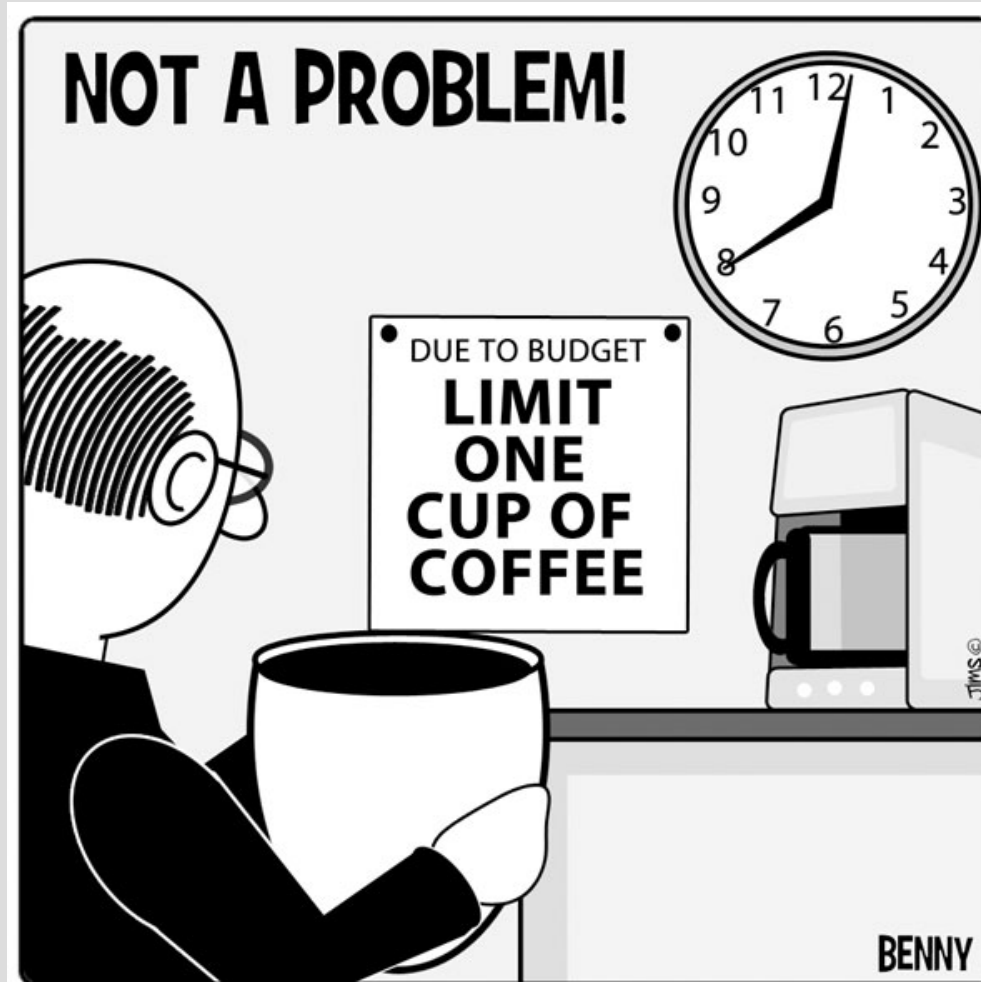


# Constraint sat. prob. (Ch. 6)



# Announcements

Midterm regrades: due Nov. 7<sup>th</sup>

# Types of constraints

Try to do this job problem with: J1, J2 and J3

Jobs cannot overlap

J3 takes 3 time units

J2 takes 2 time units

J1 takes 1 time unit

J1 must happen before J3

J2 cannot happen at time 1

All jobs must finish by time 7

(i.e. you can start J2 at time 5 but not at time 6)

# Applying constraints

We can repeatedly apply our constraint rules to shrink the domain of variables (we just shrunk NT's domain to nothing)

This reduces the size of the domain, making it easier to check:

- If the domain size is zero, there are no solutions for this problem
- If the domain size is one, this variable must take on that value (the only one in domain)

# Applying constraints

AC-3 checks all 2-consistency constraints:

1. Add all binary constraints to queue
2. Pick a binary constraint  $(X_i, Y_j)$  from queue
3. If  $x$  in  $\text{domain}(X_i)$  and no consistent  $y$  in  $\text{domain}(Y_j)$ , then remove  $x$  from  $\text{domain}(X_i)$
4. If you removed in step 3, update all other binary constraints involving  $X_i$  (i.e.  $(X_i, X_k)$ )
5. Goto step 2 until queue empty

# Applying constraints

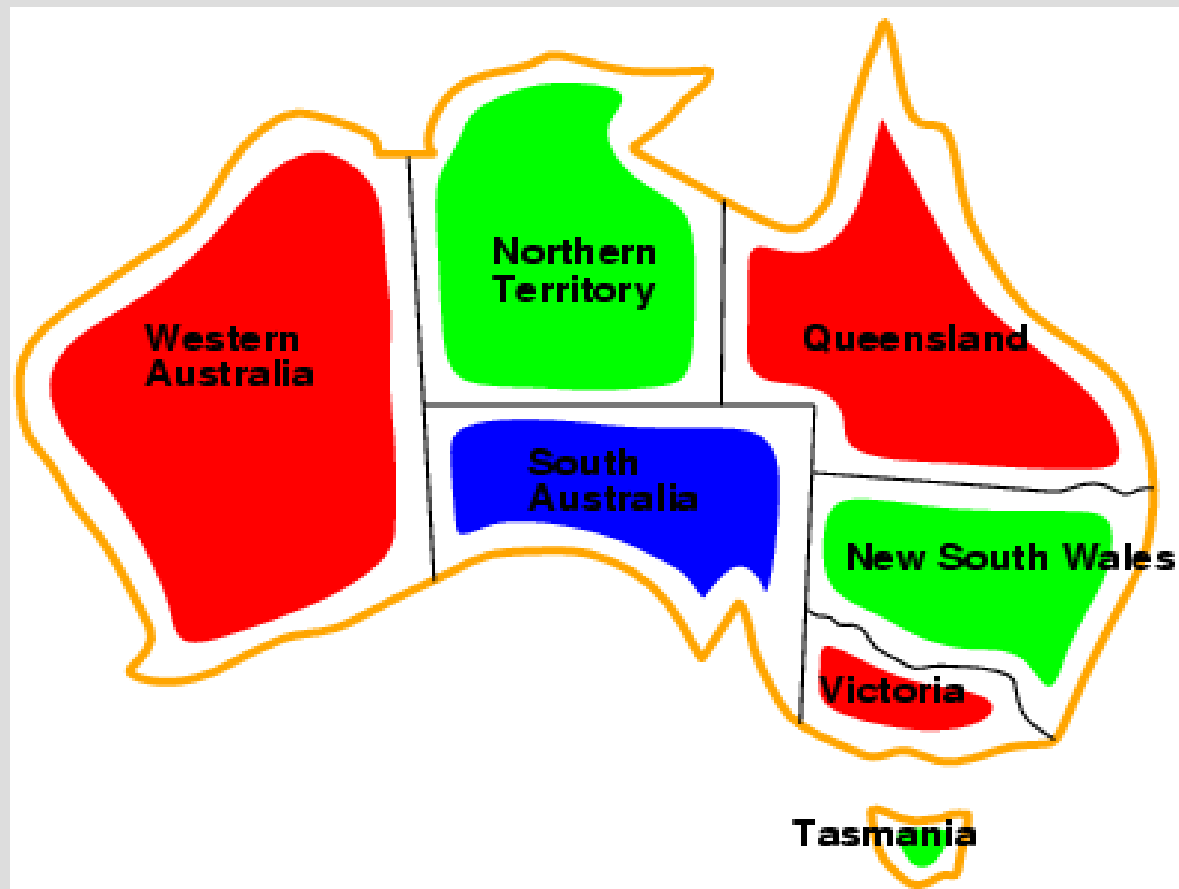
Some problems can be solved by applying constraint restrictions (such as sudoku) (i.e. the size of domain is one after reduction)

Harder problems this is insufficient and we will need to search to find a solution

Which is what we will do... now

# CSP vs. search

Let us go back to Australia coloring:



How can you color using search techniques?

# CSP vs. search

We can use an incremental approach:

State = currently colored provinces (and their color choices)

Action = add a new color to any province that does not conflict with the constraints

Goal: To find a state where all provinces are colored



# CSP vs. search

Is there a problem?

# CSP vs. search

Is there a problem?

Let  $d$  = domain size (number of colorings),  
 $n$  = number of variables (provinces)

The number of leaves are  $n! * d^n$

However, there are only  $d^n$  possible states  
in the CSP so there must be a lot of duplicate  
leaves (not including mid-tree parts)

# CSP vs. search

CSP assumes one thing general search does not: the order of actions does not matter

In CSP, we can assign a value to a variable at any time and in any order without changing the problem (all we care about is the end state)

So all we need to do is limit our search to one variable per depth, and we will have a match with CSP of  $d^n$  leaves (all combinations)

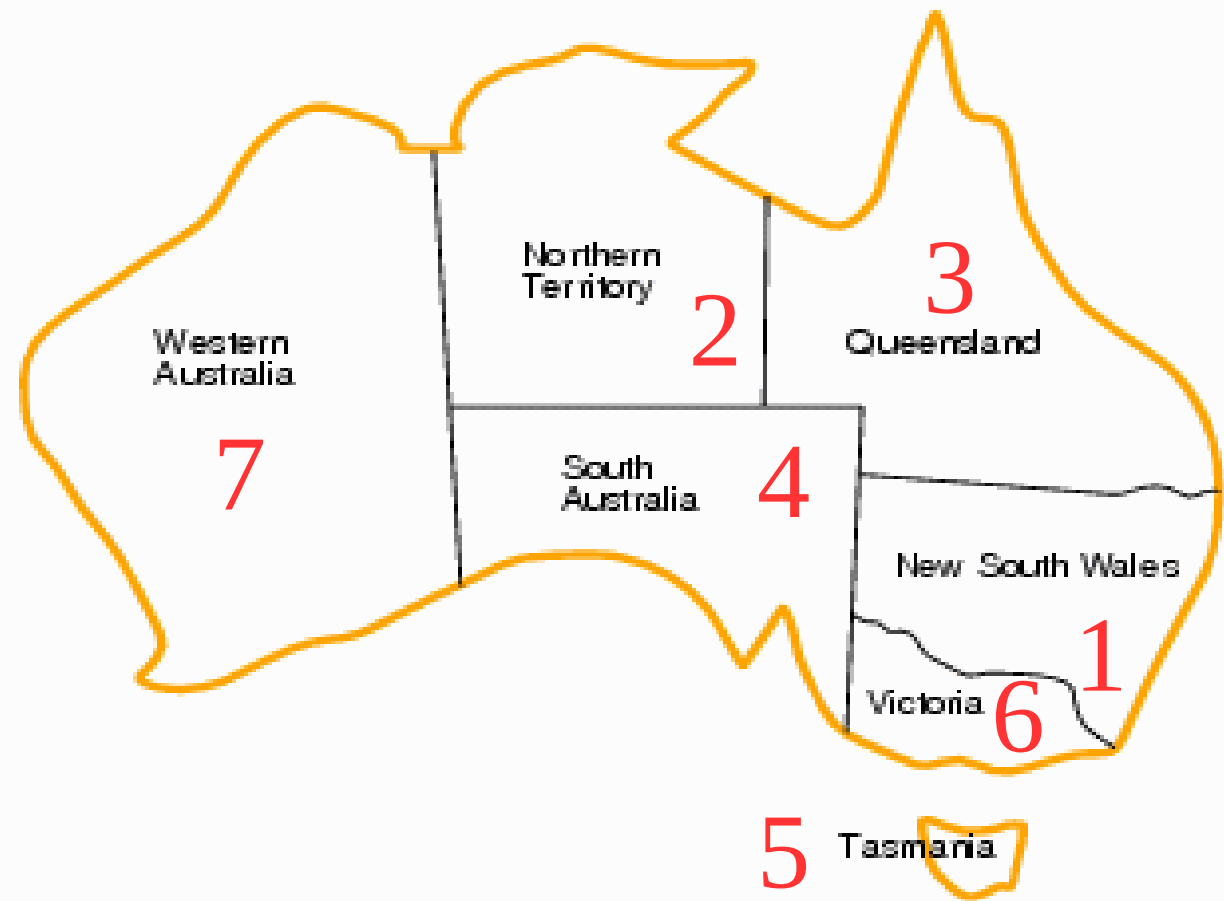
# CSP vs. search

Let's apply CSP modified DFS on Australia:  
(assign values&variables in alphabetical order)

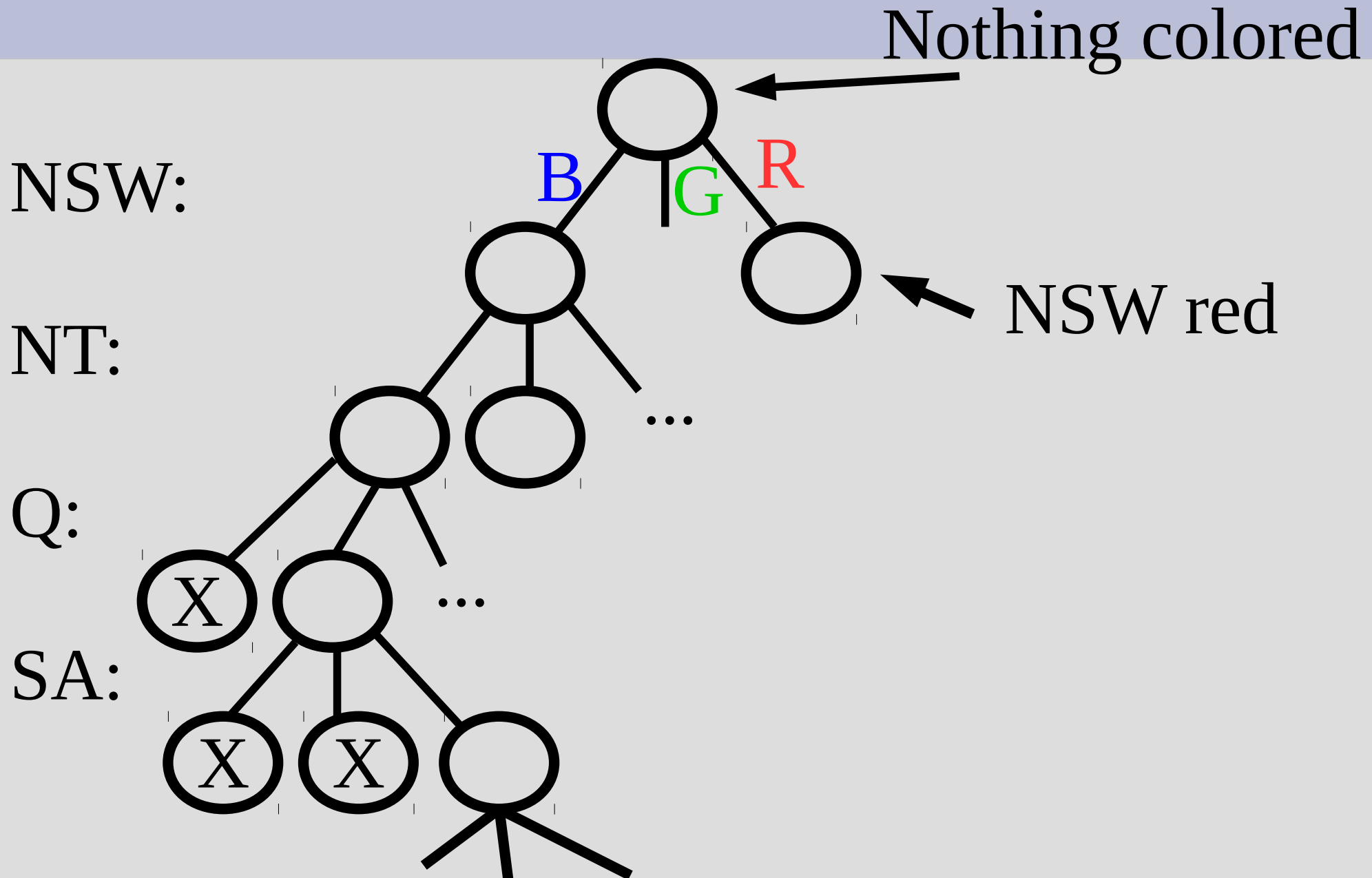
1<sup>st</sup>: blue

2<sup>nd</sup>: green

3<sup>rd</sup>: red



# CSP vs. search



# CSP vs. search

STOP PICKING BLUE EVERY TIME!!!!



**THIRD PARTY FACE PALM**

For when there is so much fail.... you need that extra bit of outside help..

# CSP backtracking

However, this is still hope for searching (called backtracking search (it backups up at conflict))

We will improve it by...

1. The order we pick variables
2. The order we pick values for variables
3. Mix search with inference
4. Smarter backtracking

# 1. What variable?

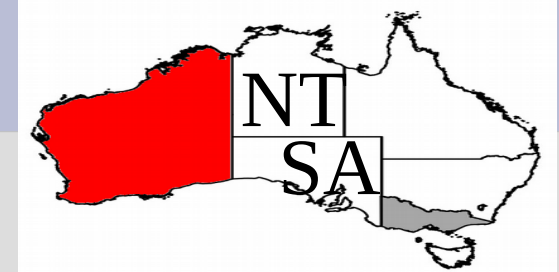
When picking the variables, we want to the variable with the smallest domain (the most restricted variable)

The best-case is that there is only one value in the domain to remain consistent

By picking the most constrained variables, we fail faster and are able to prune more of the tree



# 1. What variable?



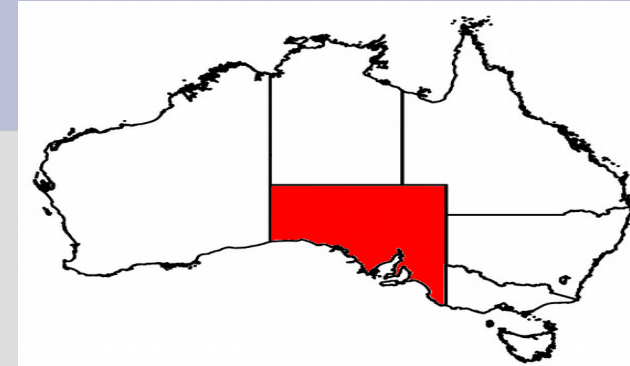
Suppose we pick  $\{WA = \text{red}\}$ , it would be silly to try and color  $V$  next

Instead we should try to color NT or SA, as these only have 2 possible colorings, while the rest have 3

This will immediately let the computer know that it cannot color NT or SA red (prune these branches right way)

# 1. What variable?

But we can do even better!



If there is a tie for possible values to take, we pick the variable with the most connections

This ensures that other nodes are more restricted to again prune earlier

For example, we should color SA first as it connects to 5 other provinces

## 2. What value?

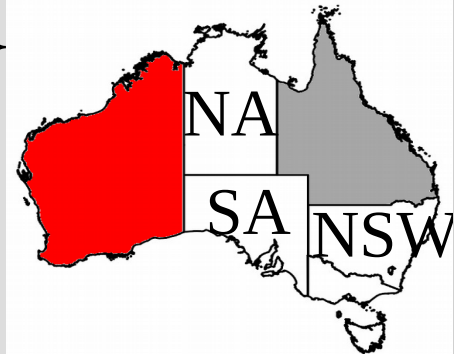
After we picked a variable to look at, we must assign a value

Here we want to do the opposite: choose the value which constrains the neighbors the least

This is “putting your best foot forward” or trying your best to find a goal (while failing fast helps pruning, we do actually want to find a goal not prune as much as possible)

## 2. What value?

For example, if we color {WA = red}  
then pick Q next



Our options for Q are {red, green or blue}, but  
picking {green or blue} limit NT & SA to  
only one valid color and NSW to 2

If we pick {Q=red}, then NT, SA & NSW all  
have 2 valid possibilities (and this happens to  
be on a solution path)

# 1. & 2.

An analogy to 1&2 is: “trying our best (2) to solve the weakest link (1)”

By tackling the weakest link first, it will be easier for less constrained nodes to adapt/  
pick up the slack

However, we do want to try and solve the problem, not find the quickest way to fail (i.e. always picking blue... .. >.<)

# 3. Mix search & inference?

We described how AC-3 can use inference to reduce the domain size

Inference does not need to run in isolation; it works better to assign a value then apply inference to prune before even searching

This works well in combination with 1 as uses the domain size to choose the variable and 3 shrinks domain sizes to be consistent

# 3. Mix search & inference?

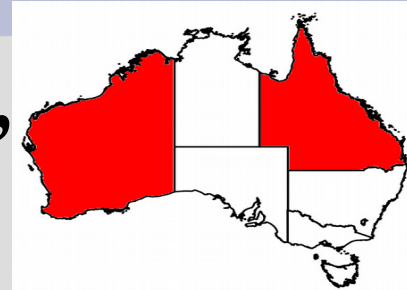
This is somewhat similar to providing a heuristic for our original search

Inference lets us know an estimation of what colors are left and can be done efficiently

We can use this estimate to guide our search more directly towards the goal

### 3. Mix search & inference?

In the previous example:  $\{WA = \text{red}\}$ ,  
then color Q



We want to choose  $\{Q = \text{red}\}$  to allow the most  
choices for NT and SA

Without inference we will not know about this  
restriction and just have assign and realize  
this constraint when we create a conflict



# 4. Smart backtracking

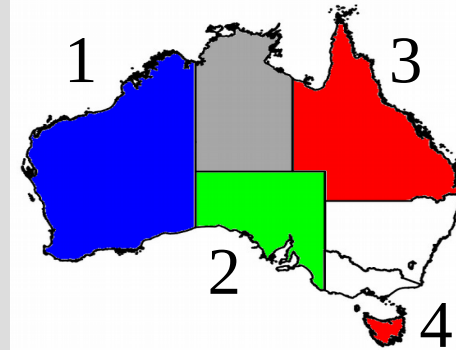
Instead of moving our search back up a single layer of the tree and picking from there...

We could backup to the first node above the conflict that was actually involved in the conflict

This avoids in-between nodes which did not participate in the conflict

# 4. Smart backtracking

Suppose we assigned (in this order):  
{WA = B, SA = G, Q = R, T = R}  
then pick NT

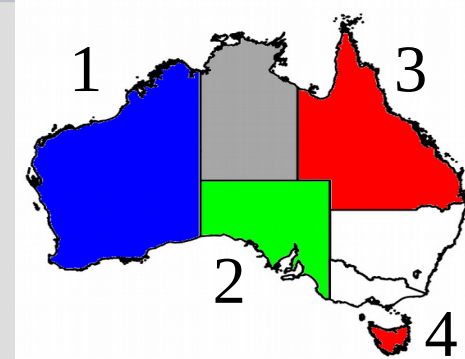


NT has all three colors neighboring it, so a conflict is reached

In normally, we would backtrack and try to change T (i.e. 4), but this was actually not involved in the conflict (1, 2 & 3 were)

# 4. Smart backtracking

This smart backtracking can be done by looking to see who was in conflict with the last choice



Here we were picking NT, who has constraints with: {WA, SA, Q}

Q was the most recent pick in this set, so we should go there (if there are no options for Q, we carry over constraints + Q's constraints)

# Example

Suppose we have the following statement:

$$\begin{array}{r} T W O \\ + T W O \\ = F O U R \end{array}$$

We want to assign each character a single digit to make this a valid math equation (each different letter is a different digit)

How do you represent this as a CSP?

# Example

Suppose we have the following statement:

$$\begin{array}{r} T W O \\ + T W O \\ = F O U R \end{array}$$

$$R = O + O \pmod{10}$$

$$U = W + W + \text{floor}((O+O)/10) \pmod{10}$$

$$O = T+T+\text{floor}((W+W+(O+O)/10)/10) \pmod{10}$$

$$F = \text{floor}((T+T+(W+W)/10)/10) \pmod{10}$$

$$T \neq W \neq O \neq F \neq U \neq R$$

# Example

$$R = O + O \pmod{10}$$

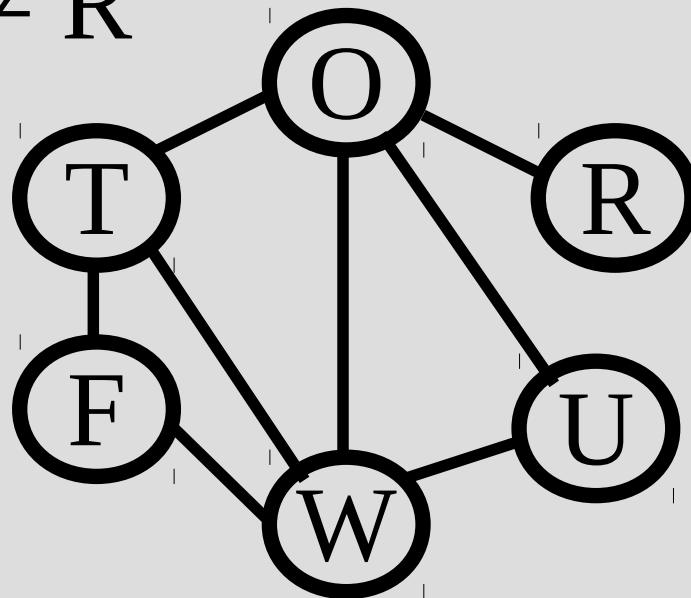
$$U = W + W + \text{floor}((O+O)/10) \pmod{10}$$

$$O = T+T+\text{floor}((W+W+(O+O)/10)/10) \pmod{10}$$

$$F = \text{floor}((T+T+(W+W)/10)/10) \pmod{10}$$

$$T \neq W \neq O \neq F \neq U \neq R$$

Pictorially:  
(relationships)



# Example

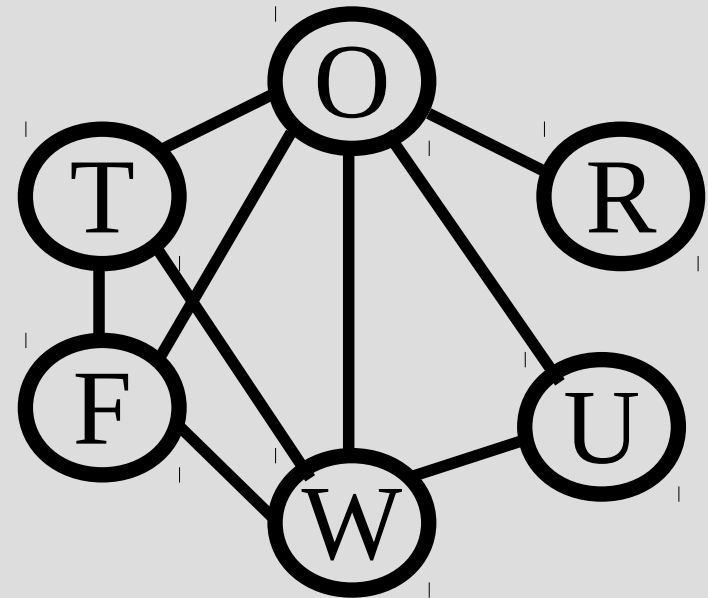
Domains are (as they are digits):

$O = R = U = W = \{0,1,2,3,4,5,6,7,8,9\}$

$F=T=\{1,2,3,4,5,6,7,8,9\}$

(not 0 as leading digit)

However, we can simplify this by adding more variables to represent the “carry over” amounts



# Example

$$R = O + O \bmod 10$$

$$U = W + W + \text{floor}((O+O)/10) \bmod 10$$

$$O = T+T+\text{floor}((W+W+(O+O)/10)/10) \bmod 10$$

$$F = \text{floor}((T+T+(W+W)/10)/10) \bmod 10$$

$$T \neq W \neq O \neq F \neq U \neq R$$

We can simplify the floor by adding auxiliary variables:  $C_{10}$ ,  $C_{100}$  and  $C_{1000}$  representing

the “carry over” value from the addition

Specifically,  $\text{floor}((O+O)/10) = C_{10}$



# Example

$$R = O + O \bmod 10$$

$$U = W + W + C_{10} \bmod 10$$

$$O = T + T + C_{100} \bmod 10$$

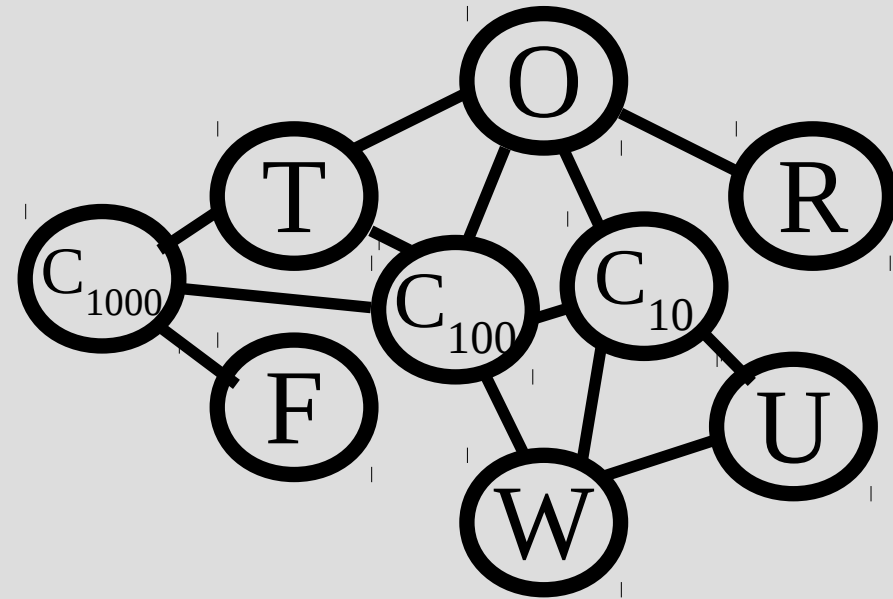
$$F = C_{1000} \bmod 10$$

$$T \neq W \neq O \neq F \neq U \neq R$$

$$C_{10} = \text{floor}((O+O)/10) \bmod 10$$

$$C_{100} = \text{floor}((W+W + C_{10})/10) \bmod 10$$

$$C_{1000} = \text{floor}((T+T + C_{100})/10) \bmod 10$$



# Example

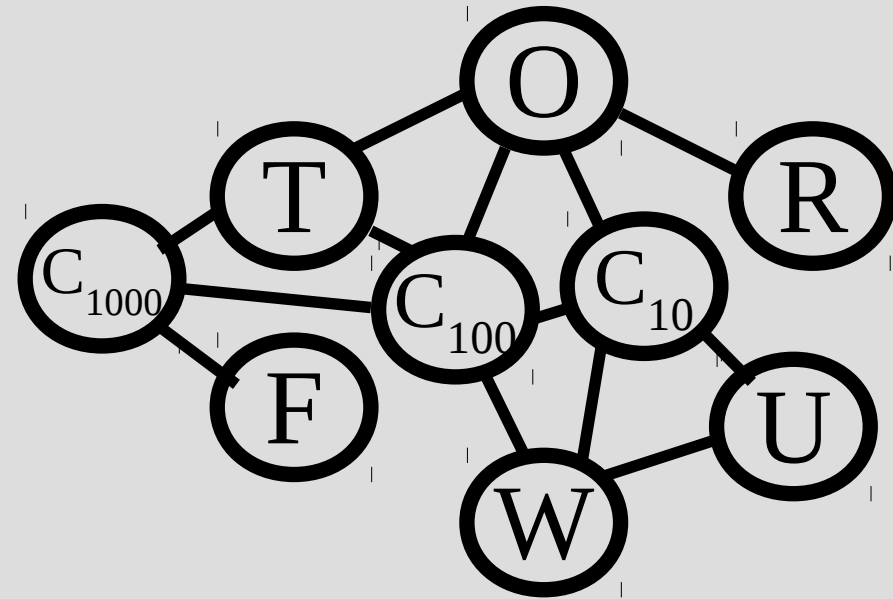
Domains:

$O = R = U = W =$   
 $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

$F = T = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$

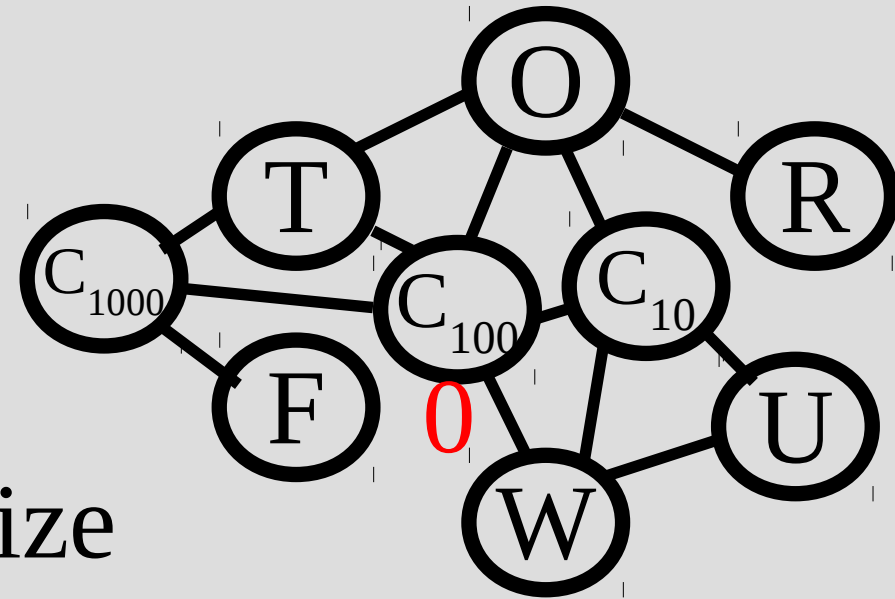
$C_{10} = C_{100} = C_{1000} = \{0, 1\}$

(as they are the sum of two single digits)



# Example

We want to pick the variable with the smallest domain



All  $C_x$  tie with a domain size of two, so we pick the one with the most connections:  $C_{100}$

So try  $C_{100} = 0$

# Example

If  $C_{100} = 0$ , we see if we can shrink any of the domains that involve  $C_{100}$ ...

*Constraints involving  $C_{100}$ :*

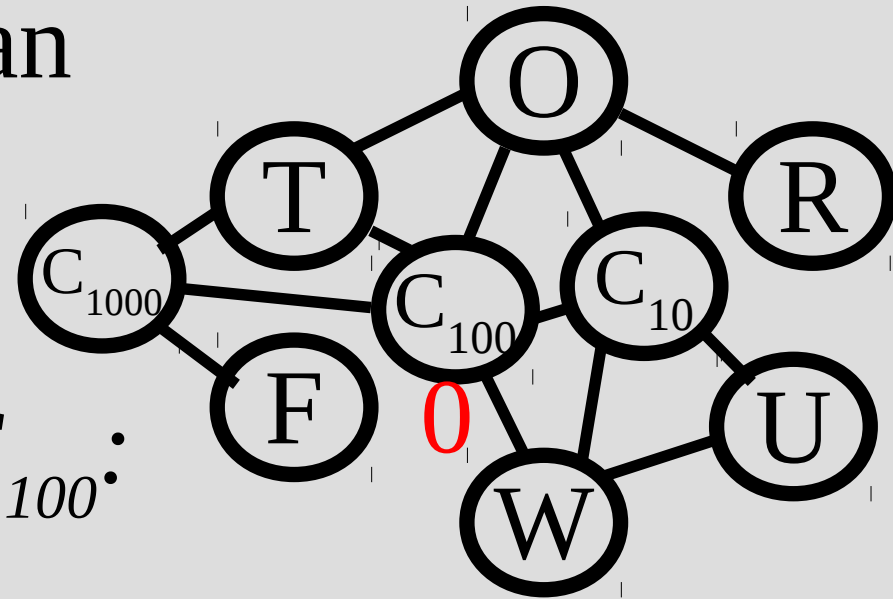
$$O = T + T + C_{100} \pmod{10}$$

$$C_{100} = \text{floor}((W+W + C_{10})/10) \pmod{10}$$

$$C_{1000} = \text{floor}((T+T + C_{100})/10) \pmod{10}$$

We can get:  $O = \{0, 2, 4, 6, 8\}$  (as  $O = 2T$ ),

$W = \{0, 1, 2, 3, 4\}$  (as  $\text{floor}(W/5) = 0$ )



# Example

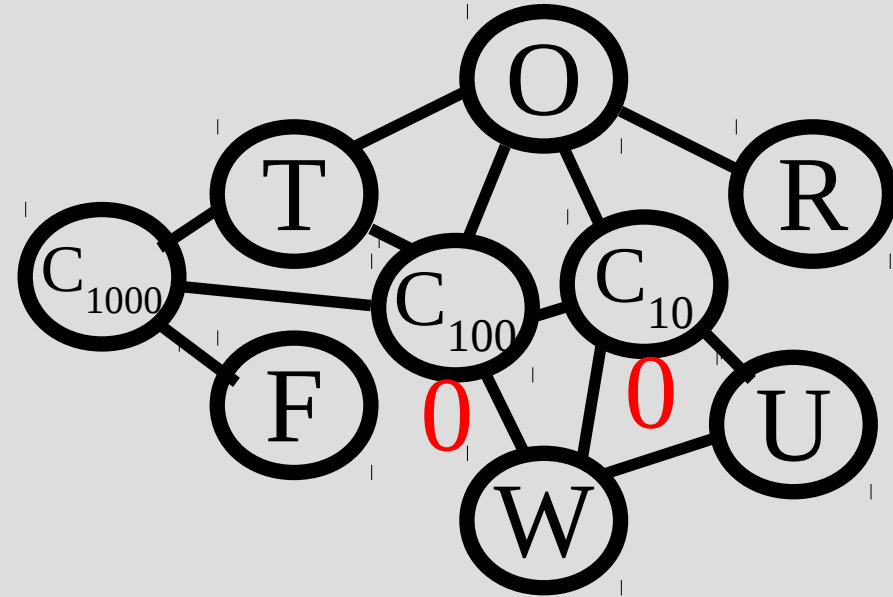
Then pick next:

$C_{10} = 0$ , then infer

$O = \{0, 2, 4\}$

$U = \{0, 2, 4, 6, 8\}$

W and T no change



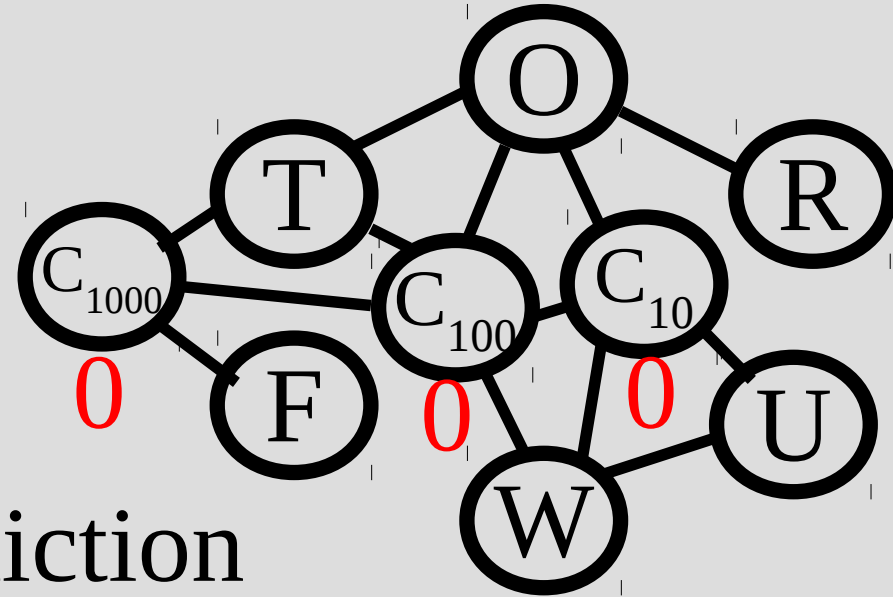
(You could do further inference to reduce U by using “MAC” inference (i.e. find U must be even), but I only shrink domains of things directly related to the pick)

# Example

Then pick next:

$C_{1000} = 0$ , then infer

$F = \{ \}$ , a contradiction



So backup... This contradiction involved  $C_{1000}$  and F, so we just need to

re-pick  $C_{1000}$ ,  $C_{1000} = 1$

Thus we can infer:

$F = \{1\}$ ,  $T = \{5,6,7,8,9\}$

# Example

At this point our picks are:

$$C_{10} = 0$$

$$C_{100} = 0$$

$$C_{1000} = 1$$

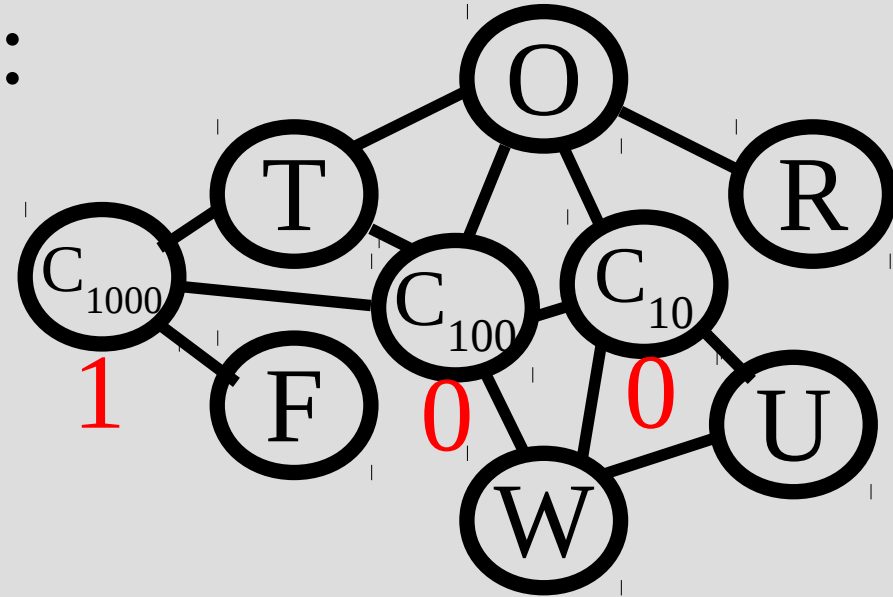
Domains:

$$F = \{1\}$$

$$T = \{5,6,7,8,9\}$$

$$W = \{0,1,2,3,4\}, O = \{0,2,4\}$$

$$U = \{0,2,4,6,8\}, R = \{0,1,2,3,4,5,6,7,8,9\}$$



# Example

Next smallest domain is F:  
Only one pick,  $F=1$

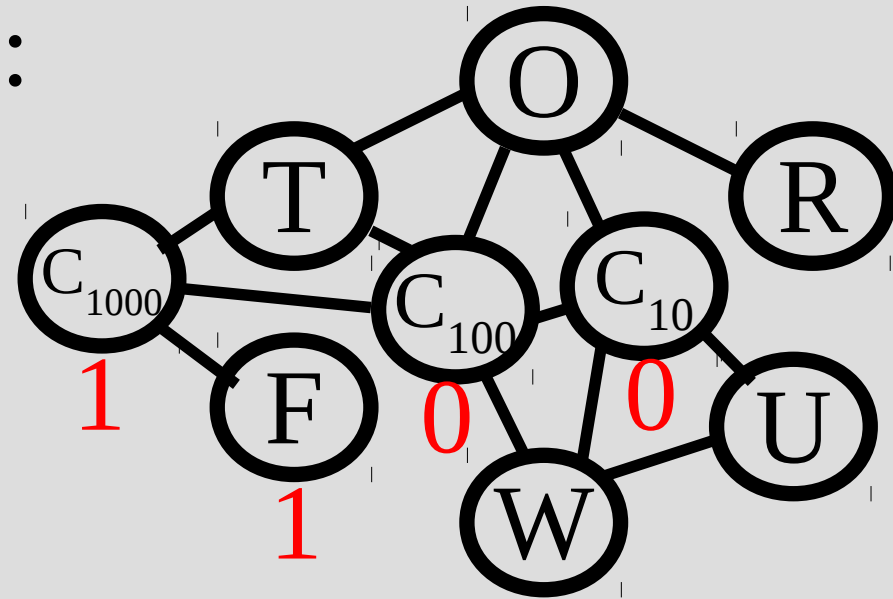
Since F has to be a  
unique digit we can infer:

$$W = \{0, 2, 3, 4\}, O = \{0, 2, 4\}$$

$$R = \{0, 2, 3, 4, 5, 6, 7, 8, 9\}$$

$$T \text{ unchanged} = \{5, 6, 7, 8, 9\}$$

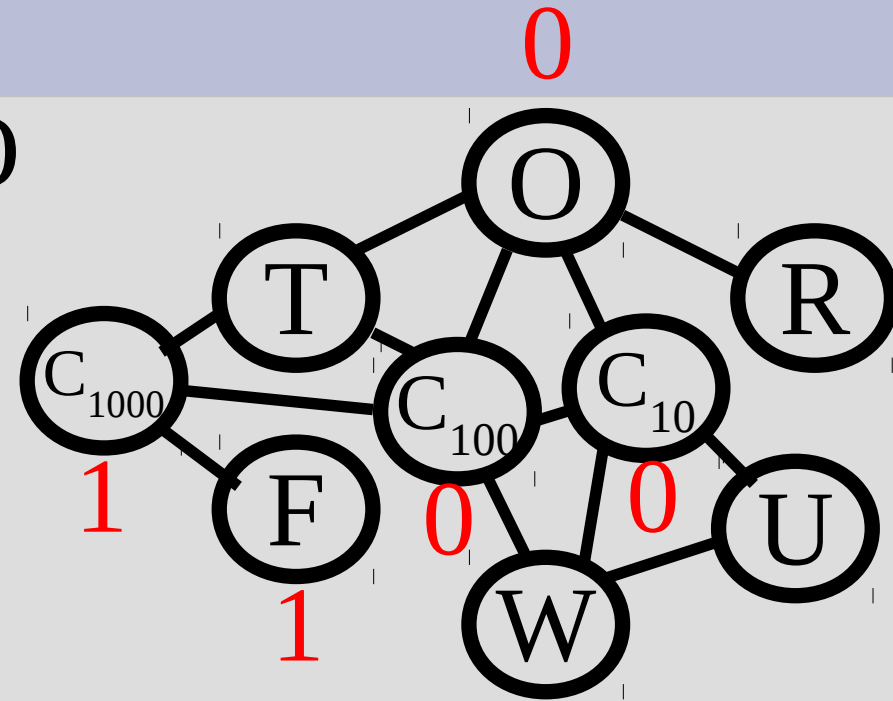
$$U \text{ unchanged} = \{0, 2, 4, 6, 8\}$$





# Example

Next smallest domain is 0



Try  $O=0$  and infer:

$W = \{2,3,4\}, R = \{ \} \leftarrow$  Invalid

...due to  $R = 2 * O = 0 \dots$  but  $R \neq 0$

$U = \{2,4,6,8\}, T = \{ \} \leftarrow$  Invalid

...due to  $O = T + T + C100$  means  $T = 0$ , but  $T \neq 0$

# Example

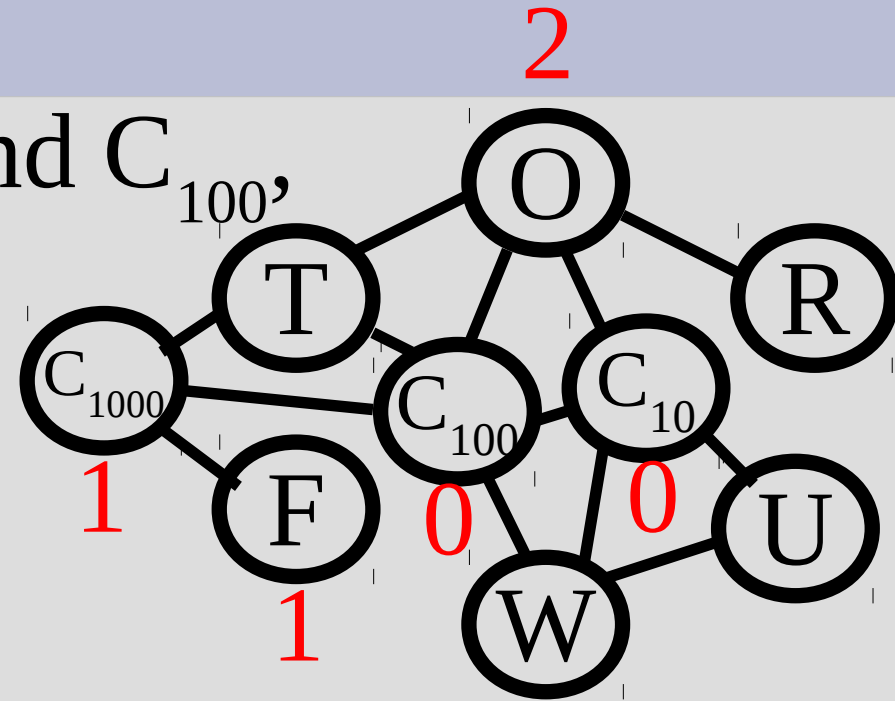
Conflict: T involving O and  $C_{100}$ ,  
most recent pick is O

Change to  $O=2$ , infer:

$T = \{ \}$  ← Invalid

$W = \{0,3,4\}$ ,  $R = \{4\}$

$U = \{0,3,4,5,6,7,8,9\}$



# Example

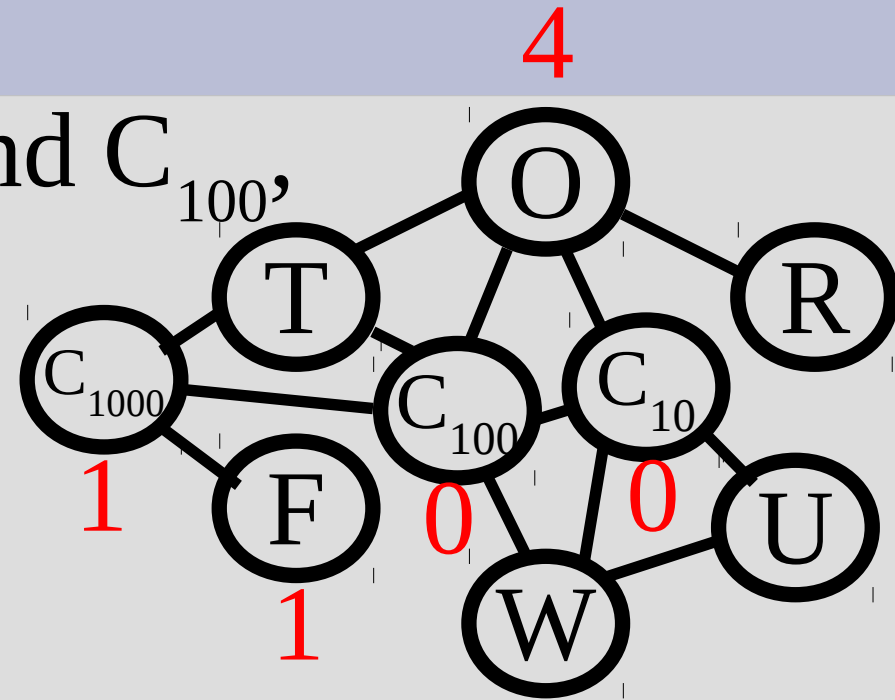
Conflict: T involving O and  $C_{100}$ ,  
most recent pick is O

Change to  $O=4$ , infer:

$T = \{ \} \leftarrow$  Invalid

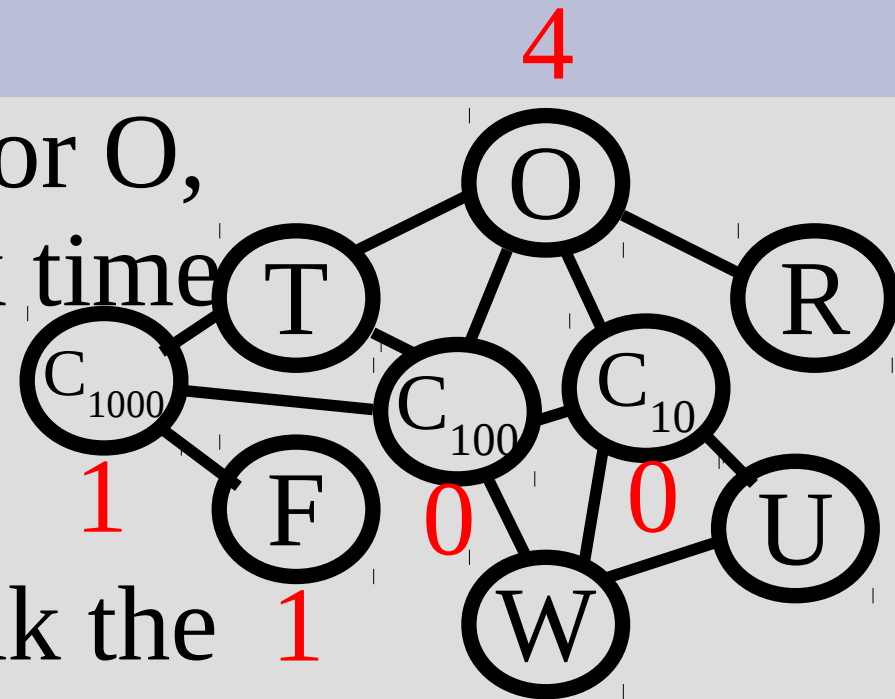
$W = \{0,2,3\}$ ,  $R = \{8\}$

$U = \{0,2,3,5,6,7,8,9\}$



# Example

Tried all possible values for O,  
none worked so backtrack time



O is constrained by:

C<sub>10</sub> and C<sub>100</sub> (as they shrank the

domain... also edge in graph (no  $\neq$  constraints))

so we go back and choose C<sub>10</sub> = 1 (not C<sub>1000</sub>)

(Go back to O, but O has no more options.

Then go past F, and C<sub>1000</sub> to C<sub>10</sub>)

# Example

Currently have:  $C_{100}=0$ ,  $C_{10}=1$

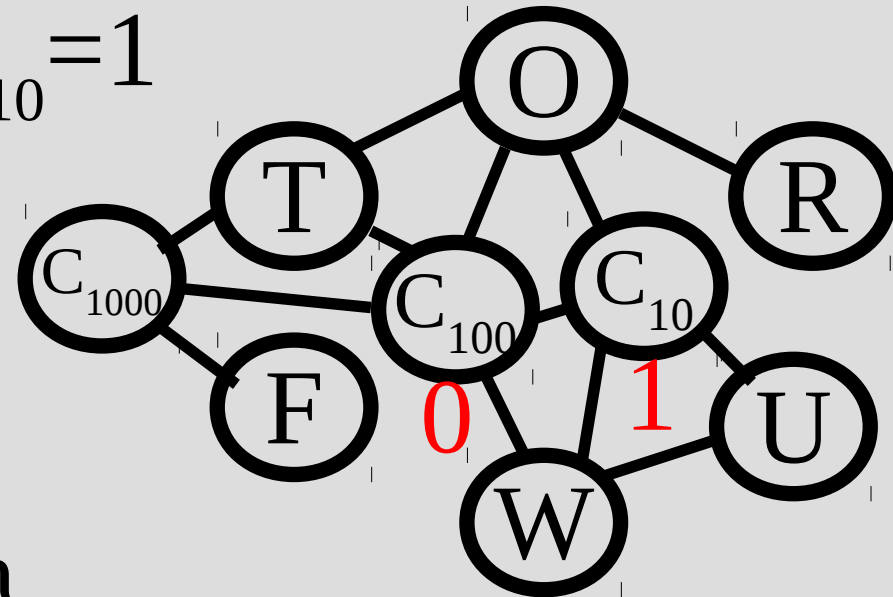
Domains from  $C_{100}=0$ :

$$C_{1000} = \{0, 1\}$$

$$F = T = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$$

$$U = R = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$$

$$O = \{0, 2, 4, 6, 8\}, W = \{0, 1, 2, 3, 4\}$$



# Example

From picking  $C_{10}=1$ , we deduce:

$O \geq 5$ ,  $U = \text{odd}$

New domains:

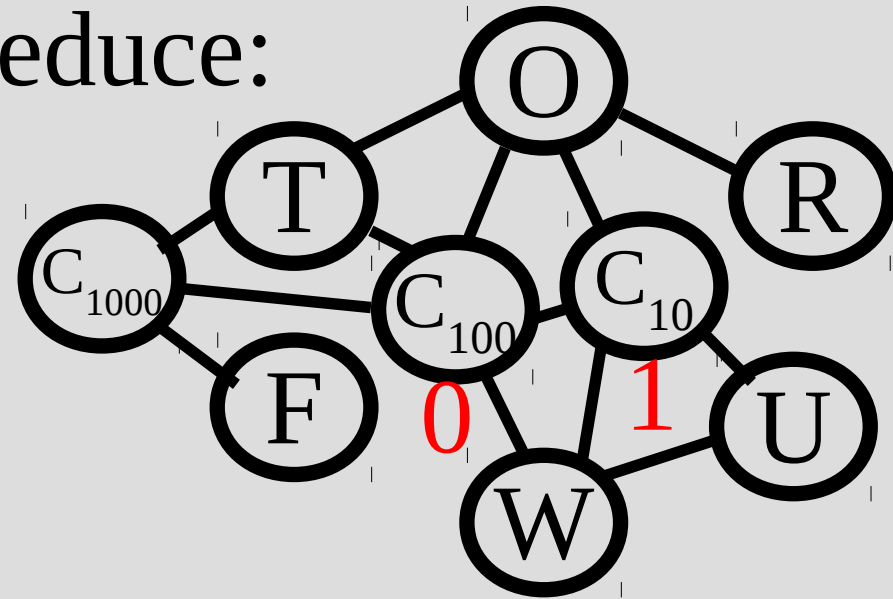
$C_{1000} = \{0, 1\}$

$F = T = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$

$R = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

$O = \{6, 8\}$ ,  $W = \{0, 1, 2, 3, 4\}$

$U = \{1, 3, 5, 7, 9\}$



# Example

Tie for smallest domain ( $O$  &  $C_{1000}$ ),

$O$  has more connections:

Pick  $O=6$

Constraints:  $O=2T+0(\text{mod}10)$ ,

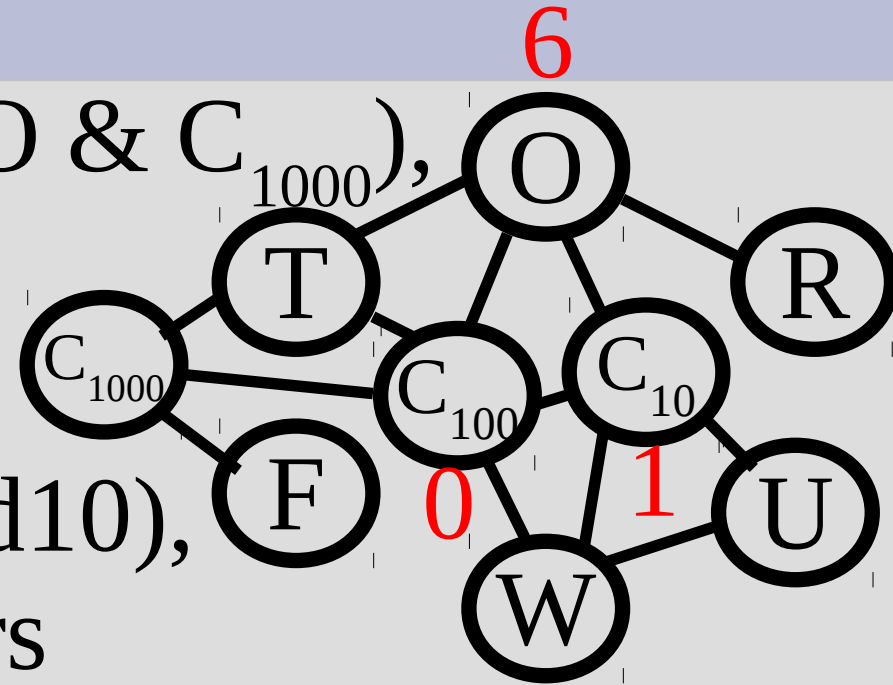
$R=2*O(\text{mod} 10)$ ,  $O \neq \text{others}$

Domains:

$C_{1000} = \{0, 1\}$ ,  $T = \{3, 8\}$ ,  $R = \{2\}$

$F = \{1, 2, 3, 4, 5, 7, 8, 9\}$

$W = \{0, 1, 2, 3, 4\}$ ,  $U = \{1, 3, 5, 7, 9\}$



# Example

R has smallest domain,

Pick  $R=2$

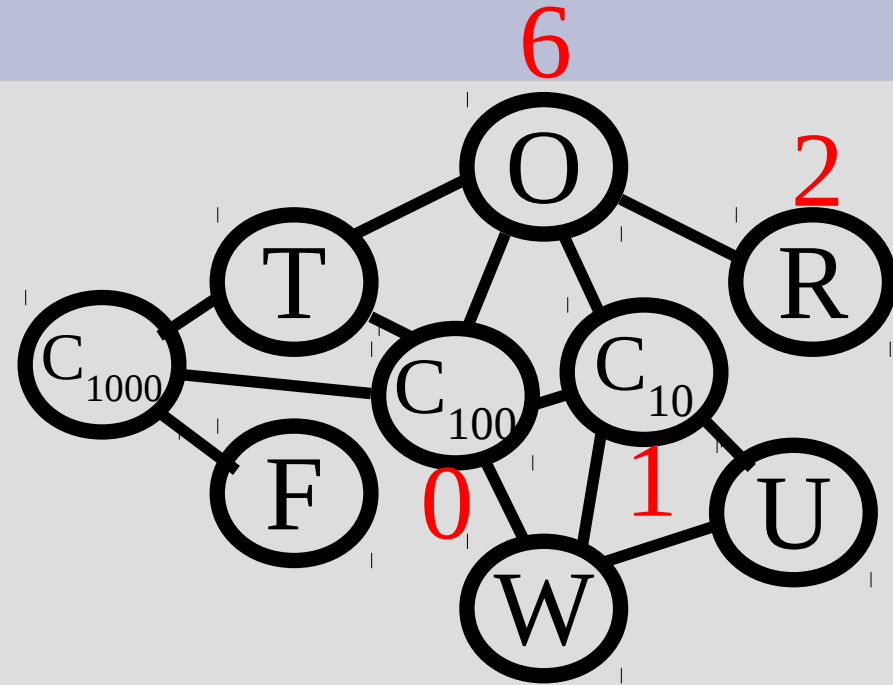
Constraints:  $R \neq \text{others}$

Domains:

$C_{1000} = \{0, 1\}$ ,  $T = \{3, 8\}$ ,

$F = \{1, 3, 4, 5, 7, 8, 9\}$

$W = \{0, 1, 3, 4\}$ ,  $U = \{1, 3, 5, 7, 9\}$





# Example

Tie for smallest domain (T&C<sub>1000</sub>)

T has more connections:

Pick T=3

Constraints:  $C_{1000} = 2T + 0$ ,

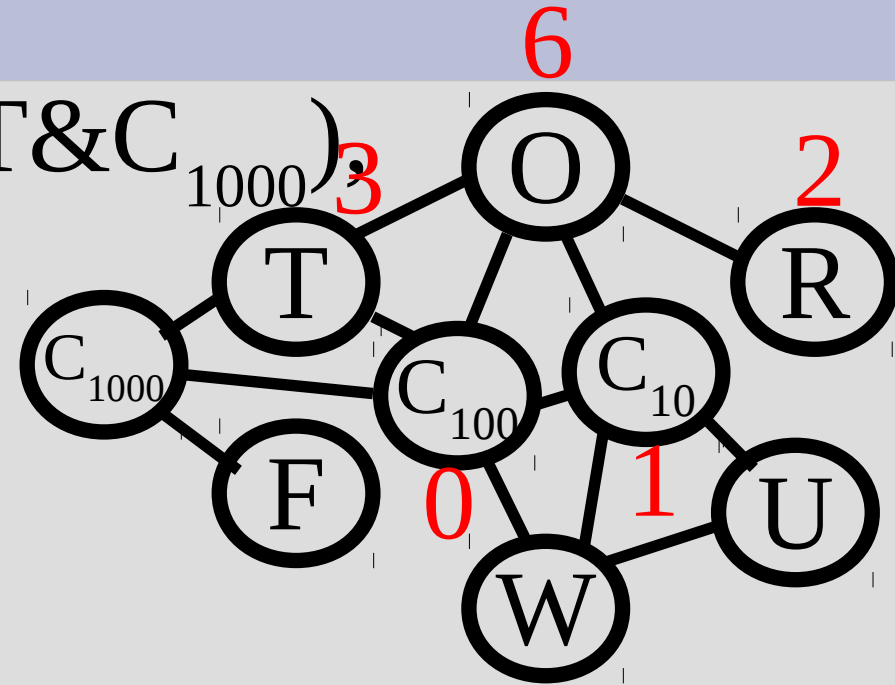
T ≠ others

Domains:

$C_{1000} = \{0\}$ ,

$F = \{1, 4, 5, 7, 8, 9\}$

$W = \{0, 1, 4\}$ ,  $U = \{1, 5, 7, 9\}$



# Example

$C_{1000}$  has smallest domain

Pick  $C_{1000} = 0$

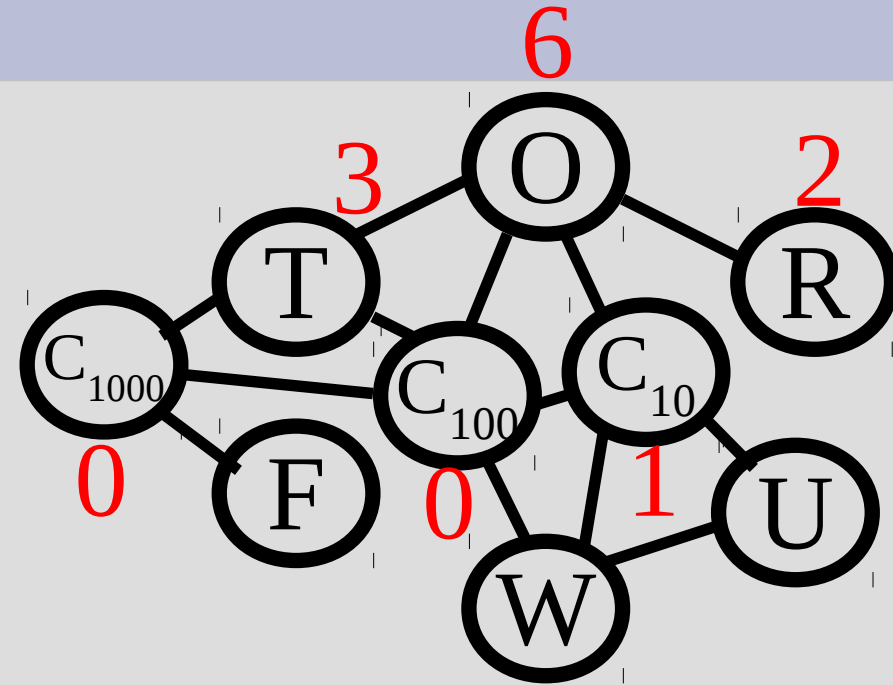
Constraints:  $C_{1000} = F$ ,

Domains:

$C_{1000} = \{0\}$ ,

$F = \{\}$  ← Invalid

$W = \{0, 1, 4\}$ ,  $U = \{1, 5, 7, 9\}$



# Example

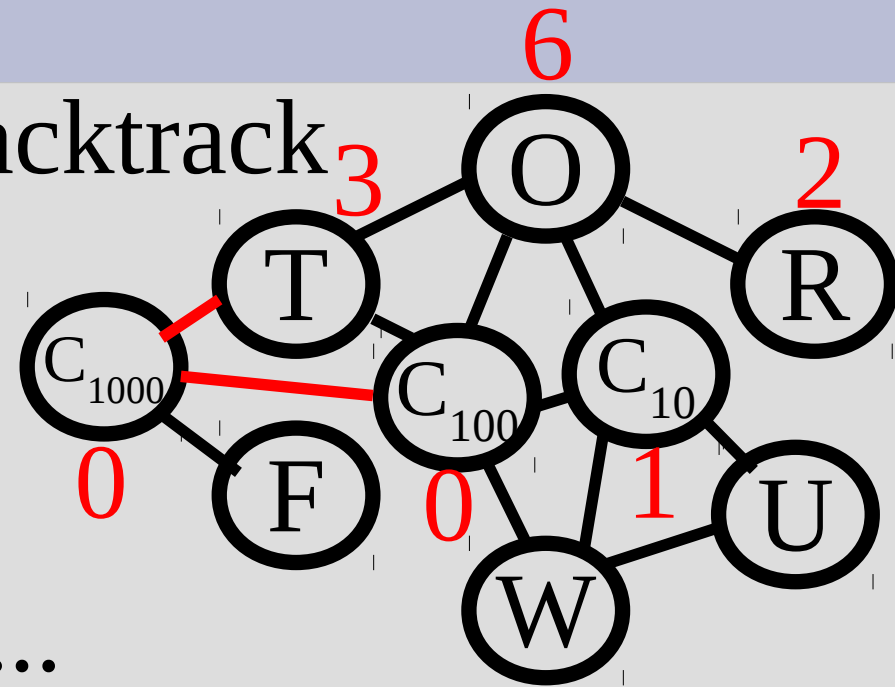
Reached a dead end, so backtrack

Variables constraining

$C_{1000}$  are T and  $C_{100}$

(this is visually apparent  
by the edges on the graph...

though  $\neq$  conditions are missing)



Most recent is T, so we go there...

(When we assigned R, T's domain was {3,8})

# Example

Pick  $T=8$

Constraints:  $C_{1000} = 2T + 0$ ,

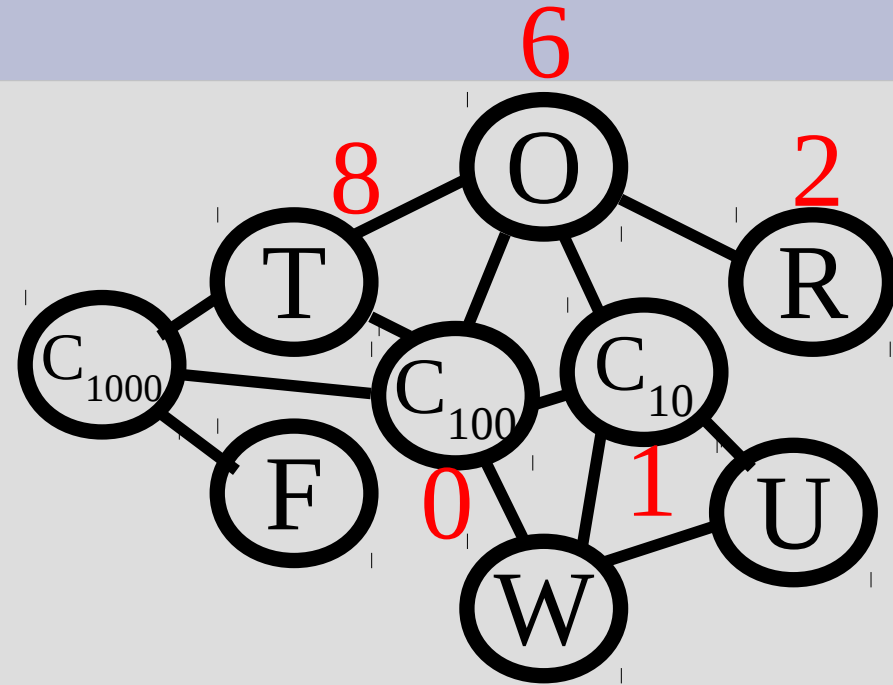
$T \neq \text{others}$

Domains:

$C_{1000} = \{1\}$ ,

$F = \{1, 3, 4, 5, 7, 9\}$

$W = \{0, 1, 3, 4\}$ ,  $U = \{1, 3, 5, 7, 9\}$



# Example

Smallest domain is  $C_{1000}$

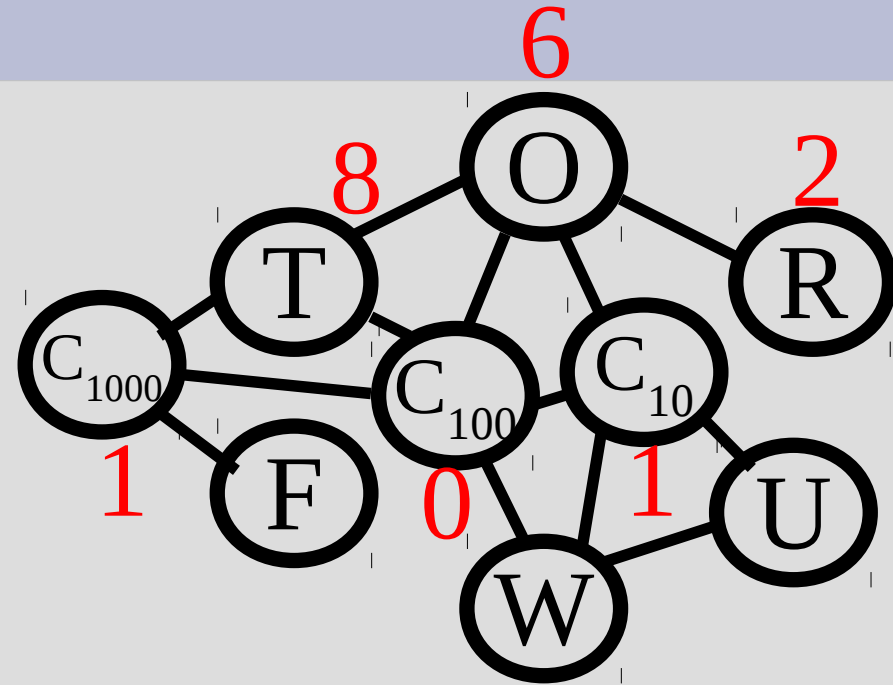
Pick  $C_{1000} = 1$

Constraints:  $C_{1000} = F$ ,

Domains:

$F = \{1\}$

$W = \{0, 1, 3, 4\}$ ,  $U = \{1, 3, 5, 7, 9\}$



# Example

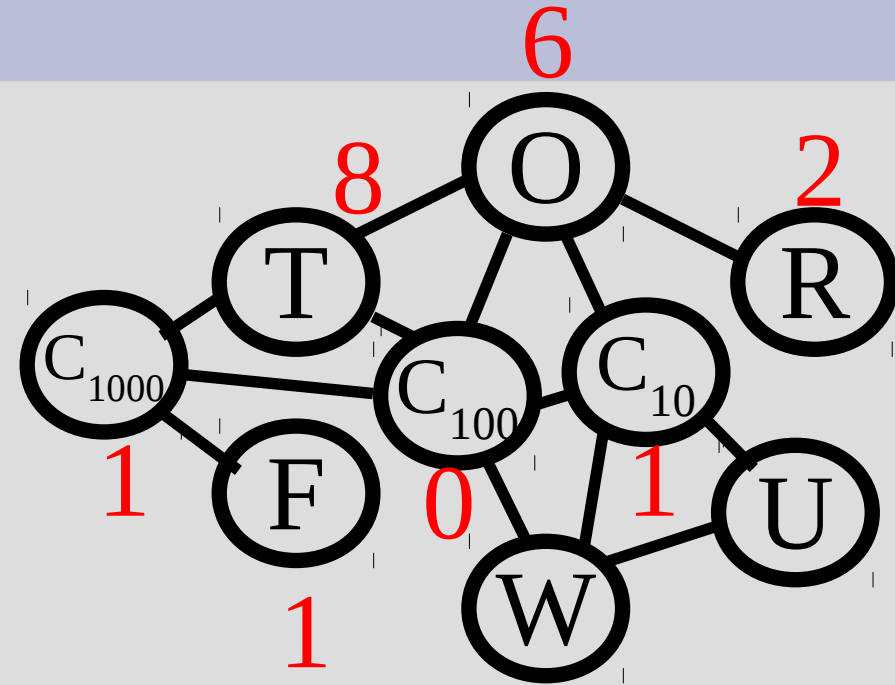
Smallest domain is F

Pick  $F=1$

Constraints:  $F \neq \text{others}$

Domains:

$W = \{0, 3, 4\}$ ,  $U = \{3, 5, 7, 9\}$



# Example

Smallest domain is W

Pick  $W=0$  from  $\{0,3,4\}$

Constraints:  $W \neq U$ ,

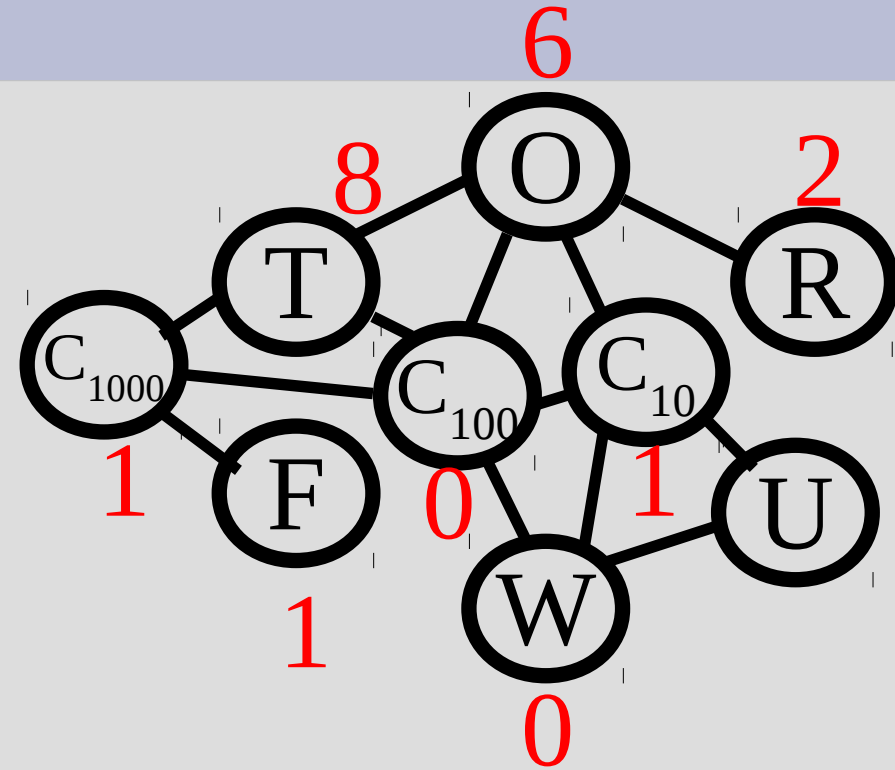
$U = 2W + 1 \pmod{10}$

Domains:

Old  $U = \{3, 5, 7, 9\}$

... U needs to be 1, which is not here so

$U = \{\}$  ← Invalid



# Example

Pick  $W=3$  from  $\{0,3,4\}$

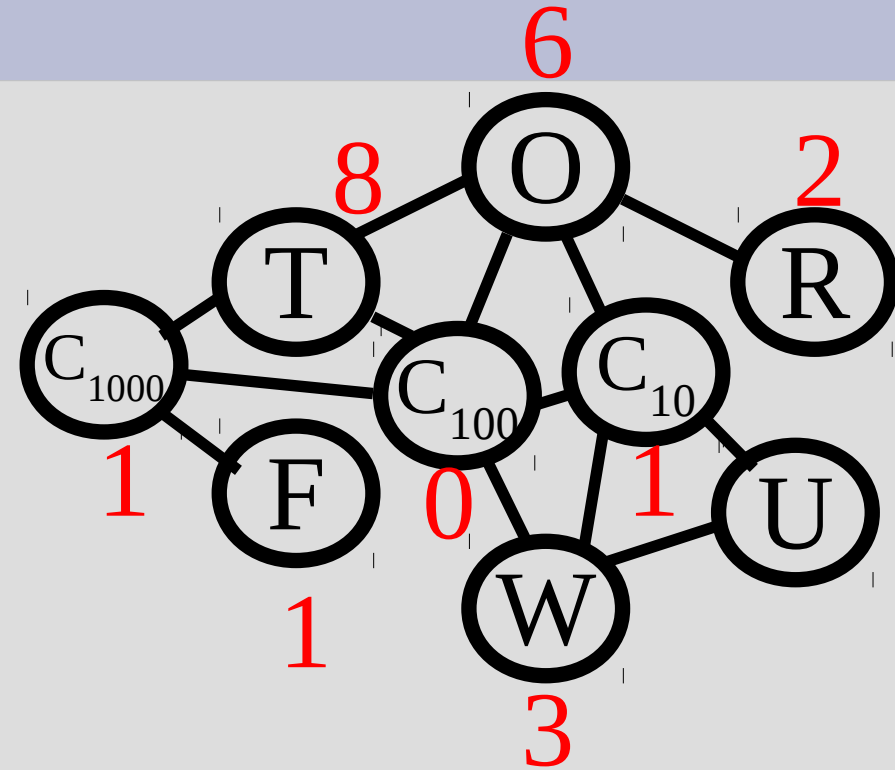
Constraints:  $W \neq U$ ,  
 $U = 2W + 1 \pmod{10}$

Domains:

Old  $U = \{3, 5, 7, 9\}$

...  $U$  needs to be 7

$U = \{7\}$





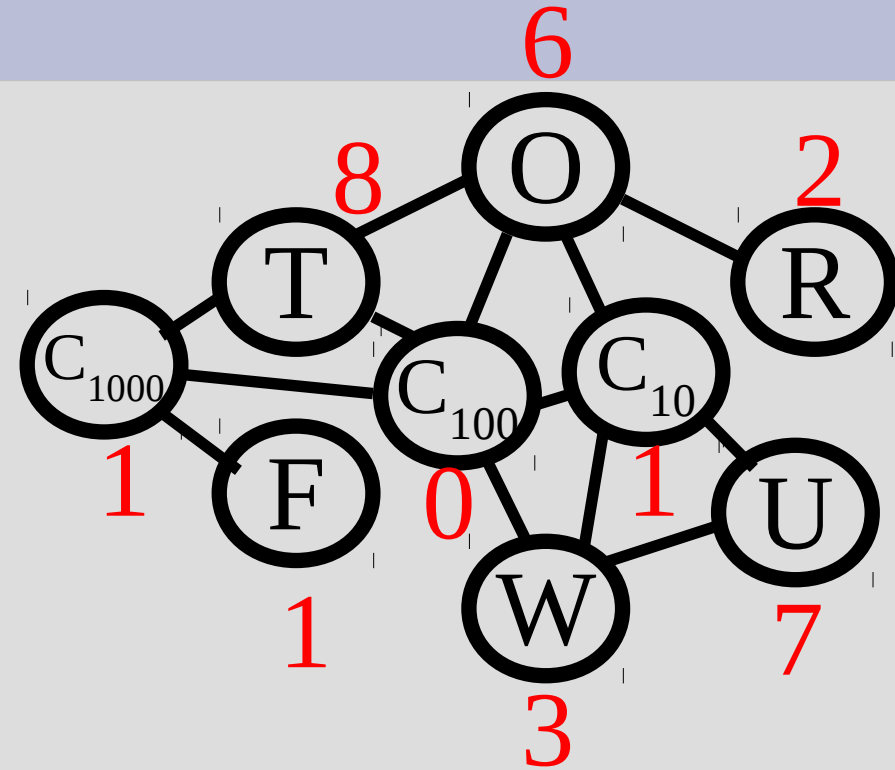
# Example

Only U left... so  $U=7$

We found a solution:

$T=8$	$F=1$
$W=3$	$O=6$ (as on left)
$O=6$	$U=7$
	$R=2$

TWO	836
+TWO	+836
=FOUR	=1672



# Example

You try for:

$$\begin{array}{r} \text{S E N D} \\ +\text{M O R E} \\ =\text{M O N E Y} \end{array}$$

# Complete-state CSP

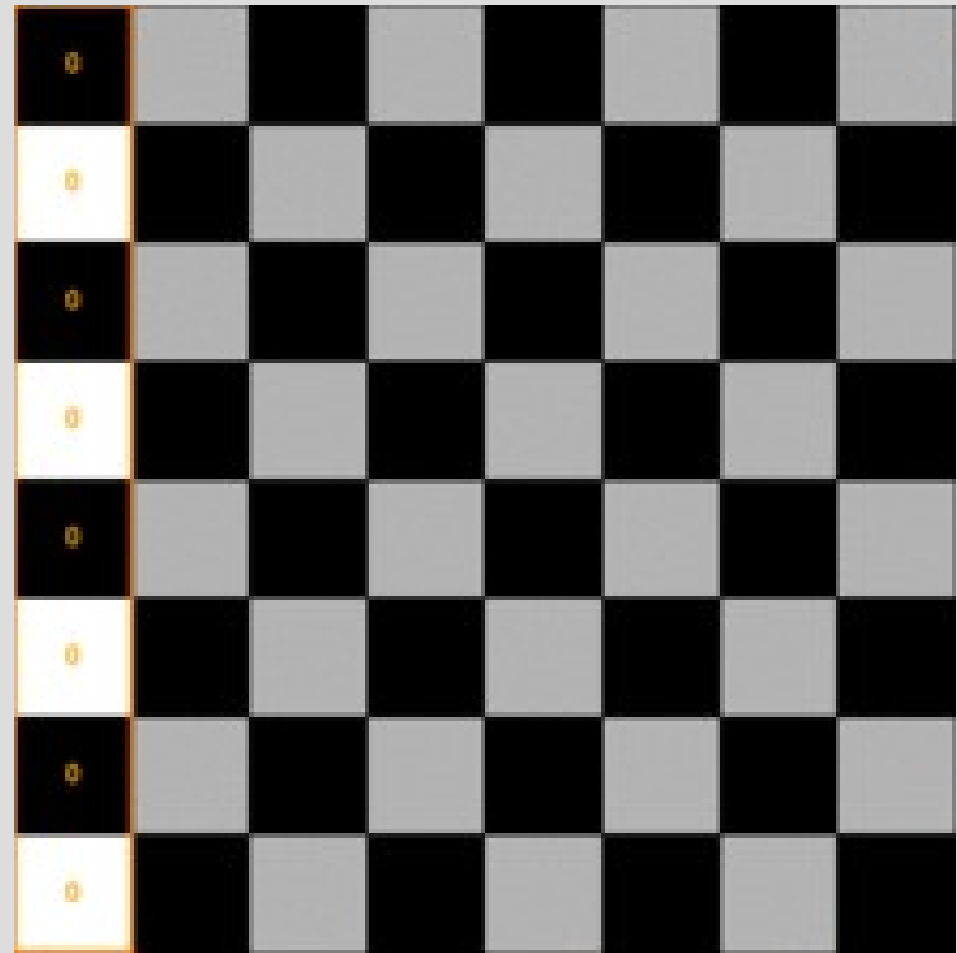
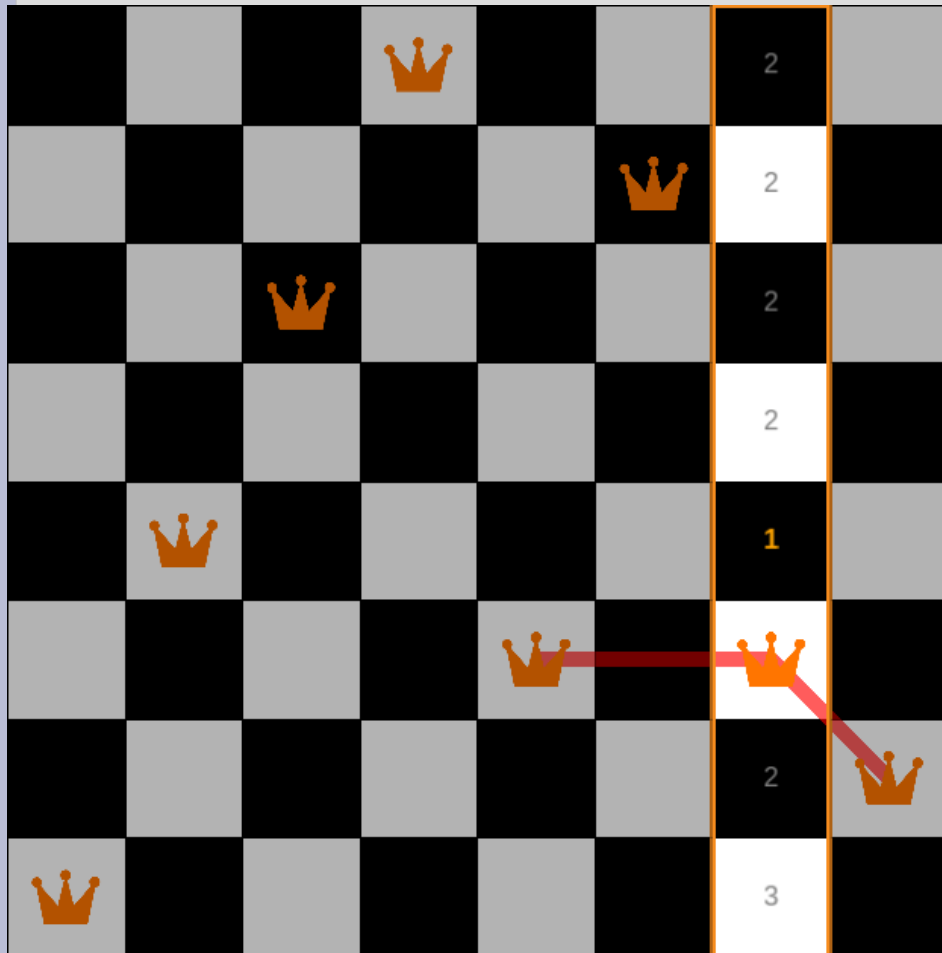
So far we have been looking at incremental search (adding one value at a time)

Complete-state searches are also possible in CSPs and can be quite effective

A popular method is to find the min-conflict, where you pick a random variable and update the choice to be one that creates the least number of conflicts

# Complete-state CSP

This works incredibly well for the n-queens problem (partially due to dense solutions)



# Complete-state CSP

As with most local searches (hill-climbing), this method has issues with plateaus

This can be mitigated by avoiding recently assigned variables (forces more exploration)

You can also apply weights to constraints and update them based on how often they are violated (to estimate which constraints are more restrictive than others)

# Complete-state CSP

Local search does not have “locally optimal” solution our general search does

As we have a CSP, the “local optimal” may occur, but if it is not 0 then we know we are not satisfied (unless we searched the whole space and find no goal)

This is almost as if we had an almost perfect heuristic built in to the problem!