

# Advanced Topics in AI Filtering



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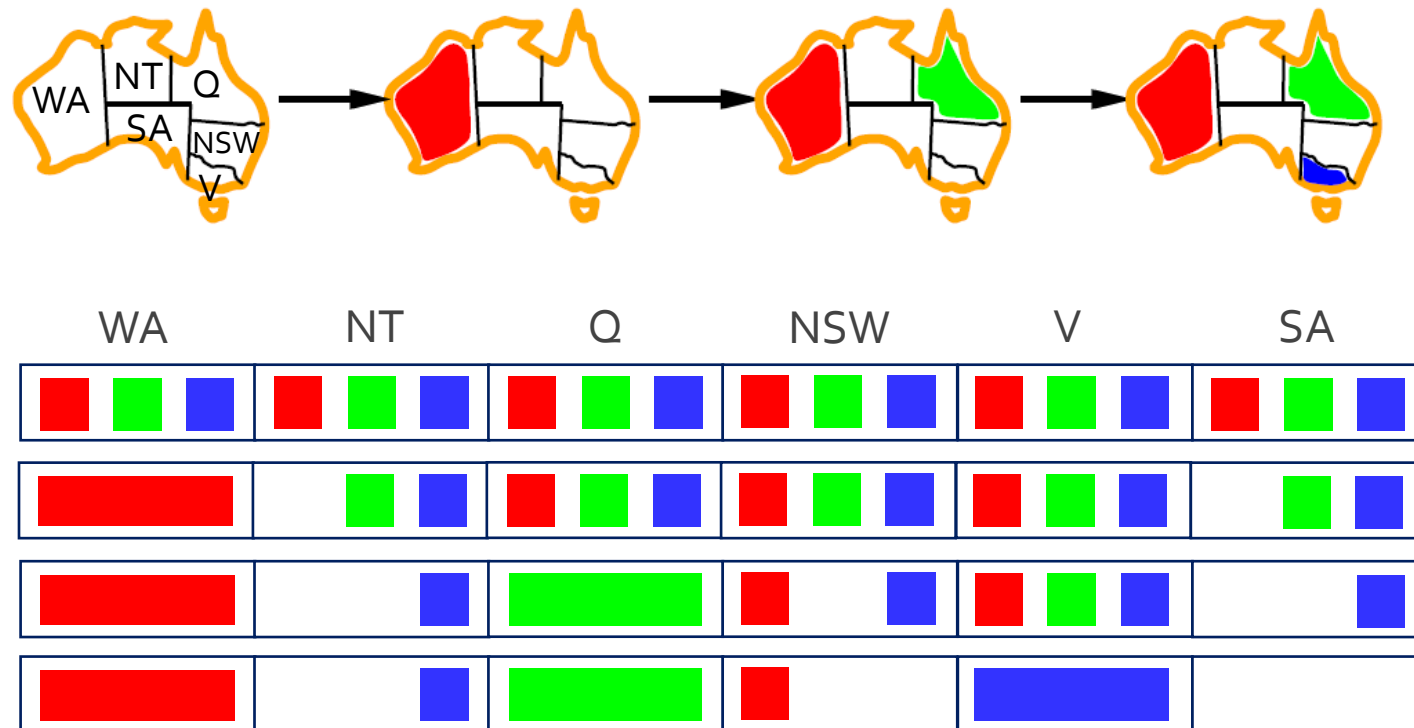
[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All materials are available at <http://ai.berkeley.edu>.]



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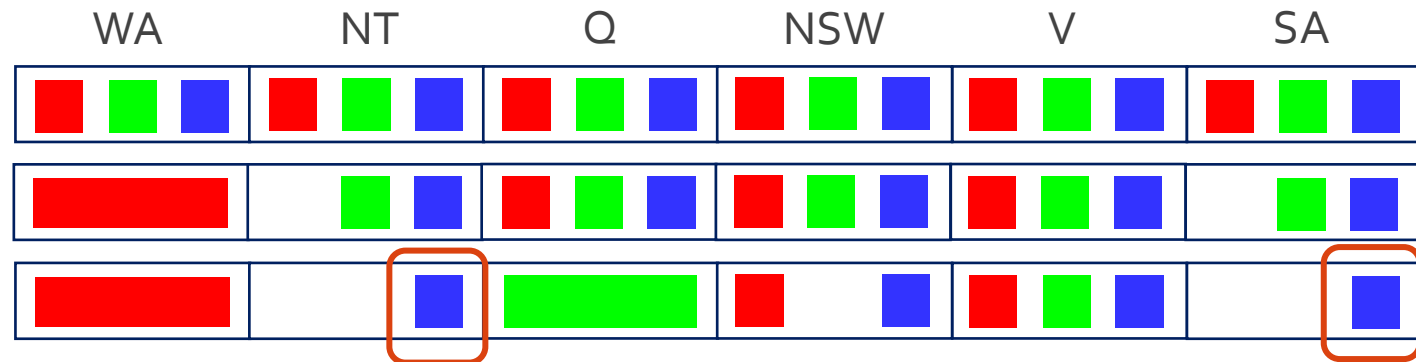
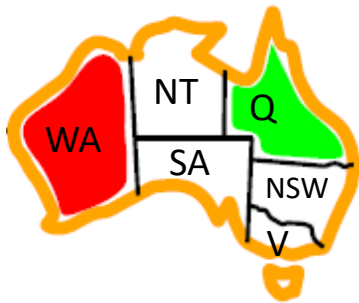
# Filtering: Forward Checking

- 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



# Filtering: Constraint Propagation

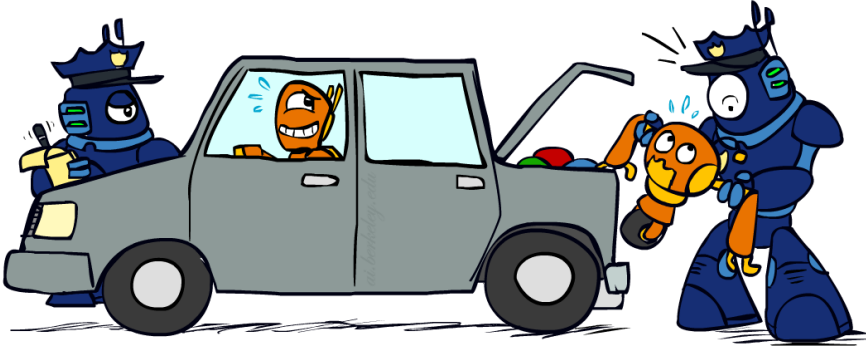
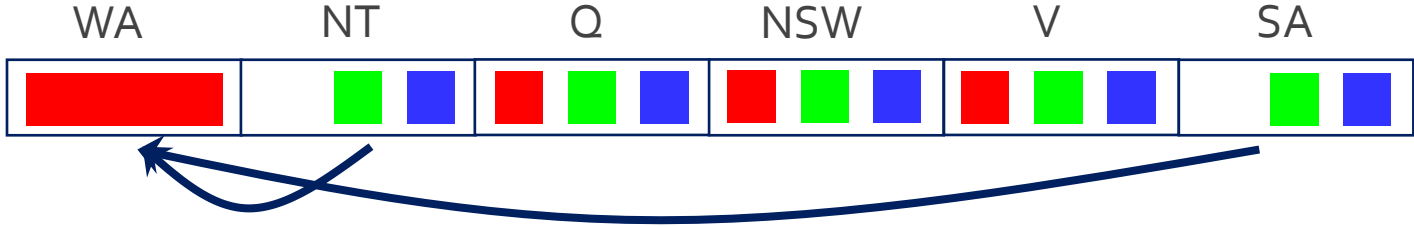
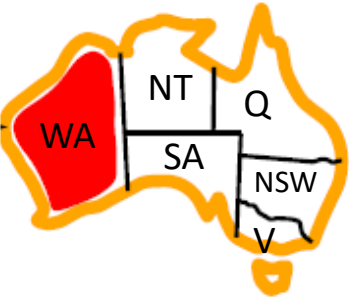
- Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:



- 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  $X \rightarrow Y$  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

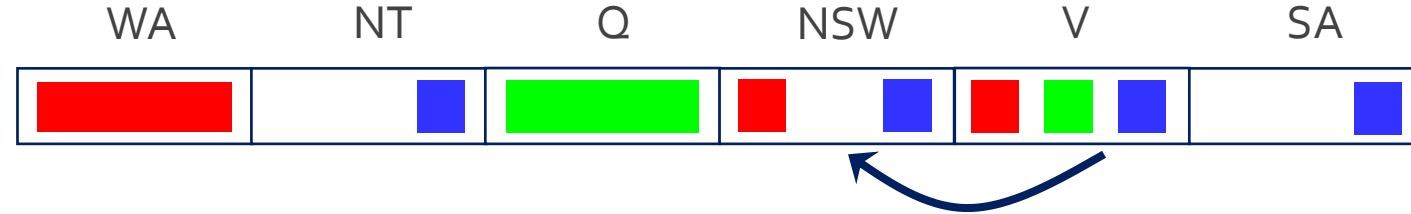
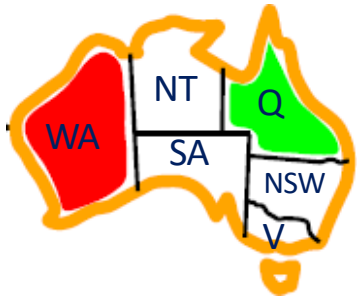


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# Arc Consistency of an Entire CSP

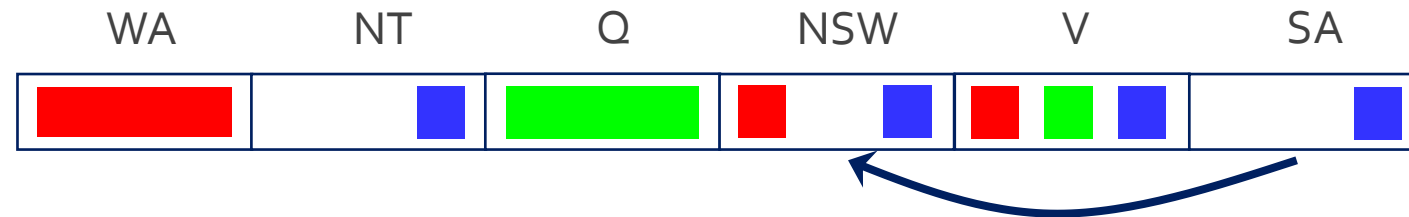
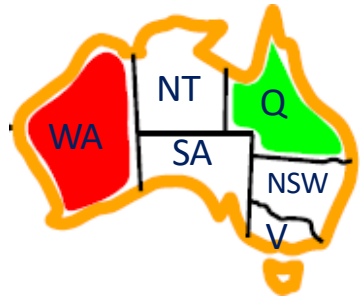
- A simple form of propagation makes sure **all** arcs are consistent:



- Arc V to NSW is consistent: for *every*  $x$  in the tail there is *some*  $y$  in the head which could be assigned without violating a constraint

# Arc Consistency of an Entire CSP

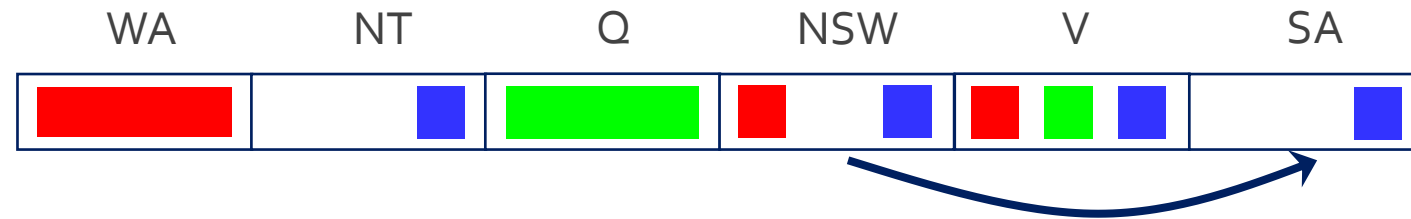
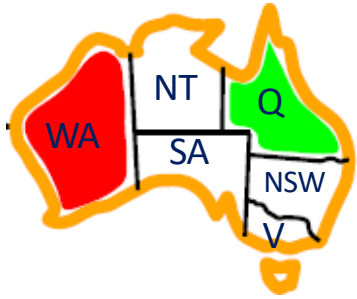
- A simple form of propagation makes sure **all** arcs are consistent:



- Arc SA to NSW is consistent: for *every*  $x$  in the tail there is *some*  $y$  in the head which could be assigned without violating a constraint

# Arc Consistency of an Entire CSP

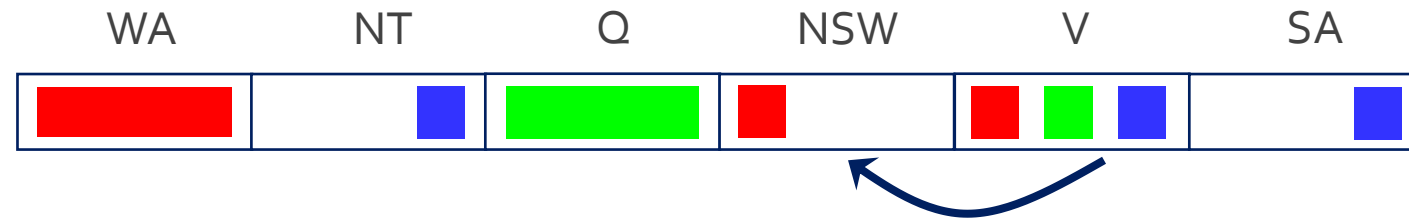
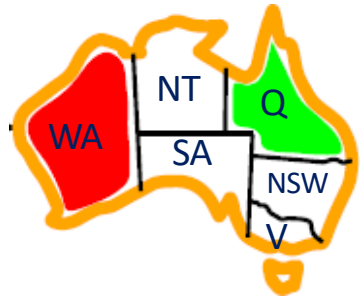
- A simple form of propagation makes sure **all** arcs are consistent:



- Arc NSW to SA is not consistent: if we assign NSW = blue, there is no valid assignment left for SA
- To make this arc consistent, we delete NSW = blue from the tail

# Arc Consistency of an Entire CSP

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

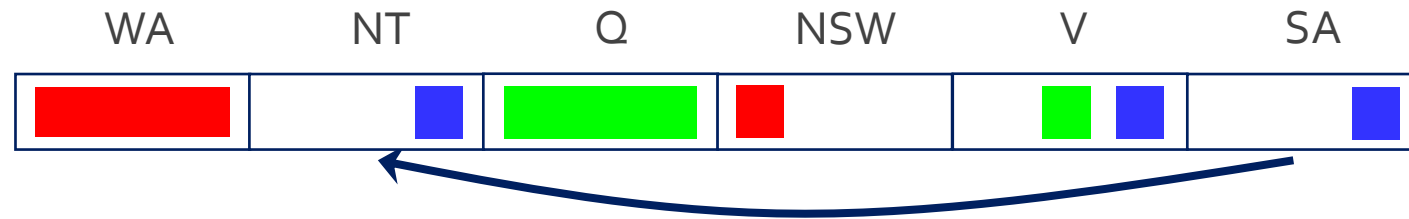
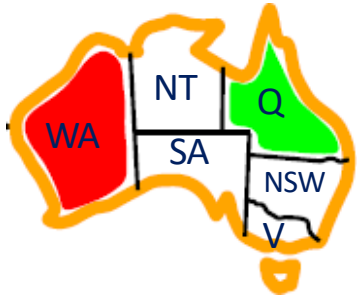


- Remember that arc V to NSW was consistent, when NSW had red and blue in its domain
- After removing blue from NSW, this arc might not be consistent anymore! We need to recheck this arc.
- **Important:** If X loses a value, neighbors of X need to be rechecked!



# Arc Consistency of an Entire CSP

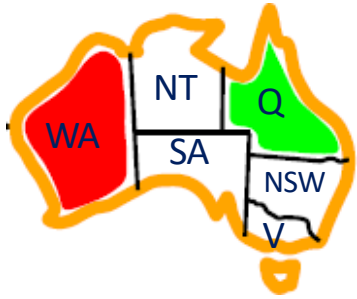
- A simple form of propagation makes sure **all** arcs are consistent:



- Arc SA to NT is inconsistent. We make it consistent by deleting from the tail (SA = blue).

# Arc Consistency of an Entire CSP

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



- SA has an empty domain, so we detect failure. There is no way to solve this CSP with WA = red and Q = green, so we backtrack.
- Arc consistency detects failure earlier than forward checking
- Can be run as a preprocessor or after each assignment

# Enforcing Arc Consistency in a CSP

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

while queue is not empty do
   $(X_i, X_j) \leftarrow \text{REMOVE-FIRST}(\textit{queue})$ 
  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
```

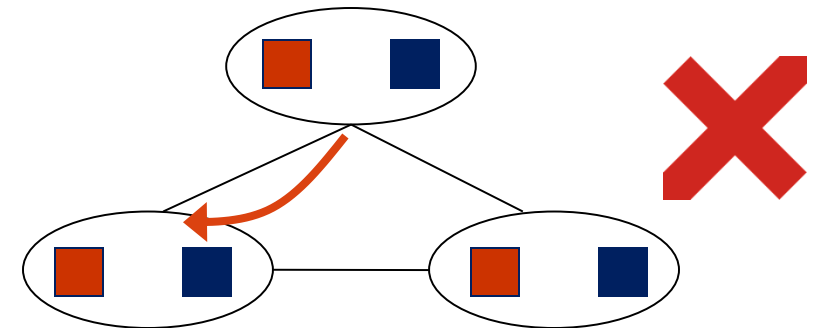
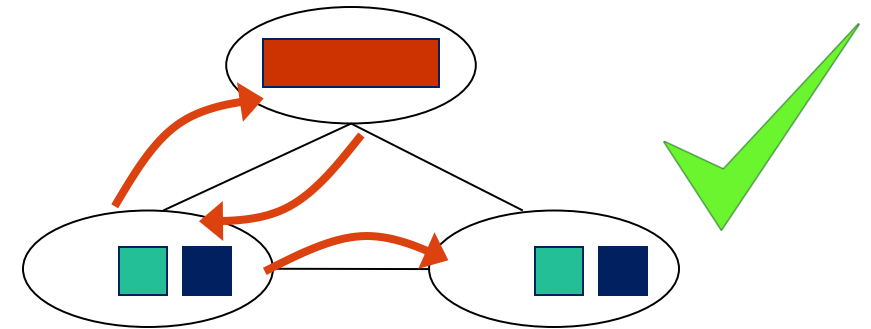
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```
function REMOVE-INCONSISTENT-VALUES( $X_i, X_j$ ) returns true iff succeeds
  removed  $\leftarrow$  false
  for each  $x$  in DOMAIN[ $X_i$ ] do
    if no value  $y$  in DOMAIN[ $X_j$ ] allows  $(x, y)$  to satisfy the constraint  $X_i \leftrightarrow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

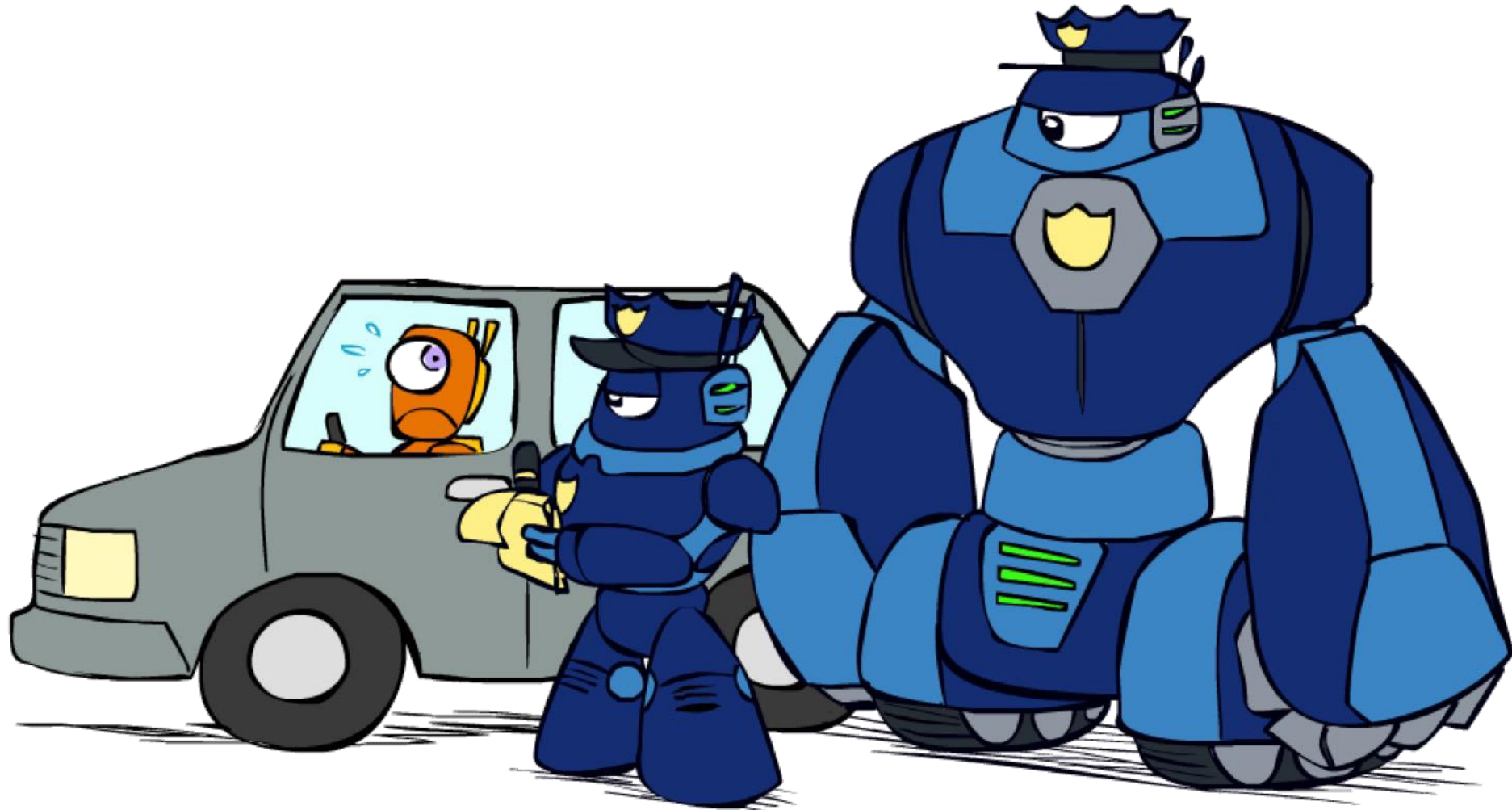
# Limitations of Arc Consistency

- 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!



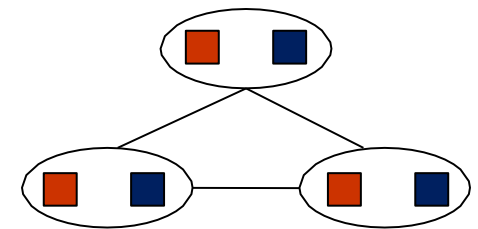
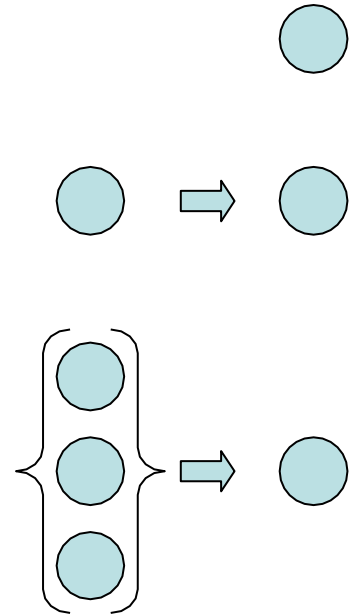
*What went wrong here?*

# 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<sup>th</sup> 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)

# Advanced Topics in AI

## Next: Ordering



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