ex: $\{WA = r, NSW = r\}$ (see previous example)
- Conflict set for X_j (aka explanations):
  (minimal) set of value assignments which caused the reduction of D_j via forward checking
  (i.e., in direct conflict with some values of X_j)
  - ex: NSW=r,NT=g in conflict with r and g values for Q resp.
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Conflict-Driven Backjumping

- Idea: When a branch fails (empty domain for variable X_i):
  1. identify nogood which caused the failure deterministically via forward checking
  2. backtrack to the most-recently assigned element in nogood,
  3. change its value

$\Longrightarrow$ May jump much higher, lots of search saved

- Identify nogood:
  1. take the conflict set C_i of empty-domain X_i (initial nogood)
  2. progressively backward-substitute inside C_i every deterministic assignments $X_j = v$ with its respective conflict set C_j:

$$C_i := C_i \cup C_j \setminus \{X_j = v\}$$

     until none is left

$\Longrightarrow$ Identify the most recent decision which caused the failure due to FC by "undoing" FC steps

- Many different strategies & variants available

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- backward-substitute assignments

$$\dfrac{\dfrac{\emptyset \quad (7)}{\{WA = r, NT = g, Q = b\}} \quad (5)}{\{WA = r, NT = g, NSW = r\}}$$

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(3) *pick*	$T = r\ [rbg]$	$\leftarrow \{\}$
(4) *pick*	$NT = g\ [bg]$	$\leftarrow \{WA = r\}$
(5) $\stackrel{fc}{\Longrightarrow}$	$Q = b\ [b]$	$\leftarrow \{NSW = r, NT = g\}$
(6) *pick*	$V = b\ [b, g]$	$\leftarrow \{NSW = r\}$
(7) $\stackrel{fc}{\Longrightarrow}$	$SA = \emptyset\ []$	$\leftarrow \{WA = r, NT = g, Q = b\}$

- backward-substitute assignments

$$\cfrac{\cfrac{\emptyset \quad (7)}{\{WA = r, NT = g, Q = b\}} \quad (5)}{\{WA = r, NT = g, NSW = r\}}$$

$\Longrightarrow$ backtrack till (3), then assign $NT = b$

$\Longrightarrow$ saves useless search on V values

Conflict-Driven Backjumping: Example [cont.]

- new failed branch:

step	*assign.*[*domain*]	$\leftarrow \{$*conflict set*$\}$
(1) *pick*	$WA = r\ [rbg]$	$\leftarrow \{\}$
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$\Longrightarrow$ backtrack till (1), then assign *NSW* another value

$\Longrightarrow$ saves useless search on *T* values

$\Longrightarrow$ overall, saves lots of search wrt. chronological backtracking

Conflict-Driven Backjumping: Example [cont.]

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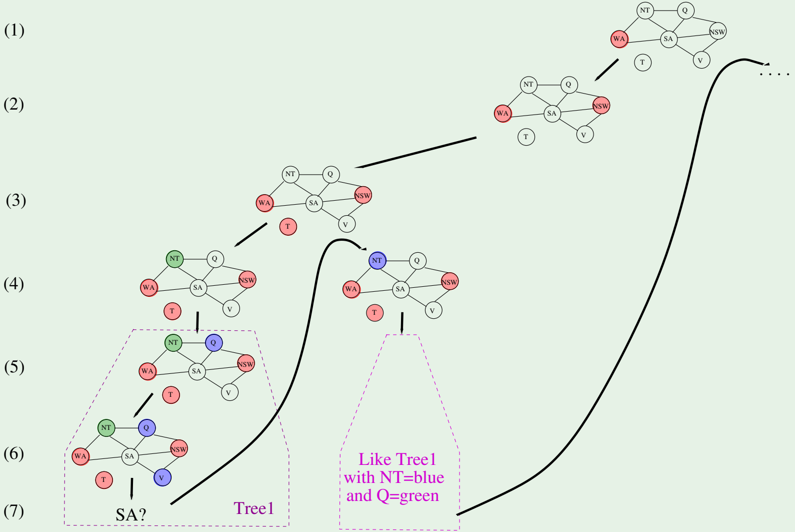
Search Tree



Learning Nogoods

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- As soon as assignment contains all but one element of a nogood, drop the value of the remaining element from variable's domain
- Example:
  - given nogood: $\{WA = r, NSW = r\}$
  - as soon as $\{NSW = r\}$ is added to assignment
    r is dropped from WA domain
- Allows for
  - early-reveal inconsistencies
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1. Constraint Satisfaction Problems (CSPs)
2. Search with CSPs
   - Inference: Constraint Propagation
   - Backtracking Search
3. **Local Search with CSPs**
4. Exploiting Structure of CSPs

Local Search with CSPs

- Extension of Local Search to CSPs straightforward
- Use complete-state representation (complete assignments)
  - allow states with unsatisfied constraints
  - "neighbour states" differ for one variable value
  - steps: reassign variable values
- Min-conflicts heuristic in hill-climbing:
  - Variable selection: randomly select any conflicted variable
  - Value selection: select new value that results in a minimum number of conflicts with the other variables
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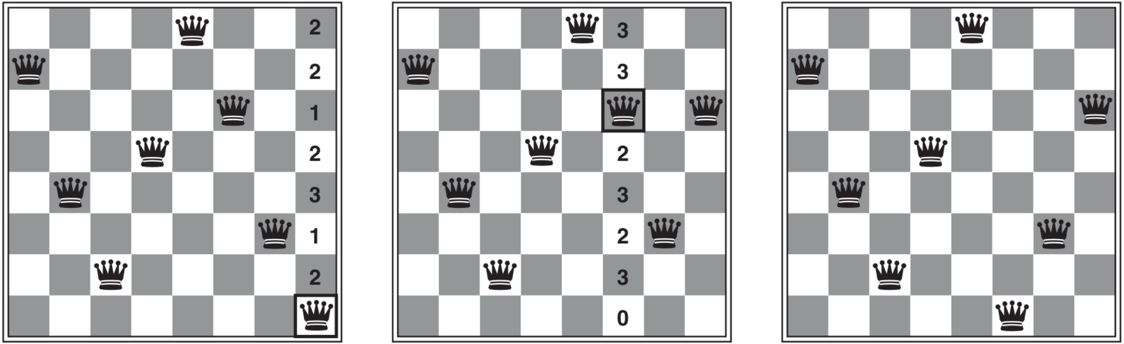
The Min-Conflicts Heuristic

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 $failure$

The Min-Conflicts Heuristic: Example

Two steps solution of 8-Queens problem



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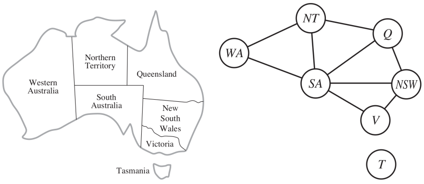
"Divide & Conquer" CSPs

- Idea (when applicable): Partition a CSP into independent CSPs
  - identify strongly-connected components in constraint graph
  - e.g. by Tarjan's algorithms (linear!)
- Ex: Tasmania and mainland are independent subproblems
- E.g. partition n-variable CSP into n/c CSPs w. c variables each:
  - from d^n to $n/c \cdot d^c$ steps in worst-case
  - if $n = 80$, $d = 2$, $c = 20$, then from $2^{80} \approx 10^{24}$ to $4 \cdot 2^{20} \approx 4 \cdot 10^6$
    $\Longrightarrow$ from 4 billion years to 0.4 secs at 10million steps/sec



(a) (b)

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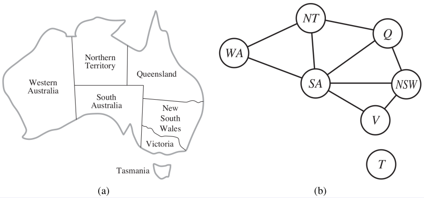

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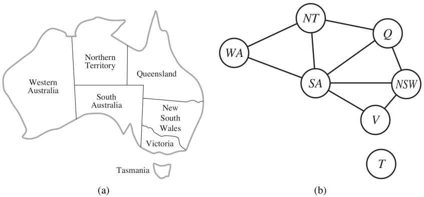

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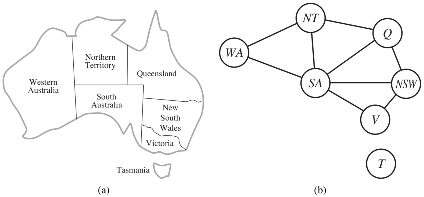

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Solving Tree-structured CSPs

Theorem:

- If the constraint graph has no loops, the CSP can be solved in $O(nd^2)$ time in worst case
  - general CSPs can be solved $O(d^n)$ time worst-case

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1. Choose a variable as root, order variables from root to leaves
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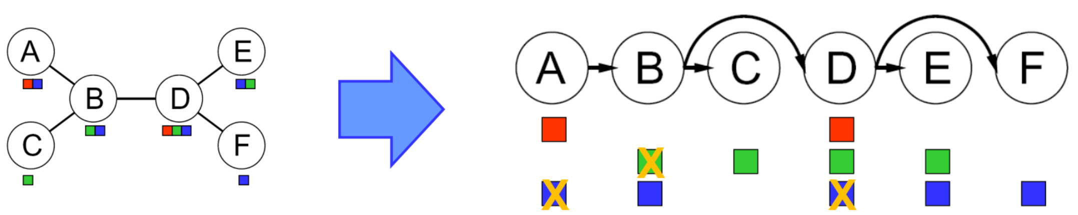
3. For $j \in 2..n$, assign X_j consistently with PARENT(X_j)



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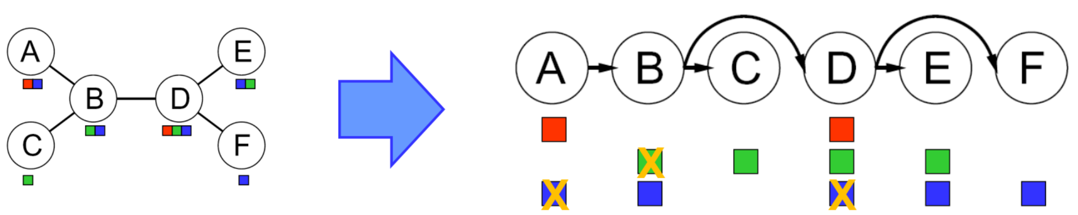

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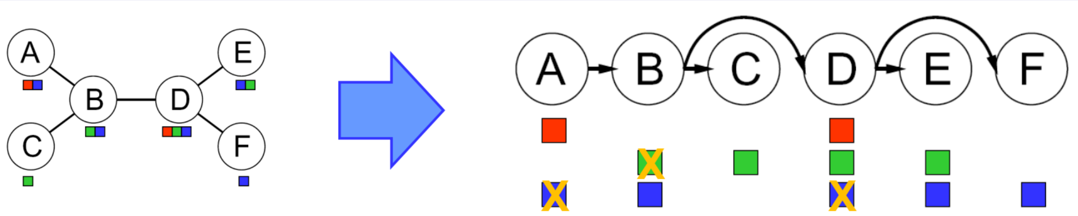

Solving Tree-structured CSPs [cont.]

function TREE-CSP-SOLVER(*csp*) **returns** a solution, or failure
  inputs: *csp*, a CSP with components X, D, C

  $n \leftarrow$ number of variables in X
  $assignment \leftarrow$ an empty assignment
  $root \leftarrow$ any variable in X
  $X \leftarrow$ TOPOLOGICALSORT(X, $root$)
  for j = n **down to** 2 **do**
    MAKE-ARC-CONSISTENT(PARENT(X_j), X_j)
    if it cannot be made consistent **then return** *failure*
  for i = 1 **to** n **do**
    $assignment[X_i] \leftarrow$ any consistent value from D_i
    if there is no consistent value **then return** *failure*
  return *assignment*

Solving Nearly Tree-Structured CSPs

Cutset Conditioning

1. Identify a (small) cycle cutset S: a set of variables s.t. the remaining constraint graph is a tree
   - finding smallest cycle cutset is NP-hard
   - fast approximated techniques known
2. For each possible consistent assignment to the variables in S
   a) remove from the domains of the remaining variables any values that are inconsistent with the assignment for S
   b) apply the tree-structured CSP algorithm
3. If $c \stackrel{\text{def}}{=} |S|$, then runtime is $O(d^c \cdot (n-c)d^2)$
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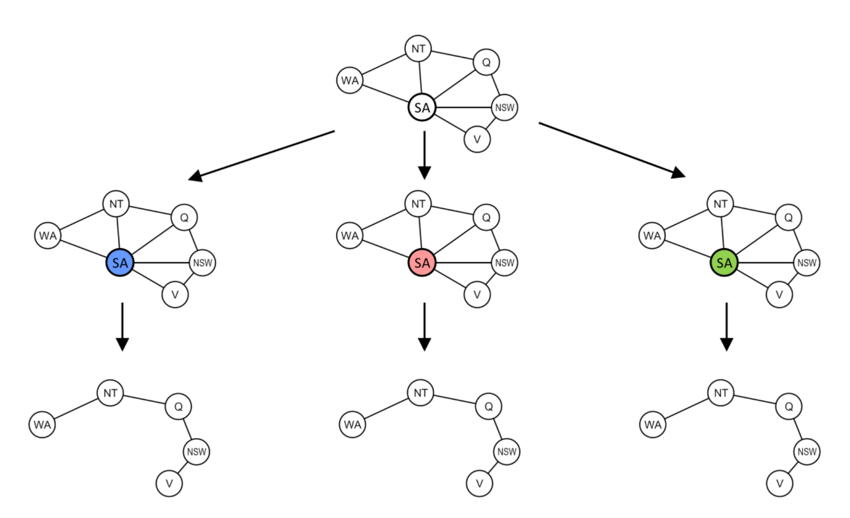

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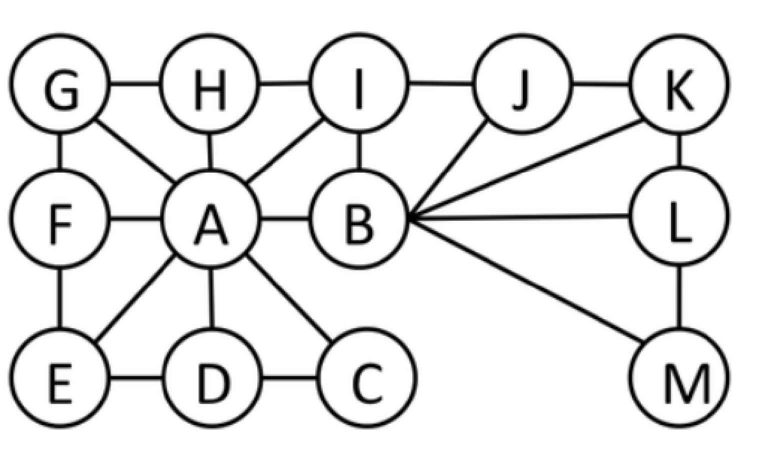
Exercise

- Solve the following 3-coloring problem by Cutset Conditioning



Breaking Value Symmetry

- Value symmetry: if domain size is n and no unary constraints
  - every solution has $n!$ solutions obtained by permuting color names
  - ex: 3-coloring, $3! = 6$ permutations for every solutions
- Symmetry Breaking: add symmetry-breaking constraints s.t. only one of the $n!$ solution is possible

  $\Longrightarrow$ reduce search space by $n!$ factor
- Add value-ordering constraints on n variables:
  - give an ordering of values (ex: $r < b < g$)
  - impose an ordering on the values of n variables s.t. $x_i \neq x_j$
    (ex: $WA < NT < SA$)

  $\Longrightarrow$ only one solution out of $n!$

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