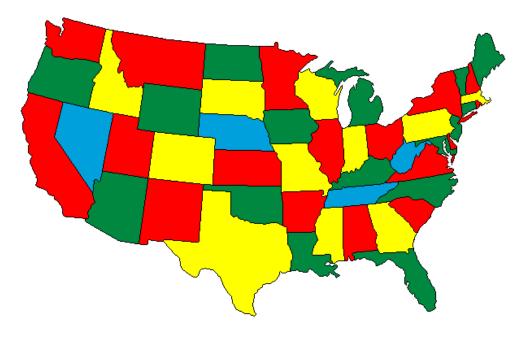
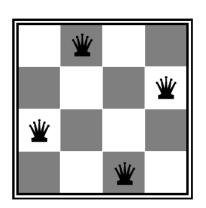
Constraint Satisfaction Problems





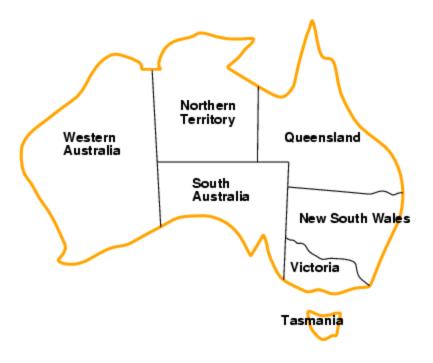
8			4		6			7
						4		
	1					6	5	
5		9		3		7	8	
				7				
	4	8		2		1		3
	5	2					9	
		1						
3			9		2			5

Dr. Shikha Mehta

Constraint satisfaction problems (CSPs)

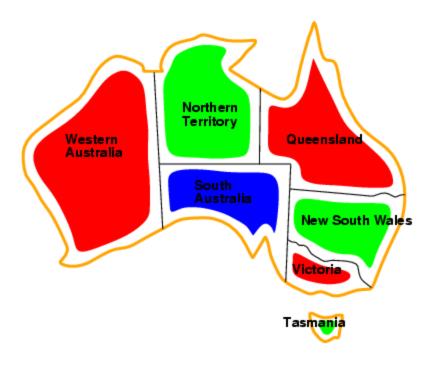
- Definition:
 - State is defined by variables X_i with values from domain D_i
 - Goal test is a set of constraints specifying allowable combinations of values for subsets of variables
 - Solution is a complete, consistent assignment
- How does this compare to the "generic" tree search formulation?
 - A more structured representation for states, expressed in a formal representation language
 - Allows useful general-purpose algorithms with more power than standard search algorithms

Example: Map Coloring



- Variables: WA, NT, Q, NSW, V, SA, T
- Domains: {red, green, blue}
- Constraints: adjacent regions must have different colors e.g., WA ≠ NT, or (WA, NT) in {(red, green), (red, blue), (green, red), (green, blue), (blue, red), (blue, green)}

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

Example: N-Queens

- Variables: X_{ij}
- **Domains:** {0, 1}
- Constraints:

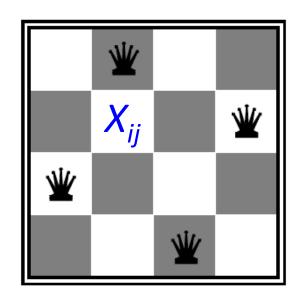
$$\Sigma_{i,j} X_{ij} = N$$

$$(X_{ij}, X_{ik}) \in \{(0, 0), (0, 1), (1, 0)\}$$

$$(X_{ij}, X_{kj}) \in \{(0, 0), (0, 1), (1, 0)\}$$

$$(X_{ij}, X_{i+k, j+k}) \in \{(0, 0), (0, 1), (1, 0)\}$$

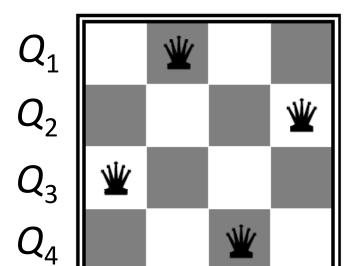
$$(X_{ij}, X_{i+k, j-k}) \in \{(0, 0), (0, 1), (1, 0)\}$$



N-Queens: Alternative formulation

- Variables: Q_i
- **Domains:** {1, ..., *N*}
- Constraints:

 $\forall i, j \text{ non-threatening } (Q_i, Q_j)$



Example: Cryptarithmetic

Variables: T, W, O, F, U, R

$$X_1, X_2$$

- **Domains**: {0, 1, 2, ..., 9}
- Constraints:

$$O + O = R + 10 * X_1$$

$$W + W + X_1 = U + 10 * X_2$$

$$T + T + X_2 = O + 10 * F$$

$$T \neq 0, F \neq 0$$

Example: Sudoku

- Variables: X_{ij}
- **Domains:** {1, 2, ..., 9}
- Constraints:

Alldiff(X_{ii} in the same *unit*)

					8			4
	8	4		1	6			
		- 0	5			1	96 10	
1		3	8			9		
6		8		Xij		4		3
	- 5	2		83 9	9	5		1
		7	Г		2	Г		
			7	8		2	6	
2			3					

Real-world CSPs

- Assignment problems
 - e.g., who teaches what class
- Timetable problems
 - e.g., which class is offered when and where?
- Transportation scheduling
- Factory scheduling

More examples of CSPs: http://www.csplib.org/

Standard search formulation (incremental)

States:

Values assigned so far

Initial state:

– The empty assignment { }

Successor function:

- Choose any unassigned variable and assign to it a value that does not violate any constraints
 - Fail if no legal assignments

Goal test:

The current assignment is complete and satisfies all constraints

Standard search formulation (incremental)

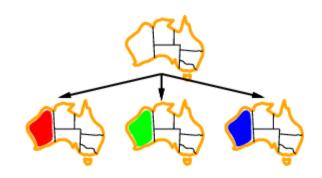
- What is the depth of any solution (assuming *n* variables)?
 n This is the good news
- Given that there are m possible values for any variable, how many paths are there in the search tree?
 - $n! \cdot m^n$ This is the bad news
- How can we reduce the branching factor?

Backtracking search

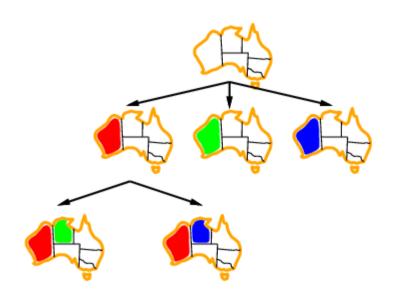
- In CSP's, variable assignments are commutative
 - For example, [WA = red then NT = green] is the same as [NT = green then WA = red]
- We only need to consider assignments to a single variable at each level (i.e., we fix the order of assignments)
 - Then there are only mⁿ leaves
- Depth-first search for CSPs with single-variable assignments is called backtracking search



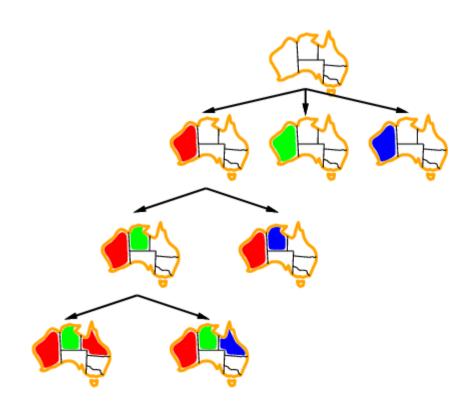














Backtracking search algorithm

```
function Recursive-Backtracking (assignment, csp)

if assignment is complete then return assignment

var \leftarrow \text{Select-Unassigned-Variable}(\text{Variables}[csp], assignment, csp)

for each value in Order-Domain-Values (var, assignment, csp)

if value is consistent with assignment given Constraints [csp]

add \{var = value\} to assignment

result \leftarrow \text{Recursive-Backtracking}(assignment, csp)

if result \neq failure then return result

remove \{var = value\} from assignment

return failure
```

- Improving backtracking efficiency:
 - Which variable should be assigned next?
 - In what order should its values be tried?
 - Can we detect inevitable failure early?

Most constrained variable:

- Choose the variable with the fewest legal values
- A.k.a. minimum remaining values (MRV) heuristic

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Most constraining variable:

- Choose the variable that imposes the most constraints on the remaining variables
- Tie-breaker among most constrained variables

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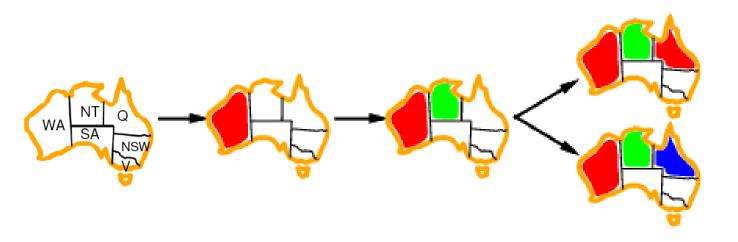
Given a variable, in which order should its values be tried?

- Choose the least constraining value:
 - The value that rules out the fewest values in the remaining variables

Given a variable, in which order should its values be tried?

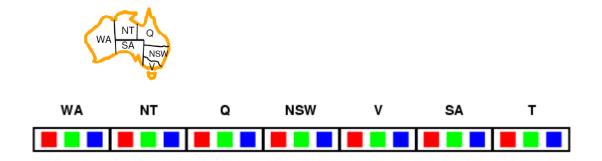
- Choose the least constraining value:
 - The value that rules out the fewest values in the remaining variables

Which assignment for Q should we choose?

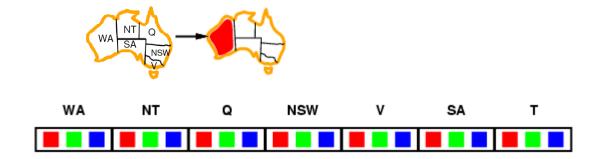


- Keep track of remaining legal values for unassigned variables
- Terminate search when any variable has no legal values

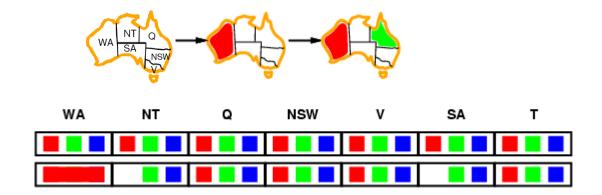
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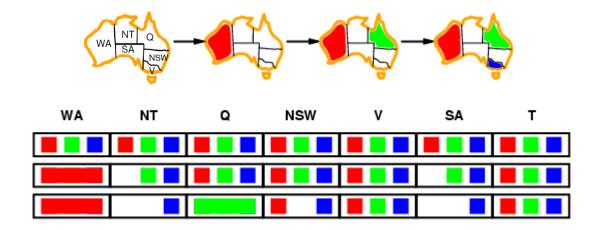
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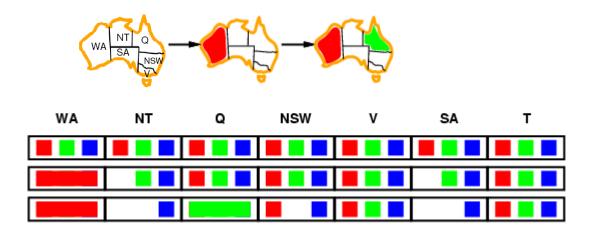


- Keep track of remaining legal values for unassigned variables
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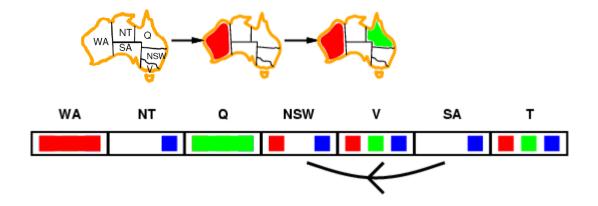
Constraint propagation

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

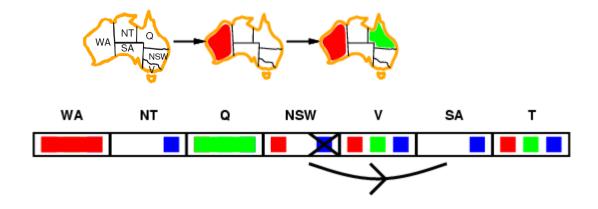


- NT and SA cannot both be blue!
- Constraint propagation repeatedly enforces constraints locally

- Simplest form of propagation makes each pair of variables consistent:
 - $-X \rightarrow Y$ is consistent iff for every value of X there is some allowed value of Y
 - When checking $X \rightarrow Y$, throw out any values of X for which there isn't an allowed value of Y

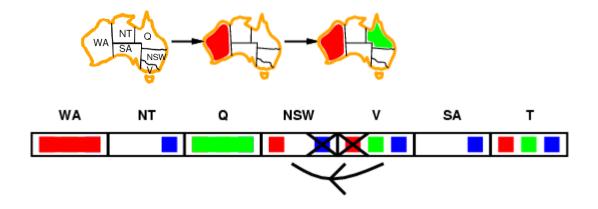


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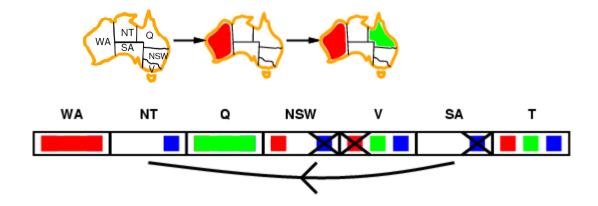
• If X loses a value, all pairs $Z \rightarrow X$ need to be rechecked

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- Arc consistency detects failure earlier than forward checking
- Can be run as a preprocessor or after each assignment

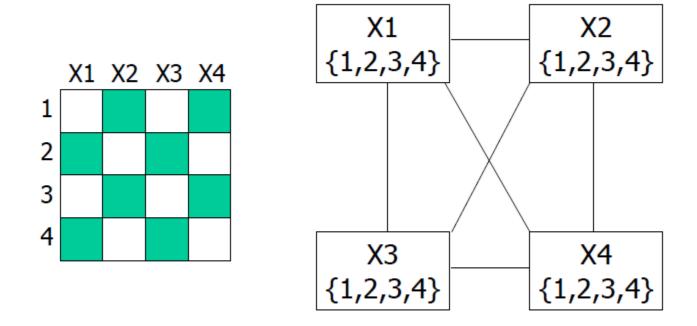
Arc consistency algorithm AC-3

```
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 (X_i, X_j) \leftarrow \text{Remove-First}(queue) if \text{Remove-Inconsistent-Values}(X_i, X_j) then for each X_k in \text{Neighbors}[X_i] do add (X_k, X_i) to queue function \text{Remove-Inconsistent-Values}(X_i, X_j) returns true iff succeeds
```

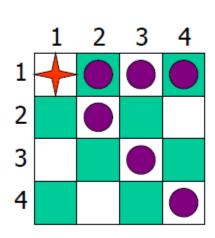
function AC-3(csp) returns the CSP, possibly with reduced domains

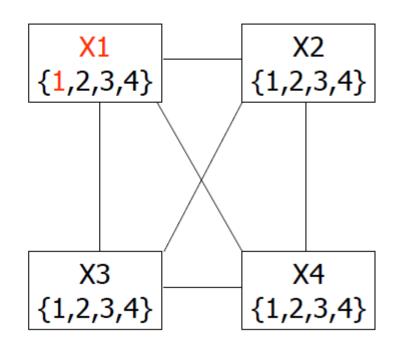
 $removed \leftarrow false$ for each x in $Domain[X_i]$ if no value y in $Domain[X_j]$ allows (x,y) to satisfy the constraint $X_i \leftrightarrow X_j$ then delete x from $Domain[X_i]$; $removed \leftarrow true$ return removed

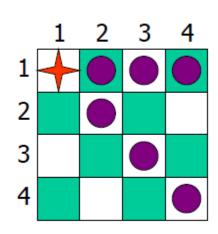
4 Queens problem

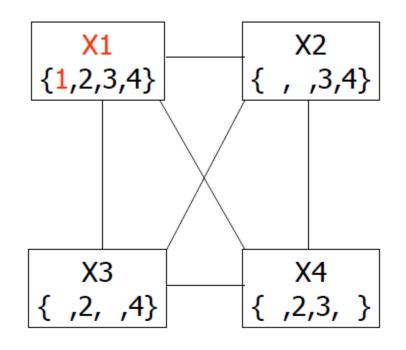


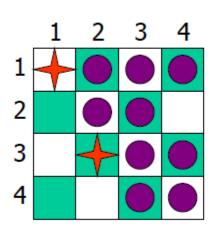
(From Bonnie Dorr, U of Md, CMSC 421)

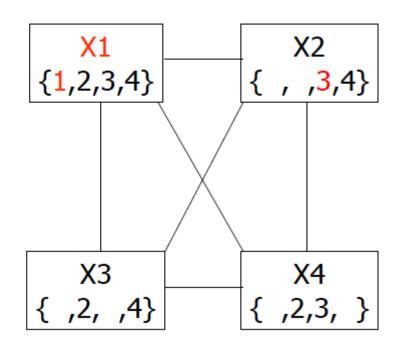


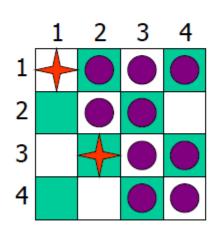


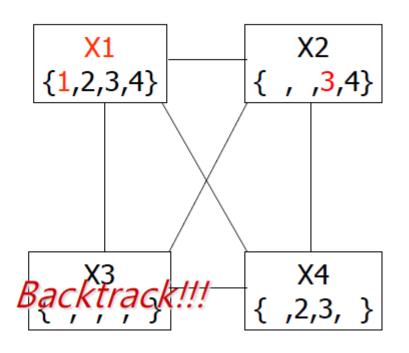




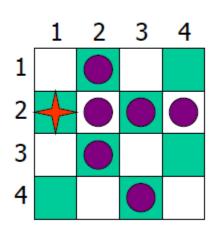


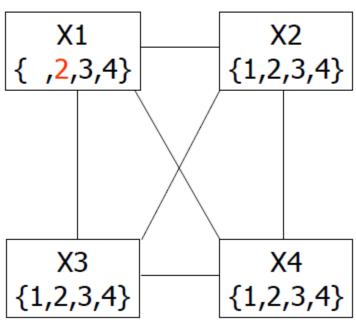


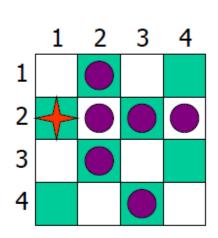


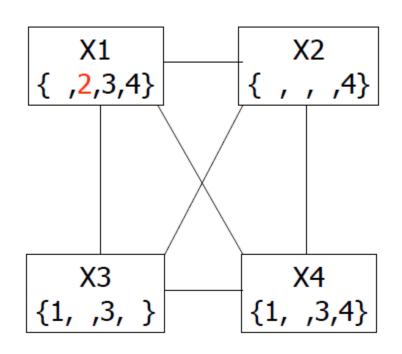


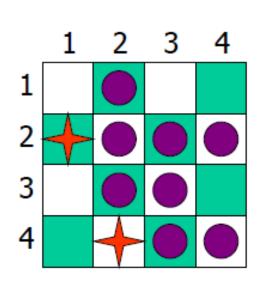
Picking up a little later after two steps of backtracking....

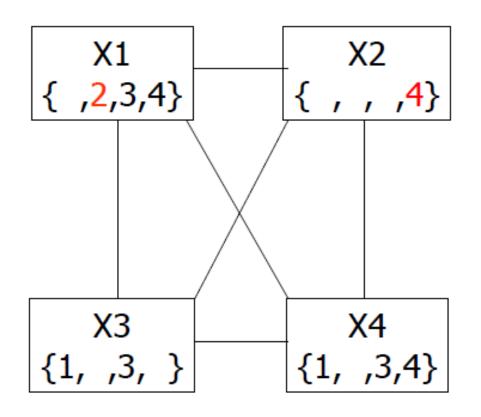


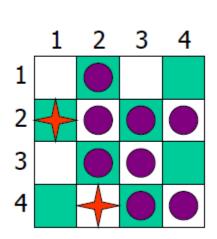


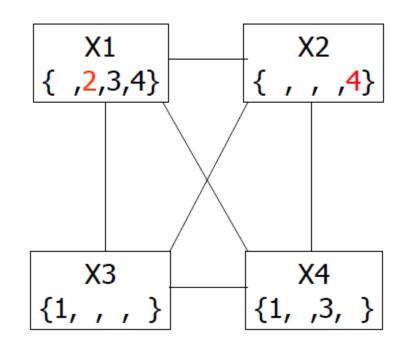


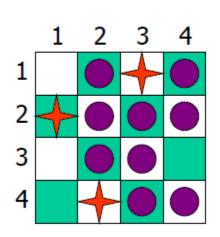


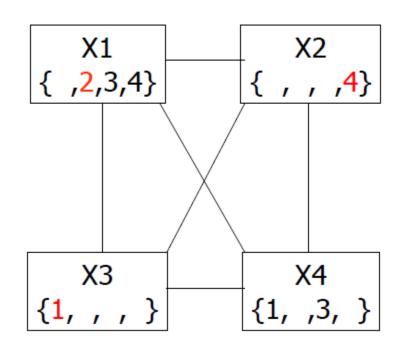


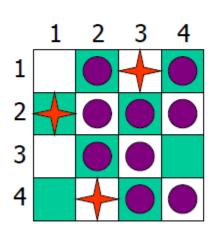


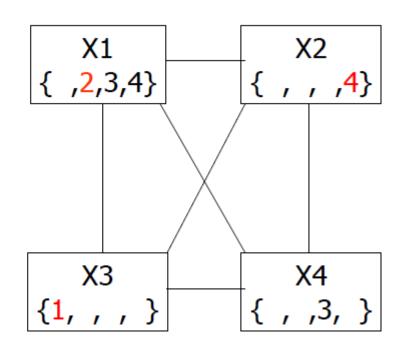


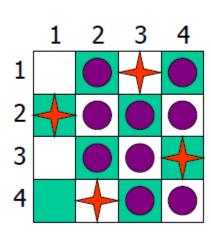


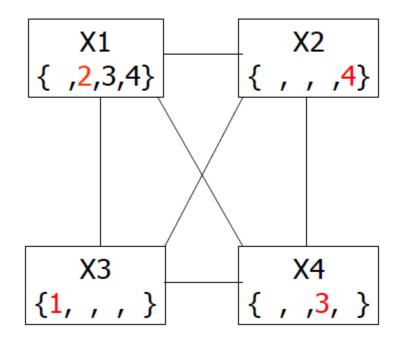












Exercise

CROSS + ROADS

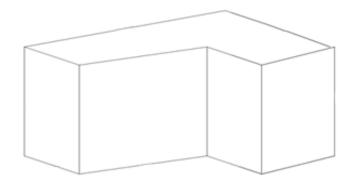
DANGER

Summary

- CSPs are a special kind of search problem:
 - States defined by values of a fixed set of variables
 - Goal test defined by constraints on variable values
- Backtracking = depth-first search where successor states are generated by considering assignments to a single variable
 - Variable ordering and value selection heuristics can help significantly
 - Forward checking prevents assignments that guarantee later failure
 - Constraint propagation (e.g., arc consistency) does additional work to constrain values and detect inconsistencies
- Local search can be done by iterative min-conflicts

CSP in computer vision: Line drawing interpretation

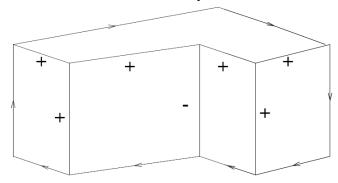
An example polyhedron:



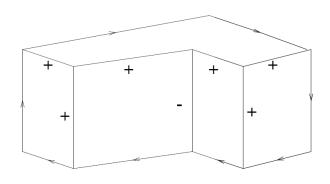
Variables: edges

Domains: $+, -, \rightarrow, \leftarrow$

Desired output:



CSP in computer vision: Line drawing interpretation

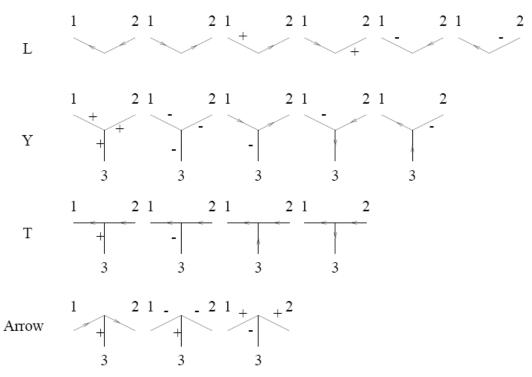


Four vertex types:

L Y



Constraints imposed by each vertex type:



CSP in computer vision: 4D Cities

- 1. When was each photograph taken?
- 2. When did each building first appear?
- 3. When was each building removed?

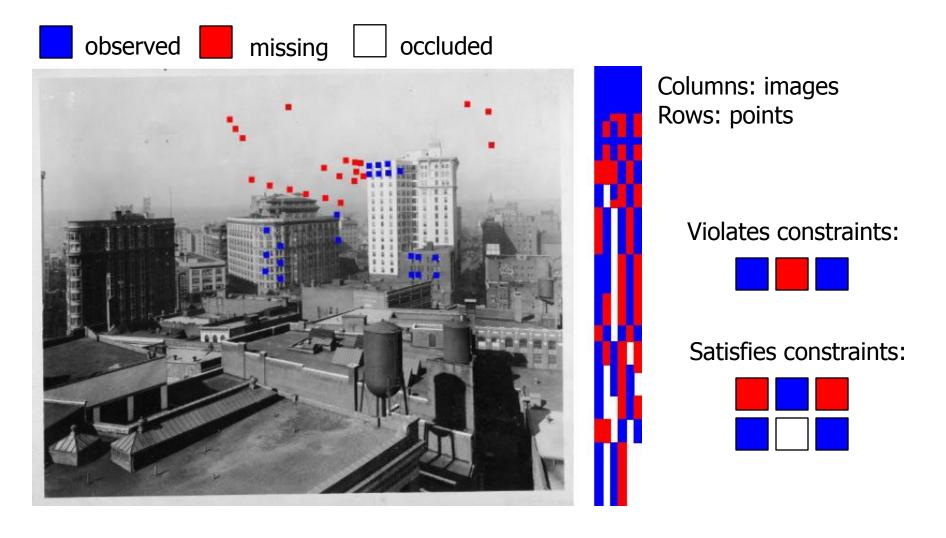
Set of Photographs:



G. Schindler, F. Dellaert, and S.B. Kang, <u>Inferring Temporal Order of Images From 3D Structure</u>, IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2007.

http://www.cc.gatech.edu/~phlosoft/

CSP in computer vision: 4D Cities



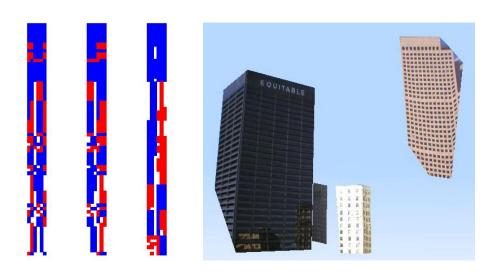
Goal: reorder images (columns) to have as few violations as possible

CSP in computer vision: 4D Cities

- Goal: reorder images (columns) to have as few violations as possible
- Local search: start with random ordering of columns, swap columns or groups of columns to reduce the number of conflicts



 Can also reorder the rows to group together points that appear and disappear at the same time – that gives you buildings



CSPs and NP-completeness

- The satisfiability (SAT) problem:
 - Given a Boolean formula, find out whether there exists an assignment of the variables that makes it evaluate to true, e.g.:

$$(X_1 \vee \overline{X}_7 \vee X_{13}) \wedge (\overline{X}_2 \vee X_{12} \vee X_{25}) \wedge \dots$$

- SAT is <u>NP-complete</u> (Cook, 1971)
 - It's in NP and every other problem in NP can be reduced to it
 - So are graph coloring, n-puzzle, generalized sudoku, and the traveling salesman problem