CS 188: Artificial Intelligence

Constraint Satisfaction Problems II

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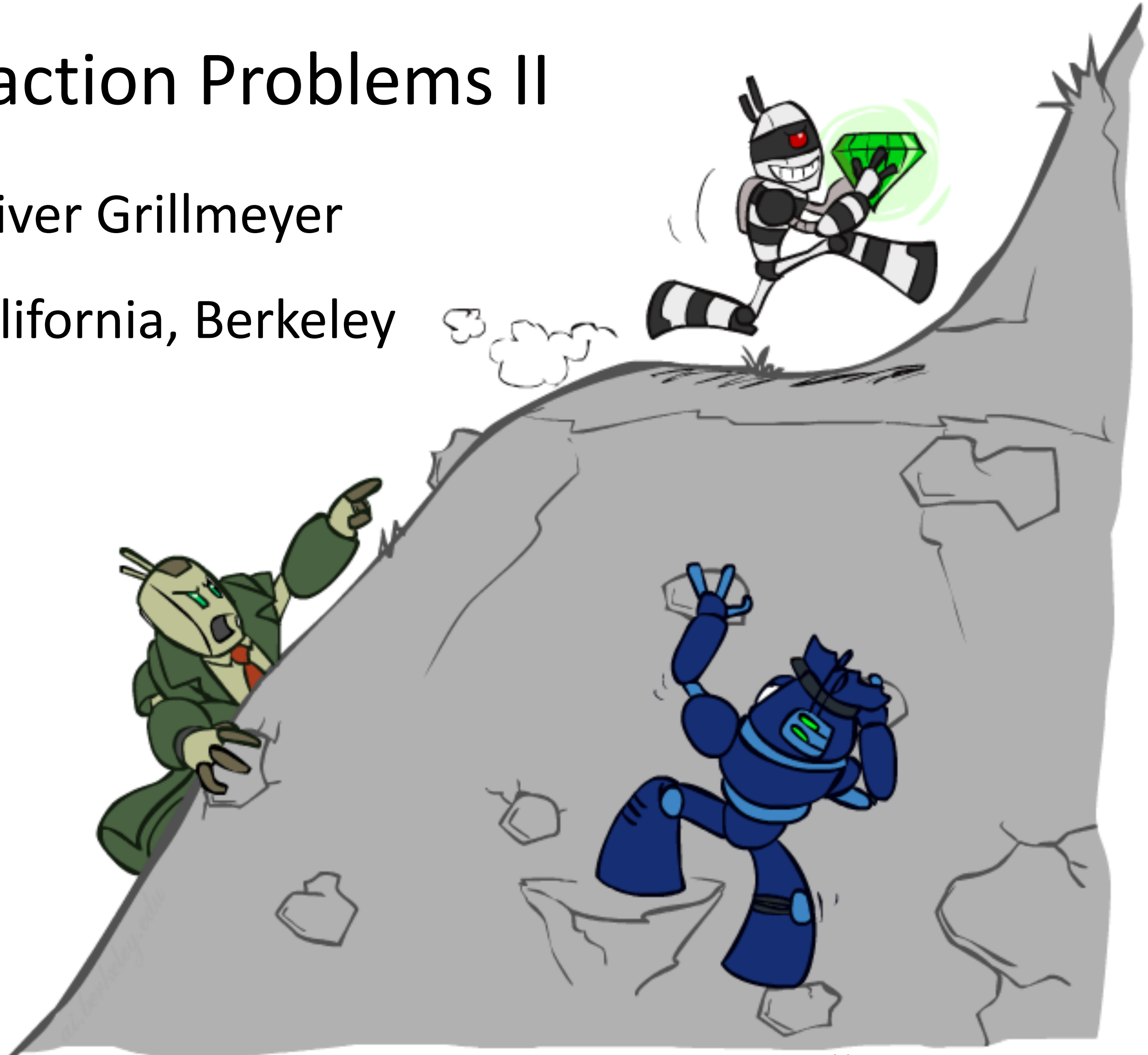


[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at http://ai.berkeley.edu.]

Announcements

- HW1 is due **Tuesday, July 1**, 11:59 PM PT
- HW2 is due **Thursday, July 3**, 11:59 PM PT
- HW3 is due **Tuesday, July 8**, 11:59 PM PT
- HW4 is due **Thursday, July 10**, 11:59 PM PT
- Project 1 is due **Friday, July 4**, 11:59 PM PT
- Project 2 is due **Friday, July 11**, 11:59 PM PT

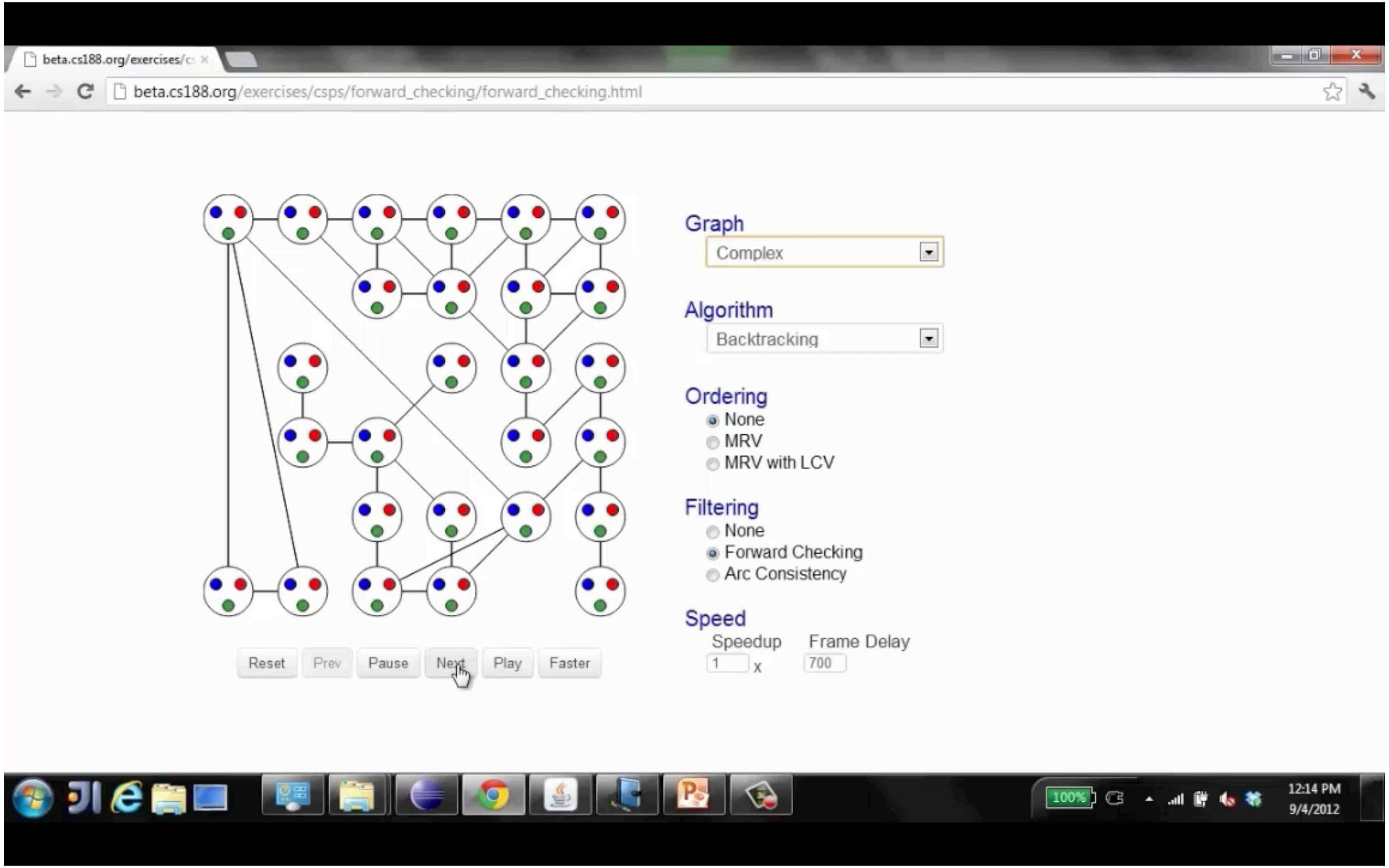
Today

Efficient Solution of CSPs

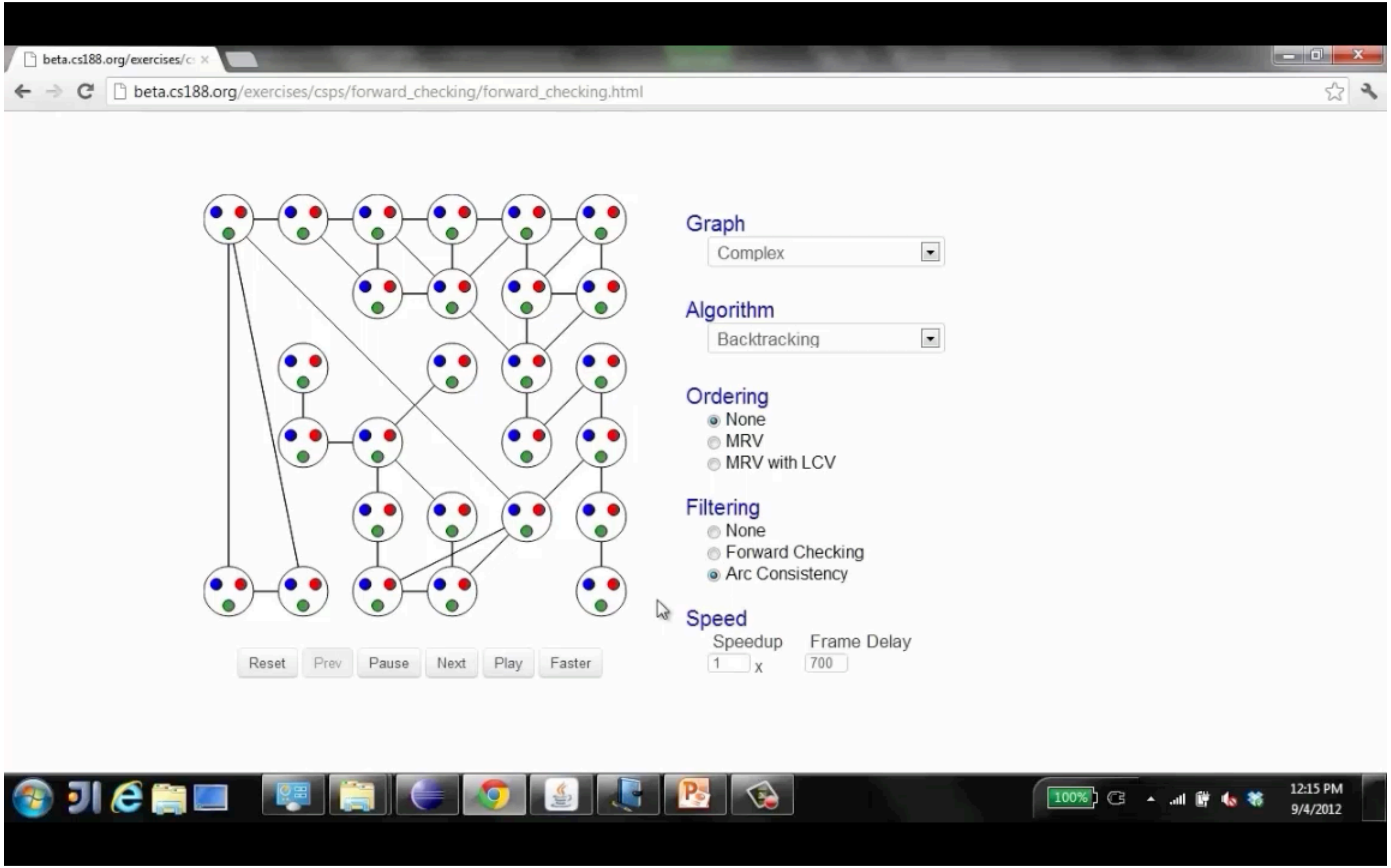
Local Search

Filtering

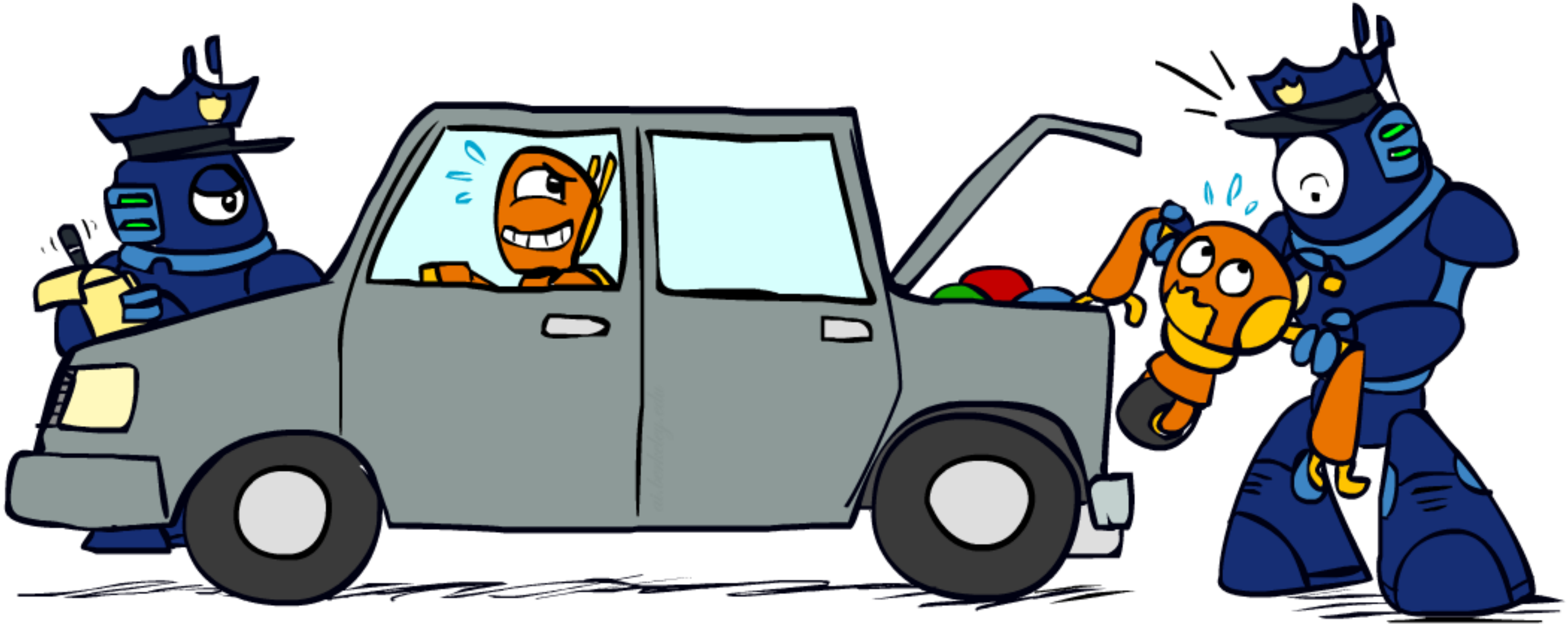
Video of Demo Coloring – Backtracking with Forward Checking – Complex Graph



Video of Demo Coloring – Backtracking with Arc Consistency – Complex Graph



Arc Consistency and Beyond

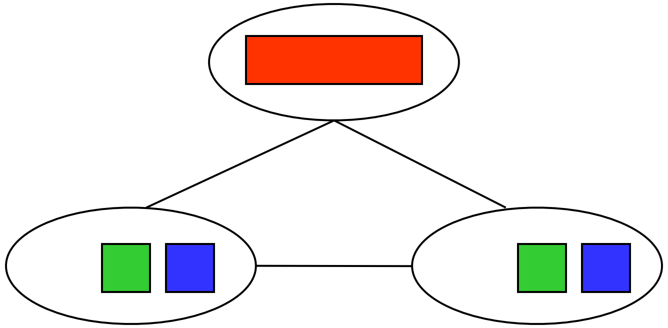


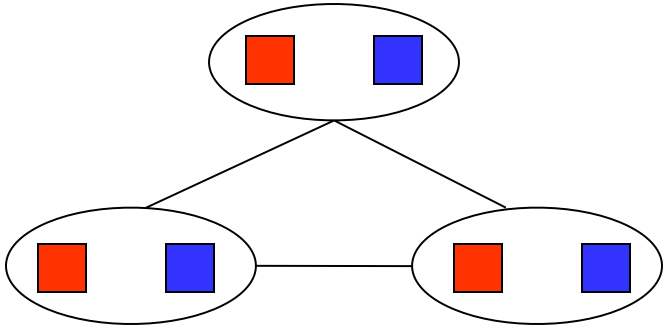
Limitations of Arc Consistency

After enforcing arc consistency:

- Can have one solution left
- Can have multiple solutions left
- Can have no solutions left (and not know it)

Arc consistency still runs inside a backtracking search!

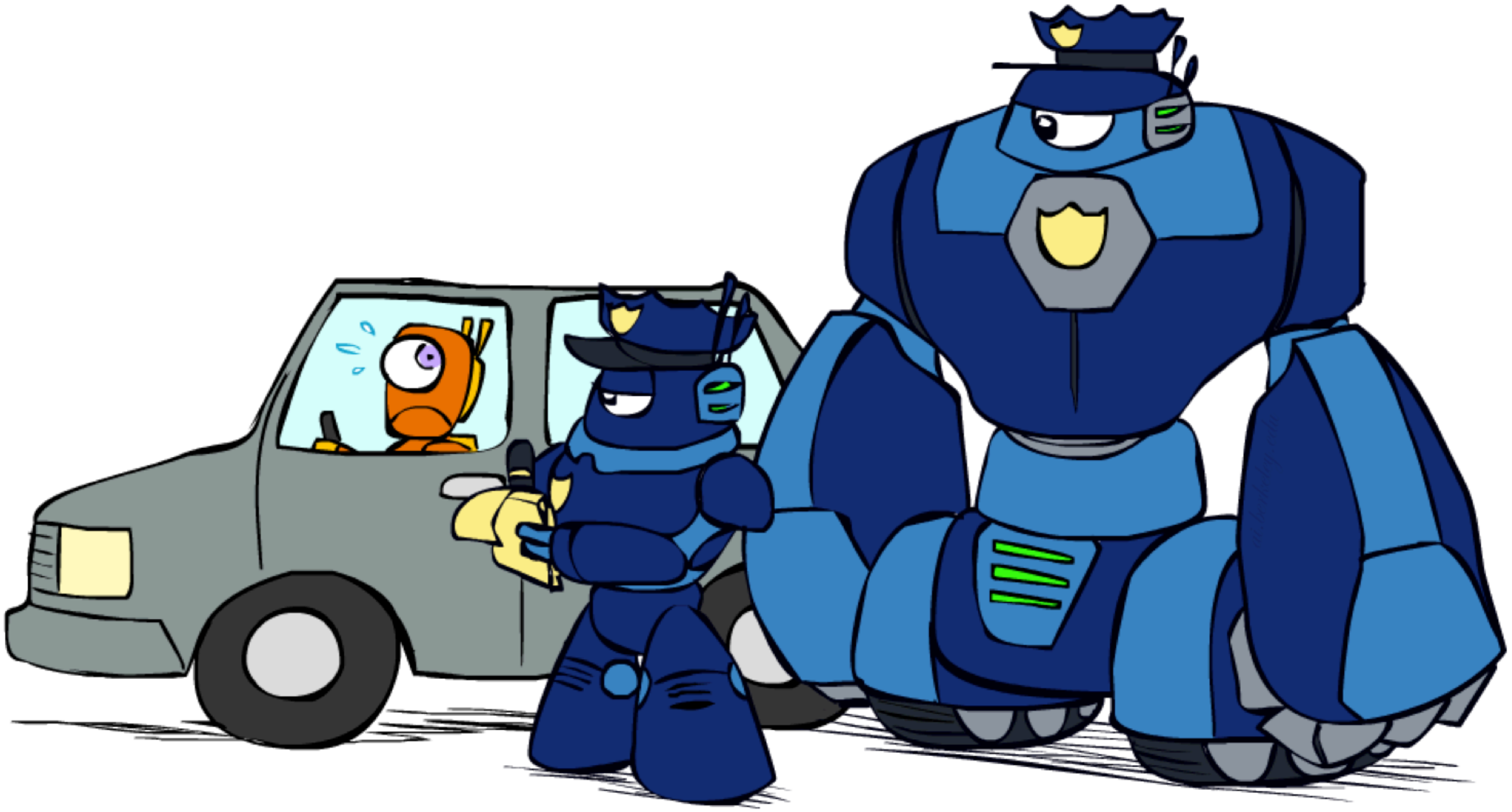




What went wrong here?

[Demo: coloring -- forward checking]
[Demo: coloring -- arc consistency]

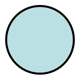
K-Consistency



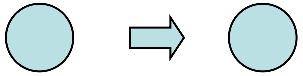
K-Consistency

Increasing degrees of consistency

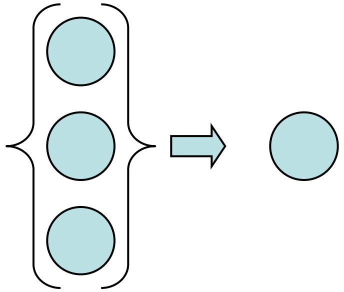
1-Consistency (Node Consistency): Each single node's domain has a value which meets that node's unary constraints



2-Consistency (Arc Consistency): For each pair of nodes, any consistent assignment to one can be extended to the other

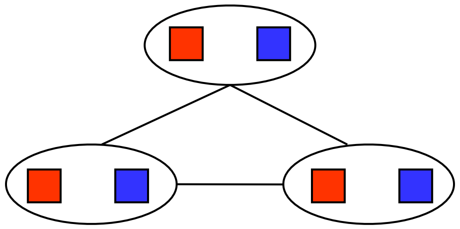


K-Consistency: For each k nodes, any consistent assignment to k-1 can be extended to the k^{th} node.



Higher k more expensive to compute

(You need to know the k=2 case: arc consistency)



Strong K-Consistency

Strong k-consistency: also k-1, k-2, … 1 consistent

Claim: strong n-consistency means we can solve without backtracking!

Why?

- Choose any assignment to any variable
- Choose a new variable
- By 2-consistency, there is a choice consistent with the first
- Choose a new variable
- By 3-consistency, there is a choice consistent with the first 2
- …

Lots of middle ground between arc consistency and n-consistency! (e.g. k=3, called path consistency)

Ordering

Ordering: Minimum Remaining Values

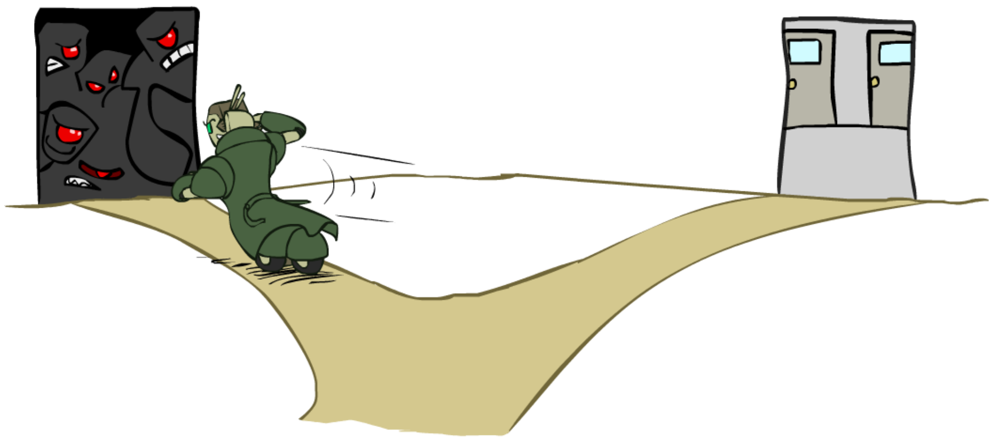
Variable Ordering: Minimum remaining values (MRV):

Choose the variable with the fewest legal left values in its domain

Why min rather than max?

Also called "most constrained variable"

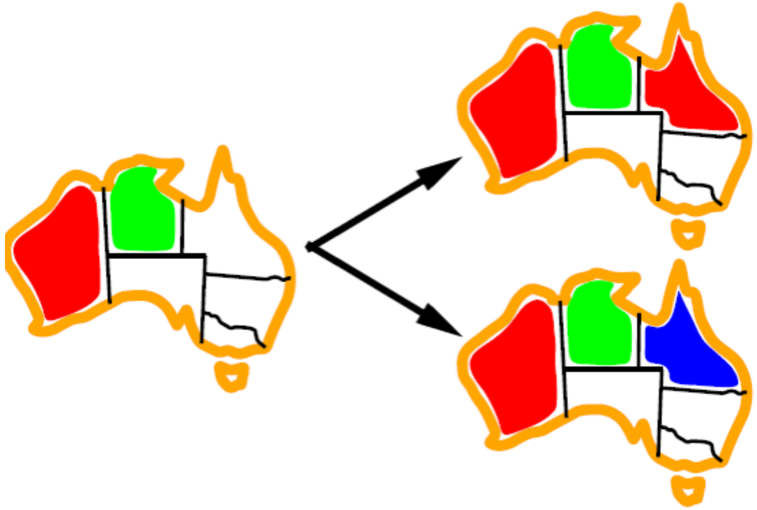
"Fail-fast" ordering



Ordering: Least Constraining Value

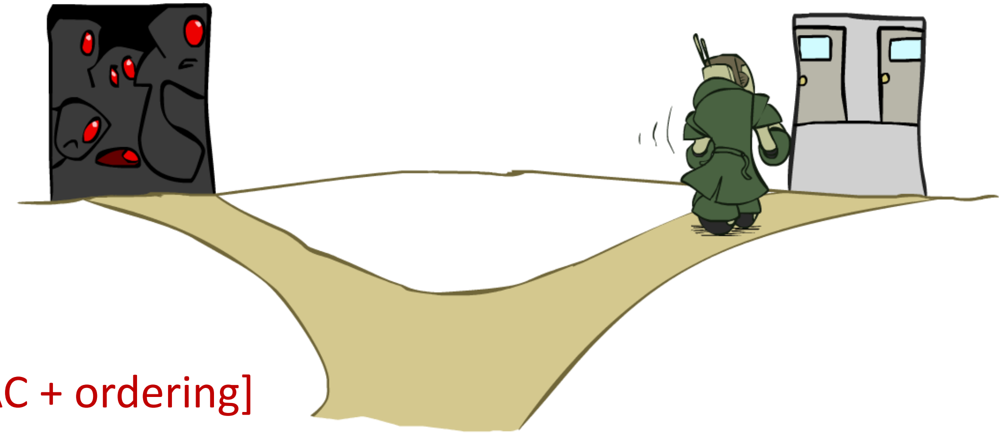
Value Ordering: Least Constraining Value

- Given a choice of variable's value, choose the *least constraining value*
- I.e., the one that rules out the fewest values in the remaining variables
- Note that it may take some computation to determine this! (E.g., rerunning filtering)



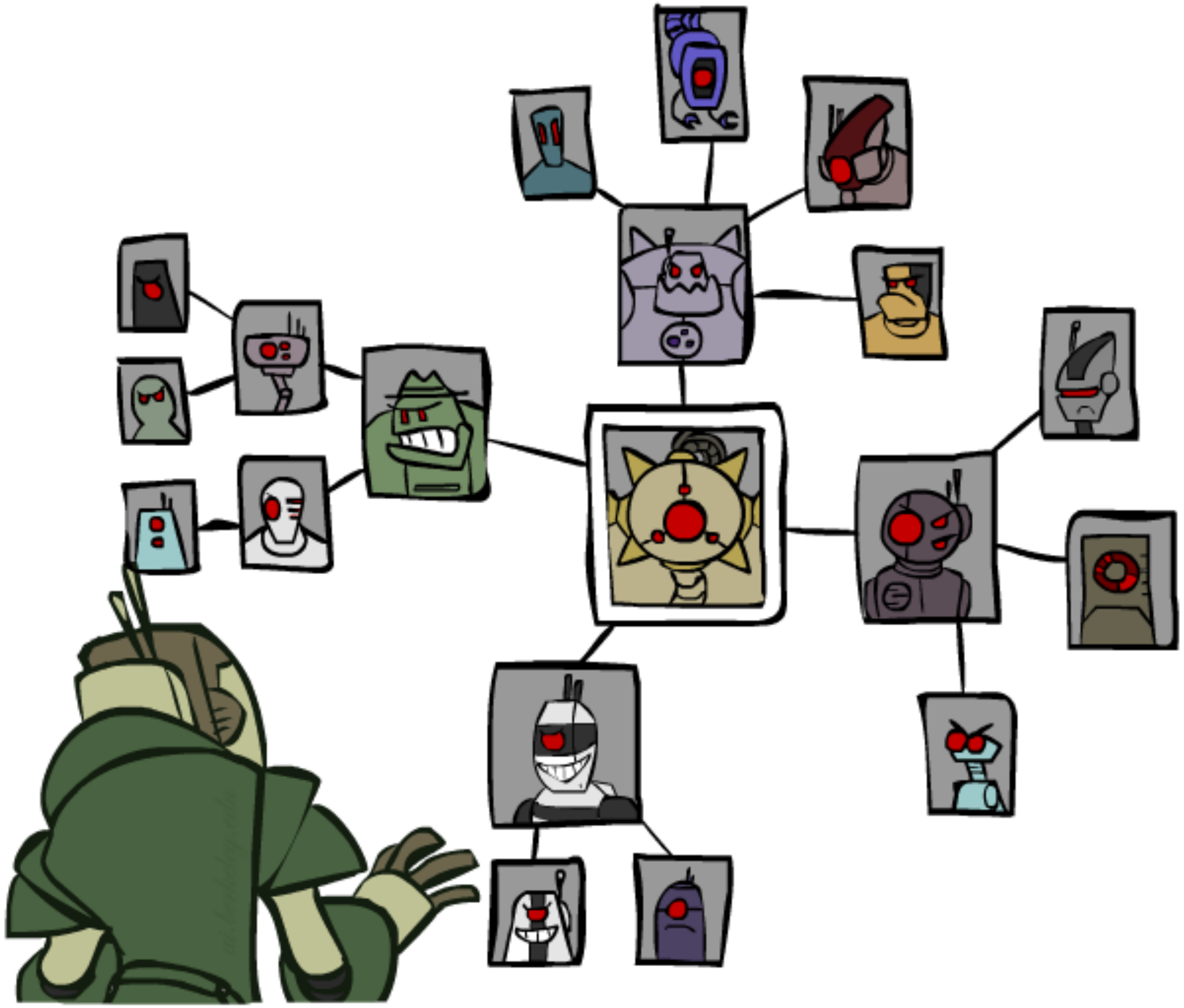
Why least rather than most?

Combining these ordering ideas makes 1000 queens feasible

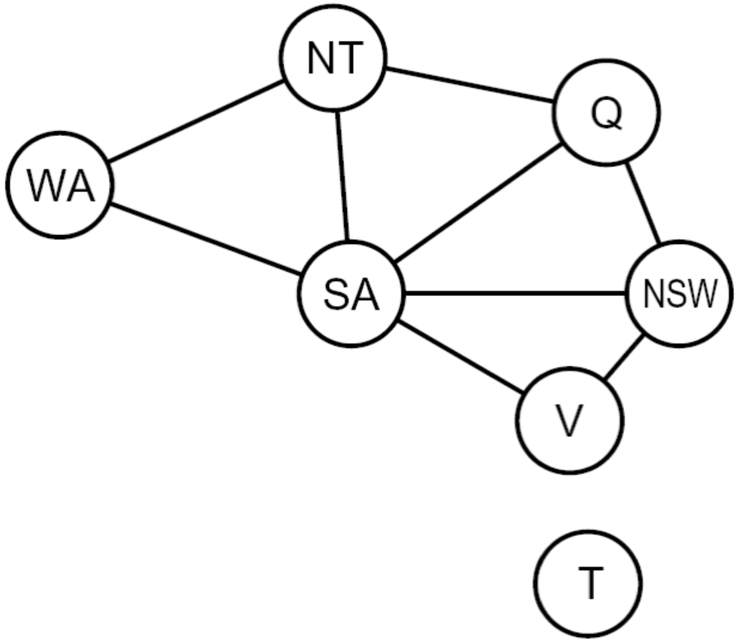


[Demo: coloring – backtracking + AC + ordering]

Structure



Problem Structure



Extreme case: independent subproblems

Example: Tasmania and mainland do not interact

Independent subproblems are identifiable as connected components of constraint graph

Suppose a graph of n variables can be broken into subproblems of only c variables:

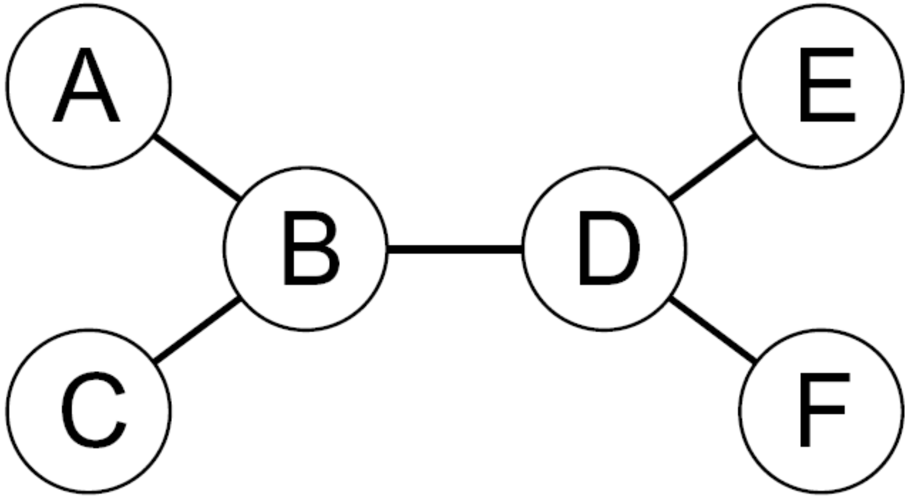
Worst-case solution cost is $O((n/c)(d^c))$, linear in n

E.g., n = 80, d = 2, c =20

2^{80} = 4 billion years at 10 million nodes/sec

$(4)(2^{20})$ = 0.4 seconds at 10 million nodes/sec

Tree-Structured CSPs



Theorem: if the constraint graph has no loops, the CSP can be solved in $O(n\, d^2)$ time

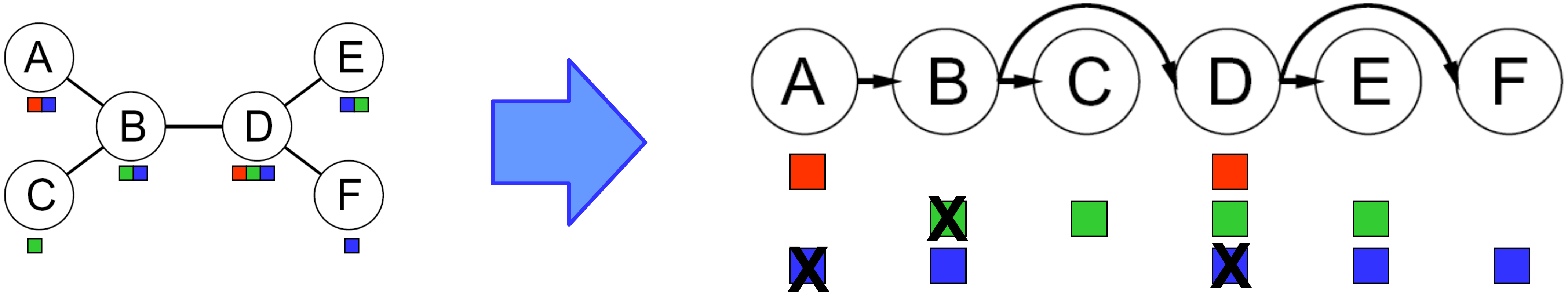
Compare to general CSPs, where worst-case time is $O(d^n)$

This property also applies to probabilistic reasoning (later): an example of the relation between syntactic restrictions and the complexity of reasoning

Tree-Structured CSPs

Algorithm for tree-structured CSPs:

Order: Choose a root variable, order variables so that parents precede children



Remove backward: For i = n : 2, apply RemoveInconsistent(Parent(X_i),X_i)

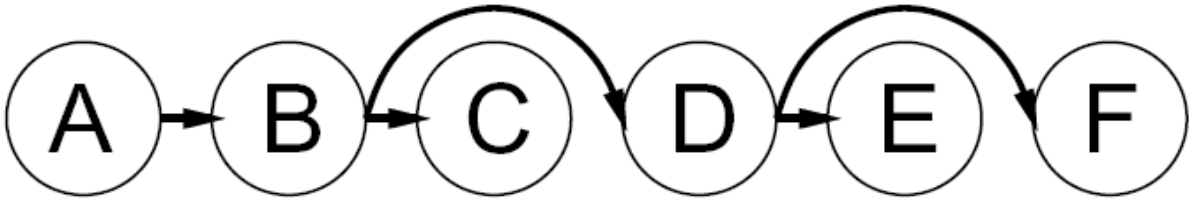
Assign forward: For i = 1 : n, assign X_i consistently with Parent(X_i)

Runtime: O(n d^2) (why?)

Tree-Structured CSPs

Claim 1: After backward pass, all root-to-leaf arcs are consistent

Proof: Each X→Y was made consistent at one point and Y's domain could not have been reduced thereafter (because Y's children were processed before Y)



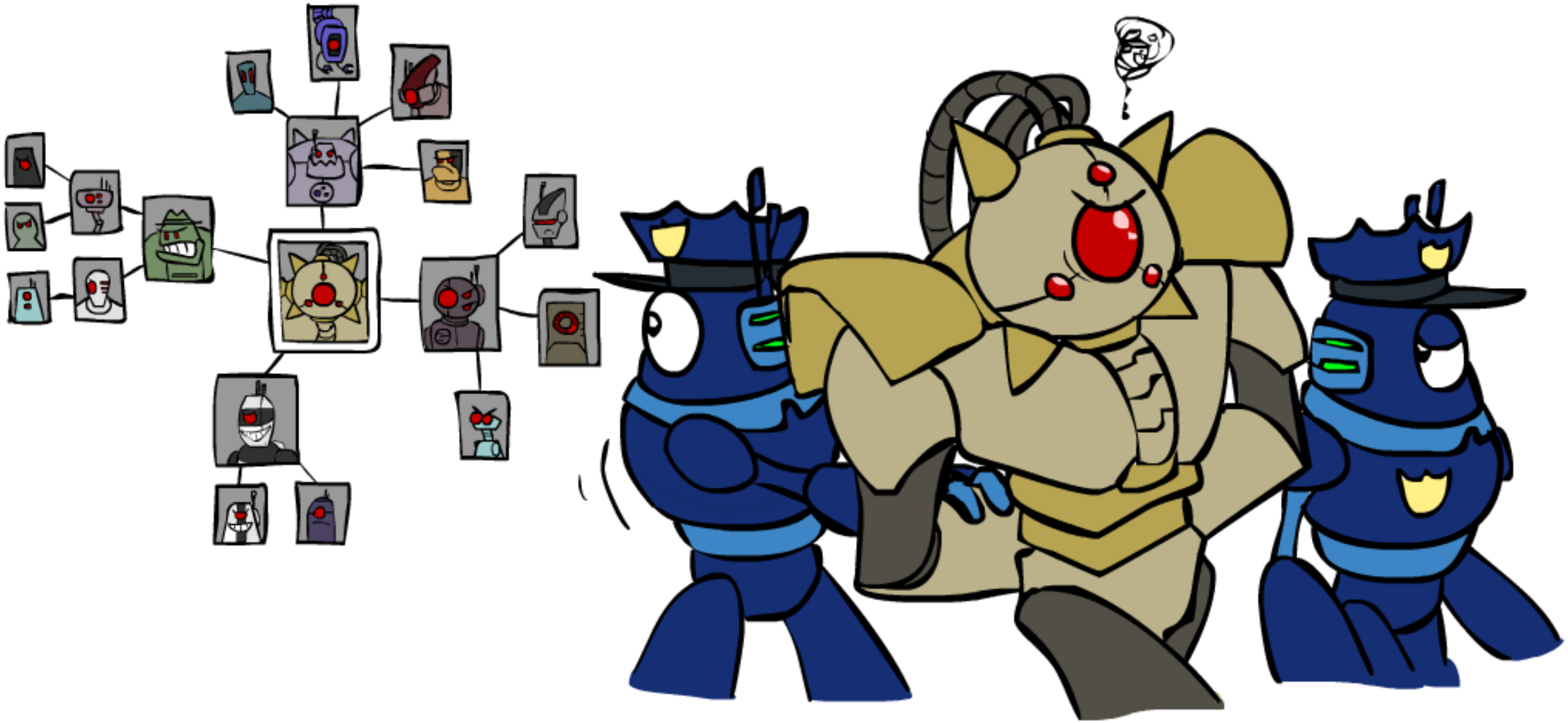
Claim 2: If root-to-leaf arcs are consistent, forward assignment will not backtrack

Proof: Induction on position

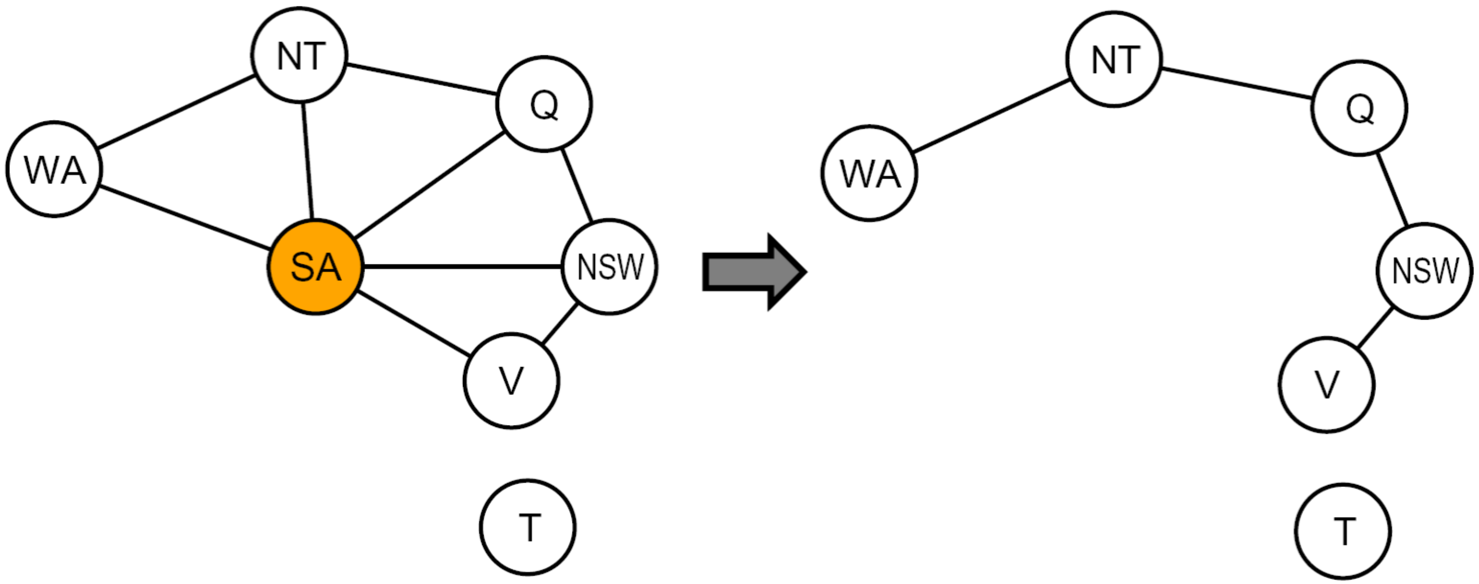
Why doesn't this algorithm work with cycles in the constraint graph?

Note: we'll see this basic idea again with Bayes' nets

Improving Structure



Nearly Tree-Structured CSPs



Conditioning: instantiate a variable, prune its neighbors' domains

Cutset conditioning: instantiate (in all ways) a set of variables such that the remaining constraint graph is a tree

Cutset size c gives runtime $O((d^c) (n-c) d^2)$, very fast for small c

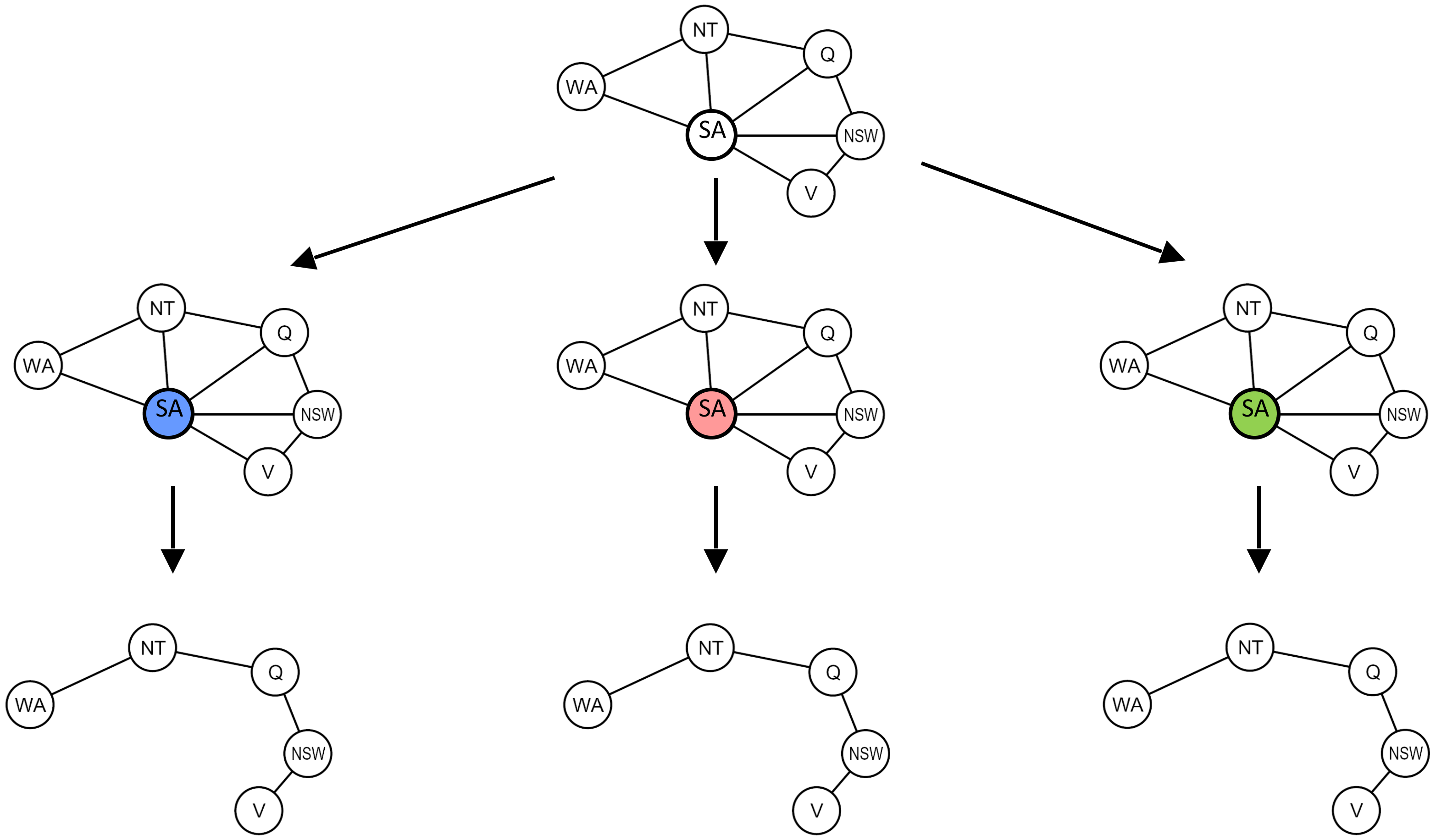
Cutset Conditioning

Choose a cutset

Instantiate the cutset (all possible ways)

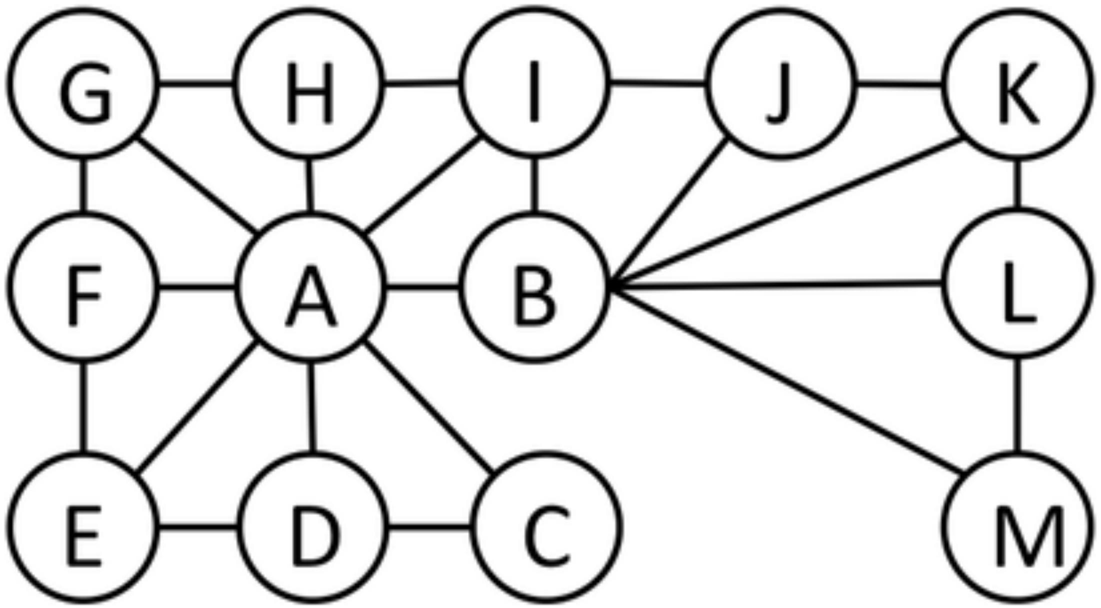
Compute residual CSP for each assignment

Solve the residual CSPs (tree structured)



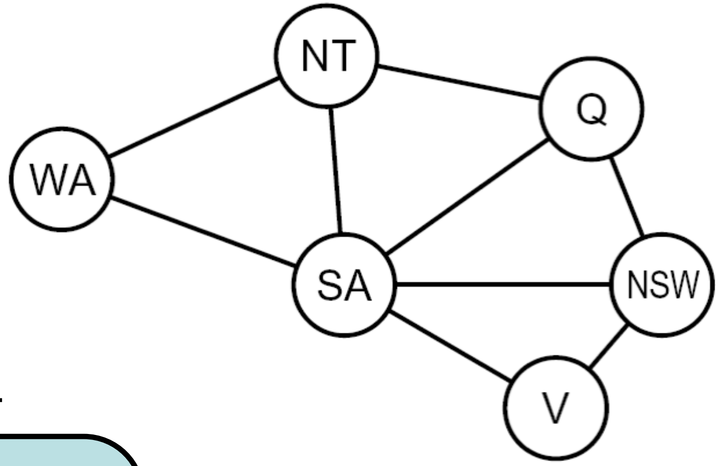
Cutset Quiz

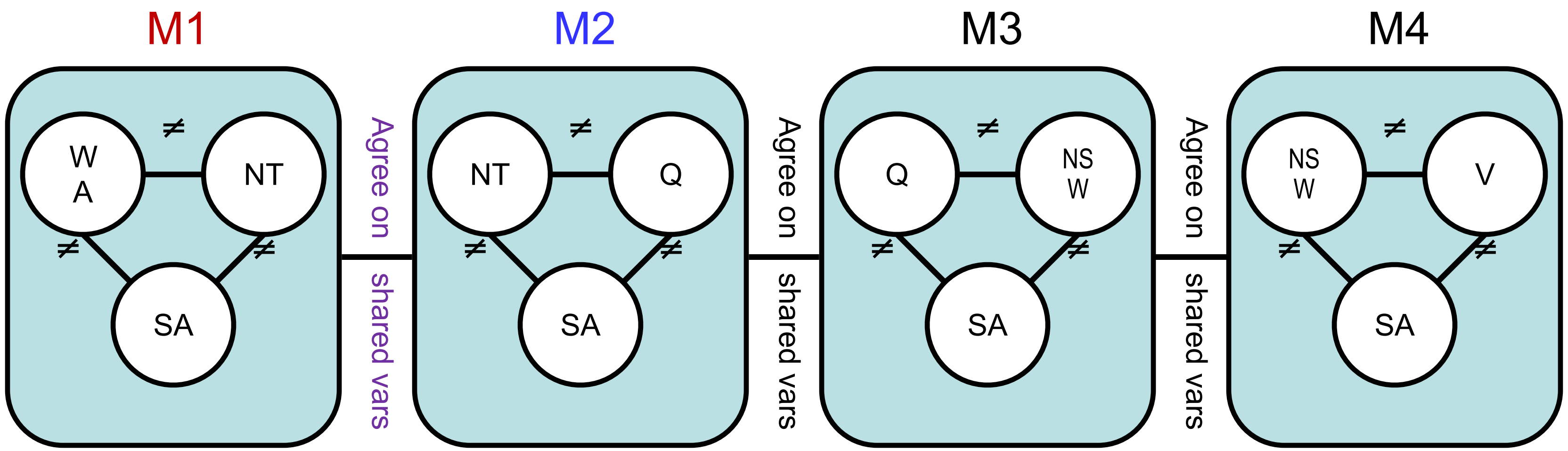
Find the smallest cutset for the graph below.



Tree Decomposition*

- Idea: create a tree-structured graph of mega-variables
- Each mega-variable encodes part of the original CSP
- Subproblems overlap to ensure consistent solutions



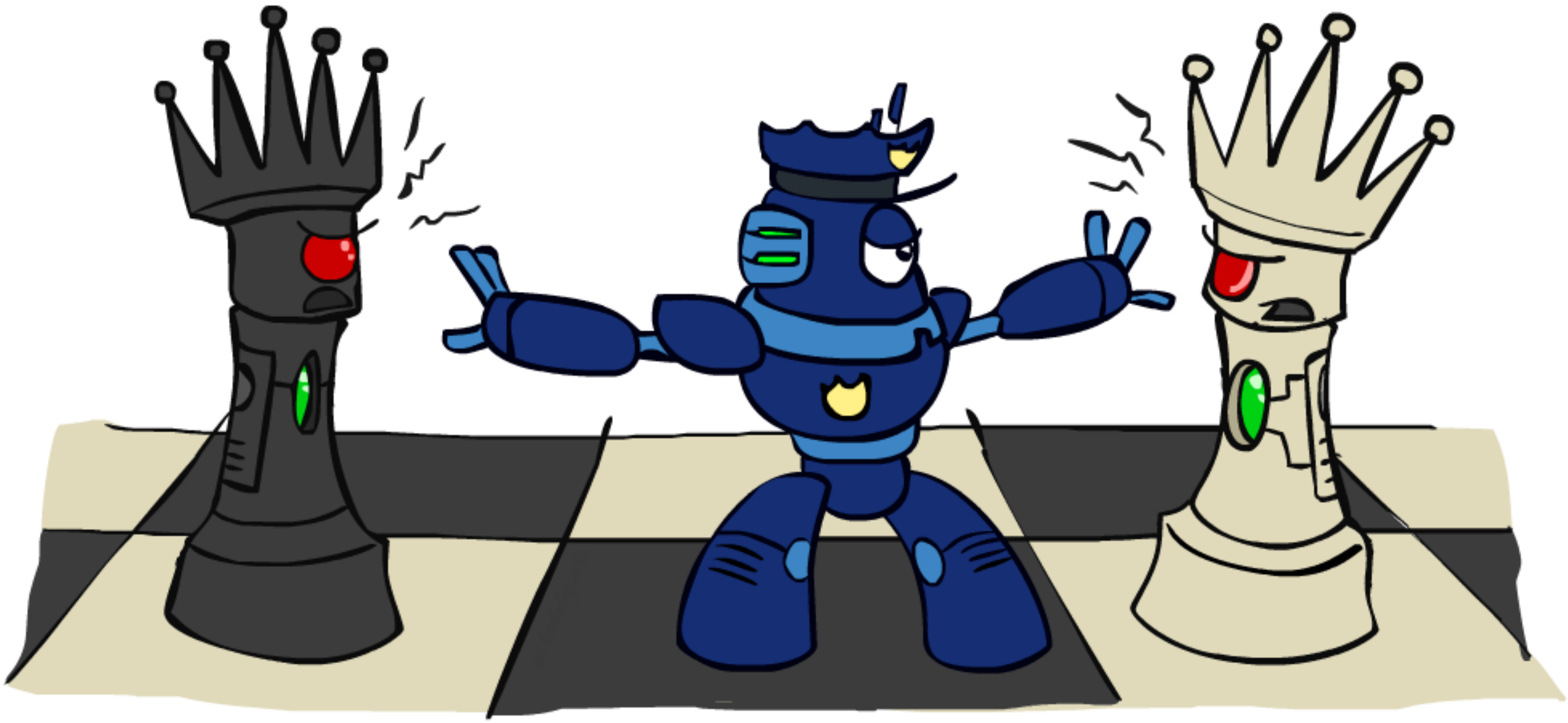


{(WA=r,SA=g,NT=b),
(WA=b,SA=r,NT=g),
…}

{(NT=r,SA=g,Q=b),
(NT=b,SA=g,Q=r),
…}

Agree: (M1,M2) $\in$
{((WA=g,SA=g,NT=g), (NT=g,SA=g,Q=g)), …}

Iterative Improvement

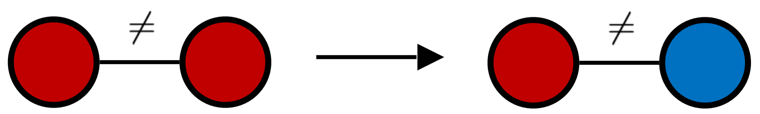


Iterative Algorithms for CSPs

Local search methods typically work with "complete" states, i.e., all variables assigned

To apply to CSPs:

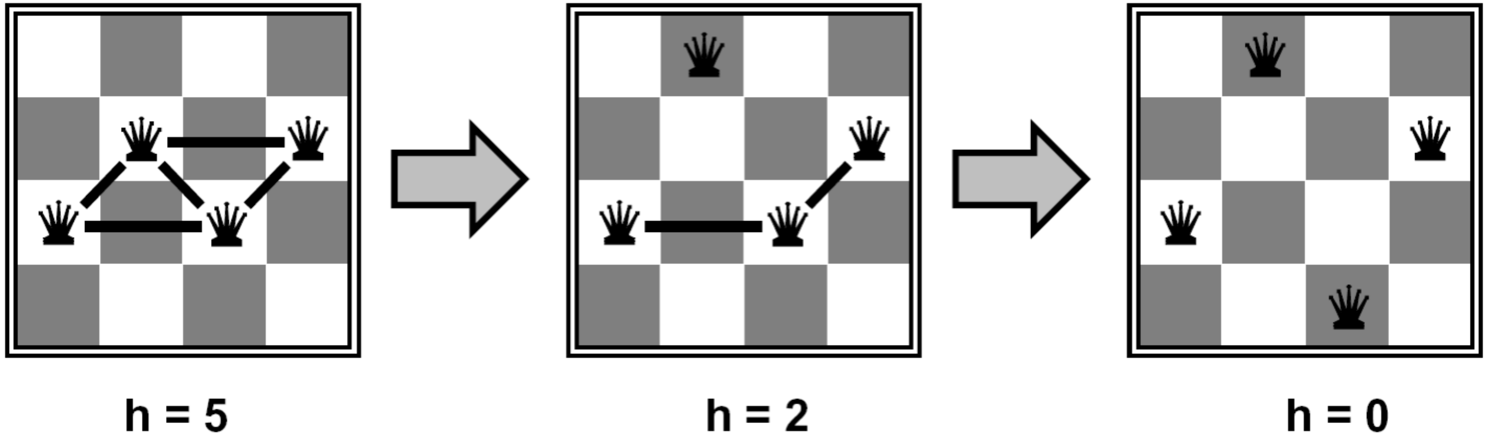
- Take an assignment with unsatisfied constraints
- Operators *reassign* variable values
- No fringe! Live on the edge.



Algorithm: While not solved,

- Variable selection: randomly select any conflicted variable
- Value selection: min-conflicts heuristic:
  - Choose a 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)

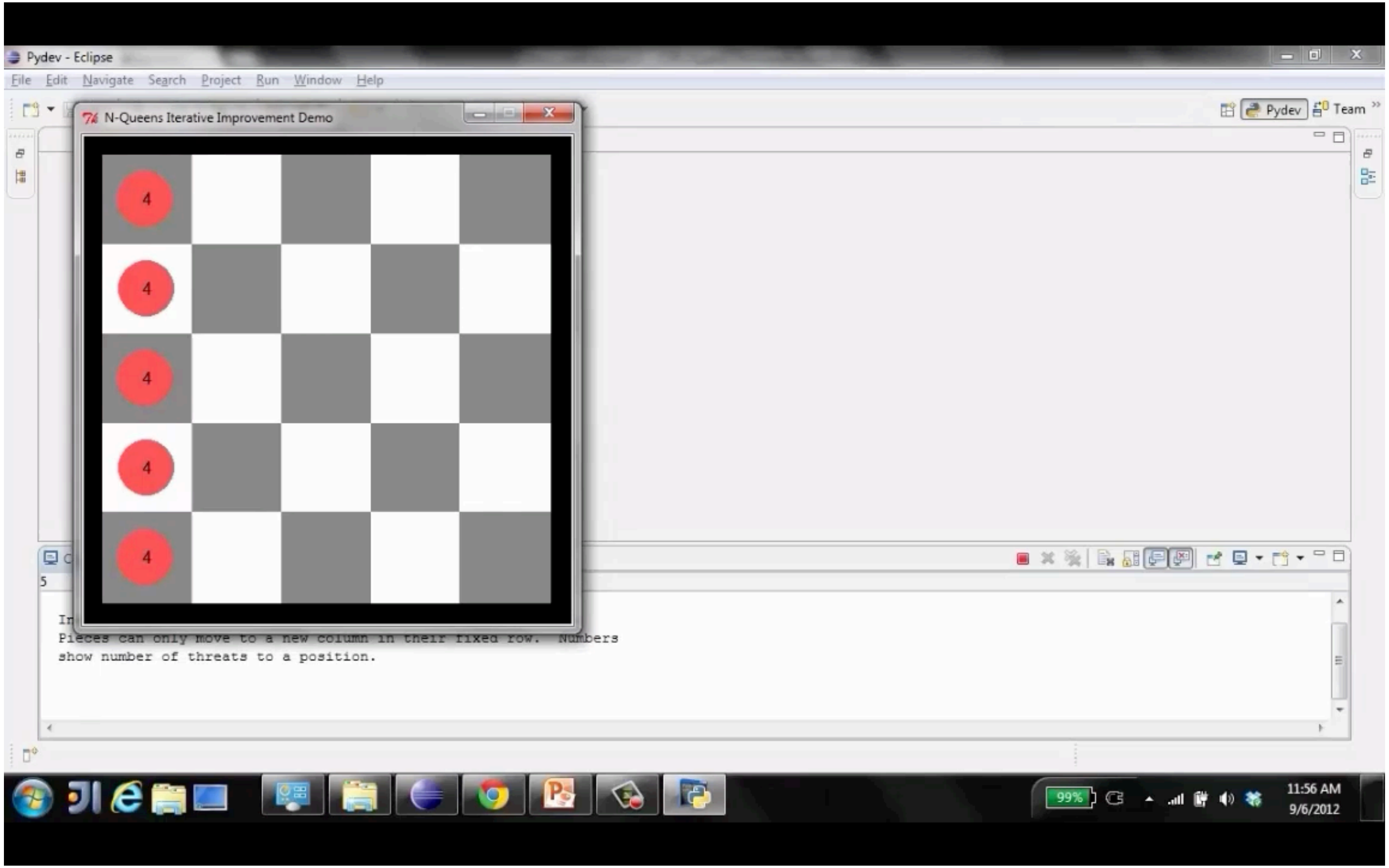
Operators: move queen in column

Goal test: no attacks

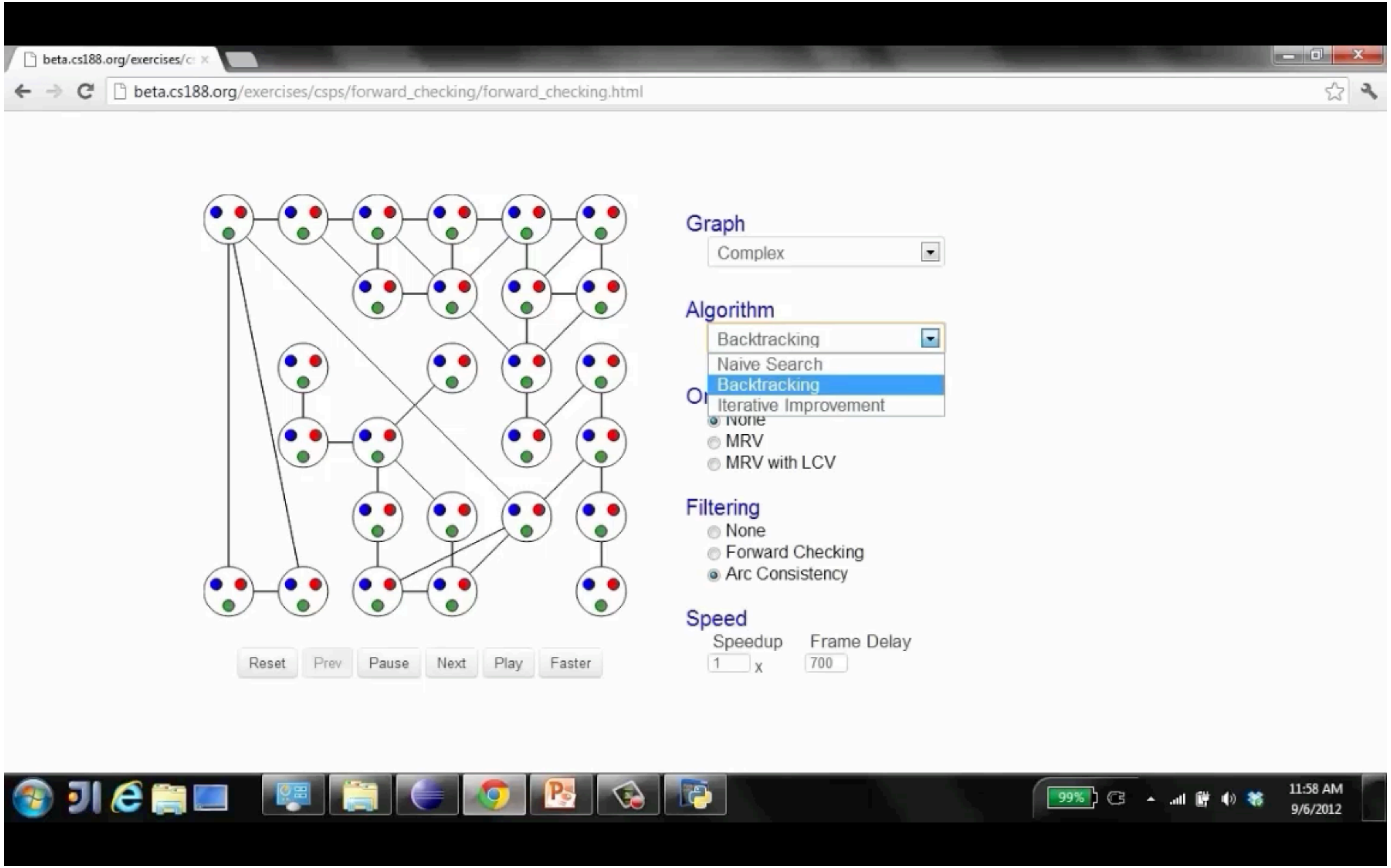
Evaluation: c(n) = number of attacks

[Demo: n-queens – iterative improvement (L5D1)]
[Demo: coloring – iterative improvement]

Video of Demo Iterative Improvement – n Queens



Video of Demo Iterative Improvement – Coloring

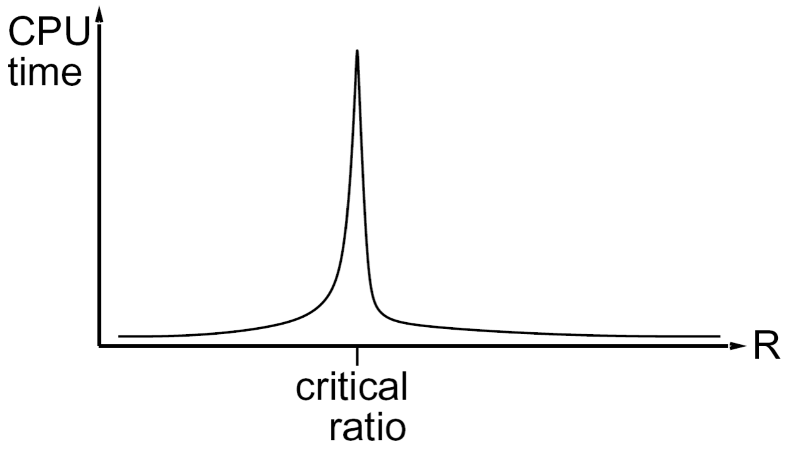


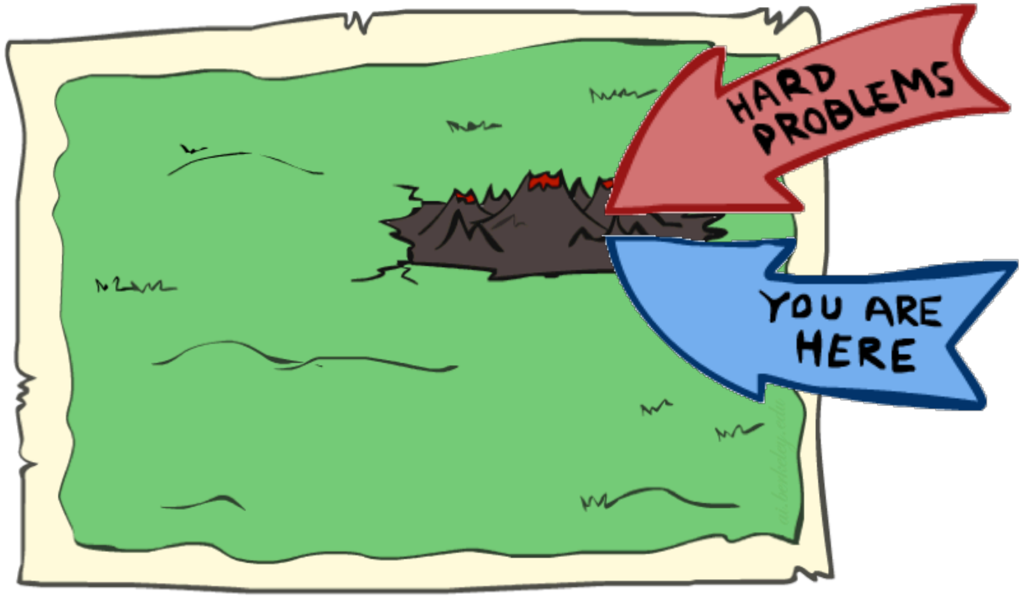
Performance of Min-Conflicts

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

The same appears to be true for any randomly-generated CSP *except* in a narrow range of the ratio

$$R = \frac{\text{number of constraints}}{\text{number of variables}}$$





Summary: CSPs

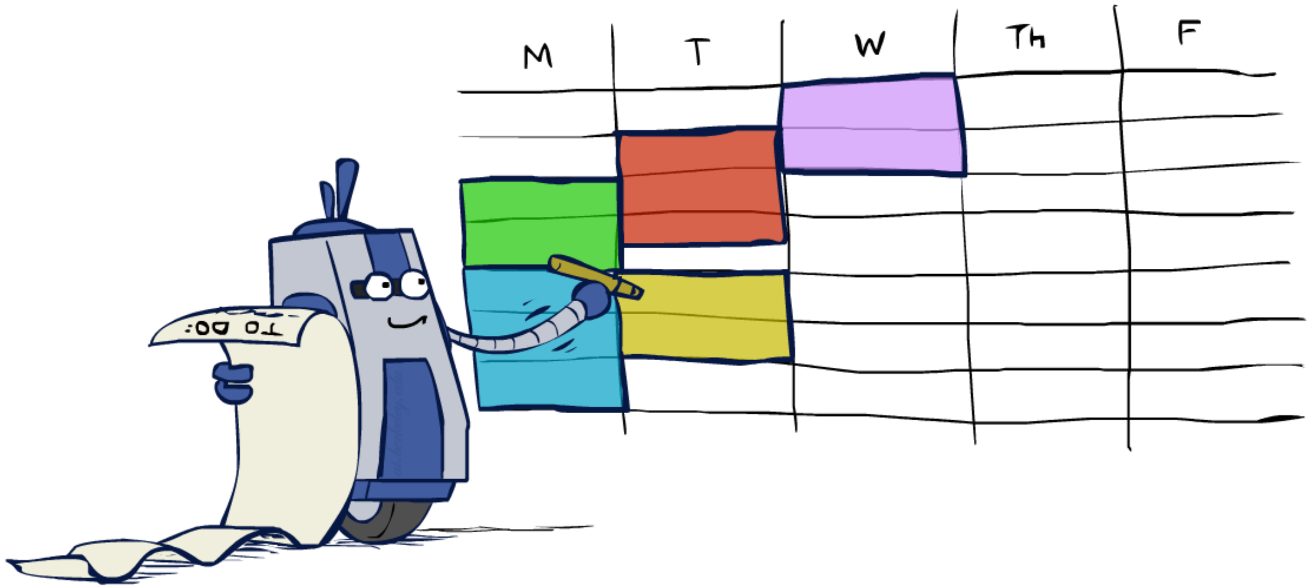
CSPs are a special kind of search problem:

- States are partial assignments
- Goal test defined by constraints

Basic solution: backtracking search

Speed-ups:

- Ordering
- Filtering
- Structure



Iterative min-conflicts is often effective in practice

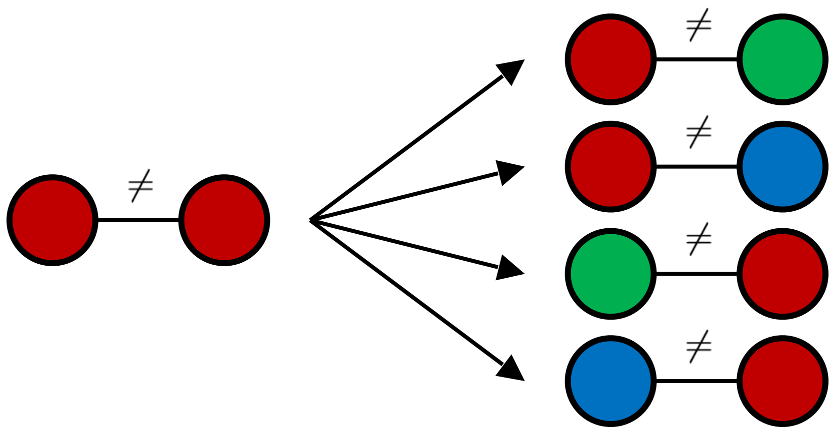
Local Search

Local Search

Tree search keeps unexplored alternatives on the fringe (ensures completeness)

Local search: improve a single option until you can’t make it better (no fringe!)

New successor function: local changes



Generally much faster and more memory efficient (but incomplete and suboptimal)

Hill Climbing

Simple, general idea:

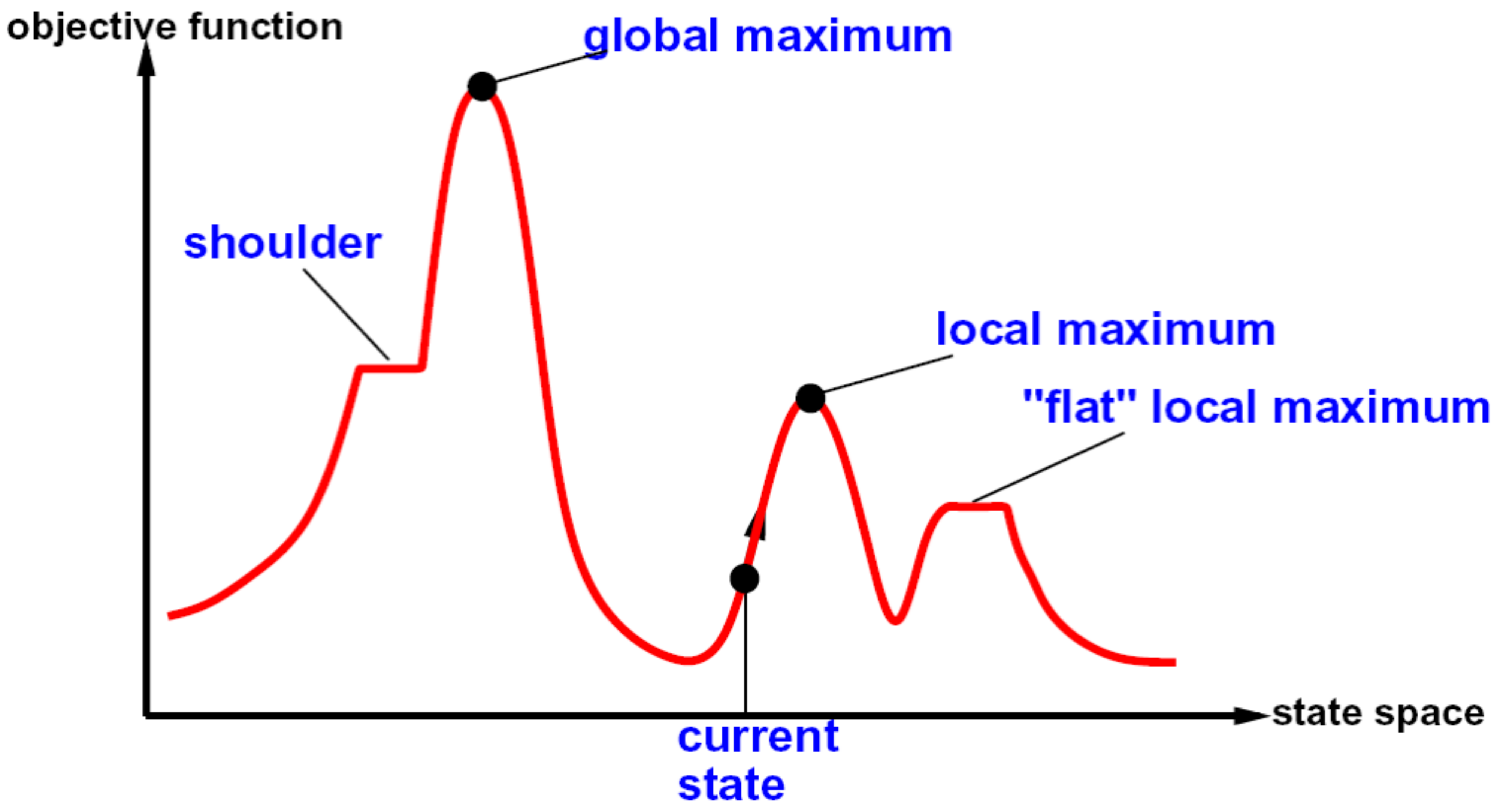
- Start wherever
- Repeat: move to the best neighboring state
- If no neighbors better than current, quit

What's bad about this approach?

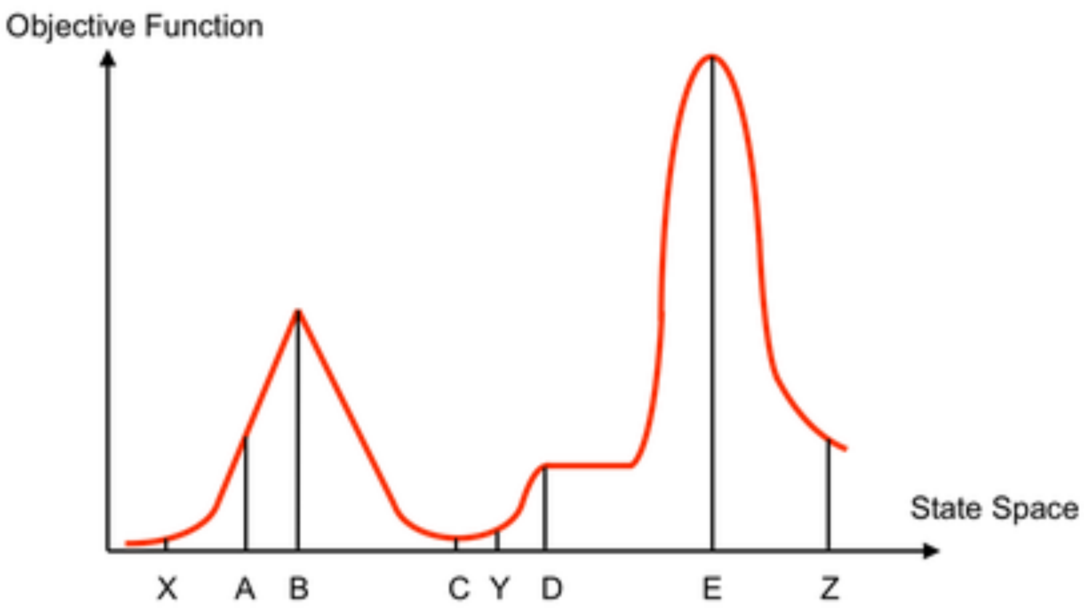
- Complete?
- Optimal?

What's good about it?

Hill Climbing Diagram



Hill Climbing Quiz



Starting from X, where do you end up ?

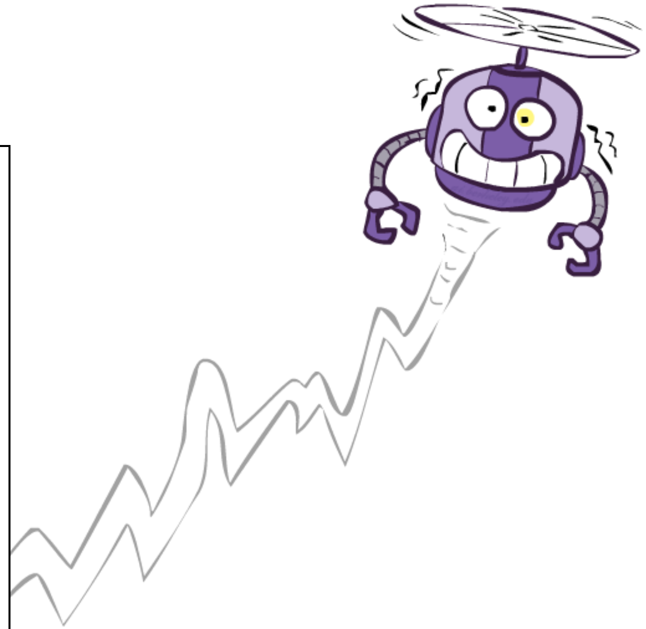
Starting from Y, where do you end up ?

Starting from Z, where do you end up ?

Simulated Annealing

Idea: Escape local maxima by allowing downhill moves

But make them rarer as time goes on



function SIMULATED-ANNEALING(*problem*, *schedule*) **returns** a solution state
  inputs: *problem*, a problem
      schedule, a mapping from time to "temperature"
  local variables: *current*, a node
      next, a node
      T, a "temperature" controlling prob. of downward steps

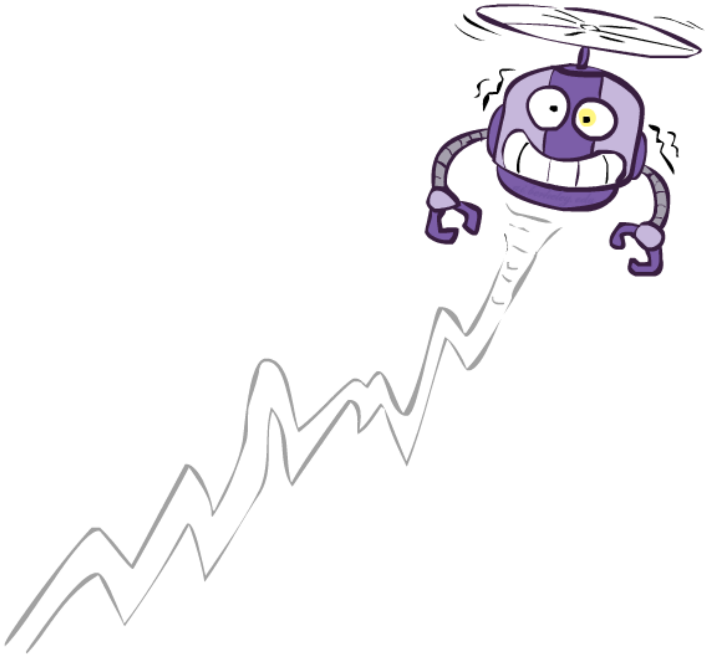
  current ← MAKE-NODE(INITIAL-STATE[*problem*])
  for $t \leftarrow 1$ **to** ∞ **do**
    $T \leftarrow$ *schedule*[t]
    if $T = 0$ **then return** *current*
    next ← a randomly selected successor of *current*
    $\Delta E \leftarrow$ VALUE[*next*] – VALUE[*current*]
    if $\Delta E > 0$ **then** *current* ← *next*
    else *current* ← *next* only with probability $e^{\Delta E/T}$

Simulated Annealing

Theoretical guarantee:

Stationary distribution: $p(x) \propto e^{\frac{E(x)}{kT}}$

If T decreased slowly enough,
will converge to optimal state!



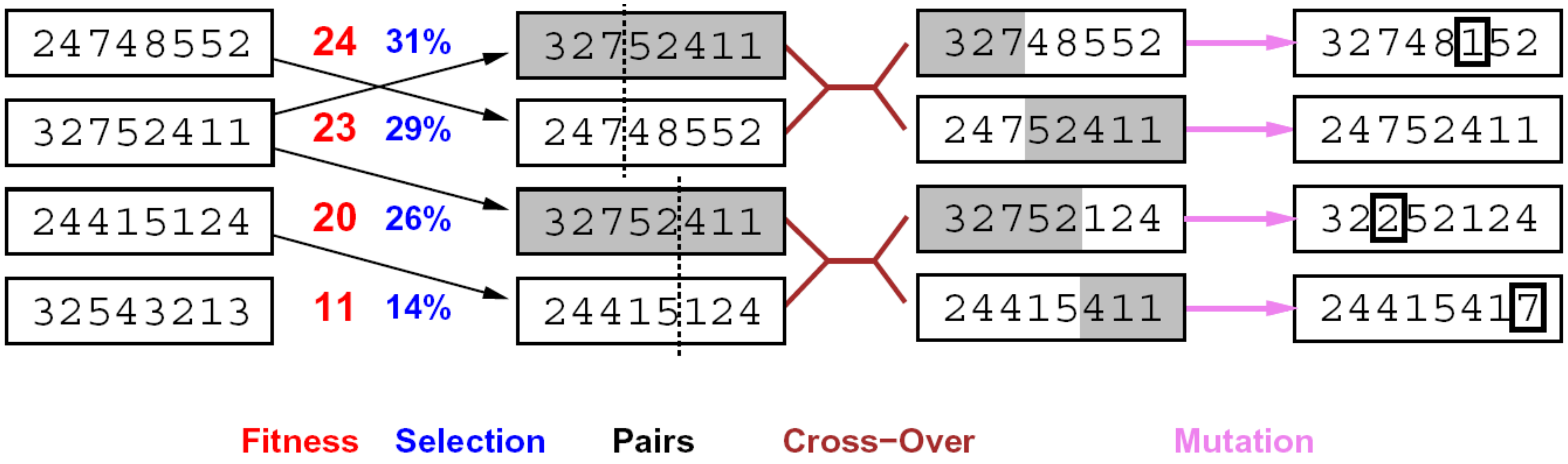
Is this an interesting guarantee?

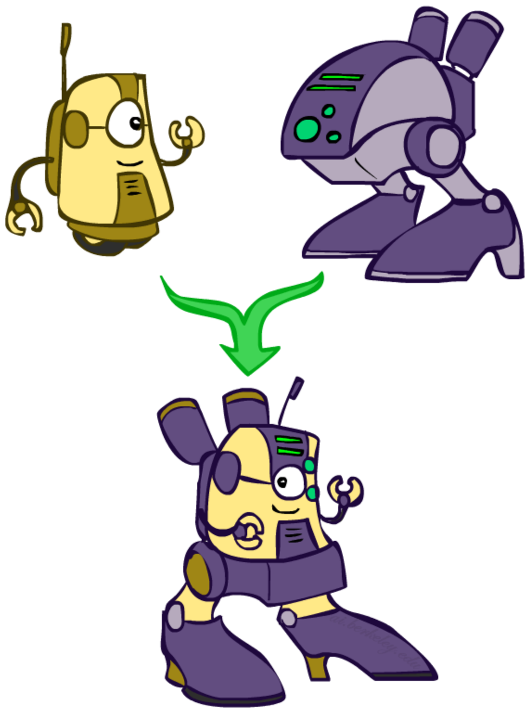
Sounds like magic, but reality is reality:

The more downhill steps you need to escape a local optimum, the less likely you are to ever make them all in a row

People think hard about *ridge operators* which let you jump around the space in better ways

Genetic Algorithms





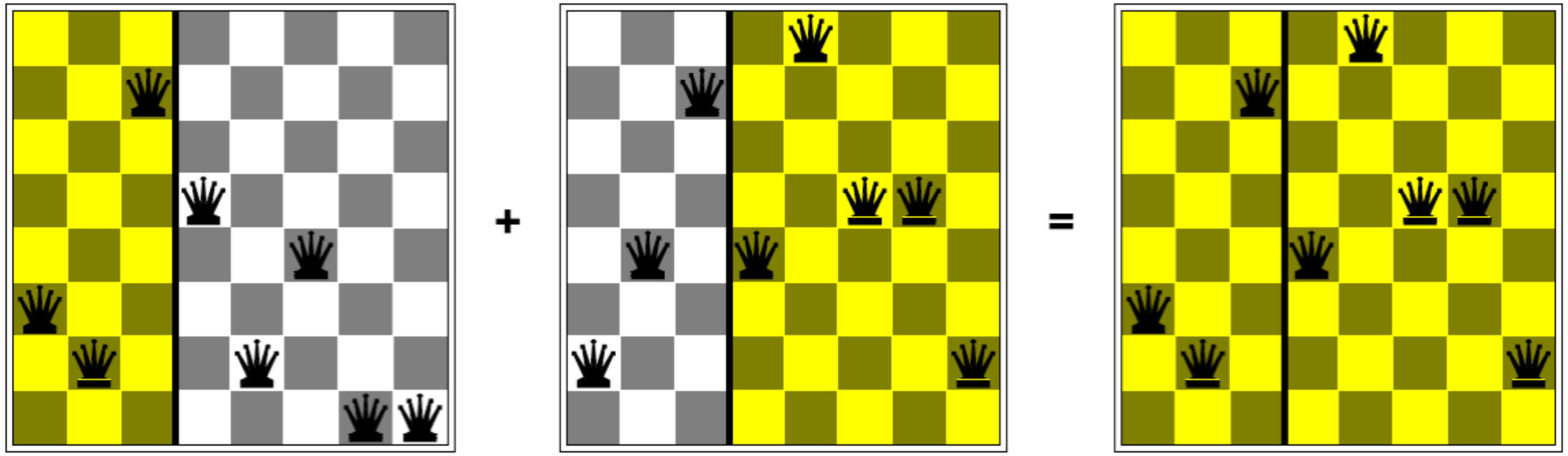
Genetic algorithms use a natural selection metaphor

Keep best N hypotheses at each step (selection) based on a fitness function

Also have pairwise crossover operators, with optional mutation to give variety

Possibly the most misunderstood, misapplied (and even maligned) technique around

Example: N-Queens



Why does crossover make sense here?

When wouldn't it make sense?

What would mutation be?

What would a good fitness function be?

Next Time: Adversarial Search!