

Artificial Intelligence (AI)

CCS-3880 – 3rd Semester 2023

CO5: Constraint Satisfaction Problems (CSP)

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Constraint Satisfaction Problems (CSP)

CO5: Investigate constraint satisfaction for a given set of problems.

- **Defining Constraint Satisfaction Problems**

- Example: *Map coloring*
- Real-world CSPs
- Constraint Graph
- Varieties of CSPs
- Varieties of Constraints
- Example: *Cryptarithmic*

- **CSP as a Standard Search Problem**

- **Backtracking Search**

- Improving Backtracking Efficiency
- Minimum Remaining Values (MRV) Heuristic
- Degree Heuristic
- Least Constraining Value

- **Forward Checking**

- Drawback in Forward Checking

- **Local Search for CSPs**

- Min-conflicts Heuristic



Defining Constraint Satisfaction Problems

- We use a factored representation for each state: a set of variables, each of which has a value.
- A problem is solved when each variable has a value that satisfies all the constraints on the variable.
- A problem described this way is called a *constraint satisfaction problem*, or CSP.

What is a CSP?

- Finite set of variables V_1, V_2, \dots, V_n
- Non-empty domain of possible values for each variable $D_{V_1}, D_{V_2}, \dots, D_{V_n}$
- Finite set of constraints C_1, C_2, \dots, C_m
 - Each constraint C_i limits the values that variables can take, e.g., $V_1 \neq V_2$
- A state is an assignment of values to some or all variables.
- Consistent assignment: assignment does not violate the constraints.



CSP- Components

A constraint satisfaction problem consists of **three components**, **X**, **D**, and **C** :

- **X** is a set of variables, $\{X_1, \dots, X_n\}$.
 - **D** is a set of domains, $\{D_1, \dots, D_n\}$, one for each variable.
 - **C** is a set of constraints that specify allowable combinations of values.
-
- To solve a CSP, we need to define a state space and the notion of a solution.
 - Each state in a CSP is defined by an assignment of values to some or all of the variables, $\{X_i = v_i, X_j = v_j, \dots\}$.
 - An assignment that does not violate any constraints is called a **consistent** or legal assignment.
 - A **complete assignment** is one in which every variable is assigned, and a **solution** to a CSP is a consistent, complete assignment.
 - A **partial assignment** is one that assigns values to only some of the variables.



Example problem:

Map coloring



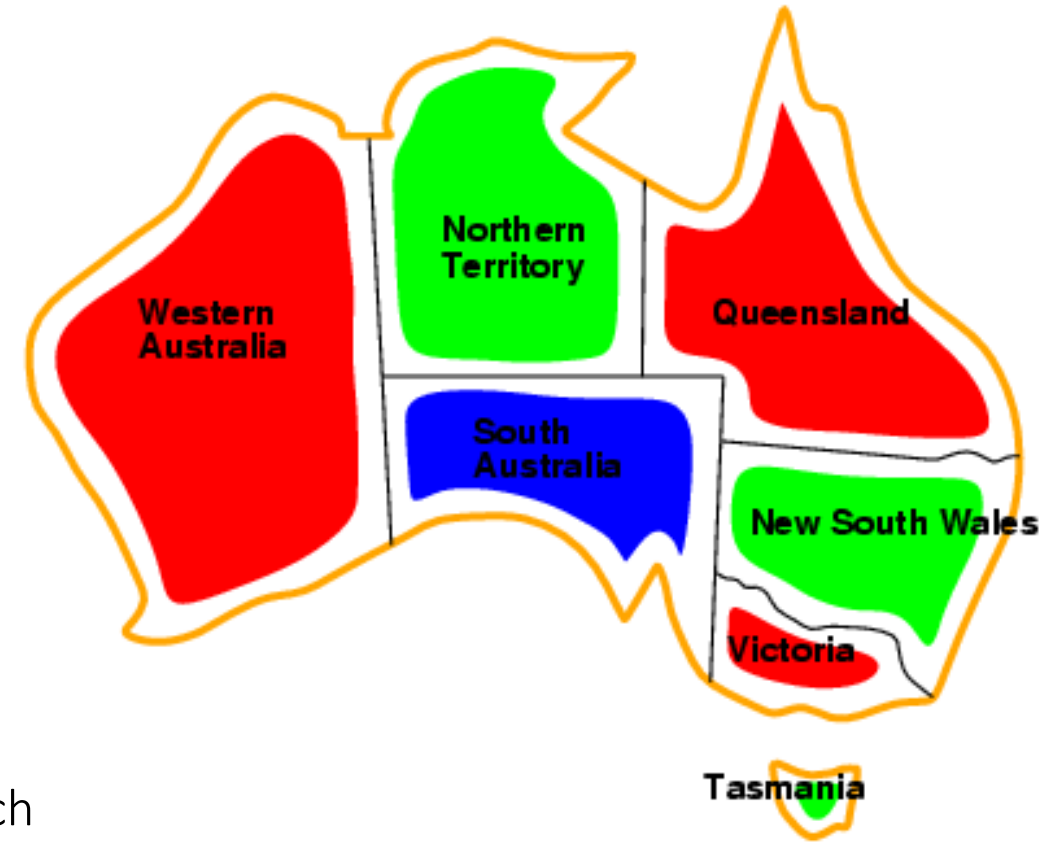
- Variable $X = \{WA, NT, Q, NSW, V, SA, T\}$.
- Domain $D = \{\text{red}, \text{green}, \text{blue}\}$.
- Constraint $C = \{\text{neighboring regions to have distinct colors}\}$



Example problem:

Map coloring

- For $\{SA = \text{blue}\}$ in the Australia problem, none of the five neighboring variables can take on the value blue.
- Without taking advantage of constraint propagation, a search procedure would have to consider $3^5 = 243$ assignments for the five neighboring variables; with constraint propagation we never have to consider blue as a value, so we have only $2^5 = 32$ assignments to look at, a reduction of 87%.



Real-world CSPs

- **Assignment problems**
 - e.g., who teaches what class
- **Timetabling problems**
 - e.g., which class is offered when and where?
- **Job scheduling**
 - Whenever a task T_1 must occur before task T_2 , and task T_1 takes duration d_1 to complete, we add an arithmetic constraint of the form $T_1 + d_1 \leq T_2$.
- **Transportation scheduling**
- **Factory scheduling**
- **Notice that many real-world problems involve real-valued variables**



Varieties of Variables

- **Discrete variables**

- finite domains:

- n variables, domain size $d \rightarrow O(d^n)$ complete assignments

- infinite domains:

- integers, strings, etc.

- e.g., job scheduling, variables are start/end days for each job

- need a constraint language, e.g., $StartJob_1 + 5 \leq StartJob_3$

- **Continuous variables**

- e.g., start/end times for Hubble Space Telescope observations



Varieties of Constraints

- **Unary** constraints involve a single variable,
e.g., $SA \neq \text{"green"}$
- **Binary** constraints involve pairs of variables,
e.g., $SA \neq WA$
- **Higher-order** constraints involve 3 or more variables
e.g., cryptarithmic column constraints
- **Preference** (soft constraints) e.g. red is better than green can be represented by a cost for each variable assignment
=> **Constrained optimization problems.**



Example: Cryptarithmic

- **Variables:** F T U W R O X_1 X_2 X_3
- **Domain:** {0,1,2,3,4,5,6,7,8,9}
- **Constraints:** Alldiff (F,T,U,W,R,O)
 - $O + O = R + 10 \cdot X_1$
 - $X_1 + W + W = U + 10 \cdot X_2$
 - $X_2 + T + T = O + 10 \cdot X_3$
 - $X_3 = F, T \neq 0, F \neq 0$

$$\begin{array}{r}
 \text{TWO} \\
 + \text{TWO} \\
 \hline
 \text{FOUR}
 \end{array}$$



CSP as a standard search problem

A CSP can easily be expressed as a standard search problem.

- **Initial State:** the empty assignment {}.
- **Operators:** Assign value to unassigned variable provided that there is no conflict.
- **Goal test:** assignment consistent and complete.
- **Path cost:** constant cost for every step.

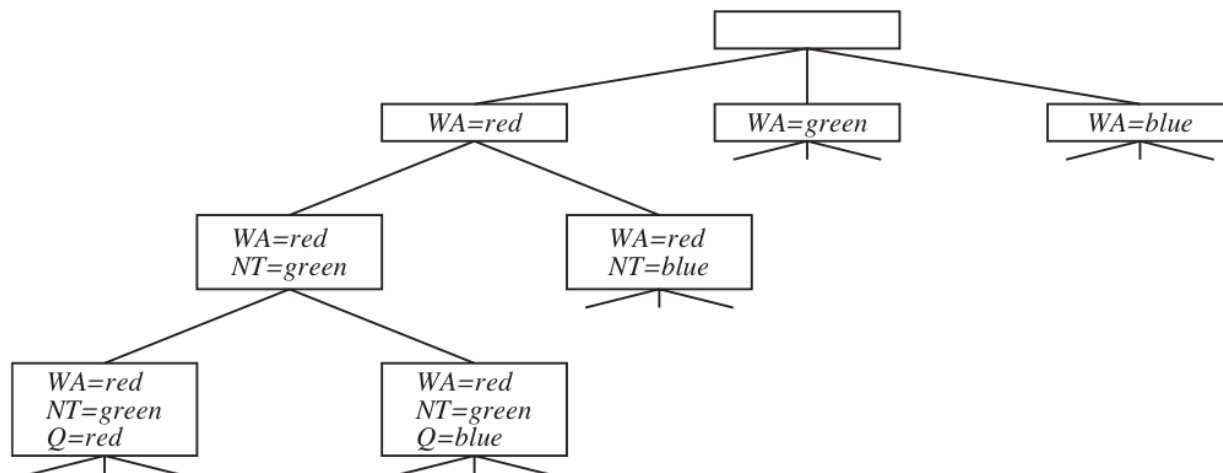


Backtracking Search

- Variable assignments are *commutative*,
E.g [*WA = red then NT = green*] equivalent to [*NT = green then WA = red*]
- Only need to consider assignments to a single variable at each node
→ $b = d$ and there are d^n leaves
- Depth-first search for CSPs with single-variable assignments is called *backtracking* search
- Backtracking search basic uninformed algorithm for CSPs



Backtracking Search



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

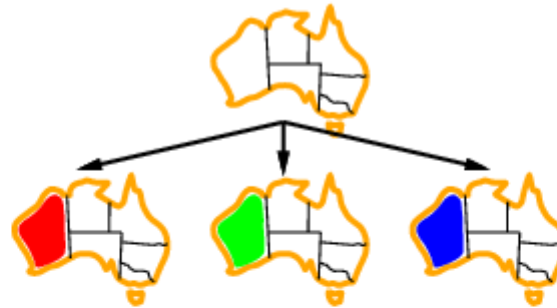
function BACKTRACK(*assignment*, *csp*) **returns** a solution, or failure
if *assignment* is complete **then return** *assignment*
 $var \leftarrow \text{SELECT-UNASSIGNED-VARIABLE}(csp)$
for each *value* **in** ORDER-DOMAIN-VALUES(*var*, *assignment*, *csp*) **do**
 if *value* is consistent with *assignment* **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*
 remove { *var* = *value* } and *inferences* from *assignment*
return failure



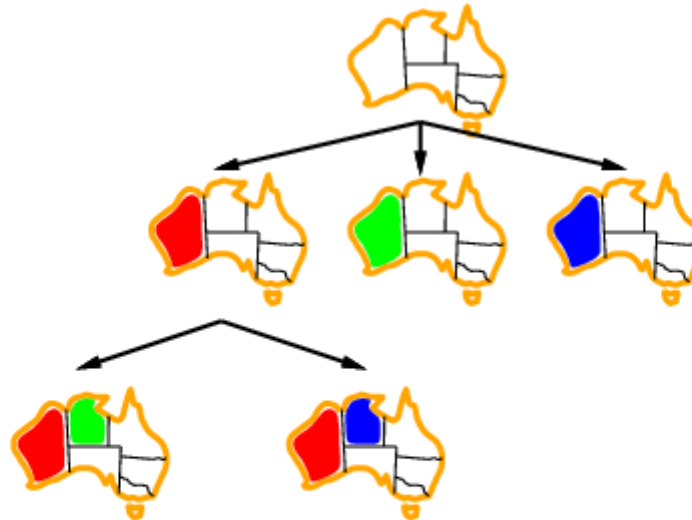
Backtracking Search



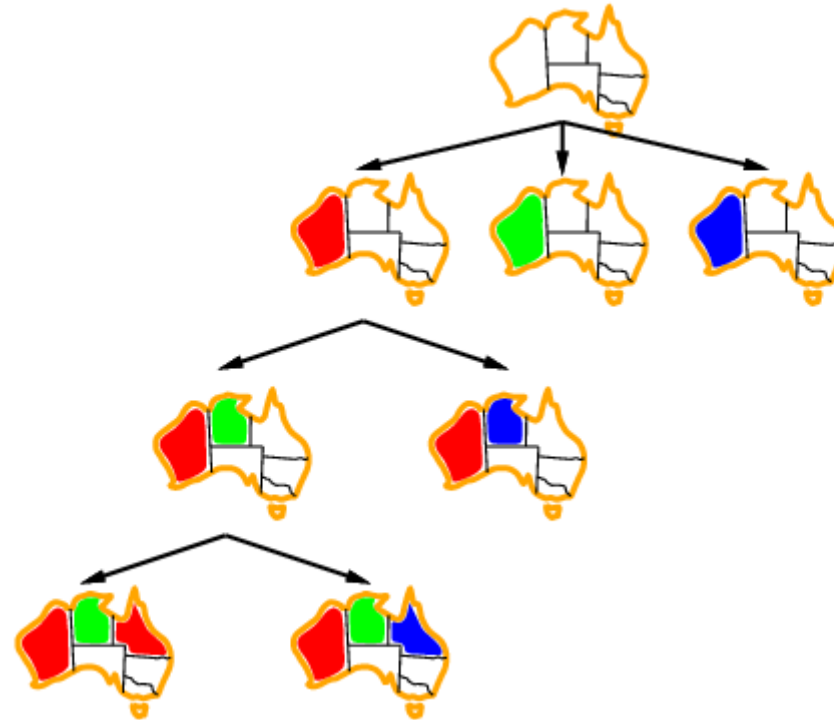
Backtracking Search



Backtracking Search



Backtracking Search



Improving Backtracking Efficiency

General-purpose methods can give huge speed gains:

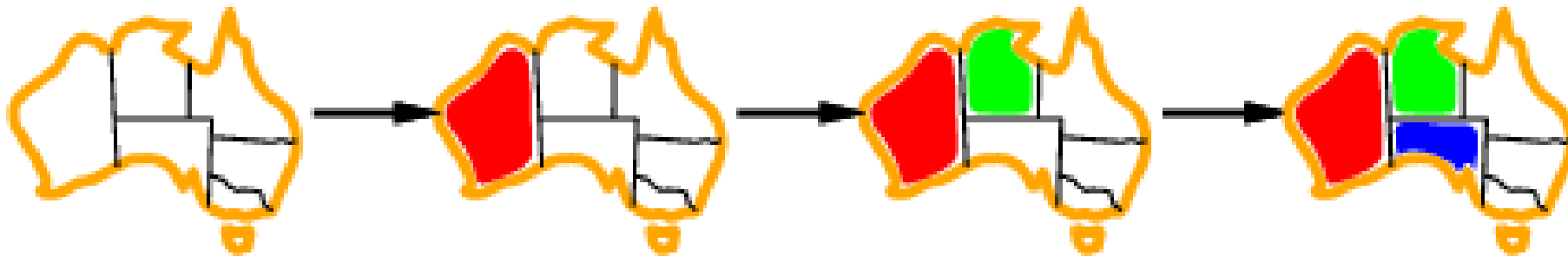
- Which variable should be assigned next? (*Select-unassigned-variable*)
- In what order should its values be tried? (*Order-domain-values*)
- Can we detect inevitable failure early? (*Inference*)
- When the search arrives at an assignment that violates a constraint,
can the search avoid repeating this failure?



Most Constrained Variable

a.k.a. minimum remaining values (MRV) heuristic

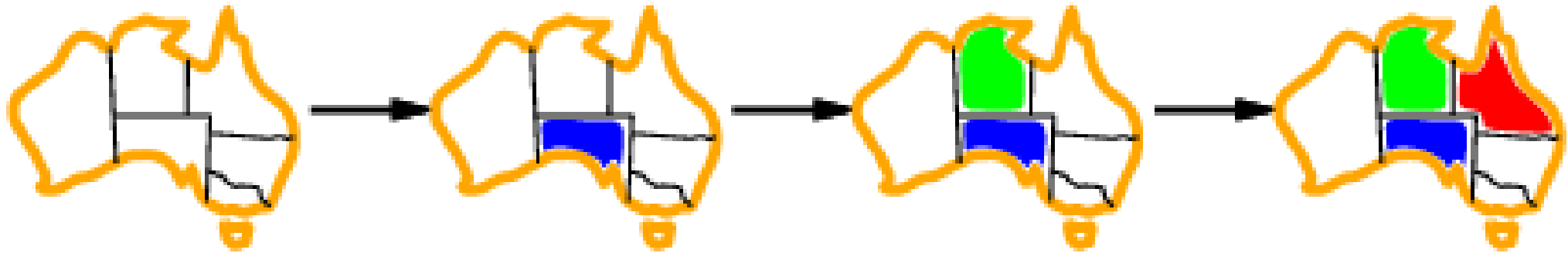
Idea: *choose the variable with the fewest legal values*



- The simplest strategy for **SELECT-UNASSIGNED-VARIABLE** is to choose the next unassigned variable in order, $\{X_1, X_2, \dots\}$. This static variable ordering rarely results in the most efficient search.
- For example, after the assignments for WA = red and NT = green, there is only one possible value for SA, so it makes sense to assign SA = blue next rather than assigning Q.



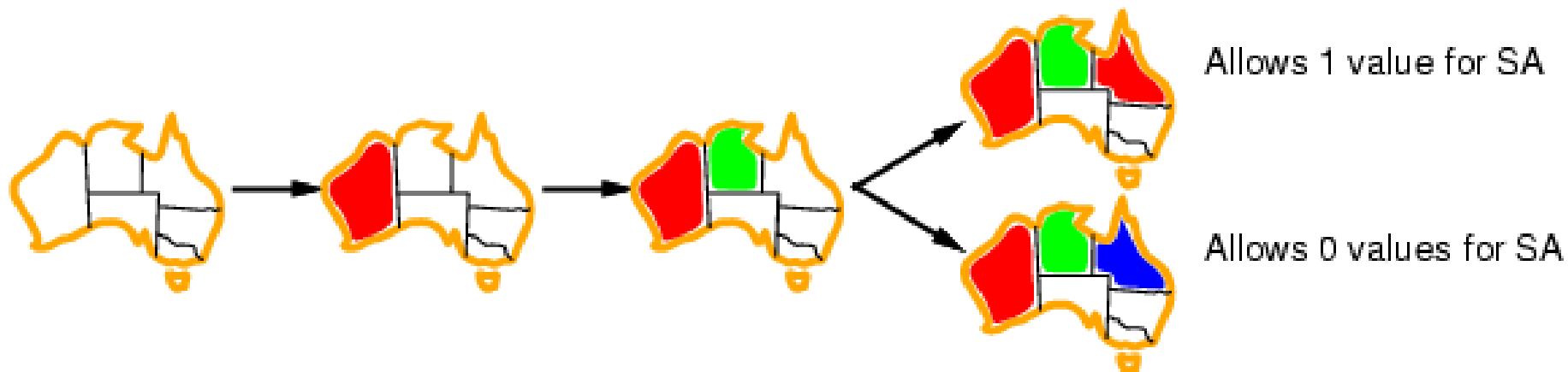
Degree Heuristic



- The MRV heuristic doesn't help at all in choosing the first region to color in Australia, because initially every region has three legal colors.
- In this case, the **degree heuristic** comes in handy. It attempts to reduce the branching factor on future choices by selecting the variable that is involved in the largest number of constraints on other unassigned variables.
- In the figure, SA is the variable with highest degree, 5; the other variables have degree 2 or 3, except for T, which has degree 0.
- In fact, once SA is chosen, applying the degree heuristic solves the problem without any false steps—you can choose *any* consistent color at each choice point and still arrive at a solution with no backtracking.

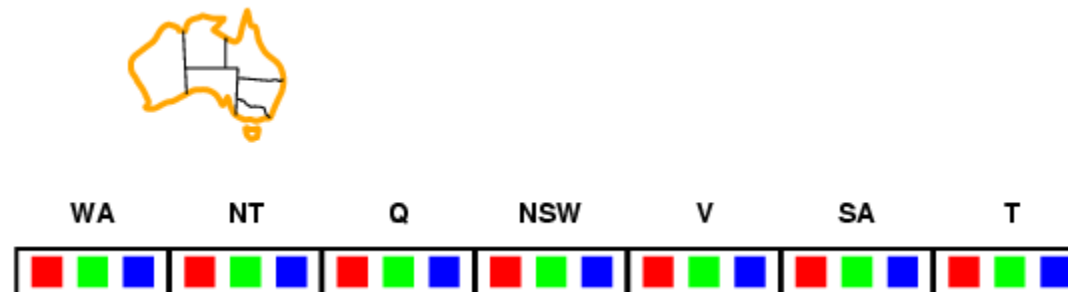
Least Constraining Value

- Given a variable, choose the least constraining value.
- For example, we have generated the partial assignment with WA = red and NT = green and that our next choice is for Q. Blue would be a bad choice because it eliminates the last legal value left for Q's neighbor, SA. The least-constraining-value heuristic therefore prefers red to blue.
- In general, the heuristic is trying to leave the maximum flexibility for subsequent variable assignments.



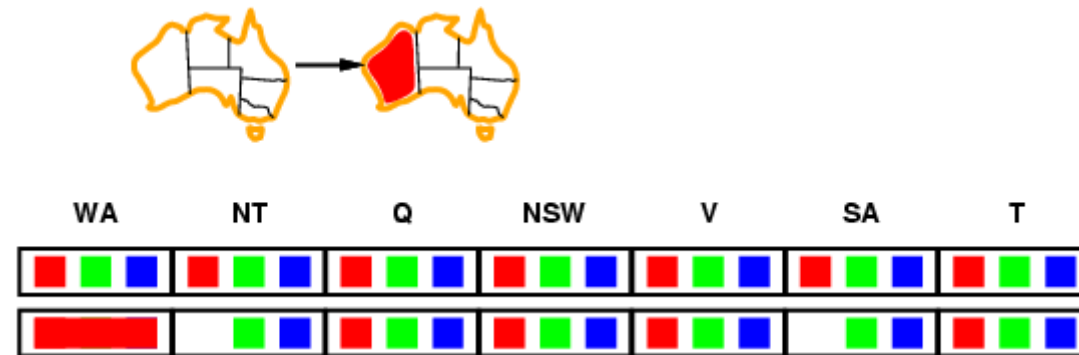
Forward Checking

- One of the simplest forms of inference is called **forward checking**.
- **Idea**: Keep track of remaining legal values for unassigned variables
- Terminate search when any variable has no legal values
- Whenever a variable X is assigned, the forward-checking process establishes arc consistency for it:
for each unassigned variable Y that is connected to X by a constraint, delete from Y's domain any value that is inconsistent with the value chosen for X.



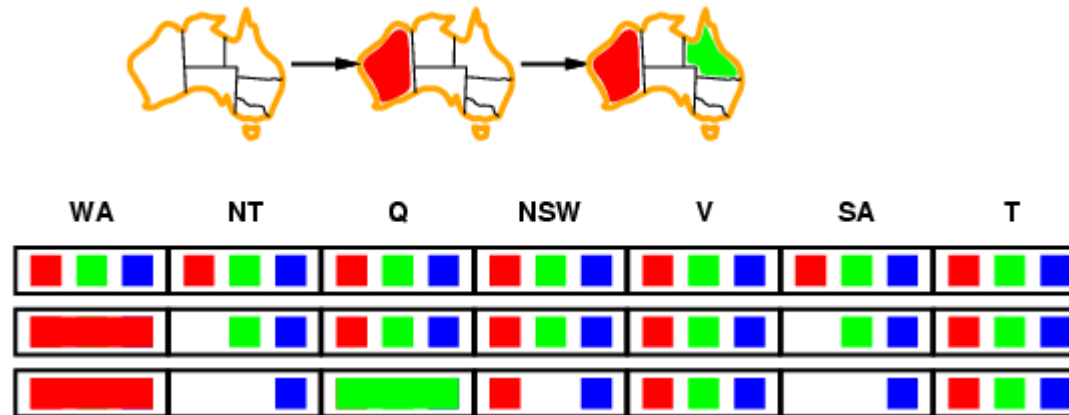
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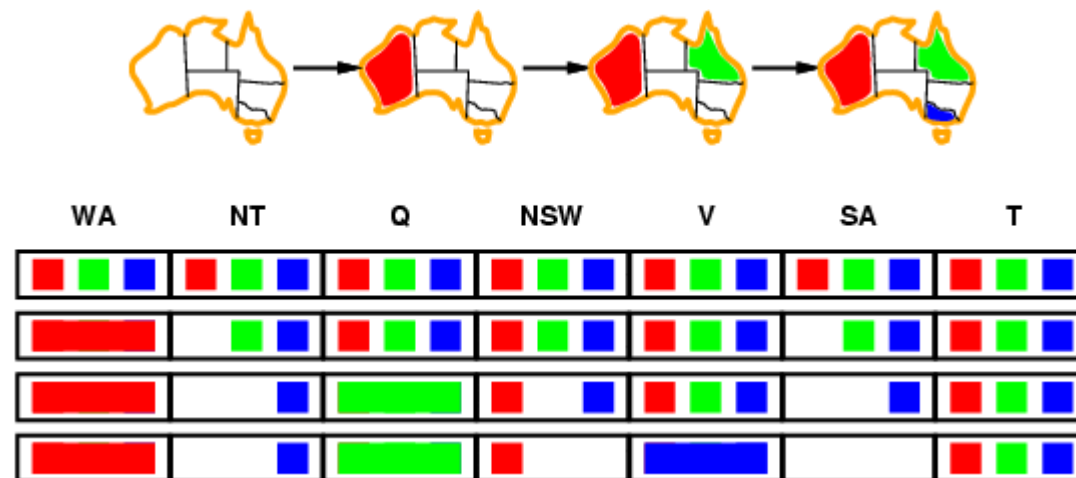
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Forward Checking

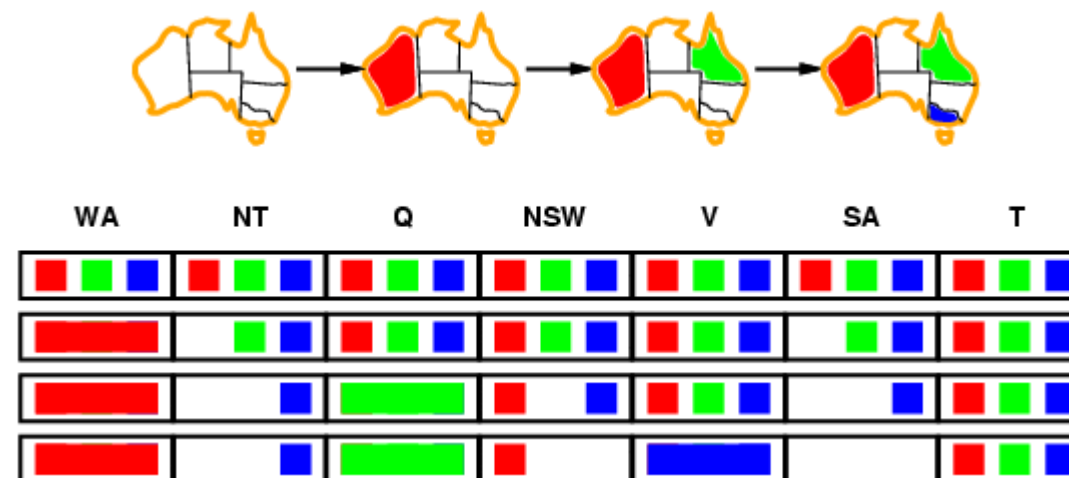
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No more value for SA: backtrack

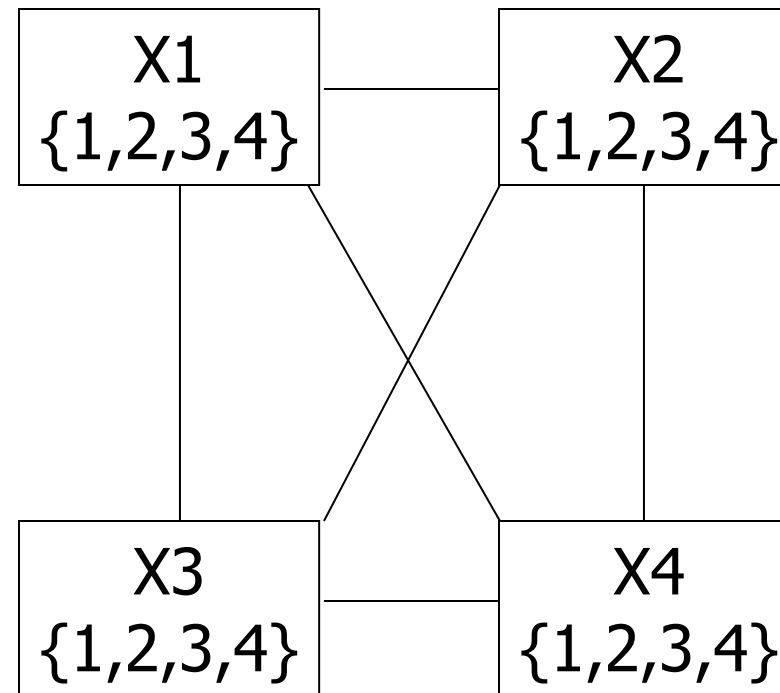
Drawback in Forward Checking

- Although forward checking detects many inconsistencies, it does not detect all of them. The problem is that it makes the current variable **arc-consistent** but **doesn't look ahead and make all the other variables arc-consistent**.
- For example, consider the Figure. It shows that when WA is red and Q is green, both NT and SA are forced to be blue.
- Forward checking does not look far enough ahead** to notice that this is an inconsistency: NT and SA are adjacent (neighboring) and so cannot have the same value.










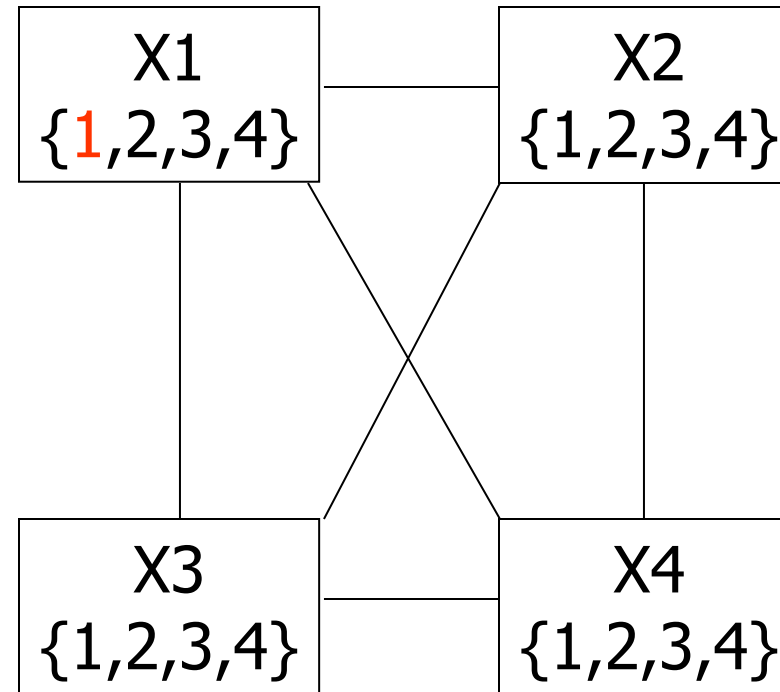
Example: 4-Queens Problem

	1	2	3	4
1				
2				
3				
4				










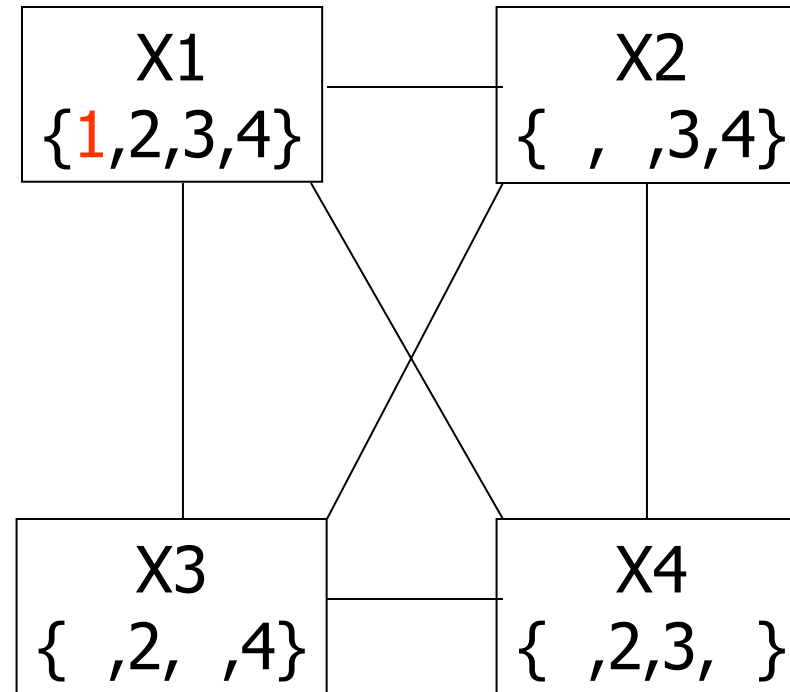
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	1	2	3	4
1				
2				
3				
4				



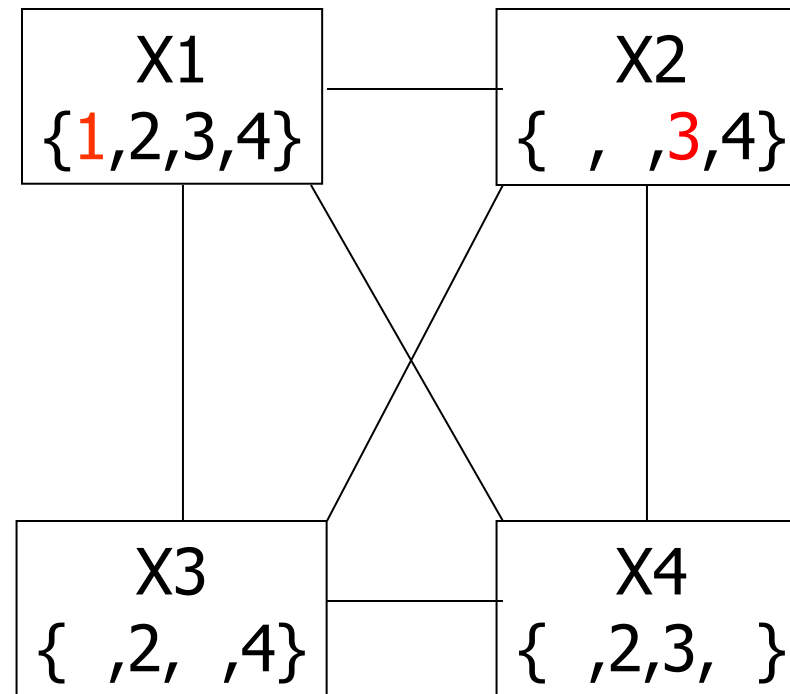
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	1	2	3	4
1				
2				
3				
4				



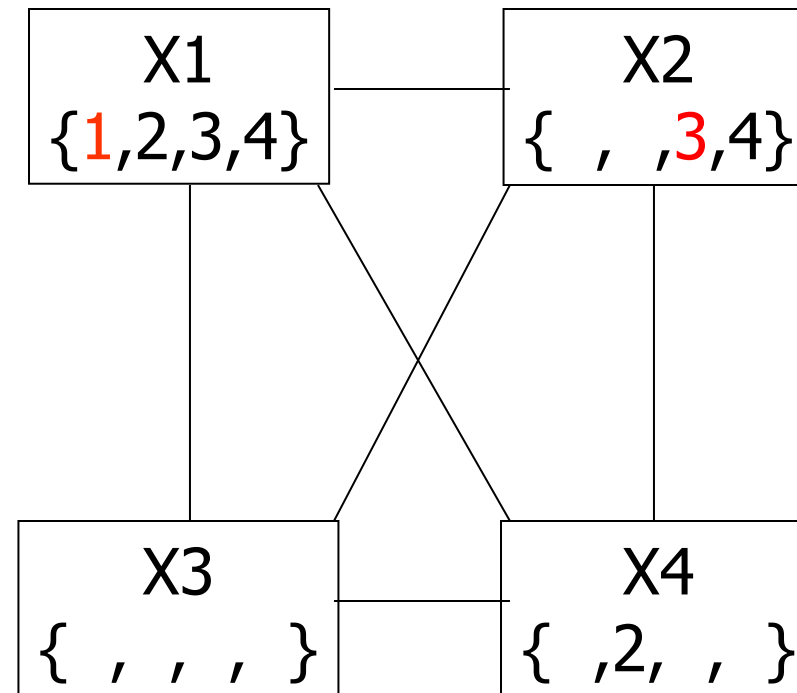
Example: 4-Queens Problem

	1	2	3	4
1	★	●	●	●
2		●	●	
3		★	●	●
4			●	●



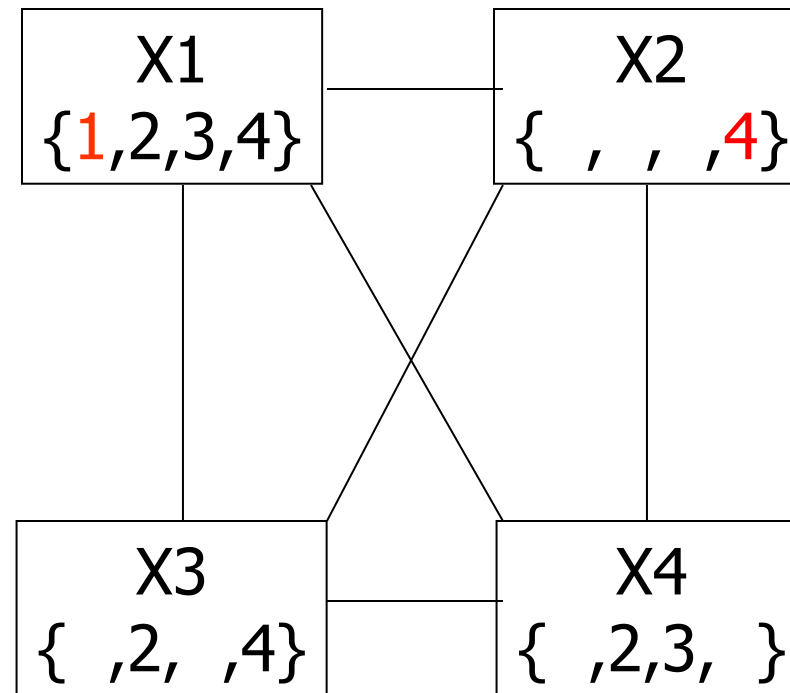
Example: 4-Queens Problem

	1	2	3	4
1	★	●	●	●
2	■	●	●	□
3	□	★	●	●
4	■	□	●	●



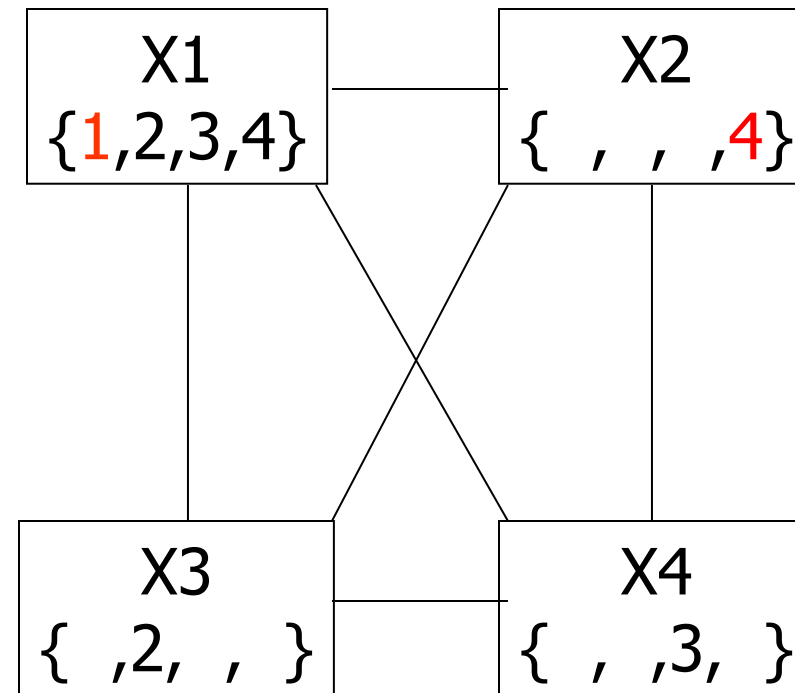
Example: 4-Queens Problem

	1	2	3	4
1	★	●	●	●
2	■	●	■	●
3	□	●	●	■
4	■	★	●	●



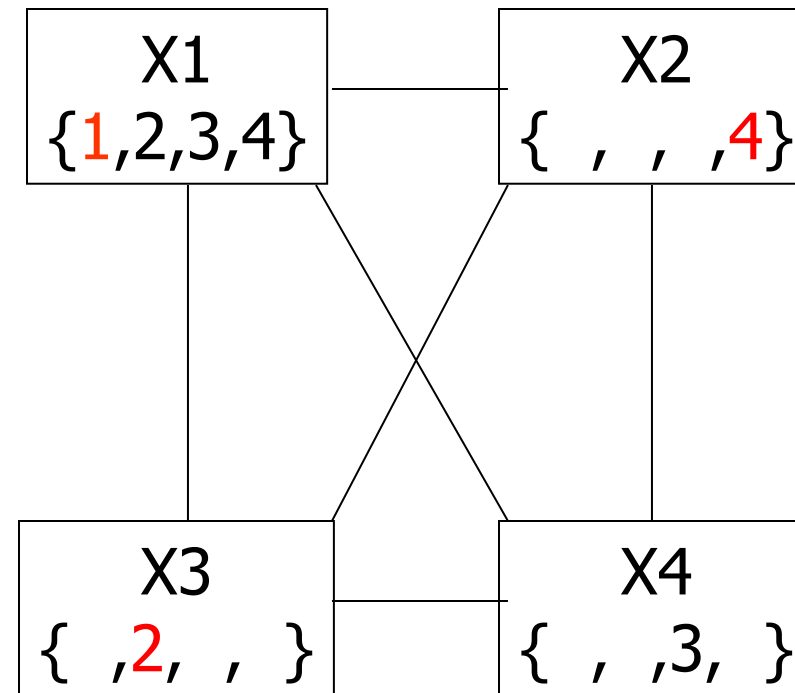
Example: 4-Queens Problem

	1	2	3	4
1	★	●	●	●
2	■	●	■	●
3	□	●	●	■
4	■	★	●	●



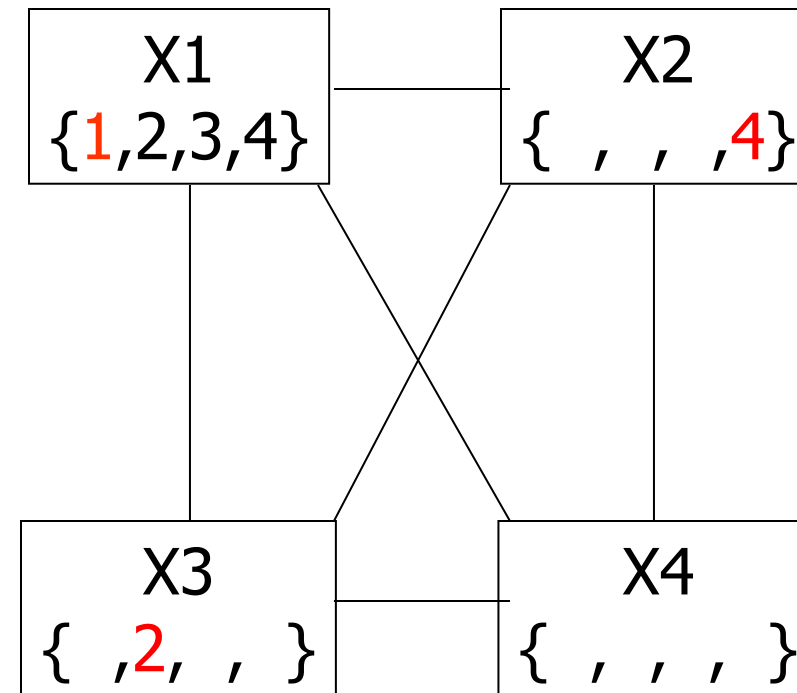
Example: 4-Queens Problem

	1	2	3	4
1	★	●	●	●
2	●	●	★	●
3	●	●	●	●
4	●	★	●	●



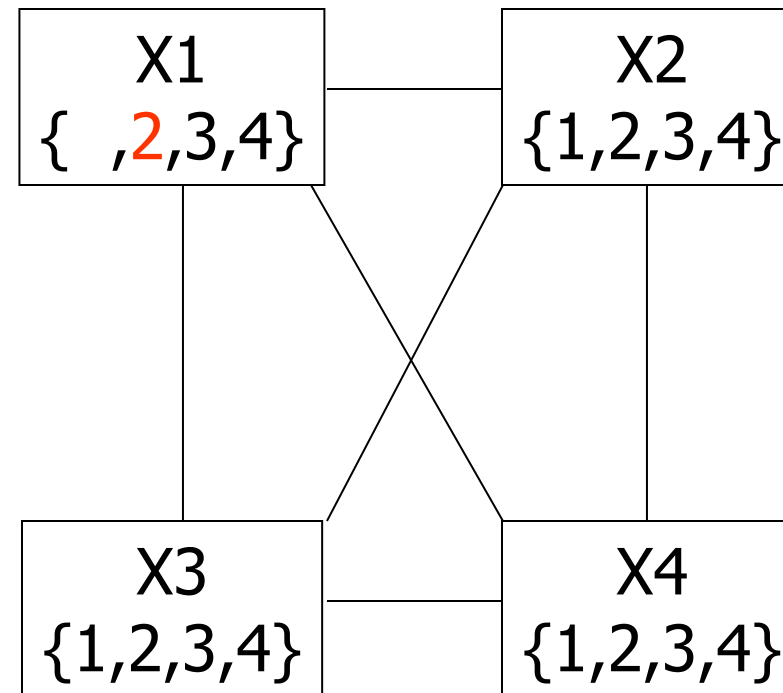
Example: 4-Queens Problem

	1	2	3	4
1	★	●	●	●
2	●	●	★	●
3	●	●	●	●
4	●	★	●	●



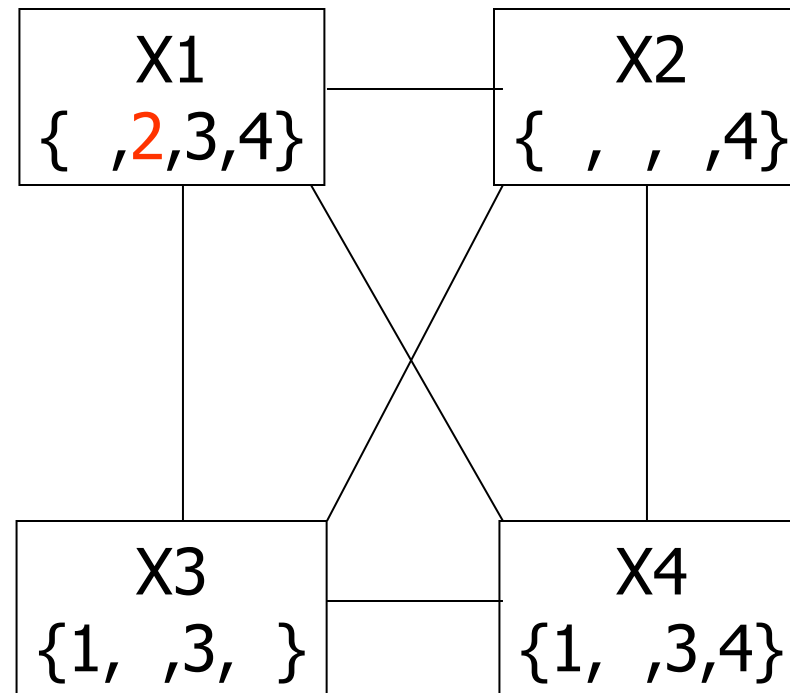
Example: 4-Queens Problem

	1	2	3	4
1		●		
2	★	●	●	●
3		●		
4			●	



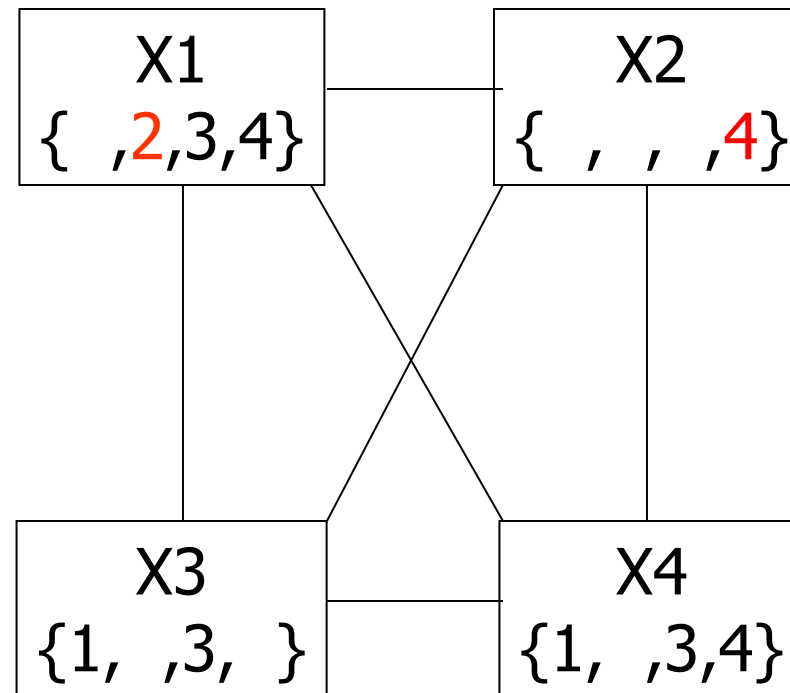
Example: 4-Queens Problem

	1	2	3	4
1		●		
2	★	●	●	●
3		●		
4			●	



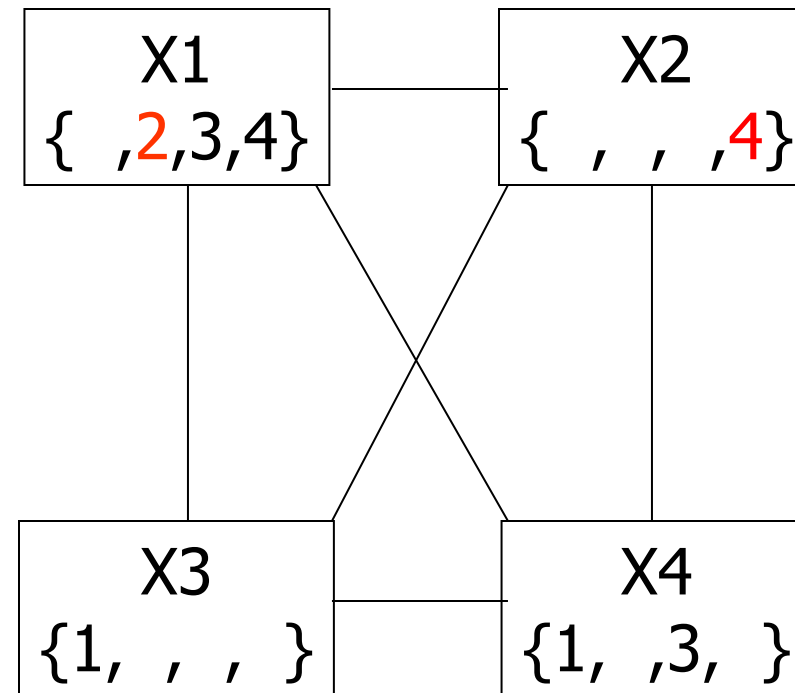
Example: 4-Queens Problem

	1	2	3	4
1		●		
2	★	●	●	●
3		●	●	
4		★	●	●



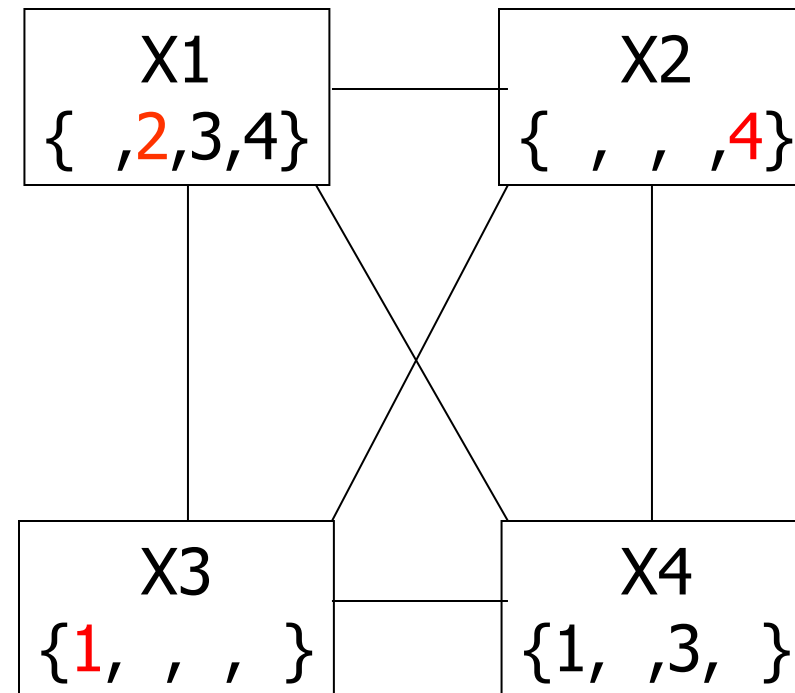
Example: 4-Queens Problem

	1	2	3	4
1		●		
2	★	●	●	●
3		●	●	
4		★	●	●



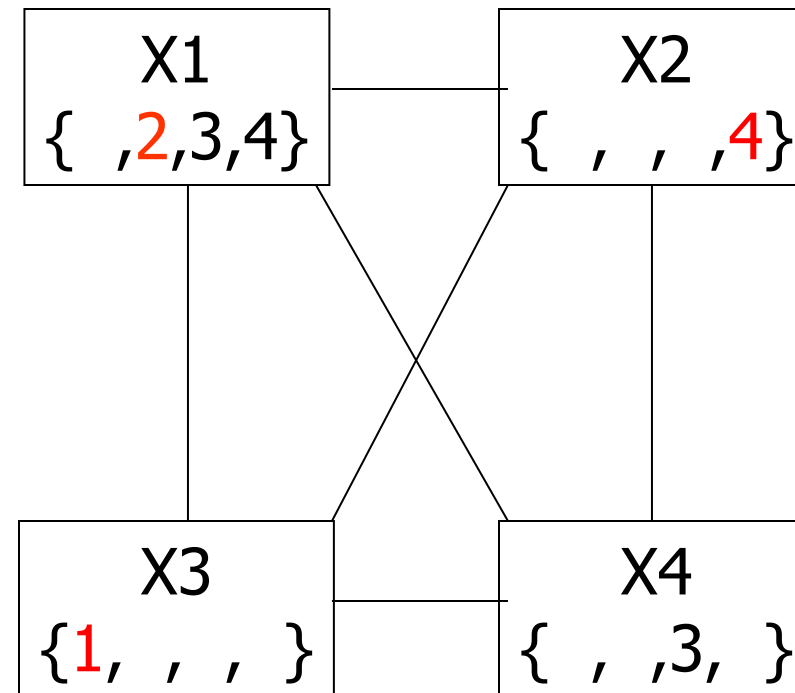
Example: 4-Queens Problem

	1	2	3	4
1		●	★	●
2	★	●	●	●
3		●	●	
4		★	●	●



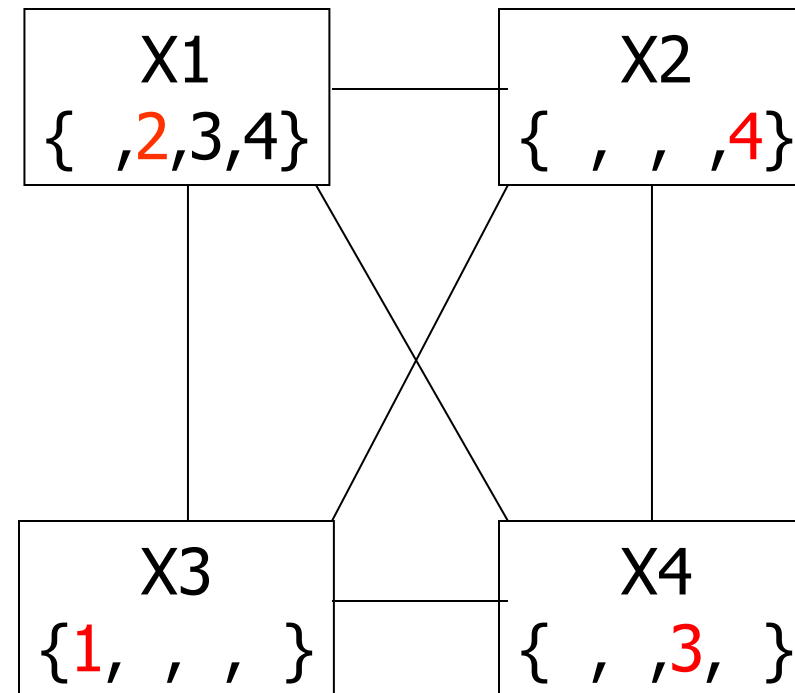
Example: 4-Queens Problem

	1	2	3	4
1		●	★	●
2	★	●	●	●
3		●	●	
4		★	●	●



Example: 4-Queens Problem

	1	2	3	4
1		●	★	●
2	★	●	●	●
3		●	●	★
4	●	★	●	●



Local Search for CSPs: min-conflicts heuristic

- ♦ **Use complete-state representation**

- Initial state = all variables assigned values
- Successor states = change 1 (or more) values

- ♦ **For CSPs**

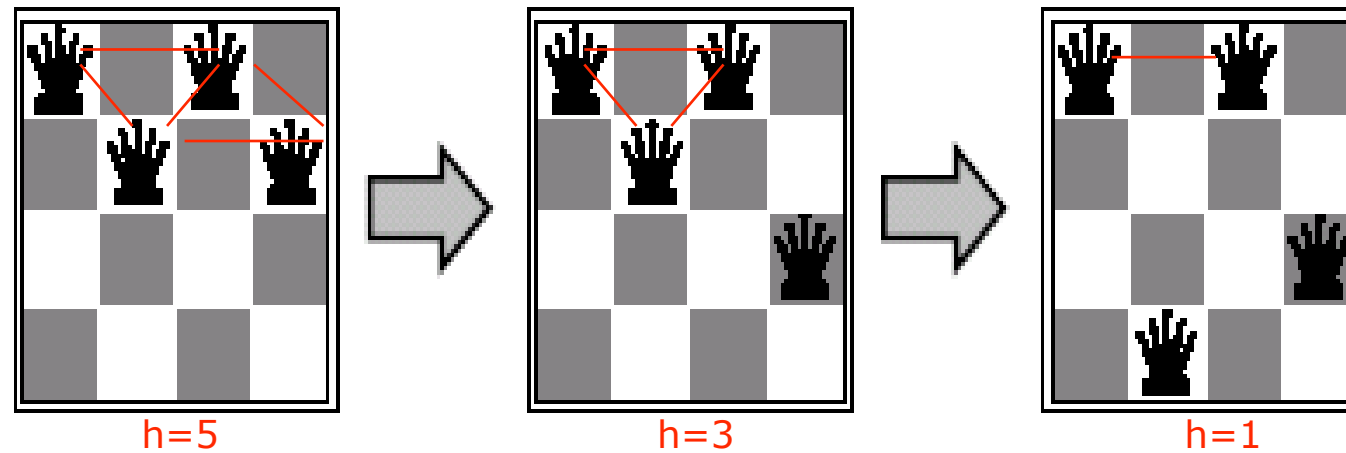
- Allow states with unsatisfied constraints (unlike backtracking)
- Operators **reassign** variable values
- Hill-climbing with n-queens is an example

- ♦ **Variable selection:**

- Randomly select any conflicted variable.
- Select new value that results in a minimum number of conflicts with the other variables



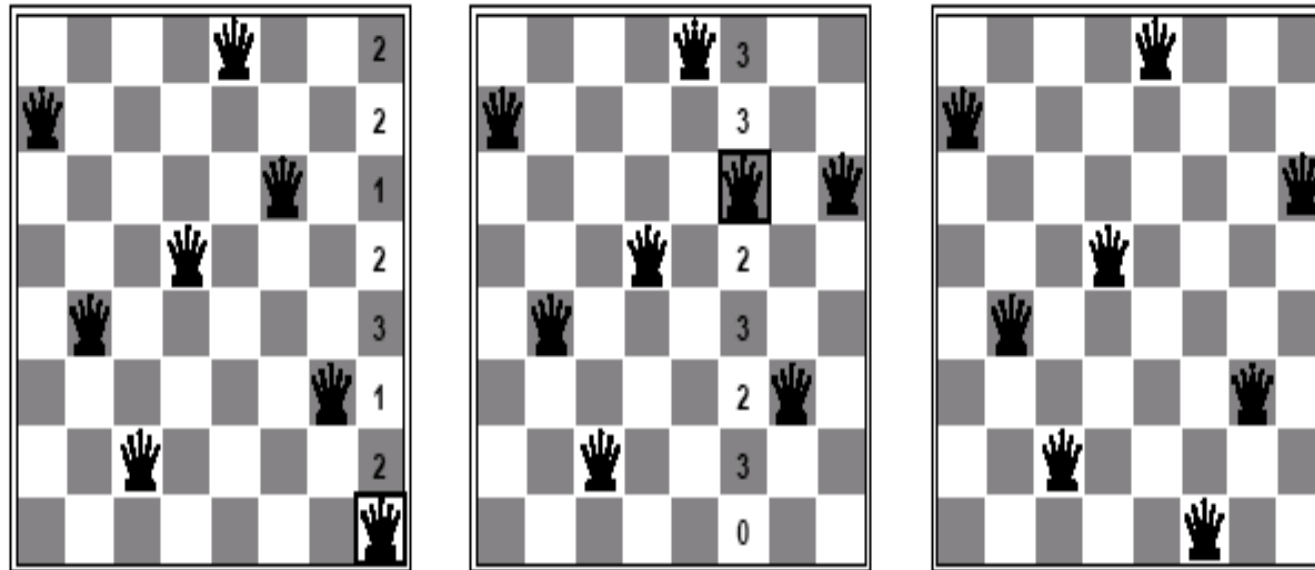
Min-conflicts: **example 1**



Use of min-conflicts heuristic in hill-climbing.



Min-conflicts: example 2



- A two-step solution for an 8-queens problem using min-conflicts heuristic
- At each stage a queen is chosen for reassignment in its column
- The algorithm moves the queen to the min-conflict square breaking ties randomly.



Advantages of local search

- ♦ Local search can be particularly useful in an online setting
 - Airline schedule example
 - Much better (and faster) in practice than finding an entirely new schedule.

- ♦ The runtime of min-conflicts is roughly [independent of problem size](#).
 - Can solve the millions-queen problem in roughly 50 steps.



Summary

- CSPs are a special kind of problem:
 - states defined by values of a fixed set of variables
 - goal test defined by constraints on variable values
- **Backtracking** = depth-first search with one variable assigned per node
- Variable ordering and value selection heuristics help significantly
- Forward checking prevents assignments that guarantee later failure.
- Constraint propagation (e.g., **arc consistency**, **read it yourself**) additionally constrains values and detects inconsistencies.
- Iterative **min-conflicts** is usually effective in practice



Contents for the next lecture

- Games as Search
- Introduction to Machine Learning
- Introduction to Deep Learning (Artificial neural network)
- Natural Language Processing (NLP)

Any questions?

