

Artificial Intelligence

ENCS 434

Constraint Satisfaction Problems

Constraint Satisfaction

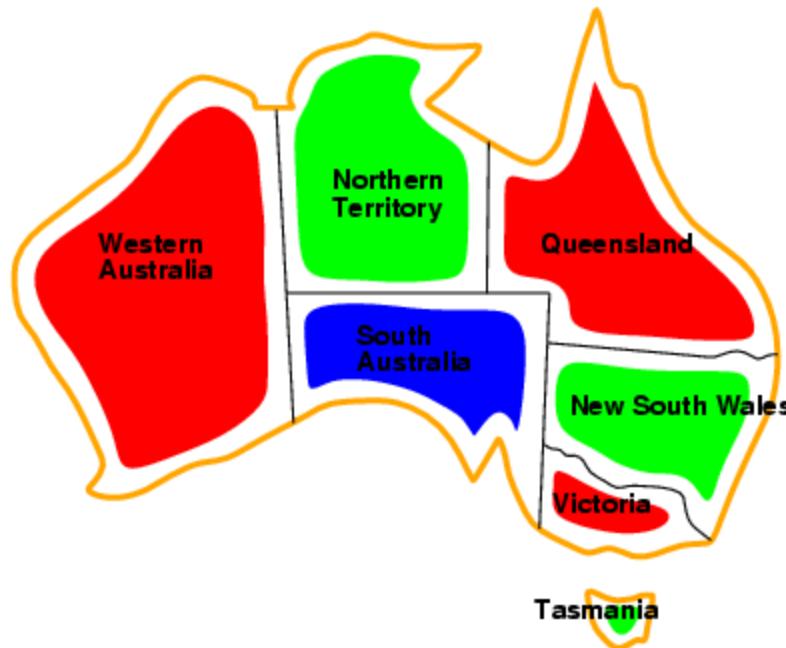
- satisfies additional structural properties of the problem
 - may depend on the representation of the problem
- the problem is defined through a set of variables and a set of domains
 - variables can have possible values specified by the problem
 - constraints describe allowable combinations of values for a subset of the variables
- ***state*** in a CSP
 - defined by an assignment of values to some or all variables
- ***solution*** to a CSP
 - must assign values to all variables
 - must satisfy all constraints
 - solutions may be ranked according to an objective function

Example: Map-Coloring



- Variables WA, NT, Q, NSW, V, SA, T
- Domains $D_i = \{\text{red, green, blue}\}$
- Constraints: adjacent regions must have different colors
 - e.g., $WA \neq NT$

Example: Map-Coloring



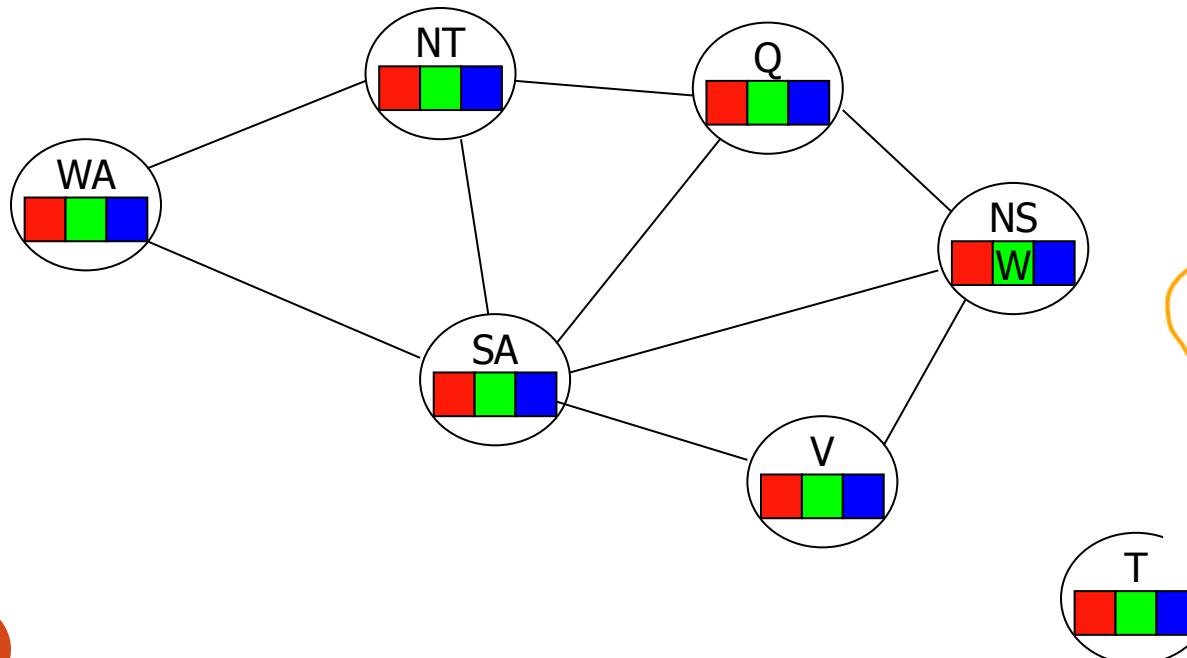
- Solutions are **complete** and **consistent** assignments, e.g.,

WA = **red**, NT = **green**, Q = **red**, NSW = **green**, V = **red**, SA = **blue**, T = **green**

- A **state** may be incomplete e.g., just WA=**red**

Constraint graph

- It is helpful to visualize a CSP as a **constraint graph**
 - **Binary CSP:** each constraint relates two variables
 - **Constraint graph:** nodes are variables, arcs are constraints



Varieties of CSPs

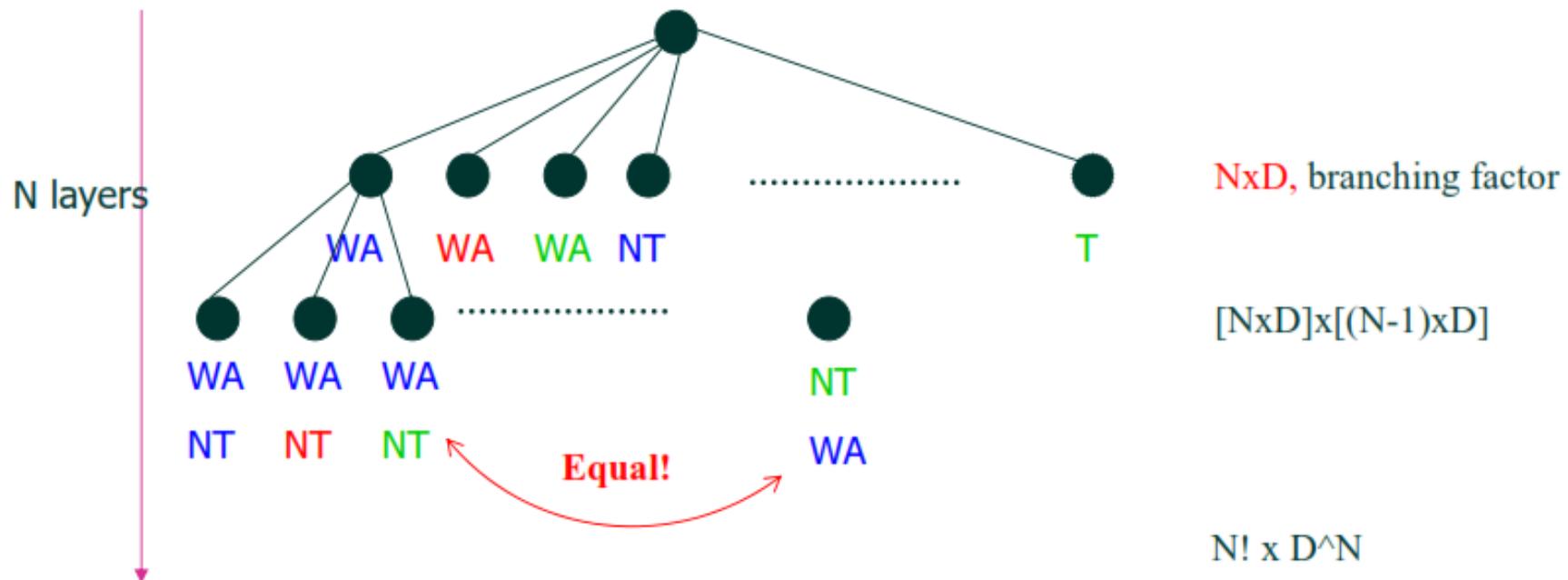
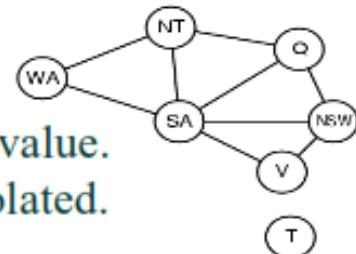
- Discrete variables
 - finite domains:
 - n variables, domain size $d \square O(d^n)$ complete assignments
 - e.g., Boolean CSPs, incl. \sim Boolean satisfiability (NP-complete)
 - infinite domains:
 - integers, strings, etc.
 - e.g., job scheduling, variables are start/end days for each job
 - need a constraint language, e.g., $\text{StartJob1} + 5 \leq \text{StartJob3}$
- Continuous variables
 - e.g., start/end times for Hubble Space Telescope observations
 - linear constraints solvable in polynomial time by linear programming

CSP as Incremental Search Problem

- initial state
 - all (or at least some) variables unassigned
- successor function
 - assign a value to an unassigned variable
 - must not conflict with previously assigned variables
- goal test
 - all variables have values assigned
 - no conflicts possible
 - not allowed in the successor function
- path cost
 - e.g. a constant for each step
 - may be problem-specific

Constraint graph Formulation

- **Node:** variable
- **Arc:** constraint
- **Initial state:** none of the variables has a value (color)
- **Successor state:** assign a value to one of the variables without a value.
- **Goal:** all variables have a value and none of the constraints is violated.



There are $N! \times D^N$ nodes in the tree but only D^N distinct states

CSPs and Search

- in principle, any search algorithm can be used to solve a CSP
 - awful branching factor
 - n^*d for n variables with d values at the top level, $(n-1)^*d$ at the next level, etc.
 - not very efficient, since they neglect some CSP properties
 - commutativity: the order in which values are assigned to variables is irrelevant, since the outcome is the same

Backtracking Search for CSPs

- a variation of depth-first search that is often used for CSPs
 - values are chosen for one variable at a time
 - if no legal values are left, the algorithm backs up and changes a previous assignment
 - very easy to implement
 - initial state, successor function, goal test are standardized
 - not very efficient
 - can be improved by trying to select more suitable unassigned variables first

Improving backtracking efficiency

- General-purpose methods can give huge gains in speed:
 - Which variable should be assigned next?
 - In what order should its values be tried?
 - Can we detect inevitable failure early?

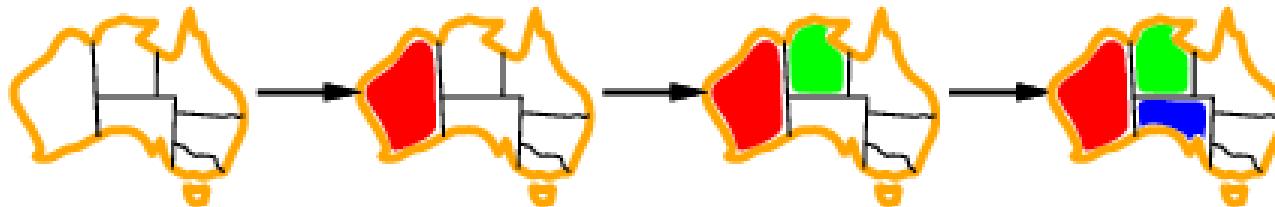
Heuristics for CSP

- most-constrained variable (minimum remaining values, “fail-first”)
 - variable with the fewest possible values is selected
 - tends to minimize the branching factor
- most-constraining variable
 - variable with the largest number of constraints on other unassigned variables
- least-constraining value
 - for a selected variable, choose the value that leaves more freedom for future choices

Most constrained variable

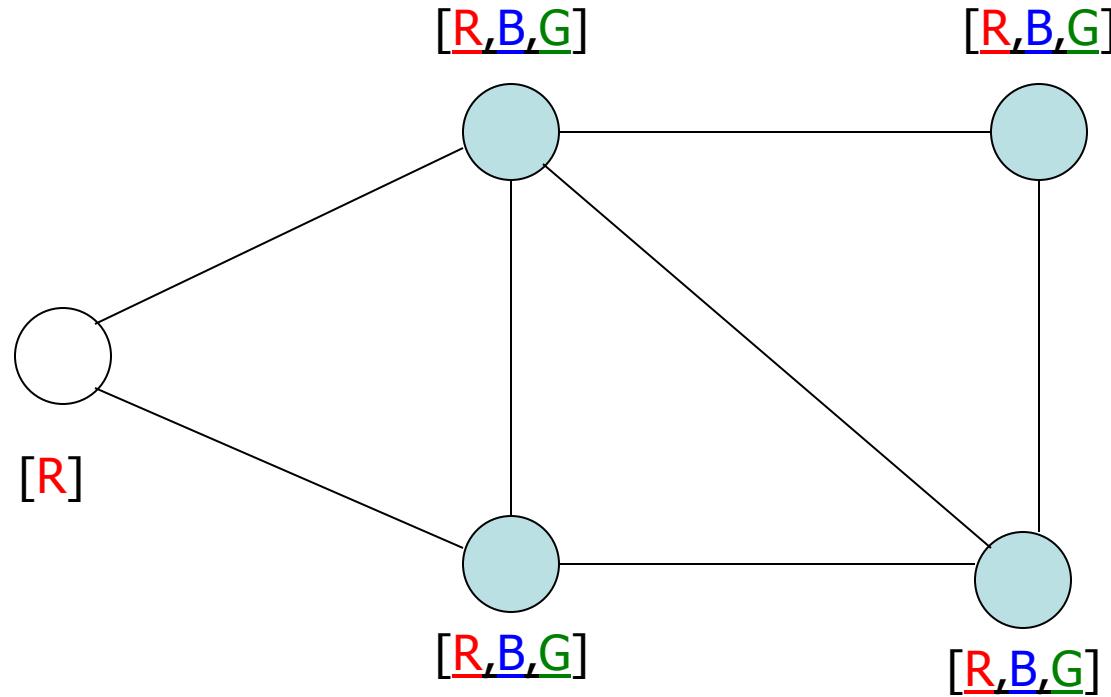
Minimum Remaining Values (MRV)

- Most constrained variable:
choose the variable with the fewest legal values

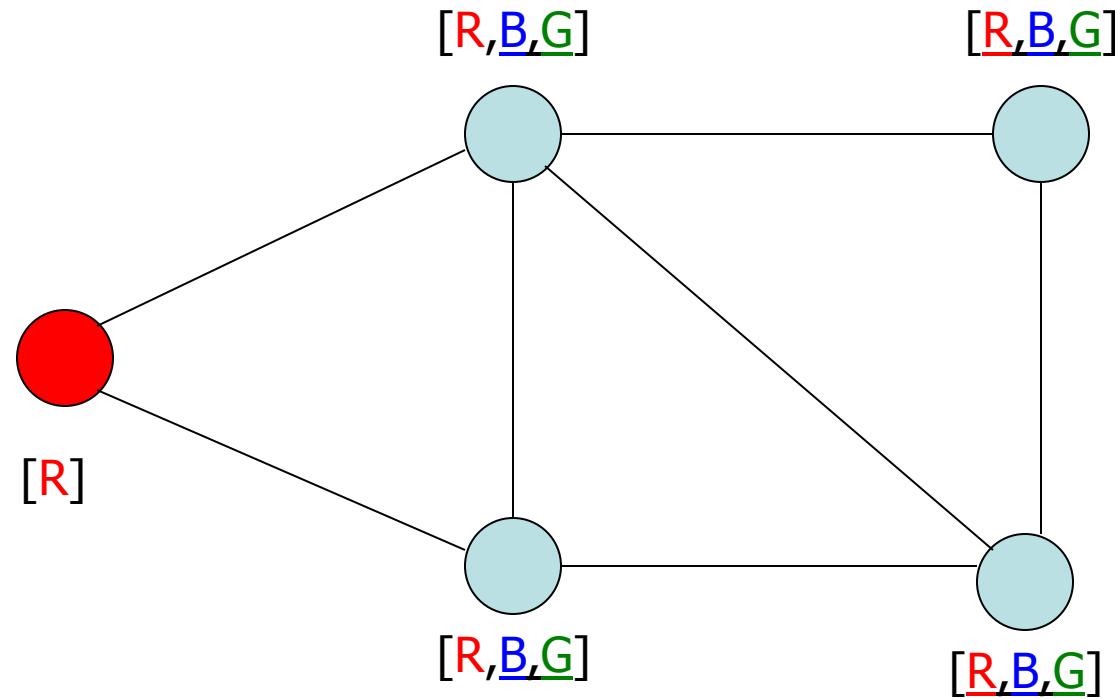


- Called **minimum remaining values (MRV)** heuristic
- “fail-first” heuristic: Picks a variable which will cause failure as soon as possible, allowing the tree to be pruned.

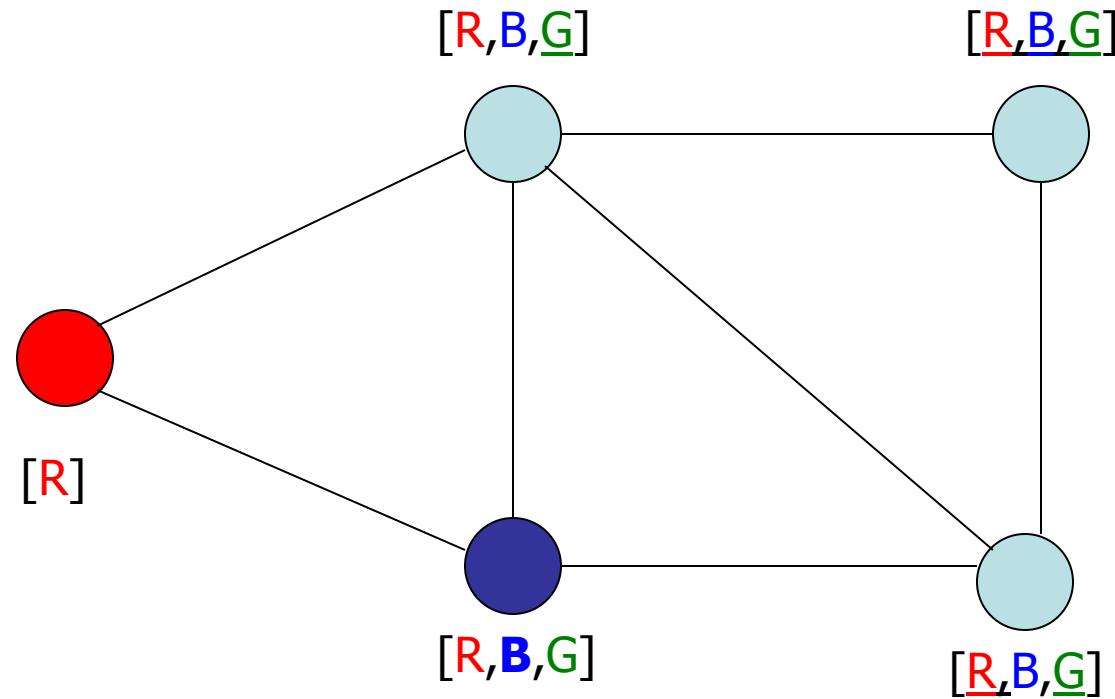
Backpropagation - MRV



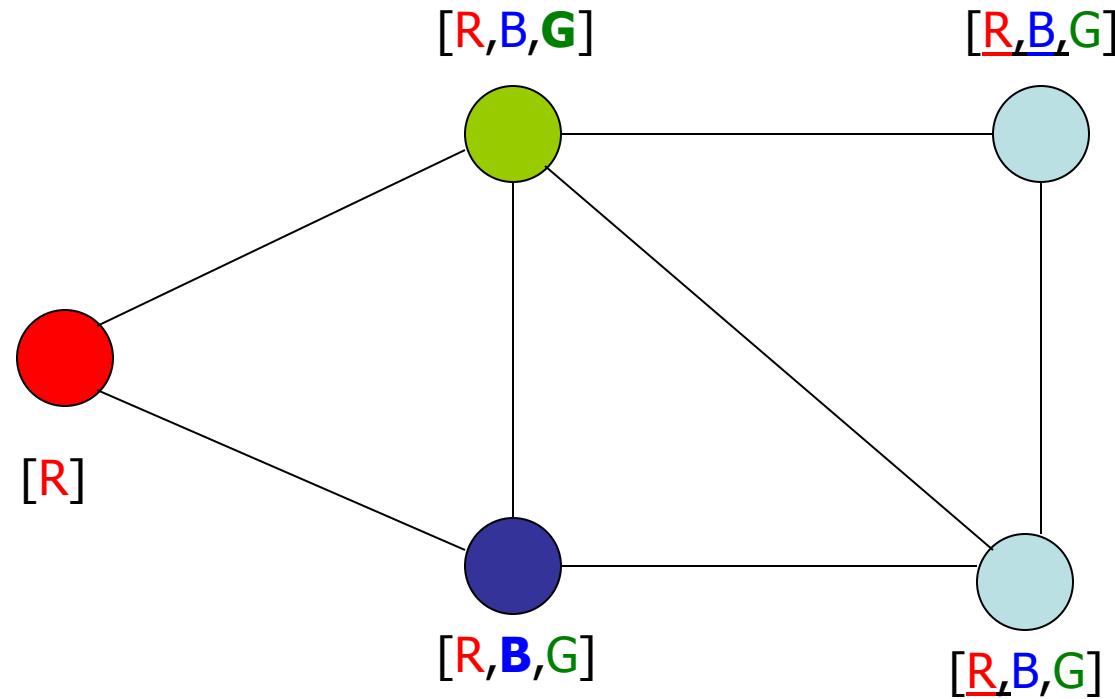
Backpropagation - MRV



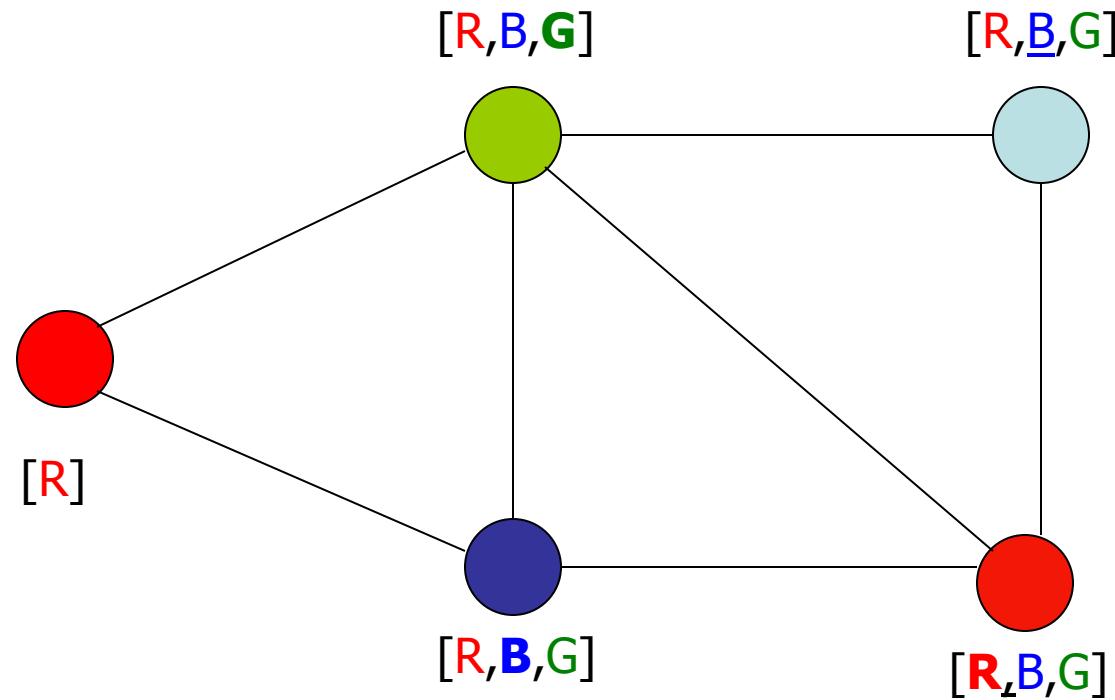
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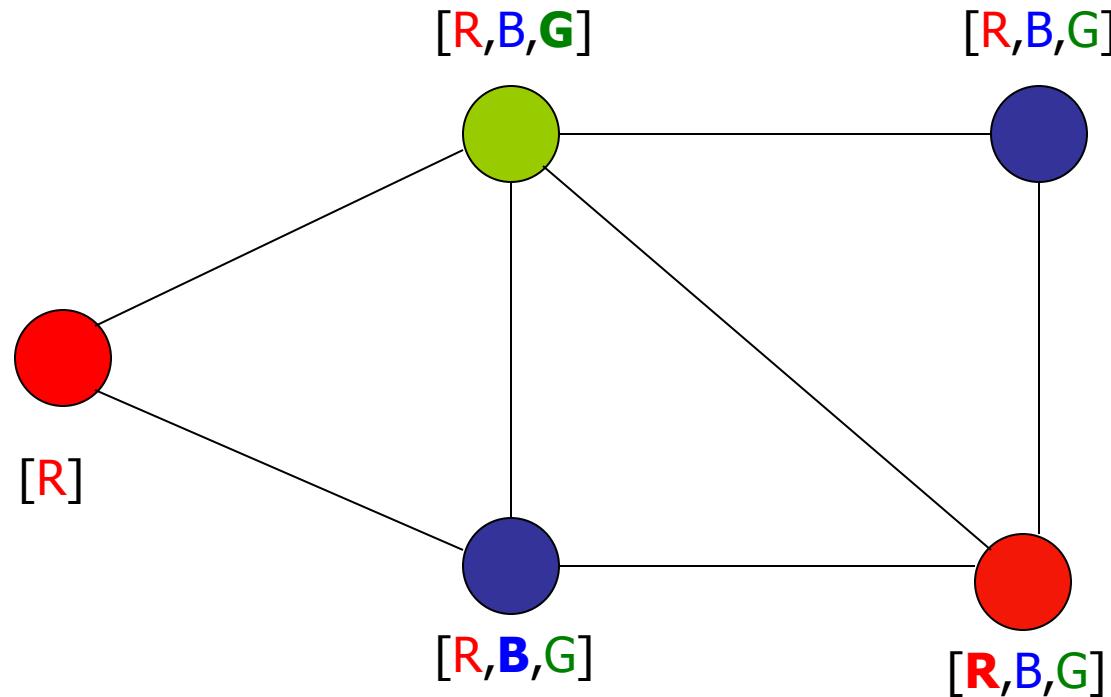
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Backpropagation - MRV



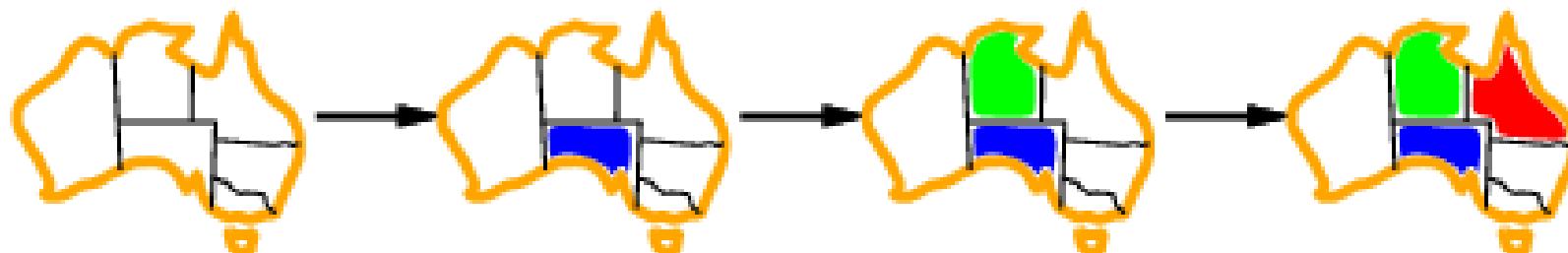
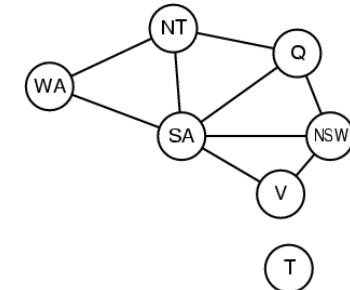
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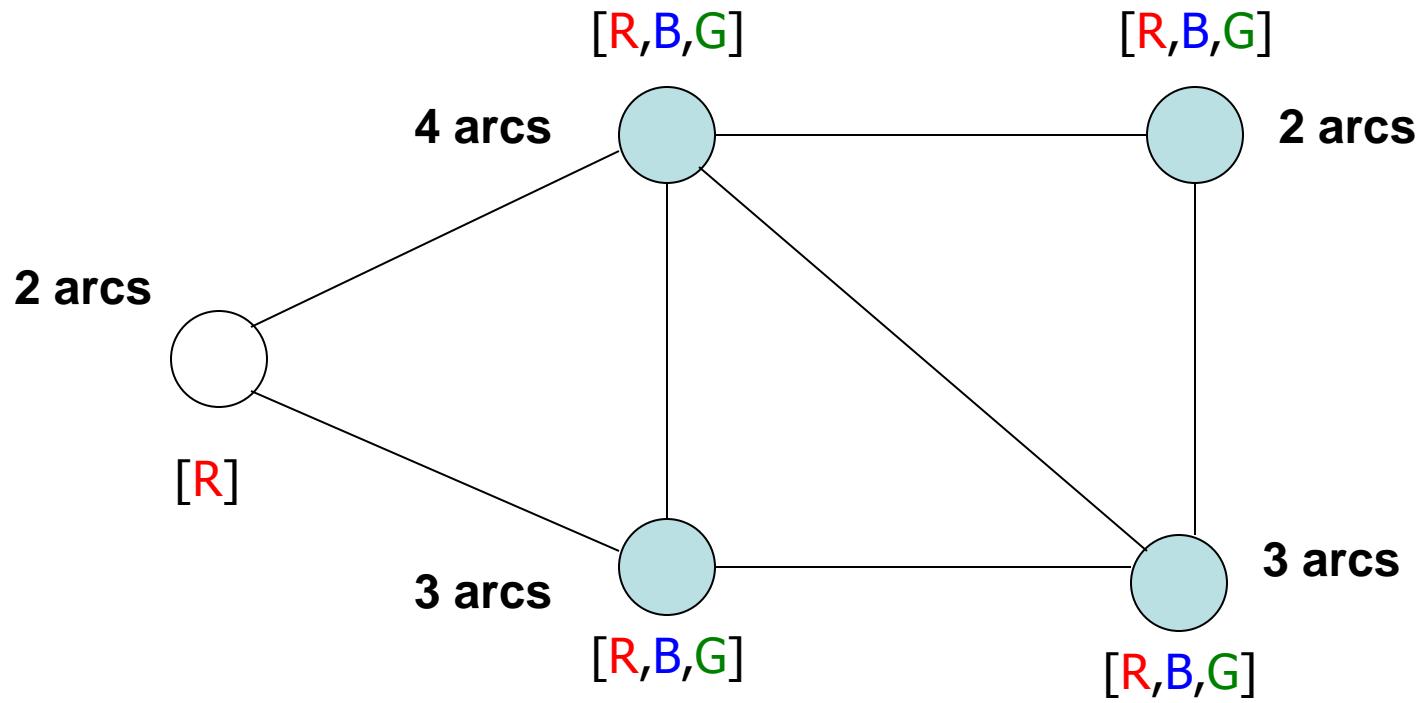
Solution !!!

Most constraining variable - MCV

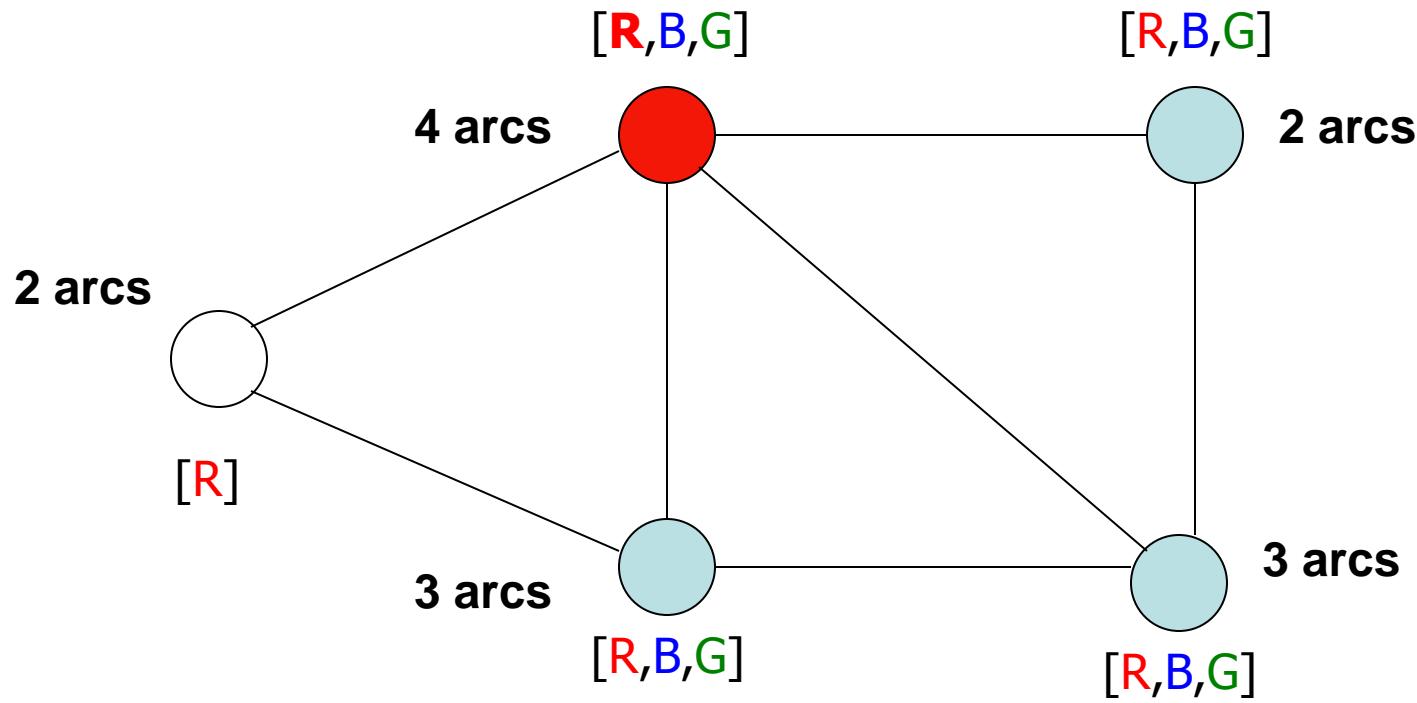
- Tie-breaker among most constrained variables
- Most constraining variable:
 - choose the variable **with the most constraints on remaining variables** (select variable that is involved in the largest number of constraints - edges in graph on other unassigned variables)



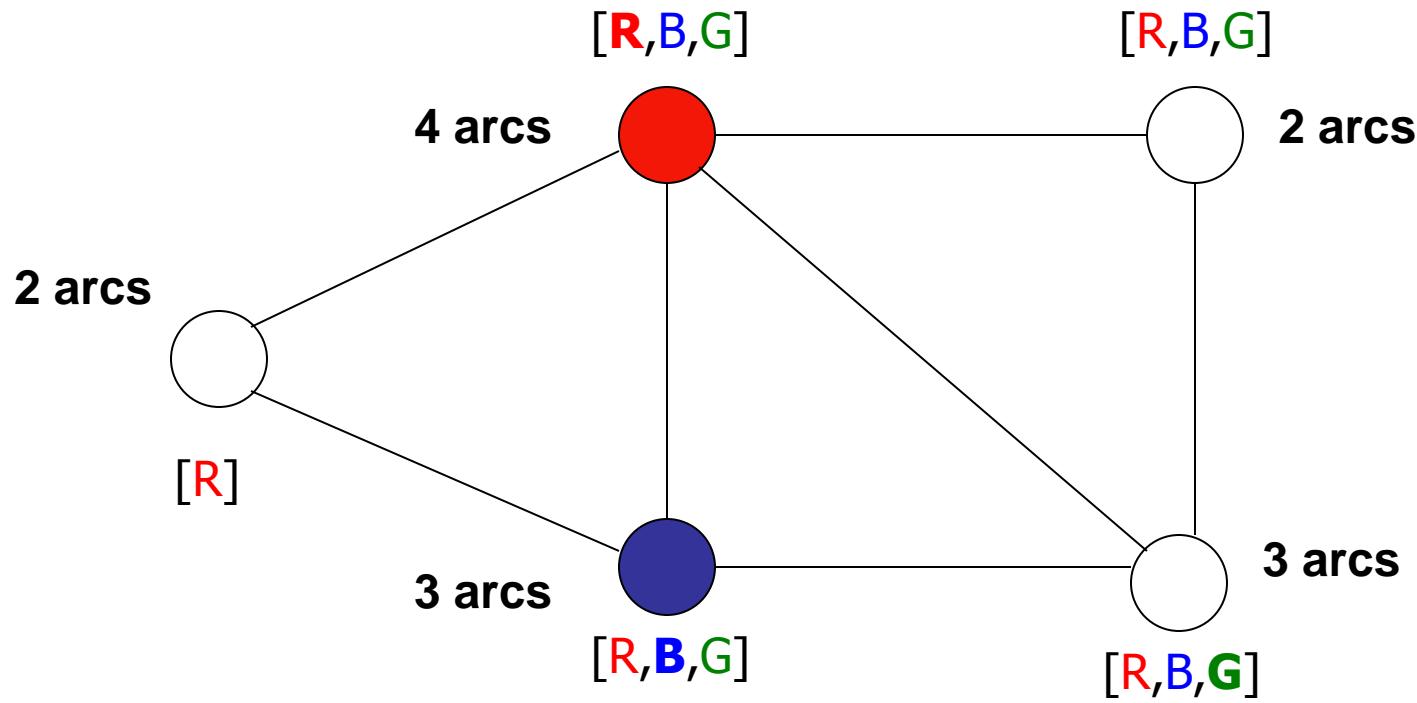
Backpropagation - MCV



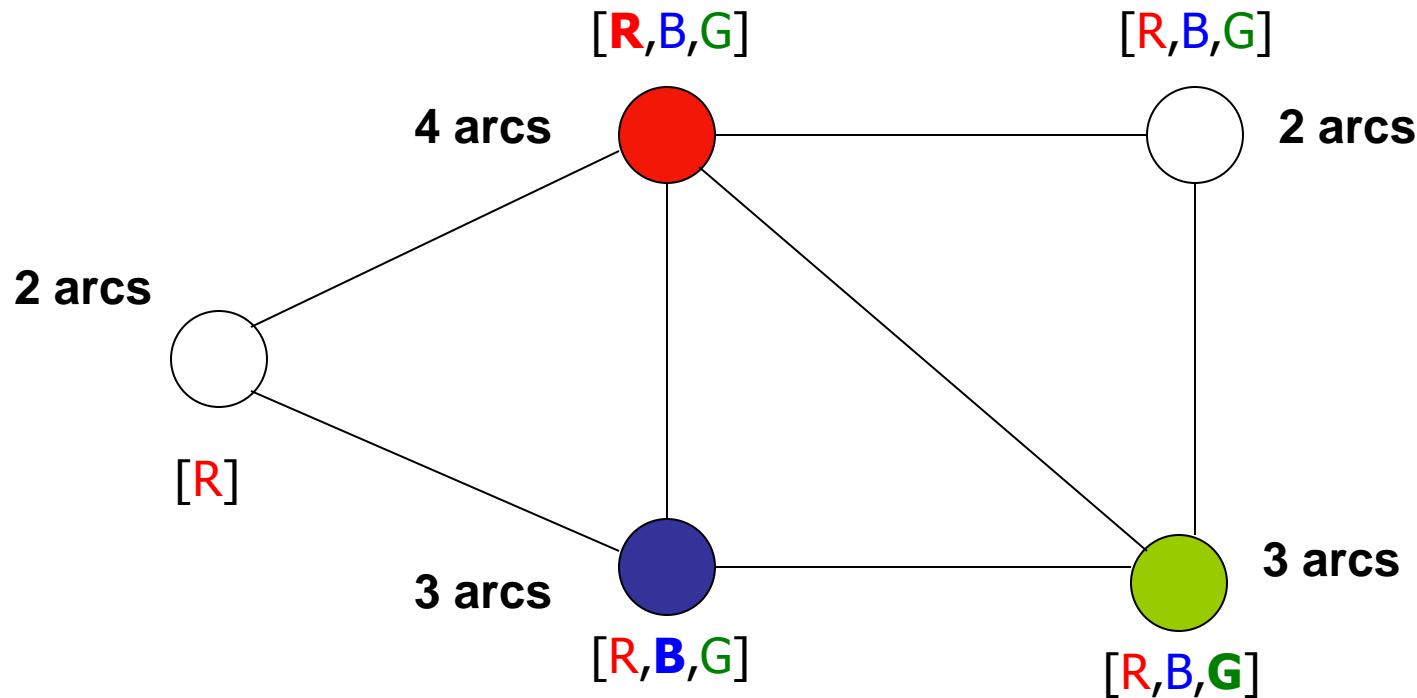
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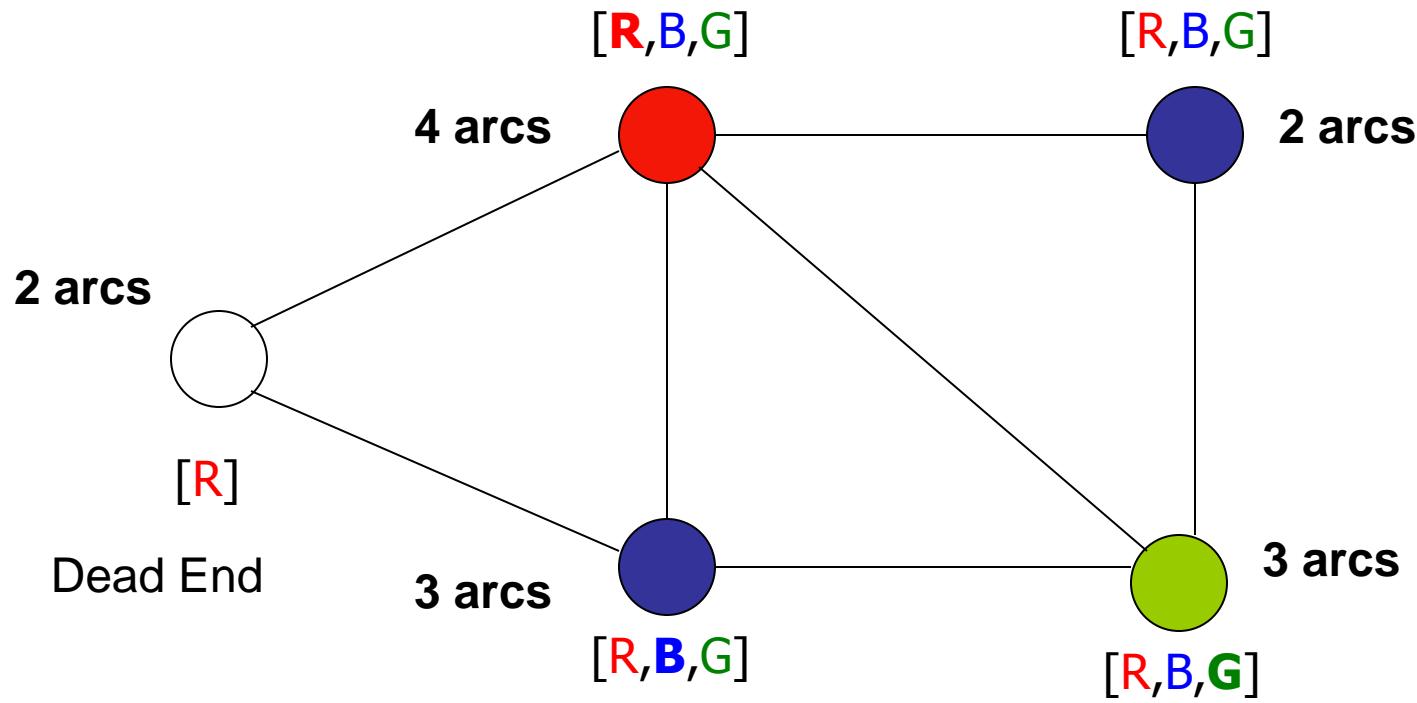
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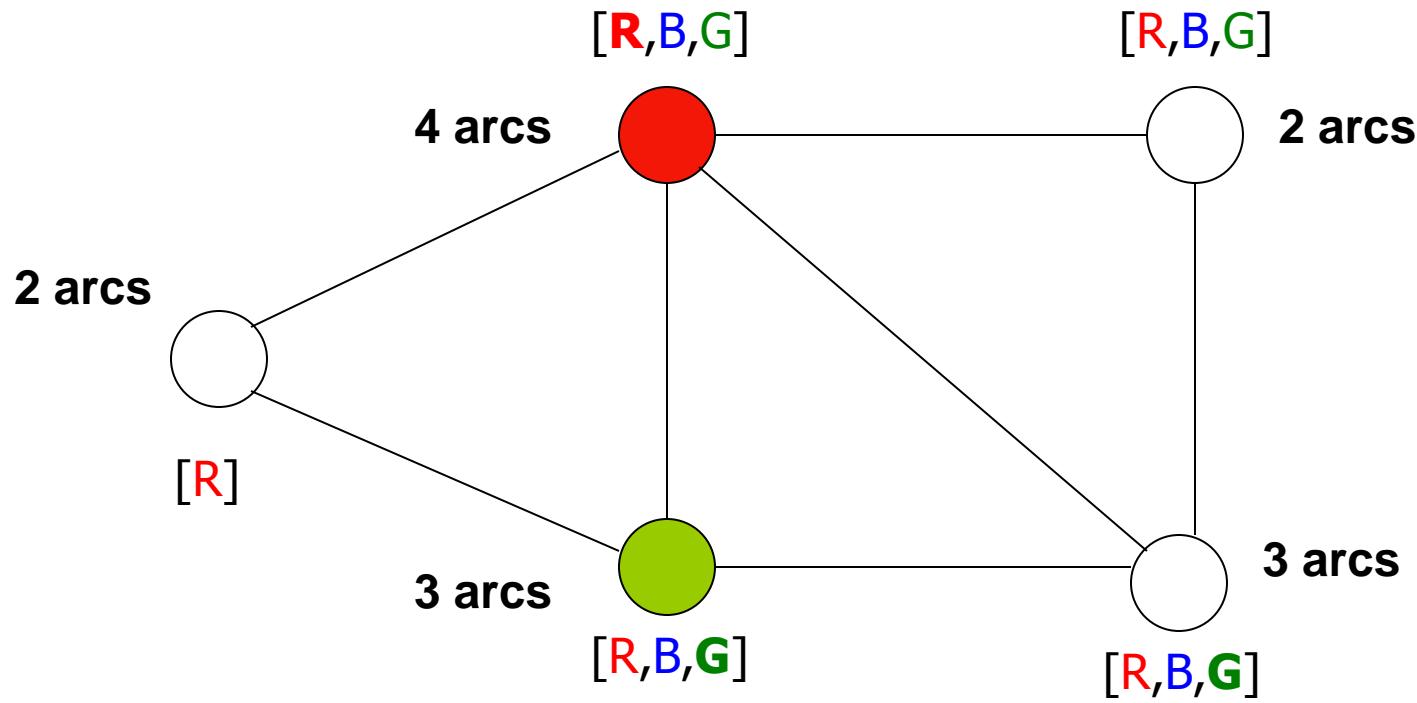
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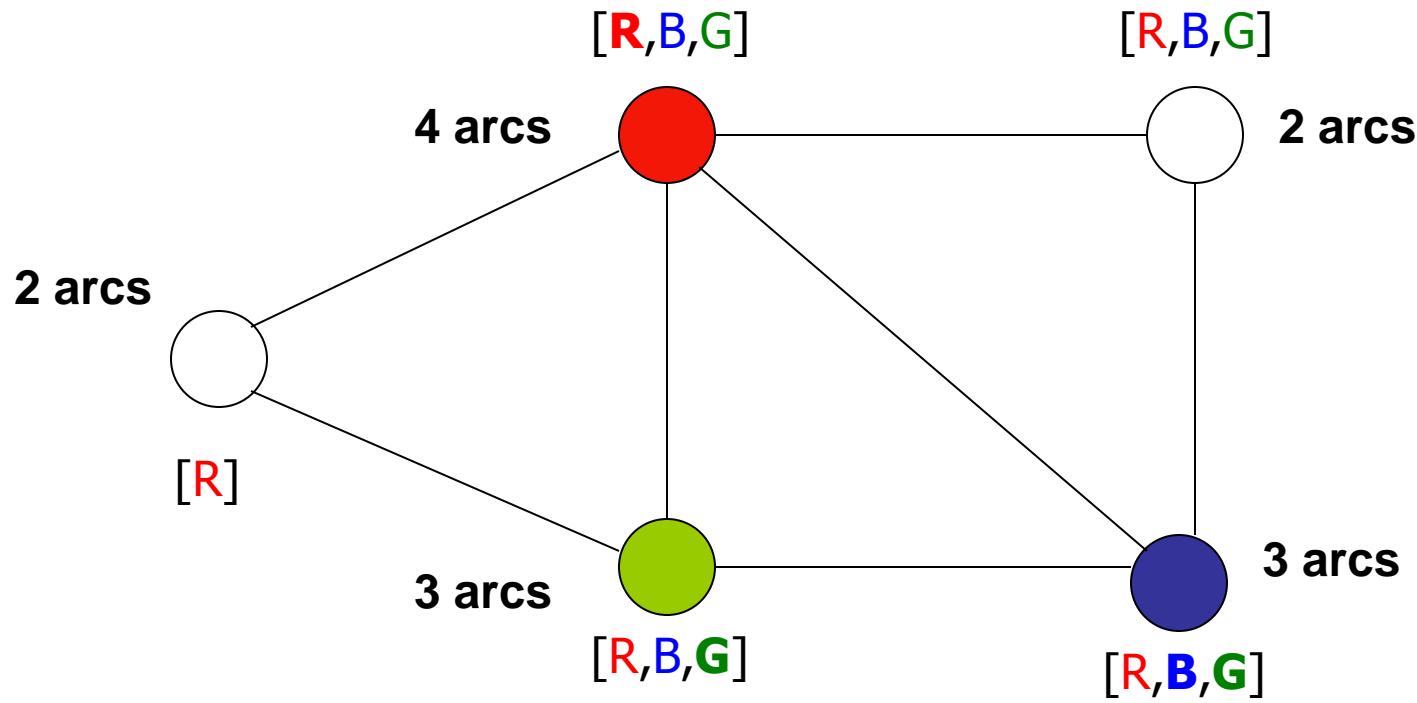
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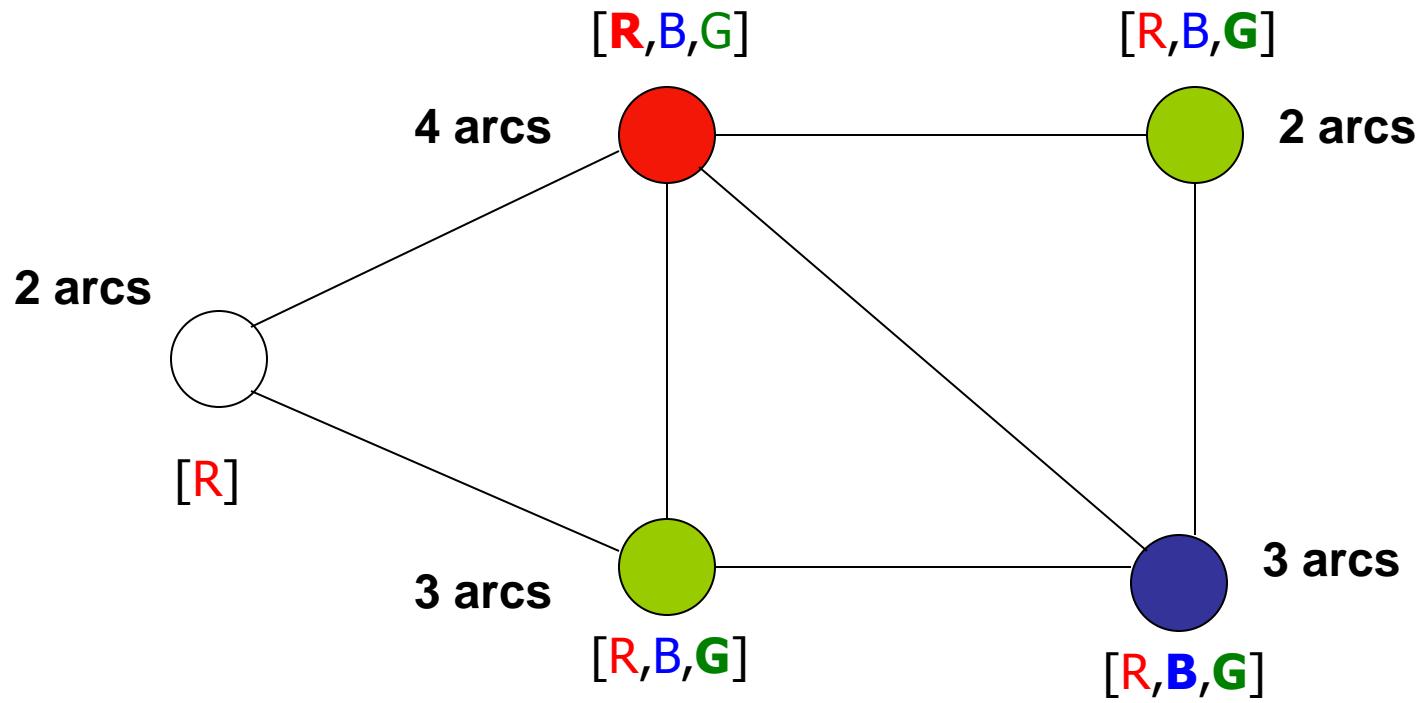
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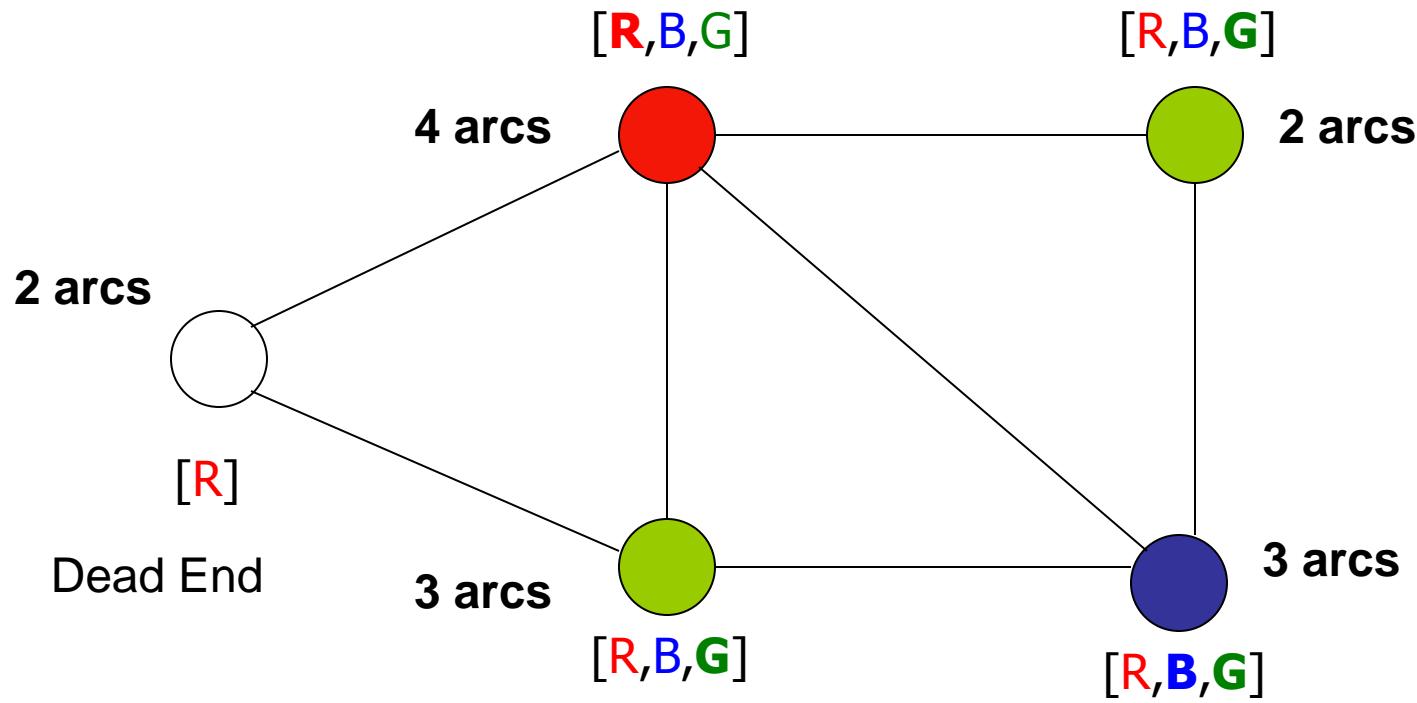
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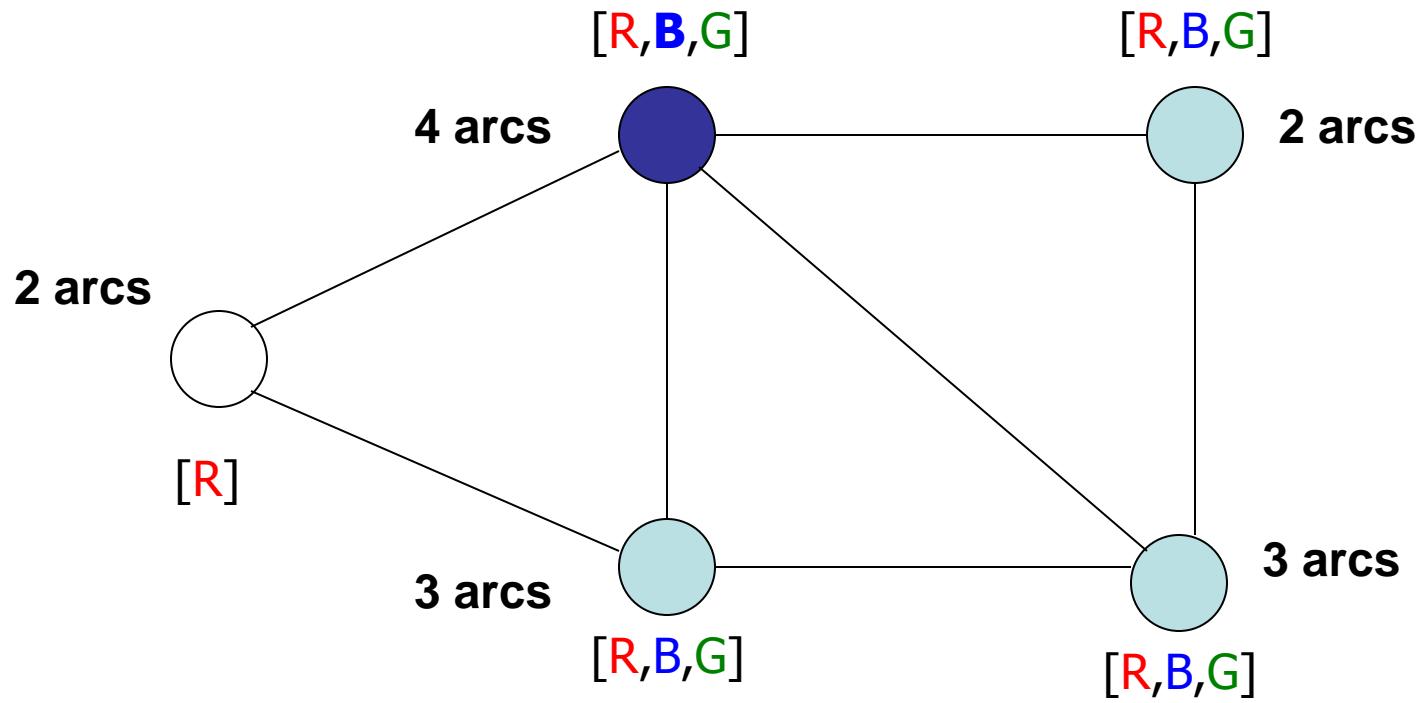
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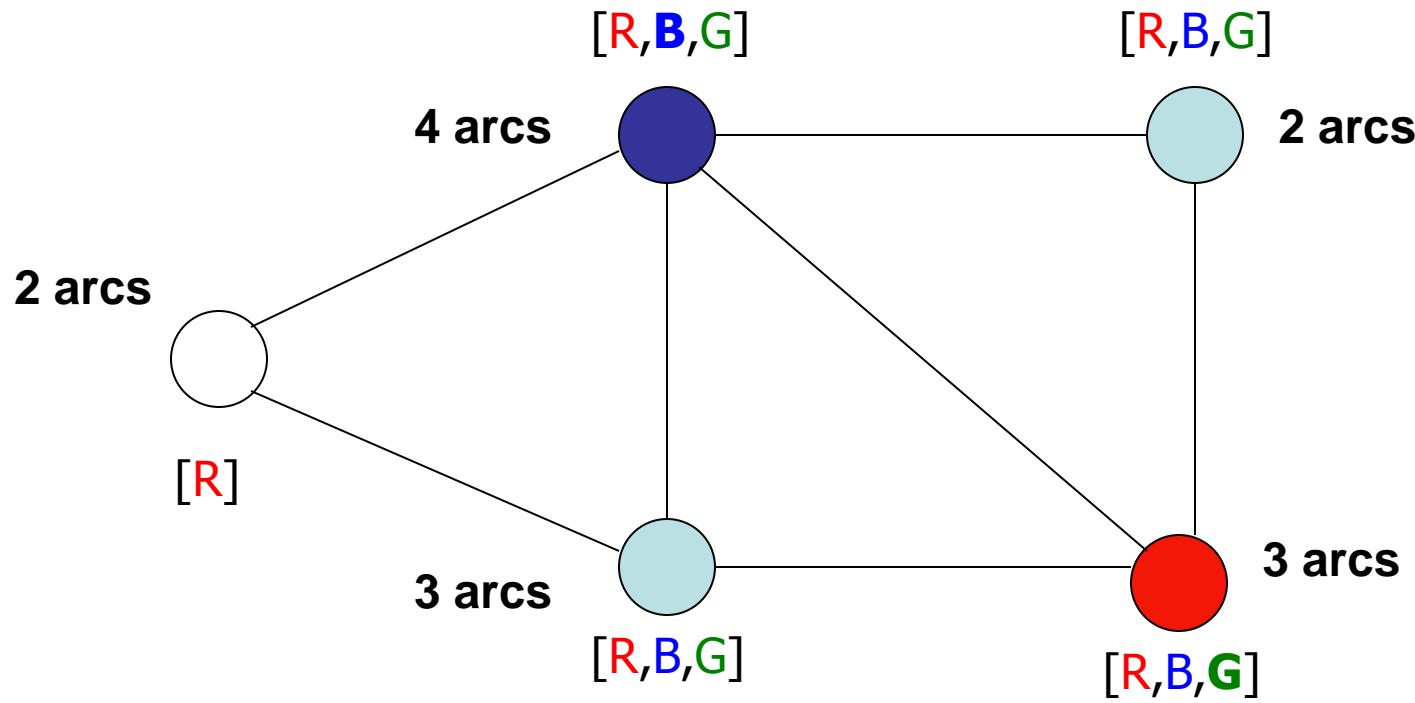
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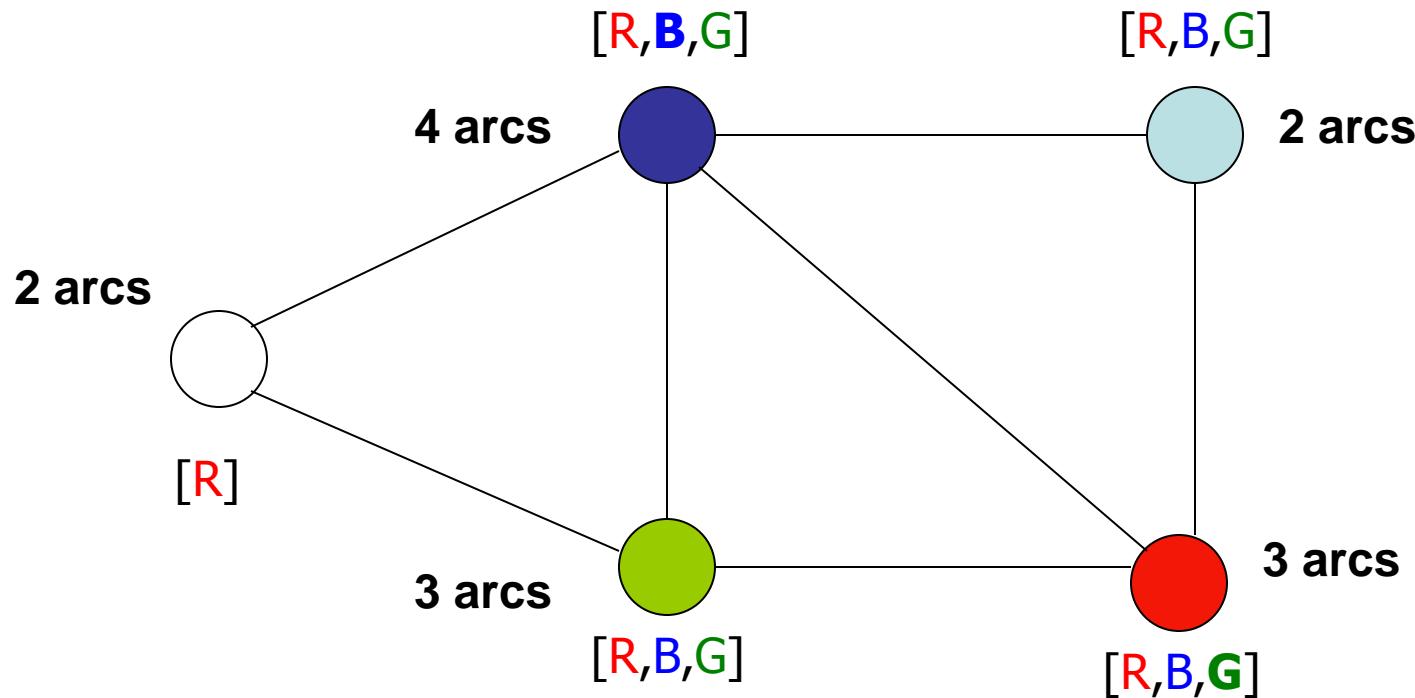
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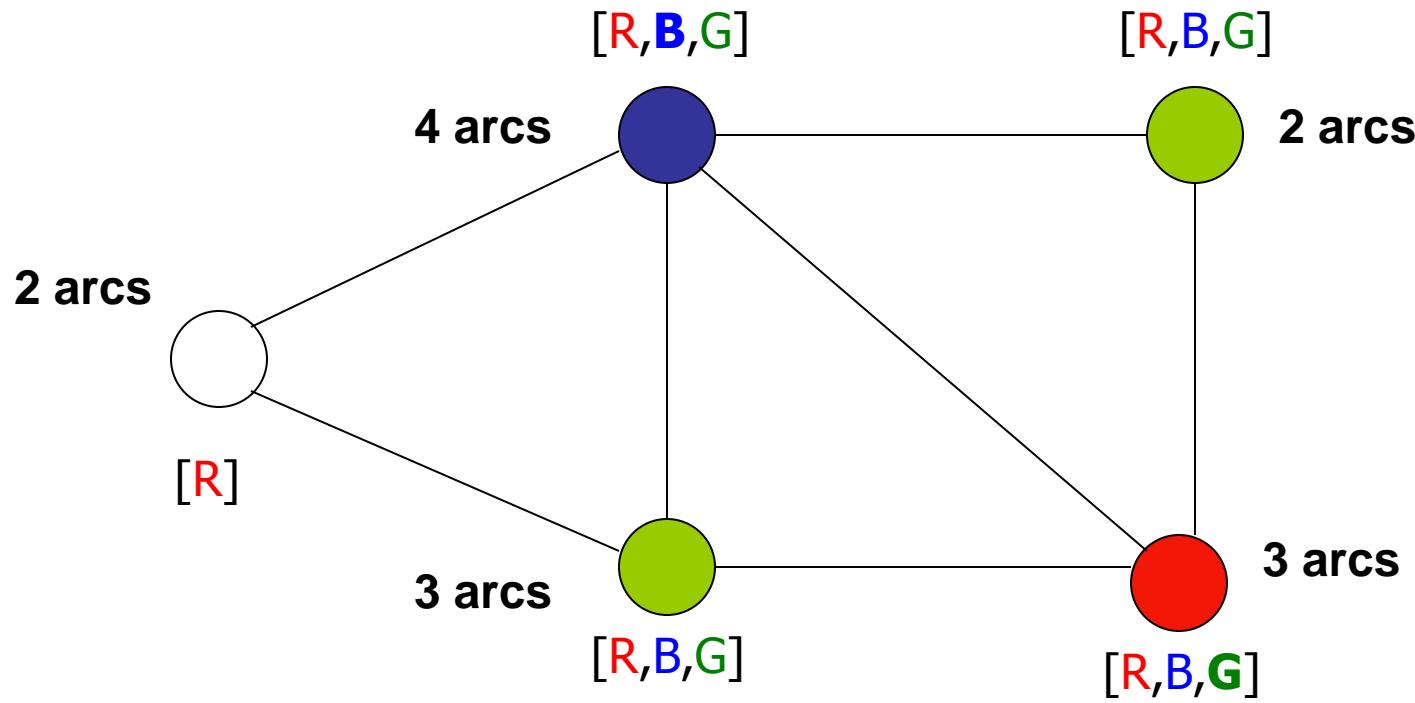
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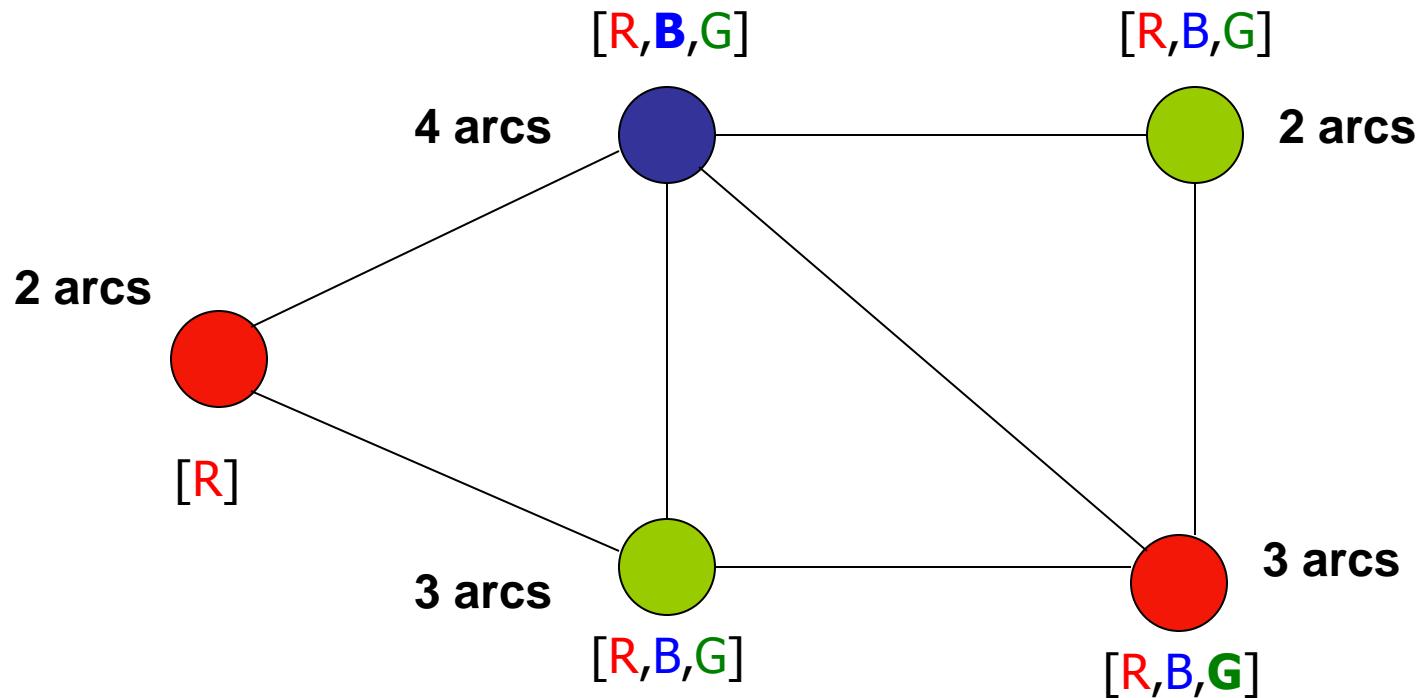
Backpropagation - MCV



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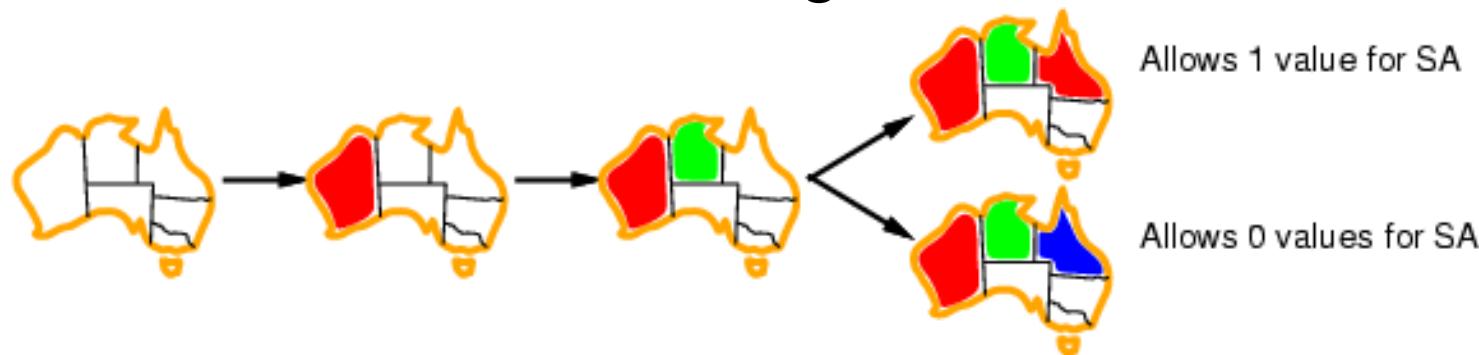
Backpropagation - MCV



Solution !!!

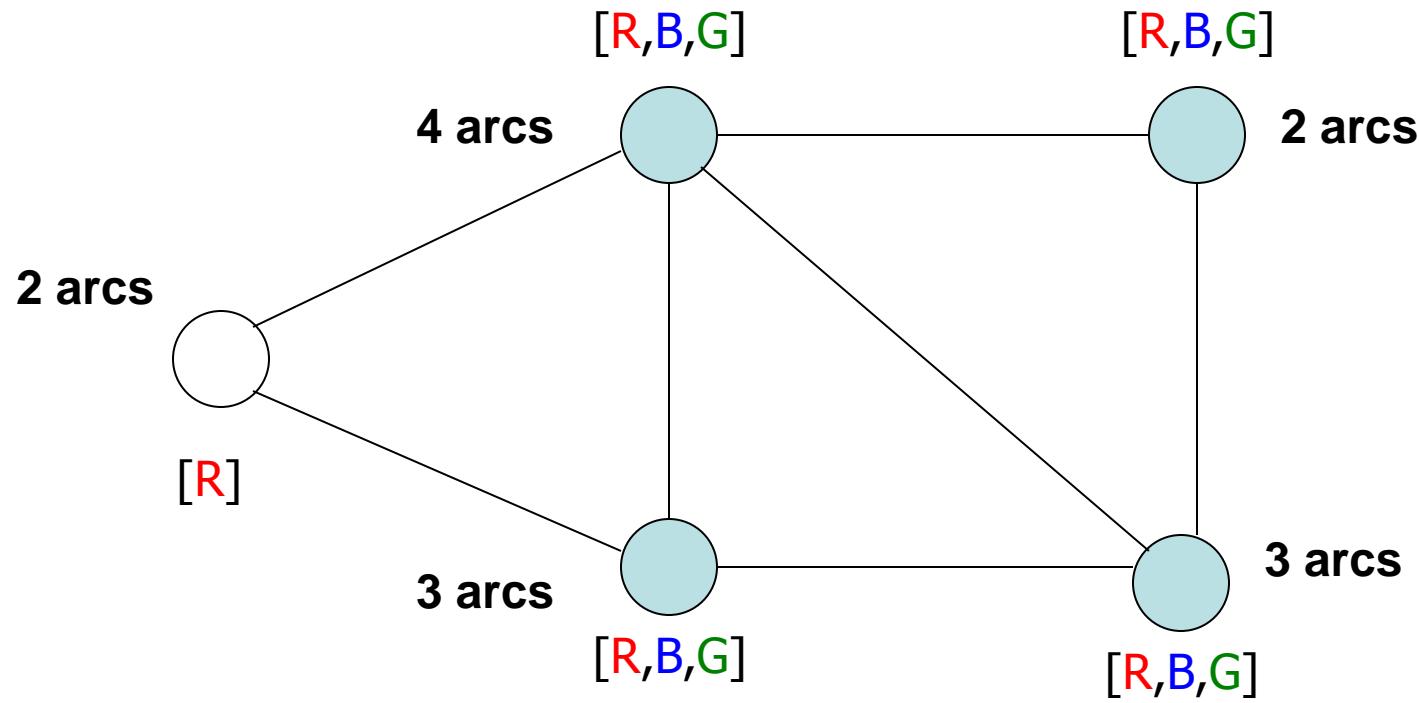
Least constraining value - LCV

- Given a variable, choose the least constraining value:
 - the one that rules out (eliminate) the fewest values in the remaining variables

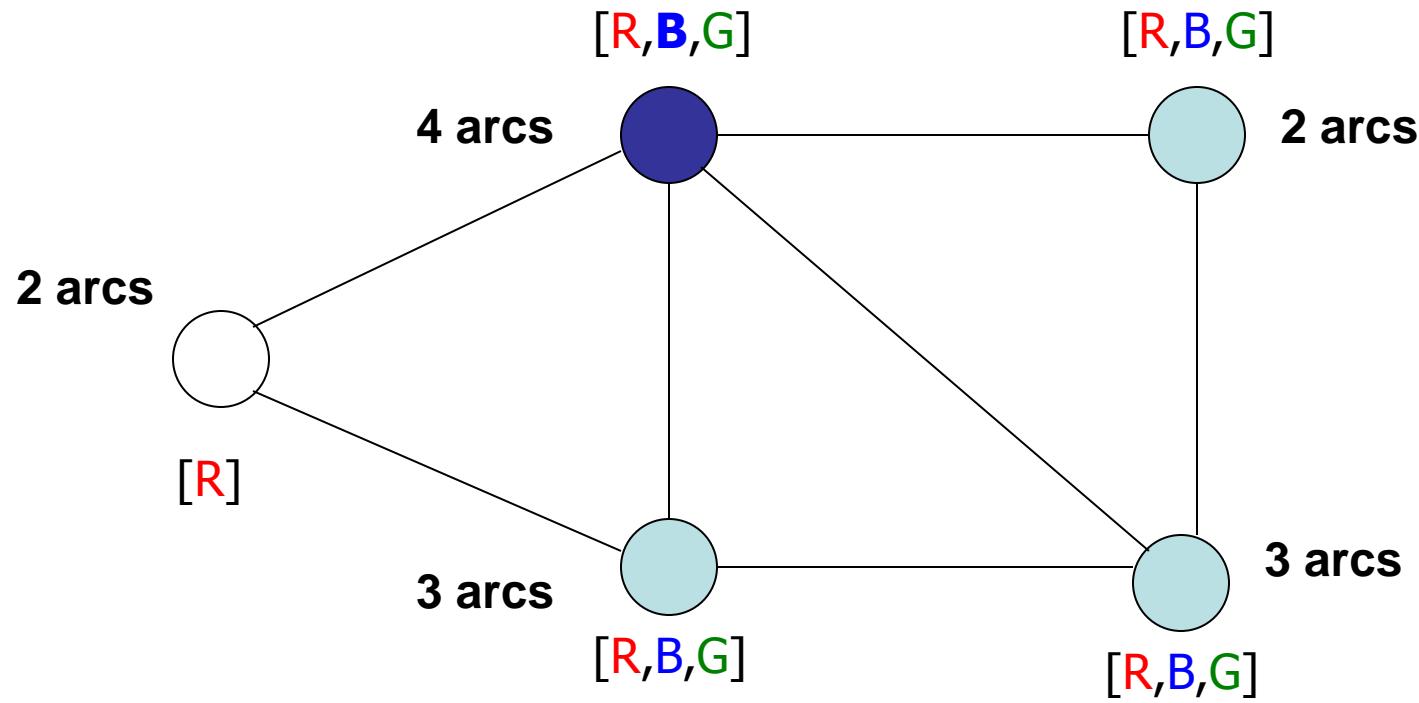


- Combining these heuristics makes 1000 queens feasible

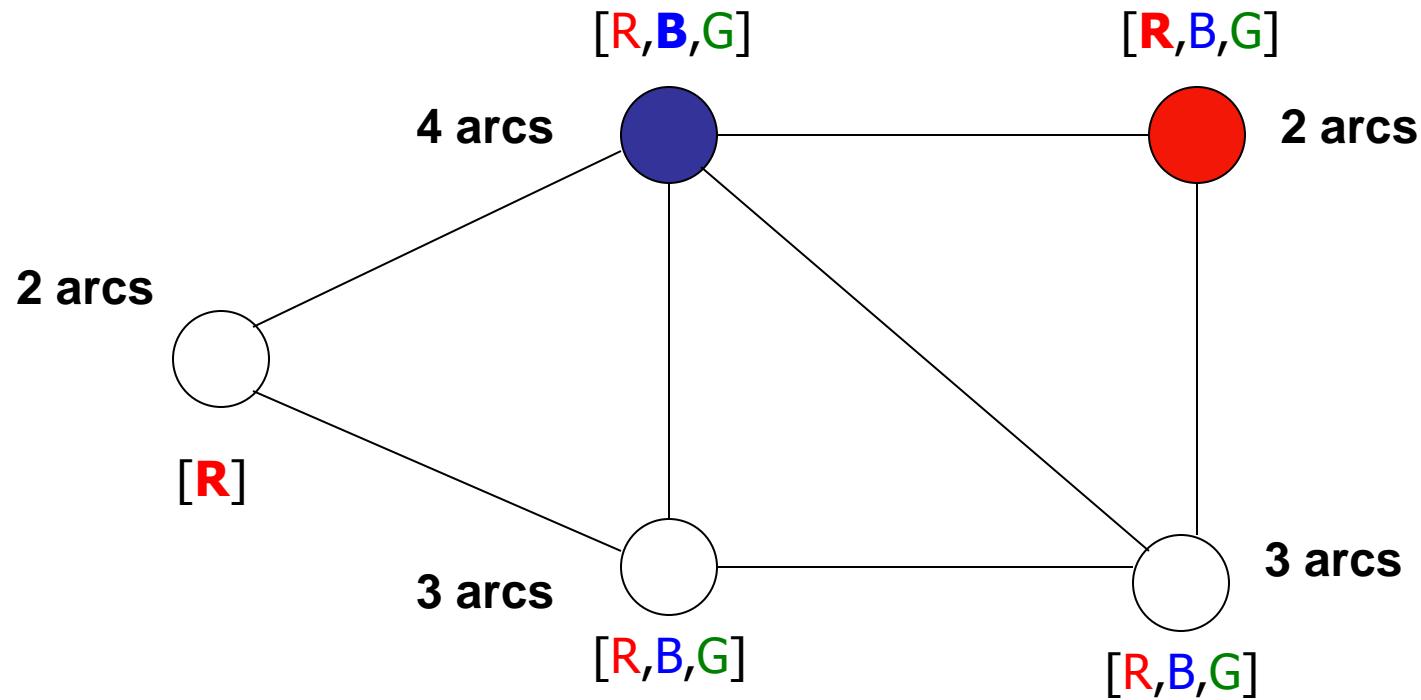
Backpropagation - LCV



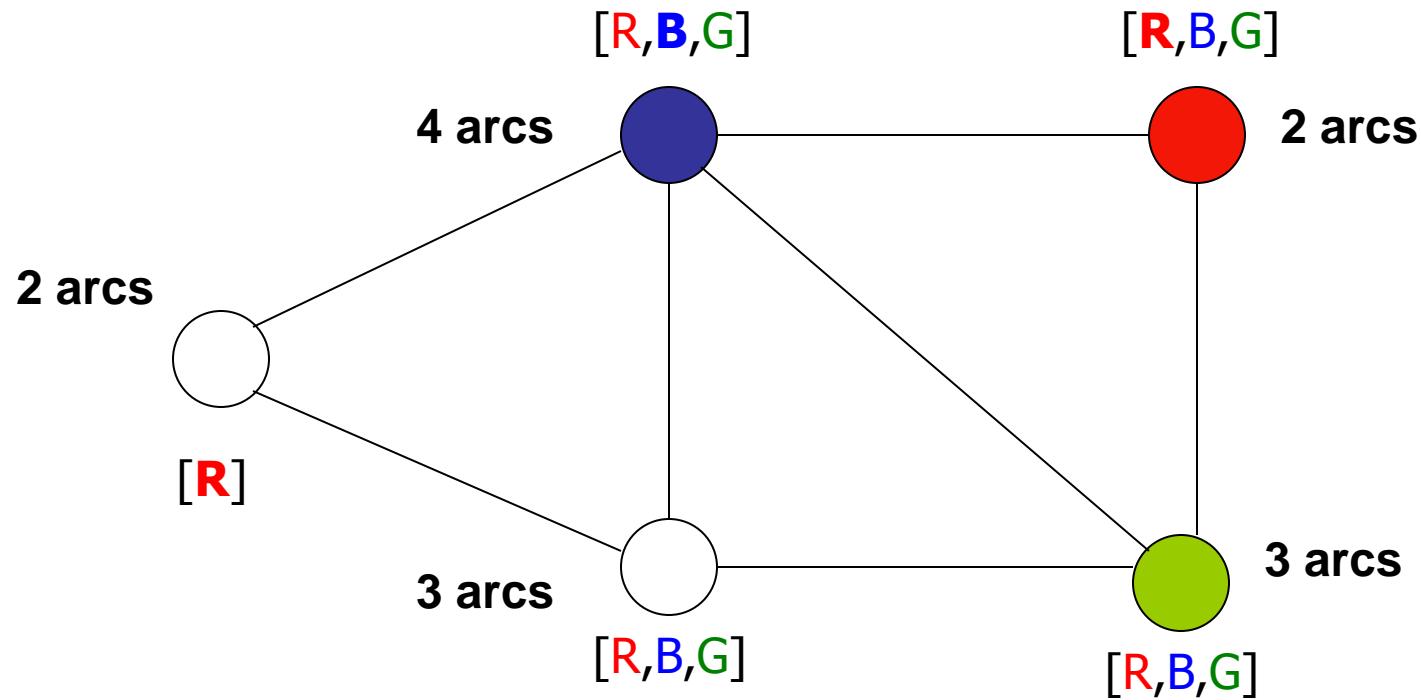
Backpropagation - LCV



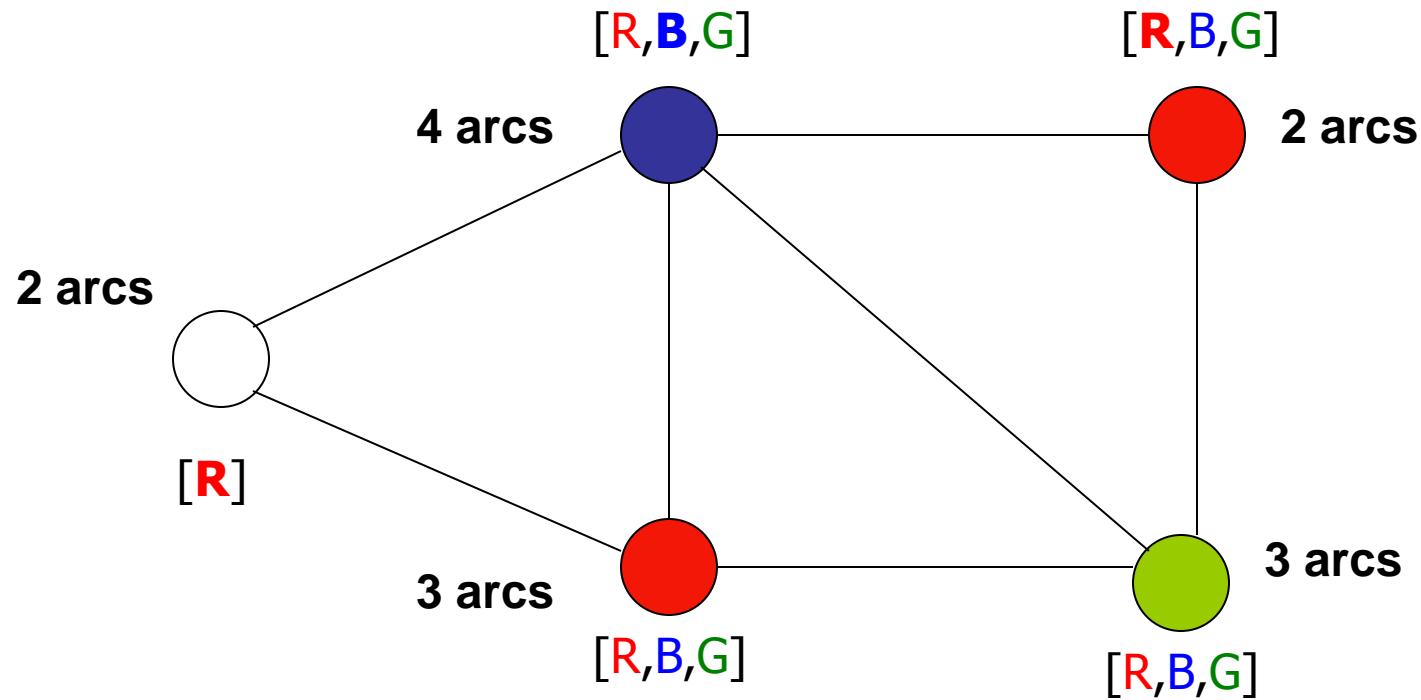
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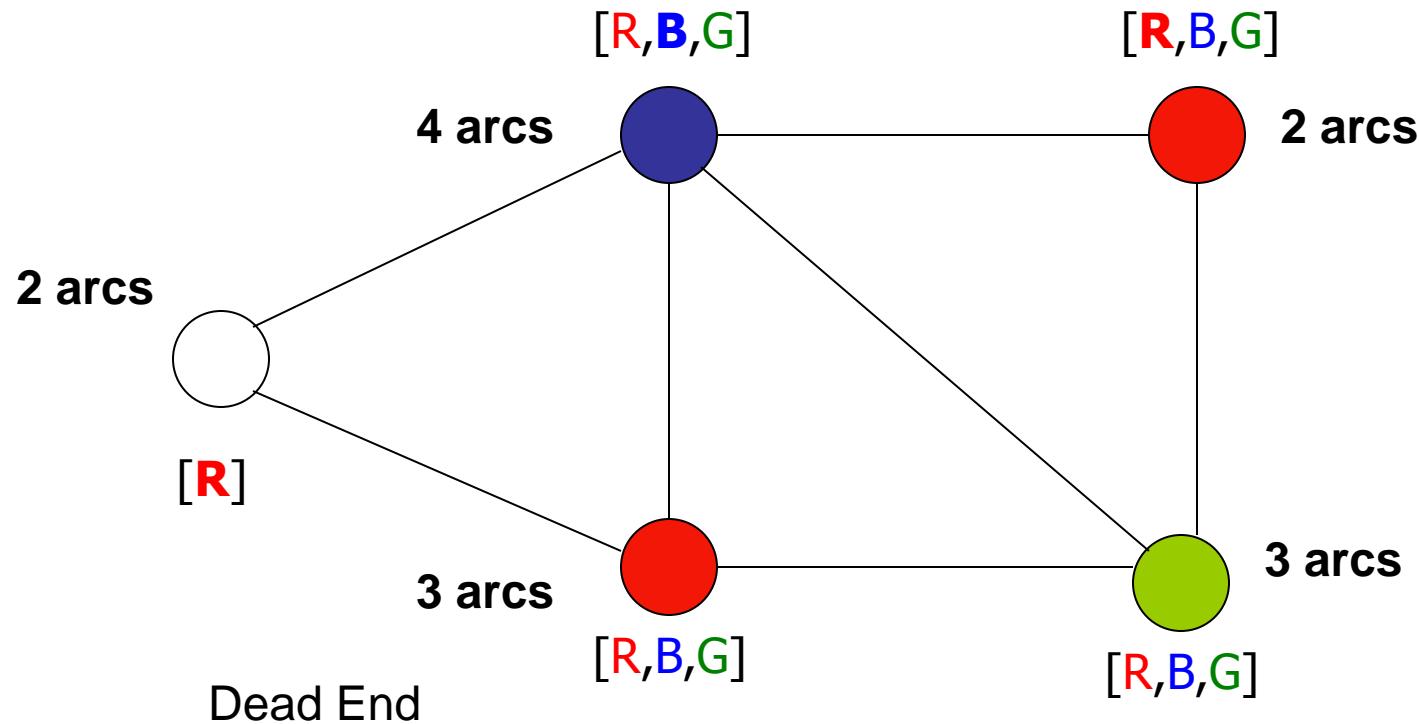
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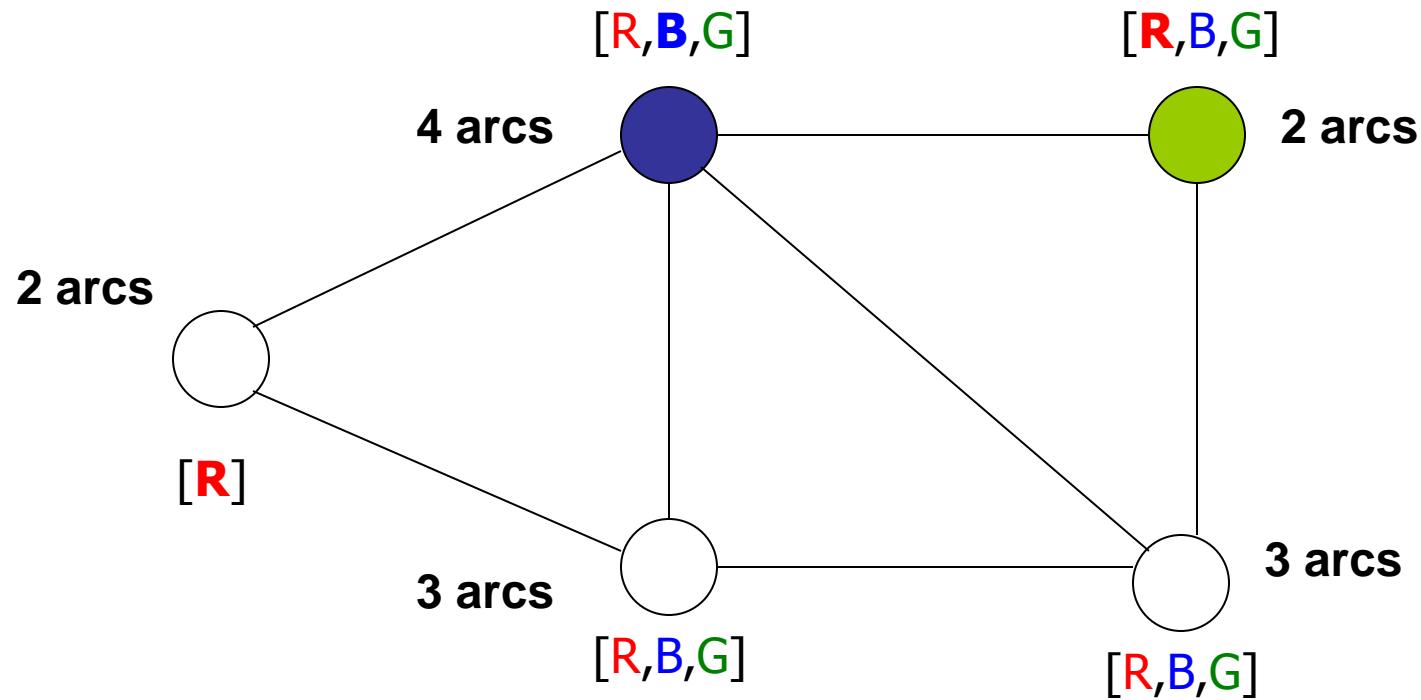
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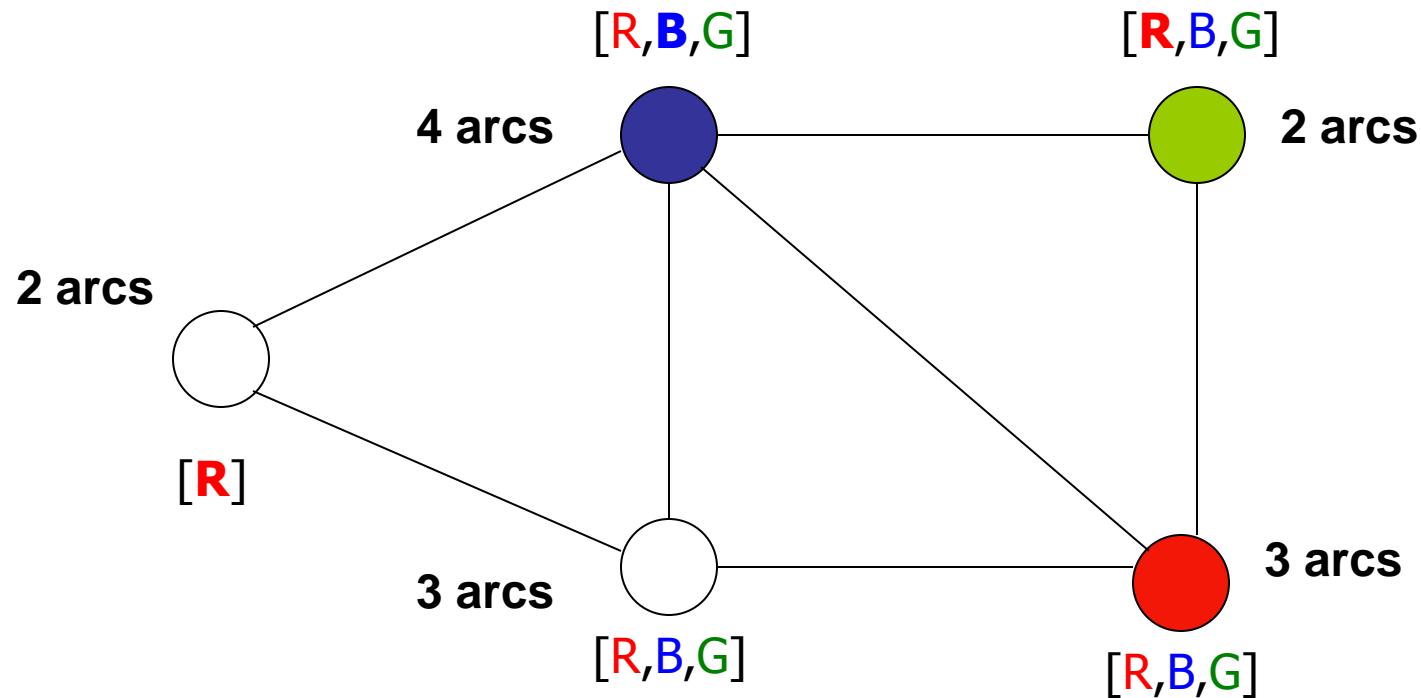
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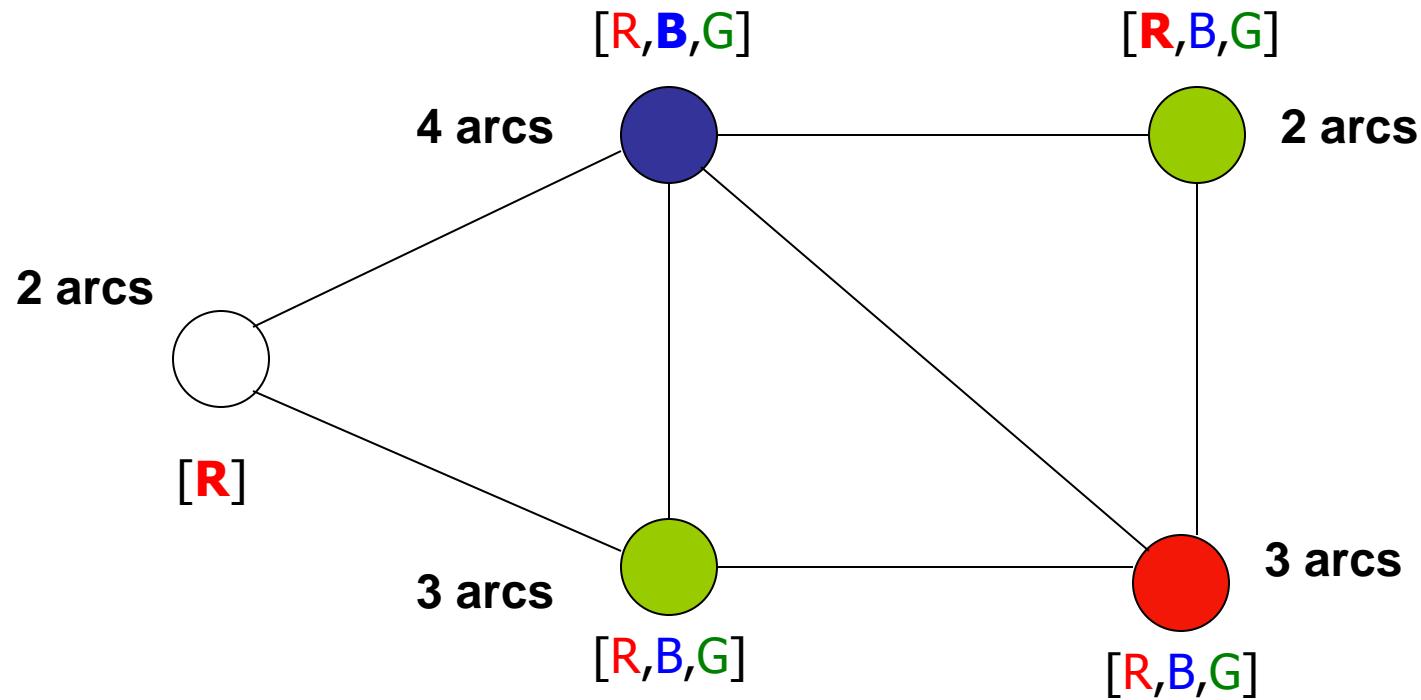
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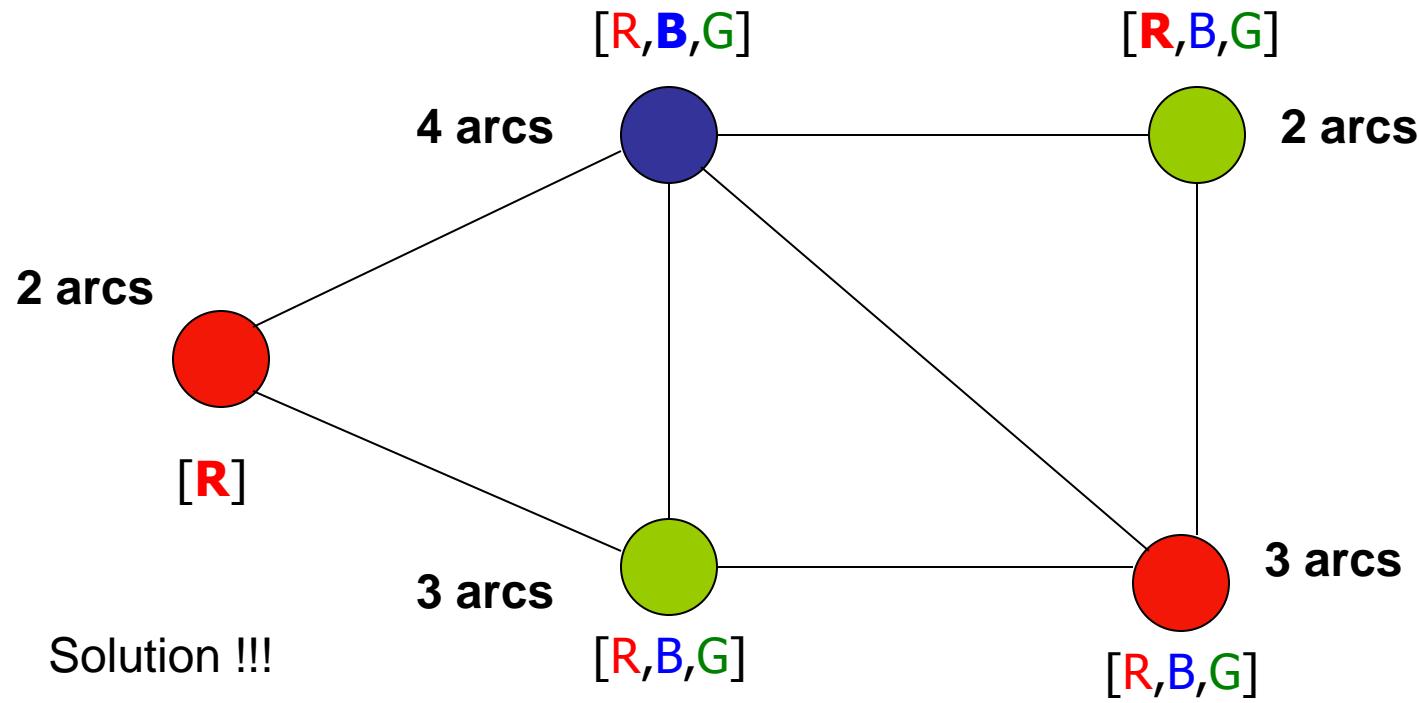
Backpropagation - LCV



Backpropagation - LCV



Backpropagation - LCV



Analyzing Constraints

- forward checking
 - when a value X is assigned to a variable, inconsistent values are eliminated for all variables connected to X
 - identifies “dead” branches of the tree before they are visited
- constraint propagation
 - analyses interdependencies between variable assignments via *arc consistency*
 - an arc between X and Y is consistent if for every possible value x of X , there is some value y of Y that is consistent with x
 - more powerful than forward checking, but still reasonably efficient
 - but does not reveal every possible inconsistency

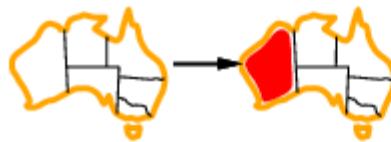
Forward checking

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



Forward checking

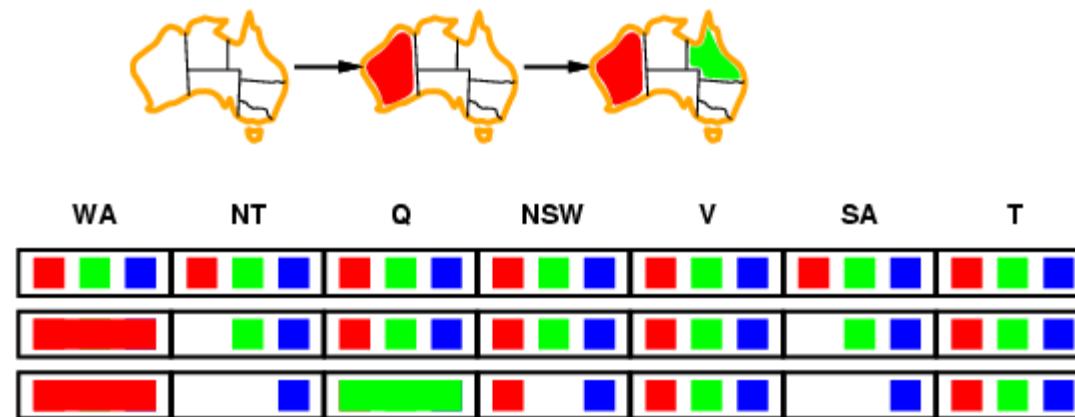
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WA	NT	Q	NSW	V	SA	T
Red Green Blue						
Red	Green Blue	Red Green Blue	Red Green Blue	Red Green Blue	Green Blue	Red Green Blue

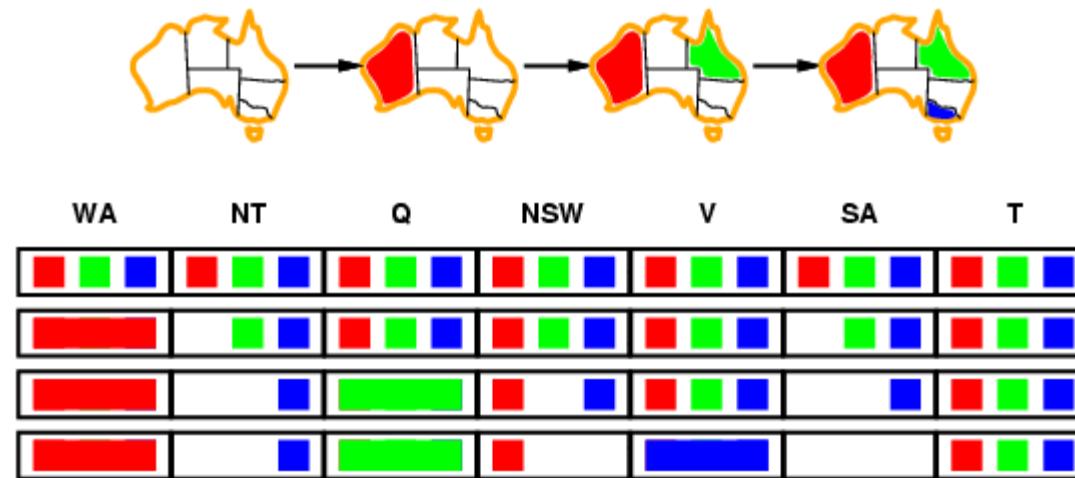
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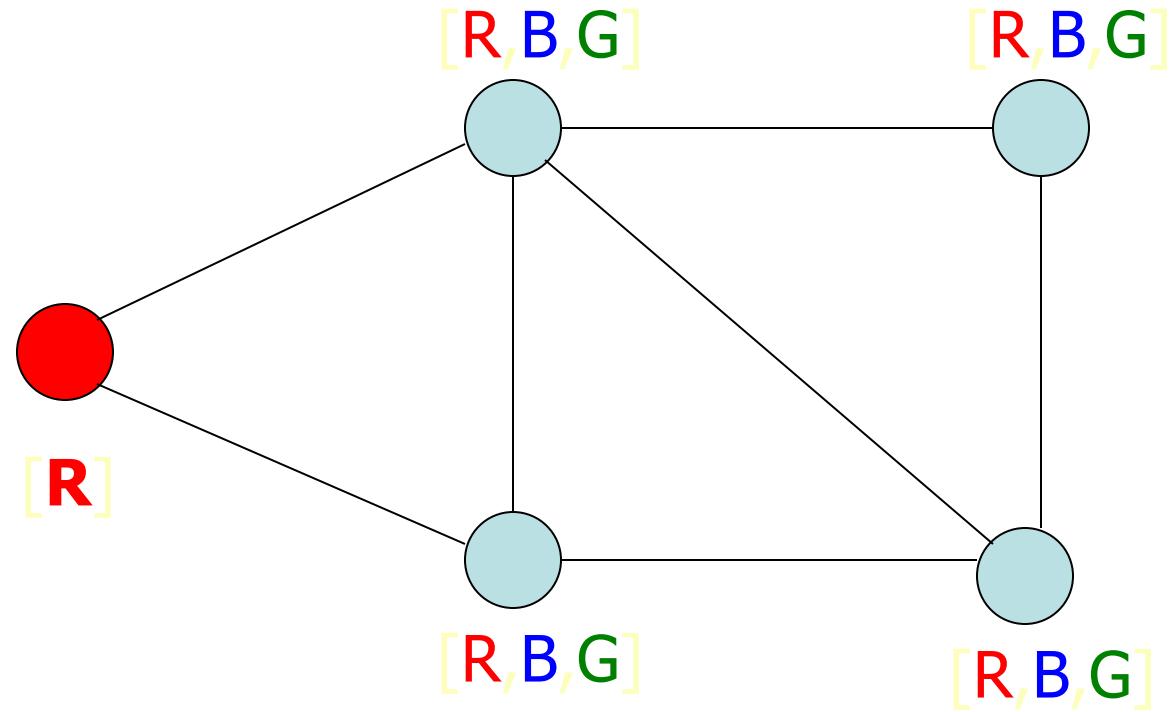


Forward checking

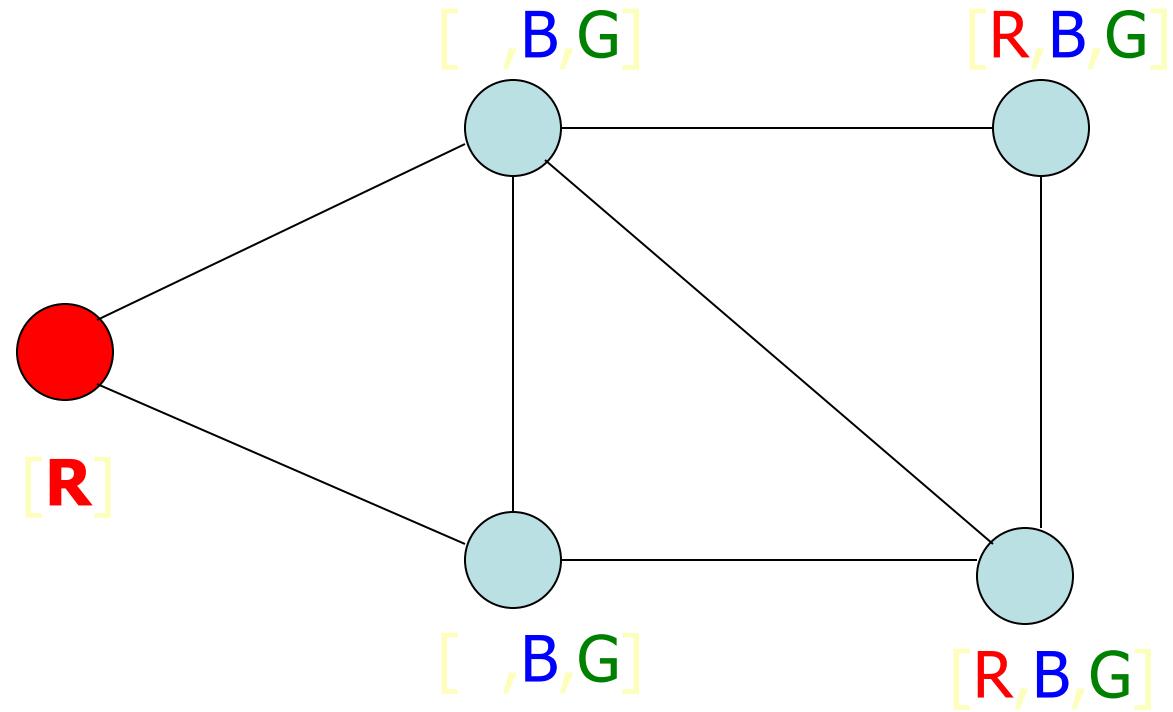
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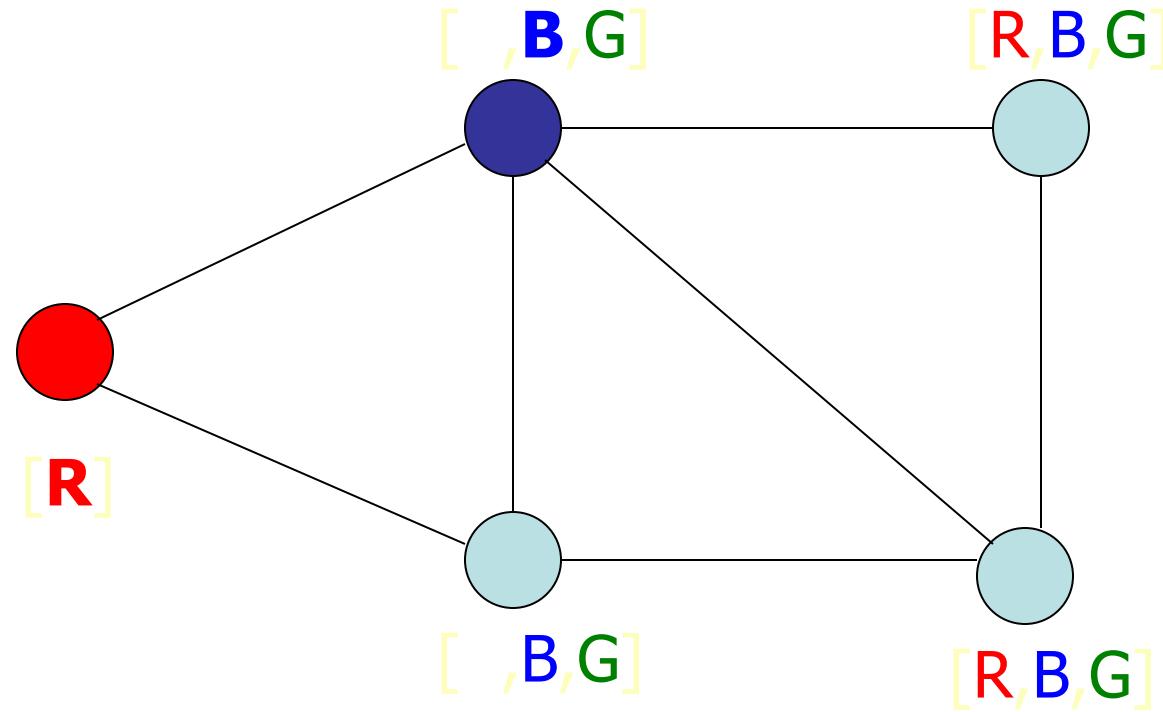
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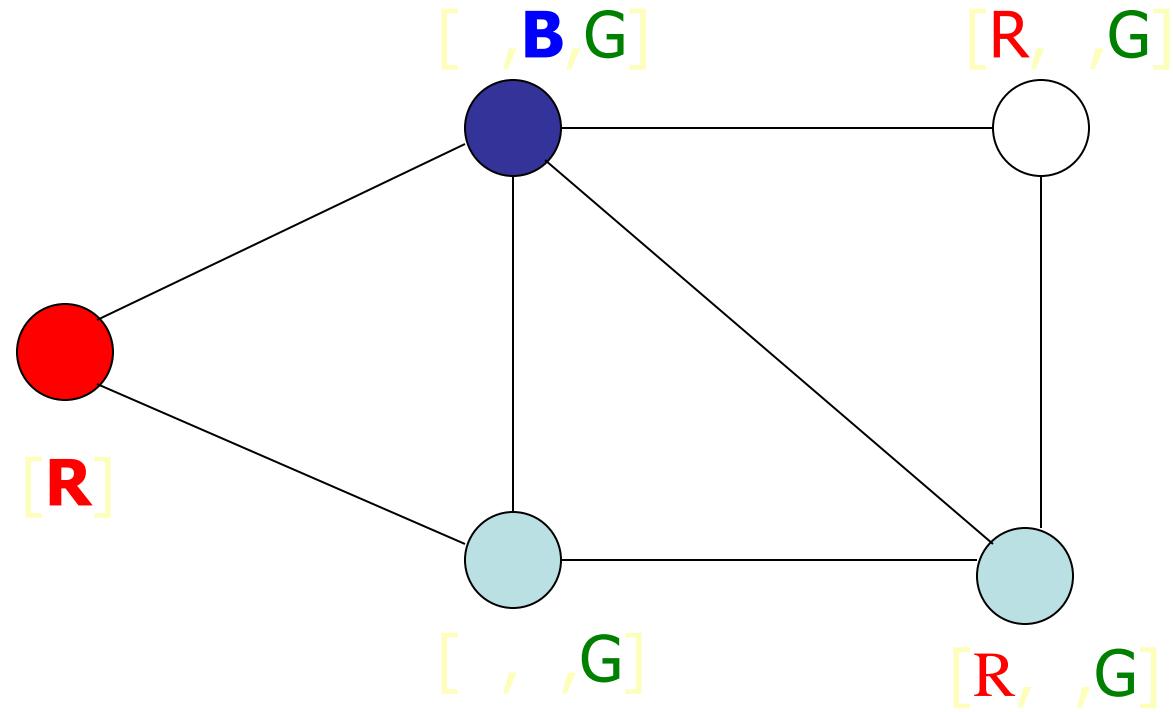
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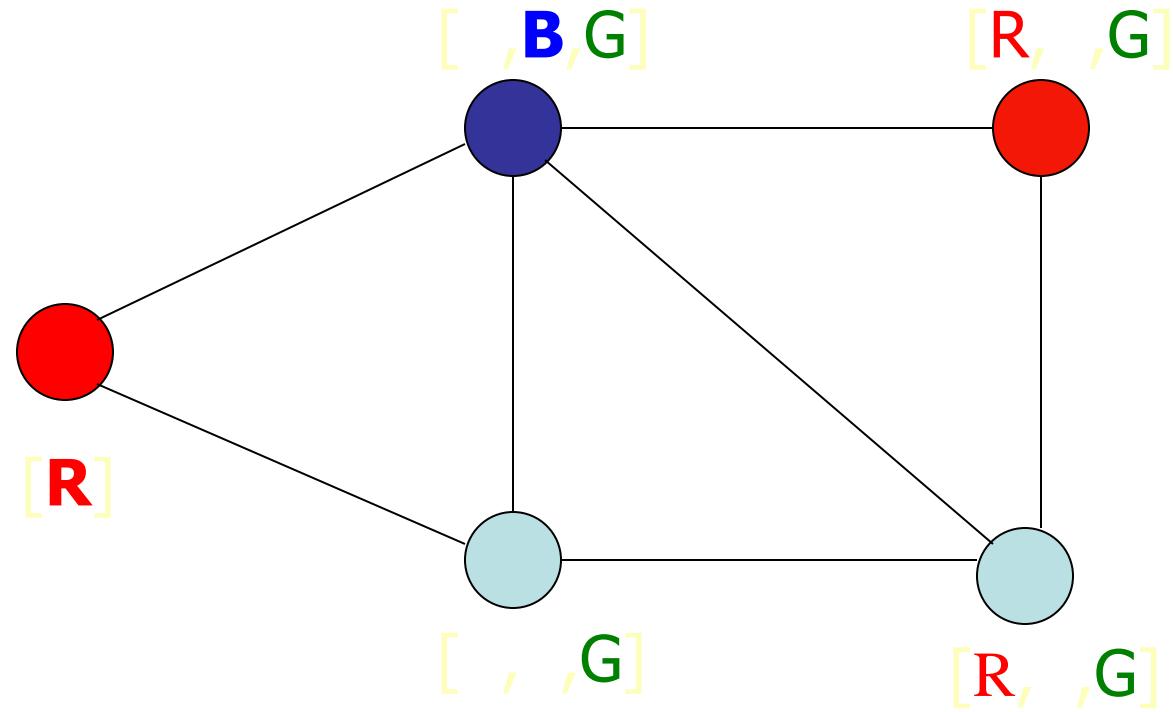
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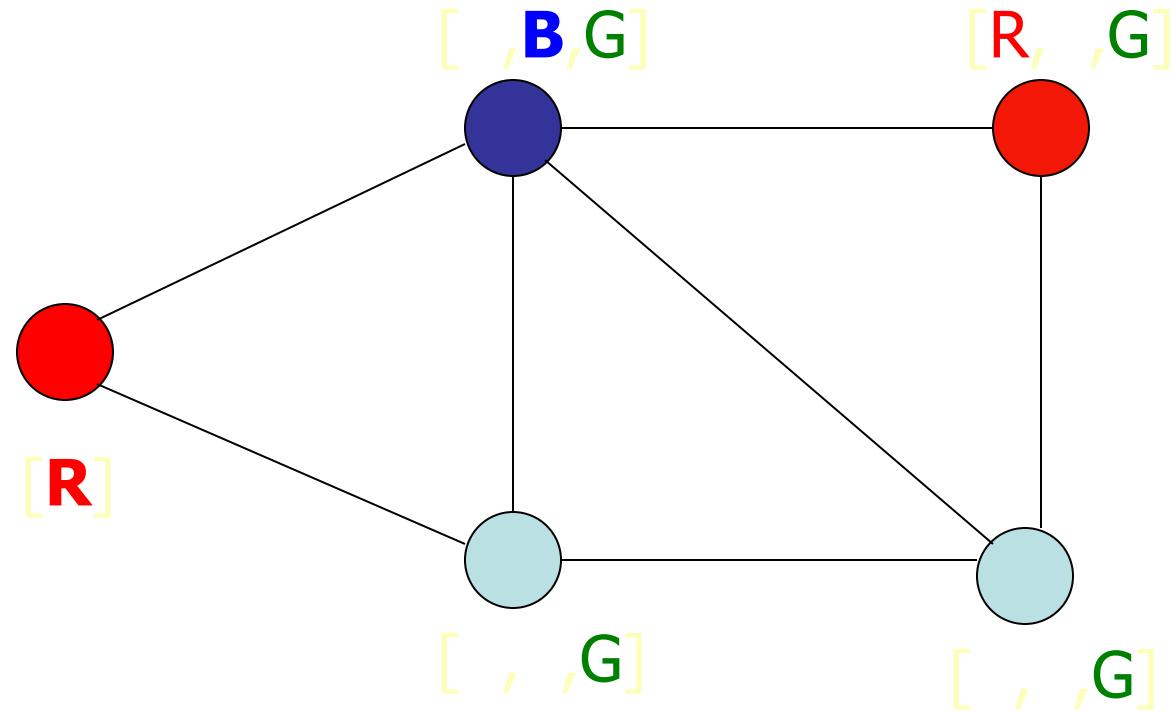
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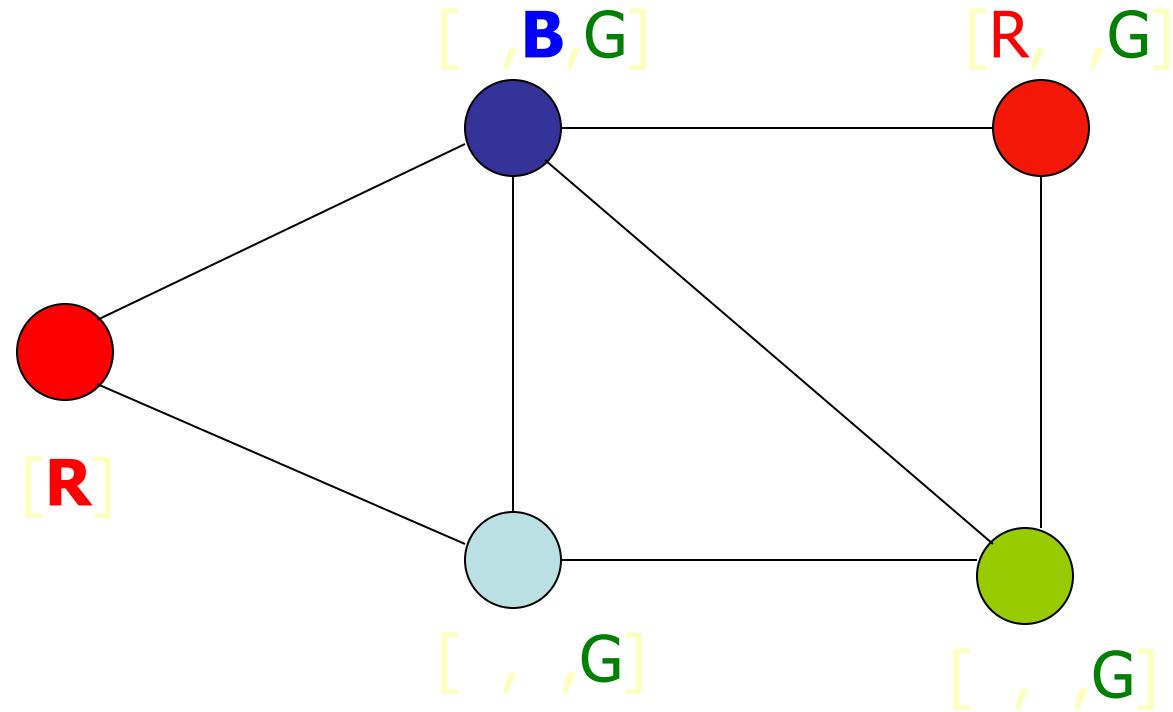
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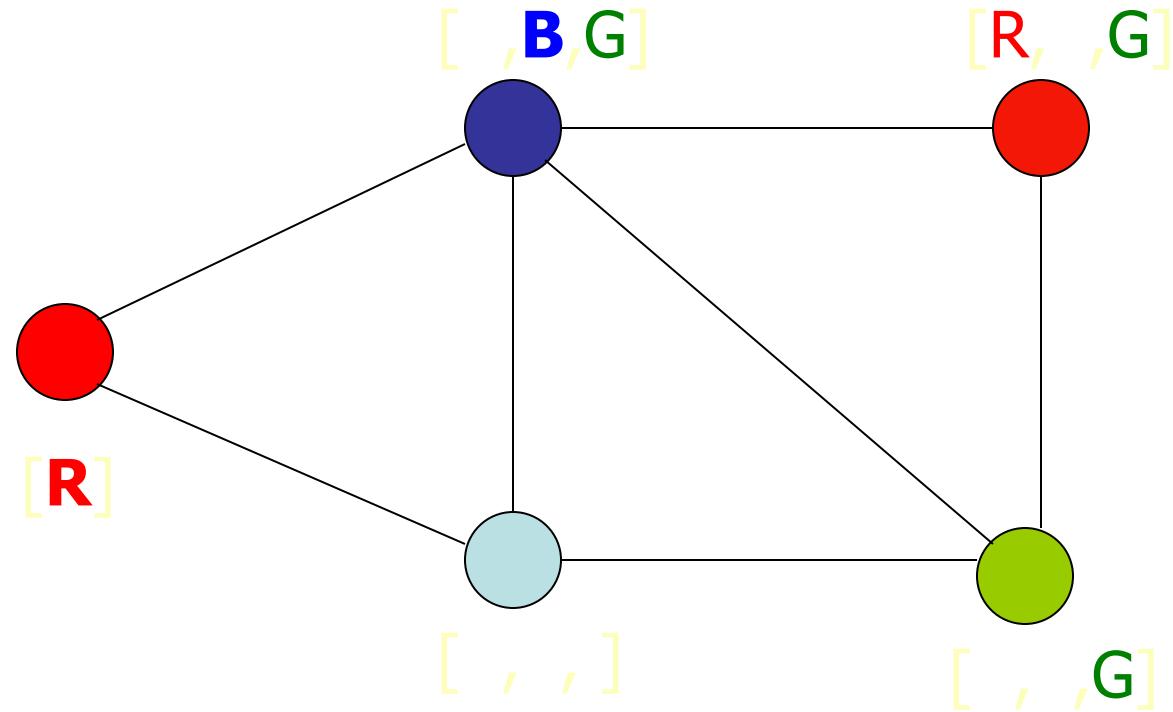
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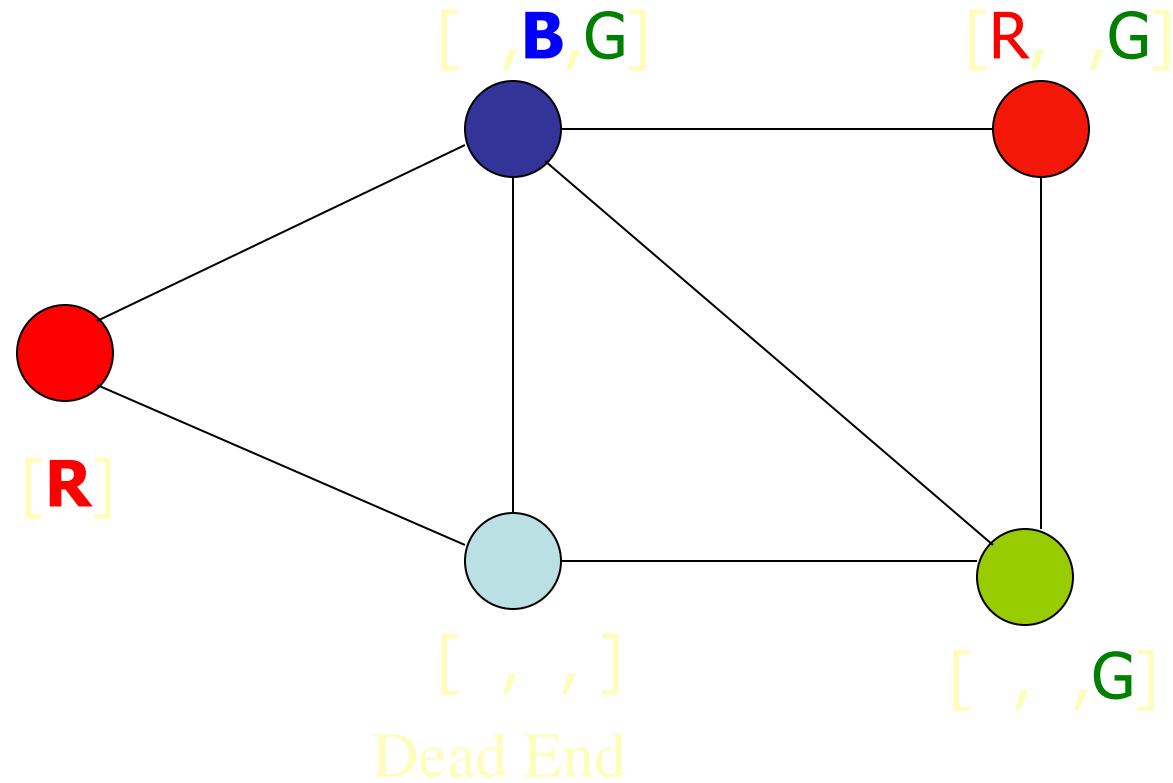
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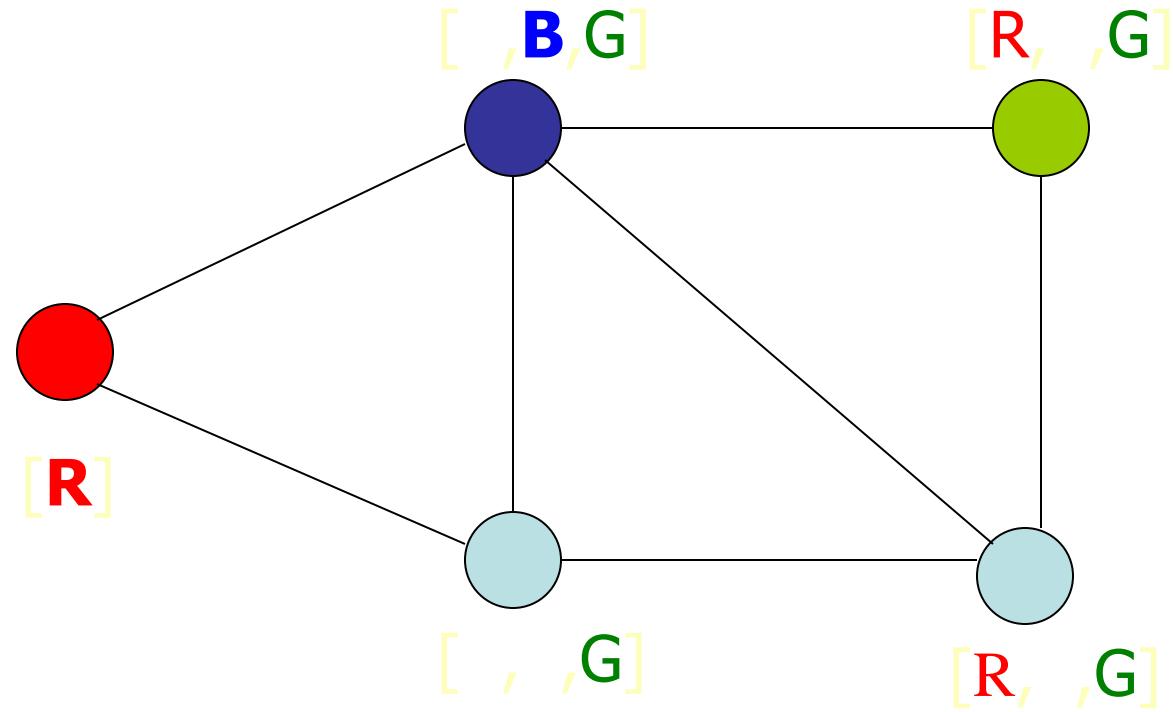
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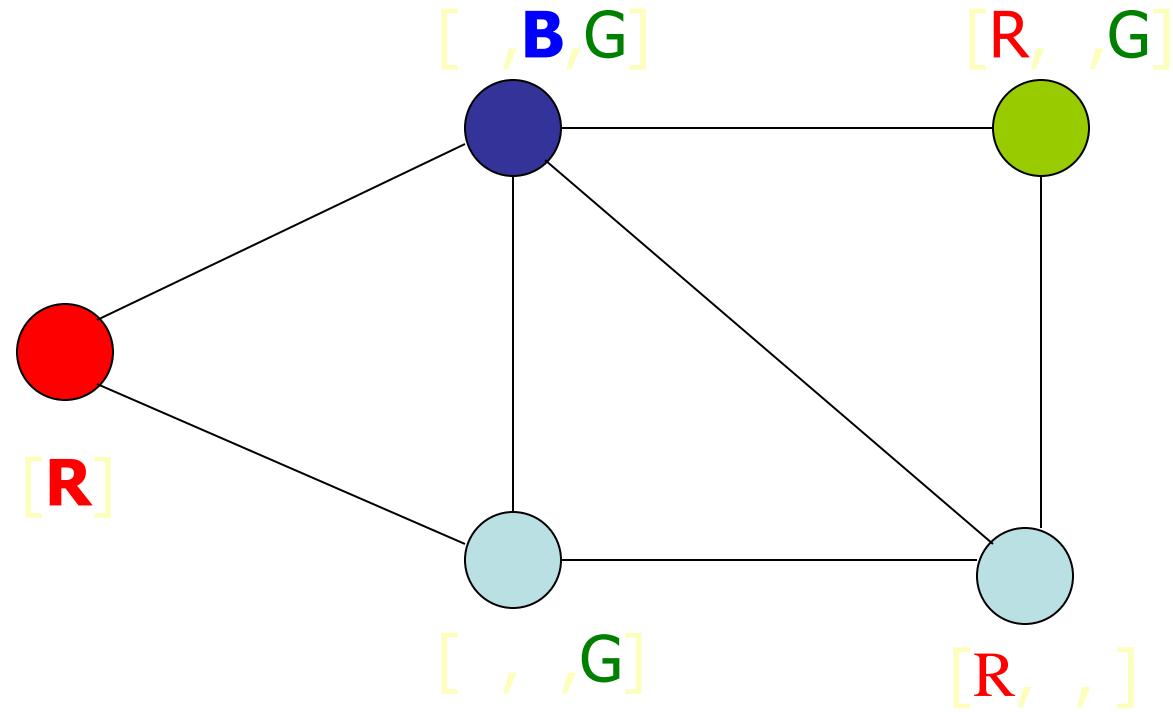
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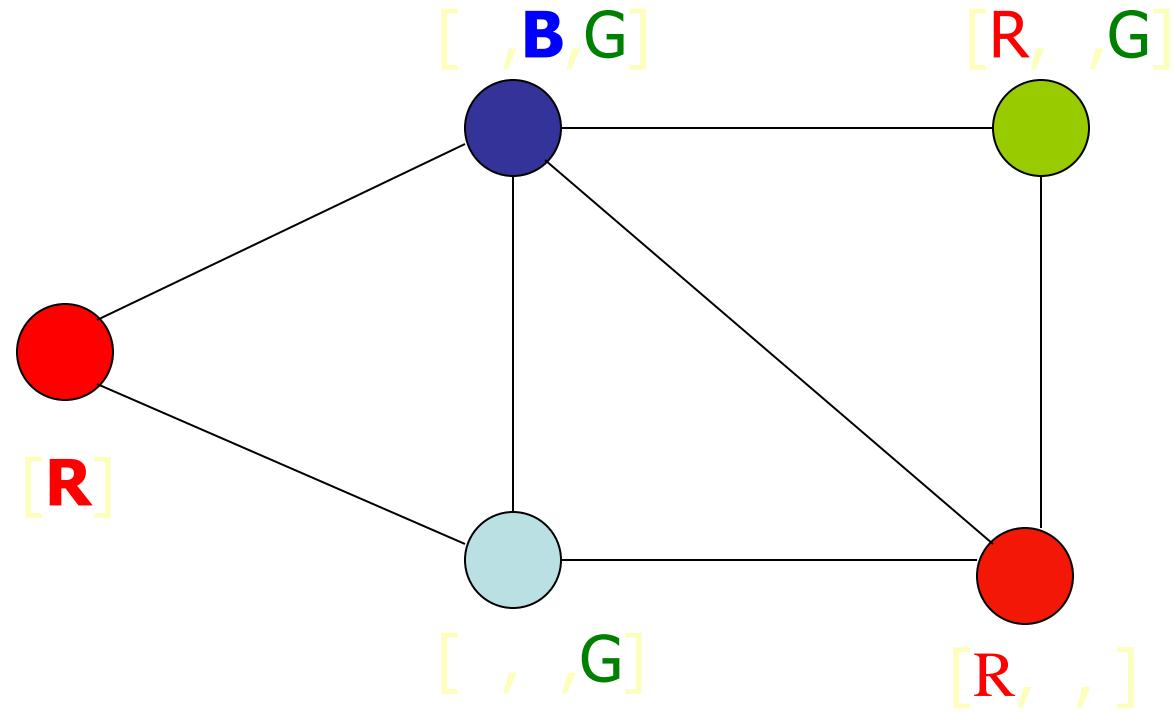
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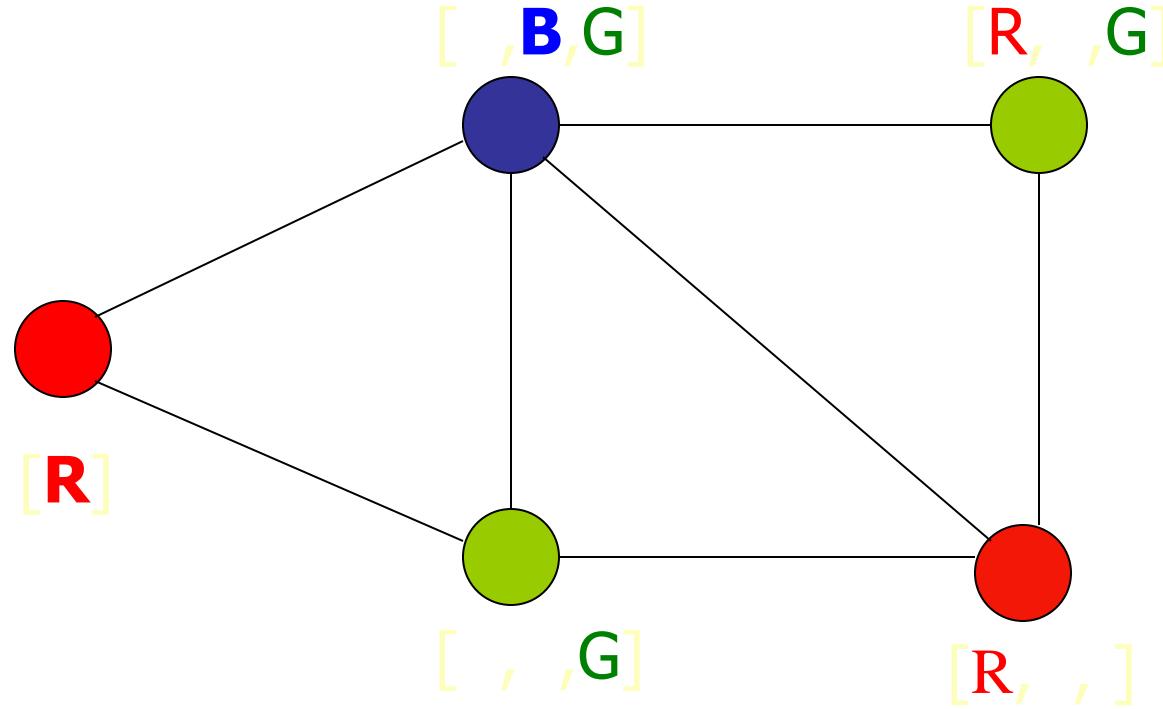
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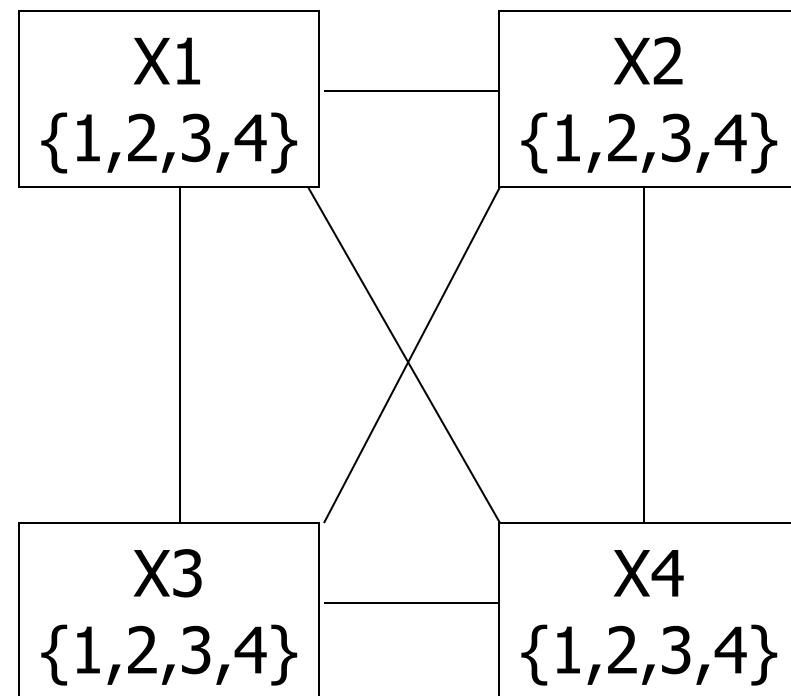
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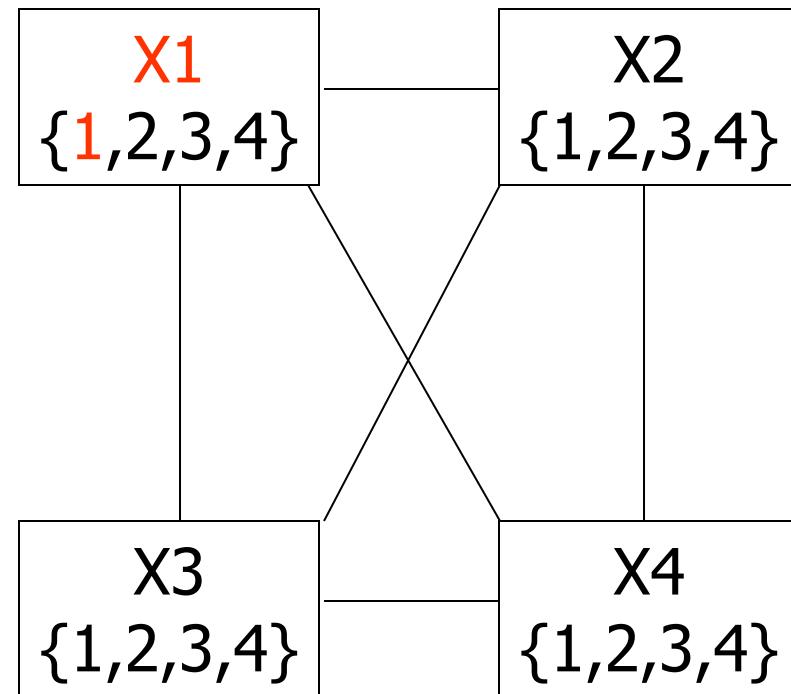
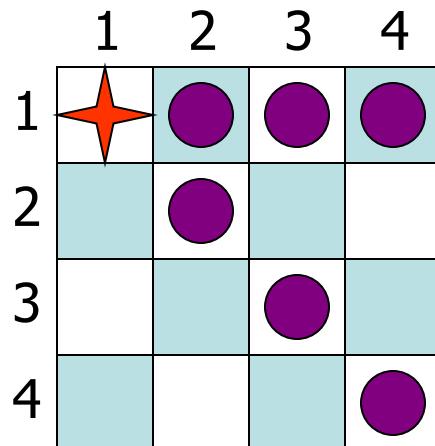
Solution !!!

Example: 4-Queens Problem

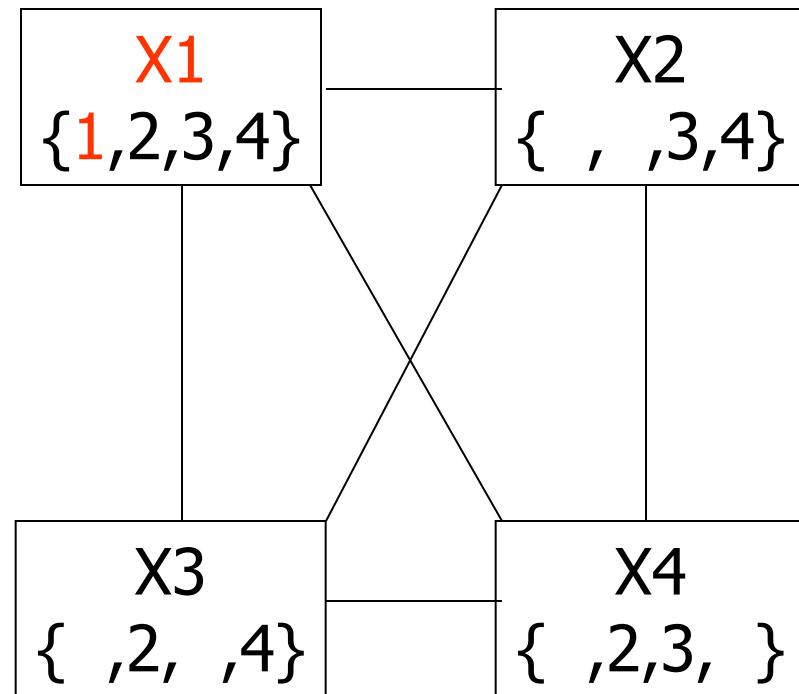
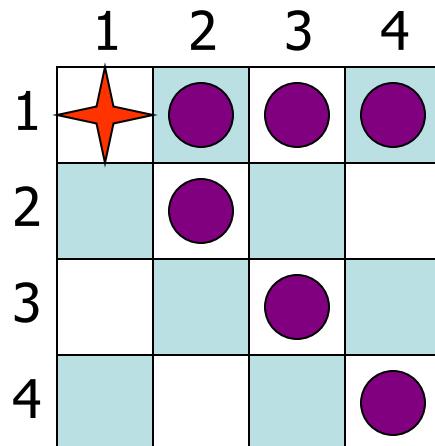
	1	2	3	4
1				
2				
3				
4				



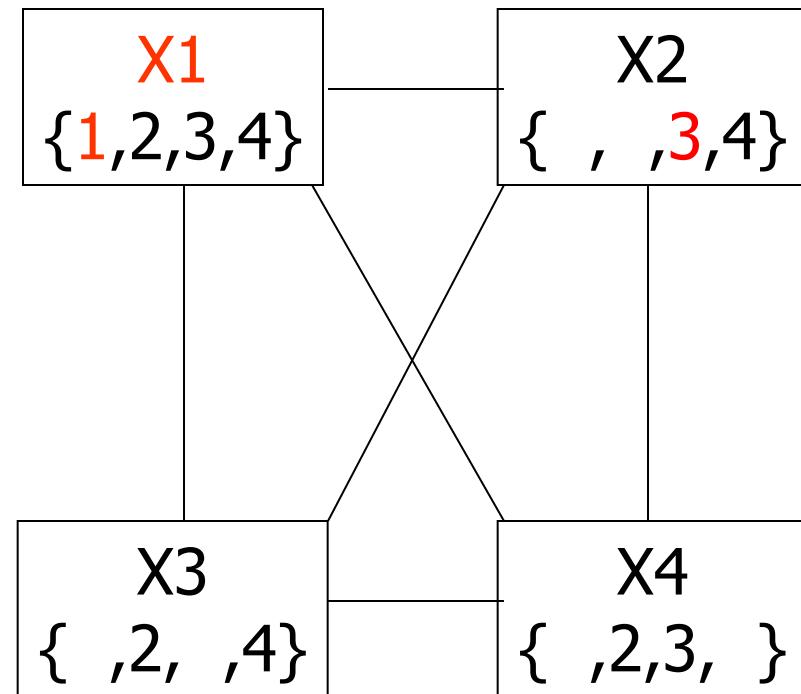
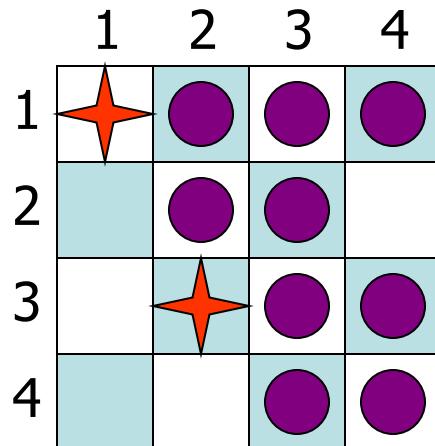
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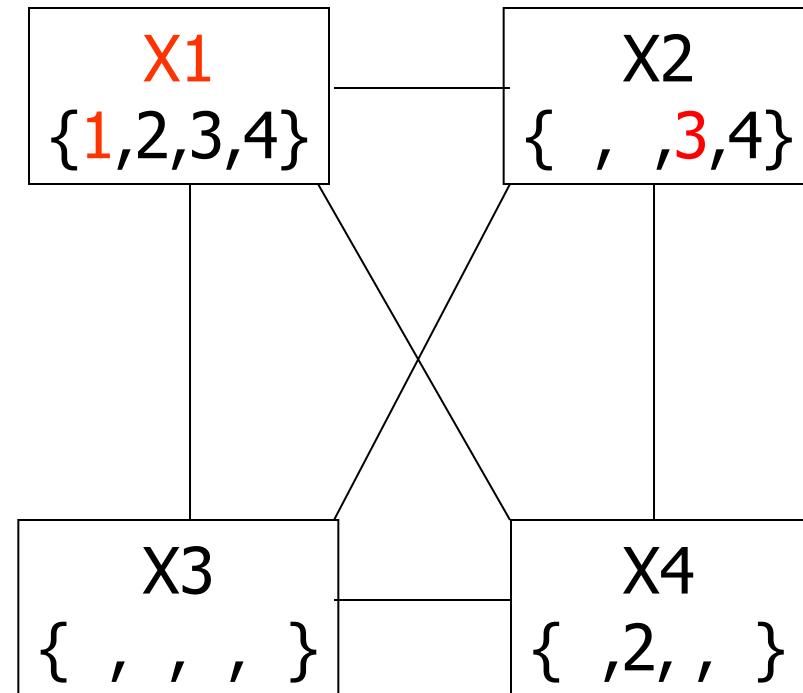
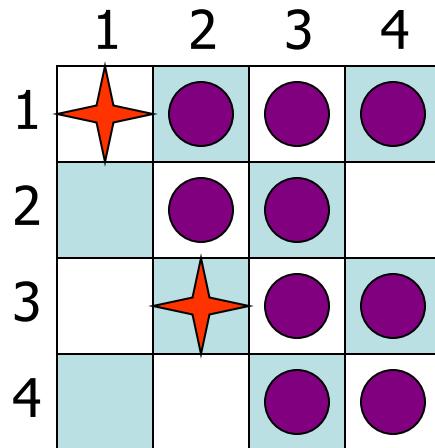
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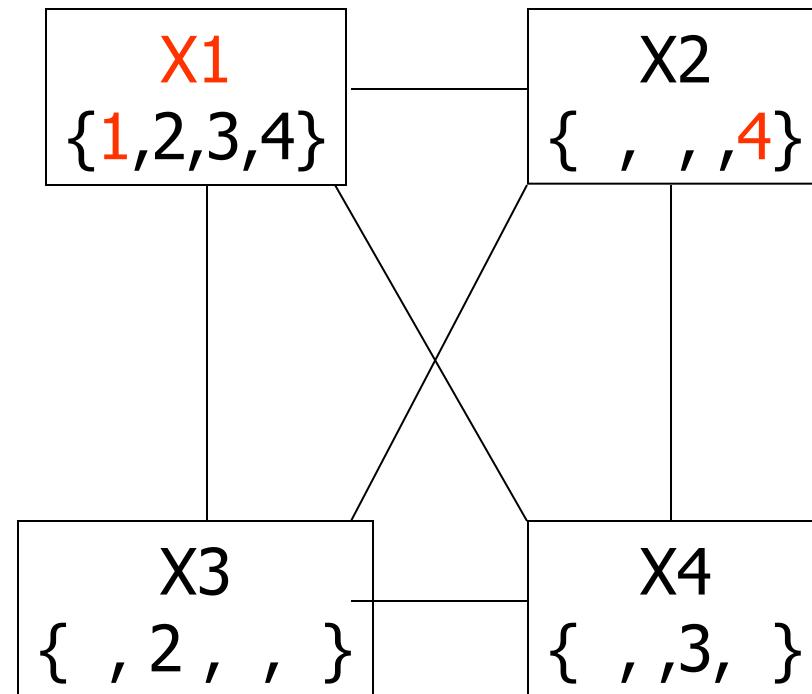
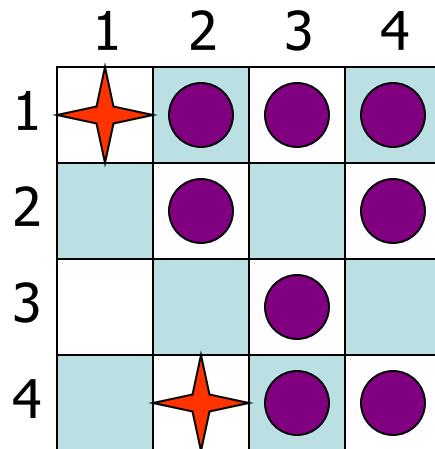


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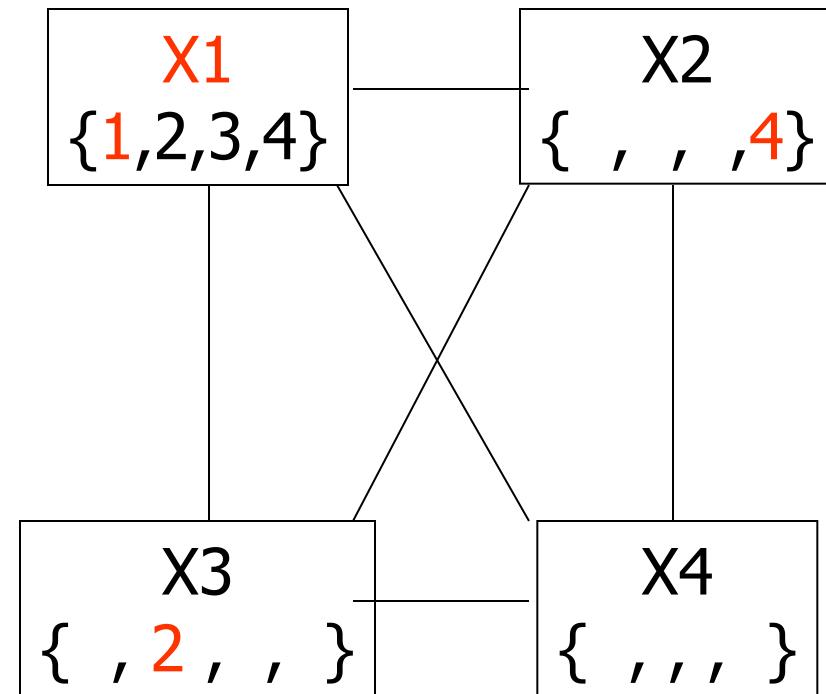
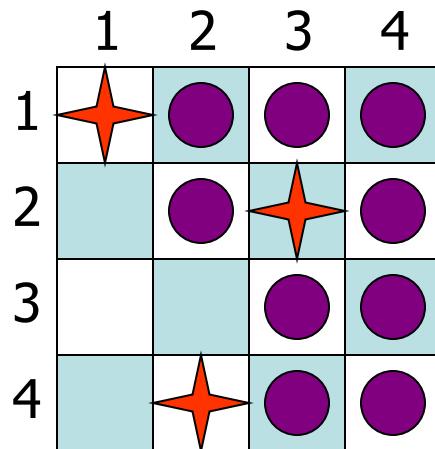


Dead End → Backtrack

Example: 4-Queens Problem

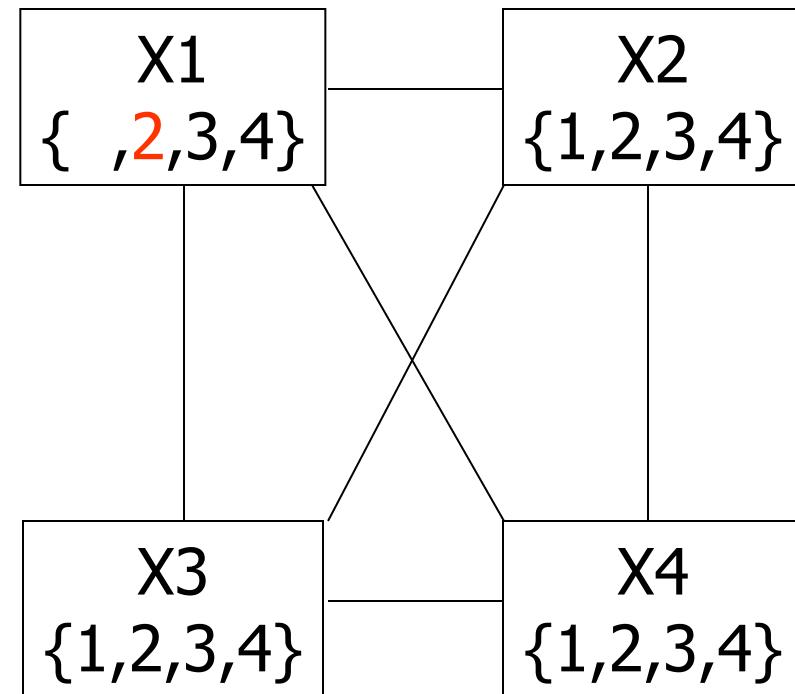
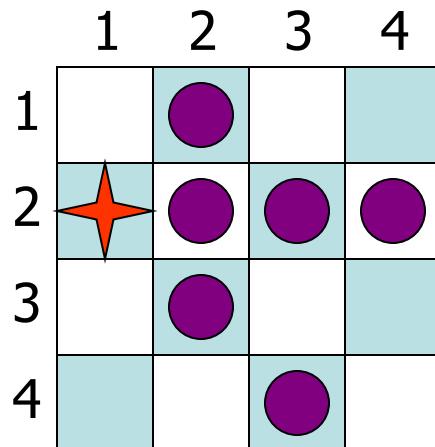


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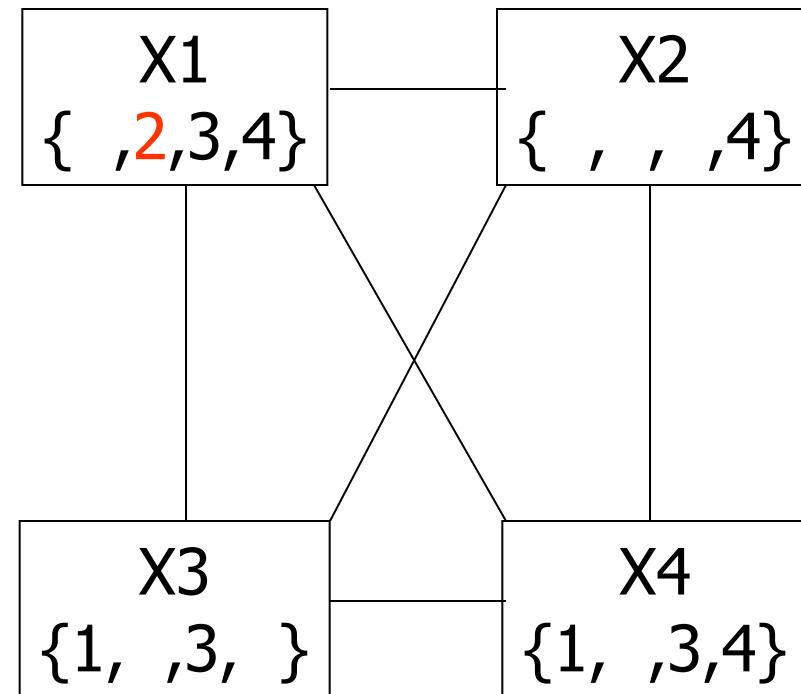
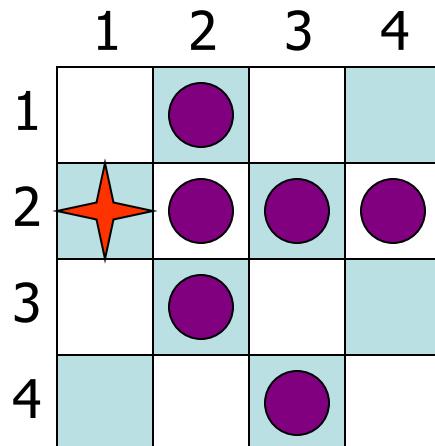


Dead End → Backtrack

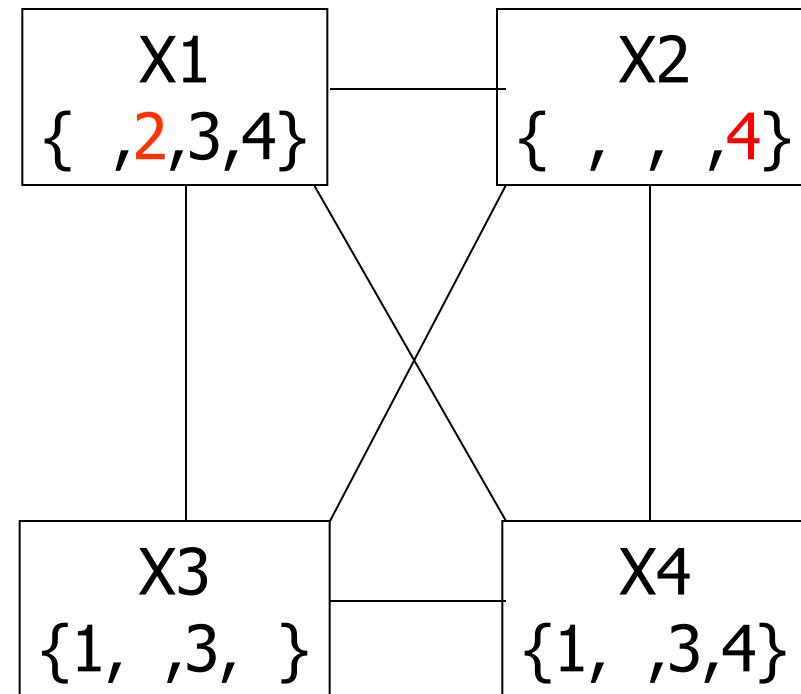
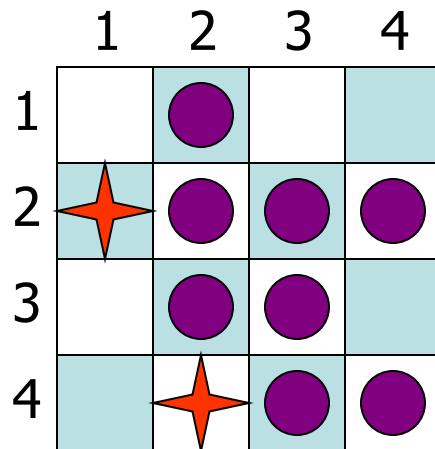
Example: 4-Queens Problem



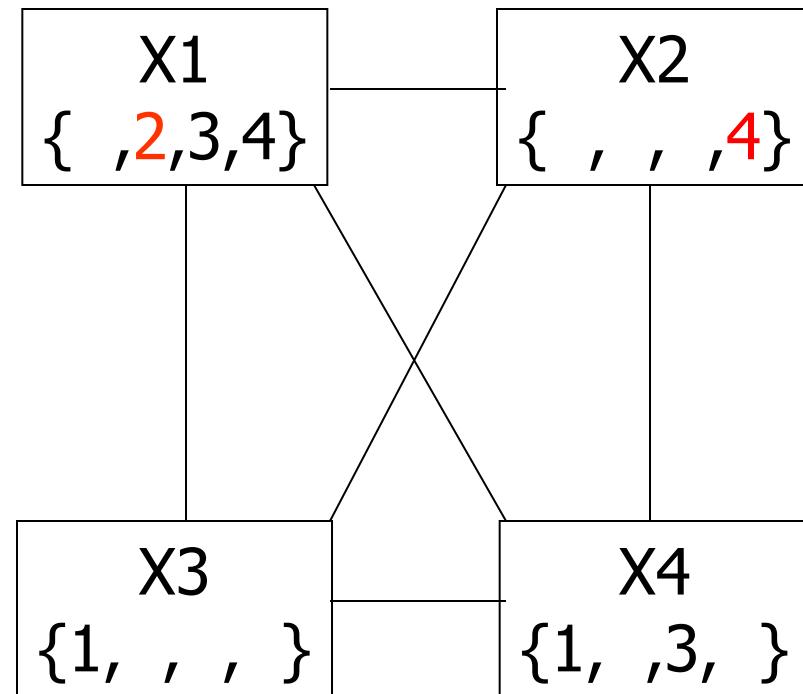
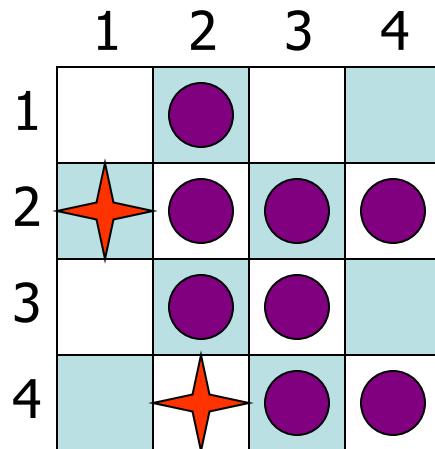
Example: 4-Queens Problem



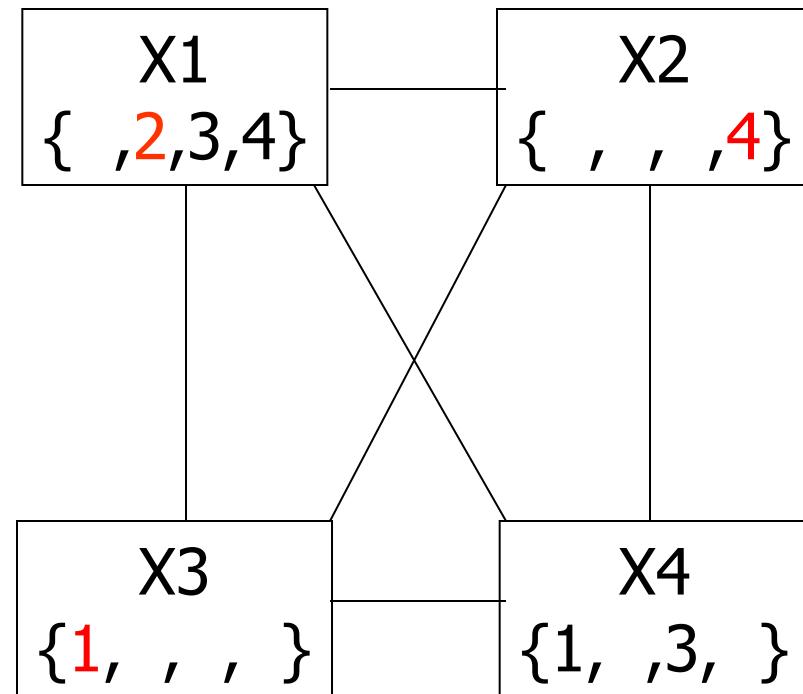
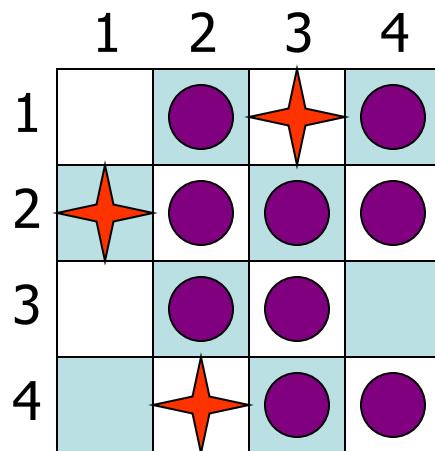
Example: 4-Queens Problem



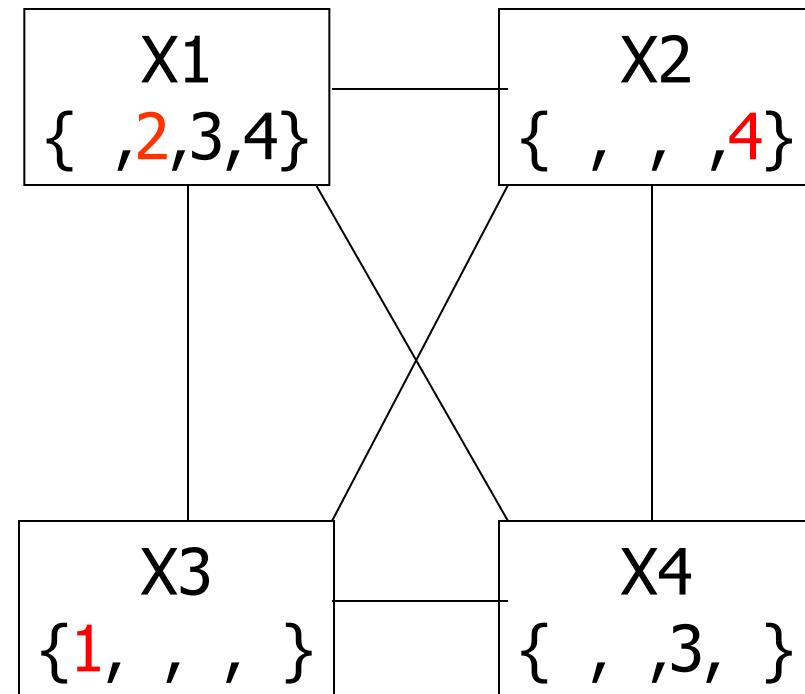
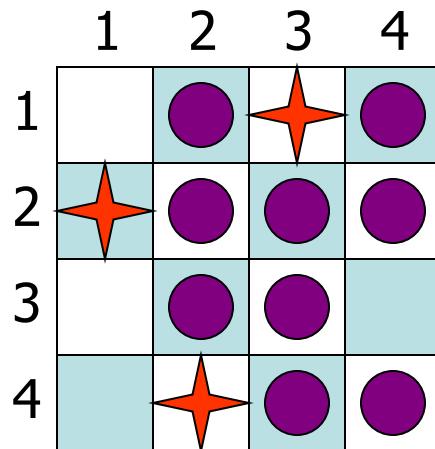
Example: 4-Queens Problem



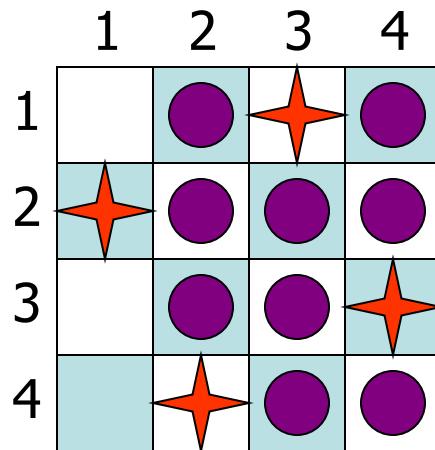
Example: 4-Queens Problem



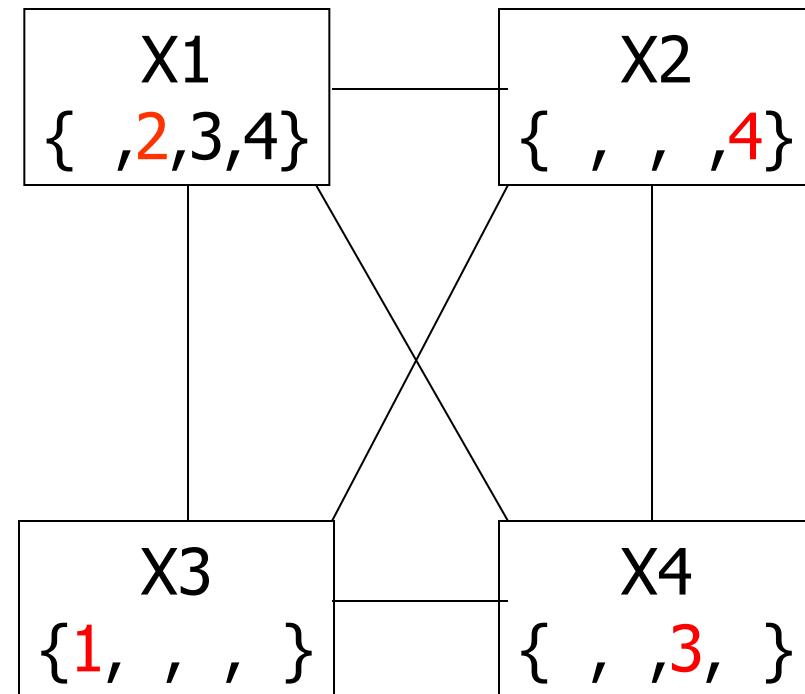
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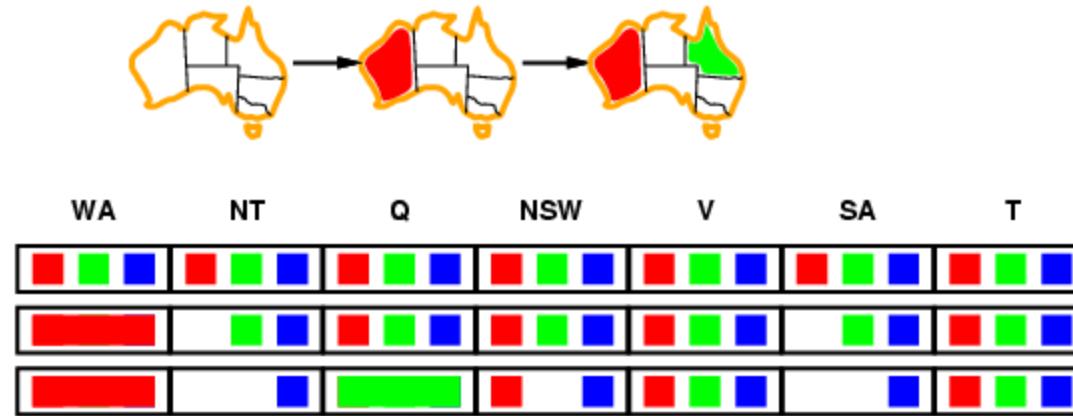


Solution !!!!



Constraint propagation

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

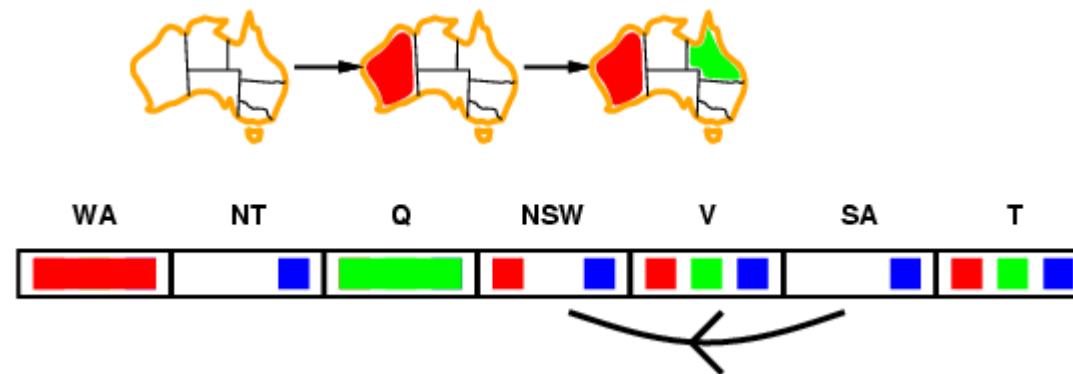


- NT and SA cannot both be blue!
- Constraint propagation repeatedly enforces constraints locally

Arc consistency

- Simplest form of propagation makes each arc **consistent**
- $X \rightarrow Y$ is consistent iff

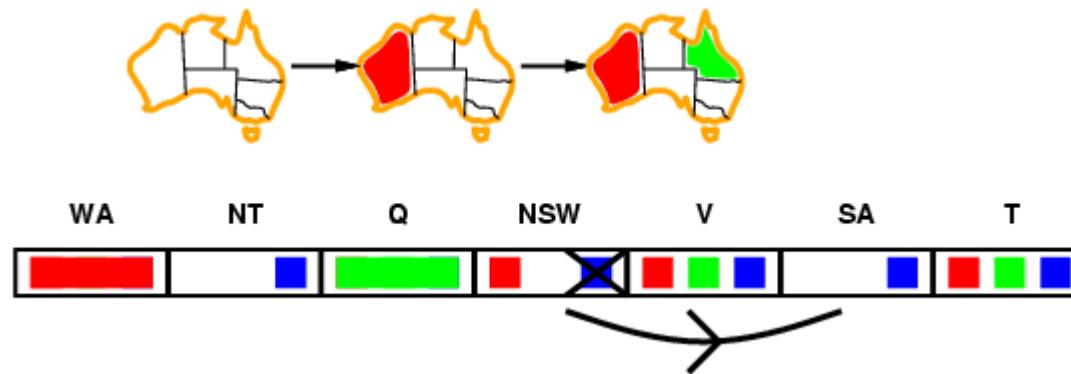
for **every** value X of X there is **some** allowed Y



Arc consistency

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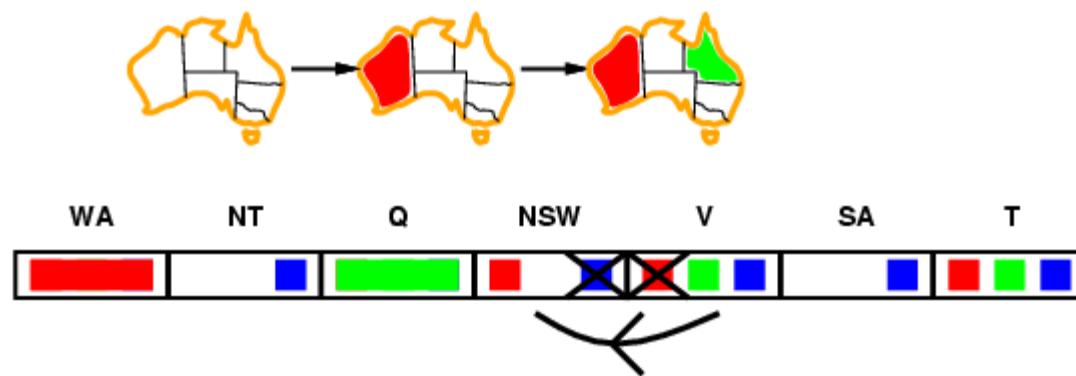
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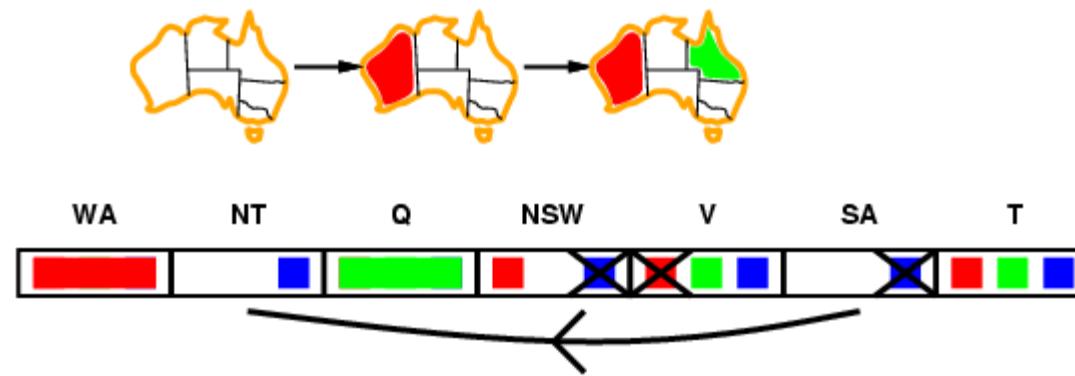
for **every** value X of X there is **some** allowed Y



- If X loses a value, neighbors of X need to be rechecked

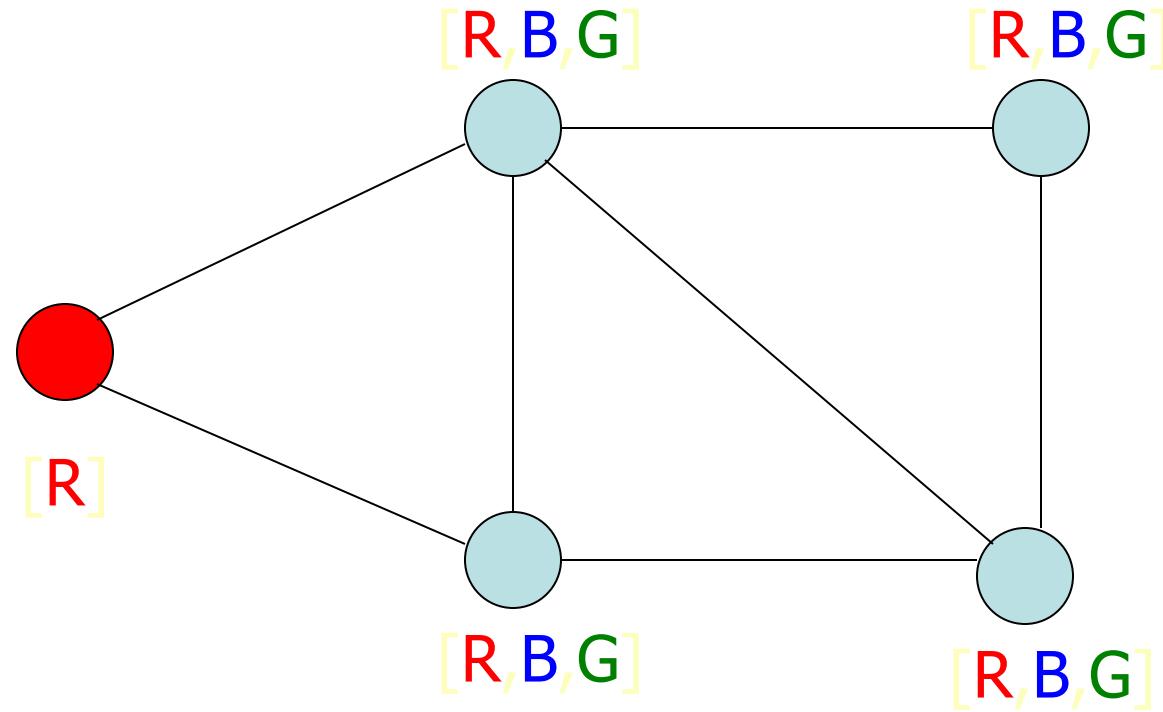
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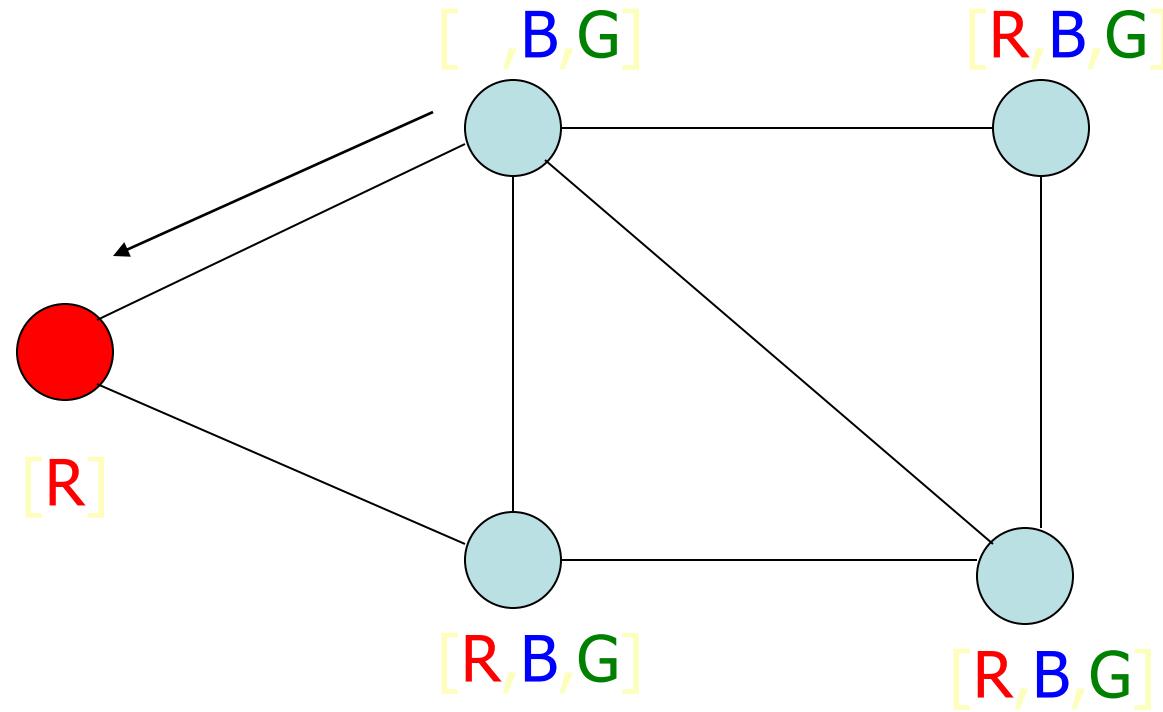


- If X loses a value, neighbors of X need to be rechecked
- Arc consistency detects failure earlier than forward checking
- Can be run as a preprocessor or after each assignment

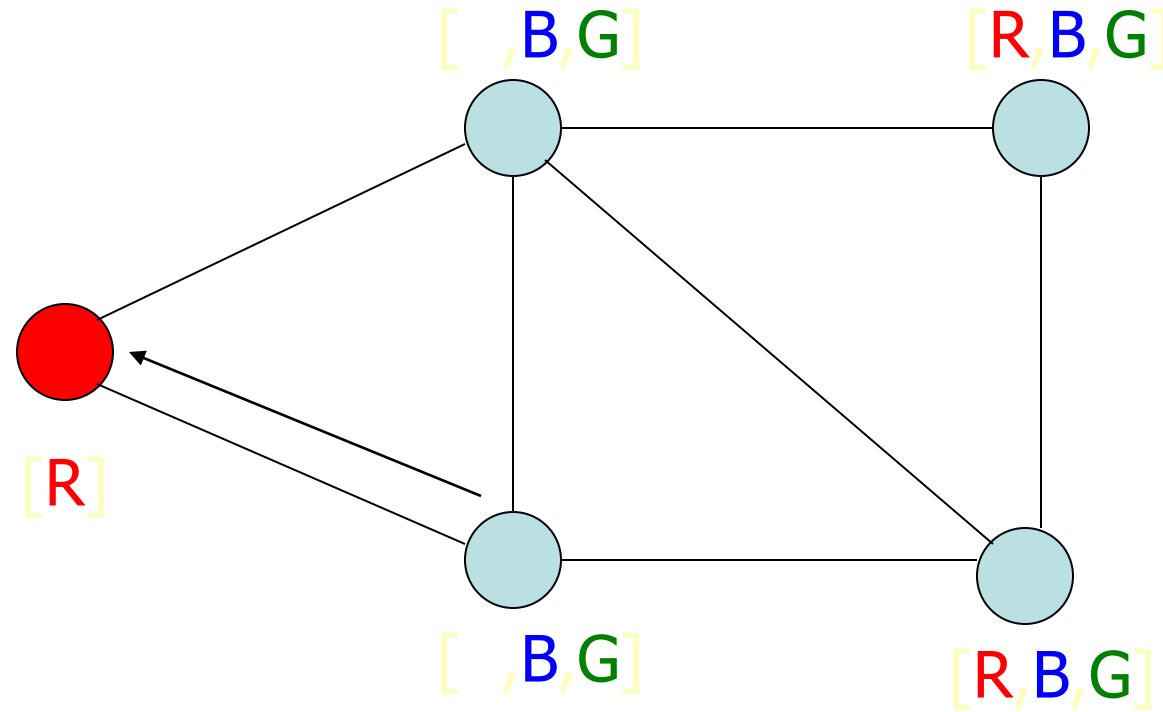
Arc Consistency: AC3



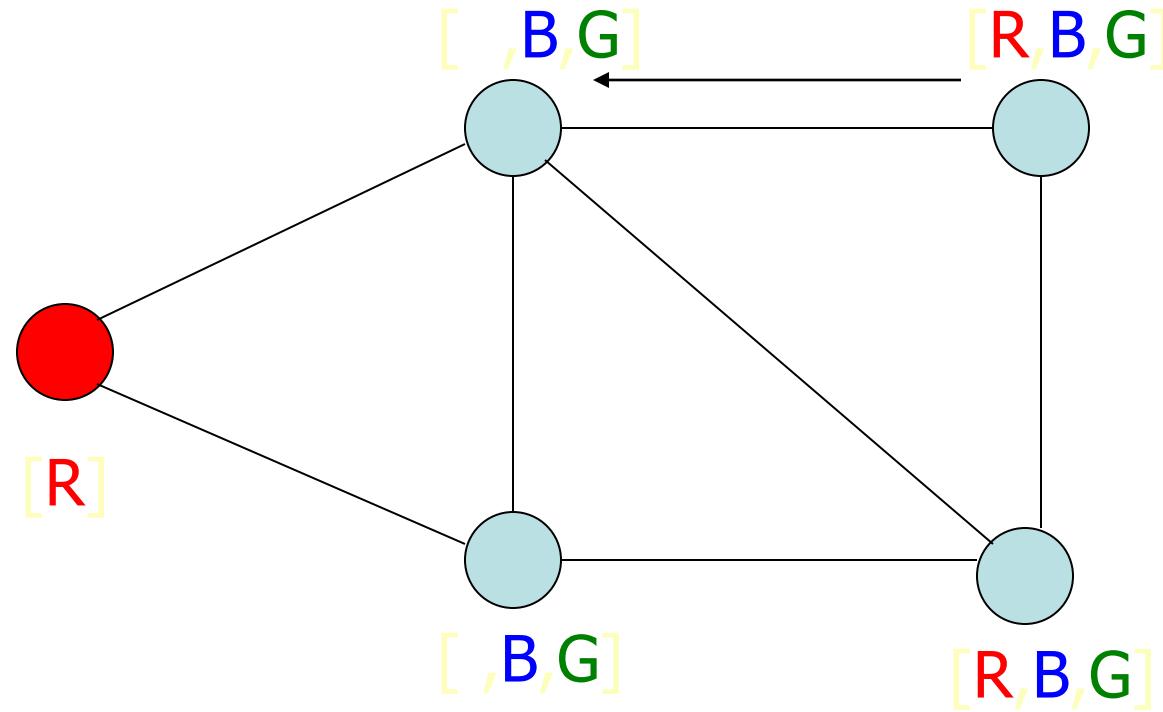
Arc Consistency: AC3



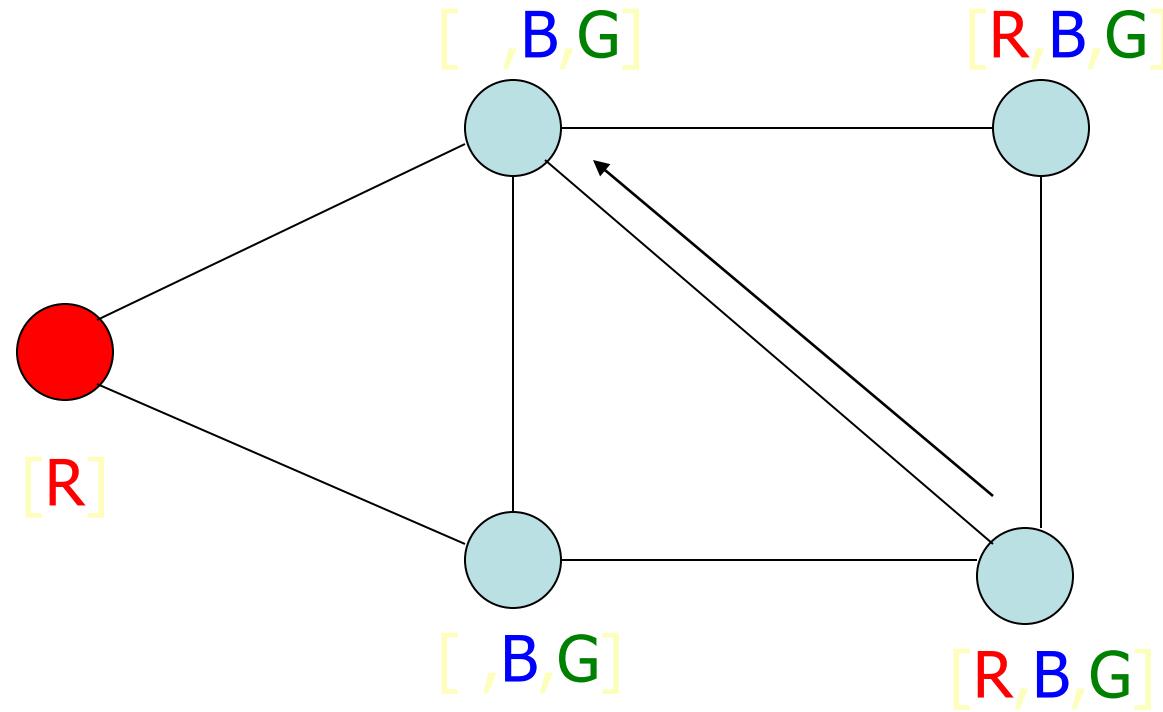
Arc Consistency: AC3



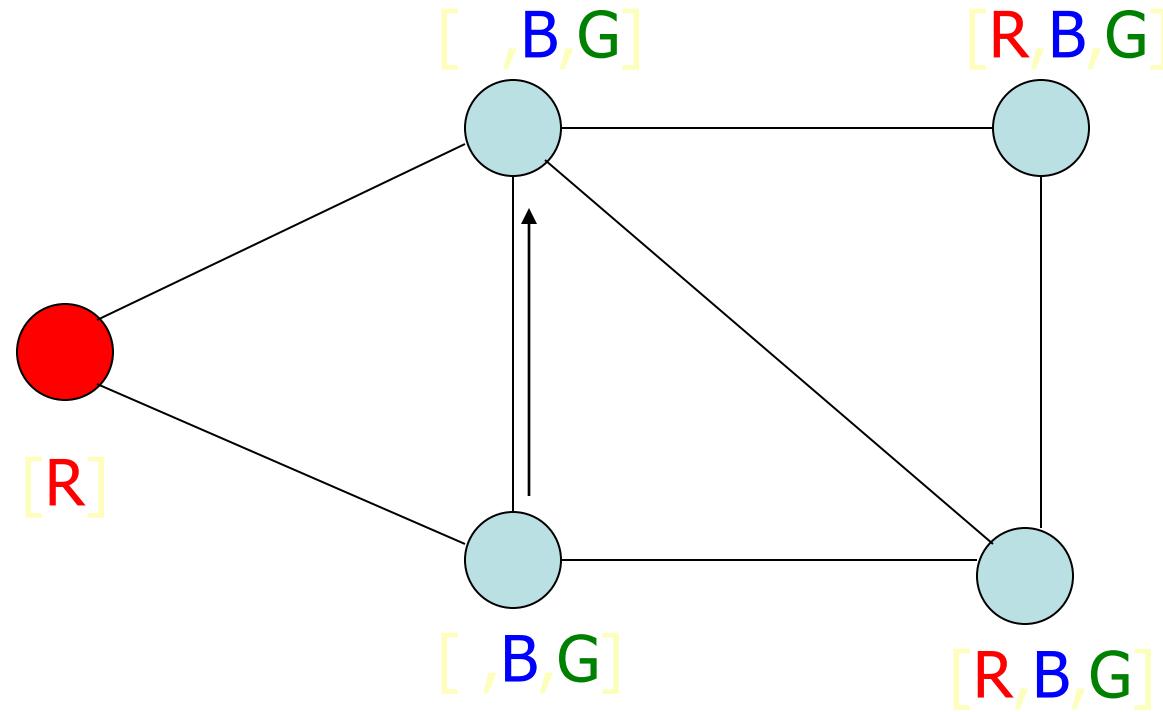
Arc Consistency: AC3



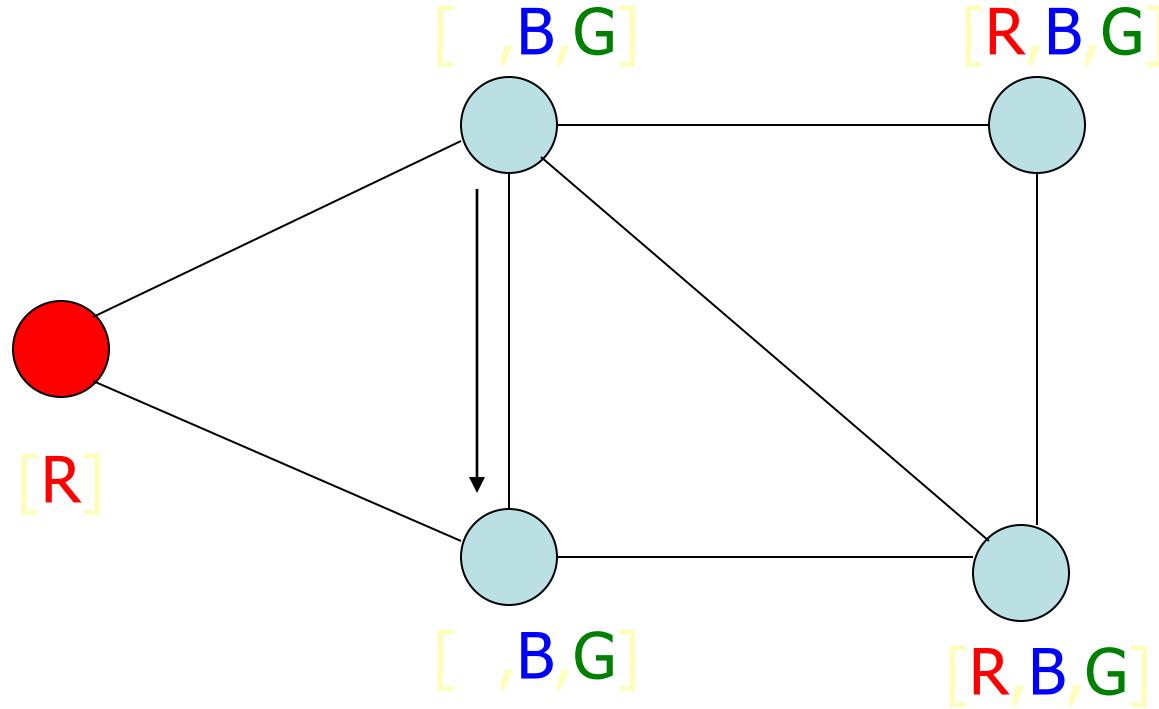
Arc Consistency: AC3



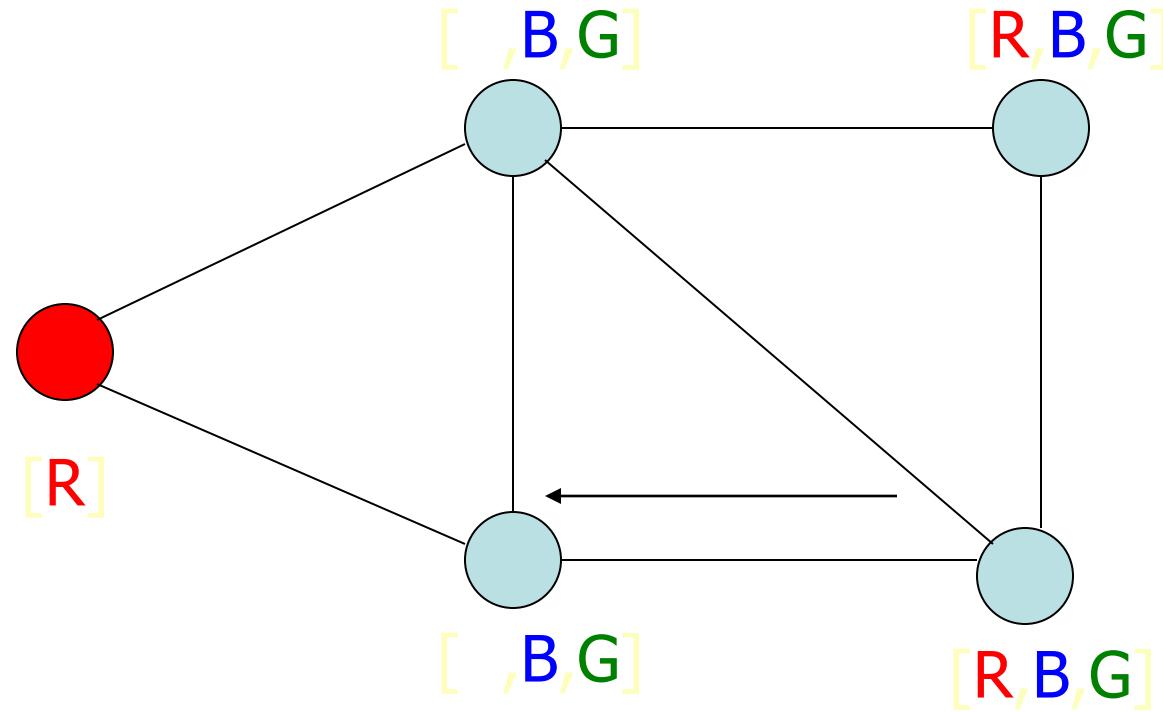
Arc Consistency: AC3



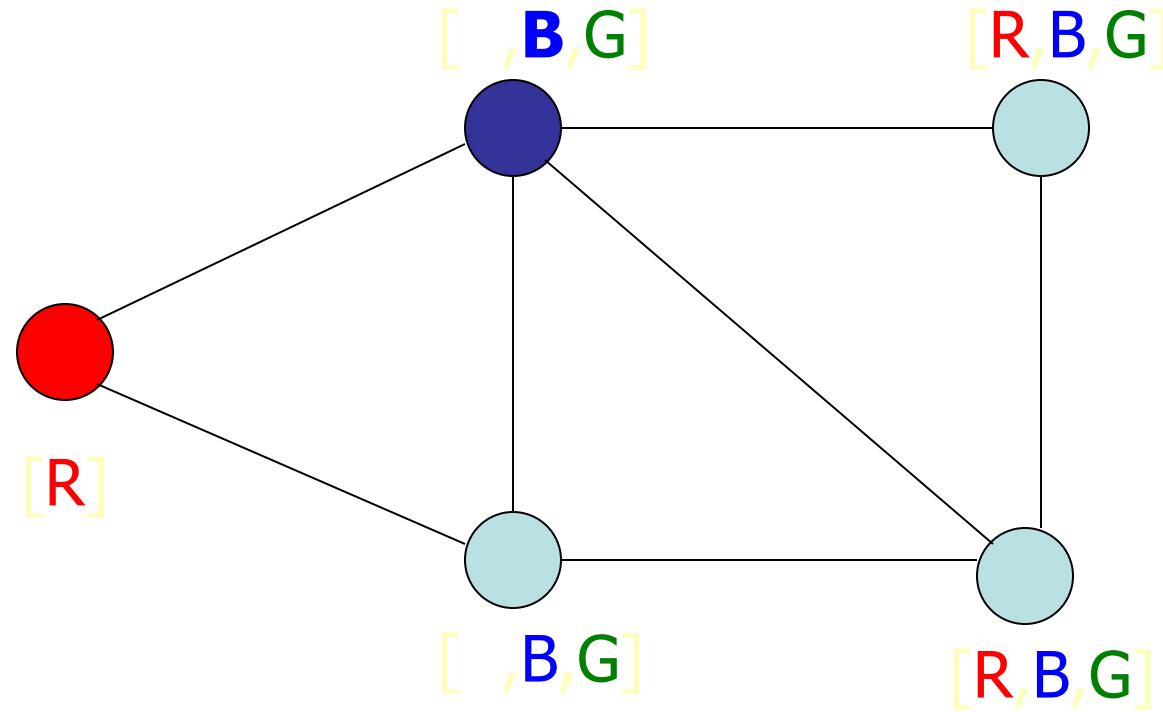
Arc Consistency: AC3



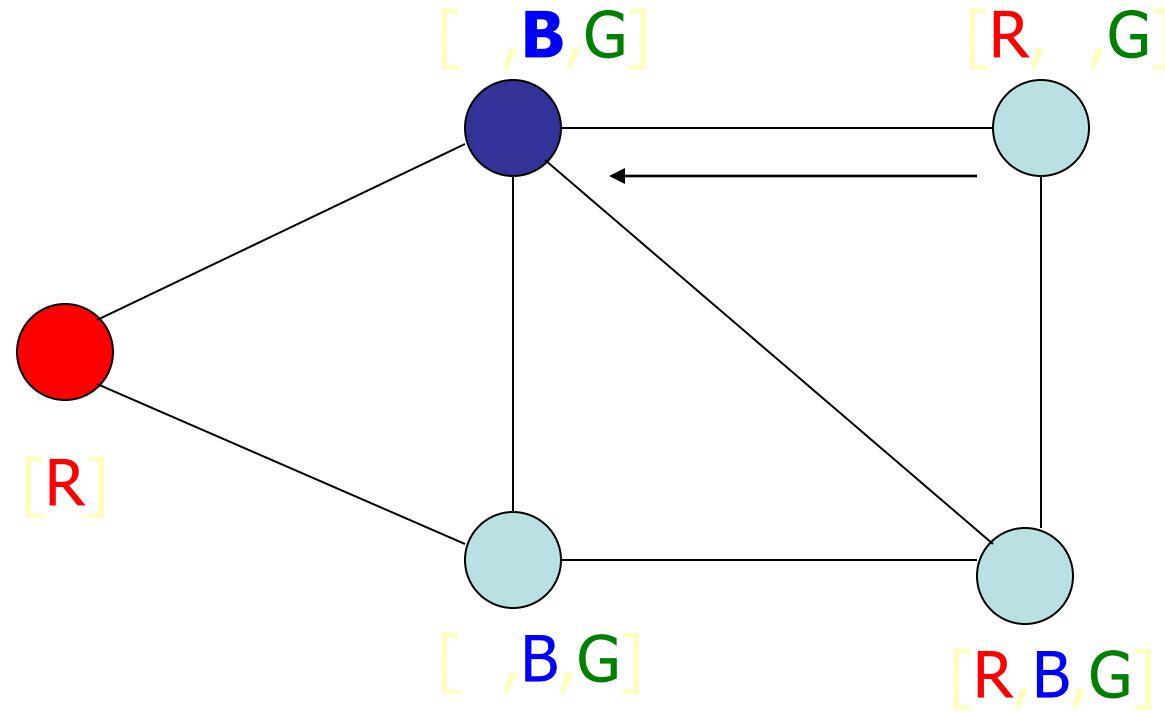
Arc Consistency: AC3



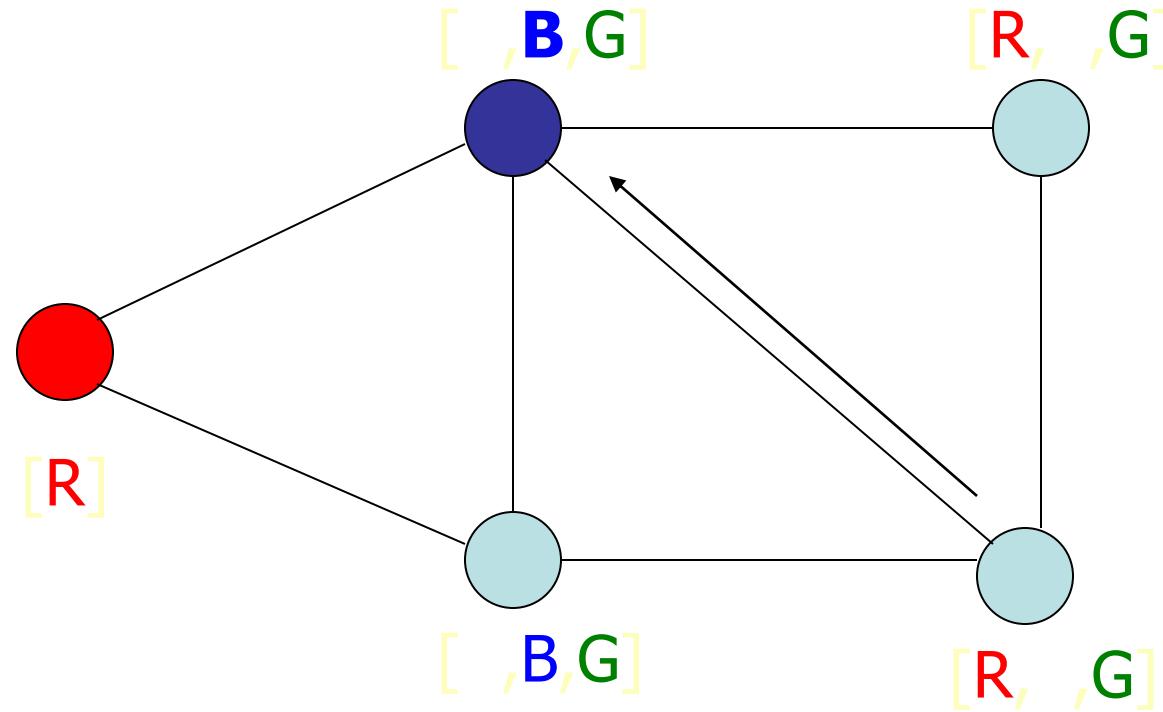
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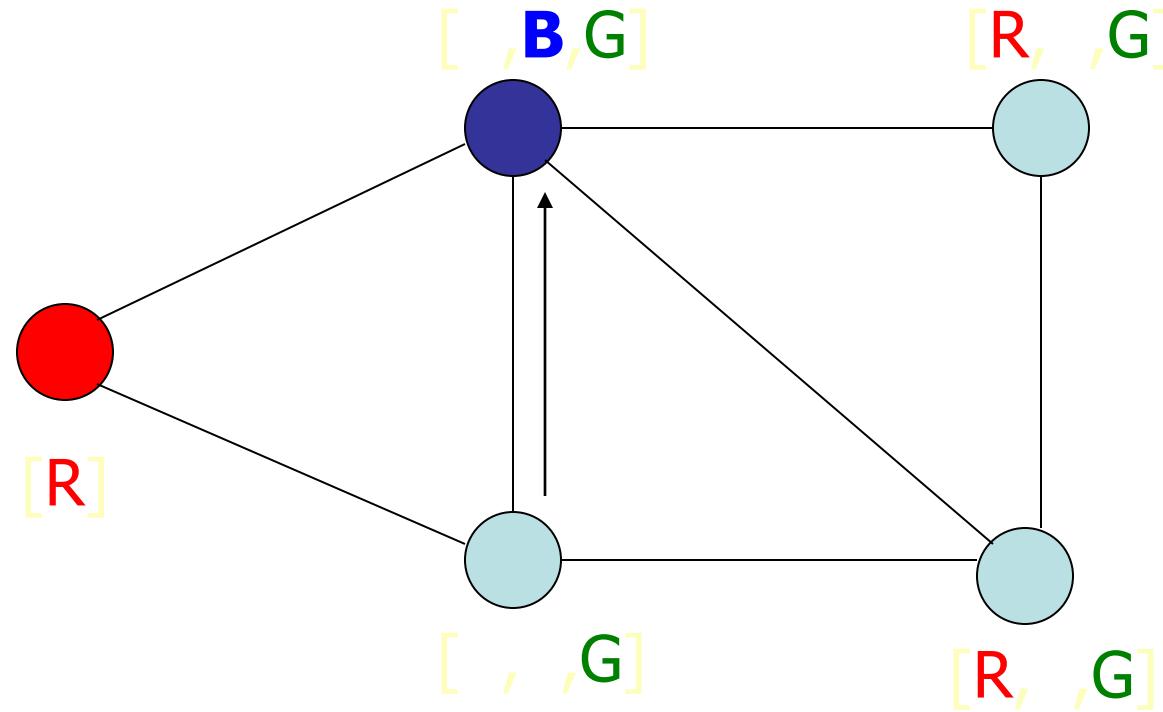
Arc Consistency: AC3



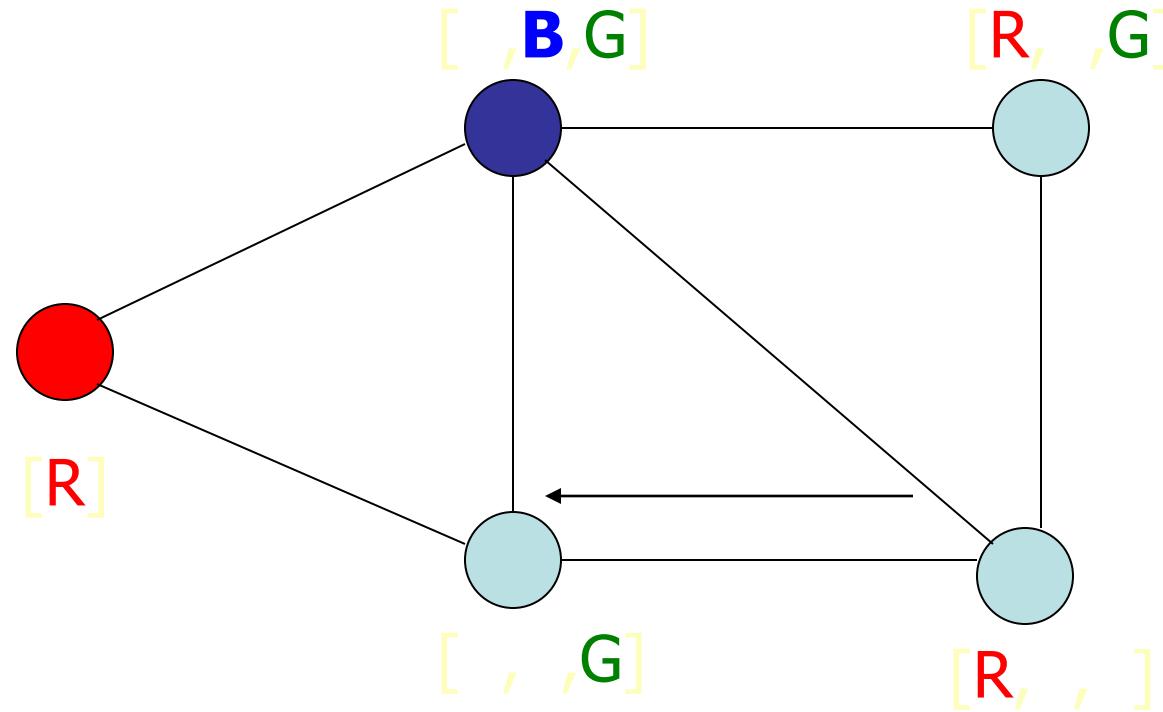
Arc Consistency: AC3



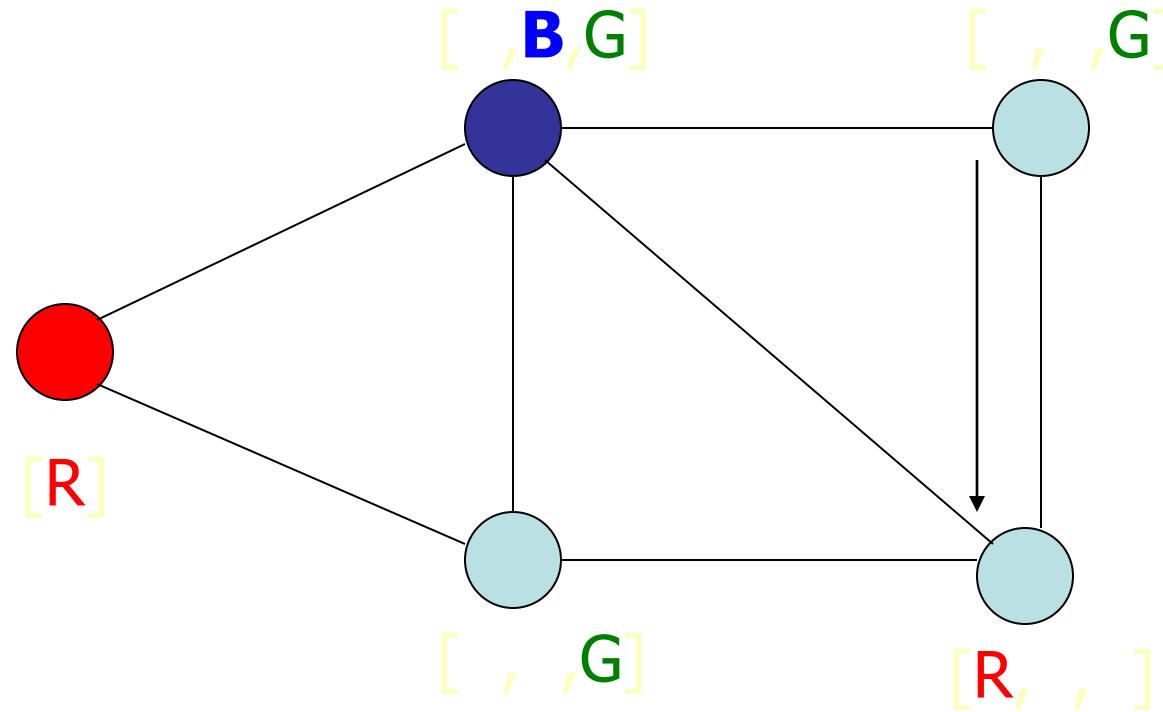
Arc Consistency: AC3



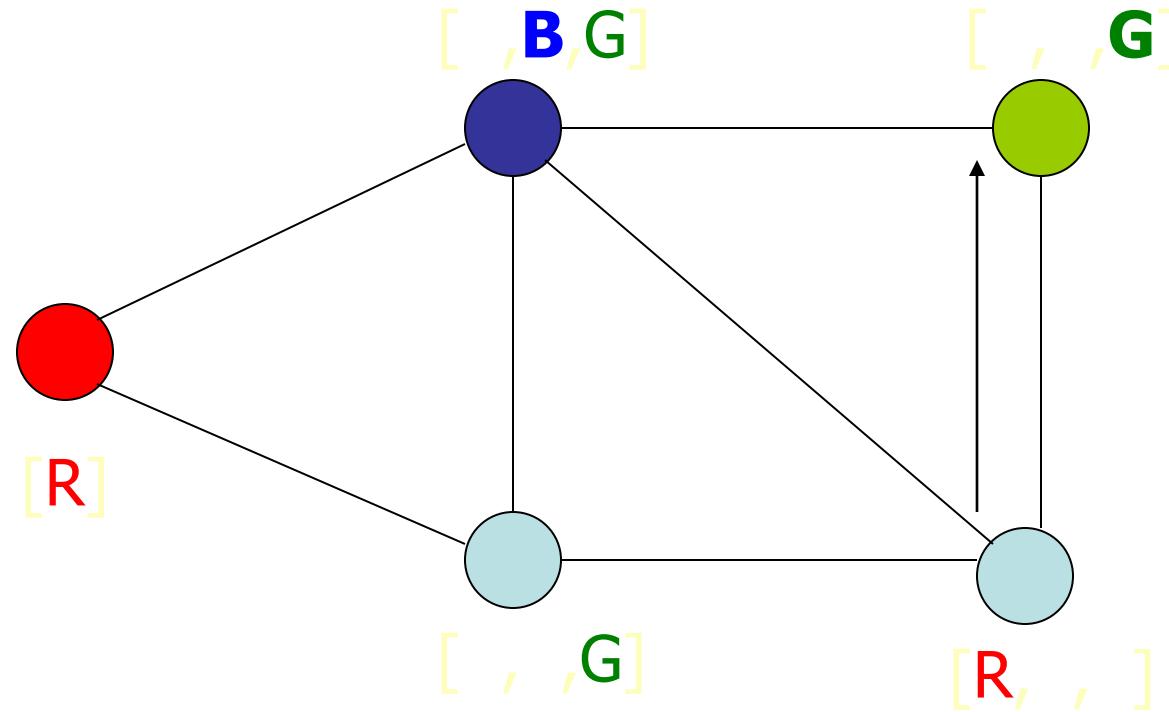
Arc Consistency: AC3



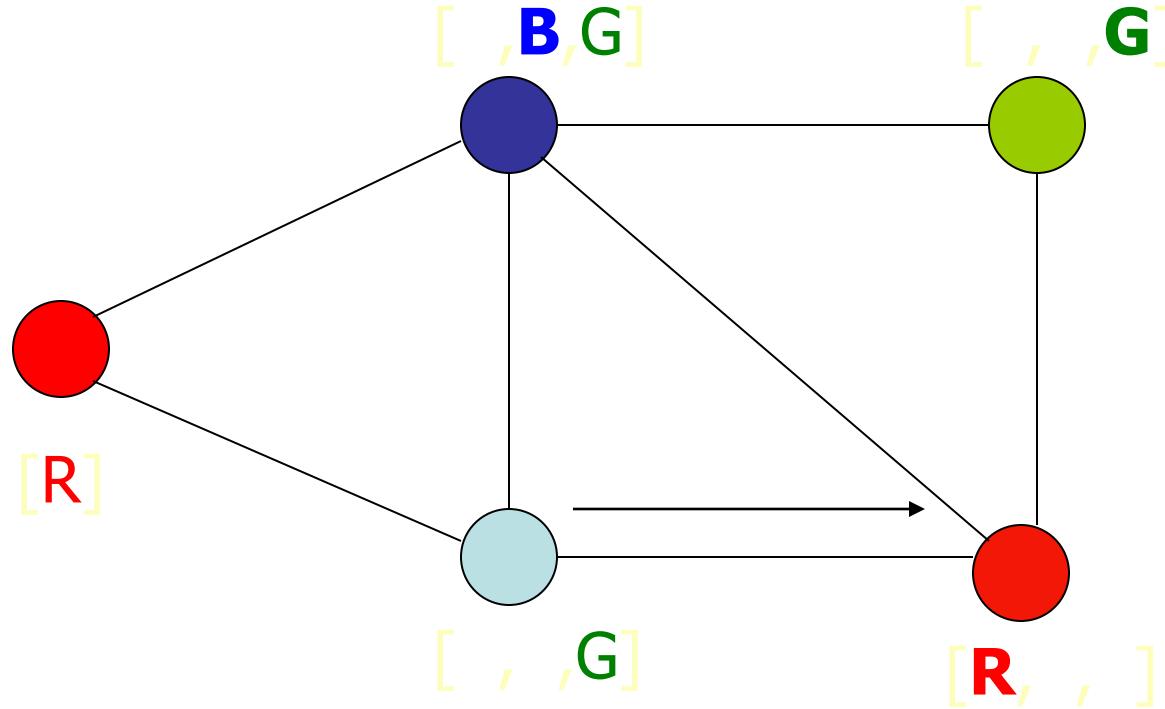
Arc Consistency: AC3



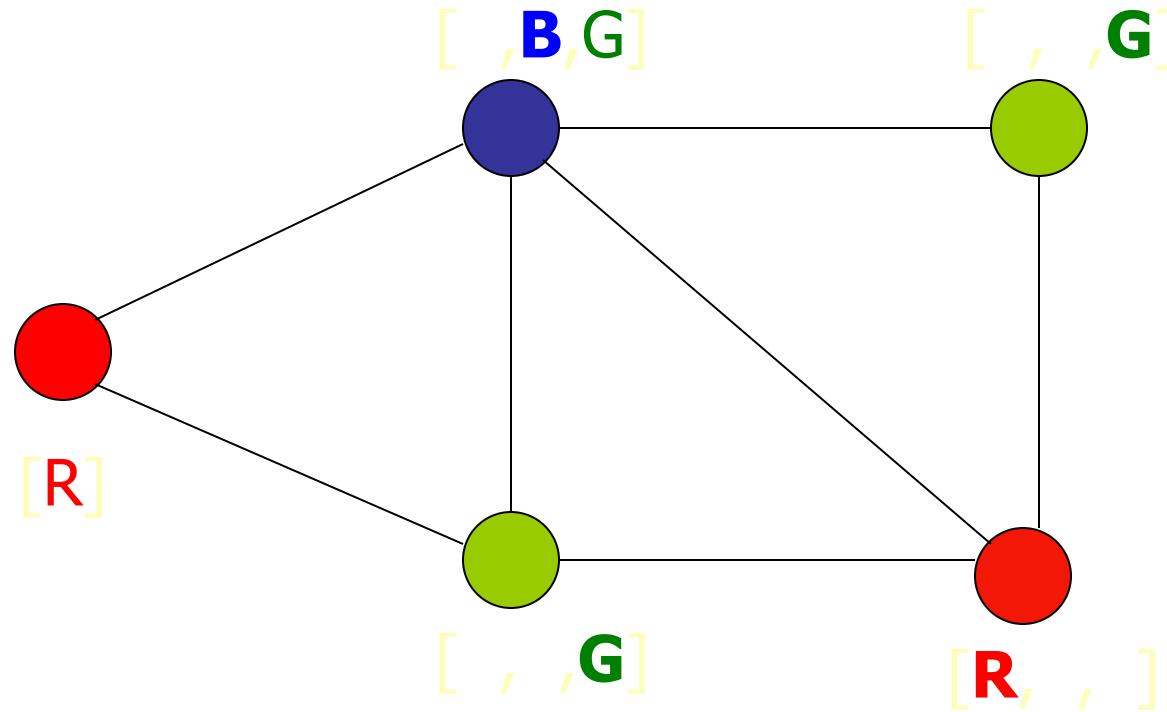
Arc Consistency: AC3



Arc Consistency: AC3



Arc Consistency: AC3



Solution !!!

Local Search and CSP

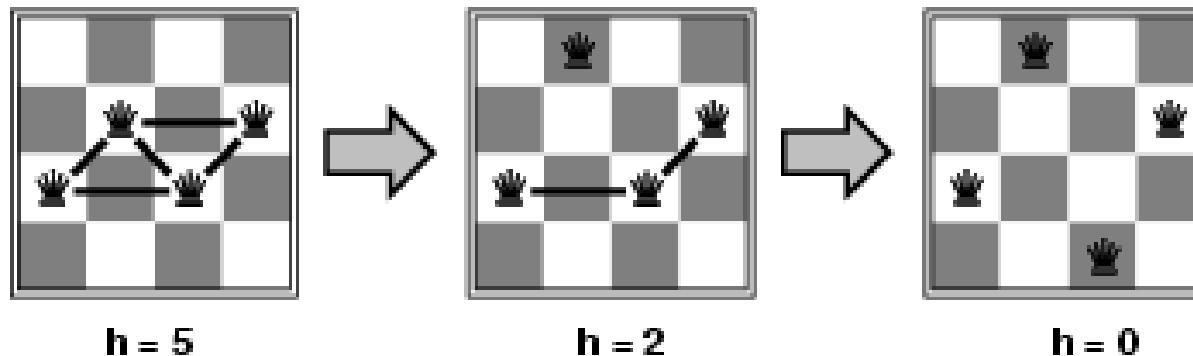
- local search (iterative improvement) is frequently used for constraint satisfaction problems
 - values are assigned to all variables
 - modification operators move the configuration towards a solution
- often called heuristic repair methods
 - repair inconsistencies in the current configuration
- simple strategy: min-conflicts
 - minimizes the number of conflicts with other variables
 - solves many problems very quickly
 - million-queens problem in less than 50 steps
- can be run as *online* algorithm
 - use the current state as new initial state

Local search for CSPs

- Hill-climbing, simulated annealing typically work with "complete" states, i.e., all variables assigned
- To apply to CSPs:
 - allow states with unsatisfied constraints
 - operators **reassign** variable values
- Variable selection: randomly select any conflicted variable
- Value selection by **min-conflicts** heuristic:
 - choose value that violates the fewest constraints
 - i.e., hill-climb with $h(n)$ = total number of violated constraints

Example: 4-Queens

- **States:** 4 queens in 4 columns ($4^4 = 256$ states)
- **Actions:** move queen in column
- **Goal test:** no attacks
- **Evaluation:** $h(n)$ = number of attacks



- Given random initial state, can solve n -queens in almost constant time for arbitrary n with high probability (e.g., $n = 10,000,000$)