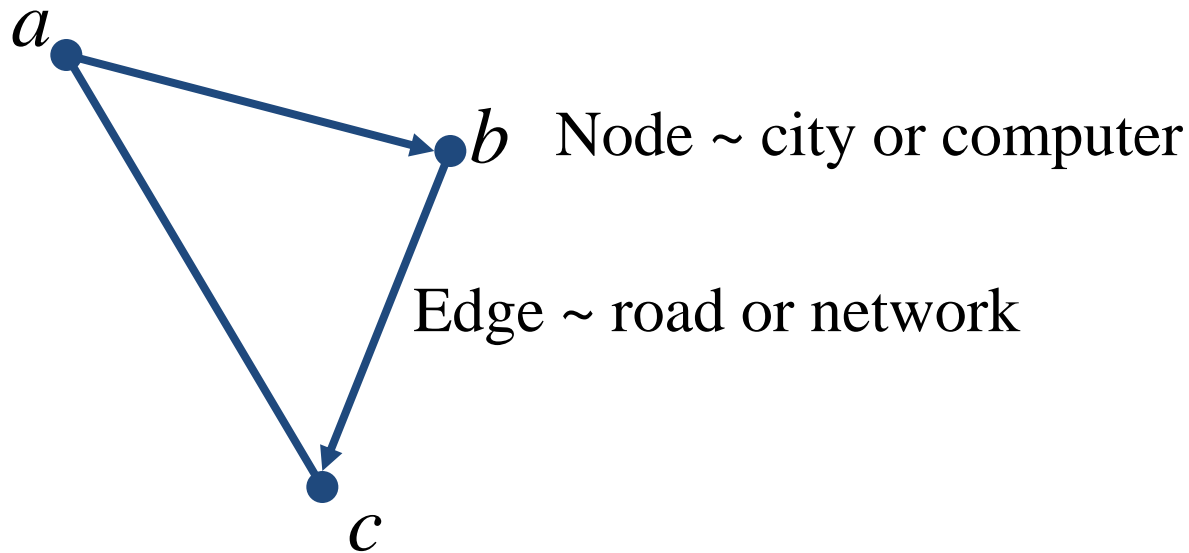


ADVANCED DATA STRUCTURES AND ALGORITHMS

Optimization Problems-Graph Search Algorithms

- Generic Search
- Breadth First Search
- Dijkstra's Shortest Paths Algorithm
- Depth First Search
- Linear Order

Graph



Undirected or Directed

A surprisingly large number of problems in computer science can be expressed as a graph theory problem.

Generic Search-Graph Search

Specification: Reachability-from-single-source s

- <preCond>:

The input is a graph G
(either directed or undirected)
and a source node s .

- <postCond>:

Output all the nodes u that are
reachable by a path in G from s .

Graph Search

Basic Steps:



- Suppose you know that u is reachable from s & there is an edge from u to v
- You know that v is reachable from s
- Build up a set of reachable nodes.

algorithm *Search* (G, s)

(pre-cond): G is a (directed or undirected) graph and s is one of its nodes.

(post-cond): The output consists of all the nodes u that are reachable by a path in G from s .

begin

foundHandled = \emptyset

foundNotHandled = $\{s\}$

 loop

(loop-invariant): See above.

 exit when *foundNotHandled* = \emptyset

 let u be some node from *foundNotHandled*

 for each v connected to u

 if v has not previously been found then

 add v to *foundNotHandled*

 end if

 end for

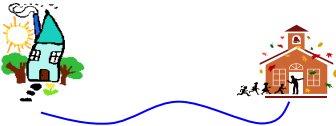

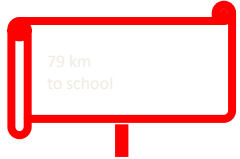
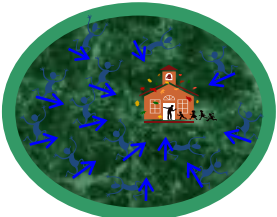
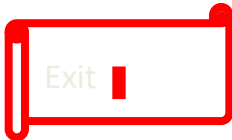
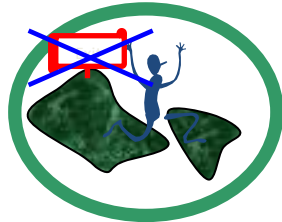
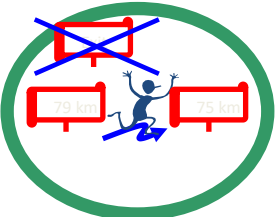
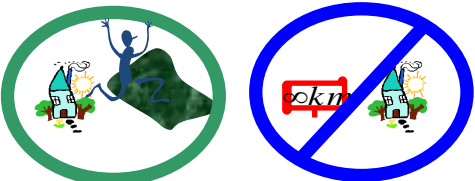
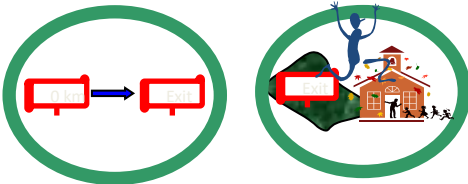
 move u from *foundNotHandled* to *foundHandled*

 end loop

 return *foundHandled*

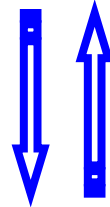
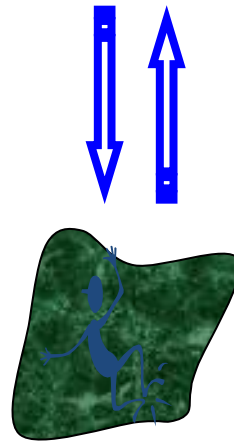
end algorithm

Graph Search

| | | |
|---|--|---|
| <p>Define Problem</p>  | <p>Define Loop Invariants</p>  | <p>Define Measure of Progress</p>  |
| <p>Define Step</p>  | <p>Define Exit Condition</p>  | <p>Maintain Loop Inv</p>  |
| <p>Make Progress</p>  | <p>Initial Conditions</p>  | <p>Ending</p>  |

Breadth First Search(BFS)

<preCond> & <postCond>



Algorithm

BFS

What order are the nodes found?

So far, the nodes have been found in order of length from s .

<postCond>: Finds a shortest path from s
to each node v and its length.

To prove path is shortest:

Prove there is a path of this length.

Prove there are no shorter paths.



Give a path
(witness)

BFS

Basic Steps:



- The shortest path to u has length d & there is an edge from u to v
- There is a path to v with length $d+1$.

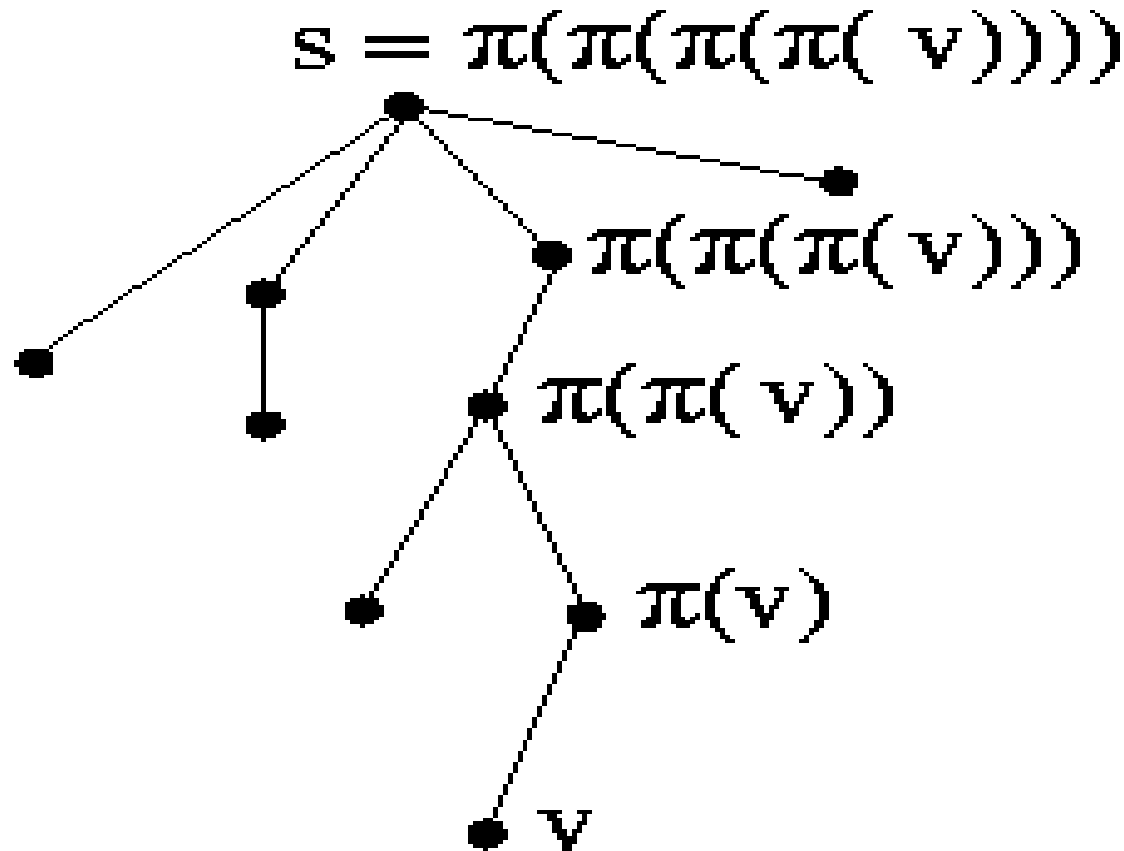
BFS

- What order are the nodes found?
- So far, the nodes have been found in order of length from s .
- $\langle \text{postCond} \rangle$:
- Finds a shortest path from s to each node v and its length.
- Prove there are no shorter paths.
- When we find v , we know there isn't a shorter path to it because ?
- Otherwise, we would have found it already.

BFS

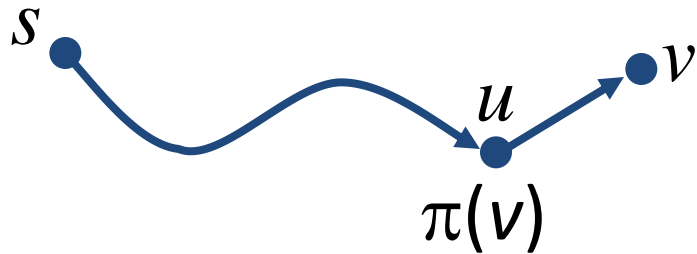
Data structure for storing tree:

- For each node v , store $\pi(v)$ to be parent of v .



BFS

Basic Steps:



Path to u & there is an edge from u to v

Parent of v is $\pi(v) = u.$

algorithm *ShortestPath* (G, s)

(pre-cond): G is a (directed or undirected) graph and s is one of its nodes.

(post-cond): π specifies a shortest path from s to each node of G and d specifies their lengths.

begin

$foundHandled = \emptyset$

$foundNotHandled = \{s\}$

$d(s) = 0, \pi(s) = \epsilon$

 loop

(loop-invariant): See above.

 exit when $foundNotHandled = \emptyset$

 let u be the node in the front of the queue $foundNotHandled$

 for each v connected to u

 if v has not previously been found then

 add v to $foundNotHandled$

$d(v) = d(u) + 1$

$\pi(v) = u$

 end if

 end for

 move u from $foundNotHandled$ to $foundHandled$

 end loop

 (for unfound $v, d(v) = \infty$)

 return $\langle d, \pi \rangle$

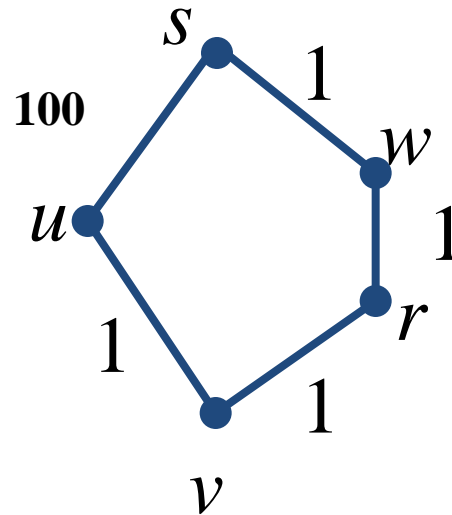
end algorithm

Dijkstra's Shortest-Weighted Paths

- Specification: Dijkstra's Shortest-Weighted Paths
- Reachability-from-single-source s
 - <preCond>:
The input is a graph G
(either directed or undirected)
with positive edge weights
and a source node s .
 - <postCond>:
Finds a shortest weighted path from s
to each node v and its length.

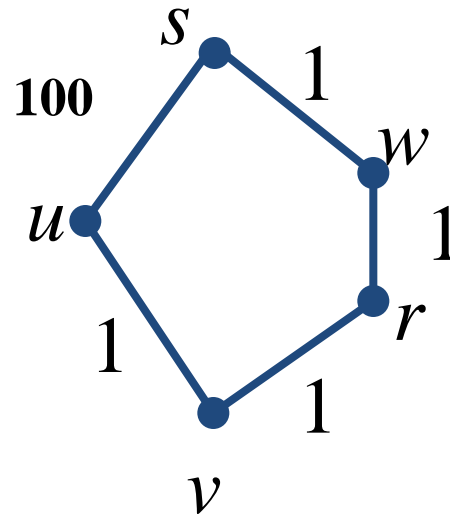
Dijkstra's Shortest-Weighted Paths

- Length of shortest path from s to u ?



BFS

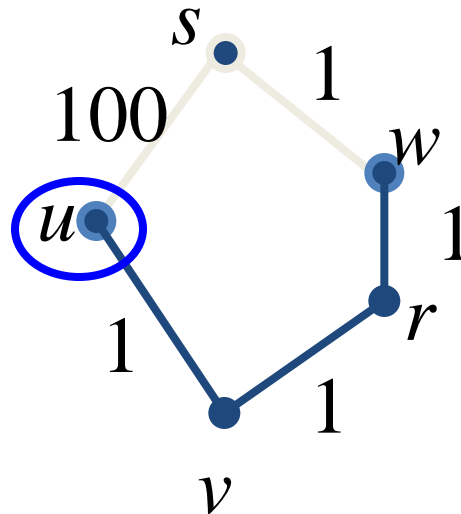
- So far, the nodes have been found in order of length from s .
- Is the same true for Dijkstra's Algorithm?



Which node is found first?

BFS

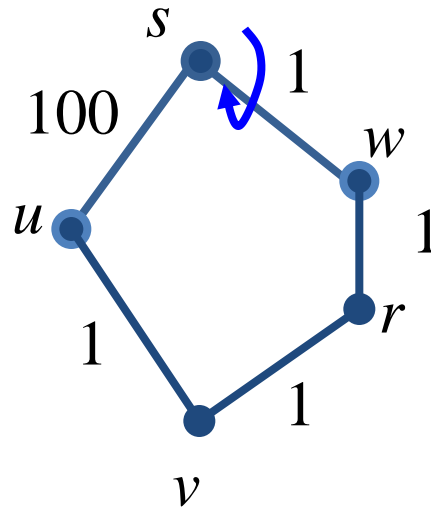
- So far, the nodes have been found in order of length from s .
- Is the same true for Dijkstra's Algorithm?



- Which node is found first?
- It has the longest path from s .

Dijkstra's

- So far, the nodes have been found in order of length from s . handled
- In what order do we handle the foundNotHandled nodes?



Handle node that “seems” to be closest to s .

Dijkstra's

- So far, the nodes have been handled in order of length from s .

<postCond>:

- Finds a shortest weighted path from s to each node v and its length.
- To prove path is shortest:
- Prove there is a path of this length.
- Prove there are no shorter paths.
- Give a path (witness)

Dijkstra's

- So far, the nodes have been handled in order of length from s .
- `<postCond>`:
- Finds a shortest weighted path from s to each node v and its length.
- To prove path is shortest:
- Prove there is a path of this length.
- Prove there are no shorter paths.
- When we handle v , we know there isn't a shorter path to it because?

Dijkstra's

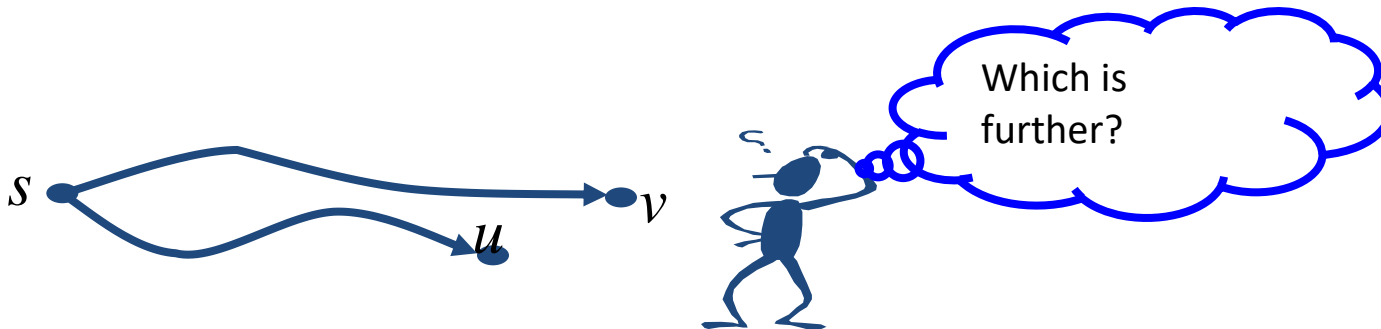
Basic Steps:



Handle node that “seems” to be closest to s .

Need to keep approximate shortest distances.

- Path that we have “seen so far” will be called handled paths.
- Let $d(v)$ the length of the shortest such path to v .



Dijkstra's

Basic Steps:



Updating $d(u)$.

The shortest of handled paths to v has length $d(v)$



- The shortest of handled paths to u has length $d(u)$ & there is an edge from u to v
- The shortest known path to v has length $\min(d(v), d(u)+w_{<u,v> })$.

algorithm *ShortestWeightedPath*(G, s)

<pre-cond>: G is a weighted (directed or undirected) graph and s is one of its nodes.

<post-cond>: π specifies a shortest weighted path from s to each node of G and d specifies their lengths.

begin

$d(s) = 0, \pi(s) = \epsilon$

 for other $v, d(v) = \infty$ and $\pi(v) = nil$

 • $handled = \emptyset$

 • $notHandled$ = priority queue containing all nodes. Priorities given by $d(v)$.

 loop

<loop-invariant>: See above.

 exit when $notHandled = \emptyset$

 let u be a node from $notHandled$ with smallest $d(u)$

 for each v connected to u

$foundPathLength = d(u) + w_{(u,v)}$

 if $d(v) > foundPathLength$ then

$d(v) = foundPathLength$

 (update the $notHandled$ priority queue)

$\pi(v) = u$

 end if

 end for

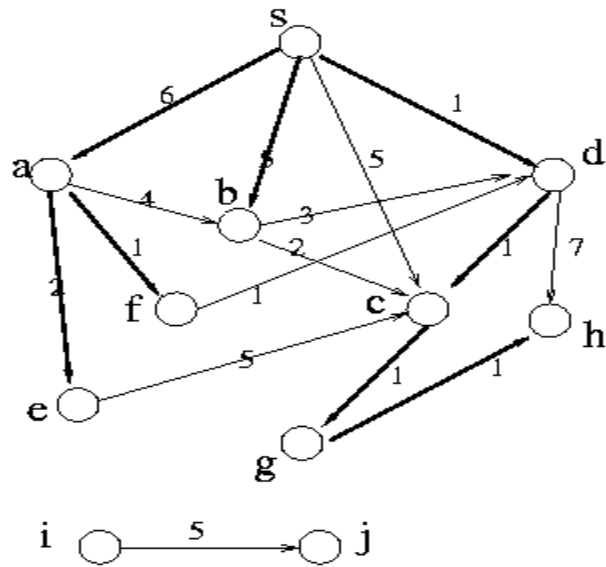
 move u from $notHandled$ to $handled$

end loop

return $\langle d, \pi \rangle$

end algorithm

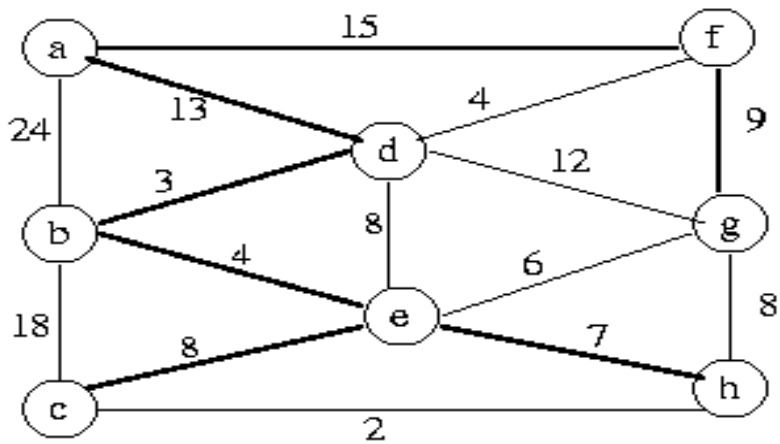
Dijkstra's



Handled d values

| | s | a | b | c | d | e | f | g | h | i | j |
|---|-----|-----|-----|---|-----|-----|-----|-----|-----|---|---|
| s | ① 0 | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ |
| d | | 6 | 5 | 5 | ① 1 | | | | 8 | | |
| c | | | | | ② 2 | | | ③ 3 | | | |
| g | | | | | | | | | ④ 4 | | |
| h | | | ⑤ 5 | | | | | | | | |
| b | | ⑥ 6 | | | | | | | | | |
| a | | | | | | 8 | ⑦ 7 | | | | |
| f | | | | | | ⑧ 8 | | | | | |
| e | | | | | | | | | | | |
| i | | | | | | | | | | ∞ | |
| j | | | | | | | | | | | ∞ |

Dijkstra's



Handled d values

| | a | b | c | d | e | f | g | h |
|---|---|----|----|---|----|----|----|----|
| | ⓪ | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ | ∞ |
| a | | 24 | | ⓫ | ↓ | 15 | ↓ | |
| d | | 16 | | | 21 | ⓭ | 25 | |
| f | | ⓬ | | | ↓ | | 24 | |
| b | | | 34 | | ⓯ | | | |
| e | | | 28 | | | | ⓮ | 27 |
| g | | | ↓ | | | | | ⓰ |
| h | | | ⓱ | | | | | |
| c | | | | | | | | |

Depth First Search

- Breadth first search makes a lot of sense for dating in general actually.
- It suggests dating a bunch of people casually before getting serious rather than having a series of five year relationships.

algorithm *DepthFirstSearch*(G, s)

⟨pre-cond⟩: G is a (directed or undirected) graph and s is one of its nodes.

⟨post-cond⟩: The output is a depth-first search tree of G rooted at s .

begin

foundHandled = \emptyset

foundNotHandled = $\{\langle s, 0 \rangle\}$

 loop

⟨loop-invariant⟩: See above.

 exit when *foundNotHandled* = \emptyset

 pop $\langle u, i \rangle$ off the stack *foundNotHandled*

 if u has an $(i+1)^{\text{st}}$ edge $\langle u, v \rangle$

 push $\langle u, i+1 \rangle$ onto *foundNotHandled*

 if v has not previously been found then

$\pi(v) = u$

$\langle u, v \rangle$ is a tree edge

 push $\langle v, 0 \rangle$ onto *foundNotHandled*

 else if v has been found but not completely handled then

$\langle u, v \rangle$ is a back edge

 else (v has been completely handled)

$\langle u, v \rangle$ is a forward or cross edge

 end if

 else

 move u to *foundHandled*

 end if

 end loop

 return *foundHandled*

end algorithm

Recursive Depth First Search

algorithm *DepthFirstSearch* (*s*)

<pre-cond>: An input instance consists of a (directed or undirected) graph *G* with some of its nodes marked *found* and a source node *s*.

<post-cond>: The output is the same graph *G* except all nodes *v* reachable from *s* without passing through a previously found node are now also marked as being found.

```

begin
  if s is marked as found then
    do nothing
  else
    mark s as found
    for each v connected to s
      DepthFirstSearch (v)
    end for
  end if
end algorithm
  
```

Our Stack Frame

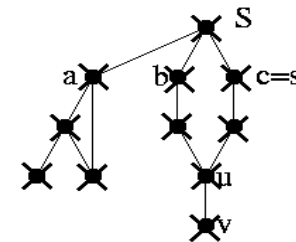
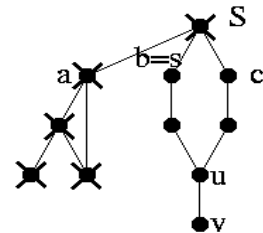
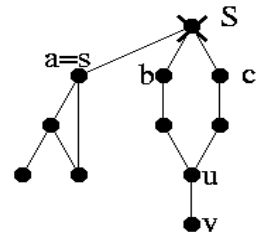
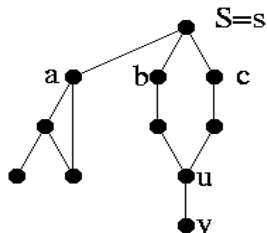
First Friend

Second Friend

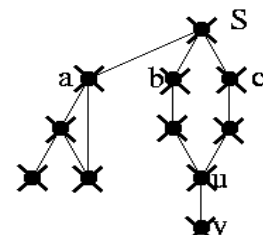
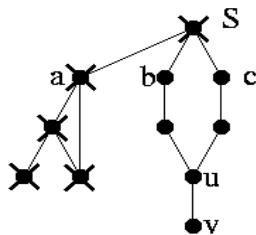
Third Friend

Our Stack Frame

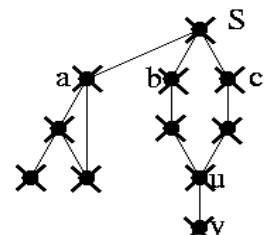
Instance

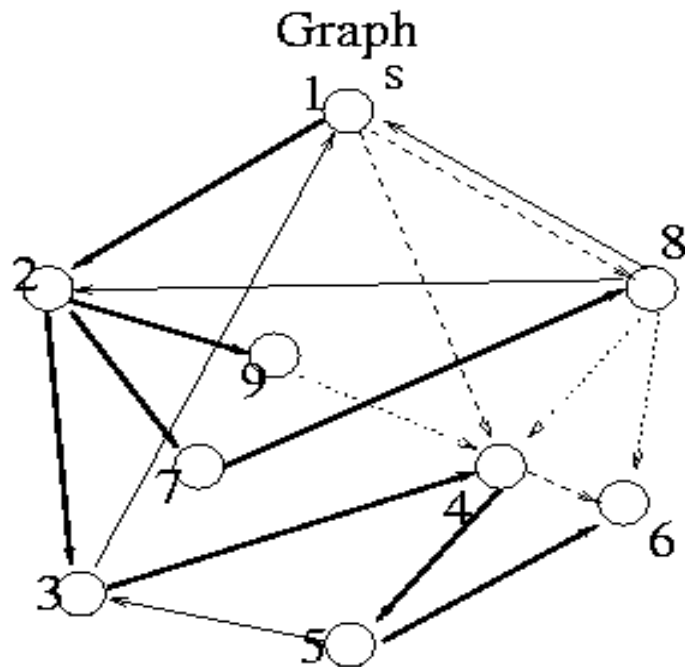


Graph when
routine returns

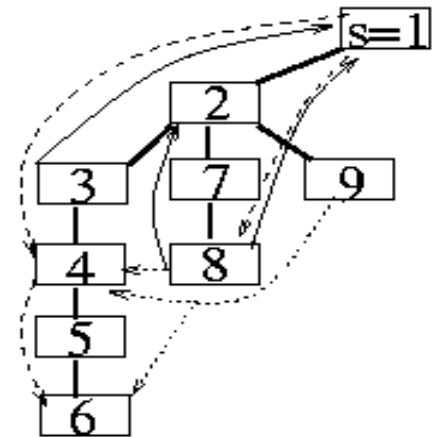


unchanged





Recursive Stack Frames



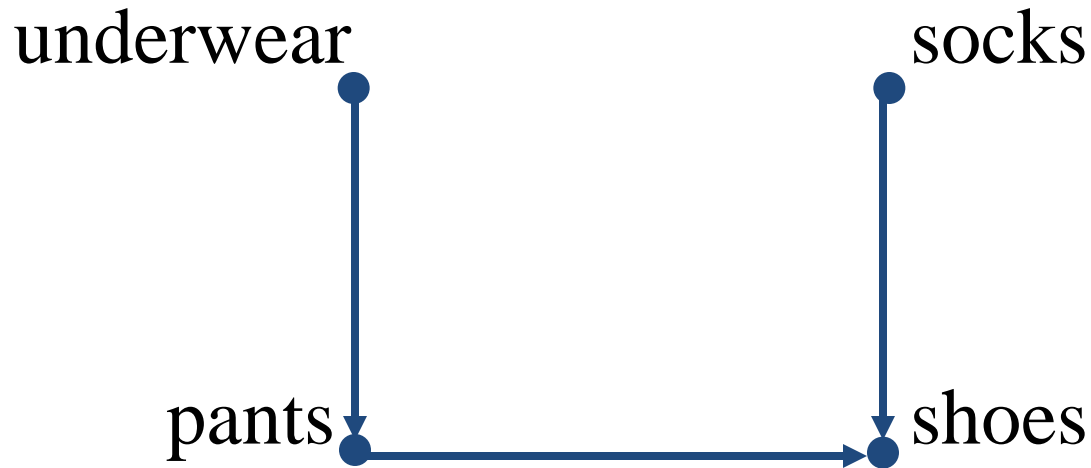
Iterative Alg

| <u>Stack</u> | <u>Handled</u> |
|---------------|-------------------|
| {s=1} | |
| {1,2,3,4,5,6} | |
| {1,2} | 6,5,4,3 |
| {1,2,7,8} | 6,5,4,3 |
| {1,2} | 6,5,4,3,8,7 |
| {1,2,9} | 6,5,4,3,8,7 |
| | 6.5.4.3.8.7.9.2.1 |

Types of Edges

| | |
|---------------|--------------|
| Tree edges | —————> |
| Back edges | - - - - -> |
| Forward edges |> |
| Cross edges | - · - · - ·> |

Linear Order of a Partial Order

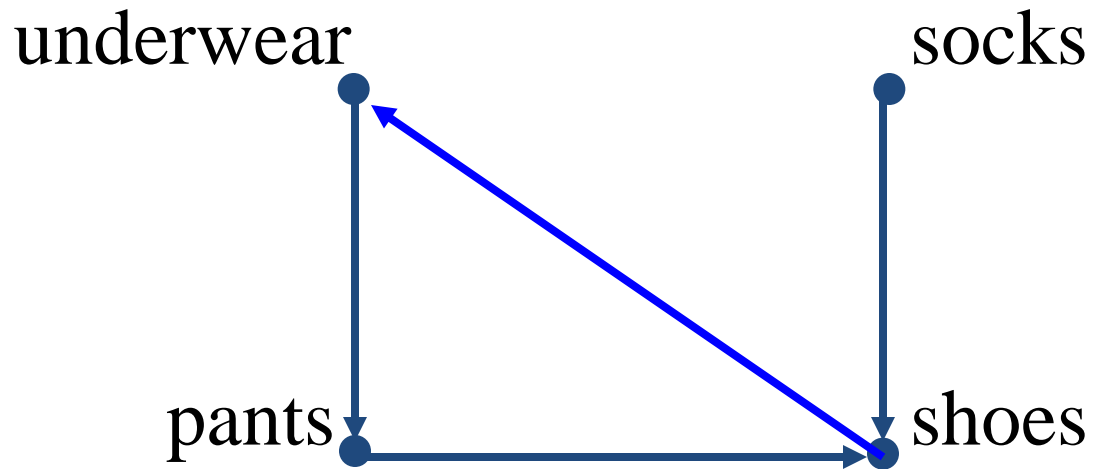


underwear
pants
socks
shoes

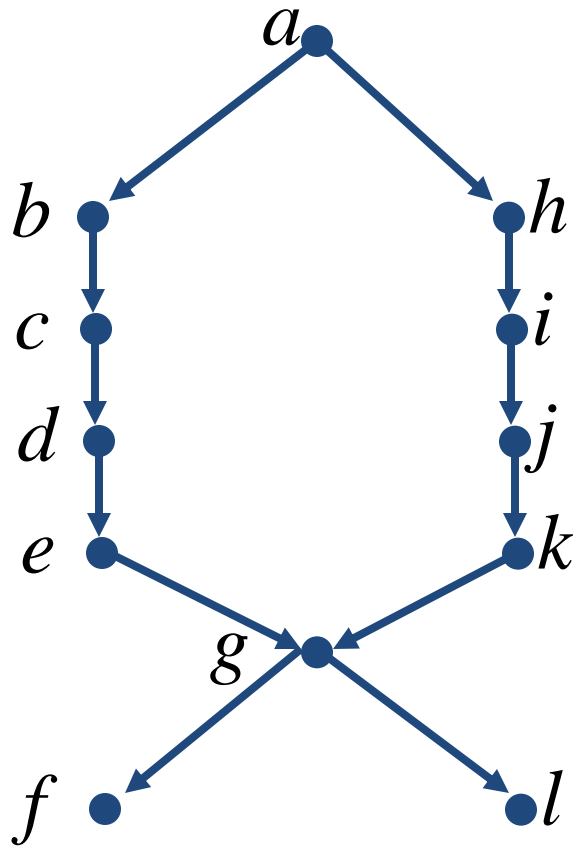


socks
underwear
pants
shoes

Linear Order



Linear Order



<preCond>:

A Directed Acyclic
Graph(DAG)

<postCond>:

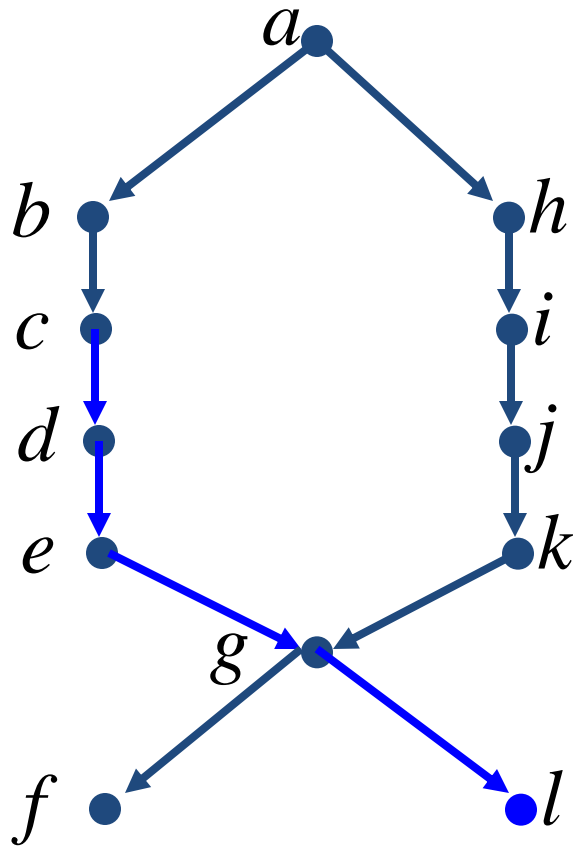
Find one valid linear order

Algorithm:

- Find a sink ?
- Put it last in order.
- Delete & Repeat

..... *l*

Linear Order



<preCond>:

A Directed Acyclic Graph(DAG)

<postCond>:

Find one valid linear order

Algorithm:

- Find a sink.
- Put it last in order.
- Delete & Repeat

$\Theta(n)$

$\Theta(n^2)$

..... *l*

Network Flow & Linear Programming

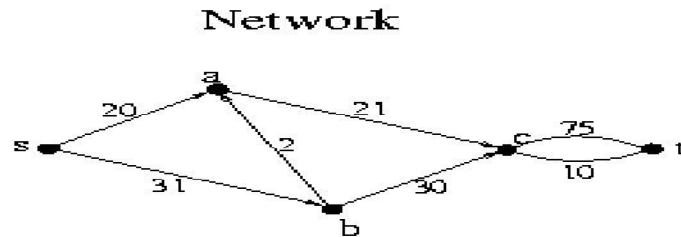
Optimization Problems

- Ingredients:
 - Instances: The possible inputs to the problem.
 - Solutions for Instance: Each instance has an exponentially large set of solutions.
 - Cost of Solution: Each solution has an easy to compute cost or value.
- Specification
 - Preconditions: The input is one instance.
 - Postconditions: An valid solution with optimal cost. (minimum or maximum)

Network Flow

- Instance:

- A Network is a directed graph G
- Edges represent pipes that carry flow
- Each edge $\langle u,v \rangle$ has a maximum capacity $c_{\langle u,v \rangle}$
- A source node s out of which flow leaves
- A sink node t into which flow arrives
- Goal: Max Flow



Network Flow

- For some edges/pipes, it is not clear which direction the flow should go
in order to maximize the flow from s to t .
- Hence we allow flow in both directions.
- Solution:
 - The amount of flow $F_{\langle u,v \rangle}$ through each edge.
 - Flow $F_{\langle u,v \rangle}$ can't exceed capacity $c_{\langle u,v \rangle}$.
 - No leaks, no extra flow.

For each node v : flow in = flow out

$$\sum_u F_{\langle u,v \rangle} = \sum_w F_{\langle v,w \rangle}$$

- Value of Solution:
 - Flow from s into the network
 - minus flow from the network back into s .
 - $\text{rate}(F) = \sum_u F_{\langle s,u \rangle} - \sum_v F_{\langle v,s \rangle}$
- Goal: Max Flow

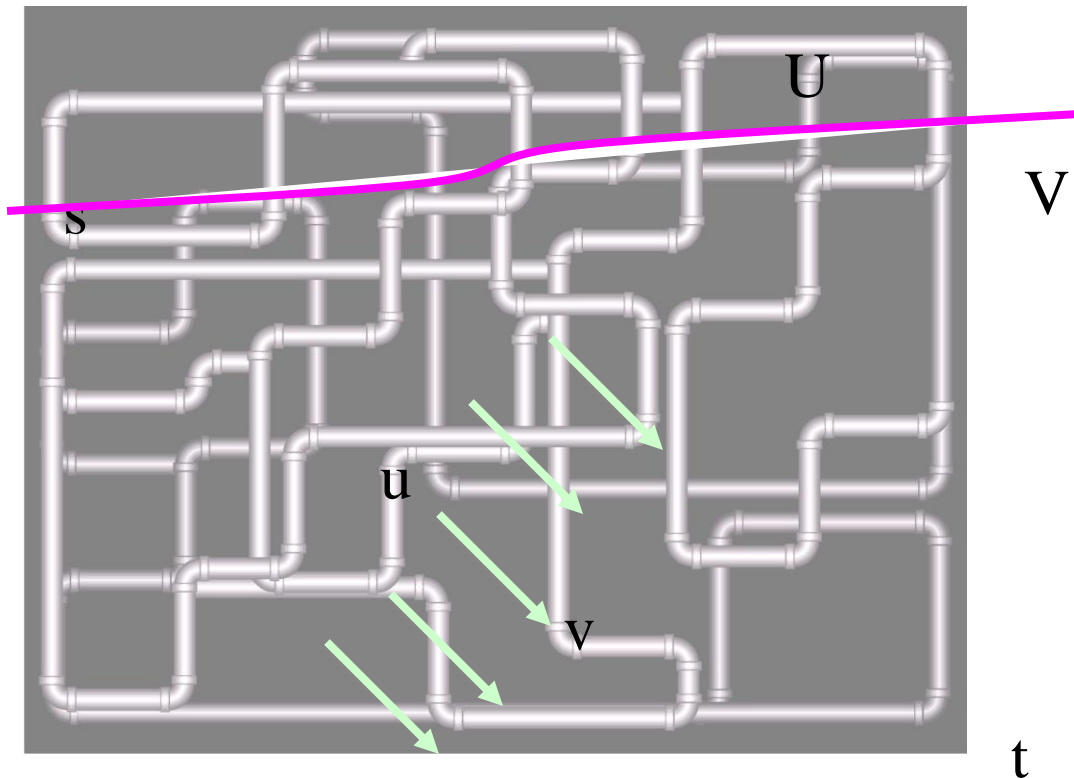
Min Cut

• Value Solution $C = \langle U, V \rangle$:

$\text{cap}(C) =$ how much can flow from U to V

$$= \sum_{u \in U, v \in V} c_{\langle u, v \rangle}$$

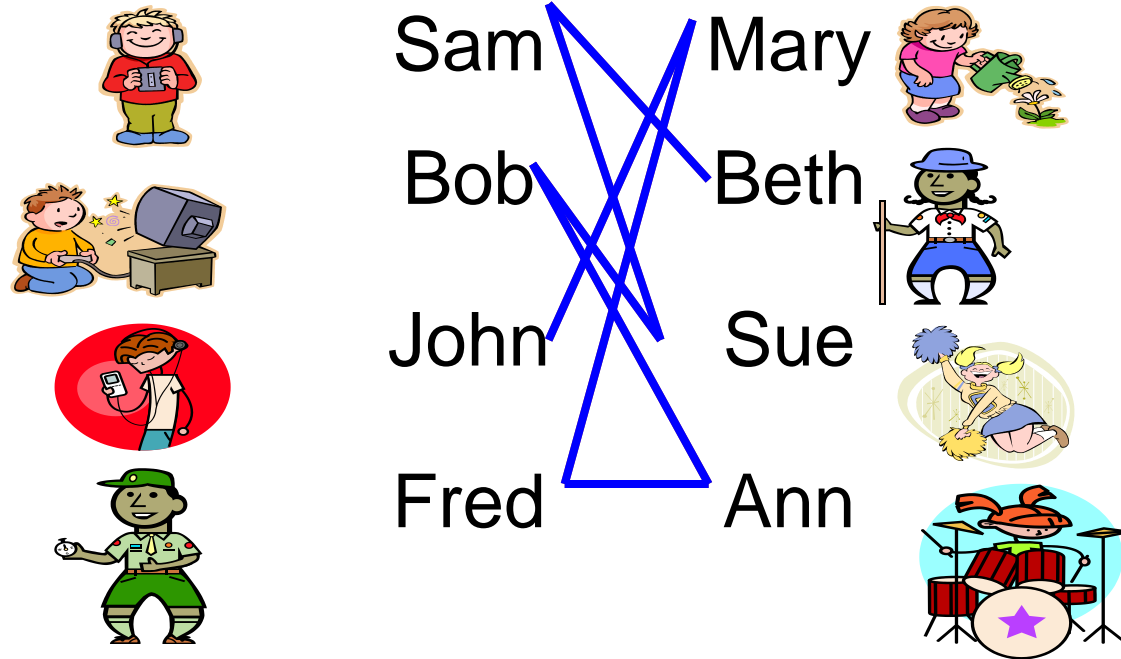
Goal: Min Cut



Max Flow = Min Cut

- Theorem:
 - For all Networks $\text{Max}_F \text{rate}(F) = \text{Min}_C \text{cap}(C)$
- Prove: $\forall F, C \quad \text{rate}(F) \leq \text{cap}(C)$
- Prove: \forall flow F , alg either
 - finds a better flow F
 - or finds cut C such that $\text{rate}(F) = \text{cap}(C)$
- Algorithm stops with an F and C for which $\text{rate}(F) = \text{cap}(C)$
 - F witnesses that the optimal flow can't be less
 - C witnesses that it can't be more.

An Application: Matching



3 matches

Can we do better?

4 matches

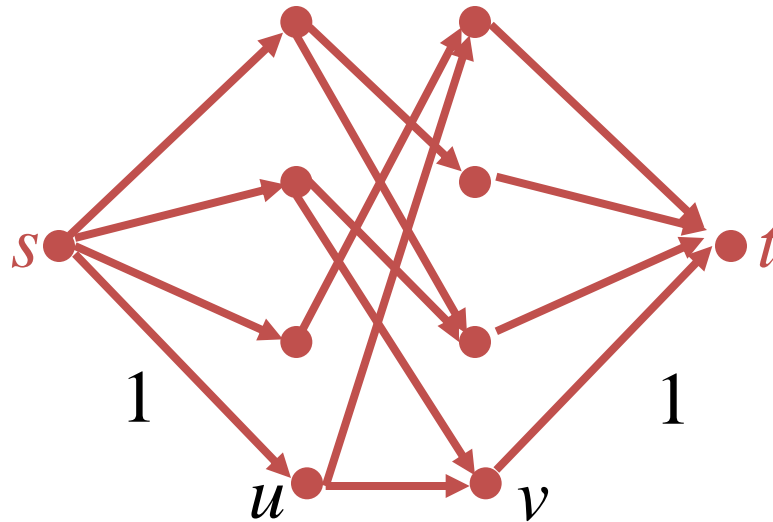
Who likes whom?

Who should be matched with whom?

so as many as possible matched

and nobody matched twice?

An Application: Matching



$$c_{\langle s, u \rangle} = 1$$

- Total flow out of u = flow into $u \leq 1$
- Boy u matched to at most one girl.

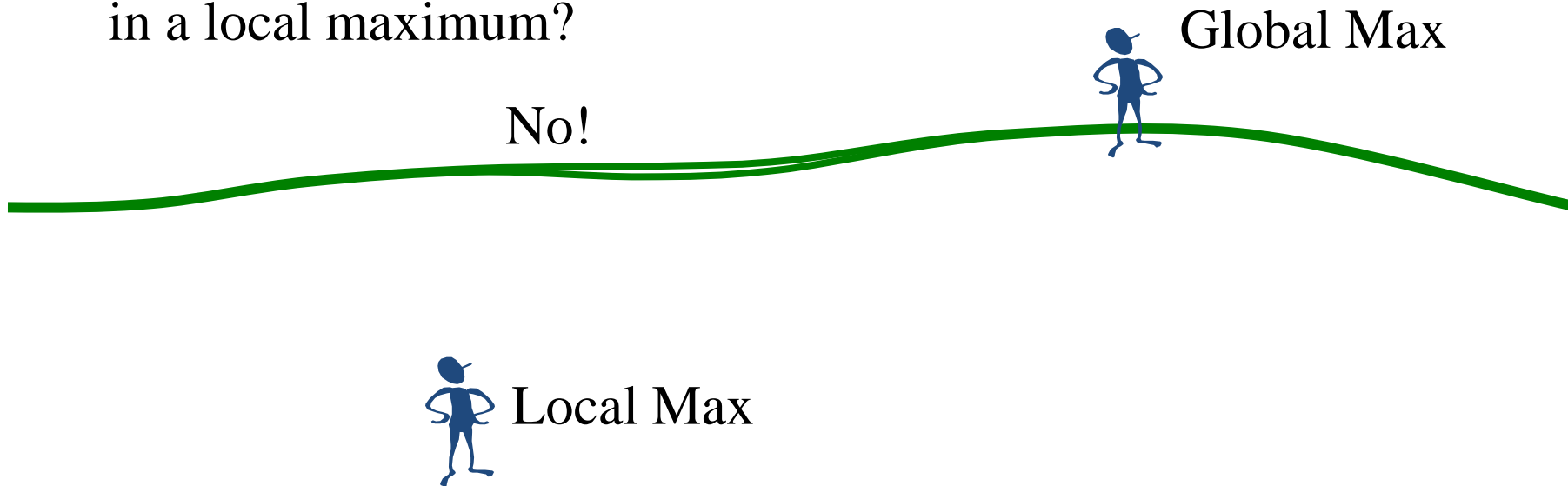
$$c_{\langle v, t \rangle} = 1$$

- Total flow into v = flow out of $v \leq 1$
- Girl v matched to at most one boy.

Hill Climbing

Problems:

Can our Network Flow
Algorithm get stuck
in a local maximum?



Hill Climbing

Problems:

Running time?

If you take small step,
could be exponential time.



Hill Climbing

Problems:

Running time?

- If each iteration you take the biggest step possible,
 - Algorithm is poly time
 - in number of nodes
 - and number of bits in capacities.
- If each iteration you take path with the fewest edges
 - Algorithm is poly time
 - in number of nodes

Taking the biggest step possible

algorithm *LargestShortestWeight* (G, s, t)

(pre-cond): G is a weighted directed graph. s is the source node. t is the sink.

(post-cond): P specifies a path from s to t whose smallest edge weight is as large as possible.

begin

Sort the edges by weight from largest to smallest

$G' =$ graph with no edges

mark s reachable

loop

(loop-invariant): Every node reachable from s in G' is marked reachable.

exit when t is reachable

$\langle u, v \rangle =$ the next largest weighted edge in G

Add $\langle u, v \rangle$ to G'

if(u is marked reachable and v is not) then

Do a depth first search from v marking all reachable nodes not marked before.

end if

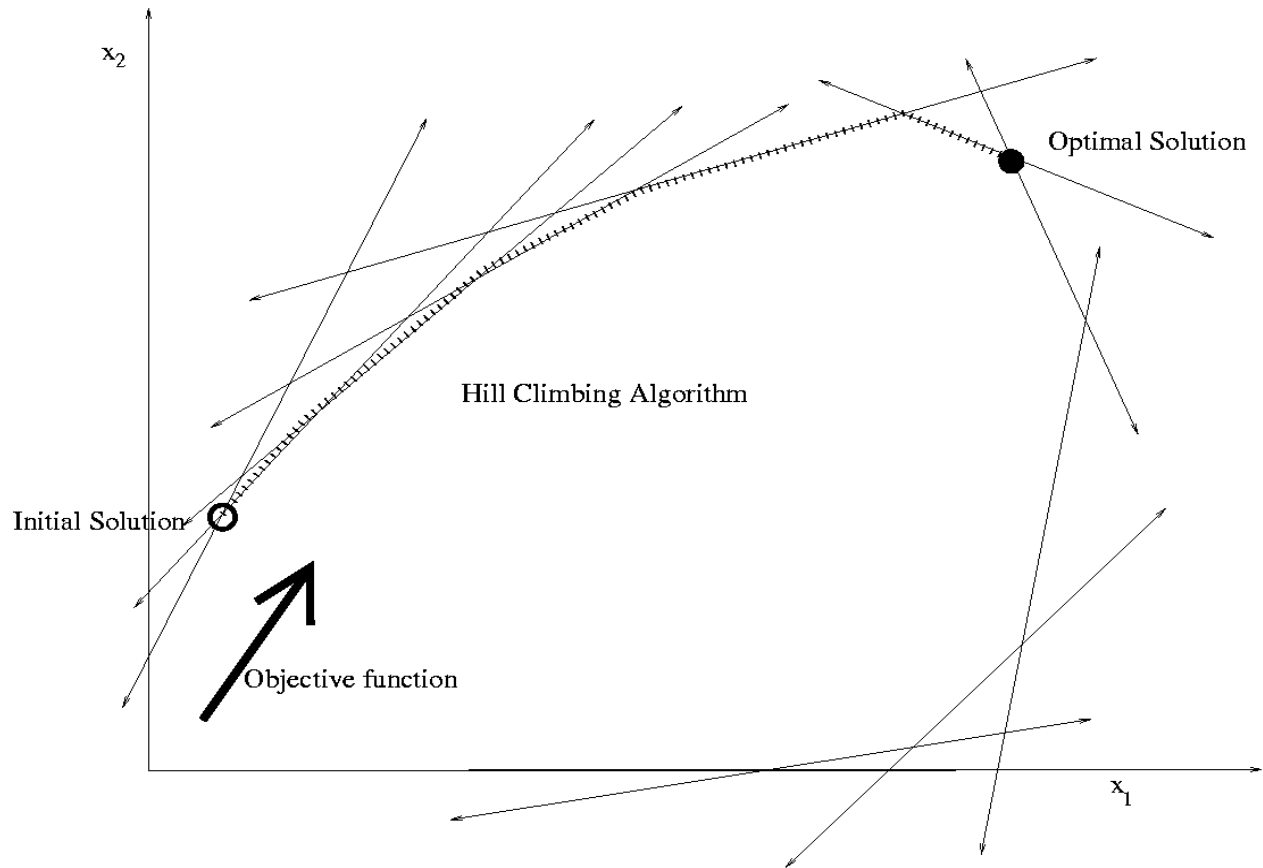
end loop

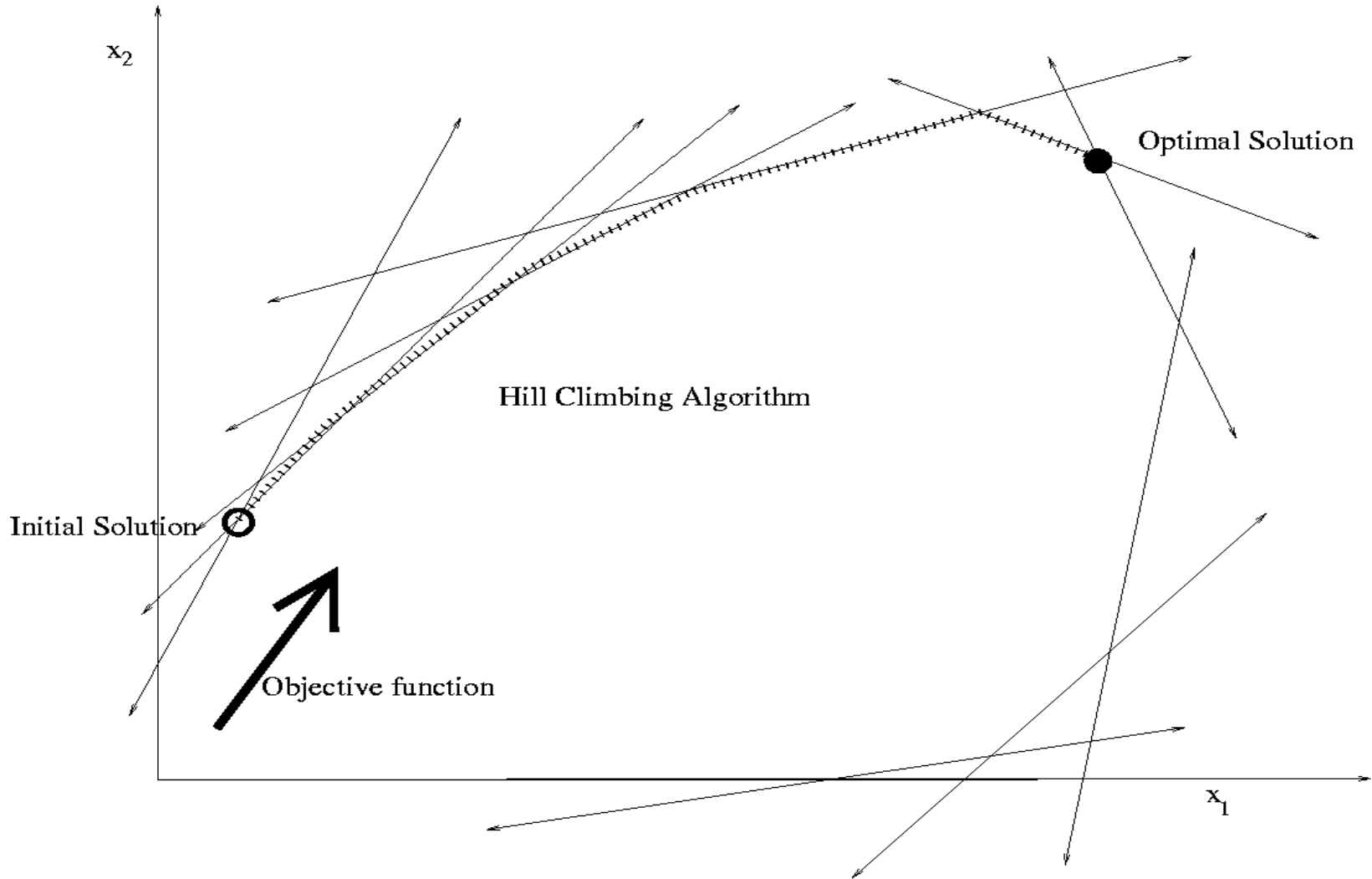
$P =$ path from s to t in G'

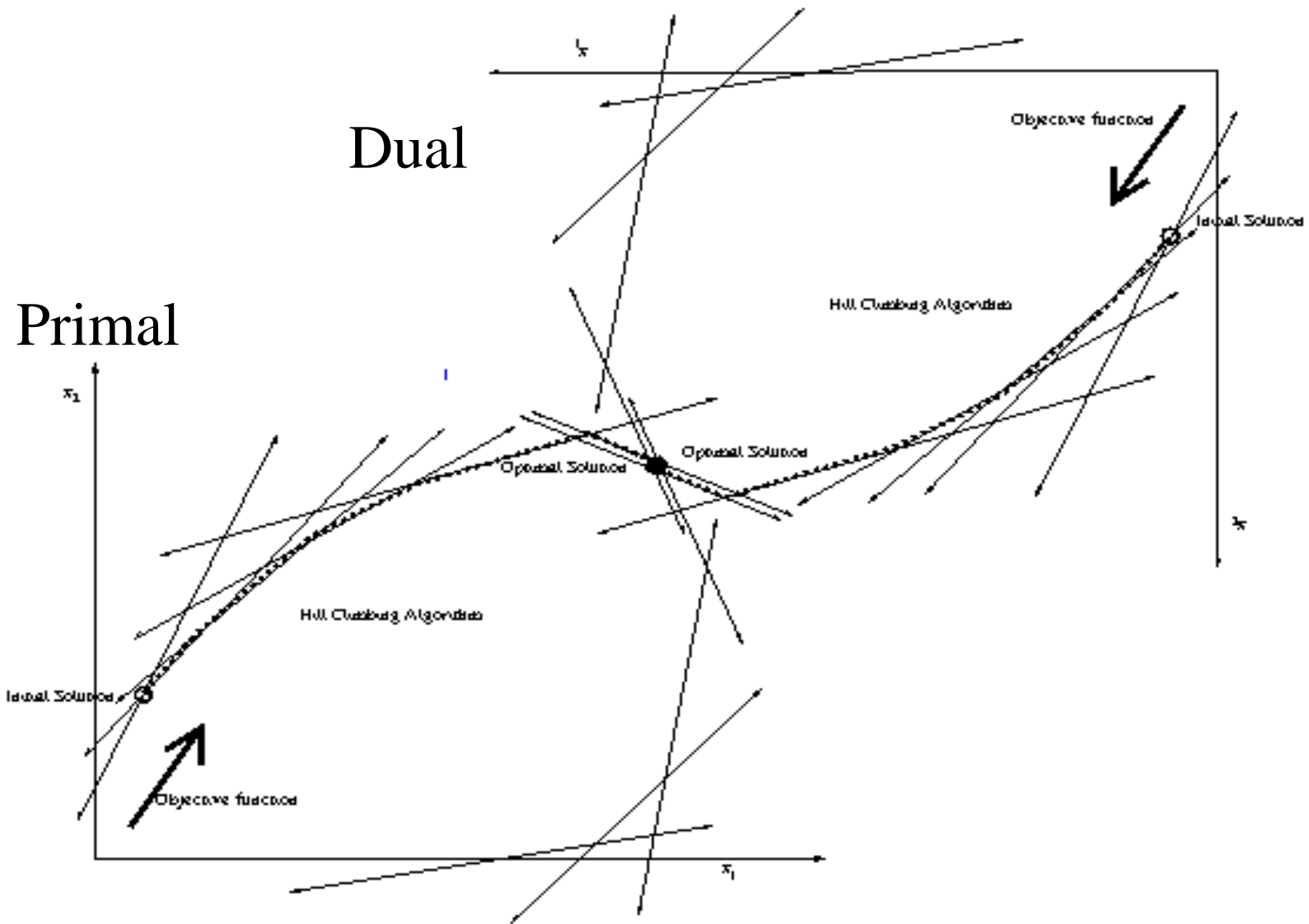
return(P)

end algorithm

Linear Programming







Linear Programming

Linear Program:

- An *optimization* problem whose *constraints* and *cost function* are linear functions
- **Goal:** Find a solution which optimizes the cost.

E.g.

Maximize Cost Function :

$$21x_1 - 6x_2 - 100x_3 - 100x_4$$

Constraint Functions:

$$5x_1 + 2x_2 + 31x_3 - 20x_4 \leq 21$$

$$1x_1 - 4x_2 + 3x_3 + 10x_4 \leq 56$$

$$6x_1 + 60x_2 - 31x_3 - 15x_4 \leq 200$$

.....

Primal-Dual Hill Climbing

Mars settlement has hilly landscape
and many layers of roofs.

Primal Problem:

- Exponential # of locations to stand.
- Find a highest one.

Dual problem:

- Exponential # of roofs.
- Find a lowest one.

Prove:

- Every roof is above every location to stand.

$$\begin{aligned} \forall R \ \forall L \ height(R) &\geq height(L) \\ \Rightarrow height(R_{min}) &\geq height(L_{max}) \end{aligned}$$

- Is there a gap?

- Prove:
- For every location to stand either:
 - the alg takes a step up or
 - the alg gives a reason that explains why not by giving a ceiling of equal height.
 - i.e. $\forall L [\exists L' \text{height}(L') \geq \text{height}(L)$ or $\exists R \text{height}(R) = \text{height}(L)]$
- But $\forall R \forall L \text{height}(R) \geq \text{height}(L)$

Recursive Backtracking

- The brute force algorithm for an optimization problem is to simply compute the cost or value of each of the exponential number of possible solutions and return the best.
- A key problem with this algorithm is that it takes exponential time.
- Another (not obviously trivial) problem is how to write code that enumerates over all possible solutions.
- Often the easiest way to do this is recursive backtracking.

An Algorithm as a Sequence of Decisions:

- An algorithm for finding an optimal solution for your instance must make a sequence of small decisions about the solution
- “Do we include the first object in the solution or not?”
- “Do we include the second?”
- “The third?” . . . , or “At the first fork in the road, do we go left or right?”

- “At the second fork which direction do we go?” “At the third?”
- As one stack frame in the recursive algorithm, our task is to deal only with the first of these decisions.
- A recursive friend will deal with the rest

Searching for the Best Animal

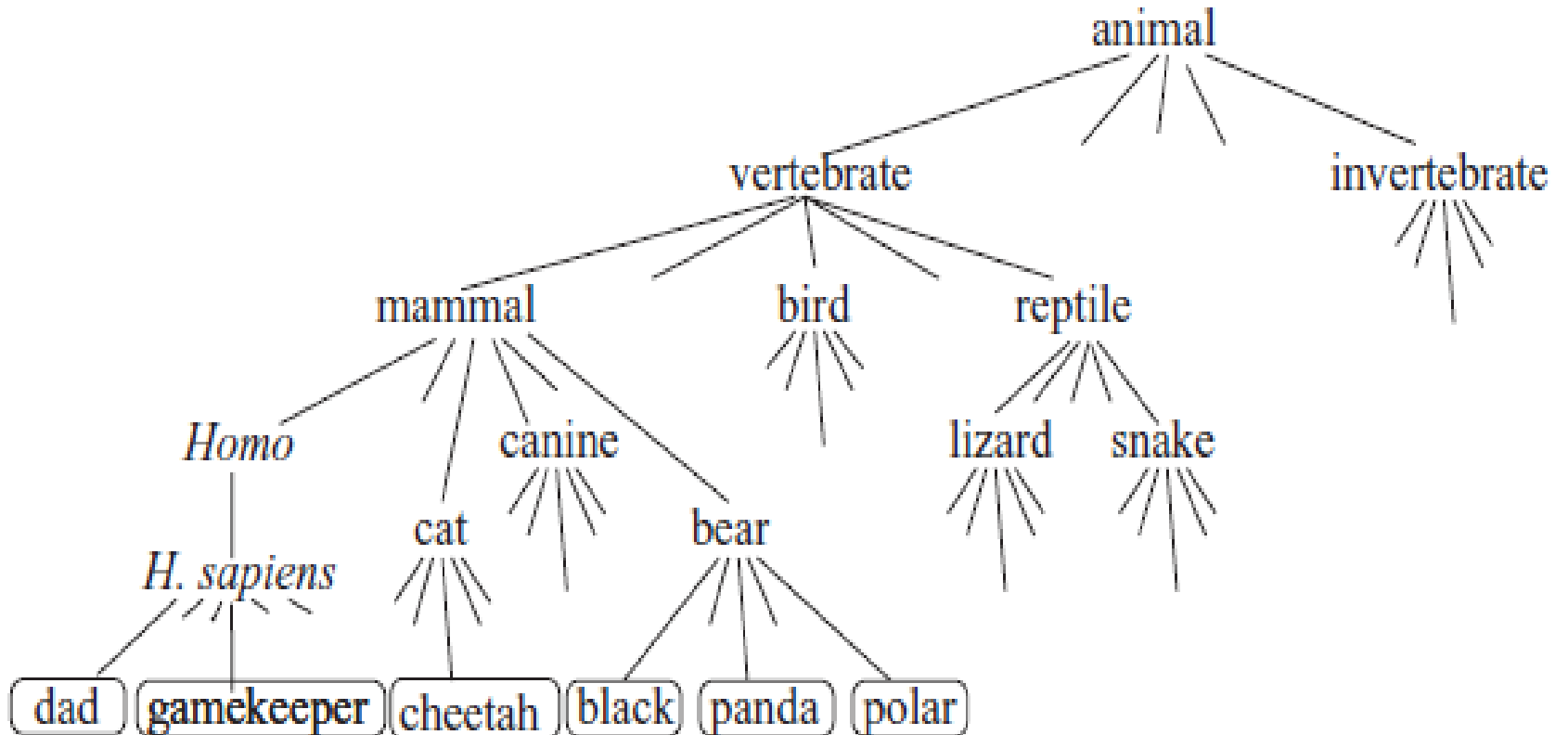
- Searching through a large set of objects, say for the best animal at the zoo.
- we break the search into smaller searches, each of which we delegate to a friend.
- We might ask one friend for the best vertebrate and another for the best invertebrate.
- We will take the better of these best as our answer.
- This algorithm is recursive.

- The friend with the vertebrate task asks a friend to find the best mammal, another for the best bird, and another for the best reptile.

A Classification Tree of Solutions:

- This algorithm unwinds into the tree of stack frames that directly mirrors the taxonomy tree that classifies animals.
- Each solution is identified with a leaf.

Classification Tree of Animals



The Little Bird Abstraction:

- A little bird abstraction to help focus on two of the most difficult and creative parts of designing a recursive backtracking algorithm.

A Flock of Stupid Birds vs. wise Little Bird:

A Flock of Stupid Birds:

- whether the optimal solution is a mammal, a bird, or a reptile has K different answers
- Giving her the benefit of doubt, we ask a friend to give us the optimal solution from among those that are consistent with this answer.

- At least one of these birds must have been telling us the truth.

Wise Little Bird:

- If little bird answers correctly, designing an algorithm would be a lot easier
- Ask the little bird “Is the best animal a bird, a mammal, a reptile, or a fish?”
- Little Bird tells us a mammal.
- Just ask our friend for the best mammal.
- Trusting the little bird and the friend, we give this as the best animal.

Developing a Recursive Backtracking Algorithm

Objectives:

- Understand backtracking algorithms and use them to solve problems
- Use recursive functions to implement backtracking algorithms
- How the choice of data structures can affect the efficiency of a program?

Backtracking

- Backtracking
 - A strategy for guessing at a solution and backing up when an impasse is reached
- Recursion and backtracking can be combined to solve problems
- Eight-Queens Problem
 - Place eight queens on the chessboard so that no queen can attack any other queen

The Eight Queens Problem

- One strategy: guess at a solution
 - There are 4,426,165,368 ways to arrange 8 queens on a chessboard of 64 squares
- An observation that eliminates many arrangements from consideration
 - No queen can reside in a row or a column that contains another queen
 - Now: only 40,320 (8!) arrangements of queens to be checked for attacks along diagonals

- Providing organization for the guessing strategy
 - Place queens one column at a time
 - If you reach an impasse, backtrack to the previous column

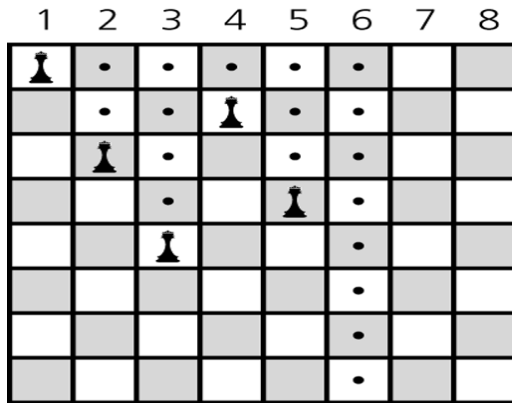
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | ♚ | | | | | | | |
| 2 | | | | | | | ♚ | |
| 3 | | | | | ♚ | | | |
| 4 | | | | | | | | ♚ |
| 5 | | ♚ | | | | | | |
| 6 | | | | ♚ | | | | |
| 7 | | | | | | ♚ | | |
| 8 | | | ♚ | | | | | |

A solution to the Eight Queens problem

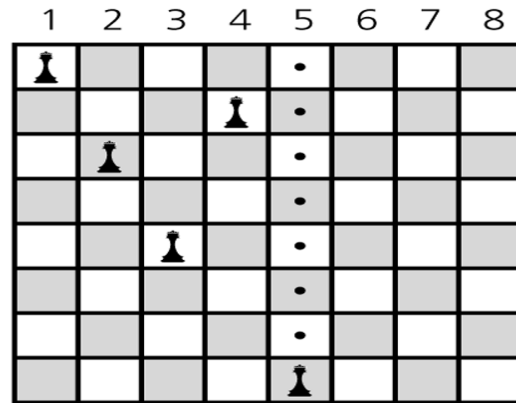
The Eight Queens Problem

- A recursive algorithm that places a queen in a column
 - Base case
 - If there are no more columns to consider
 - You are finished
 - Recursive step
 - If you successfully place a queen in the current column
 - Consider the next column
 - If you cannot place a queen in the current column
 - You need to backtrack

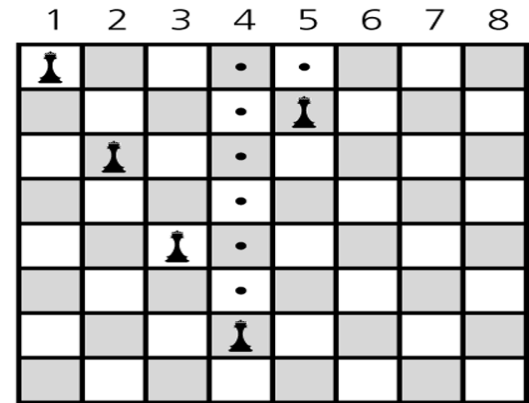
The Eight Queens Problem



(a)



(b)



(c)

- a) Five queens that cannot attack each other, but that can attack all of column 6;
- b) Backtracking to column 5 to try another square for the queen;
- c) Backtracking to column 4 to try another square for the queen and then considering column 5 again

Pruning Branches

- The typical reasons why an entire branch of the solution classification tree can be pruned off.

Invalid Solutions:

- It happens partway down the tree the algorithm has already received enough information about the solution
- Then it determine that it contains a conflict or defect making any such solution invalid.
- The algorithm can stop recursing at this point and backtrack.
- This effectively prunes off the entire subtree of solutions rooted at this node in the tree.

No Highly Valued Solutions:

- The algorithm arrives at the root of a subtree, it might realize that no solutions within this subtree are rated sufficiently high to be optimal
- Perhaps because the algorithm has already found a solution probably better than all of these.
- Again, the algorithm can prune this entire subtree from its search.

Greedy Algorithms:

- Greedy algorithms are effectively recursive backtracking algorithms with extreme pruning.
- Whenever the algorithm has a choice as to which little bird's answer to take
- Then it looks best according to some greedy criterion.

Modifying Solutions:

- Modifying any possible solution that is not consistent with the latest choice into one that has at least as good value and is consistent with this choice.

Satisfiability

- A famous optimization problem is called satisfiability.
- The recursive backtracking algorithm is referred to as the Davis–Putnam algorithm.
- An example of an algorithm whose running time is exponential for worst case inputs

Satisfiability Problem

Instances:

- An instance (input) consists of a set of constraints on the assignment to the binary variables x_1, x_2, \dots, x_n .
- A typical constraint might be x_1 *or* x_3 *or* x_8 , equivalently that either x_1 is true, x_3 is false, or x_8 is true.

Solutions:

- Each of the 2^n assignments is a possible solution.
- An assignment is valid for the given instance if it satisfies all of the constraints.

Measure of Success:

- An assignment is assigned the value one if it satisfies all of the constraints, and the value zero otherwise.

Goal:

- Given the constraints, the goal is to find a satisfying assignment.

Code:

```
algorithm DavisPutnam (c)
  ⟨ pre-cond ⟩: c is a set of constraints on the assignment to  $\vec{x}$ .
  ⟨ post-cond ⟩: If possible, optSol is a satisfying assignment and optCost is also c
  Otherwise optCost is zero.
begin
  if( c has no constraints or no variables ) then
    % c is trivially satisfiable.
    return ⟨  $\emptyset$ , 1 ⟩
  else if( c has both a constraint forcing a variable  $x_i$  to 0
    and one forcing the same variable to 1) then
    % c is trivially not satisfiable.
    return ⟨  $\emptyset$ , 0 ⟩
  else
    for any variable forced by a constraint to some value
      substitute this value into c.
    let  $x_i$  be the variable that appears the most often in c
    % Loop over the possible bird answers.
    for  $k = 0$  to 1 (unless a satisfying solution has been found)
      % Get help from friend.
      let  $c'$  be the constraints c with  $k$  substituted in for  $x_i$ 
      ⟨ optSubSol, optSubCost ⟩ = DavisPutnam ( $c'$ )
       $optSol_k = \langle \text{forced values, } x_i = k, optSubSol \rangle$ 
       $optCost_k = optSubCost$ 
    end for
    % Take the best bird answer.
     $k_{max} = \text{a } k \text{ that maximizes } optCost_k$ 
     $optSol = optSol_{k_{max}}$ 
     $optCost = optCost_{k_{max}}$ 
    return ⟨ optSol, optCost ⟩
  end if
end algorithm
```

Running Time:

- If no pruning is done, then the running time is (2^n) , as all 2^n assignments are tried.
- Considerable pruning needs to occur to make the algorithm polynomial-time.
- Certainly in the worst case, the running time is $2(n)$.