

**ECE 479/579**

**Principles of Artificial Intelligence – Part III**

**Spring 2005**

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# Initial State:

Ontable(B)

Ontable(A)

On (C,A)

Clear(C)

Clear(B)

Handempty

# Matching actions:

Pickup(?x) {B/?x}

unstack(?x,?y)

{C/?x, A/?y}

Pickup(?x)  
S= {B/?x}

unstack(?x, ?y)  
S= {C/?x, A/?y}

Ontable(A)

Ontable(B)

On(C,A)

Ontable(A)

Clear(C)

Clear(B)

Holding(B)

Clear(A)

Stack(?x, ?y)  
S= {B/?x, C/?y}

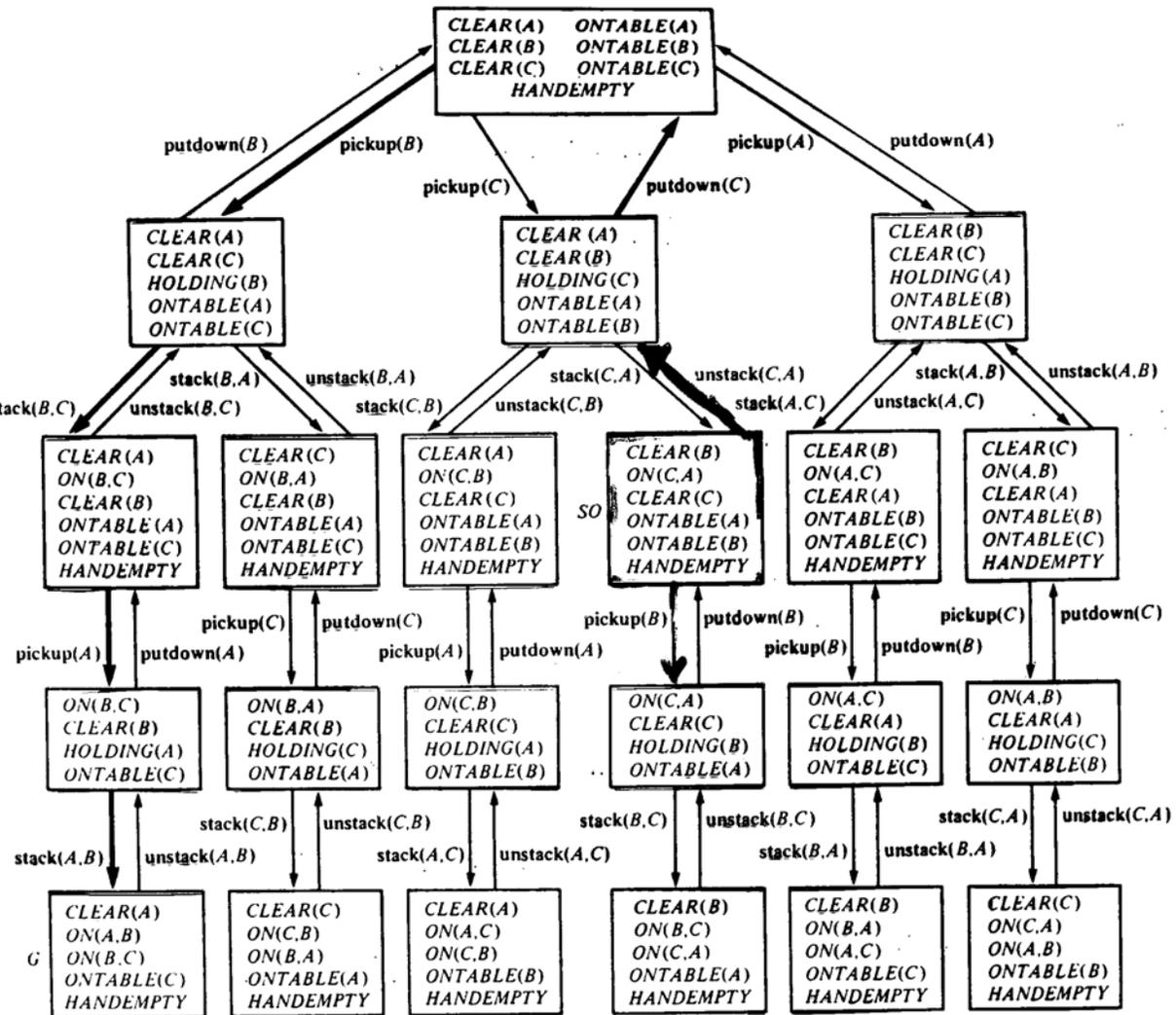
Holding(C)

Stack(?x, ?y)  
S= {C/?x, B/?y}

Putdown(?x)  
S= {B/?x}

Stack(?x, ?y)  
S= {C/?x, A/?y}

Putdown(?x)  
S= {C/?x}



*The state-space for a robot problem.*

# Triangle method for Execution and recovery from Errors:

Once we have generated the solution, then construct a triangle with the steps in the solution as follows:

Solution:

Unstack(C,A)

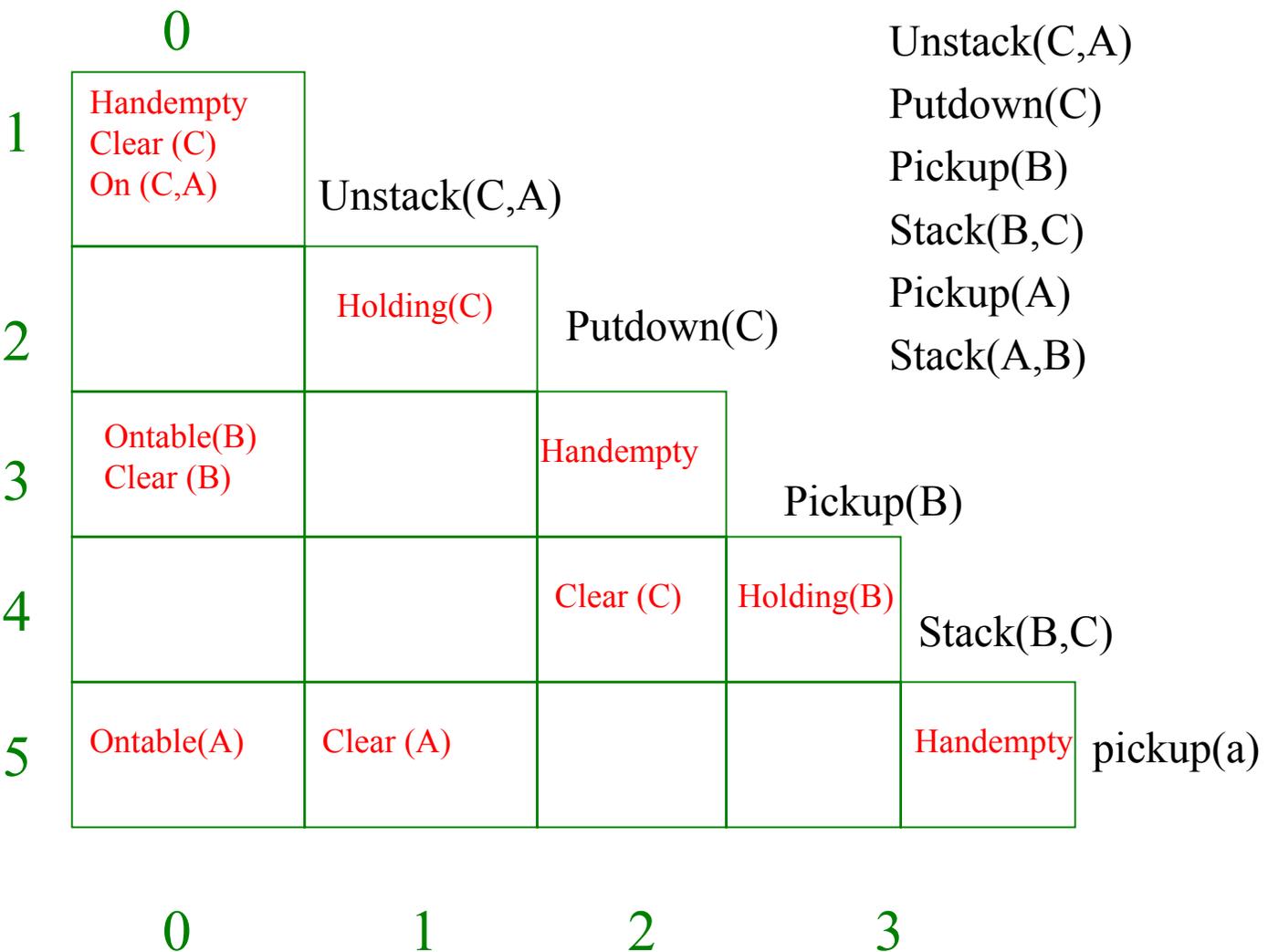
Putdown(C)

Pickup(B)

Stack(B,C)

Pickup(A)

Stack(A,B)



## Backward Planning / Problem Solving:

We have a goal  $G = G1 \wedge G2 \wedge \dots \wedge GN$

which we want to achieve, and we have initial conditions  $I = I1 \wedge I2 \dots \wedge Im$ , we will consider subgoals  $G1, G2, \dots$ , and match actions which can produce them, then we regress all subgoals through the action. The regression plus the preconditions of the action give us new subgoals  $G1' \wedge G2', \dots$

Continue this process until all subgoals match with initial conditions.

### Regression

We have a goal:

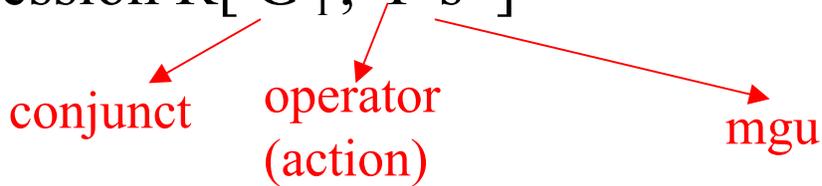
$$G = G1 \wedge G2 \wedge \dots \wedge GN$$

we have an operator that can unify with  $L$  (there is a predicate in its add list that unifies with  $L$ ). This predicate in add list of operator can be denoted  $L'$ :

$$L'S = L$$

 mgu substitution

To regress  $G$  through this operator, take every conjunct other than  $L$  and compute the regression  $R[ G_i, F_s ]$



$$\left\{ \begin{array}{l} G_i' = R[G_i, F_s] = \\ T : \text{if } F_s \text{ has literal } G_i \text{ in its add list.} \\ F : \text{if } F_s \text{ has literal } G_i \text{ in its delete list.} \\ G_i s : \text{if neither of the above.} \end{array} \right.$$

This works if  $F_s$  is a ground action.

$\Rightarrow$  no uninstantiated variables remaining.

Ex: Consider the goal

$G = \text{Holding}(B) \wedge \text{Handempty} \wedge \text{Ontable}(C) \wedge \text{Clear}(C)$

$L = \text{Holding}(B)$

$F = \text{Unstack}(\text{?x}, \text{?y}) \quad S = \{ B/\text{?x}, C/\text{?y} \}$

Precondition list of F:

$\text{Handempty} \wedge \text{Clear}(\text{?x}) \wedge \text{On}(\text{?x}, \text{?y})$

Delete list of F:

$\text{Handempty} \wedge \text{Clear}(\text{?x}) \wedge \text{On}(\text{?x}, \text{?y})$

Addlist of F:

$\text{Holding}(\text{?x}) \wedge \text{Clear}(\text{?y})$

$R[\text{Handempty}, \text{unstack}(\text{?x}, \text{?y}) \{B/\text{?x}, C/\text{?y}\}] = \mathbf{F}$

$R[\text{Ontable}(C), \text{unstack}(\text{?x}, \text{?y}) \{B/\text{?x}, C/\text{?y}\}] =$   
 $\text{Ontable}(C)$

$R[\text{Clear}(C), \text{unstack}(\text{?x}, \text{?y}) \{B/\text{?x}, C/\text{?y}\}] = \mathbf{T}$

## Regressing when we have uninstantiated variables

If a variable does not have an assigned constant in  $S$ , then regression of  $G_i$  containing this variable could result in different possible results.

Ex:

$$G = \text{Holding}(B) \wedge \text{Handempty} \wedge \\ \text{Ontable}(C) \wedge \text{Clear}(C)$$

$$L = \text{Holding}(B)$$

$$F = \text{unstack}(?x, ?y) \quad S = \{B/?x\}$$

$$R[\text{Handempty}, FS] = F$$

$$R[\text{Ontable}(C), FS] = \text{Ontable}(C)$$

$$R[\text{Clear}(C), FS] = \begin{cases} ?y = C \rightarrow T \\ ?y \neq C \rightarrow \text{Clear}(C) \end{cases}$$

Whenever more than one regression is possible for  $G_i$ ,  $G_i^{1'}$  or  $G_i^{2'}$ , then we generate two children states, one for each possible value of the variable.

the 2nd outcome for the above regression is listed as

$\text{neq} (?y C) \wedge \text{Clear} (C)$

The same method applies when  $G_i$  is in the delete list.

Regressing when we have uninstantiated variables in the delete list:

Similar to the case for the add list:

Example:

$G = \text{Clear}(C)$

$F = \text{Unstack}(?x, ?y) \quad S = \{ B / ?y \}$

$$R[\text{Clear}(C), FS] = \begin{cases} ?x=C \rightarrow F \\ ?x \neq C \rightarrow \text{Clear}(C) \end{cases}$$

logically one can write:

$[\text{equal}(?x, C) \Rightarrow F] \wedge [\text{neq}(?x, C) \Rightarrow \text{Clear}(C)]$

Thus the regression generates the following subgoal:

$[\text{neq}(?x, C) \wedge \text{Clear}(C)]$

## Summary:

The goal expression has a literal that unifies with one of the literals in the add list. The subgoal expression is created by:

1. Regress the non-matched literals of the goal through the action/ operator.
2. Generate the list that results from applying the substitution to the precondition list of the action/ operator.
3. Conjoin the results of 1 and 2.

## Ex:

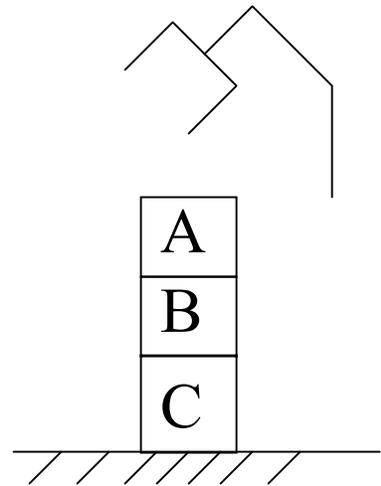
$$G = \text{On}(A,B) \wedge \text{On}(B,C)$$

$$F = \text{Stack}(?x, ?y) \quad S = \{A/?x, B/?y\}$$

## subgoal:

$$L = \text{On}(A,B)$$

1.  $R[\text{On}(B,C), Fs] = \text{On}(B, C)$
2. Precondition.  $S = \text{Holding}(A) \wedge \text{Clear}(B)$
3.  $\text{subgoal} = \text{On}(B,C) \wedge \text{Holding}(A) \wedge \text{Clear}(B)$



## Algorithm for backward planning

STRIPS(G)     G is the goal expression

                 S is the initial condition/ State

1. Until S matches G do

    begin

    2.  $g \leftarrow$  a component of G that does not match S; non-deterministic selection.

    we can backtrack and make a different selection.

    3.  $f \leftarrow$  an action/ operator whose add list contains a literal that matches g.

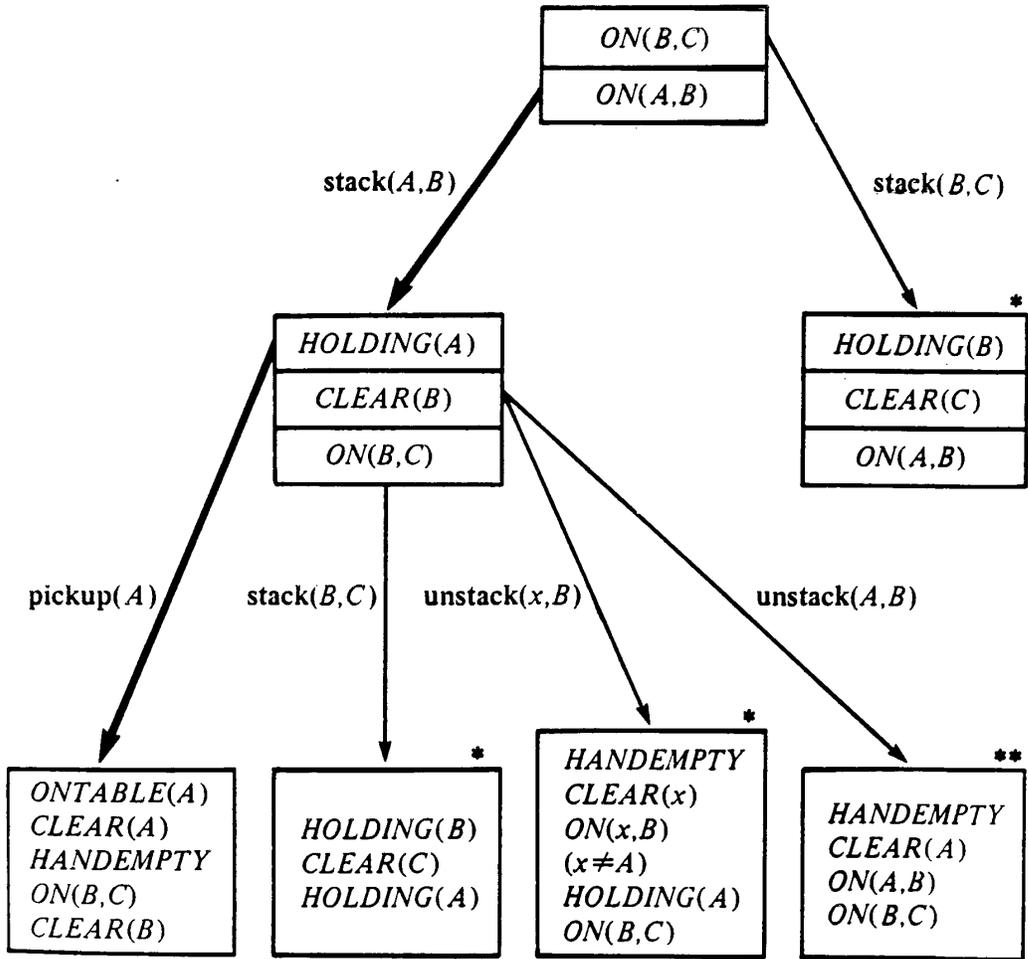
    another point we backtrack to, if earlier selection no good.

    4.  $p \leftarrow$  precondition formula for f with the unifying substitution applied to it.

    5. STRIPS(p)     recursive call to solve the subproblem.

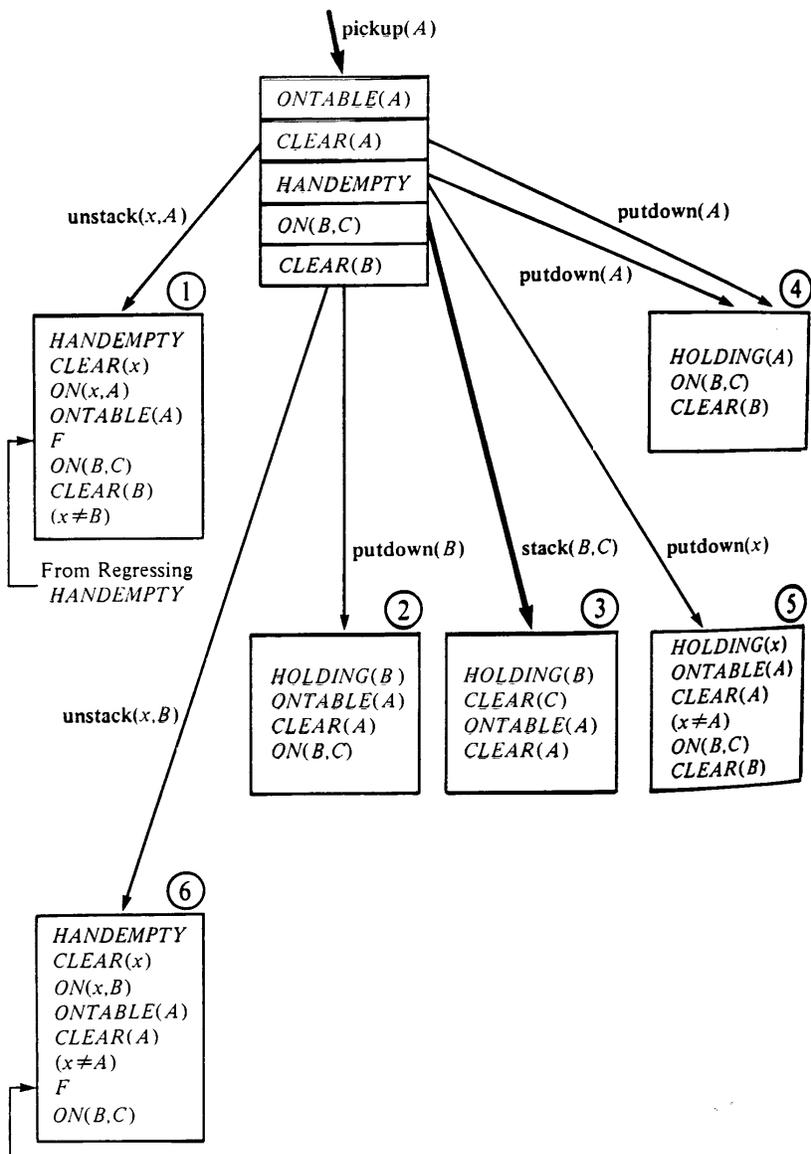
    6.  $S \leftarrow$  result of applying the action f with the unifying substitution to S.

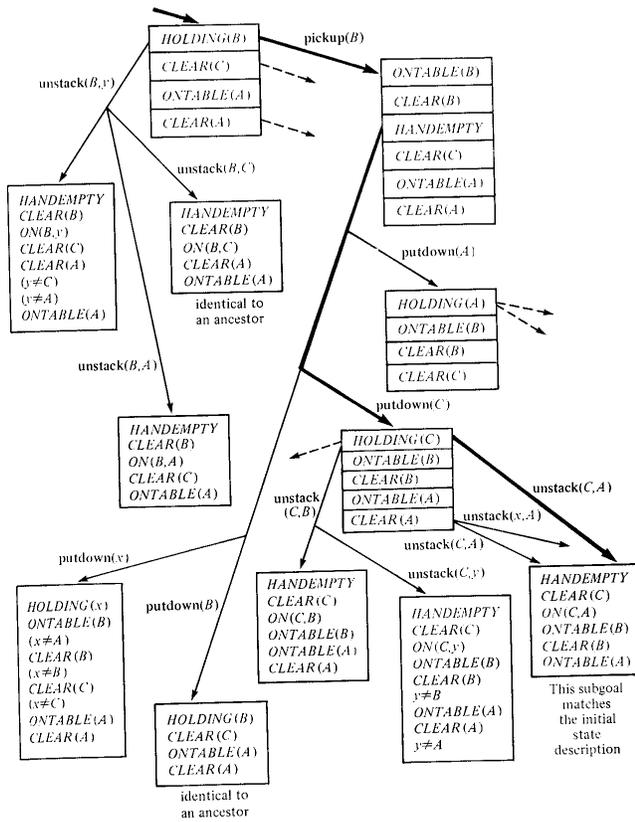
    end



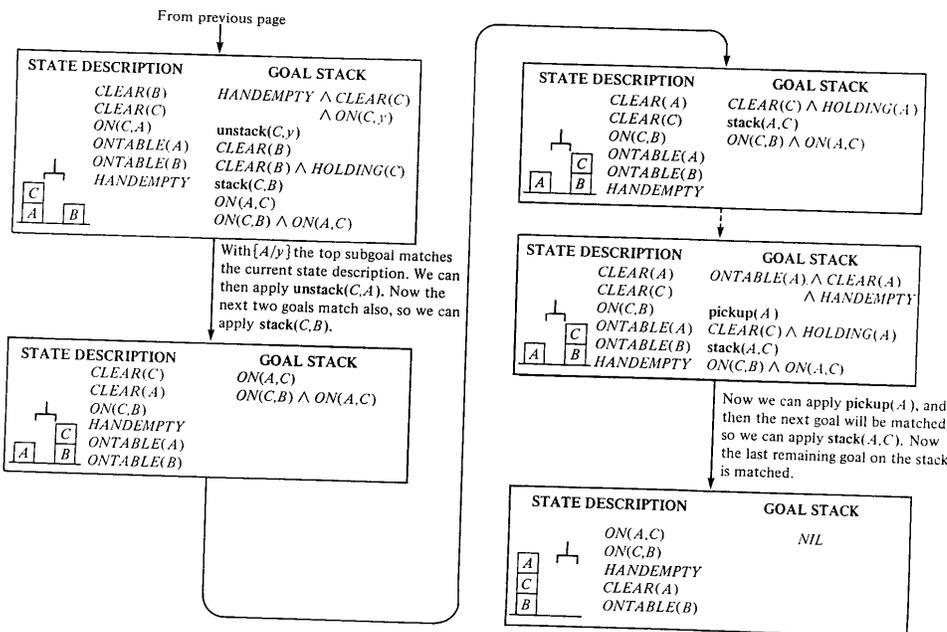
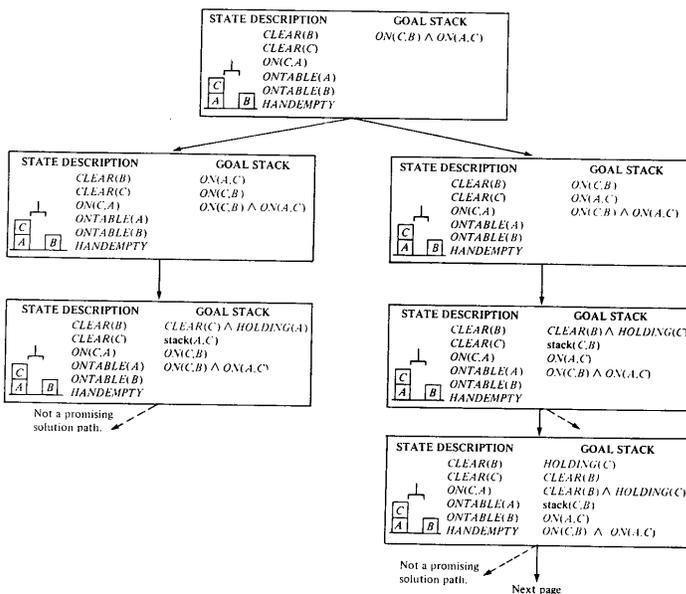
*Part of the backward (goal) search graph for a robot problem.*

BASIC PLAN-GENERATING SYSTEMS





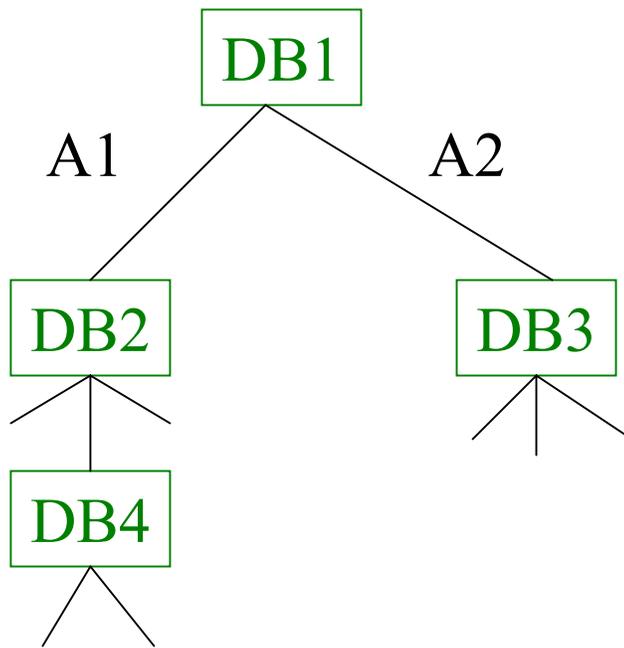
Conclusion of the backward search graph.



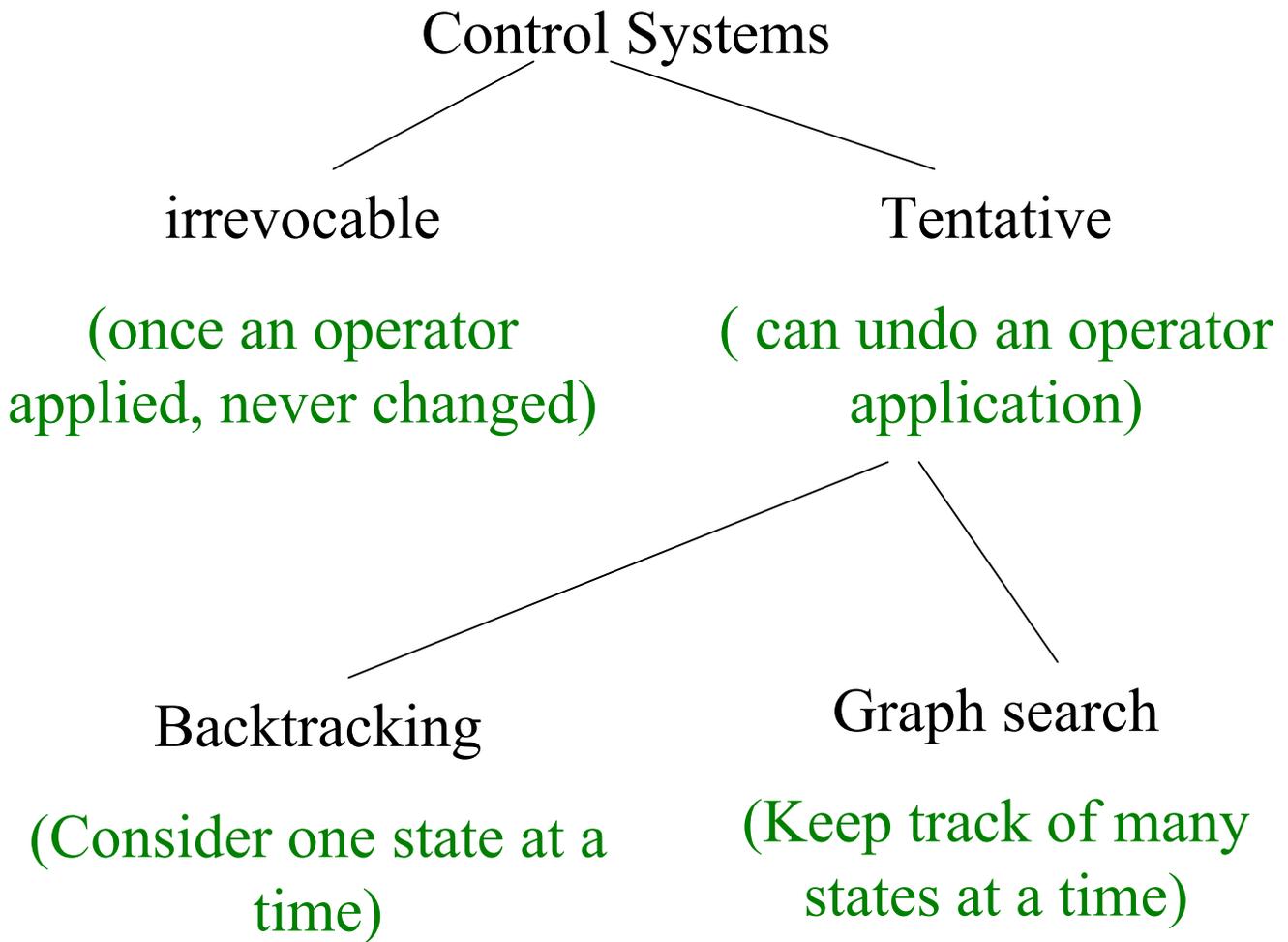
## Production systems

Generally characterized by three elements:

1. A global database
2. A set of rules or actions/operators.
3. A Control system.



Control system chooses which operator to apply and keeps on applying operators until a terminal condition is reached.

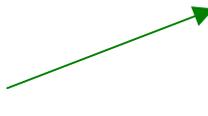


## 1. Irrevocable control

1. Consider the current state of global database.
2. Apply an operator.
3. Back to step 1 until terminal condition is met.

Selecting the operator to apply:

usually done by a function evaluation.  $f(x)$

Operator 

Pick the operator for which  $f(x)$  is minimum.

Consider the problem of solving the 8 puzzle:

2	5	3
1	6	4
7		5

Initial

1	2	3
8		4
7	6	5

Goal

Set of operators

- blank up
- blank down
- blank left
- blank right

Define  $f(x) = -$  (No of tiles out of place)

$$f(\text{initial}) = -4$$

$$f(\text{blank left}) = -5$$

$$f(\text{blank right}) = -5$$

$$f(\text{blank up}) = -3 \quad \leftarrow \text{Operator selected to apply}$$

new DB

2	8	3
1		4
7	6	5

$$f(\text{blank left}) = -3$$

$$f(\text{blank right}) = -4$$

$$f(\text{blank up}) = -3$$

$$f(\text{blank down}) = -4$$

select one of  
the min f  
operators

Advantages of irrevocable:

- simple
- fast
- less memory

Disadvantages of irrevocable:

- can get stuck on local optima
- information about past selections lost

## Backtracking control

try operators in a fixed order, and backtrack to a previous state when appropriate.

It is appropriate to backtrack when we come up with a state we have already seen before.

**Ex:** Consider the 8 puzzle example:

Fixed order of operators can be

blank left

blank right

blank up

blank down

# Algorithm for Backtracking

## Backtrack(DATA)

1. If TERM(DATA), return nil

Test whether terminal condition is satisfied.

2. If DEADEND(DATA), return fail.

All possible operators/actions are tried and exhausted.

3. Applicable-Operators  $\leftarrow$  Operators(DATA)

4. Loop:

4.1 If NULL( Applicable\_Operators), return fail

no operator can be applied.

4.2 R  $\leftarrow$  first(Applicable\_Operators)

Applicable\_Operators  $\leftarrow$  rest ( Applicable\_Operators)

4.3 newDATA  $\leftarrow$  R (DATA)

4.4 Path  $\leftarrow$  Backtrack(newDATA)

4.5 If Path= fail goto Loop

4.6 return Cons(R, Path)

DATA=


Any Row's possibilities:

$R_{i1}, R_{i2}, R_{i3}, R_{i4}$

1. TERM(DATA) X
2. DEADEND(DATA) X
3. Rules =  $(R_{12}, R_{13}, R_{11}, R_{14})$
4. Null(Rules) X
5.  $R \leftarrow R_{12}$
6. Rules  $\leftarrow (R_{13}, R_{11}, R_{14})$

7. RDATA  $\leftarrow$

	Q		

8. Path  $\leftarrow$  Backtrack

	Q		

1. Term

	Q		

? X

2. DEADEND

	Q		

? X

3. Rules  $\leftarrow (R_{21}, R_{24}, R_{22}, R_{23})$

4. Loop: Null (Rules)

5.  $R \leftarrow R_{21}$

6. Rules  $\leftarrow (R_{24}, R_{22}, R_{23})$

7.  $RDATA \leftarrow R_{21}$

	Q		

=

	Q		
Q			

8. Path  $\leftarrow$  Backtrack

	Q		
Q			

Path  $\leftarrow$  fail

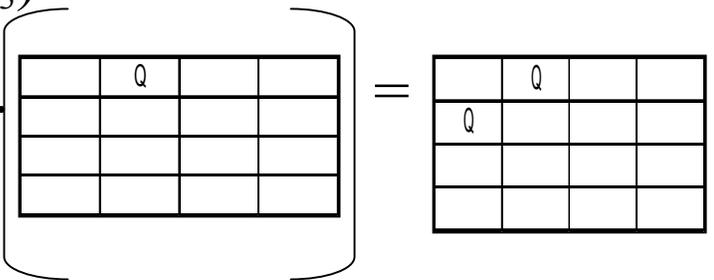
9. Path = fail  $\Rightarrow$  goto Loop

4. Null(Rules) = NULL( $R_{24}, R_{22}, R_{23}$ )? X

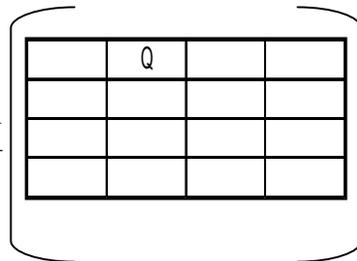
5.  $R \leftarrow R_{24}$  .

6. Rules  $\leftarrow (R_{22}, R_{23})$

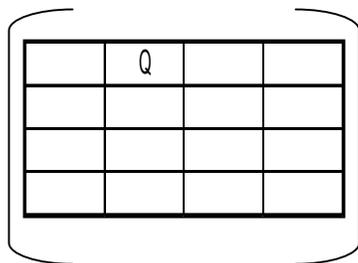
7. RDATA  $\leftarrow R_{24}$  .



8. Path  $\leftarrow$  Backtrack

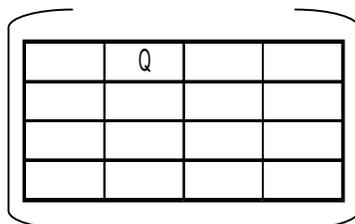


1. TERM

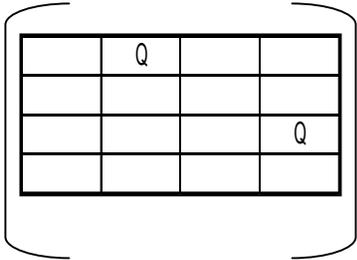


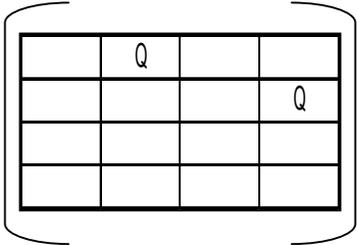
? X

2. DEADEND



? Yes  $\rightarrow$  Return  
Fail

1. TERM  ? X

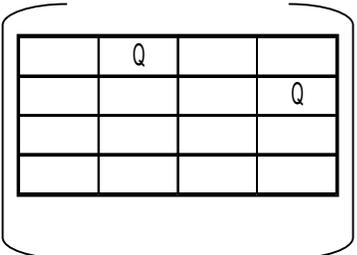
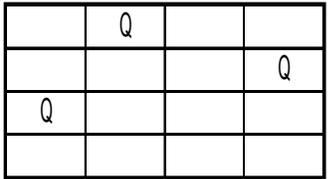
2. DEADEND  ? X

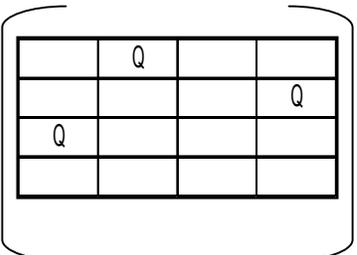
3. Rules  $\leftarrow (R_{31}, R_{34}, R_{32}, R_{33})$

4. Loop: NULL(Rules) X

5. R  $\leftarrow R_{31}$  .

6. Rules  $\leftarrow (R_{34}, R_{32}, R_{33})$

7. RDATA  $\leftarrow R_{31}$   = 

8. Path  $\leftarrow$  Backtrack 

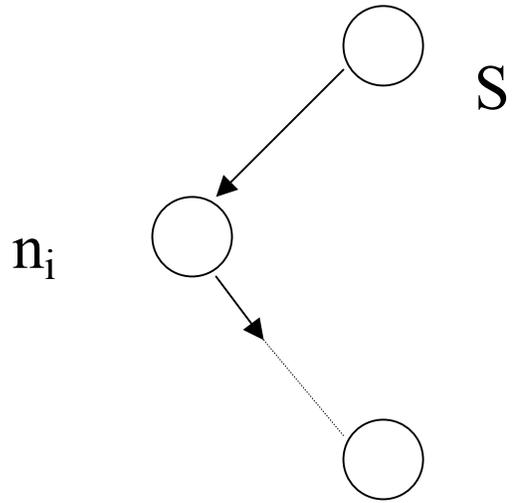
## Control Systems using Graph search

we keep track of all previous states at every iteration of the algorithm. We pick the most suitable state and expand from it.

### Definitions about graphs

- A graph consists of sets of nodes and arcs which connect the nodes
- If an arc from node  $n_i$  to node  $n_j$ , then  $n_i$  is the parent node of  $n_j$ , and  $n_j$  is the child or successor of  $n_i$ .
- If no node in the graph has more than one parent, then we have a tree.
- A node without a parent is the root.
- A terminal node is a node without a child.
- A sequence of nodes  $(n_{i0}, n_{i2}, \dots, n_{ik})$  with each  $n_{ij}$  a child of  $n_{ij-1}$  is a path of length  $K$  from  $n_{i1}$  to  $n_{ik}$ .

-  $C(n_i, n_j)$  is the cost of the arc from  $n_i$  to  $n_j$ .



We may have more than one goal node, i.e. set of  $[t_i]$  t goal node.

## Ordering of nodes in graph Search

### 1. Depth first Search:

Order nodes in the open list in descending order of depth from S.

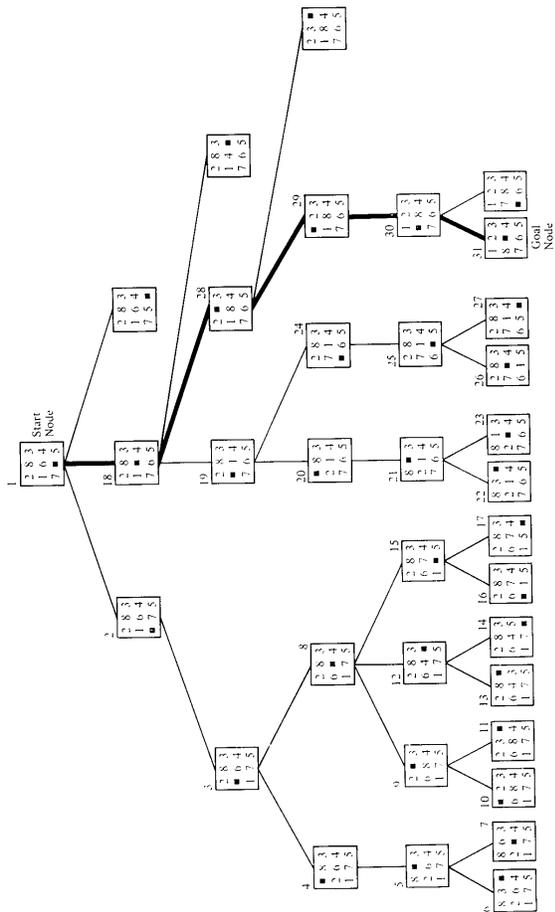
### 2. Breadth first search:

Order nodes in the open list in increasing order of depth from S.

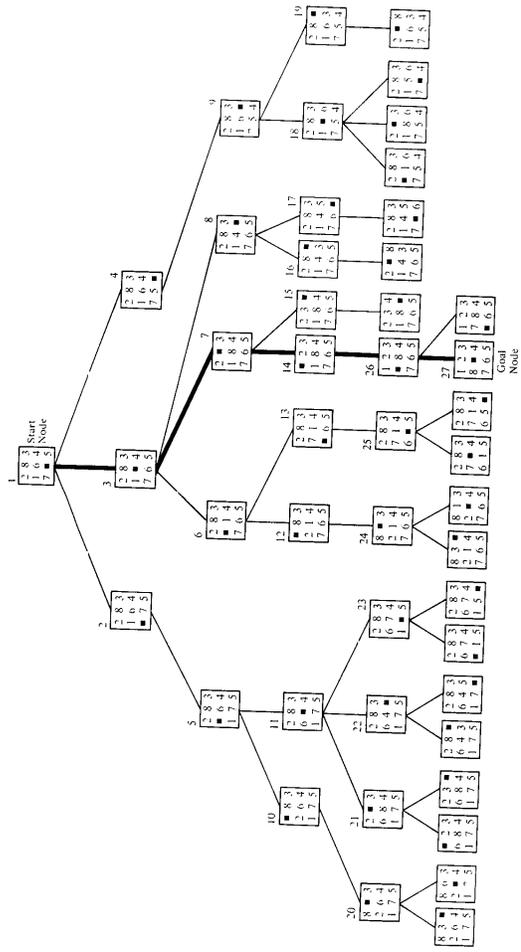
Breadth first will find the shortest length path to goal.

Both breadth\_first and depth\_first are un\_informed.

Heuristic search uses problem information.



A search tree produced by a depth-first search.



A search tree produced by a breadth-first search.

## Heuristic Search

Uses problem information to reduce search space.

Use an evaluation function,  $f()$  to measure the promise of a node.

for every node  $n$ .

$f(n)$  - value of  $f$  for goodness of node.

Ex: Consider 8-tile puzzle,

$$f(n) = g(n) + h(n)$$

$g(n)$  = depth of node  $n$  from  $s$ .

$h(n)$  = no. of tiles out of place.

Ex2: Manhattan distance:

Consider the 8-tile puzzle.

$$f(n) = g(n) + h(n)$$

$g(n)$  = depth of node  $n$  from  $s$ .

$h(n) = \sum_i$  block distance cell  $I$  is out of place from its desired position.

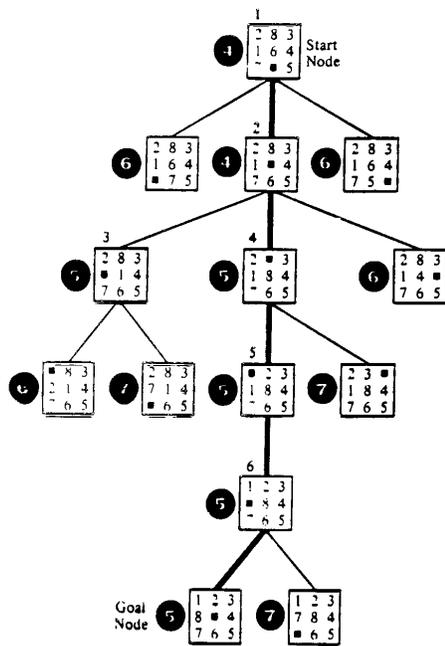
# A GENERAL GRAPH-SEARCHING PROCEDURE

The process of explicitly generating part of an implicitly defined graph can be informally defined as follows.

## Procedure GRAPHSEARCH

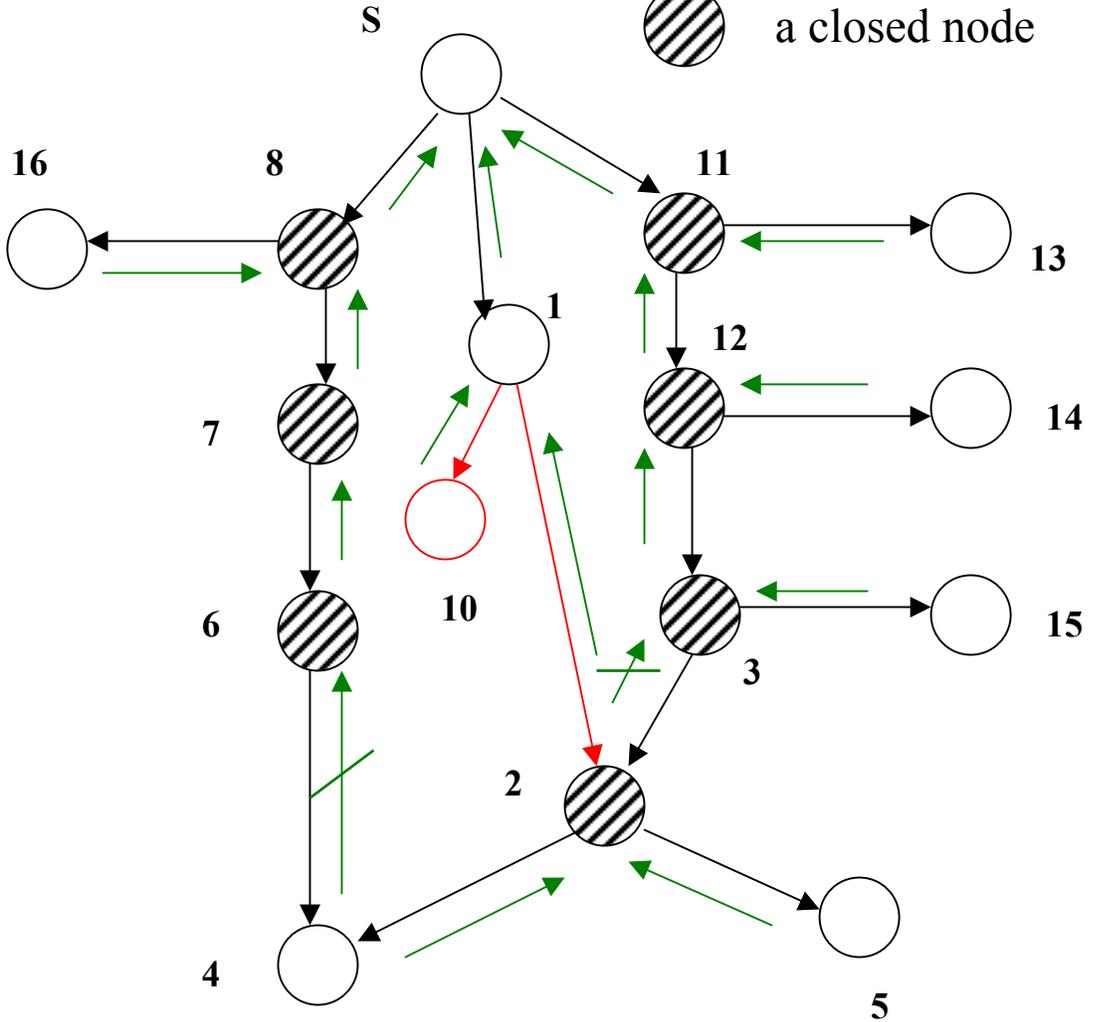
- 1 Create a search graph,  $G$ , consisting solely of the start node,  $s$ . Put  $s$  on a list called OPEN.
- 2 Create a list called CLOSED that is initially empty.
- 3 LOOP: if OPEN is empty, exit with failure.
- 4 Select the first node on OPEN, remove it from OPEN, and put it in CLOSED. Call this node  $n$ .
- 5 If  $n$  is a goal node, exit successfully with the solution obtained by tracing a path along the pointers from  $n$  to  $s$  in  $G$ . (Pointers are established in step 7.)
- 6 Expand node  $n$ , generating the set,  $M$ , of its successors and install them as successors of  $n$  in  $G$ .
- 7 Establish a pointer to  $n$  from those members of  $M$  that were not already in  $G$  (i.e. not already on either OPEN or CLOSED). Add these members of  $M$  to OPEN. For each member of  $M$  that was already on OPEN or CLOSED, decide whether or not to redirect its pointer to  $n$ . (See text.) For each member of  $M$  already on CLOSED, decide for each of its descendants in  $G$  whether or not to redirect its pointer. (Note: You have to check all descendants, not just the immediate children.)
- 8 Reorder the list OPEN, either according to some arbitrary scheme or according to heuristic merit.
- 9 Go LOOP.

## SEARCH STRATEGIES FOR AI PRODUCTION SYSTEMS



*A search tree using an evaluation function.*

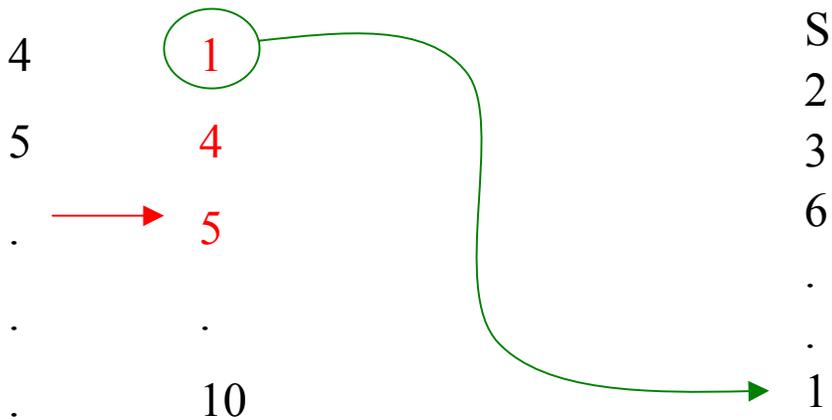
○ an open node  
 ● a closed node



Open List

Closed list

$f(n)$



$f(n)$  estimate of how much work is involved in a solution which has node  $n$  on its path.

### Admissibility:

If algorithm is admissible it always finds an optimal path from  $S$  to goal (solution).

An algorithm is admissible if

$$h(n) \leq h^*(n)$$

actual cost for the  
solution path from  $n$   
to goal.

## Informed algorithms Vs. Less informed algorithms:

Two algorithms with  $h_1(a)$  and  $h_2(n)$  respectively (both heuristic search): if  $h_1(n) \leq h_2(n) \leq h^*(n)$

then algorithm 2 using is more informed than algorithm 1.

Algorithm 2 will always do less work than algorithm 1 in finding the solution to the problem.

## Monotonicity:

If we have the following condition for a heuristic search algorithm:

(for any two nodes  $n_i$  and  $n_j$ ):

$$h(n_i) - h_2(n_j) \leq C(n_i, n_j)$$

goal node  $h(t) = 0$

Cost from  $n_i$  to  $n_j$

Thus when  $A^*$  expands a node it has already found the best path to that node, therefore there is no need to update backpointers.

## Minimax control:

Search into the search space a few levels forward, and make the best move possible (this may not be necessarily the winning move).

Assume we look forward 2 levels into the search space. Do the following:

- (1) Conduct a breadth first search until all nodes of level 2 are generated.
- (2) Apply an evaluation function to all the leaf nodes.
- (3) Propagate the values backward to make selection of next move.

Ex: take the tic-tac-toe problem.

	X	0
0	X	
	X	

Name the first player max, the other player min.

$f(n) = (\text{no of complete rows, columns, or diag. still available to max}) - (\text{no of complete rows, columns, or diag. still available to other player, min}).$

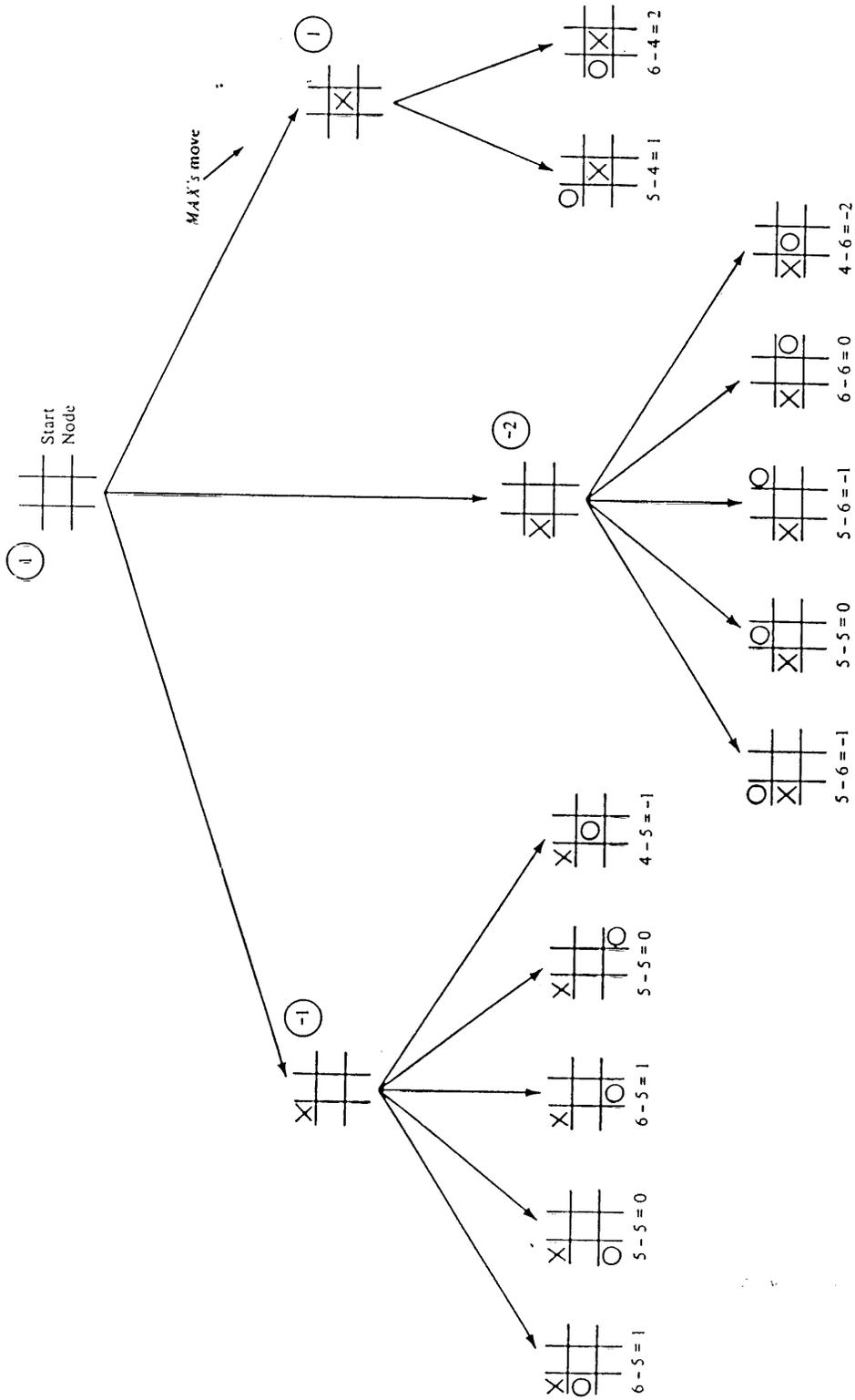
$f(n) = \infty$  ( if no winning position)

$f(n) = ?$

$n =$

0		
	X	

$= 5 - 4 = 1$



*Minimax applied to tic-tac-toe (stage 1).*





## $\alpha$ - $\beta$ Procedure

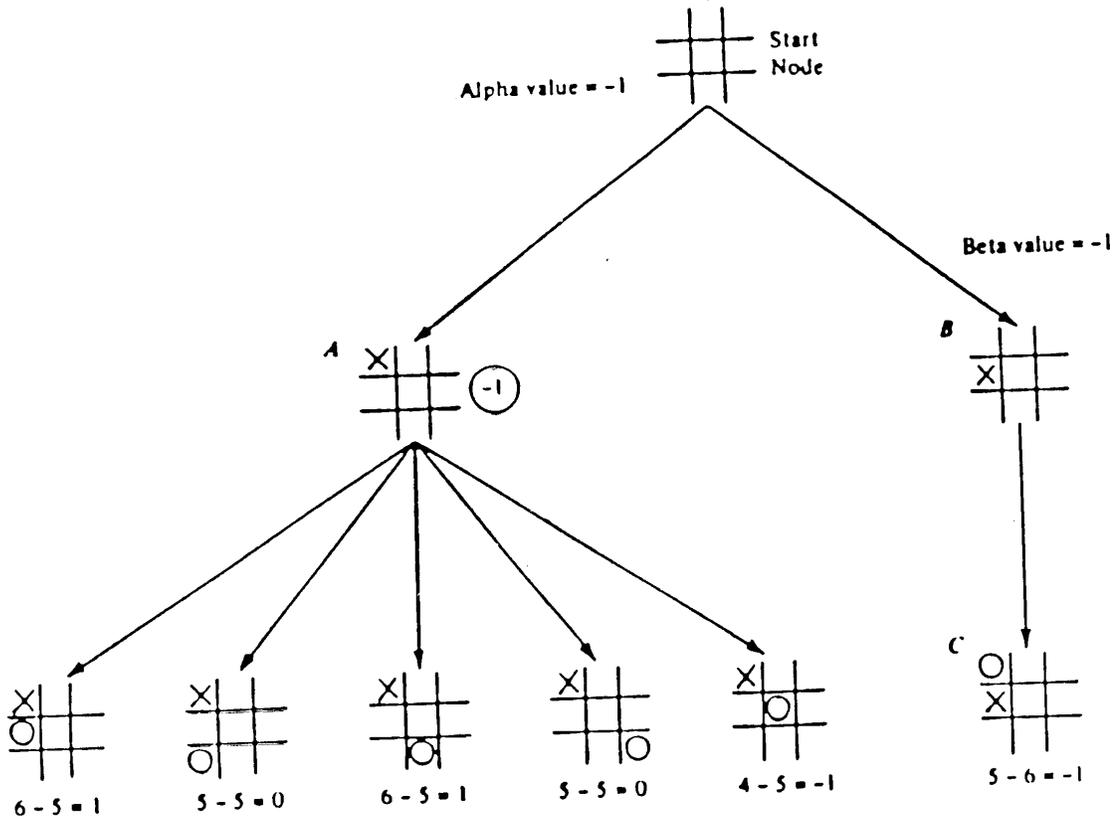
<<< Refer to Section 6.3 of the text >>>

Instead of enumerating all nodes  $K$  levels ahead, we only generate the nodes that could affect the outcome. Therefore obtain computational efficiency.

The values assigned to MAX as nodes are generated are denoted  $\alpha$  values. Similarly, values assigned to Min as nodes are generated, are denoted as  $\beta$  values.

Alpha-Beta Procedure:

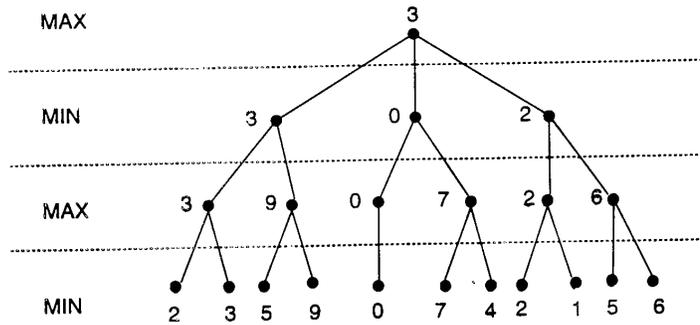
- (a) Set the alpha value of a MAX node equal to the largest final backed up value of its successors.
- (b) The beta value for a Min node is at equal to the smallest backed up value of its successors.
- (c) Discontinue search at any Min node having beta value less than or equal to the alpha value of its MAX ancestors.
- (d) Discontinue search below any MAX node having alpha value greater than or equal to Beta value of any Min node ancestors.



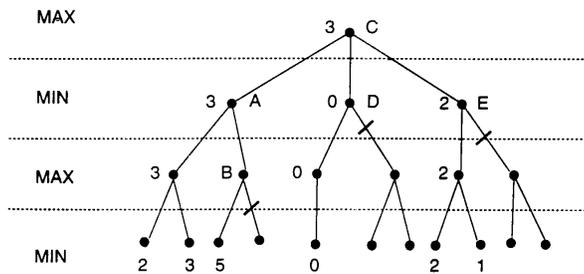
$$f = e(X) - e(O)$$

$e(X)$  = no. of complete rows, columns, or diagonals from which X can still win.

$e(O)$  = same for O.



Minimax to a hypothetical state space. Leaf states show heuristic values; internal states show backed-up values.



- A has  $\beta = 3$  (A will be no larger than 3)
- B is  $\beta$  pruned, since  $5 > 3$
- C has  $\alpha = 3$  (C will be no smaller than 3)
- D is  $\alpha$  pruned, since  $0 < 3$
- E is  $\alpha$  pruned, since  $2 < 3$
- C is 3

Alpha-beta prune applied to the state space of previous figure. States without numbers are not evaluated.