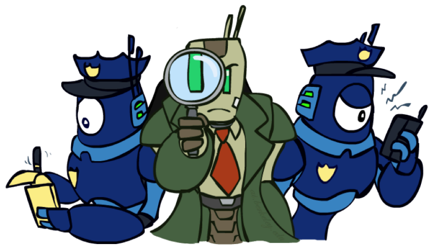
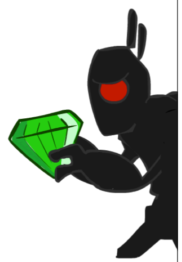
# CS 188: Artificial Intelligence

Constraint Satisfaction Problems





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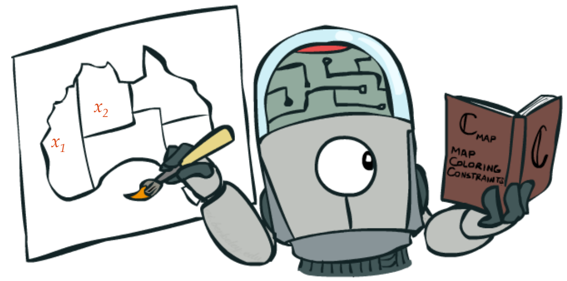
(These slides were created/modified by Dan Klein, Pieter Abbeel, Anca Dragan for CS188 at UC Berkeley)

# Constraint Satisfaction Problems

*N variables*

*domain D*

*constraints*




*states* — *partial assignment*

*goal test* — *complete; satisfies constraints*

*successor function* — *assign an unassigned variable*

# What is Search For?

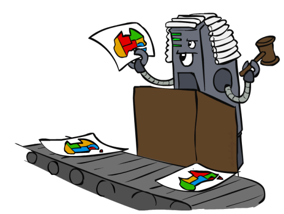
- Assumptions about the world: a single agent, deterministic actions, fully observed state, discrete state space

- Planning: sequences of actions
  - The path to the goal is the important thing
  - Paths have various costs, depths
  - Heuristics give problem-specific guidance

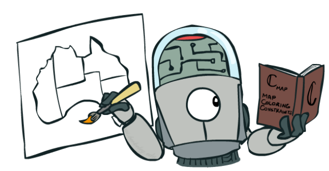
- Identification: assignments to variables
  - The goal itself is important, not the path
  - All paths at the same depth (for some formulations)
  - CSPs are specialized for identification problems

# Constraint Satisfaction Problems

- Standard search problems:
  - State is a “black box”: arbitrary data structure
  - Goal test can be any function over states
  - Successor function can also be anything



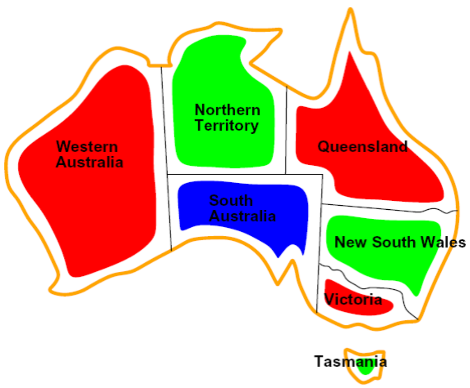
- Constraint satisfaction problems (CSPs):
  - A special subset of search problems
  - State is defined by variables $X_i$ with values from a domain $D$ (sometimes $D$ depends on $i$)
  - Goal test is a set of constraints specifying allowable combinations of values for subsets of variables



- Simple example of a *formal representation language*

- Allows useful general-purpose algorithms with more power than standard search algorithms

# CSP Examples



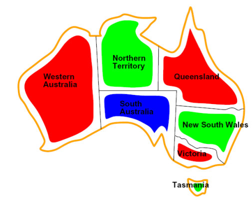

# Example: Map Coloring

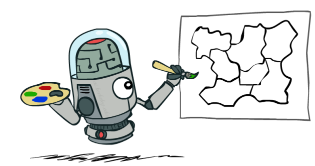
- Variables: WA, NT, Q, NSW, V, SA, T
- Domains: $D = \{red, green, blue\}$
- Constraints: adjacent regions must have different colors

  Implicit: $WA \neq NT$

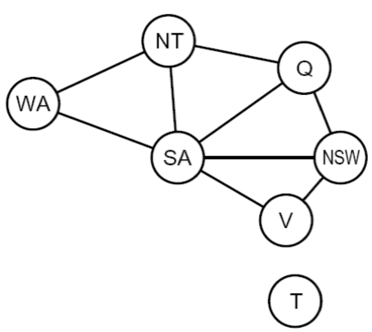
  Explicit: $(WA, NT) \in \{(red, green), (red, blue), \ldots\}$
- Solutions are assignments satisfying all constraints, e.g.:

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



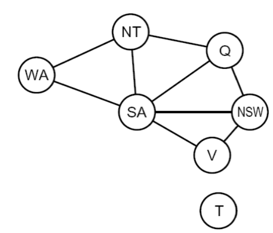



# Constraint Graphs



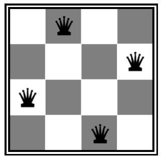

# Constraint Graphs

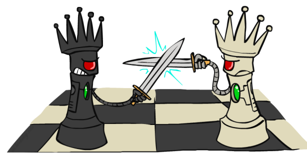
- Binary CSP: each constraint relates (at most) two variables
- Binary constraint graph: nodes are variables, arcs show constraints
- General-purpose CSP algorithms use the graph structure to speed up search. E.g., Tasmania is an independent subproblem!



# Example: N-Queens

- Formulation 1:
  - Variables: $X_{ij}$
  - Domains: $\{0, 1\}$
  - Constraints



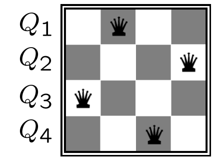


$$\forall i, j, k \;\; (X_{ij}, X_{ik}) \in \{(0,0), (0,1), (1,0)\}$$
$$\forall i, j, k \;\; (X_{ij}, X_{kj}) \in \{(0,0), (0,1), (1,0)\}$$
$$\forall i, j, k \;\; (X_{ij}, X_{i+k,j+k}) \in \{(0,0), (0,1), (1,0)\}$$
$$\forall i, j, k \;\; (X_{ij}, X_{i+k,j-k}) \in \{(0,0), (0,1), (1,0)\}$$

$$\sum_{i,j} X_{ij} = N$$

# Example: N-Queens

- Formulation 2:
  - Variables: $Q_k$
  - Domains: $\{1, 2, 3, \ldots N\}$
  - Constraints:

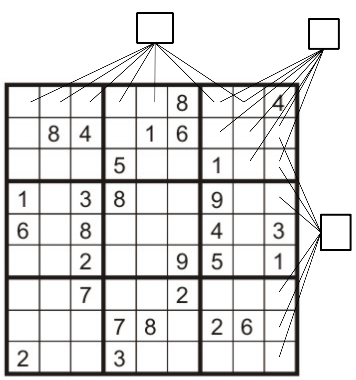



Implicit: $\forall i, j$ non-threatening$(Q_i, Q_j)$

Explicit: $(Q_1, Q_2) \in \{(1,3), (1,4), \ldots\}$

$\cdots$

# Example: Sudoku




- Variables:
  - Each (open) square
- Domains:
  - {1,2,…,9}
- Constraints:

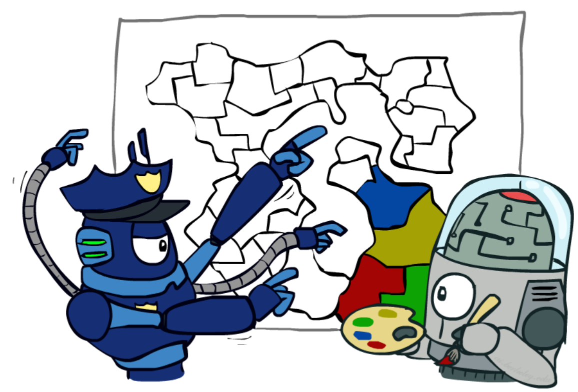
9-way alldiff for each column

9-way alldiff for each row

9-way alldiff for each region

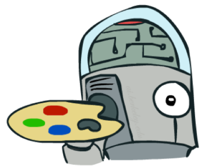
(or can have a bunch of pairwise inequality constraints)

# Varieties of CSPs and Constraints



# Varieties of CSPs

- Discrete Variables
  - Finite domains
    - Size $d$ means $O(d^n)$ complete assignments
    - E.g., Boolean CSPs, including Boolean satisfiability (NP-complete)
  - Infinite domains (integers, strings, etc.)
    - E.g., job scheduling, variables are start/end times for each job
    - Linear constraints solvable, nonlinear undecidable



- Continuous variables
  - E.g., start/end times for Hubble Telescope observations
  - Linear constraints solvable in polynomial time by LP methods (see cs170 for a bit of this theory)

# Varieties of Constraints

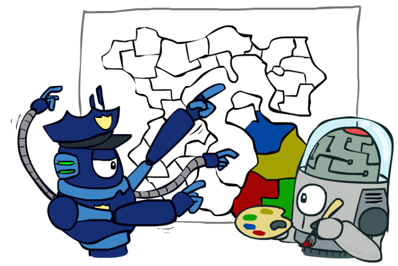
- Varieties of Constraints
  - Unary constraints involve a single variable (equivalent to reducing domains), e.g.:

$$SA \neq green$$

  - Binary constraints involve pairs of variables, e.g.:

$$SA \neq WA$$

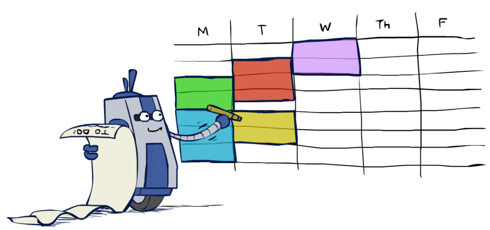
  - Higher-order constraints involve 3 or more variables:



- Preferences (soft constraints):
  - E.g., red is better than green
  - Often representable by a cost for each variable assignment
  - Gives constrained optimization problems
  - (We'll ignore these until we get to Bayes' nets)

# Real-World CSPs

- Assignment problems: e.g., who teaches what class
- Timetabling problems: e.g., which class is offered when and where?
- Hardware configuration
- Transportation scheduling
- Factory scheduling
- Circuit layout
- Fault diagnosis
- … lots more!

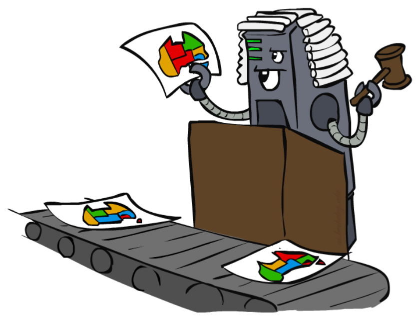



- Many real-world problems involve real-valued variables…

# Solving CSPs

## Standard Search Formulation

- Standard search formulation of CSPs
- States defined by the values assigned so far (partial assignments)
  - Initial state: the empty assignment, {}
  - Successor function: assign a value to an unassigned variable
  - Goal test: the current assignment is complete and satisfies all constraints
- We'll start with the straightforward, naïve approach, then improve it

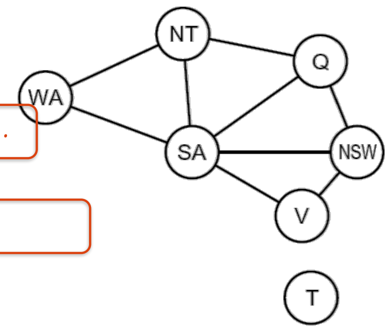


## Search Methods

- What would BFS do?

{}

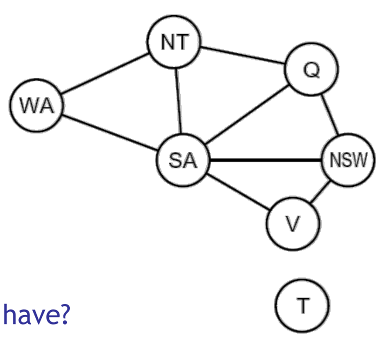
{WA=g} {WA=r} … {NT=g} …




[Demo: coloring -- dfs]

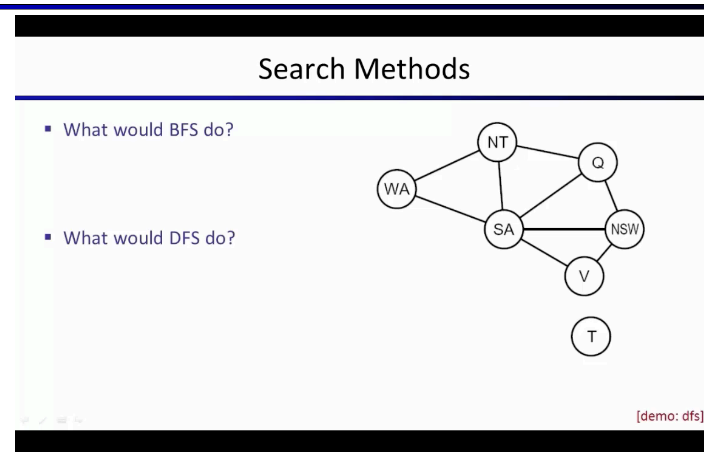
## Search Methods

- What would BFS do?
- What would DFS do?
- What problems does naïve search have?

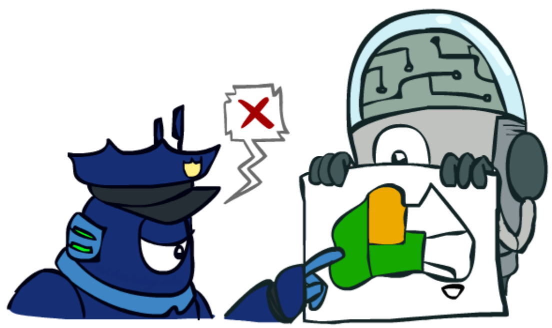



[Demo: coloring -- dfs]

## Video of Demo Coloring -- DFS



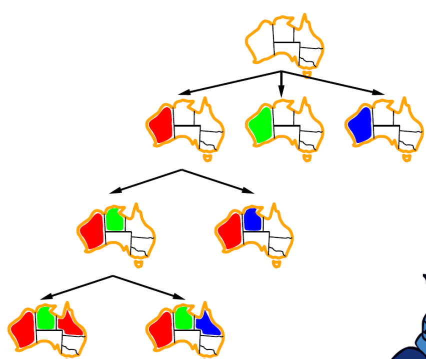
## Backtracking Search

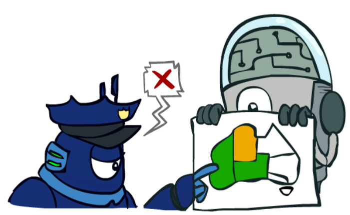


## Backtracking Search

- Backtracking search is the basic uninformed algorithm for solving CSPs
- Idea 1: One variable at a time
  - Variable assignments are commutative, so fix ordering
  - I.e., [WA = red then NT = green] same as [NT = green then WA = red]
  - Only need to consider assignments to a single variable at each step
- Idea 2: Check constraints as you go
  - I.e. consider only values which do not conflict previous assignments
  - Might have to do some computation to check the constraints
  - "Incremental goal test"
- Depth-first search with these two improvements is called *backtracking search* (not the best name)
- Can solve n-queens for n ≈ 25

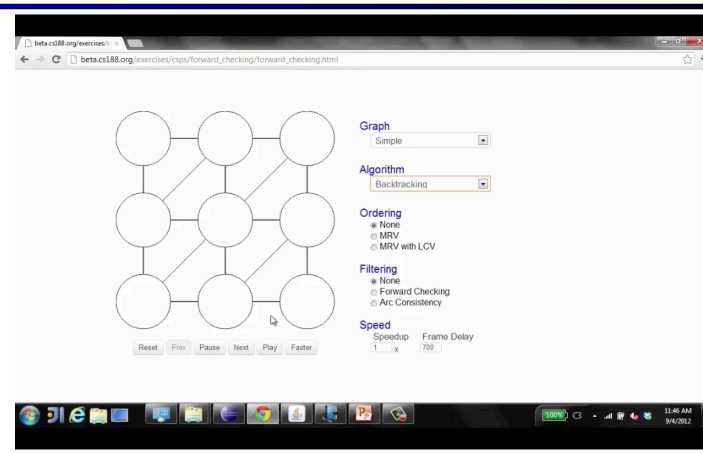
## Backtracking Example





[Demo: coloring -- backtracking]

## Video of Demo Coloring – Backtracking



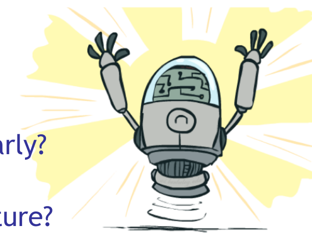
## Backtracking Search

```
function BACKTRACKING-SEARCH(csp) returns solution/failure
   return RECURSIVE-BACKTRACKING({ }, csp)
function RECURSIVE-BACKTRACKING(assignment, csp) returns soln/failure
   if assignment is complete then return assignment
   var ← SELECT-UNASSIGNED-VARIABLE(VARIABLES[csp], assignment, csp)
   for each value in ORDER-DOMAIN-VALUES(var, assignment, csp) do
       if value is consistent with assignment given CONSTRAINTS[csp] then
           add {var = value} to assignment
           result ← RECURSIVE-BACKTRACKING(assignment, csp)
           if result ≠ failure then return result
           remove {var = value} from assignment
   return failure
```

- Backtracking = DFS + variable-ordering + fail-on-violation
- What are the choice points?

## Improving Backtracking

- General-purpose ideas give huge gains in speed
- Ordering:
  - Which variable should be assigned next?
  - In what order should its values be tried?
- Filtering: Can we detect inevitable failure early?
- Structure: Can we exploit the problem structure?

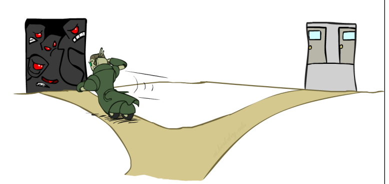


## Ordering

## Ordering: Minimum Remaining Values

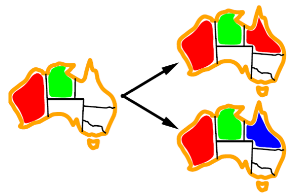
- Variable Ordering: Minimum remaining values (MRV):
  - Choose the variable with the fewest legal left values in its domain

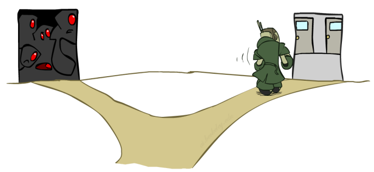
- Why min rather than max?
- Also called “most constrained variable”
- “Fail-fast” ordering



## Ordering: Least Constraining Value

- Value Ordering: Least Constraining Value
  - Given a choice of variable, 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 (and filtering) makes 1000 queens feasible





## Filtering

Keep track of domains for unassigned variables and cross off bad options

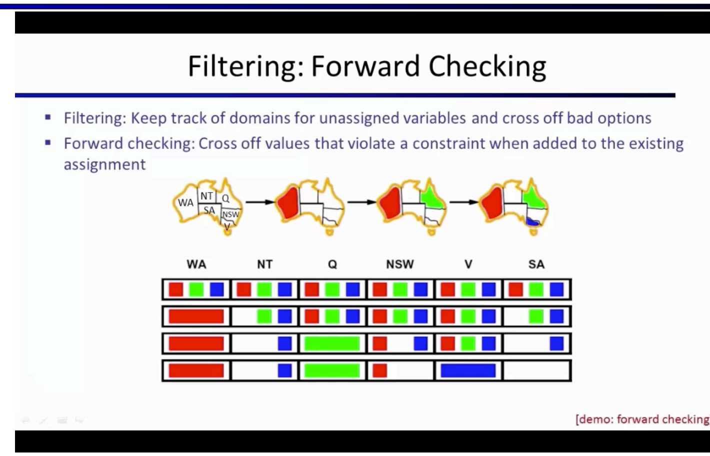
## Filtering: Forward Checking

- Filtering: Keep track of domains for unassigned variables and cross off bad options
- Forward checking: Cross off values that violate a constraint when added to the existing assignment



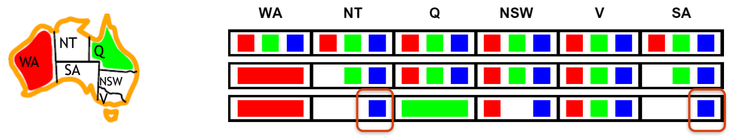
[Demo: coloring -- forward checking]

## Video of Demo Coloring – Backtracking with Forward Checking



# Filtering: Constraint Propagation

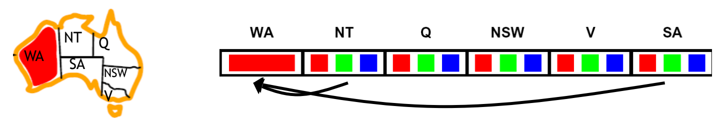
- Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:

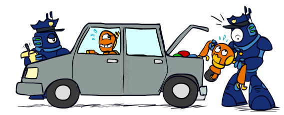



- NT and SA cannot both be blue!
- Why didn't we detect this yet?
- *Constraint propagation:* reason from constraint to constraint

# Consistency of A Single Arc

- An arc X → Y is consistent iff for *every* x in the tail there is *some* y in the head which could be assigned without violating a constraint



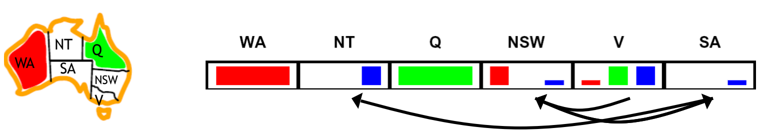



*Delete from the tail!*

Forward checking?
Enforcing consistency of arcs pointing to each new assignment

# Arc Consistency of an Entire CSP

- A simple form of propagation makes sure all arcs are consistent:




- Important: 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
- What's the downside of enforcing arc consistency?

*Remember: Delete from the tail!*

# Enforcing Arc Consistency in a CSP

**function** AC-3( $csp$) **returns** the CSP, possibly with reduced domains
  **inputs**: $csp$, a binary CSP with variables $\{X_1, X_2, \ldots, X_n\}$
  **local variables**: $queue$, a queue of arcs, initially all the arcs in $csp$

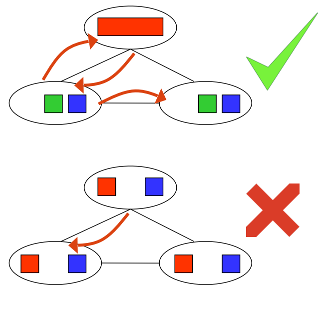
  **while** $queue$ is not empty **do**
    $(X_i, X_j) \leftarrow$ REMOVE-FIRST($queue$)
    **if** REMOVE-INCONSISTENT-VALUES($X_i$, $X_j$) **then**
      **for each** $X_k$ **in** NEIGHBORS[$X_i$] **do**
        add $(X_k, X_i)$ to $queue$

**function** REMOVE-INCONSISTENT-VALUES( $X_i$, $X_j$) **returns** true iff succeeds
  $removed \leftarrow false$
  **for each** $x$ **in** DOMAIN[$X_i$] **do**
    **if** no value $y$ in DOMAIN[$X_j$] allows $(x,y)$ to satisfy the constraint $X_i \leftrightarrow X_j$
      **then** delete $x$ from DOMAIN[$X_i$]; $removed \leftarrow true$
  **return** $removed$

- Runtime: $O(n^2d^3)$, can be reduced to $O(n^2d^2)$
- … but detecting all possible future problems is NP-hard – why?

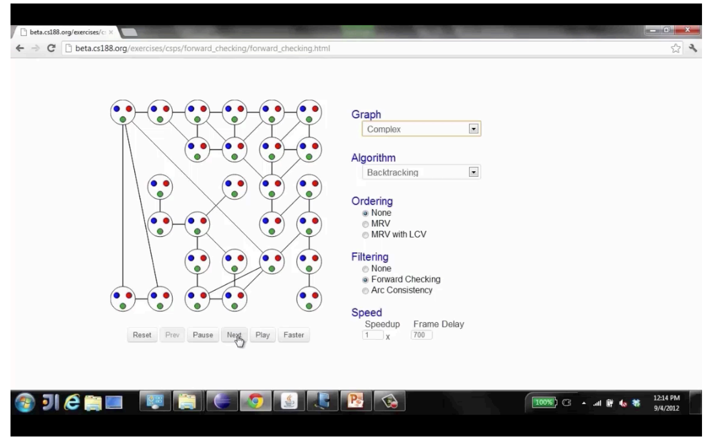
# Limitations of Arc Consistency

- 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!



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

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




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