

ITCS 451

Section 2

Lecture 1 Intro

Thanapon Noraset
Faculty of ICT, Mahidol University

Adapted from AIMA by Stuart Russell and Peter Norvig, and UC Berkeley CS188 by Dan Klein and Pieter Abbeel (ai.berkeley.edu)



Announcements & Agenda

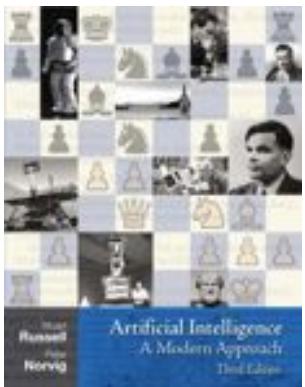
1. Please bring
notebook (computer)
next class.
2. also need pen or pencil.
3. Checkpoint 1
due on Sun.
4. Feed back 1

1. Why study AI ?
2. What is AI ?
3. Course Logistics
4. Agent , Environment,
States

Credit

This class is based on

- AIMA by Stuart Russell and Peter Norvig
- UC Berkeley CS188 by Dan Klein and Pieter Abbeel (ai.berkeley.edu)



Most of the artworks
from Berkeley CS188
course and the book.

1. Why study Artificial Intelligence?

Can you think of an application of AI?

Mid Journey → Picture AI

Spotify → music recommendation

Facebook → face detection

Shazam → music recognition

Netflix → movie rec

Github → Co-Pilot

} ML

“AI” is everywhere

Information Technology



Face ID



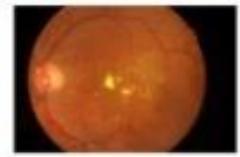
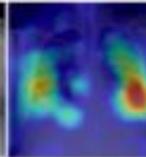
NETFLIX

Game-Playing



Healthcare

Diagnosis and Prescreening



Drug Discovery and Biochemistry



Exscientia



Surgery and other robots



“AI” is everywhere

Media



narrative science



FEAR
FIRST ENCOUNTER ASSAULT RECON

Business



Marketing



Human Resources



Finance

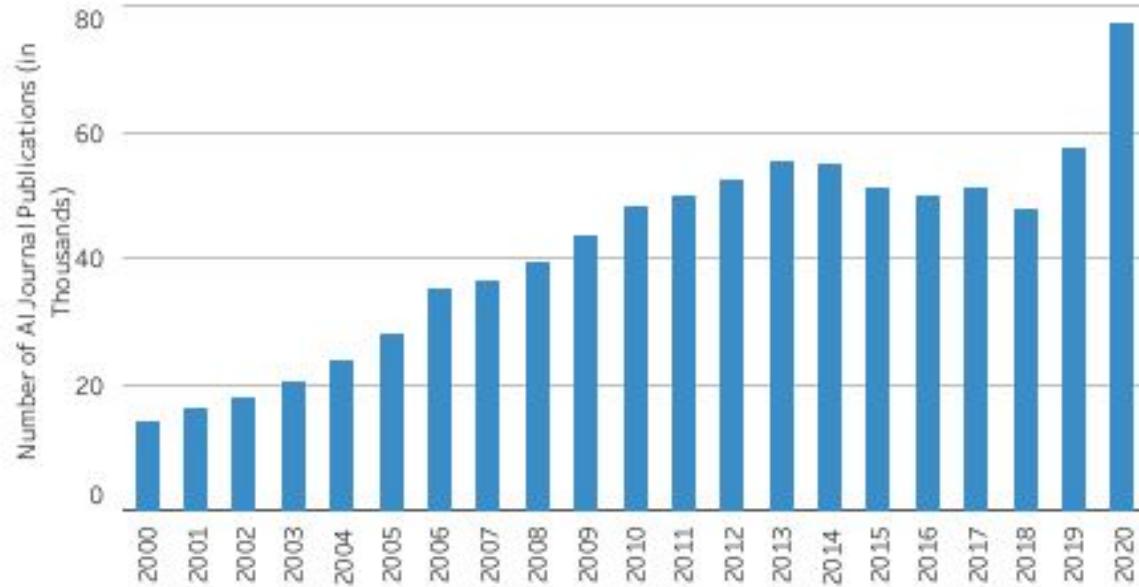


Manufacturing

more...

Global AI Trend: Research.

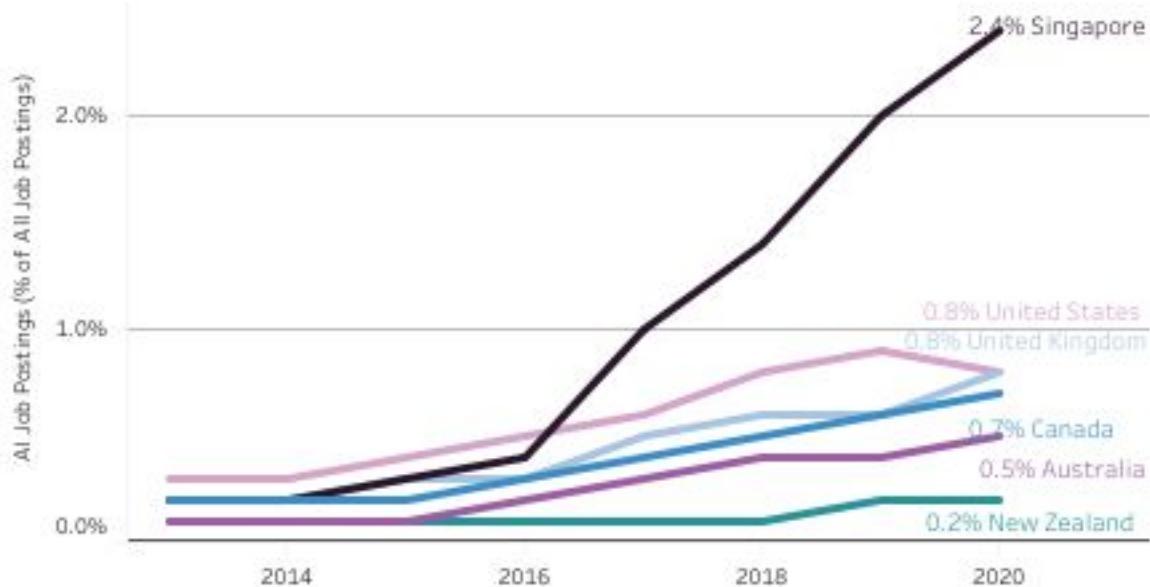
NUMBER of AI JOURNAL PUBLICATIONS, 2000-20
Source: Microsoft Academic Graph, 2020 | Chart: 2021 AI Index Report



Global AI Trend: Job Postings.

AI JOB POSTINGS (% of ALL JOB POSTINGS) by COUNTRY, 2013-20

Source: Burning Glass, 2020 | Chart: 2021 AI Index Report



AI combines “cool stuff” from many disciplines.

Outside CS

- Philosophy
- Mathematics
- Psychology
- Cognitive science
- Economics
- Control theory
- Computer Engineering

Within CS

- Algorithms
- Optimization
- Parallel Computing
- Data Management

Train our brain to be able to solve hard problems.

2. What is AI?

“Artificial” and “Intelligence”

↓
manmade

- ability to learn
- make decision (instead of us)
- smart
- a lot of knowledge
- skills

we have to define
it for the purpose of
this class.

Artificial Intelligence aims to make a machine that ...

Thinking Humanly

think like a human.

↳ Cognitive science
neuro sci

Thinking Rationally

think in the "^{Best}~~right~~" way
↓
logical thinking

* 2nd half.

Acting Humanly

act like human

↳ Turing test *

* Acting Rationally *

make the "best" decision



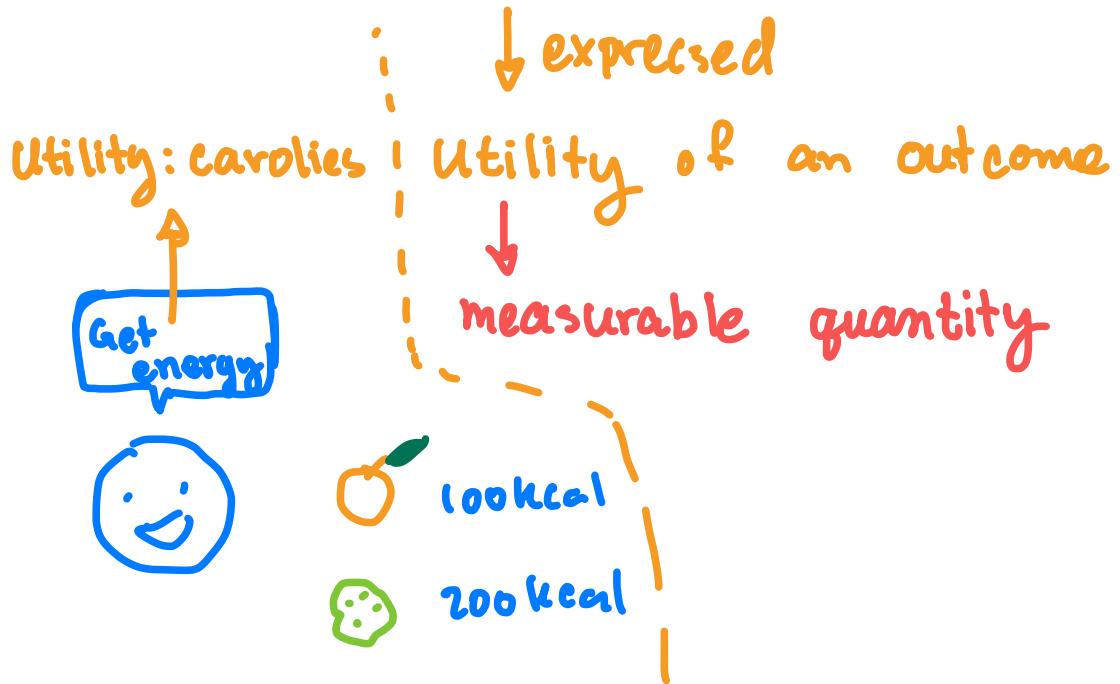
maximize
some score.

Rational Decision and Utility

↳ "maximally achieving pre-defined goals"

"Being Rational"

↓
"Act to maximize
expected utility"



Value Alignment Problem * Ethics

Walking Agents: https://www.youtube.com/watch?v=hx_bgoTF7bs

CoastRunner: <https://www.youtube.com/watch?v=tIOIHko8ySq>

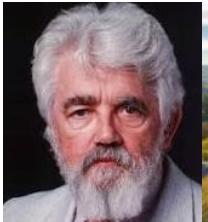
10 mins

Resume. [2 : 15 pm]

A bit of history...

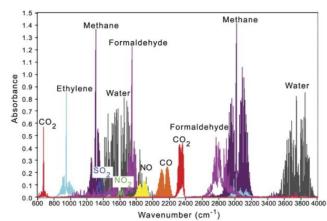
Artificial General Intelligence (AGI)

1956: The birth of “Artificial Intelligence”



Logic, Search
algorithm.

70s-80s: The expert systems **domain specific intelligence**

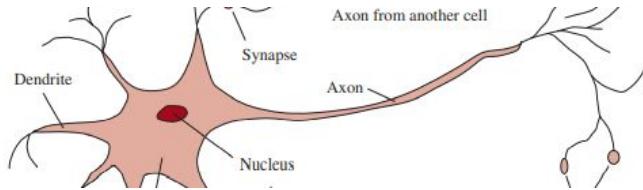


AI winter



In another timeline of AI...

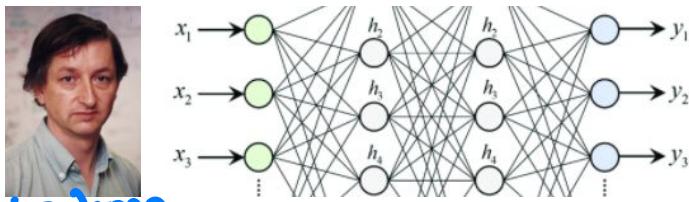
1943: Artificial neural network models (McCulloch and Pitts)



1969: Linear models could not solve XOR (Minsky and Papert)



1986: The rise of the backpropagation algorithm (Rumelhardt, Hinton, Williams)



AI as statistics...

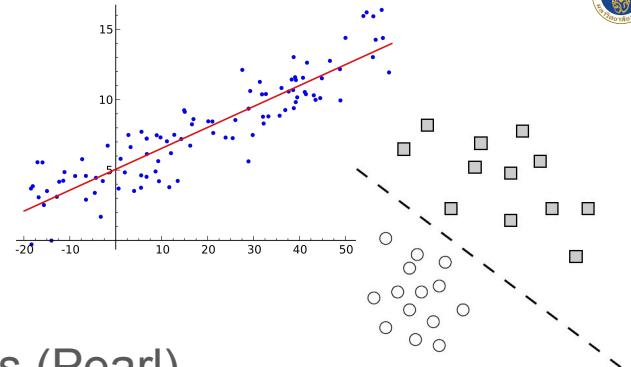
1801: Linear Regression (Gauss and Legendre)

1936: Linear Classifier (Fisher)

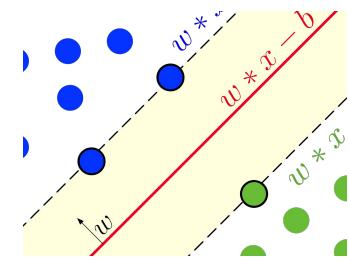
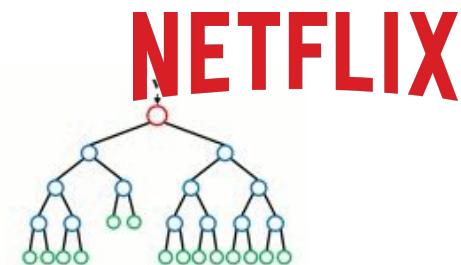
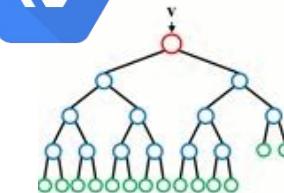
1985: Reasoning with uncertainty: Bayesian networks (Pearl)

1995: Risk minimization: Support vector machines (Cortes and Vapnik)

2000s - present: Machine Learning



kaggle



In another timeline of AI...

2010s - present: Deep Learning



Google

DeepMind

OpenAI

Facebook AI Research

3. Course Logistics

Instructors



Teaching Assistant



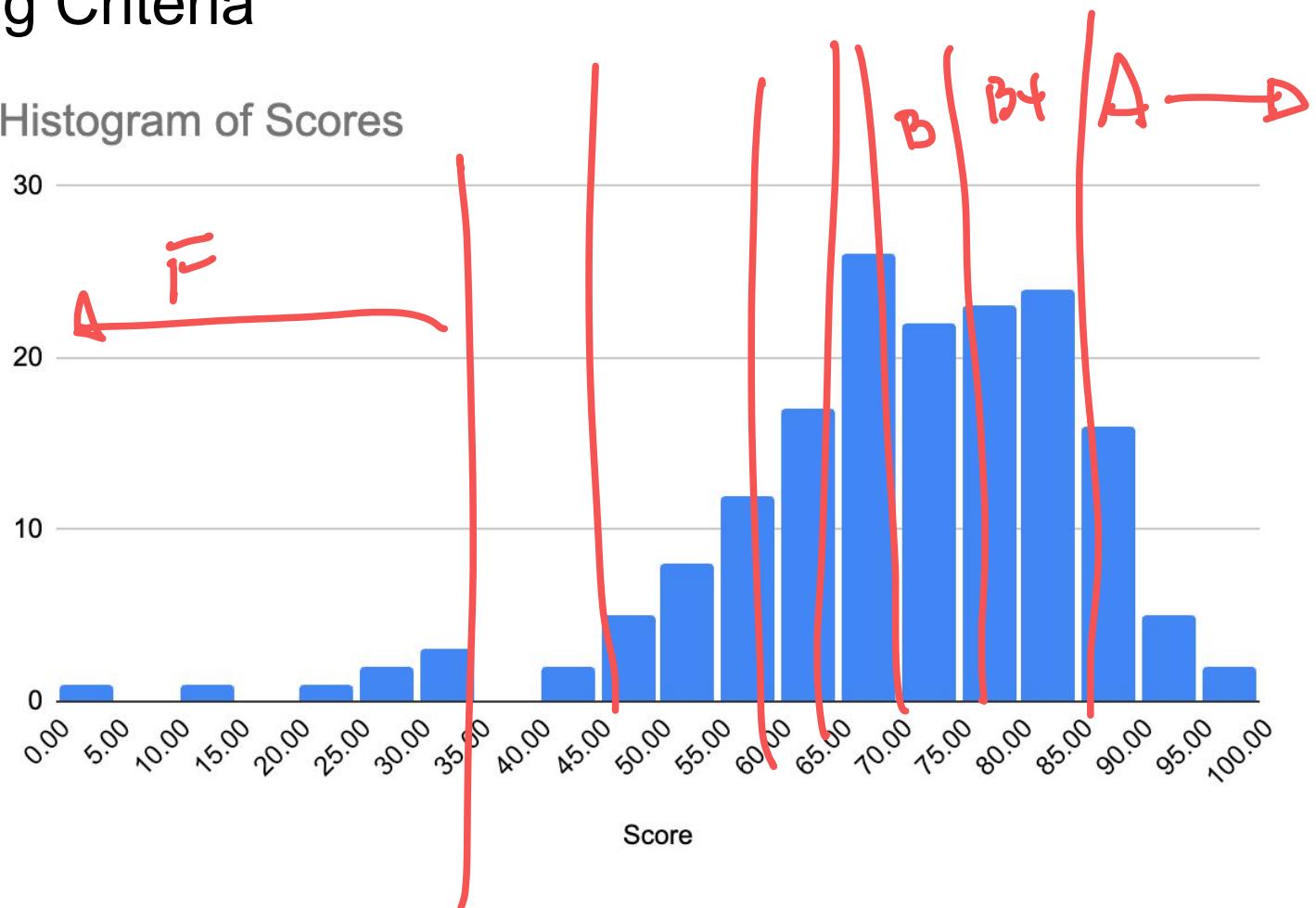
- Dr. Thanapon Noraset (thanapon.nor@mahidol.edu)
- Prof. Dr. Peter Haddawy (peter.had@mahidol.ac.th)
- Asst. Prof. Dr. Apirak Hoonlor (apirak.hoo@mahidol.ac.th)
- Phaphontee Yamchote (phaphontee.yam@student.mahidol.ac.th)

Grading Criteria

Evaluation Methods	Weight (%)	Due
Quiz Exercise	10	At the end of a topic
Examination	50	9, 17
Assignment	10	Every 2 or 3 weeks
Project I	10	8
Project II	10	14
Project III	10	17

Grading Criteria

Histogram of Scores





Assignments and Project 1

↓
Essay & Presentation

↓
Essay & Presentation

80

80

Programming

JS: Pathfinding

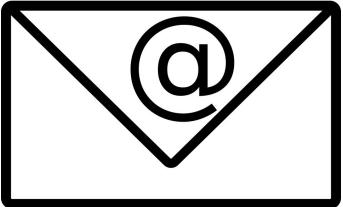
100

Programming

JS: Game playing

100

Need Help?



Ask in the
class.

Books

- [Artificial Intelligence: A Modern Approach](#) by Stuart Russell and Peter Norvig
- [Machine Learning](#) by Tom Mitchell

Courses

- [UC Berkeley CS188 Intro to AI](#)
- [Stanford CS221: AI: Principles and Techniques](#)

Course Plan



①

Problem-solving
by searching
(deterministic)



②

Probabilistic
Reasoning
(indeterministic)



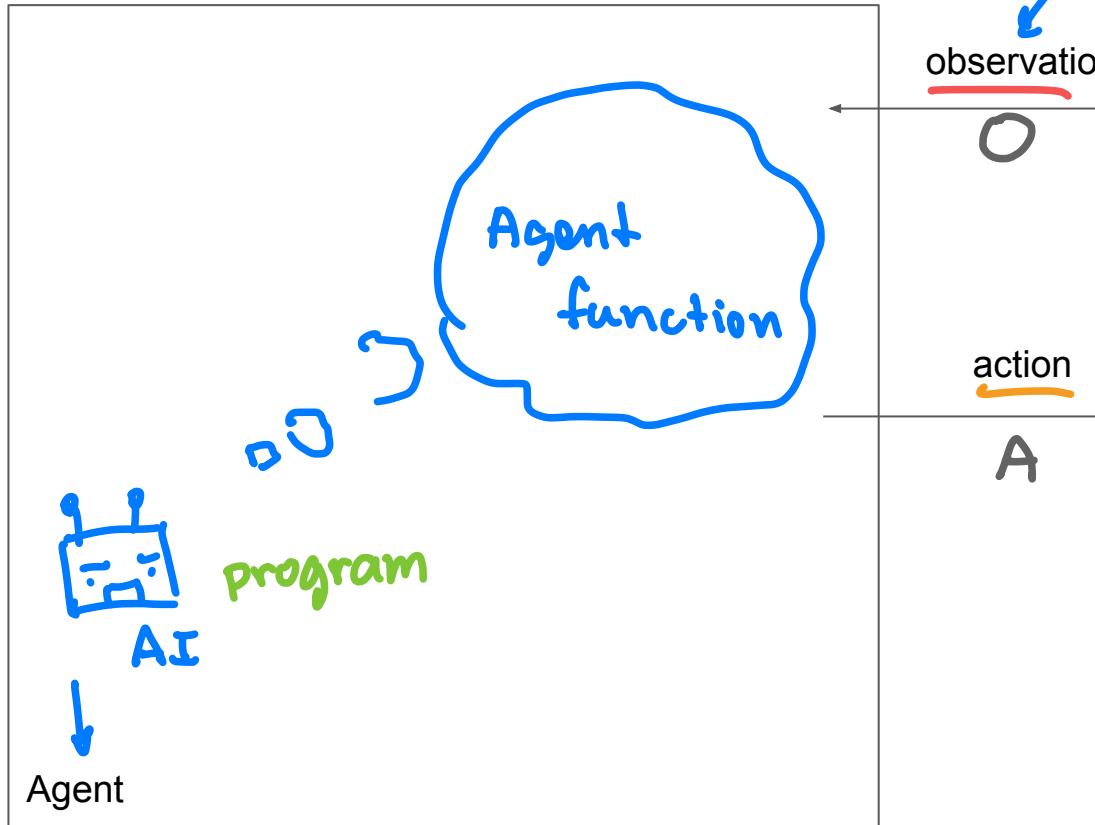
③

Advance
Topics

(CSP , ML)

4. Agent, Environment, and State

Interaction: Agent and Environment



Data from the environment

observation

action

t
0

1

Environment

$O^0 \rightarrow A^0$

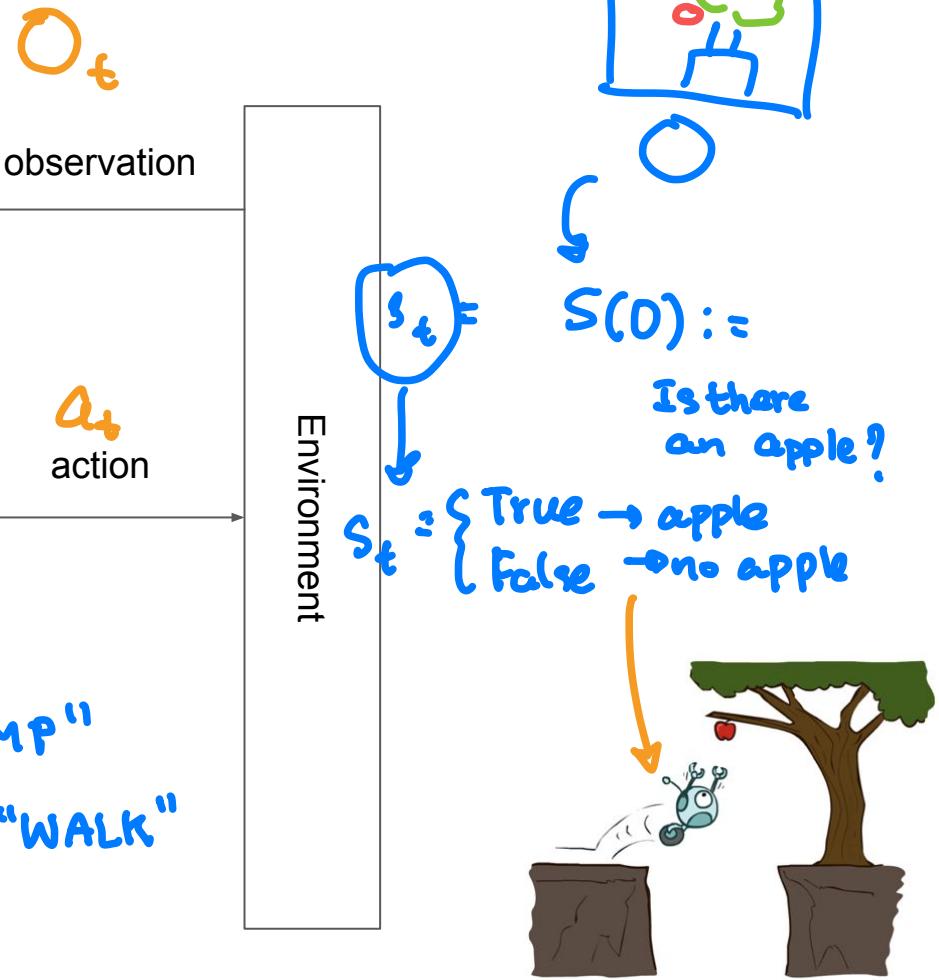
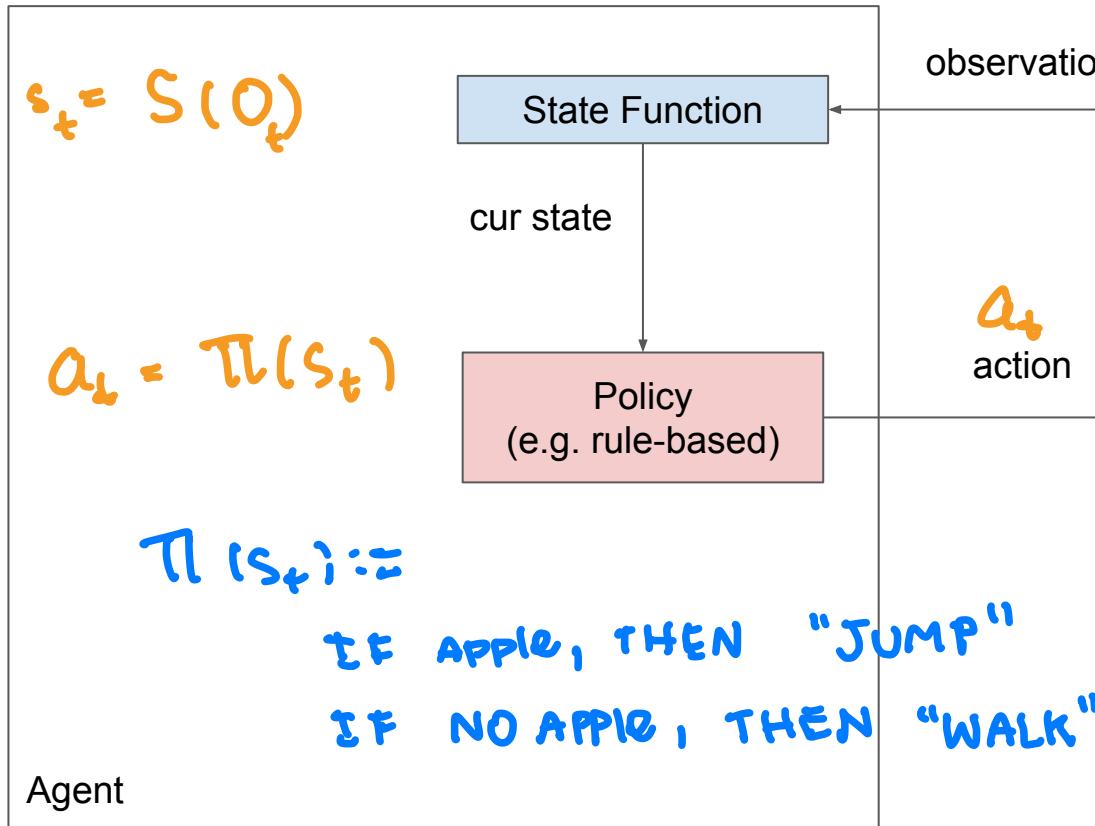
$O^1 \rightarrow A^1$

$\dots \rightarrow A_n$

max utility
outcome

O^*

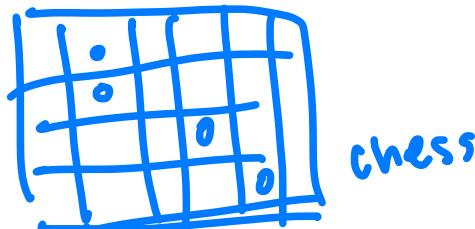
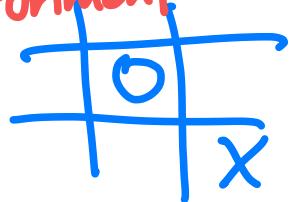
Simple reflex agent



Environment

* Fully Observable

one observation will get all data in the environment



Partially Observable

1. require many observations to get full data.
2. hidden data.

} attempt to infer from what agent can observe.

* also deterministic

configuration, description

State: A representation of a system

`char[][] board = new char[3][3];`



Environment States S^e

- Data in the environment

$$1. S_t^e \neq O_t$$

2. S_t^e usually has
too many things

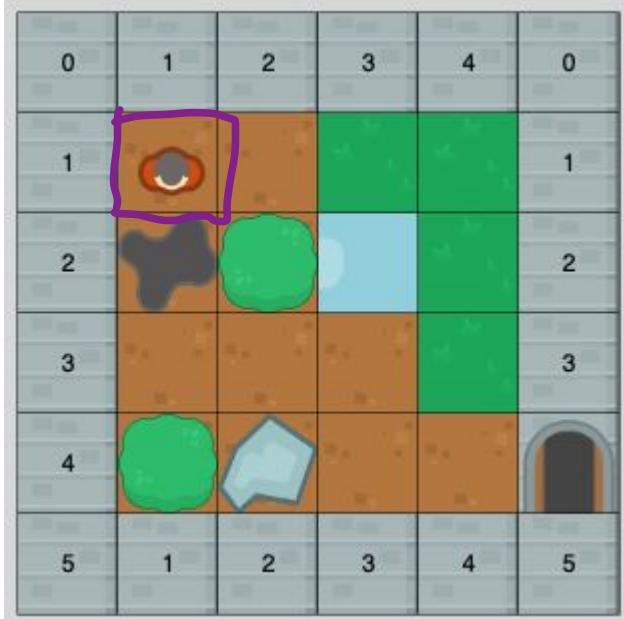
Agent States S^a

Info of the environment
inside the agent.

1. only contain what
necessary

2. sometimes, $O_b = S_t^a$

State: Examples

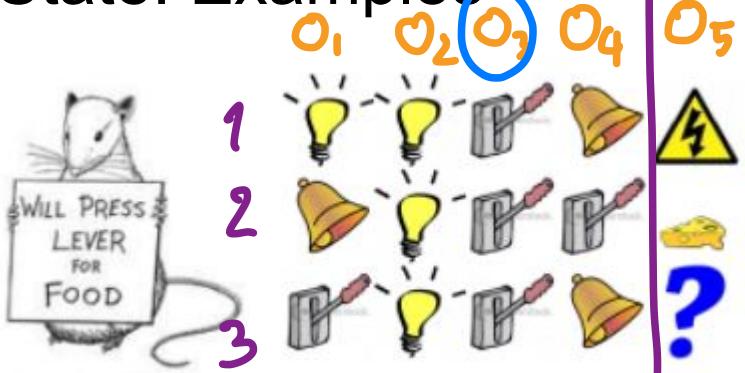


States.

- types of tiles
- cost (energy)
- distance to the goal

* [- location, x and y]

State: Examples



- 2 prev obs ↳ ep1: [0 1 1 0 0] ⚡
↳ ep2: [0 2 0 0 0] ⚡
↳ ep3: [0 1 1 0 0] ⚡

$$[S_1^{(0)} \quad 2 \quad 0 \quad 0 \quad 0] + [0 \quad 1 \quad 0 \quad 0 \quad 0] - [(S_2^{(0)}) \quad 0 \quad 0 \quad 0 \quad 0]$$

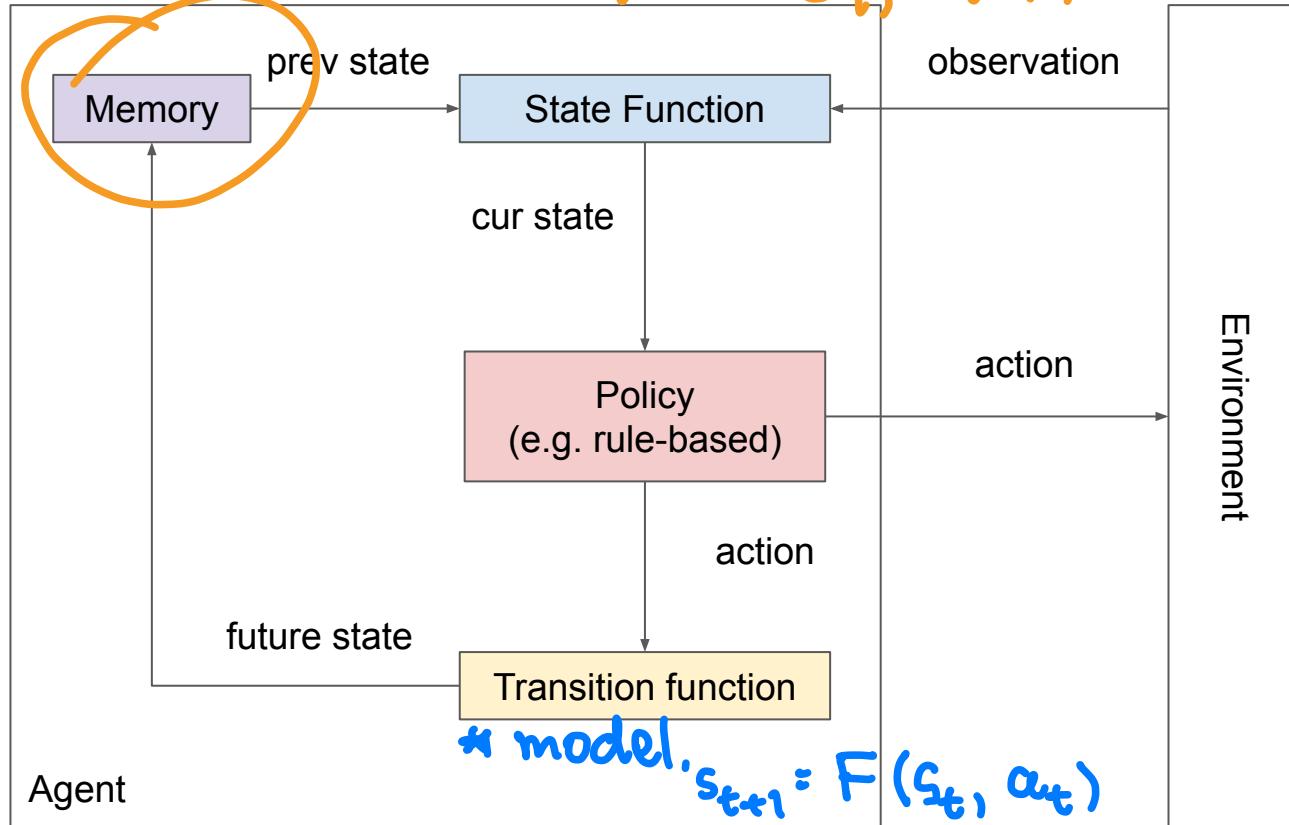
$$O_3$$

- 4 previous obs ↳ [0 1 1 0 0] ⚡
- ep1 [2 1 1 0 0] ⚡
- ep2 [1 2 1 0 0] ⚡
- ep3 [1 2 1 0 0] ⚡

memory

Model-based reflex agent

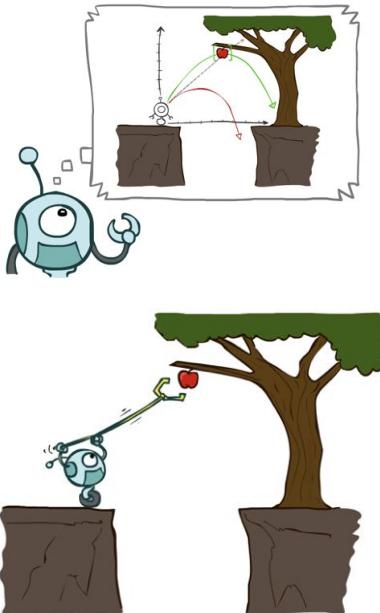
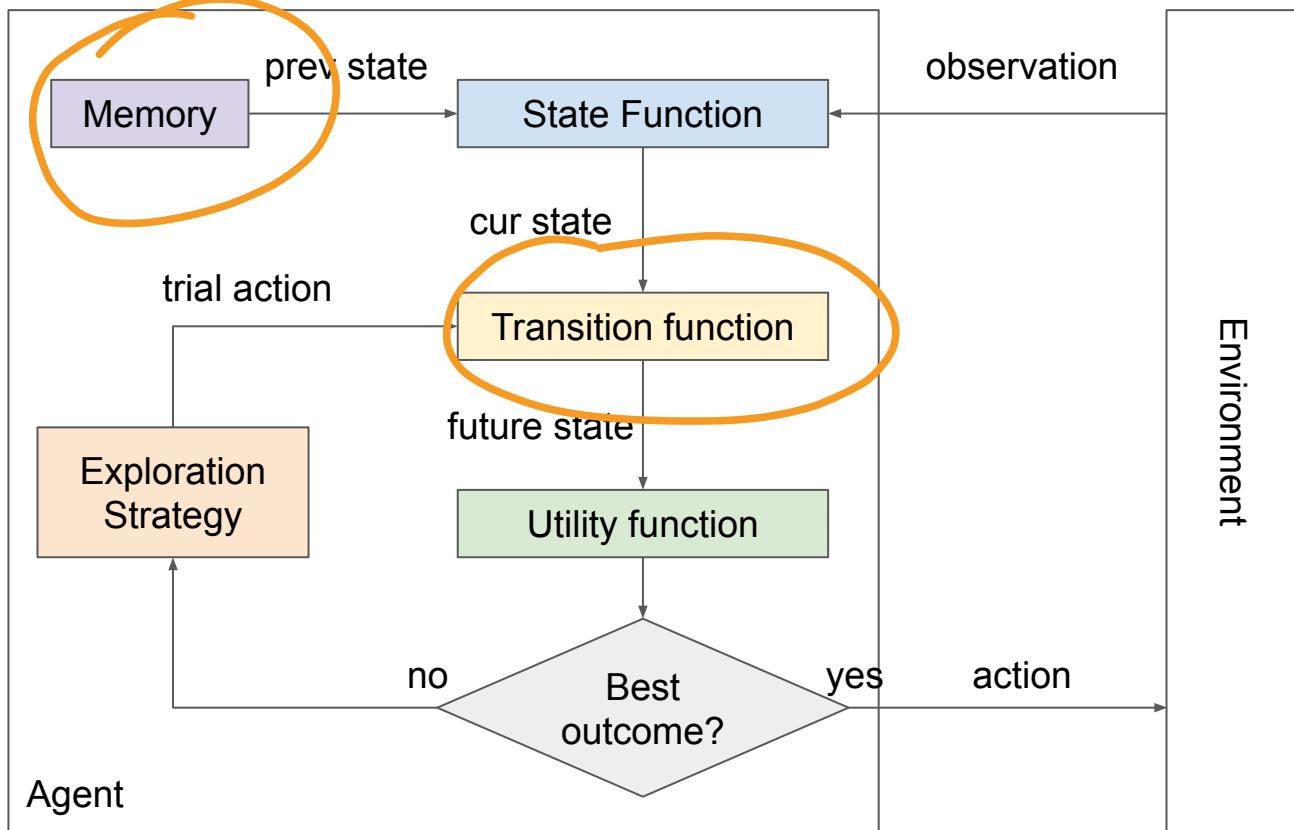
$$s_t = S(O_t, s_{t-1})$$





Rational Decisions

Model-based, utility-based agent



Summary



Further Readings

1. AIMA Chapter 1
2. AIMA Chapter 2
3. Get familiar with [p5.js](#)



ITCS 451
Section 2

Lecture 2

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Feedback Summary

1. Increase speaking volume
2. Write a bit bigger
3. Model-based reflex agent
4. States

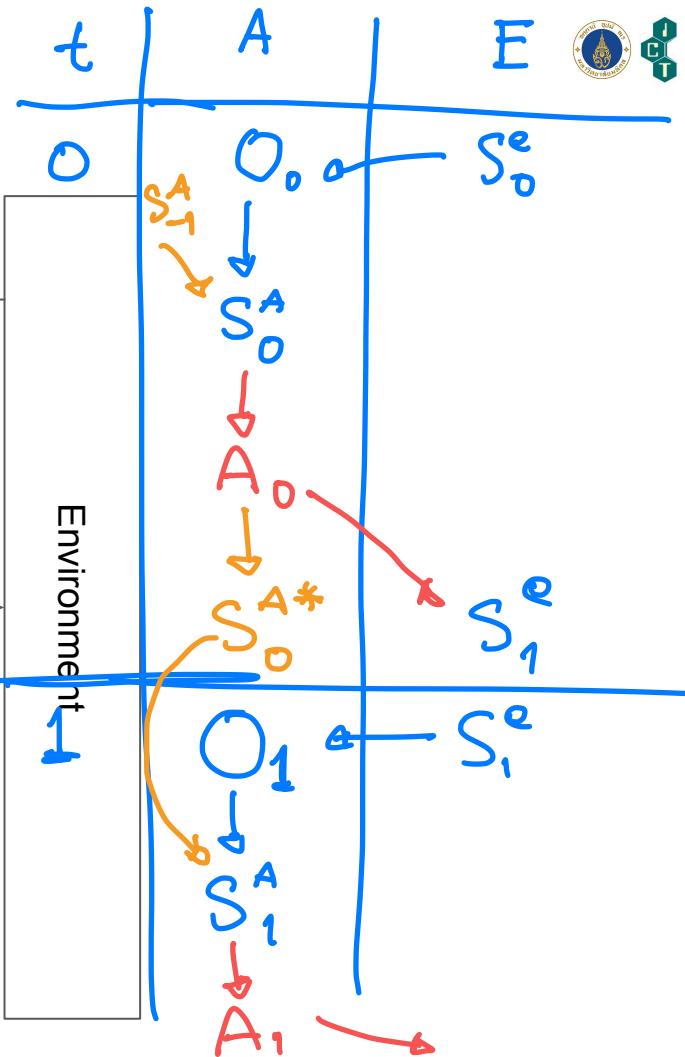
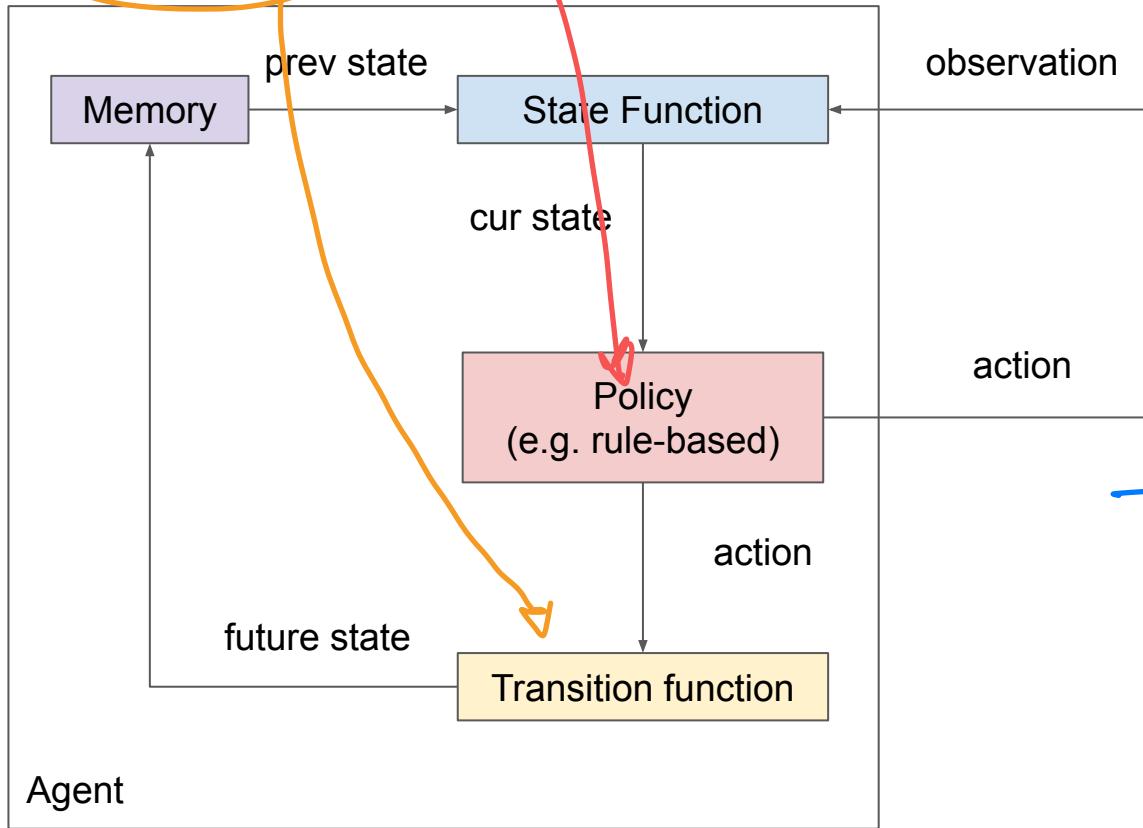
Announcements & Agenda

1. Feedback 2.
2. Checkpoint 2
due today
3. Assignment 1
will be announced
on Fri

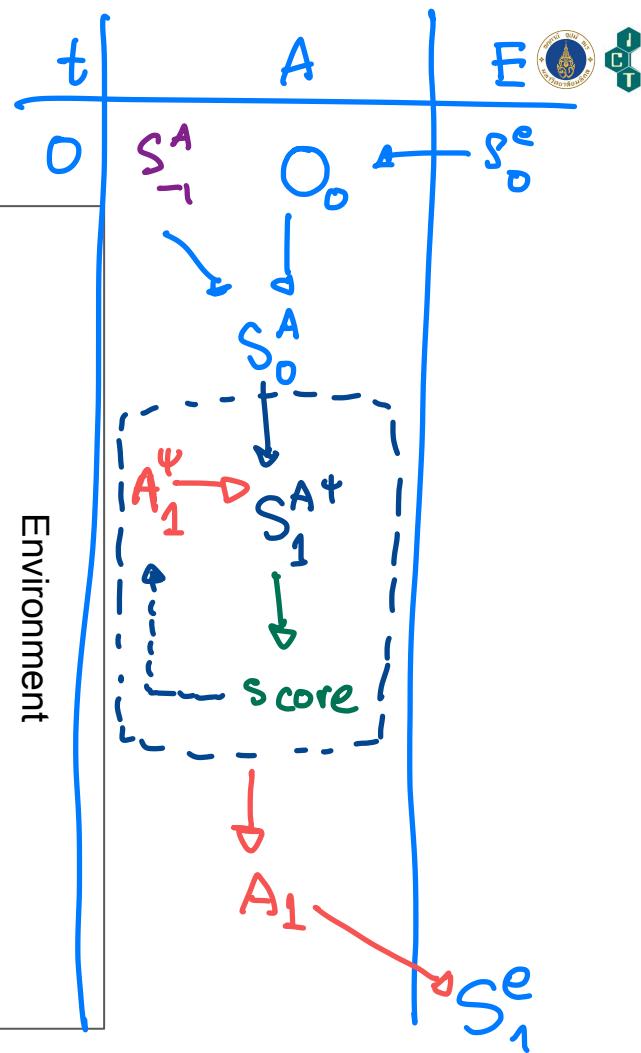
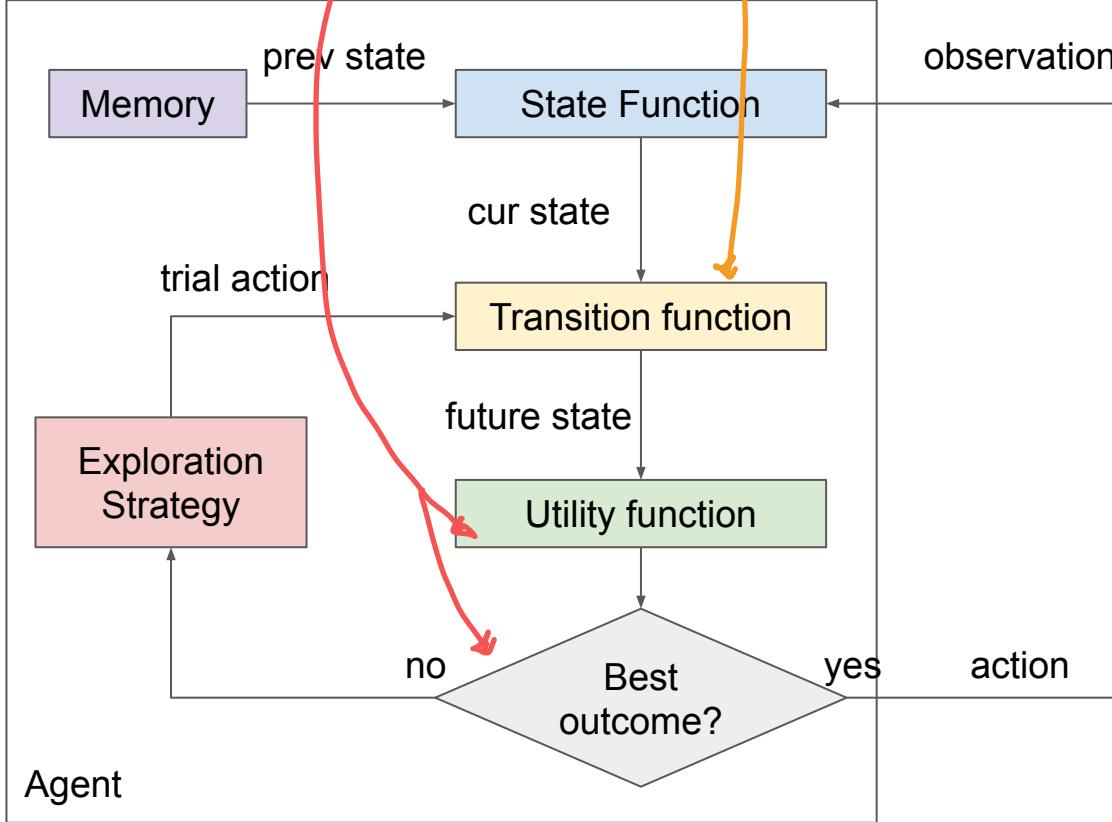
1. Agent, Environment, and State
2. Planning and State-space Exploration
3. Search Algorithms
4. Uninformed Search Strategies

1. Agent, Environment, and State

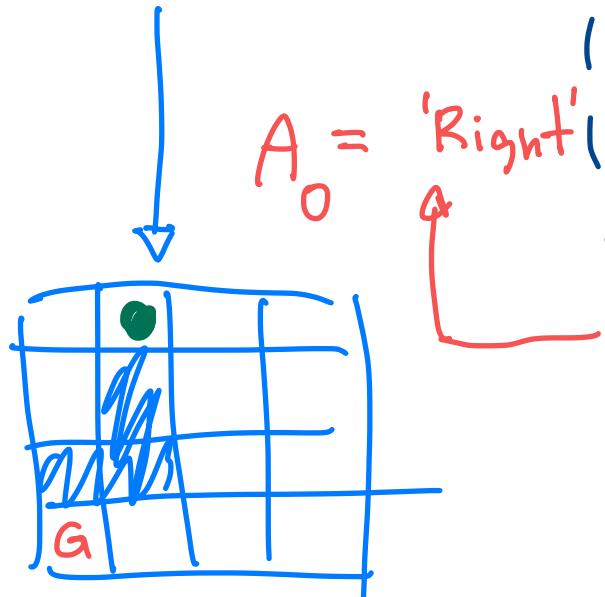
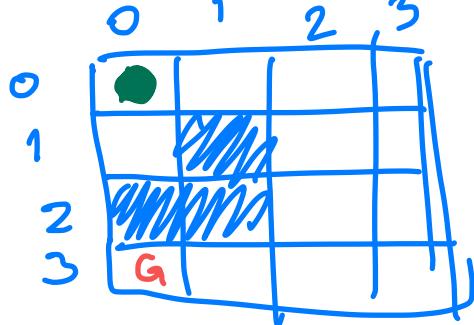
Model-based reflex agent



Utility-based, model-based Agent



Example: Pathfinding



$A_0^{\psi} = \text{'Right'}$

$A_0^{\psi} = \text{'Down'}$

$S_0^A = \overline{(0, 0)}$

$$S_1^{A\psi} = (0, 1)$$

Iter 1

$A_0^{\psi} = \text{'Right'}$

Score = 0

$$S_0^A = (0, 0)$$

Iter 2

$A_1^{\psi} = \text{'Up'}$

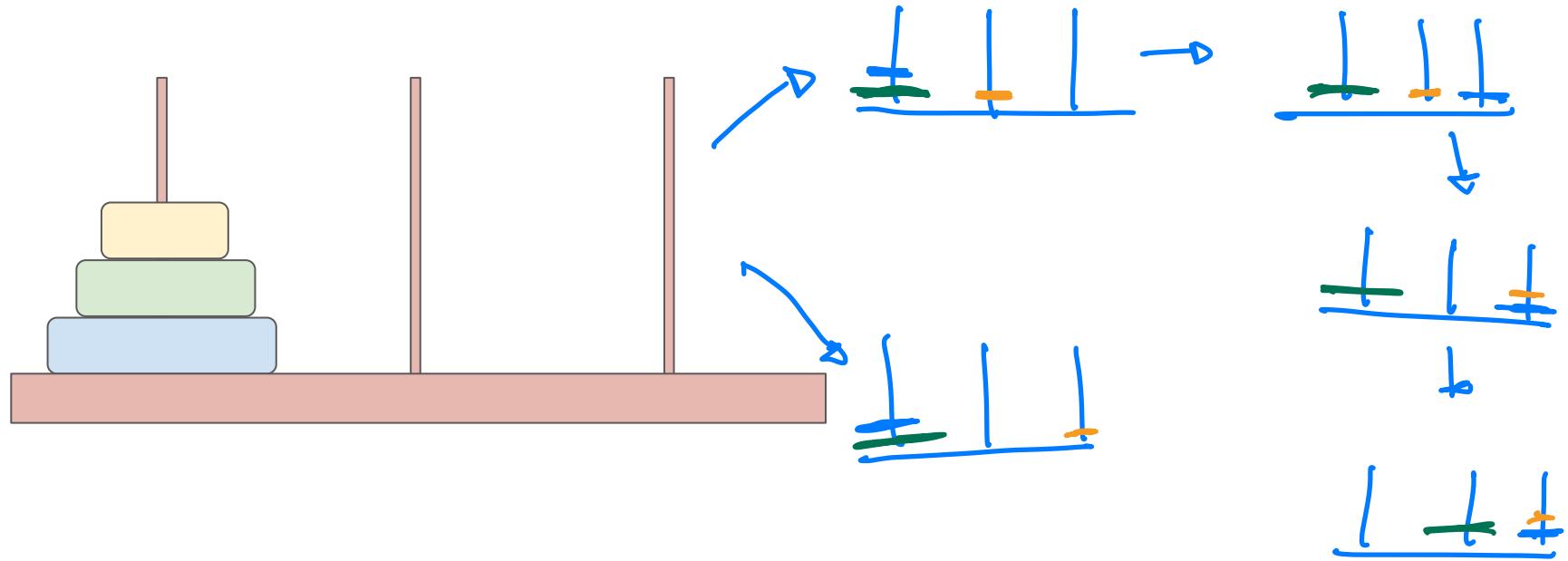
$$S_1^{A\psi} = (1, 0)$$

Score = 0

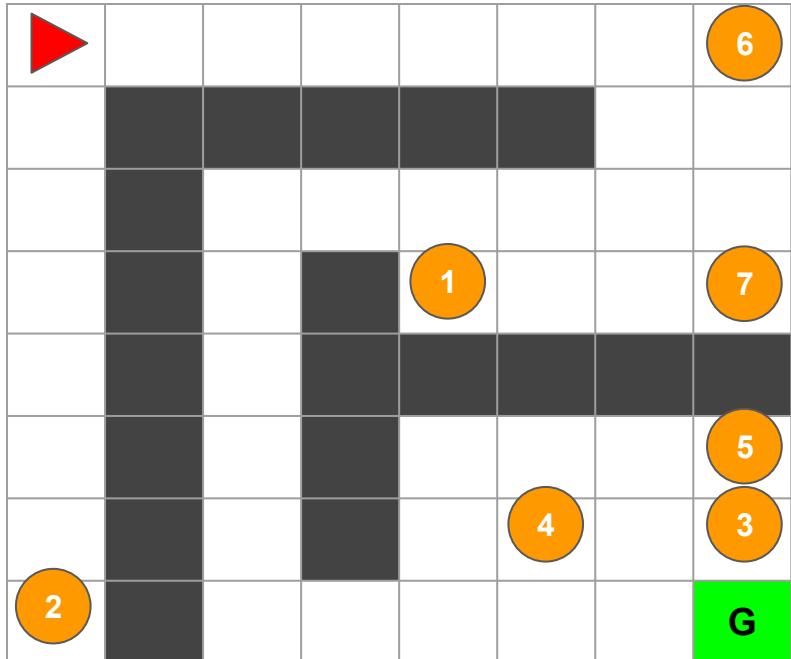
$$S_1^A = (0, 1)$$

$$S_2^A = (0, 0)$$

Example: Tower of Hanoi

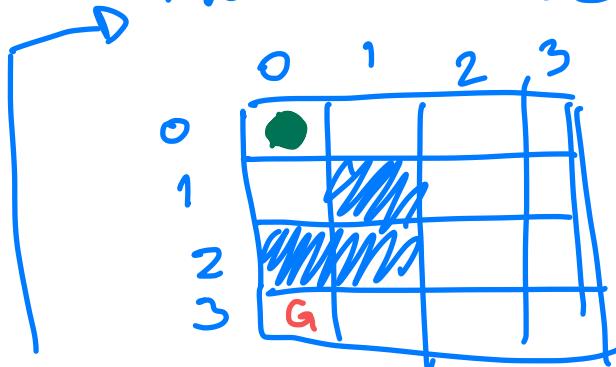


Example: Collect and Goal



Poll: Can you come up with a good order of the balls we should collect?

Plan: a sequence of actions.

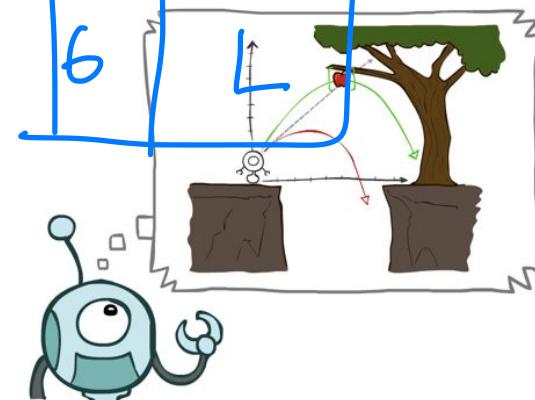


Plan ex:

R → R → D → D → D
→ L → L

T	A
0	R
1	R
2	D
3	D
4	D
5	L
6	L

2. Planning and State-space Exploration



Planning: Assumptions and Objectives

1. Fully observable environment
2. Deterministic environment
3. We have a model (transition func)

To find a plan that take an agent from an initial state to a goal state using minimum cost.
maximize utility
 $\hookrightarrow \text{utility} = -1 * \text{cost}$

Activity 1: Find a plan for the least energy path.

<https://editor.p5js.org/thanapon.nor/full/0dOqnQ7Oo>



2:30 pm

1 time
step

On a piece of paper, please answer the following questions

1. What are the actions that the agent can output? $\text{actions} = \{u, d, l, r\}$
2. What are the differences among different types of tiles (areas)?
~~1, 3, 5, 6~~
Dirt, Grass, Water, Stone, Tree, Mud
3. What are the plans and their energy requirements that you discovered?

$S \rightarrow r \rightarrow d \rightarrow r \rightarrow v \dots$: energy = 1000

at a time such as r, u, u, u, u. 11).

d, d, r, r, u, u, r, d, d, r = 32

r, r, d, d, d, r, r = 17

s, d, d, r, r, d, r, r: 15

energy:

S>d>d>r>r>d>r

s, d, d, r, r, r, d, r: 17

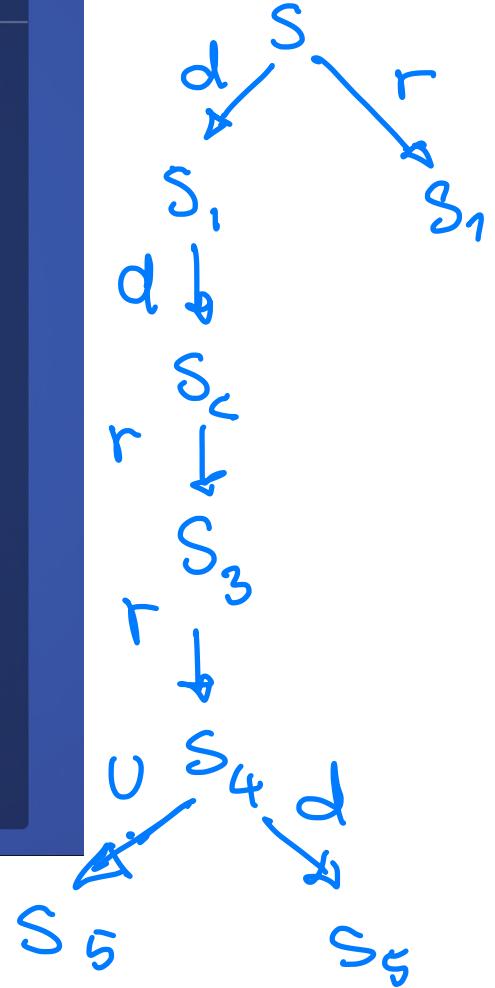
left down right a b a b

r:20

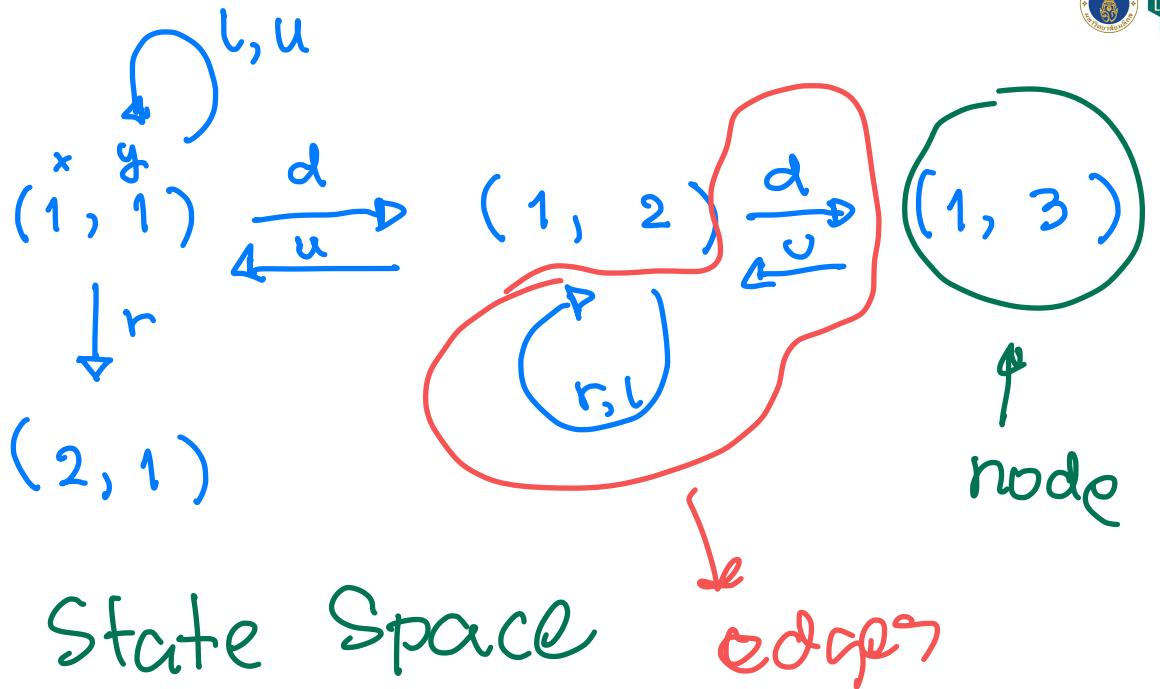
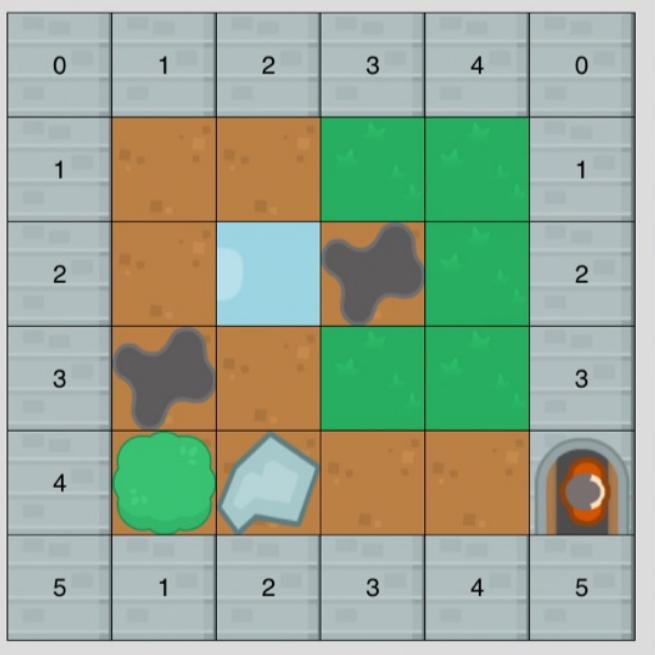
S, r, r, r, d, d, d, r: 16

ddrruurrdddr:35

d, d, r, r, d, r, r: 15

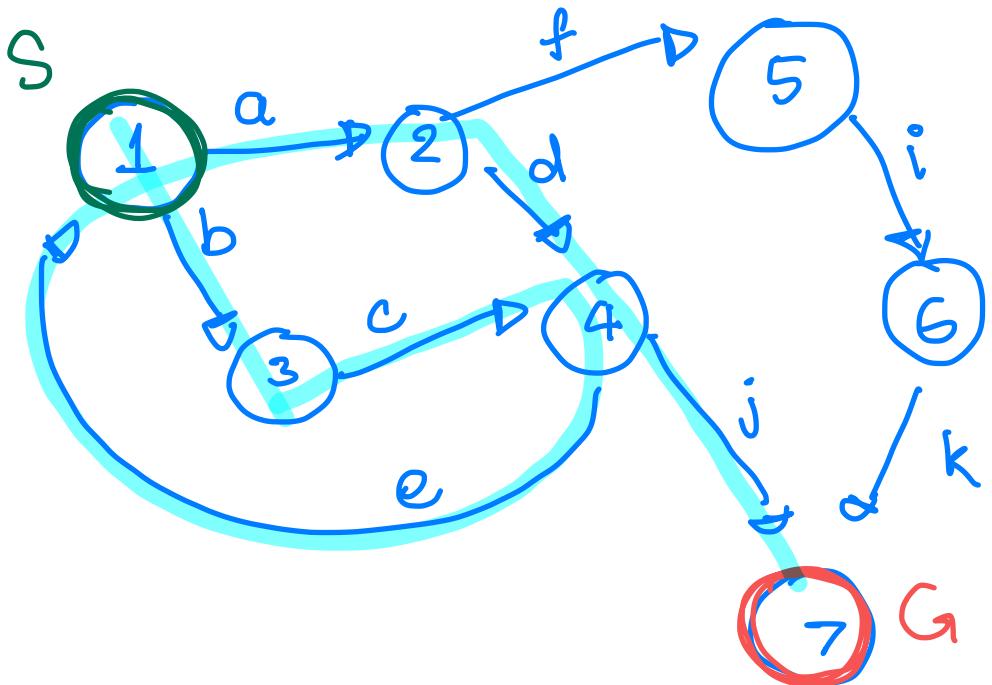


State Space



State Space
is a graph

- ↳ nodes: State
- ↳ edges: Possible actions

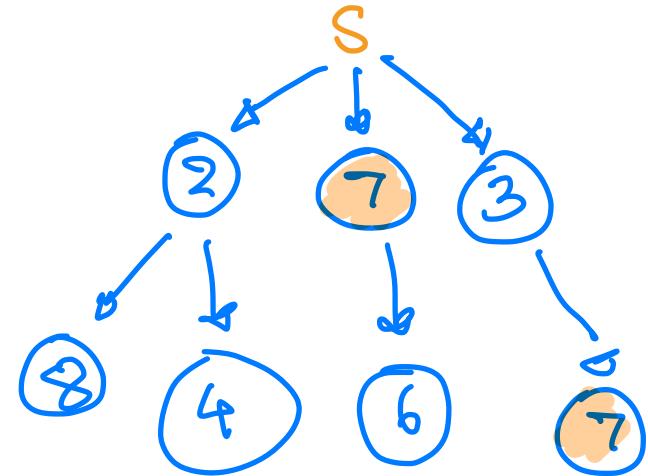
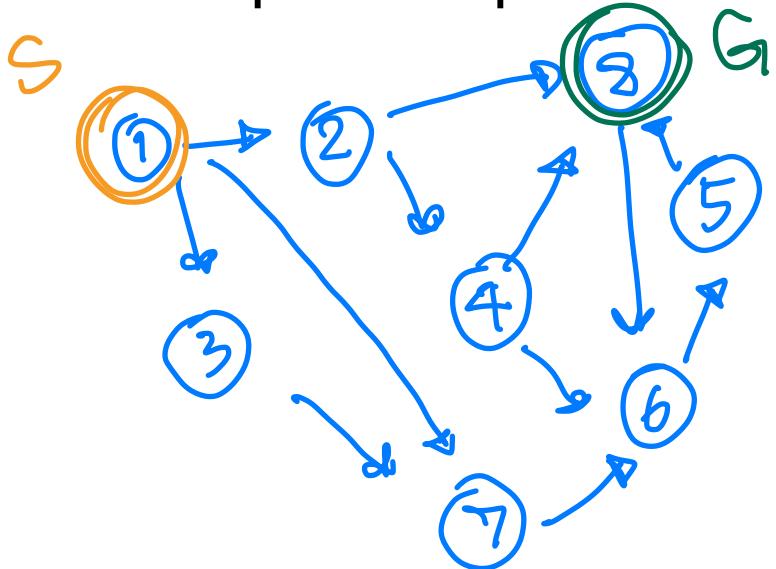


Abstract
Example.

Plan 1 : $b \rightarrow c \rightarrow e \rightarrow a \rightarrow d \rightarrow j$

cost : 6 (steps)

State-Space Exploration



State-Space Exploration
: Tree
 → nodes : current plan
 → edges : Previous-Next

Activity 2: A systematic way to explore?

<https://editor.p5js.org/thanapon.nor/full/T8Hk1cSIK>



On a piece of paper, please answer the following questions:

4. During the exploration, did you find moving back useful?
5. What are the approaches that you use to explore?

1. Cost of actions

2. Exploration Strategy

↳ transition function

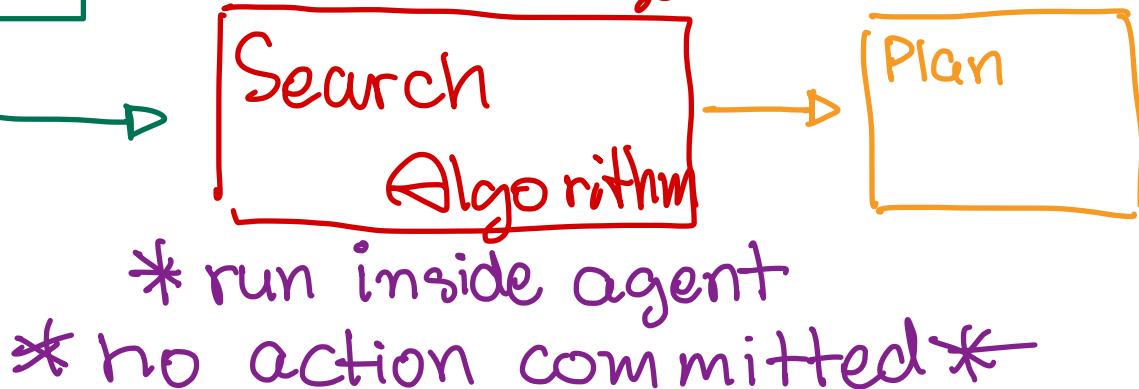
3. Search Algorithms



Search Problem Formulation

- 1 Initial State
2. Possible actions
3. Transition function
4. Goal test function
5. Cost function

Search Problem



Example: Pathfinding

Step 1 Formulation

1. Initial state : $S_0 = (x, y)$

2. Action space : { u, d, r, l }

3. Transition function

Given input state = (x, y)

if action == U, return $(x, y-1)$
 * if the action is valid

if action == D, return $(x, y+1)$

4. Goal test function:

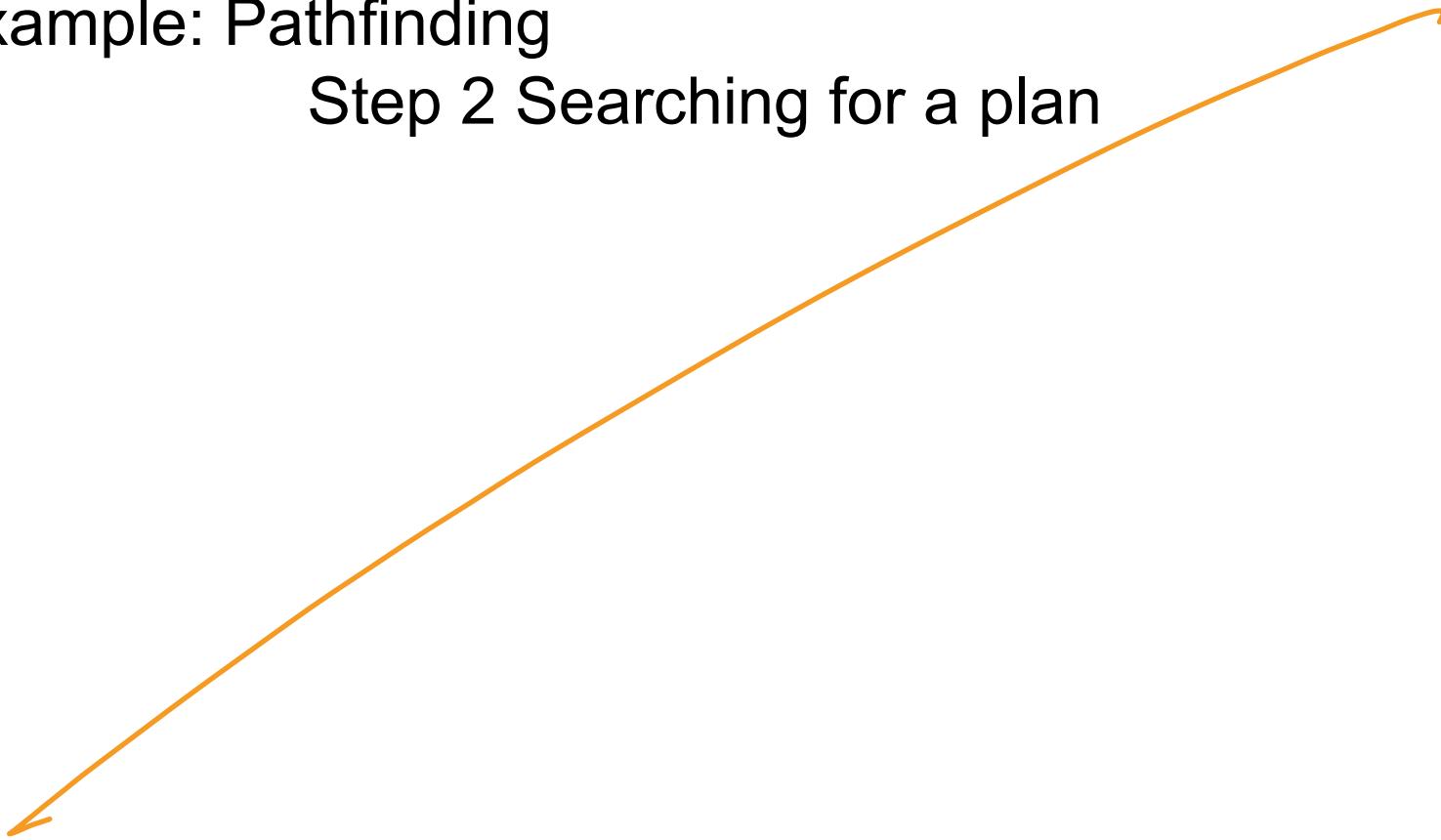
$S \approx (5, 4)$

5. Cost function

if mud, return 6
 usually cost of each action

Example: Pathfinding

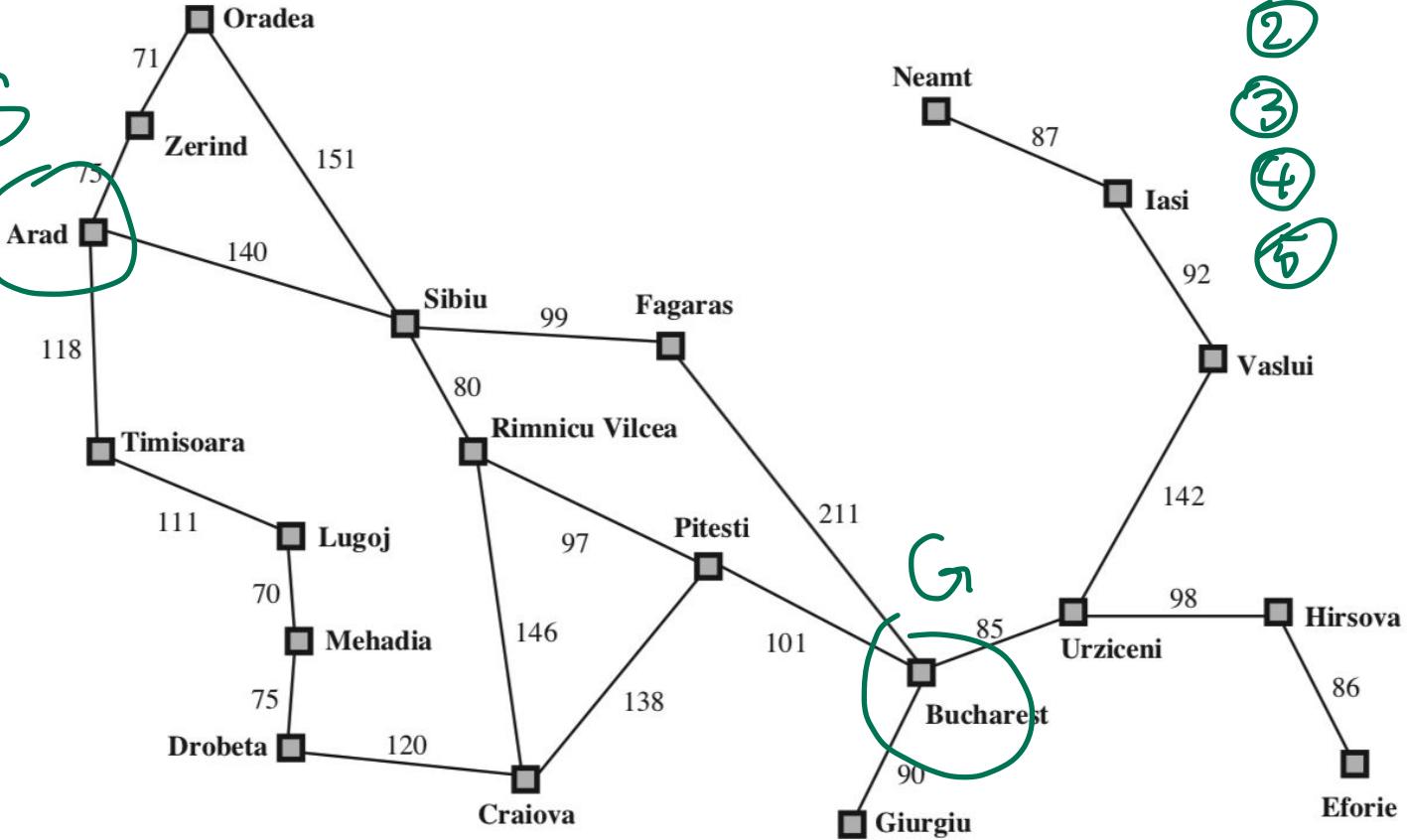
Step 2 Searching for a plan



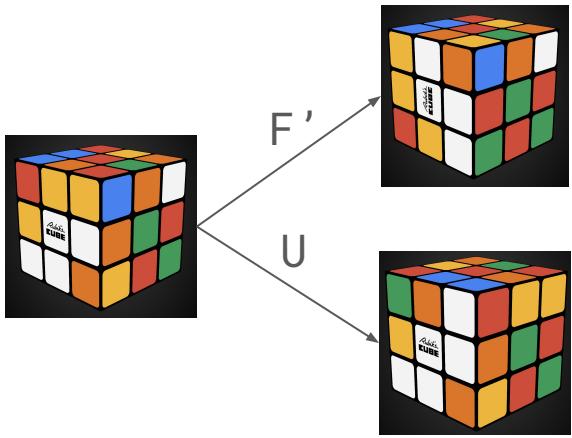
Example: Routing

Formulate this

- 1
- 2
- 3
- 4
- 5



Example: Rubik Cube

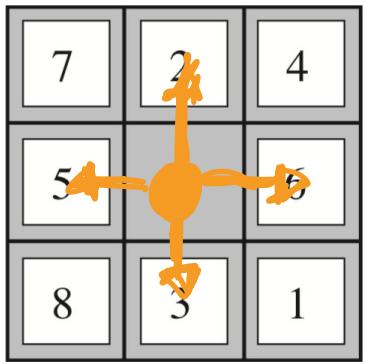


Formulate this

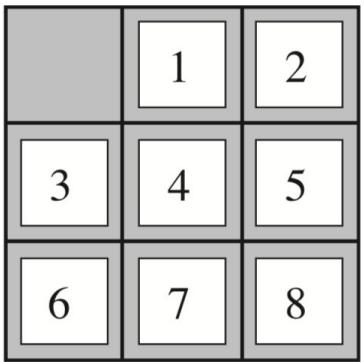
- ①
- ②
- ③
- ④
- ⑤



Example: 8-Puzzle



Start State



Goal State

Formulate this

- ①
- ②
- ③
- ④
- ⑤

Graph Search Algorithm

Search

function GRAPH-SEARCH(*problem*) **returns** a solution, or failure

initialize the frontier using the initial state of *problem*

initialize the explored set to be empty

loop do

1 if the frontier is empty **then return** failure

2. choose a leaf node and remove it from the frontier

3. if the node contains a goal state **then return** the corresponding solution

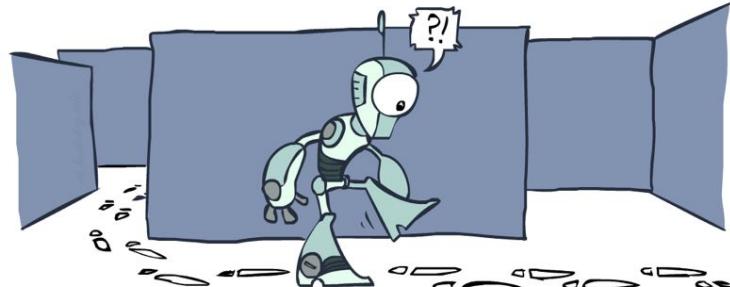
4. *add the node to the explored set*

5. expand the chosen node, adding the resulting nodes to the frontier

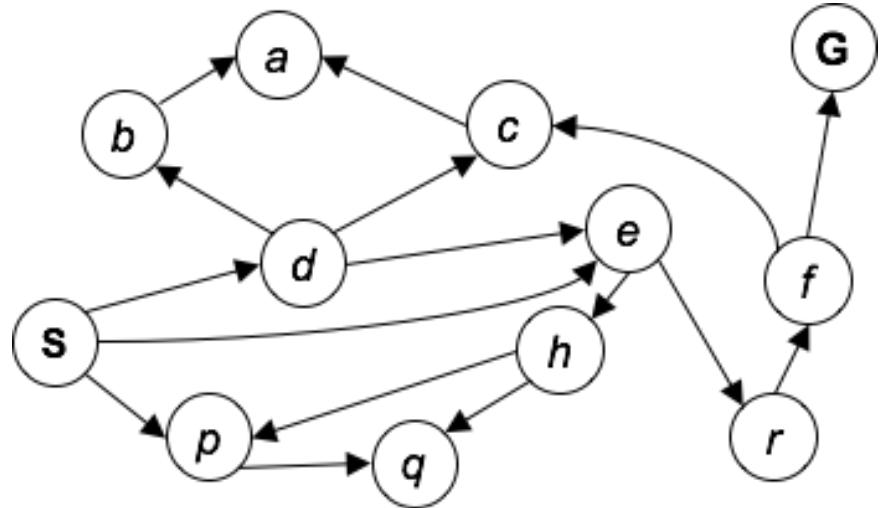
only if not in the frontier or explored set

► Prevent moving back

► Possible options
to explore.



Example: Abstract State-Space Graph



4. Uninformed-Search Strategies



Why we need a strategy?

function GRAPH-SEARCH(*problem*) **returns** a solution, or failure

initialize the frontier using the initial state of *problem*

initialize the explored set to be empty

loop do

if the frontier is empty **then return** failure

 choose a leaf node and remove it from the frontier

if the node contains a goal state **then return** the corresponding solution

add the node to the explored set

 expand the chosen node, adding the resulting nodes to the frontier

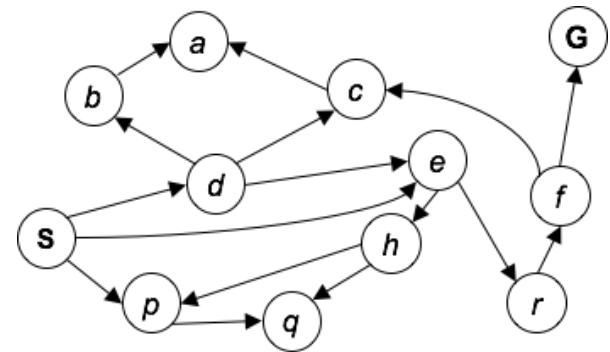
only if not in the frontier or explored set

Strategy 1: Depth-First Search (DFS)

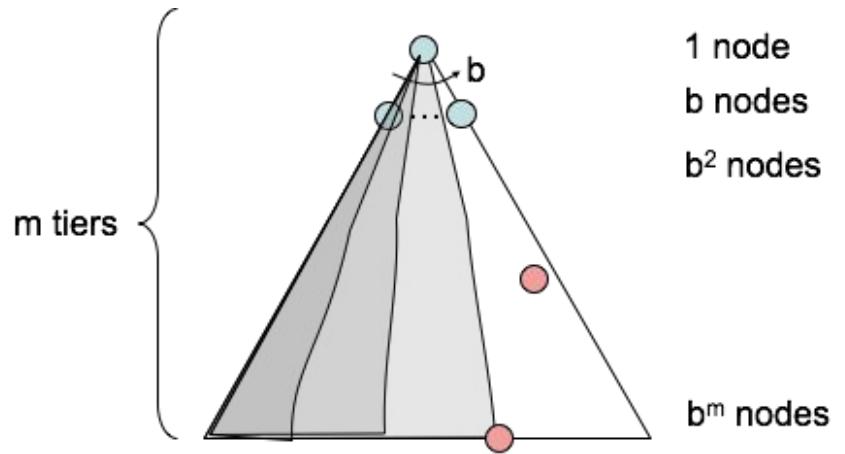
Frontier

Search Tree

Closed Set



Depth-First Search (DFS) Evaluation

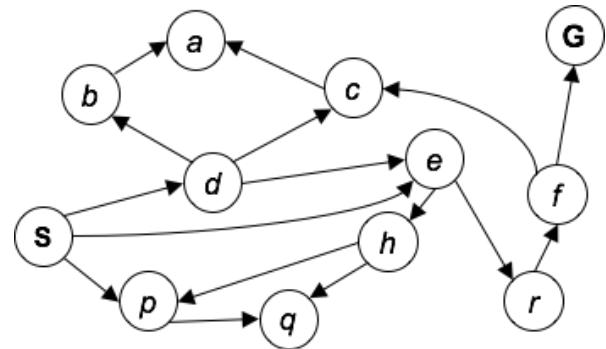


Strategy 2: Breadth-First Search (BFS)

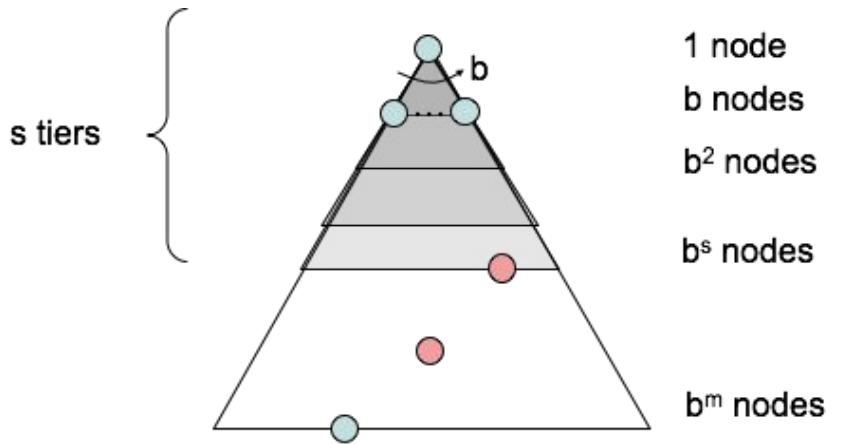
Frontier

Search Tree

Closed Set



Breadth-First Search (BFS) Evaluation



Activity 3: DFS and BFS on our environment

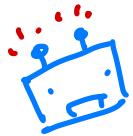
<https://editor.p5js.org/thanapon.nor/full/T8Hk1cSIK>



Repeat the activity 2 again, but this time, use DFS and BFS strategy.

On a piece of paper,

6. Write the plans and their energy requirements that you discovered for DFS and BFS.



ITCS 451
section 2

Lecture 3

Thanapon Noraset
Faculty of ICT, Mahidol University

Adapted from AIMA by Stuart Russell and Peter Norvig, and UC Berkeley CS188 by Dan Klein and Pieter Abbeel (ai.berkeley.edu)

Feedback Week 2

1. Problem Formulation

2. Exploration



Announcements & Agenda

1. Checkpoint 3
on My Courses

Fri - Sun

2. Assignment 1

Now - Sun 4
Sep

3. Feedback 3

4. Office hours will be
available soon. (TA is traveling)

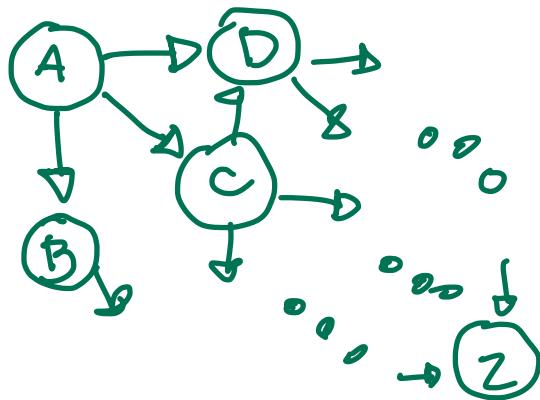
1. Uninformed Search Strategies
 - a. Depth-First Search
 - b. Breadth-First Search
 - c. Iterative-Deepening Search
 - d. Uniform-Cost Search
2. Informed Search Strategies
 - a. Heuristic Function
 - b. Greedy Search
 - c. A* Search
 - d. Admissibility and Consistency

Search Problem Formulation

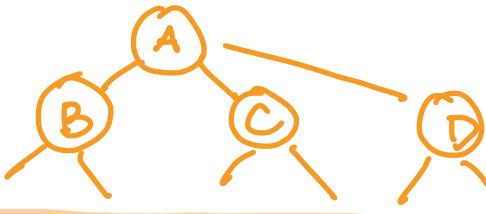
- ① Initial State
- ② Action Space
- ③ Transition func
- ④ Goal test func
- ⑤ Cost func

Search
Algorithm

State space



Search Tree



1. Uninformed-Search Strategies



Why we need a strategy?

function GRAPH-SEARCH(*problem*) **returns** a solution, or failure

initialize the frontier using the initial state of *problem*

initialize the explored set to be empty

loop do *options to try*

① if the frontier is empty **then return** failure

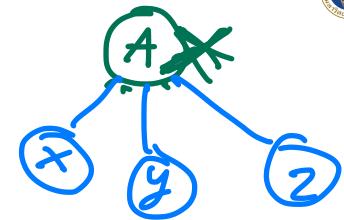
② choose a leaf node and remove it from the frontier

③ if the node contains a goal state **then return** the corresponding solution

④ *add the node to the explored set*

⑤ expand the chosen node, adding the resulting nodes to the frontier

only if not in the frontier or explored set



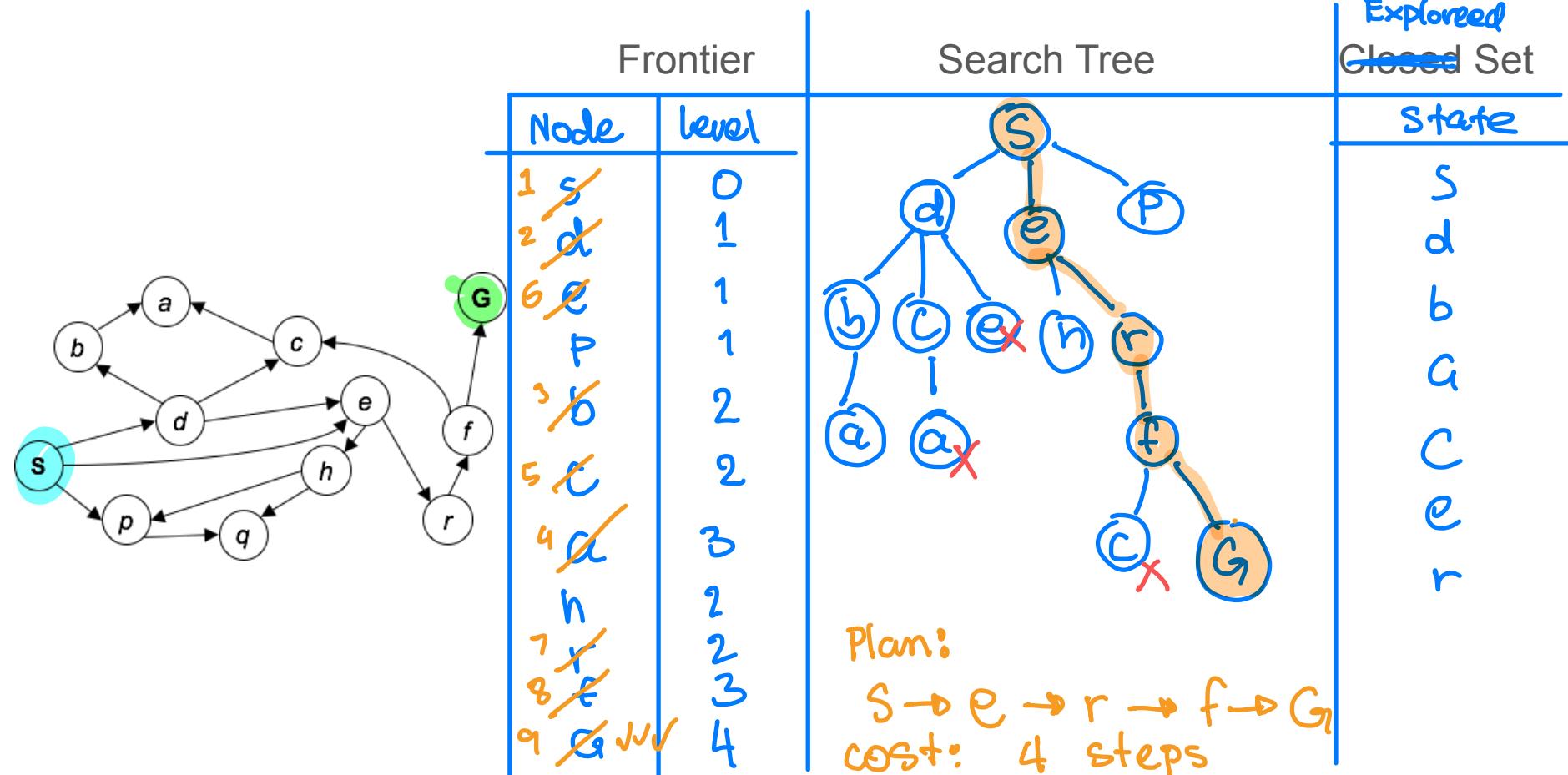
→ which one?



It depends on a
Search Strategy



Strategy 1: Depth-First Search (DFS) "Highest - level."



Depth-First Search (DFS) Evaluation

① Completed ness : always find a plan if there is one

↳ m is finite, Yes

↳ m is infinite, No

② Optimality. : minimum cost plan

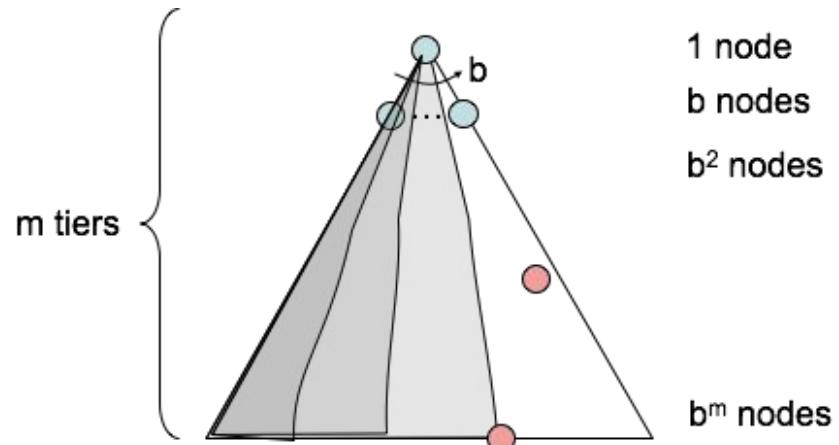
↳ NO

③ Time complexity

↳ $O(b^m)$

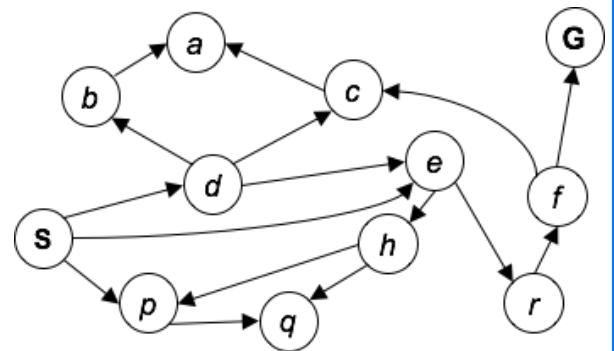
④ Space complexity

↳ $O(bm)$



Strategy 2: Breadth-First Search (BFS)

"Lowest-level.



Frontier		Search Tree	Explored	Closed Set
Node	level			State
1 S	0			S
2 A	1			a
3 E	1			e
4 P	1			p
b	2			
c	2			
h	2			
r	2			
q	2			

Plan :
 $S \rightarrow e \rightarrow r \rightarrow f \rightarrow G$

Cost: 4 steps

Breadth-First Search (BFS) Evaluation

① Completeness

- ↳ b is finite, Yes
- ↳ b is infinite, No

② Optimality

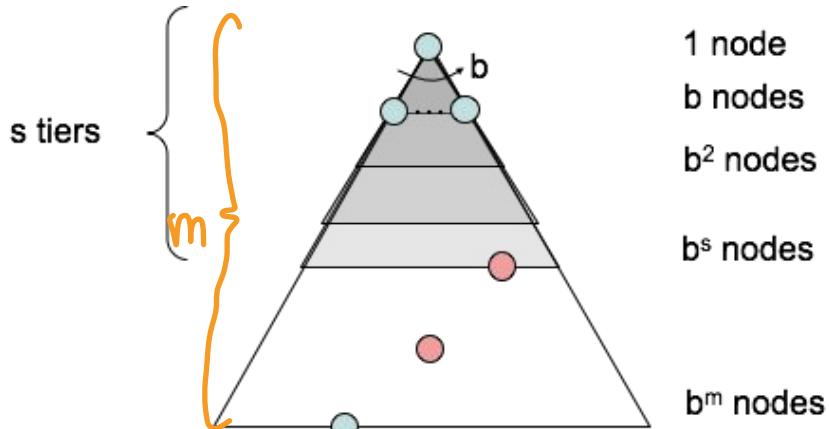
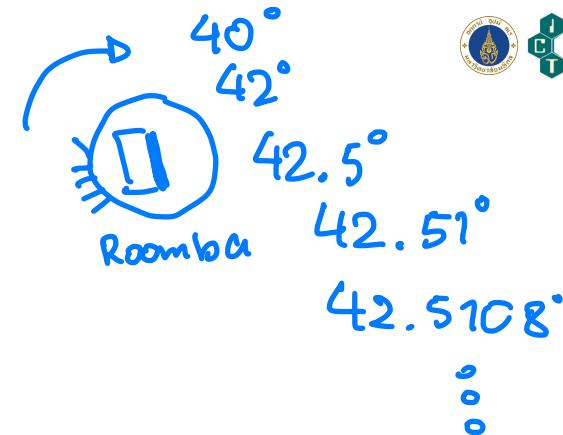
↳ Yes * shortest (not always minimum cost)

③ Time complexity

↳ $\mathcal{O}(bs)$

④ Space complexity

↳ $\mathcal{O}(b^s)$



Combining DFS and BFS

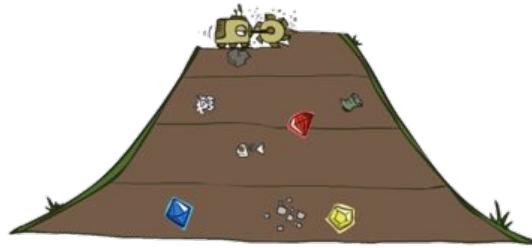
DFS



not optimal

memory: $O(bm)$

BFS



Optimal (shortest)

memory: $O(b^m)$



Iterative-Deepening Search

Strategy 3: Iterative-Deepening Search (IDS)

Strategy: Repeatedly run DFS but increasing the limit of depth each round

- Round 1: Run a DFS with depth limit 1, if no solution...
- Round 2: Run a DFS with depth limit 2, if no solution...
- Round 3: Run a DFS with depth limit 3, if no solution...
- ...
- Round n: Run a DFS with depth limit n + step

Wasteful?

Strategy 3: Iterative-Deepening Search (IDS)

Depth limit

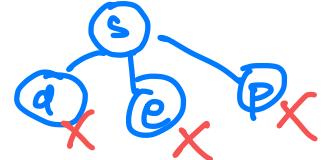
1

Frontier

~~closed set~~

~~18~~ 0

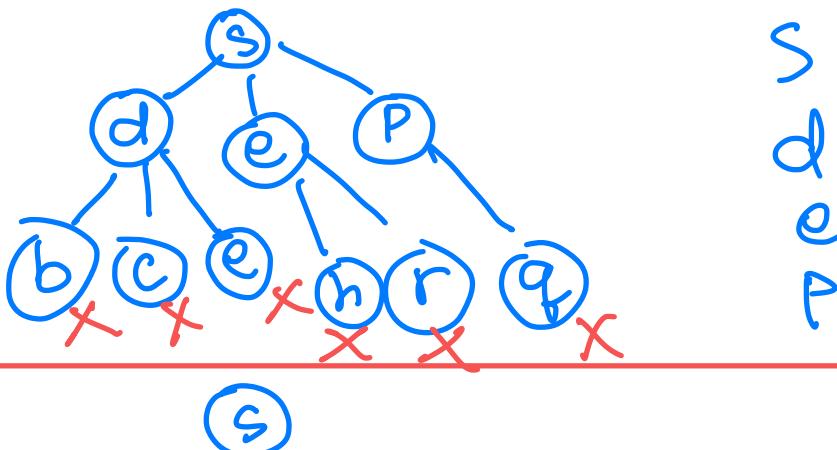
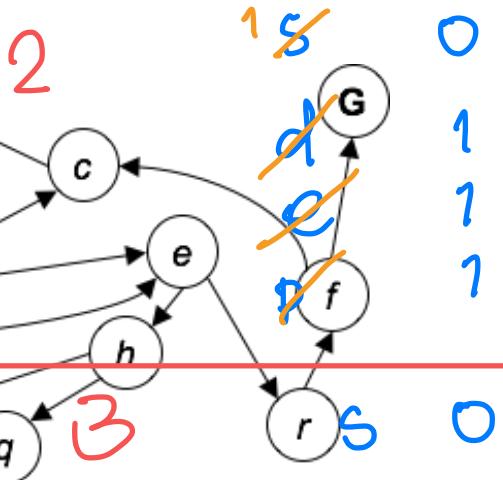
Search Tree



Explored set

~~open set~~

s



Iterative-Deepening Search (IDS) Evaluation

① Completeness

↳ BFS

② Optimality

↳ BFS ✓

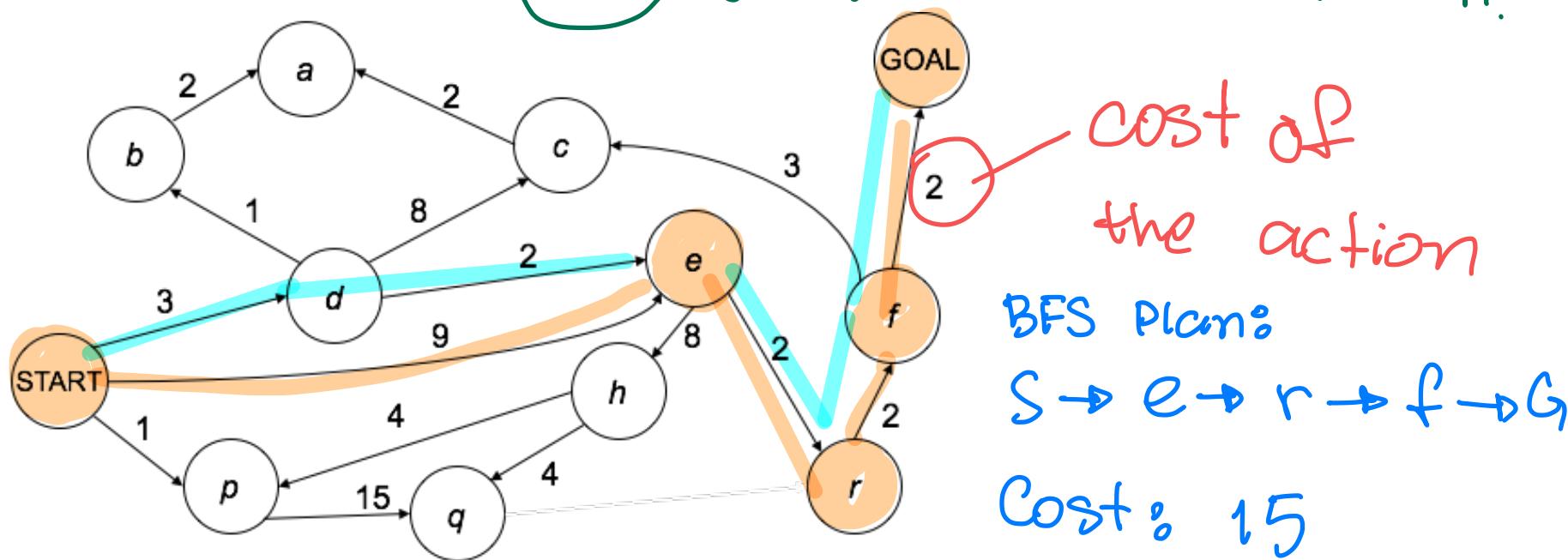


③ Time complexity

Homework

④ Memory complexity → DFS ✓

Path Cost Function: $g(n)$



Modified Graph Search Algorithm

function GRAPH-SEARCH(*problem*) **returns** a solution, or failure

 initialize the frontier using the initial state of *problem*

initialize the explored set to be empty

loop do

if the frontier is empty **then return** failure

 choose a leaf node and remove it from the frontier

if the node contains a goal state **then return** the corresponding solution

add the node to the explored set

 expand the chosen node, adding the resulting nodes to the frontier

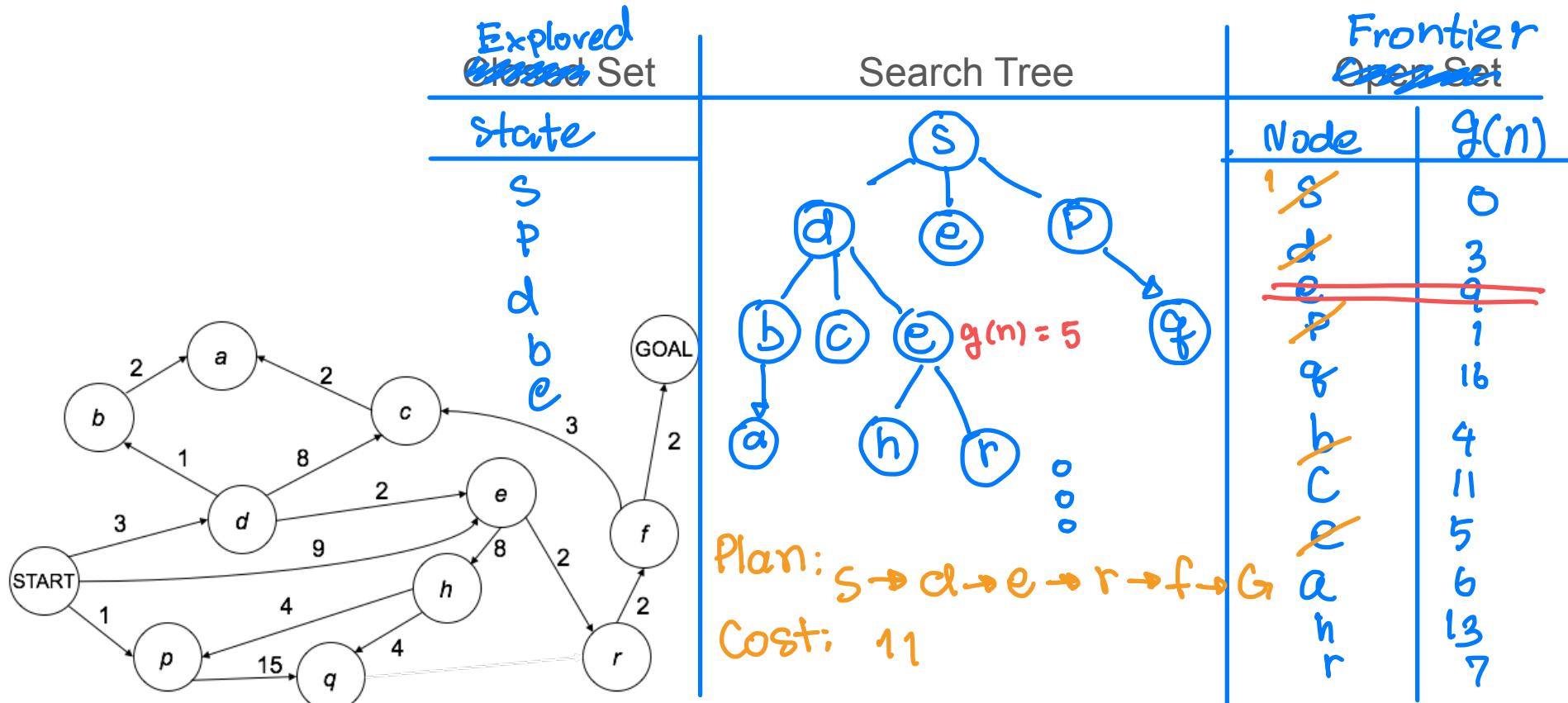
~~only if not in the frontier or explored set~~

① if in explored set, not add

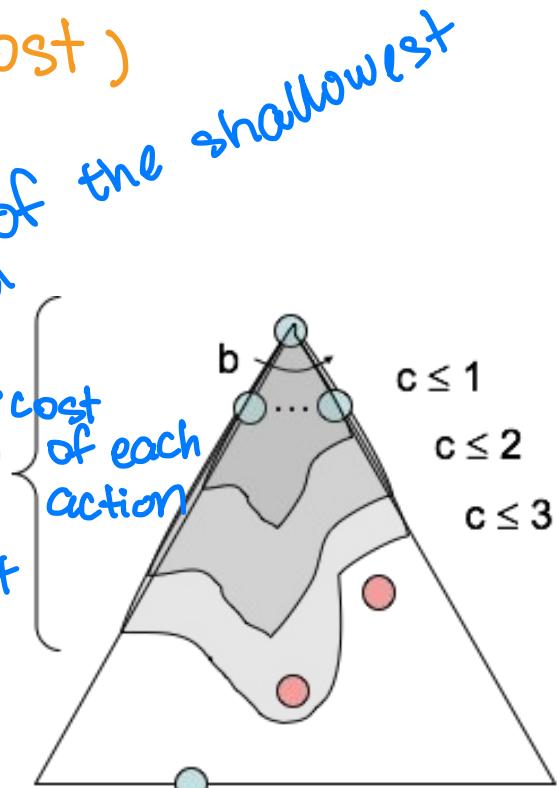
② if in frontier, keep the better node.
that contains the same state.

Strategy 4: Uniform Cost Search (UCS)

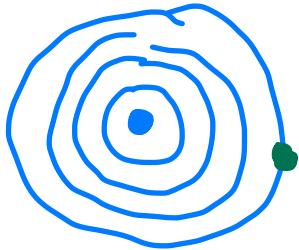
lowest $g(n)$



Uniform Cost Search (UCS) Evaluation

- ① Completeness : Yes
 - ② Optimality : Yes (minimum cost)
 - ③ Time complexity
: $O(b^{C^*/\epsilon})$
 - ④ Space complexity
: $O(b^{C^*/\epsilon})$
- $C^* = 10$ $\epsilon = 2$ levels = $\frac{10}{2} = 5$
- level of the shallowest goal
"tiers"
cost of each action
minimum cost
- 

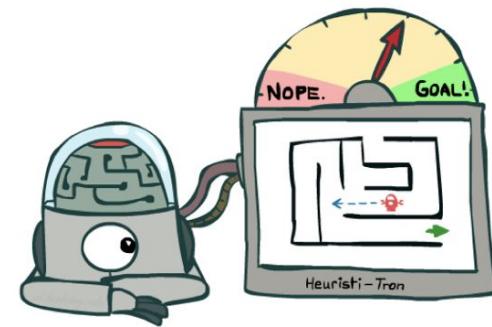
Uninformed Search



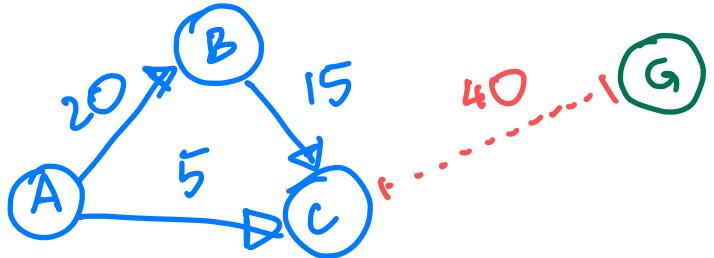
Informed Search



2. Informed Search Strategies

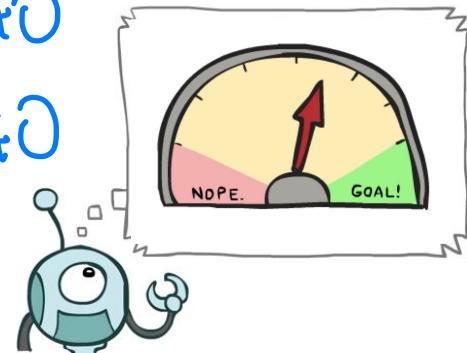


Heuristic Function: $h(s)$ must be easy to compute.
 estimate the cost from
 a state, s , to the goal
 state.

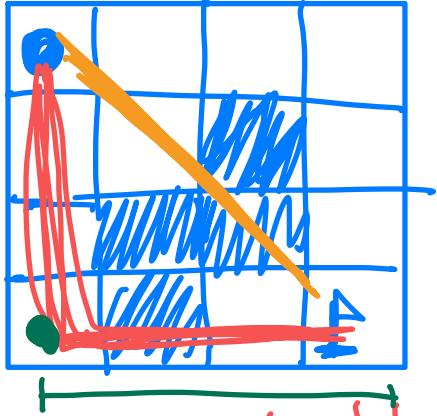


$$g(A \rightarrow B \rightarrow C) = 35, h(C) = 40$$

$$g(A \rightarrow C) = 5, h(C) = 40$$



Example: Heuristic Functions for Pathfinding



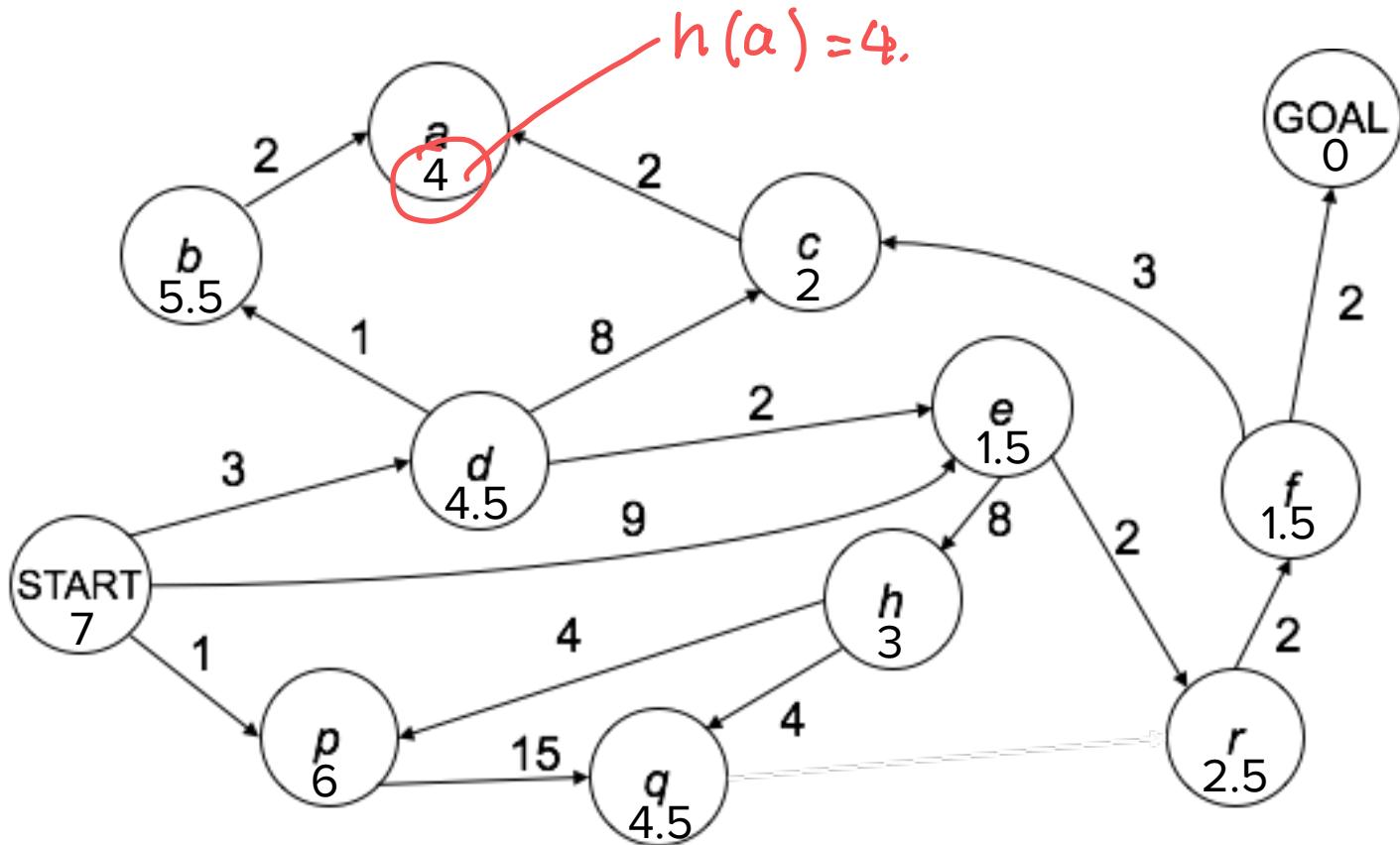
Euclidean distance

$$h(s) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

manhattan distance

$$h(s) = |x_1 - x_2| + |y_1 - y_2|$$

Example: Abstract State Space with Heuristic Values



Strategy 5: Greedy Best-First Search (GS)

Lowest
 $h(s)$

State	$h(s)$	State	$h(s)$
S	7	f	<u>1.5</u>
a	4	h	3
b	5.5	p	6
c	2	q	4.5
d	4.5	r	2.5
e	1.5	G	0

Explored
Closed Set

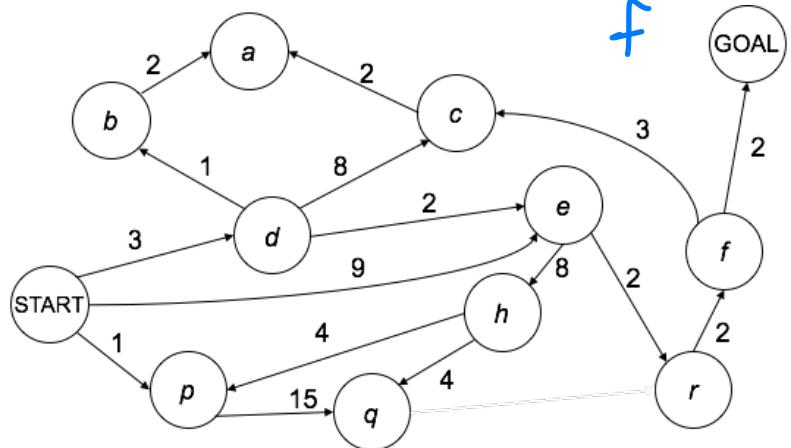
State

S

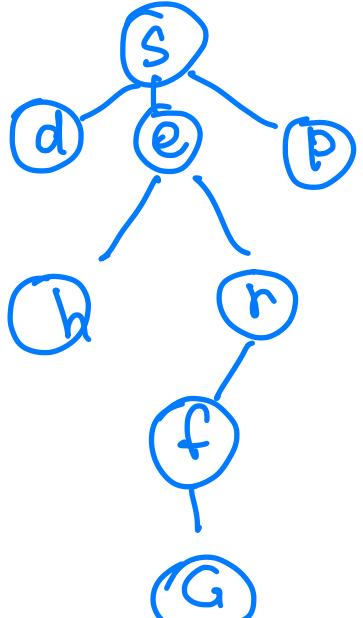
e

r

f



Search Tree



Plan: $S \rightarrow e \rightarrow r \rightarrow f \rightarrow G$
Cost 15

Frontier
Open Set

node

1 S

2 d

3 e

4 r

5 f

6 G

$h(s)$

7

4.5

1.5

6

3

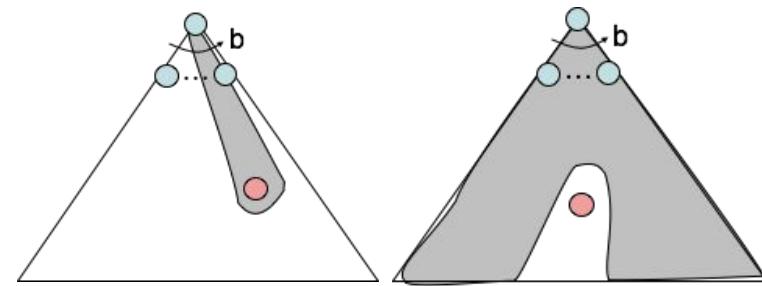
2.5

1.5

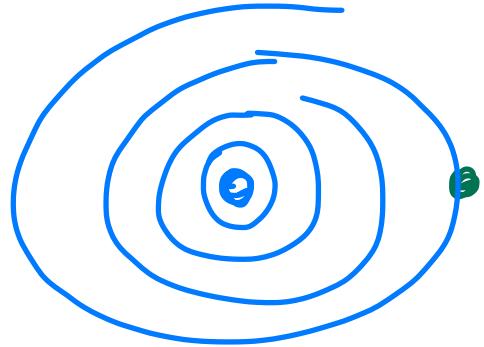
0

Greedy Best-First Search (GS) Evaluation

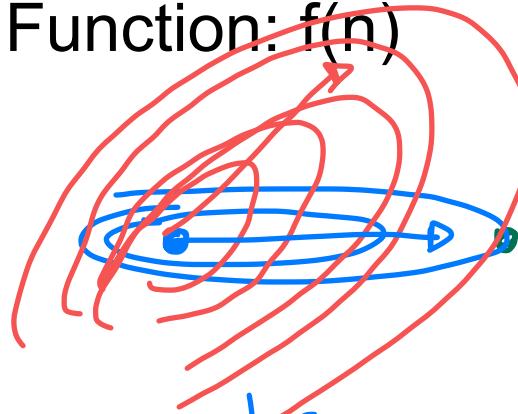
- ① Completeness : NO * bad heuristic
 - ② Optimality : No
 - ③ Time Complexity : $O(b^m)$
 - ④ Space Complexity : $O(b^m)$
- } usually better
if we have
good heuristic.



Path Cost Function + Heuristic Function: $f(n)$



$g(n)$
(UCS)



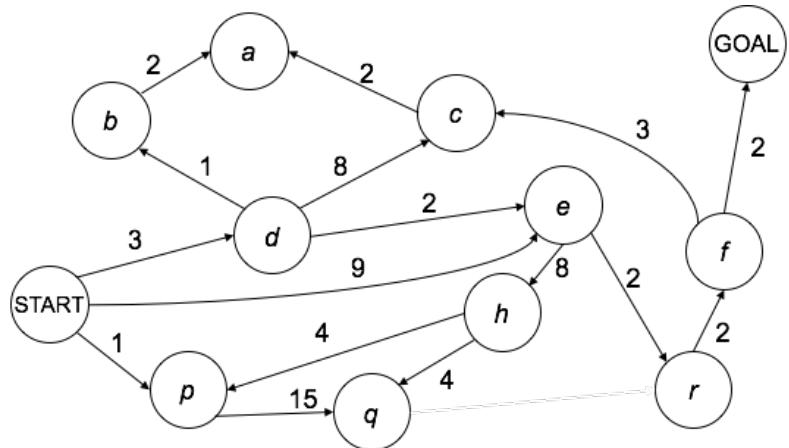
$h(s)$
(GS)

$$f(n) = g(n) + h(s \text{ of } n)$$

Strategy 6: A* Search

Lowest $f(n)$

State	$h(s)$	State	$h(s)$
s	7	f	1.5
a	4	h	3
b	5.5	p	6
c	2	q	4.5
d	4.5	r	2.5
e	1.5	G	0

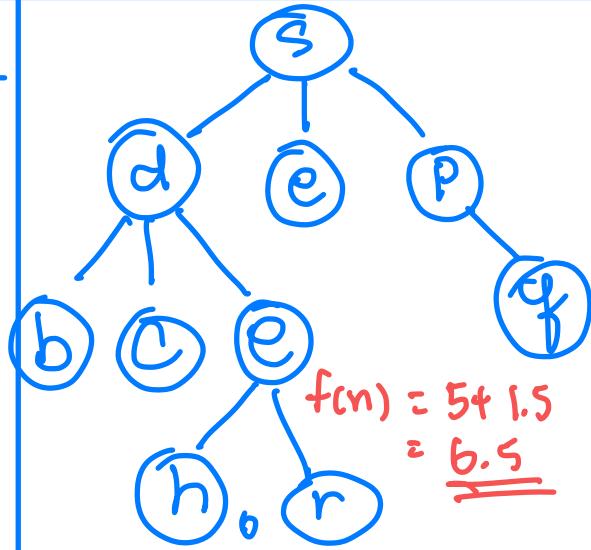


Explored
Closed Set

State

s
d
e

Search Tree



Plan $s \rightarrow d \rightarrow e \rightarrow r \rightarrow f \rightarrow G$
Cost: 11

Frontier
Open Set

Node

1 s
3 d
2 e
2 p

q
b
c

g
f
h
r

20.5
9.5
13
6.5

16
2.5

A* Evaluation

① Completeness : Yes

② Optimality : Yes

conditions
 $\rightarrow h(s)$ is admissible }
 $\rightarrow h(s)$ is consistent } next

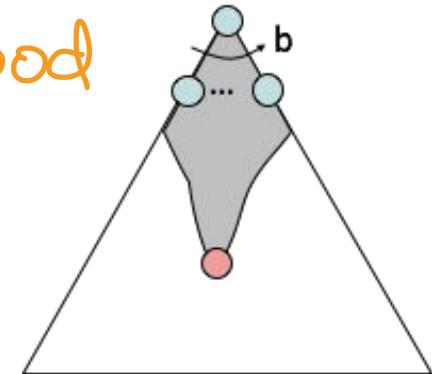
③ Time Complexity :

$$O(b^{c*/\epsilon})$$

④ Space Complexity

$$O(b^{c*/\epsilon})$$

usually better
with a good
 $h(s)$

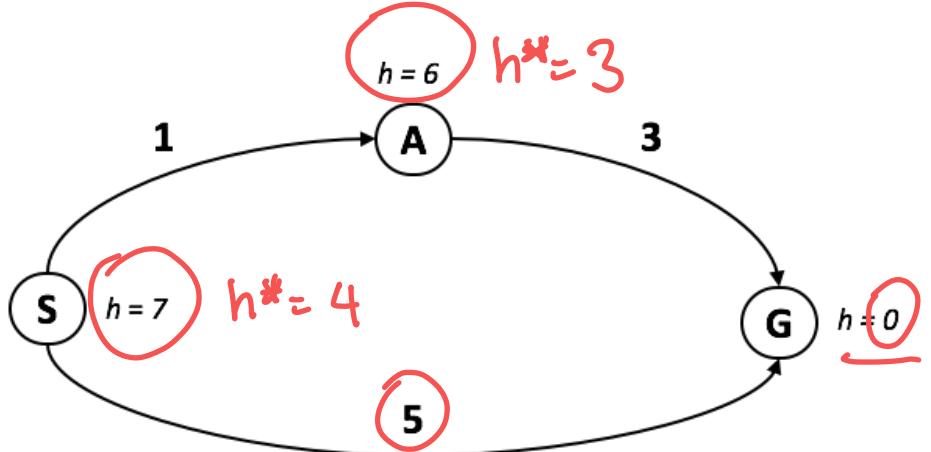


Feedback 3

- Heuristic functions
 - More detail today
- Evaluations of search strategies

	DFS	BFS	IDS	UCS	GS	A*
Completeness						
Optimality						
Time Complexity						
Space Complexity						

Optimality of A*: Admissibility



$f_{min} = 1 + 6 \cdot 1$

$f_{min} = 5 + 0$

(S) \xrightarrow{A} (G)

$S \rightarrow G, 5$

Poll: Why do you think A* fails here?

* heuristics must not overestimate the true cost.

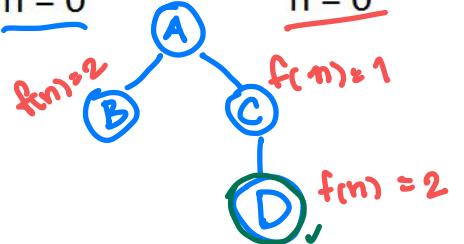
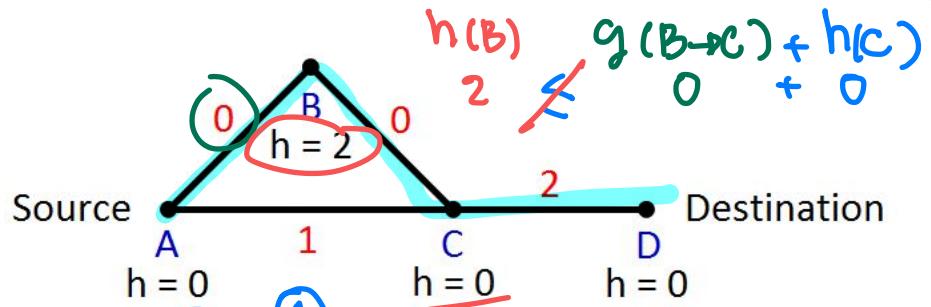
$h(s)$ is admissible, iff

$$0 \leq h(s) \leq h^*(s)$$

for all s

The true minimum cost.

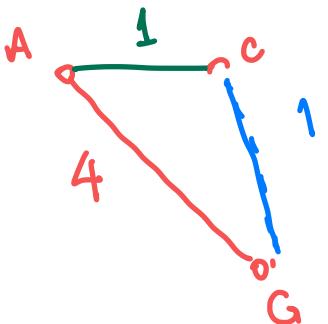
Optimality of A*: Consistency



$A \rightarrow C \rightarrow D, 3$

$$h(A) \leq g(A \rightarrow B) + h(B)$$

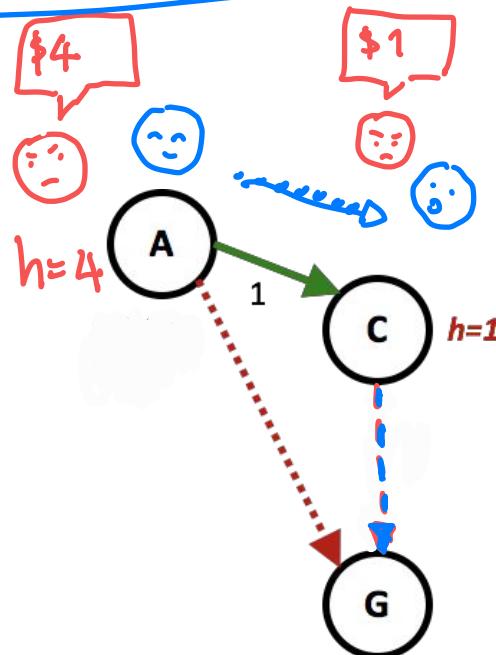
$$0 \leq 0 + 2$$



$h(s)$ is consistent, if $\forall s$

$$h(s) \leq g(s \rightarrow s') + h(s')$$

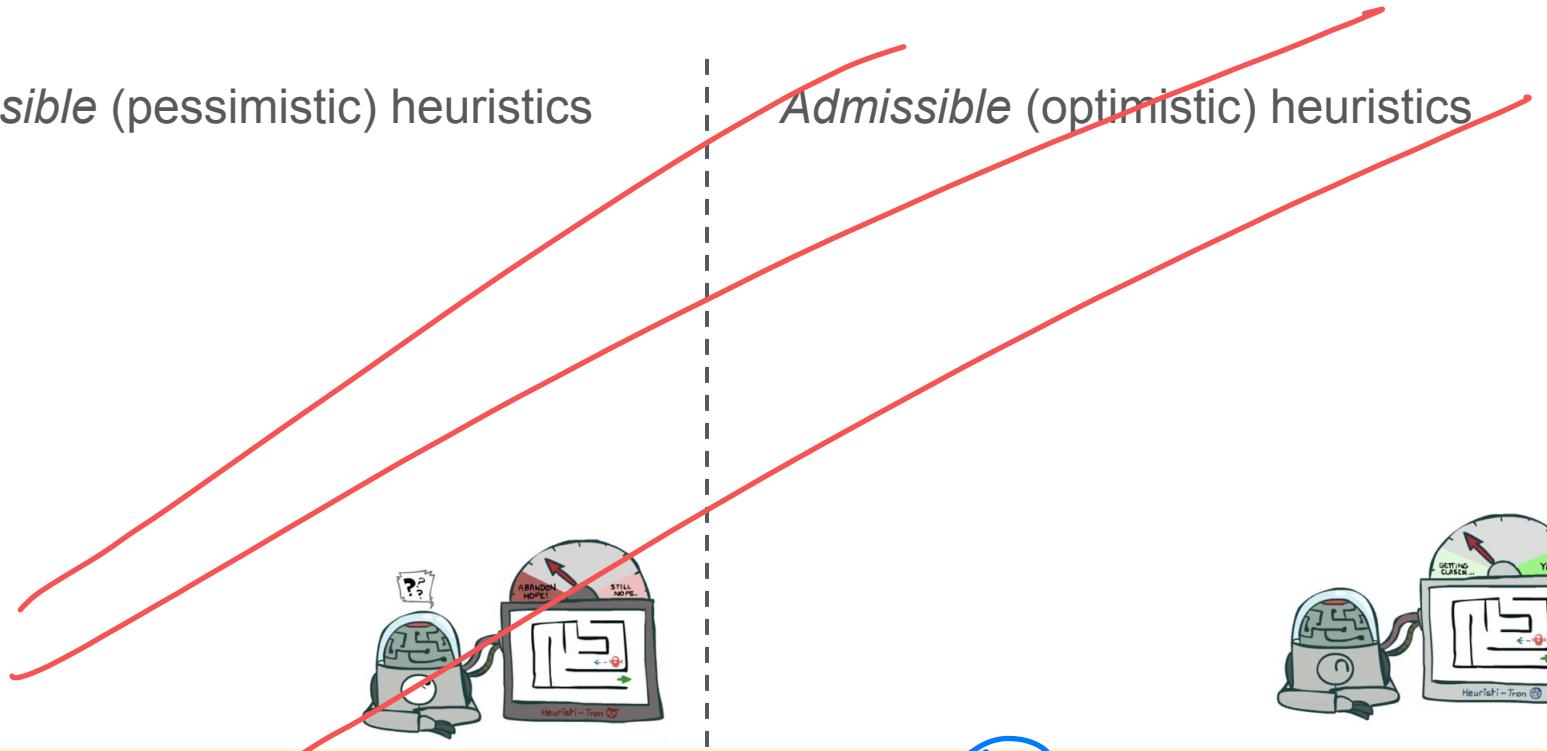
for all s



How to get admissible heuristic functions

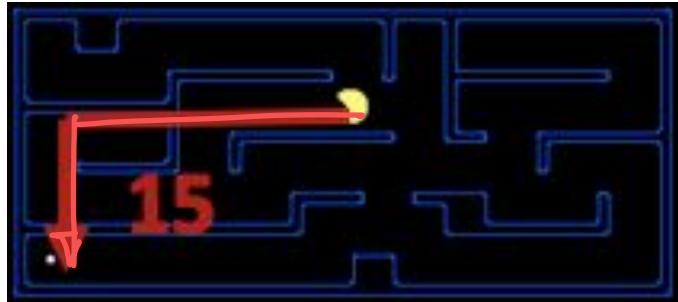
Inadmissible (pessimistic) heuristics

Admissible (optimistic) heuristics

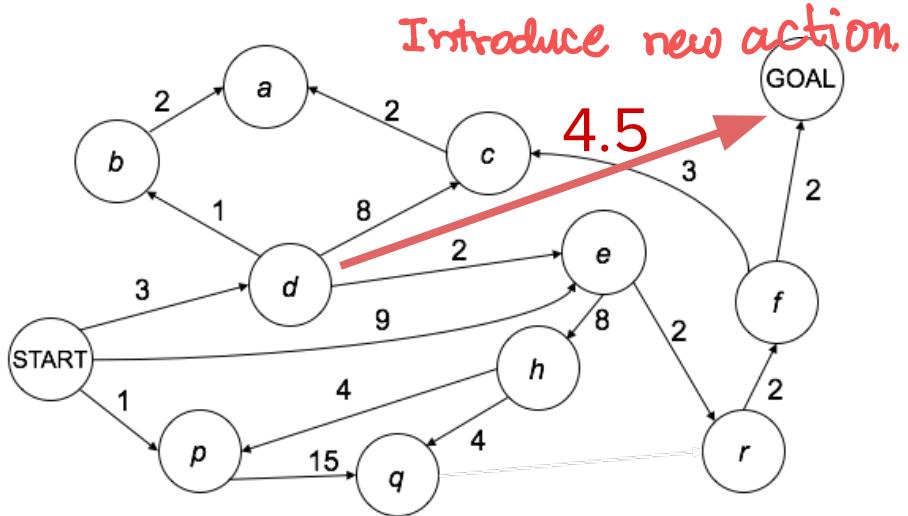


- ① Introduce new actions,
- ② Ignore rules

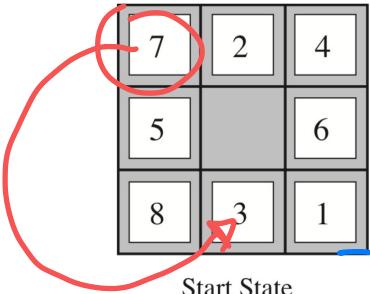
Example: Heuristic functions for pathfinding



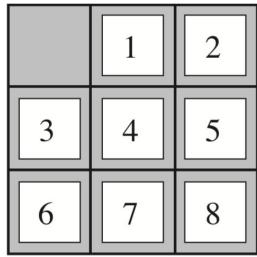
* ignore the wall.



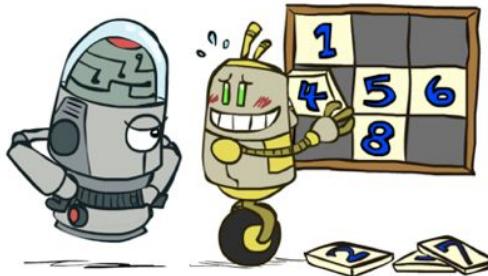
Example: Heuristic functions for 8-puzzle (1)



Start State



Goal State



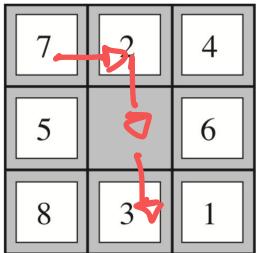
new action

* Take tile out
and put anyway.

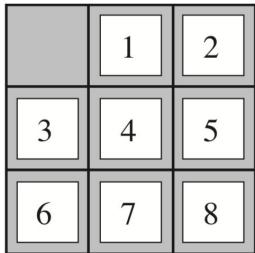
$h_1(S) = \text{number incorrect tiles.}$

$$h_1(\downarrow) = 8$$

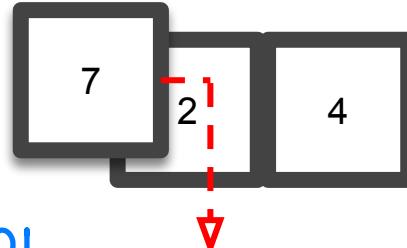
Example: Heuristic functions for 8-puzzle (2)



Start State



Goal State



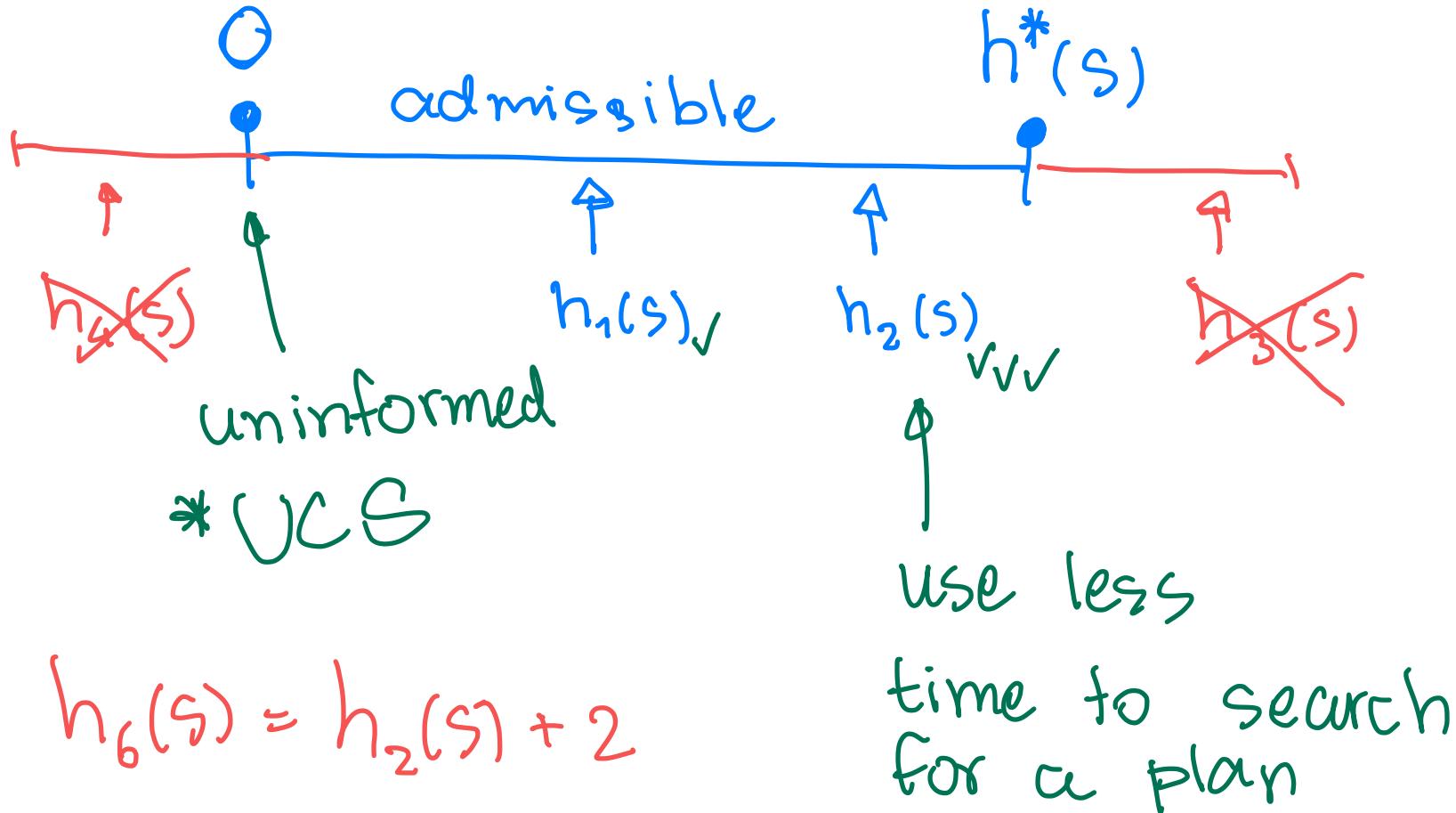
flyover
hopover

$$h_2(f) = 3 + 1 + 2 + 2 + 3 + 2 + 3 \\ = 16$$

$$A \xrightarrow{f} \xrightarrow[h_2(f)=16]{\dots} \xrightarrow{\dots} f G$$

$h_1(s) = 8$

$$h_5(s) = h_1(s)/5$$



Example: Heuristic 1 vs Heuristic 2

d	IDS	$A^*(h_1)$	$A^*(h_2)$
2	10	6	6
4	112	13	12
6	680	20	18
8	6384	39	25
10	47127	93	39
12	3644035	227	73
14	-	539	113
16	-	1301	211
18	-	3056	363
20	-	7276	676
22	-	18094	1219
24	-	39135	1641

Plan cost
in step.

~ Iterations

Summary

Run

Formulate

Implement

Planning = Search Problem → Graph Search → A sequence of actions

Exploration Strategy: Choose the _____ nodes in the open set first

1 - DFS: Deepest



Lowest
- 1 * level
level

2 - BFS: Shallowest



*3 - IDS runs DFS with depth limit several times

4 - UCS: Cheapest (path cost)



$g(n)$

5 - GS: Closest (heuristic)



$h(s)$

6 - A*: Lowest f-value



$f(n)$

- Admissibility

- Consistency

2 : 20 pm

Priority

Priority Queue.



Lecture 4

Thanapon Noraset
Faculty of ICT, Mahidol University

Adapted from AIMA by Stuart Russell and Peter Norvig, and UC Berkeley CS188 by Dan Klein and Pieter Abbeel (ai.berkeley.edu)

Announcements & Agenda

1 Assignment 1

Sep 11

2. Checkpoint 4

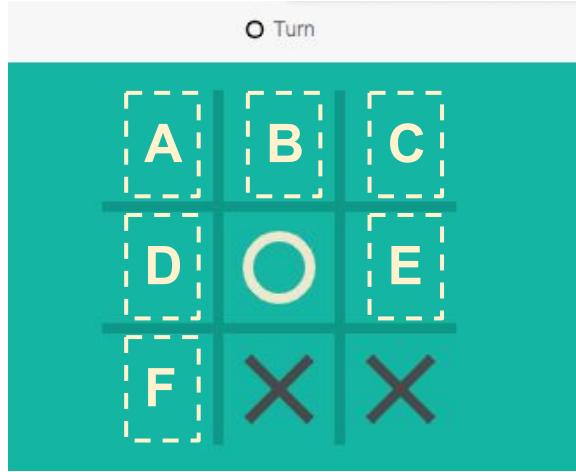
Fri
Sun

3. Feedback 4.

1. Competitive Environments
 - a. Zero-sum games
 - b. Settings of the environments
2. Adversarial Search Problem
 - a. Optimal decisions
 - b. Formulation
 - c. Minimax Decision Algorithm
3. Improving Minimax Efficiency
 - a. Alpha-Beta Pruning
 - b. Depth-limited and Evaluation function

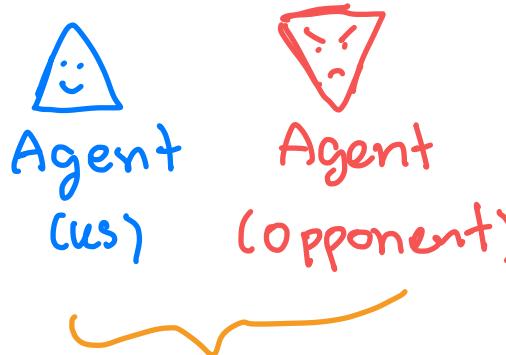
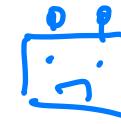
1. Competitive Environments

Which is the best “decision” for O?



- ① We can reason into the future in order to make the "best" move
* including what the Opponent is going to do.
- ② unpredictable, "sometimes".

Multi-agent Competitive Environments



Try to win

the competition

Simple form of competition

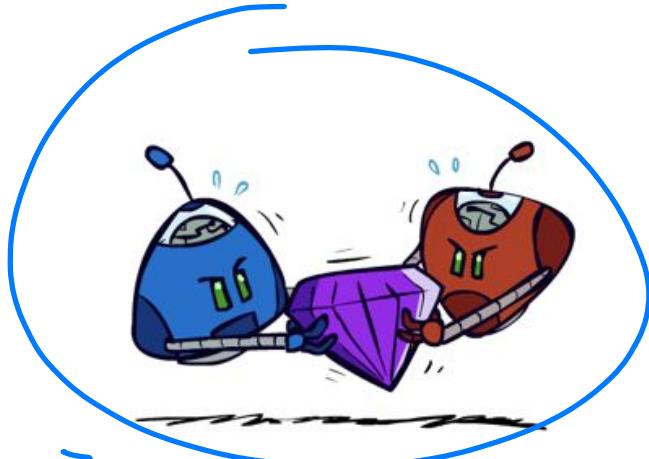
① A fixed set of rules

② well-defined ending

Game → Only zero-sum game



Zero-sum games



Zero-sum game

agents get opposite
outcomes.

- △ tries to maximize scores
- ▽ tries to minimize scores.

Different settings and Assumptions

Transition Function

$$S' = M(S, A)$$

Stochastic
card game

vs

Deterministic
tic-tac-toe

Number of Players

2 players



Imperfect
info

vs

more than 2

Information

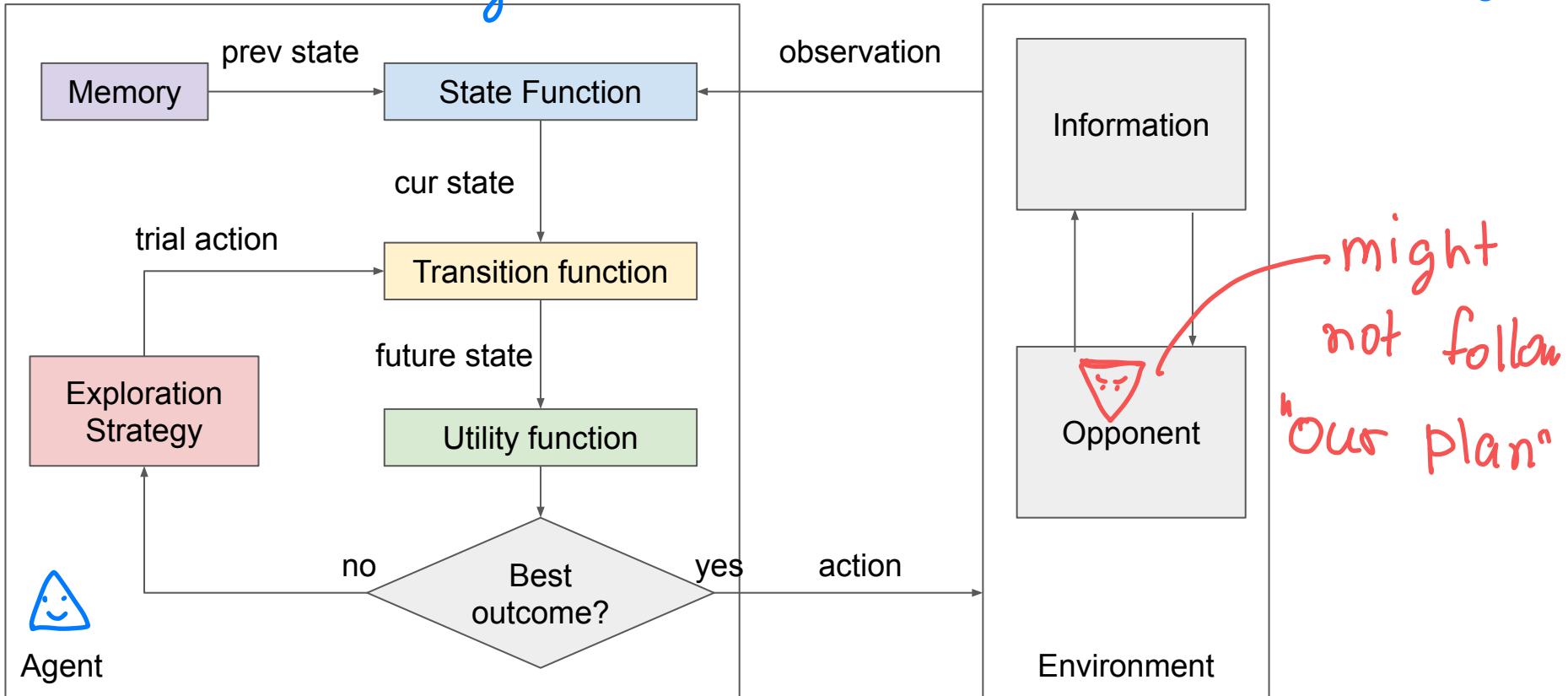
Perfect info

Competition

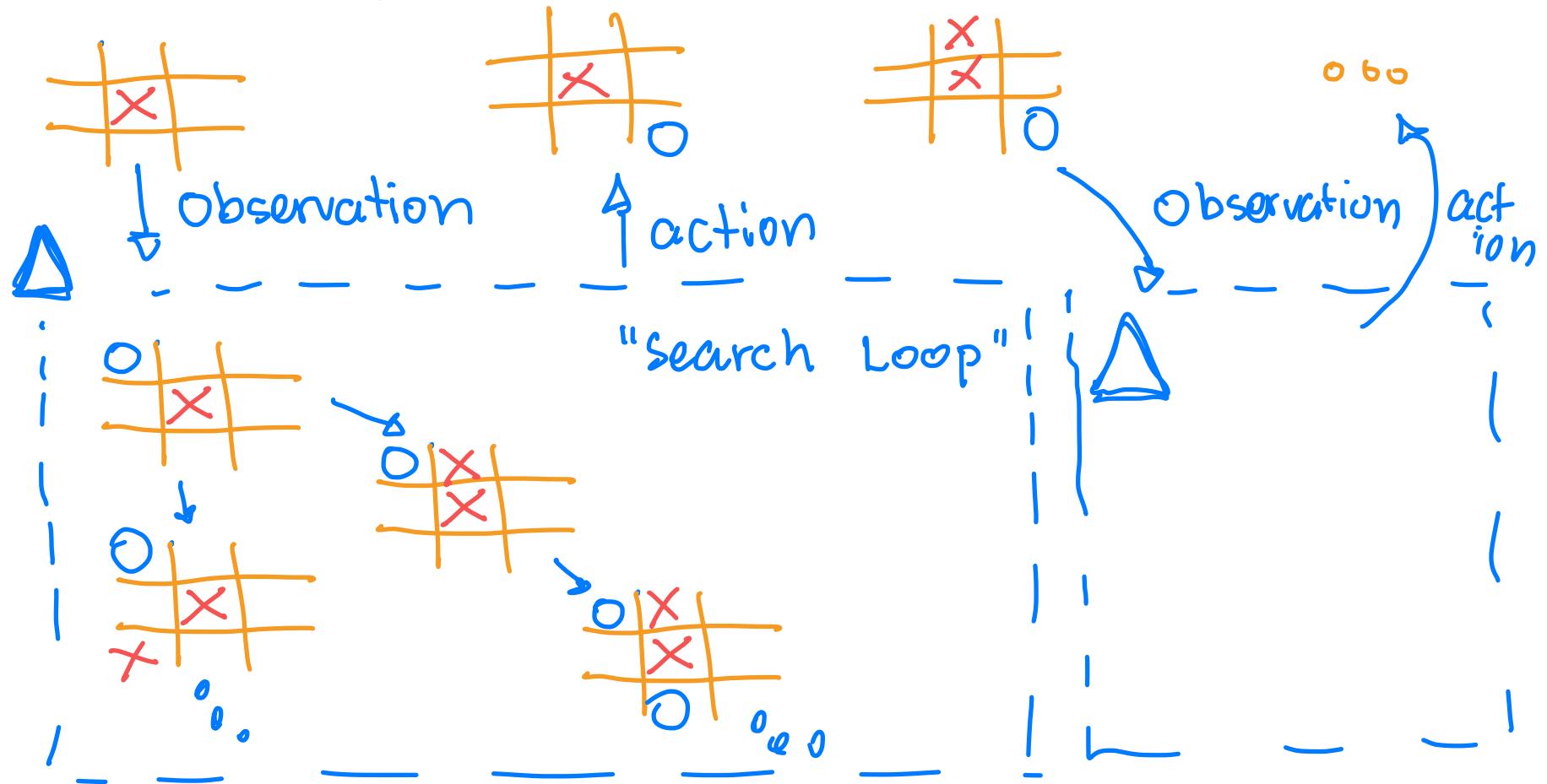
zero-sum
games

A Plan might not be valid for long...

we Only search for One "best" move.



“Re-think” every turn



Optimal decision

find the **best** move or action

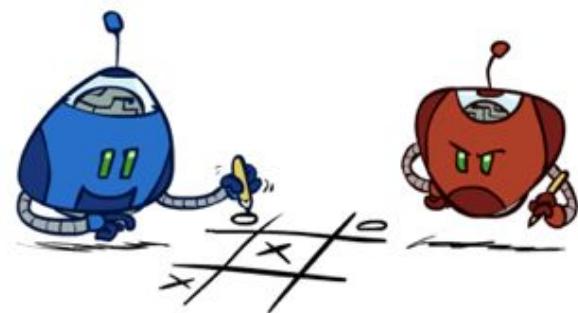


2. Adversarial Search Problem

✓ "Formulation"

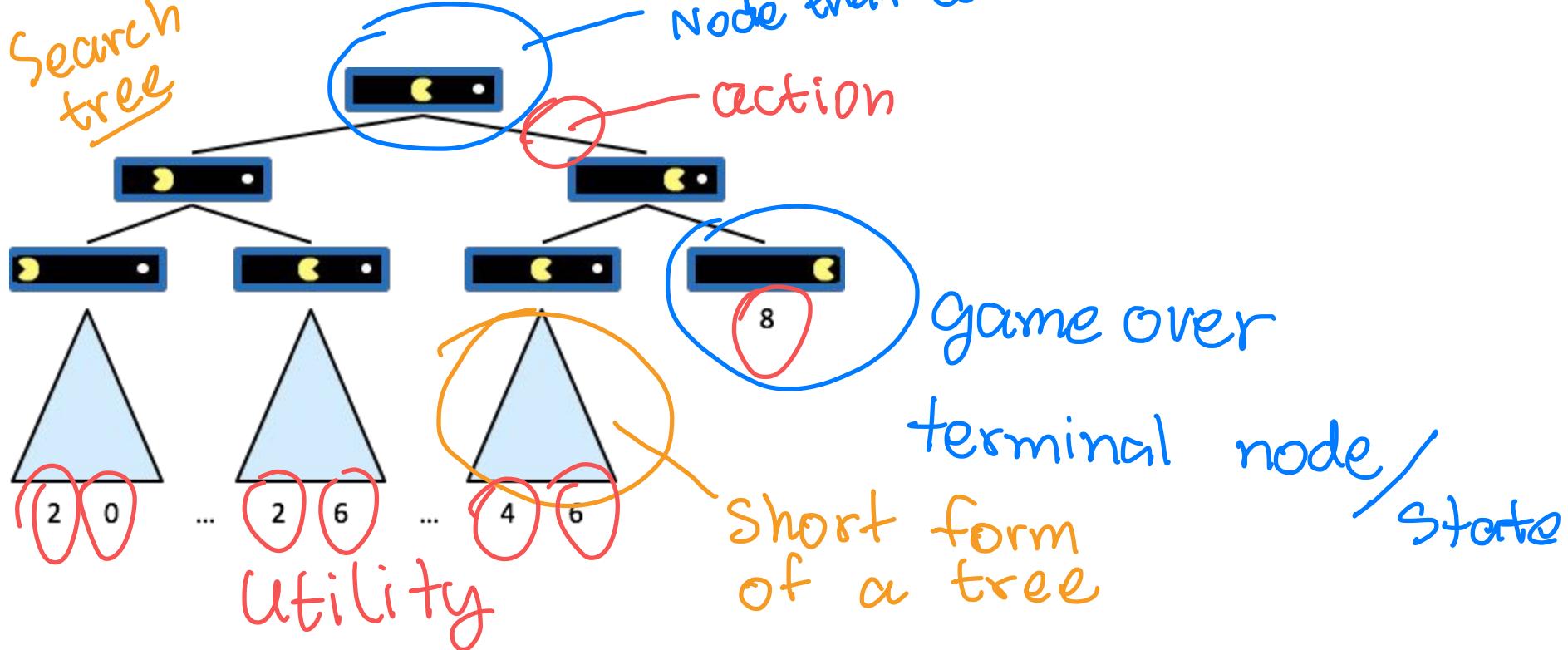
✓ "Algorithm".

▷ "Improving"



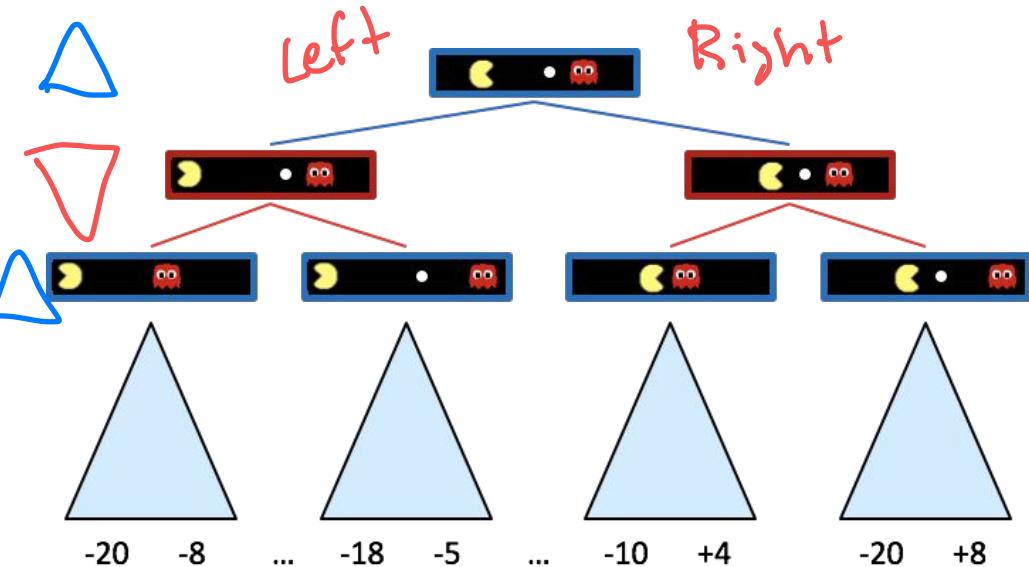
Optimal Decision: Single Agent

Poll: Would you go Left or Right?, Why?



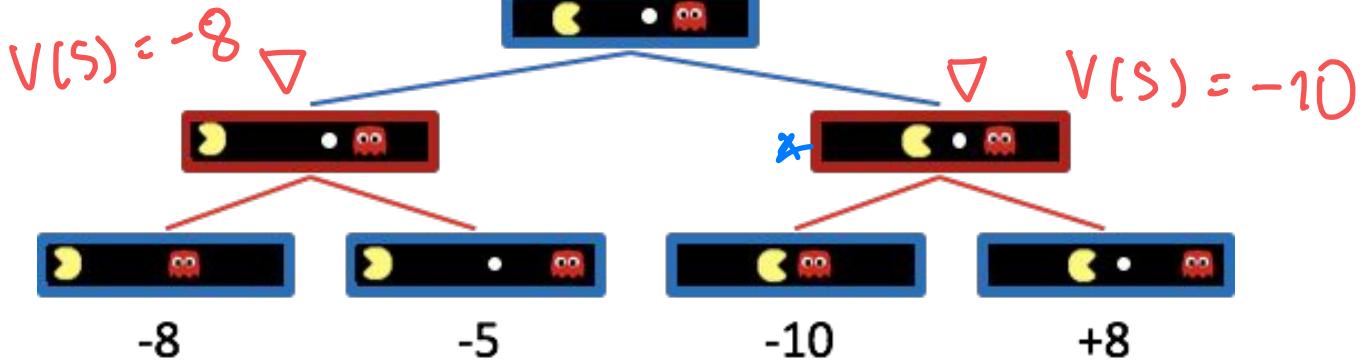
Optimal Decision: Two Agents

Poll: Would you go Left or Right?, Why?



MAX Agent, MIN opponent

 
minimax value.



For non terminal state

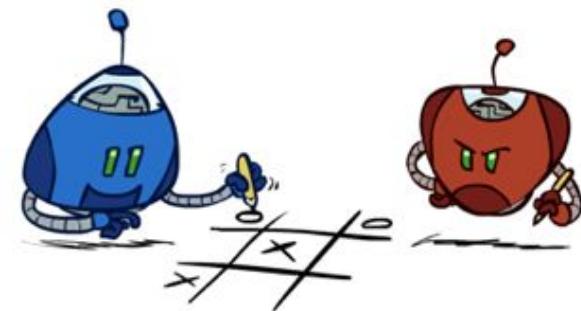
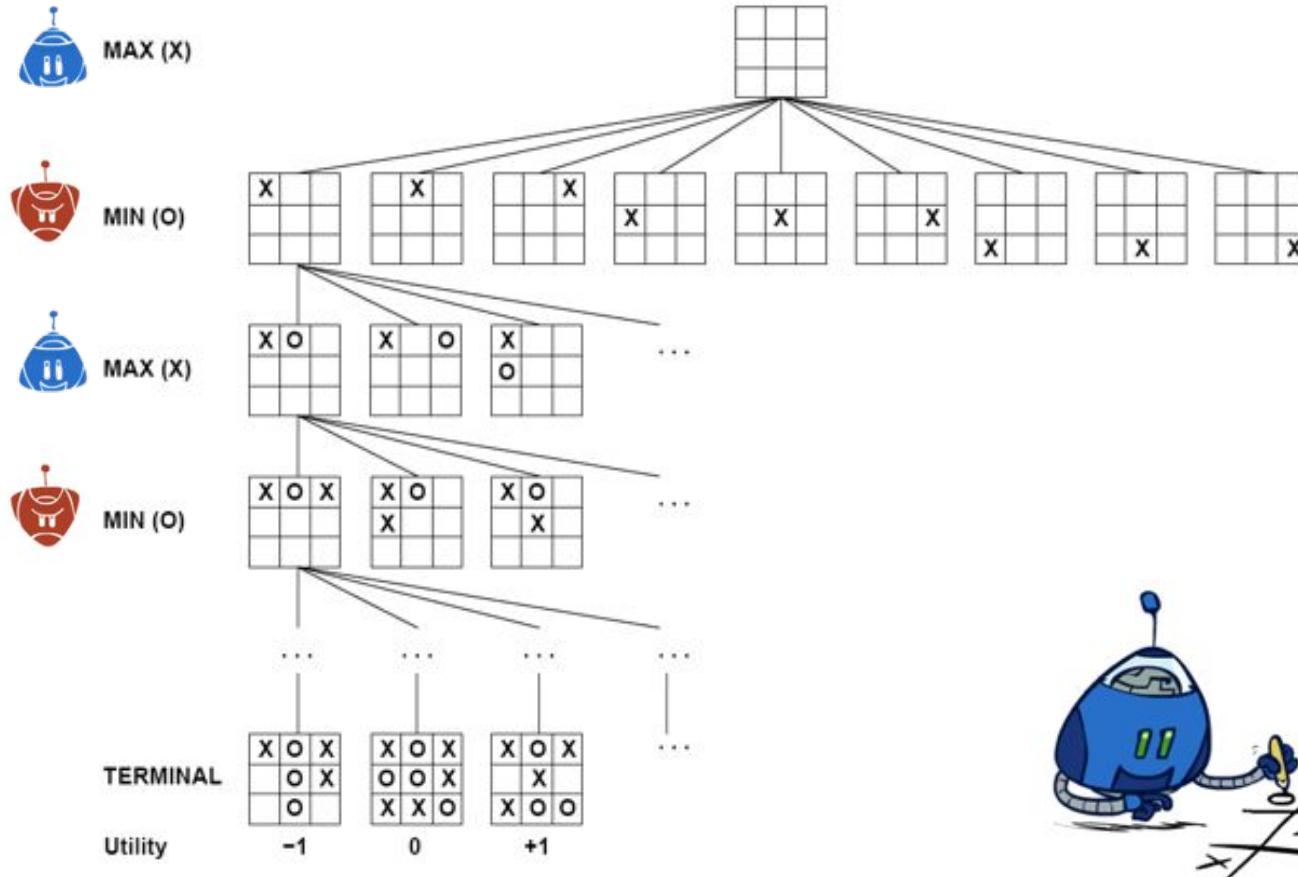
$$\hat{V}(S) = \begin{cases} \Delta, \max V(s') \\ \nabla, \min V(s') \end{cases}$$

s' is a child of S

For terminal state

$V(S) = \text{Utility}(S)$

Example: Tic-Tac-Toe



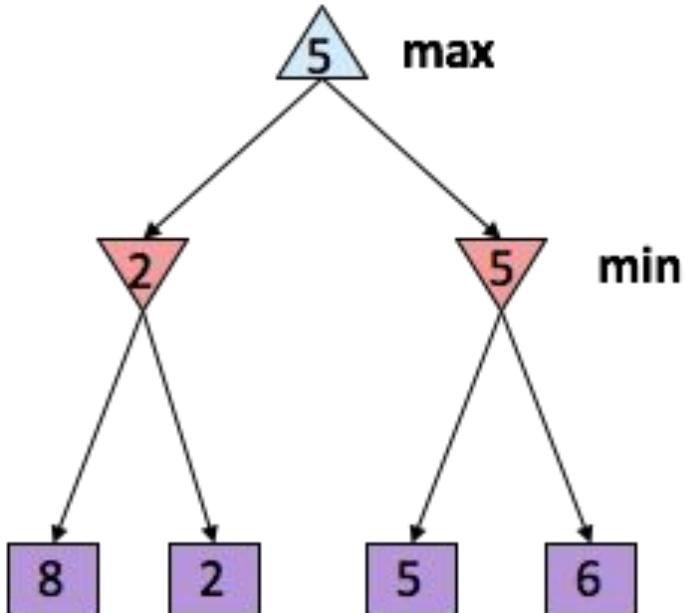
Example: Tic-Tac-Toe

Win: 1 point, Lose: -1 point, and Tie: 0 point

Utility.

Minimax Values and Optimal Action

or



An action that leads
to the highest-value
child node.

Adversarial Search Formulation

1. Initial state (Δ 's turn)

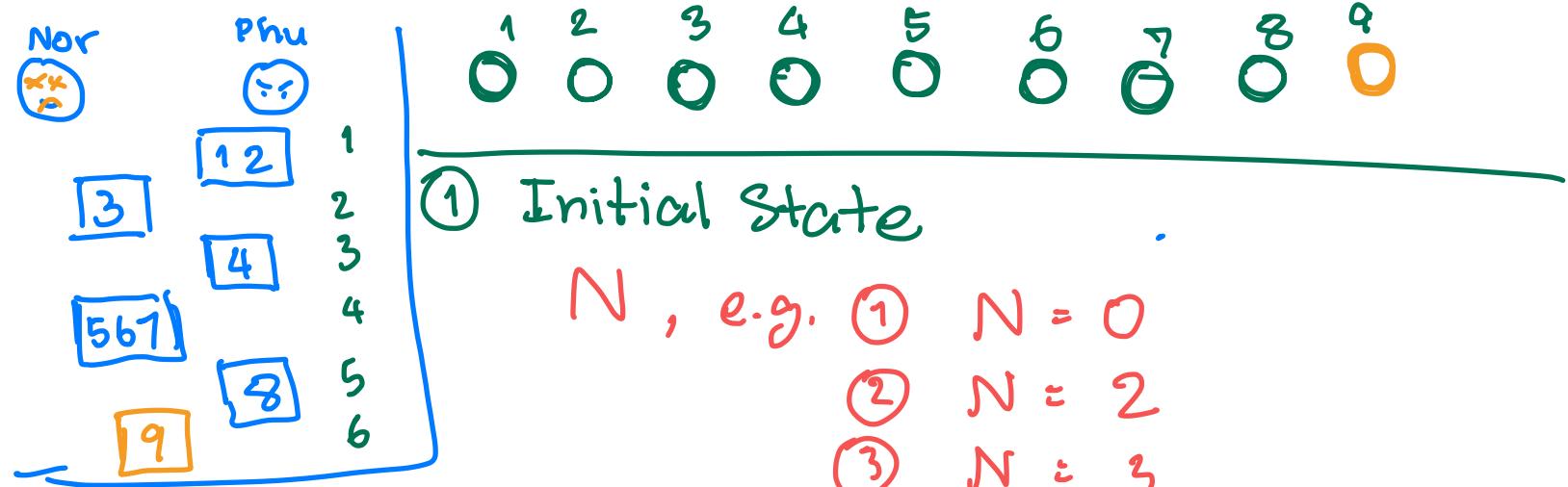
2. Players $\begin{array}{c} \Delta \\ \nabla \end{array}$ } who is who?

3. Action space (a set of all valid moves)

4. Transition func

5. Terminal test $\text{isTerminal}(s)$

6. Utility : $\text{Utility}(\text{terminal-state}, \text{player})$



① Initial State

N , e.g. ① $N = 0$

② $N = 2$

③ $N = 3$

② Player. Phu ∇
Nor Δ

④ Transition function

$$N' = N + a$$

⑤ Terminal test

$$N = 9$$

⑥ Utility

$$\{1, 2, 3 \mid a+N \leq 9\}$$

if player of the last state -1
else 1

The Minimax algorithm

First max node
(initial state)

```
function MINIMAX-DECISION(state) returns an action
    return  $\arg \max_{a \in \text{ACTIONS}(s)}$   $\text{MIN-VALUE}(\text{RESULT}(state, a))$ 
```

function MAX-VALUE(state) returns a utility value

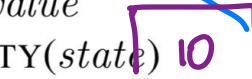
if TERMINAL-TEST(state) then return UTILITY(state)

$v \leftarrow -\infty$

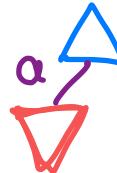
for each a in ACTIONS(state) do

$v \leftarrow \text{MAX}(v, \text{MIN-VALUE}(\text{RESULT}(s, a)))$

return v



transition
function



function MIN-VALUE(state) returns a utility value

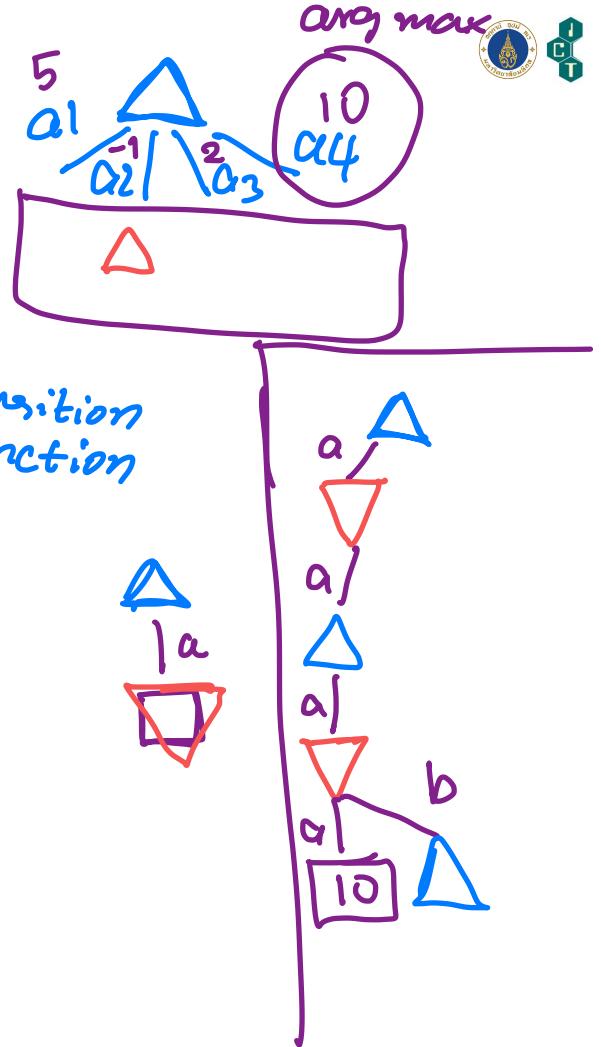
if TERMINAL-TEST(state) then return UTILITY(state)

$v \leftarrow \infty$

for each a in ACTIONS(state) do

$v \leftarrow \text{MIN}(v, \text{MAX-VALUE}(\text{RESULT}(s, a)))$

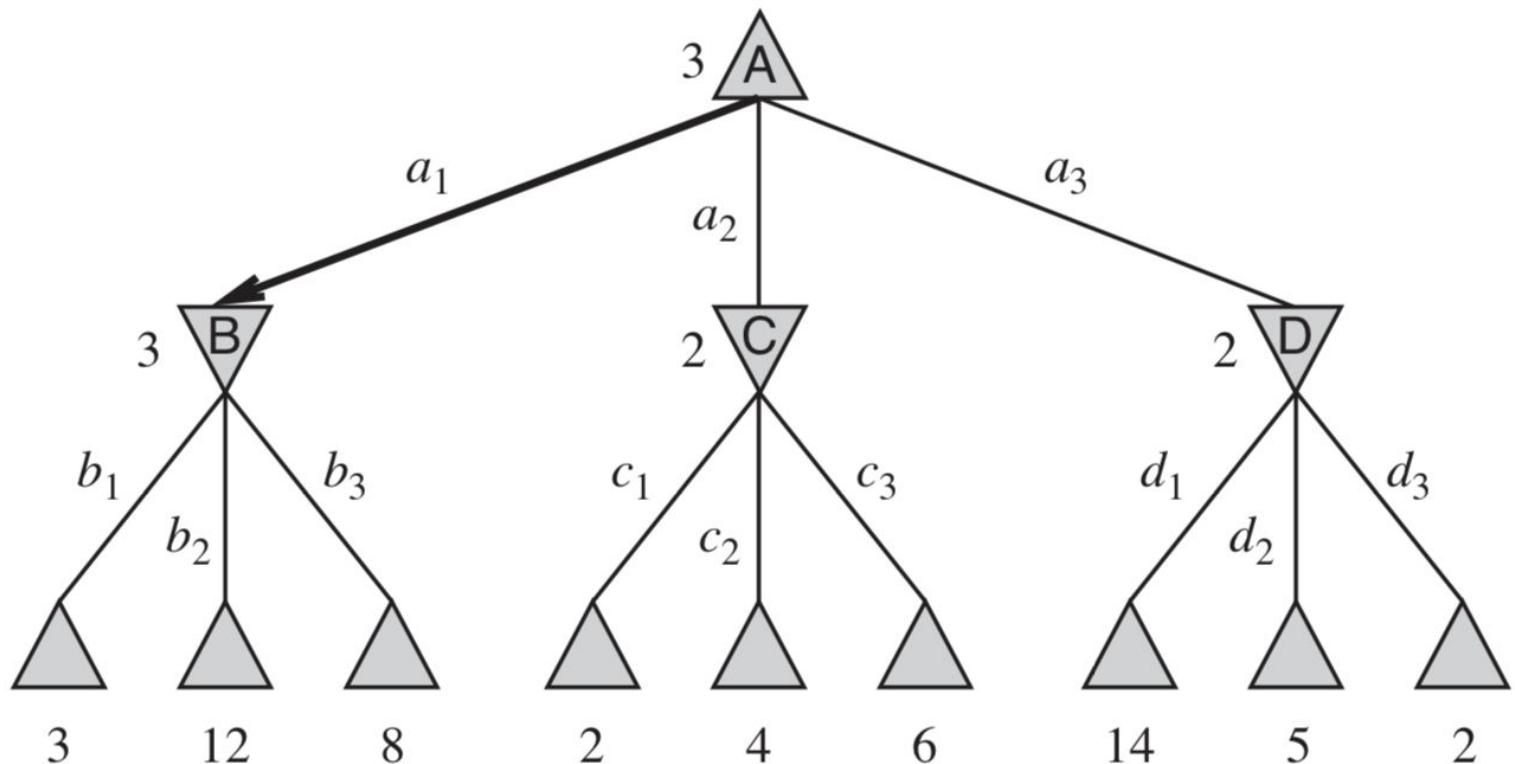
return v



Example 1

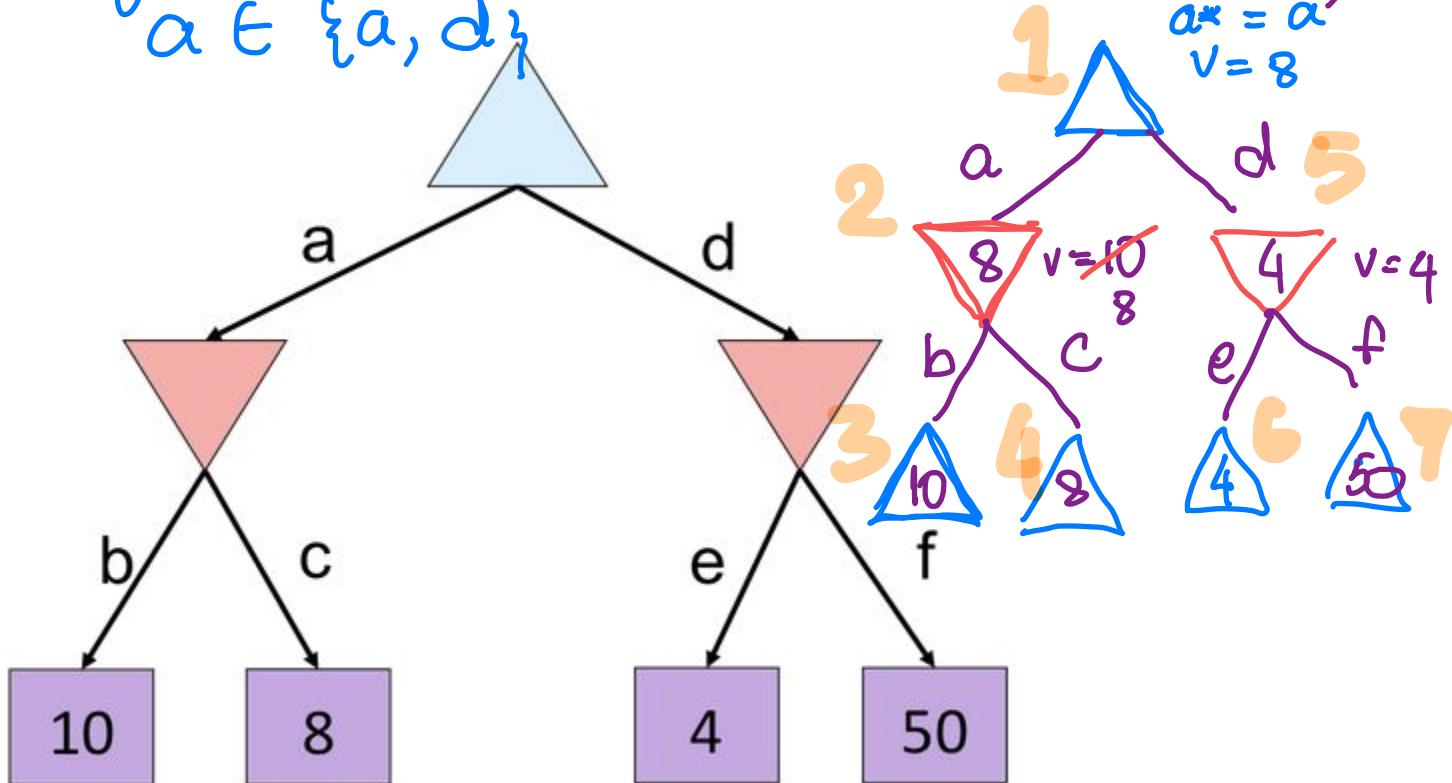
MAX

MIN

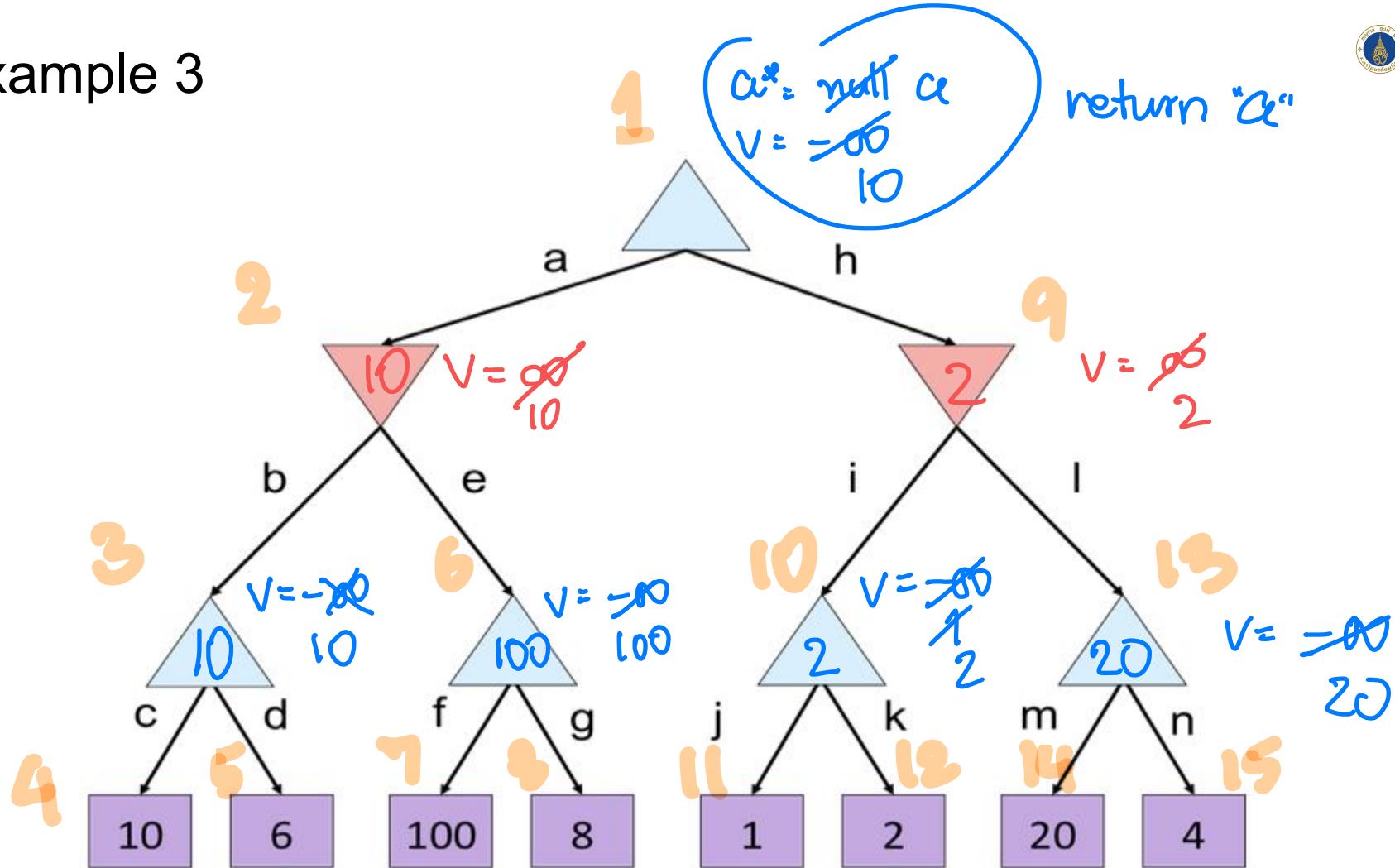


Example 2

$\underset{a \in \{a, d\}}{\operatorname{argmax}}$ min-value(transition (s, a))



Example 3



Minimax Properties

1. is minimax search optimal?

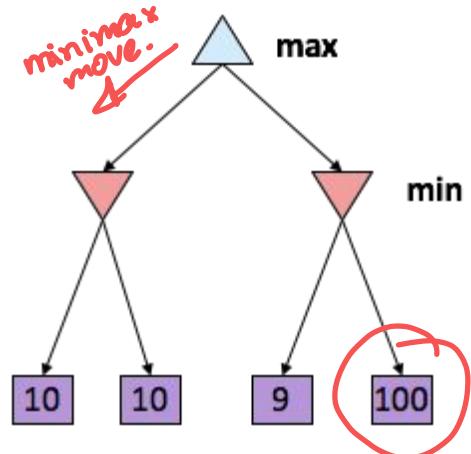
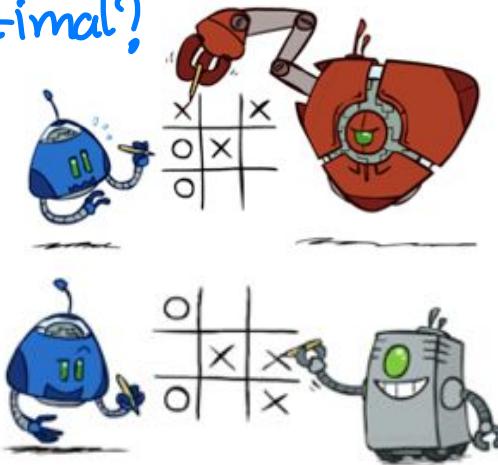
↳ Yes → only when the opponent is optimal.

2. Time complexity

$$\mathcal{O}(b^m)$$

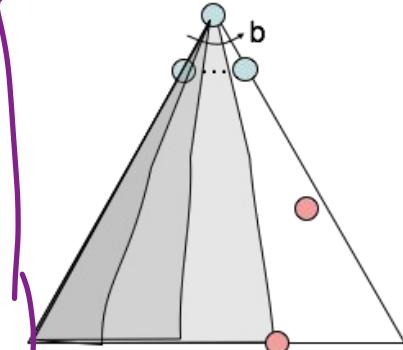
3. Space Complexity

$$\mathcal{O}(bm)$$



Chess
 $b \approx 35$
 $m \approx 100$

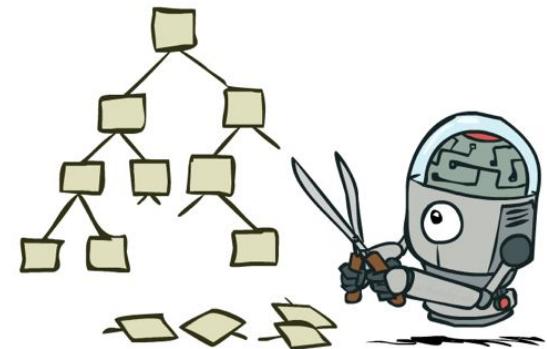
Go
 $b \approx 250$
 $m \approx 210$



1 node
 b nodes
 b^2 nodes

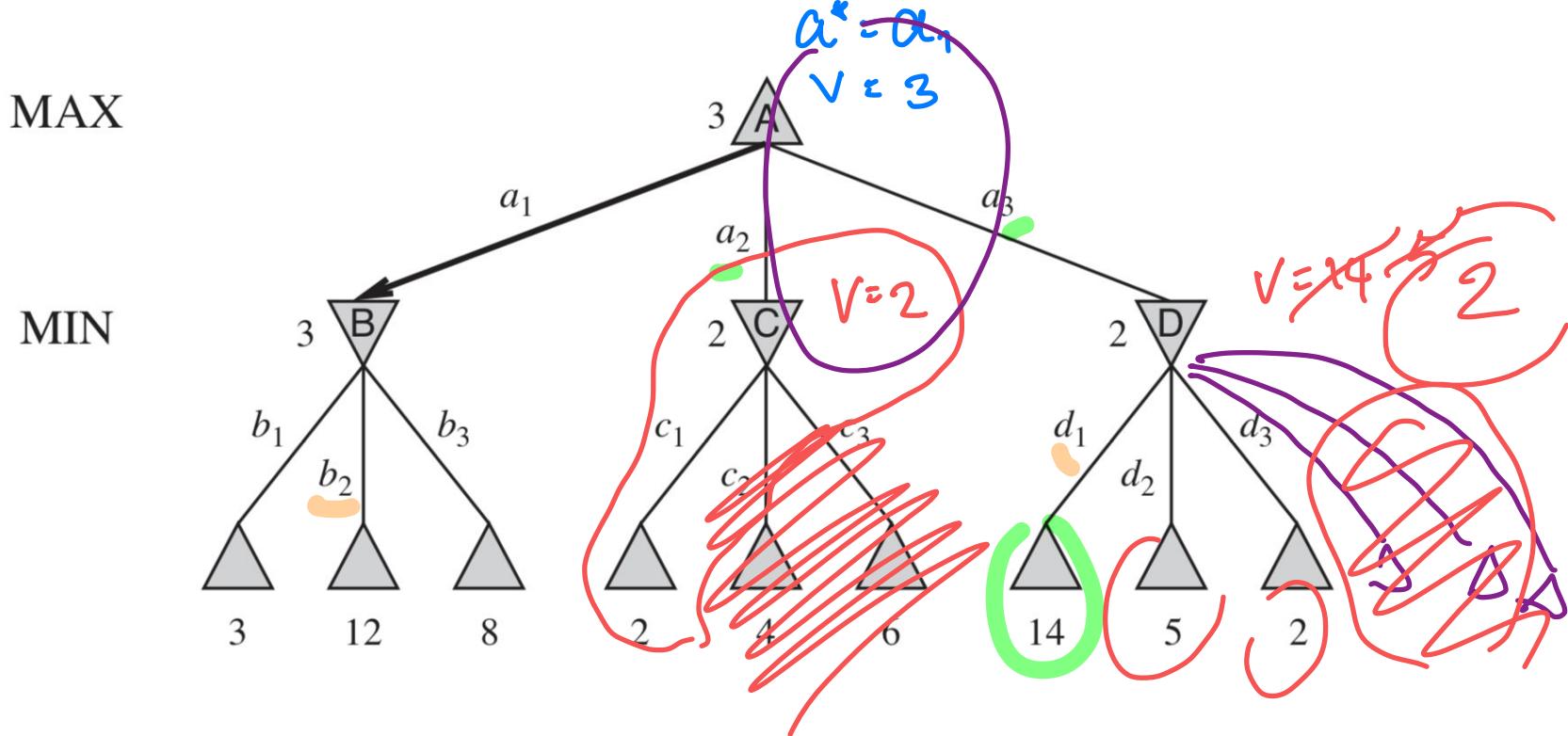
b^m nodes

3. Improving Efficiency



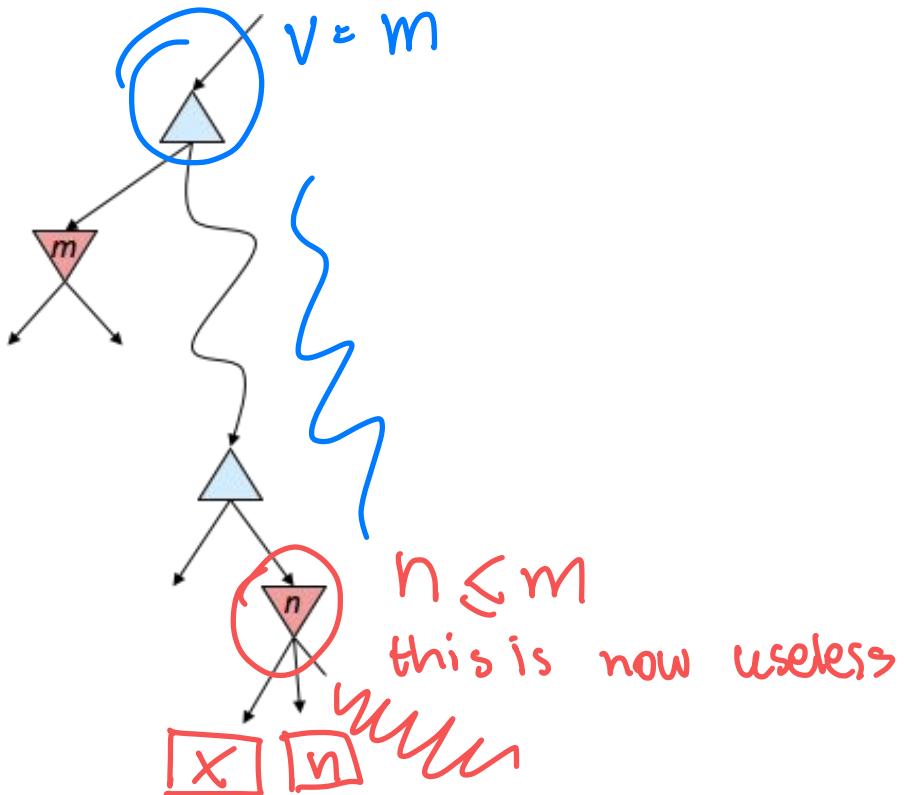
Minimax explores bad actions

Can you spot the unnecessary exploration?

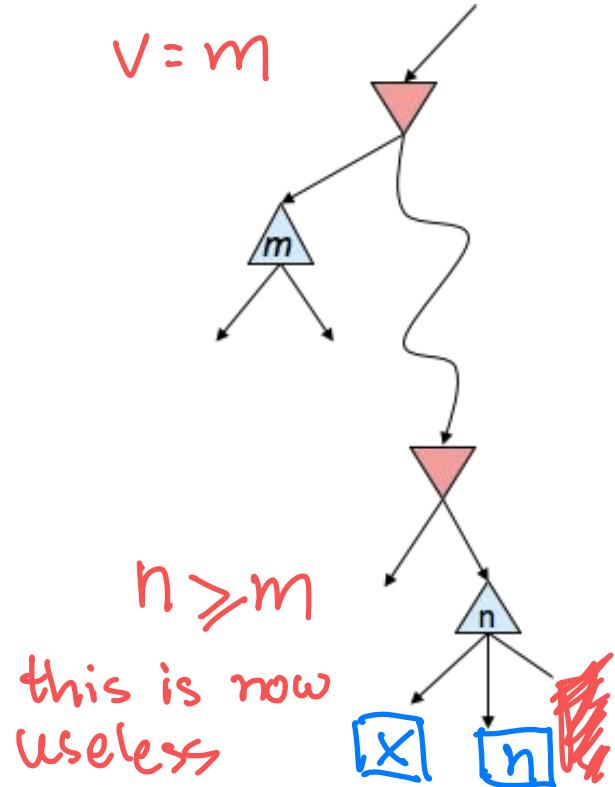


Alpha-Beta Pruning

Min case



Max case



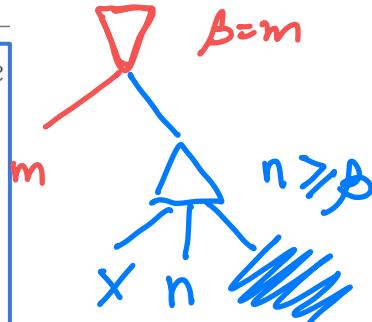
The Alpha-Beta Search algorithm (Modified Minimax)

alpha *beta*

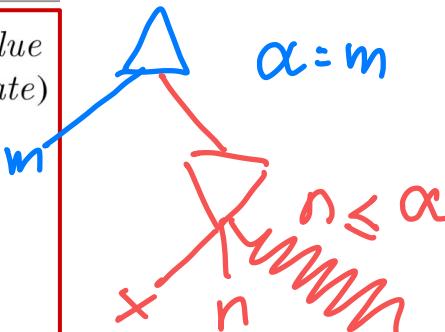
```
function ALPHA-BETA-SEARCH(state) returns an action
     $v \leftarrow \text{MAX-VALUE(state, } -\infty, +\infty)$ 
    return the action in ACTIONS(state) with value  $v$ 
```

value, *limit*

```
function MAX-VALUE(state,  $\alpha, \beta$ ) returns a utility value
    if TERMINAL-TEST(state) then return UTILITY(state)
    if depth-level  $\geq$  limit then return  $m$ 
    for each  $a$  in ACTIONS(state) do
         $v \leftarrow \text{MAX}(v, \text{MIN-VALUE}(\text{RESULT}(s, a), \alpha, \beta))$ 
        if  $v \geq \beta$  then return  $v$ 
         $\alpha \leftarrow \text{MAX}(\alpha, v)$ 
    return  $v$ 
```



```
function MIN-VALUE(state,  $\alpha, \beta$ ) returns a utility value
    if TERMINAL-TEST(state) then return UTILITY(state)
     $v \leftarrow +\infty$ 
    for each  $a$  in ACTIONS(state) do
         $v \leftarrow \text{MIN}(v, \text{MAX-VALUE}(\text{RESULT}(s, a), \alpha, \beta))$ 
        if  $v \leq \alpha$  then return  $v$ 
         $\beta \leftarrow \text{MIN}(\beta, v)$ 
    return  $v$ 
```



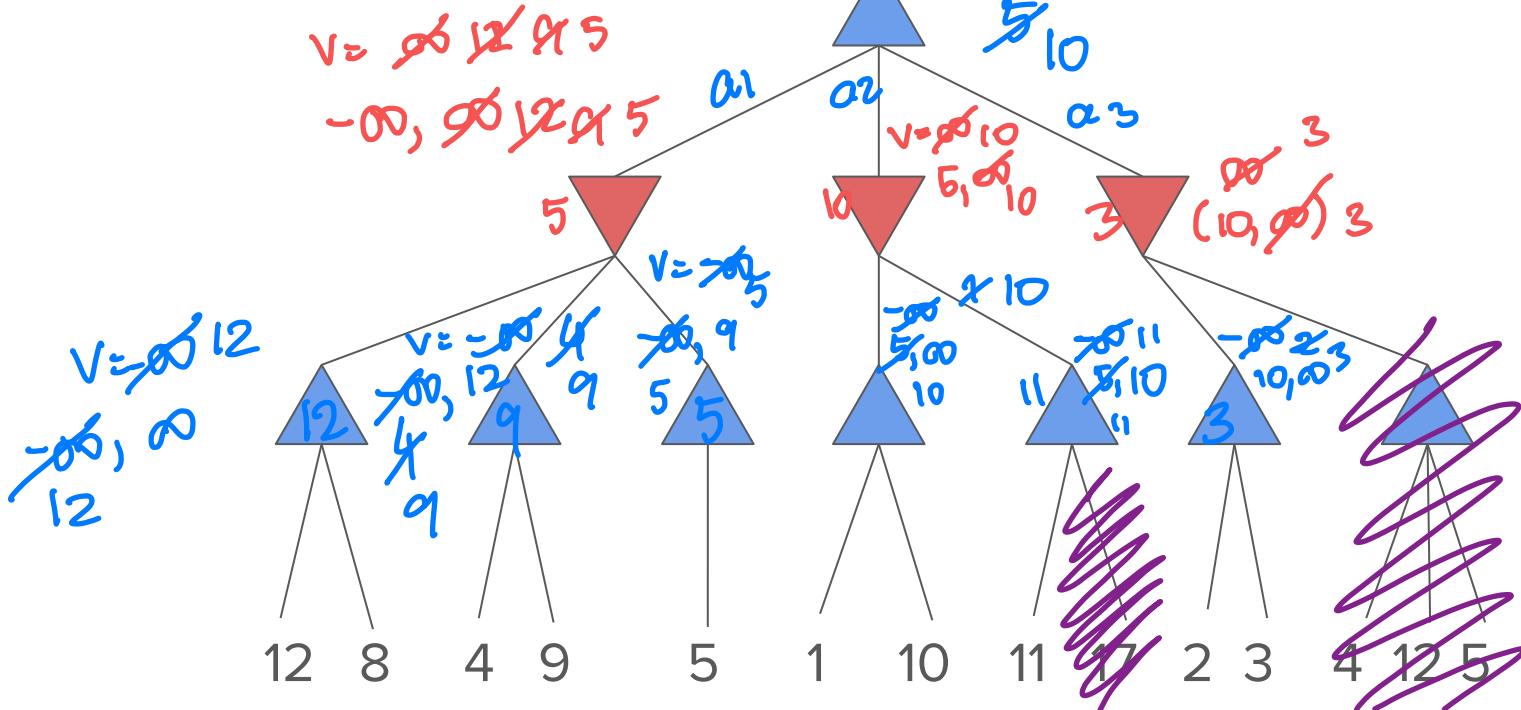
Example

$a^* = \text{null or } a_2$

$v = -\infty, 5, 10$

$\alpha, \beta = (-\infty, \infty)$

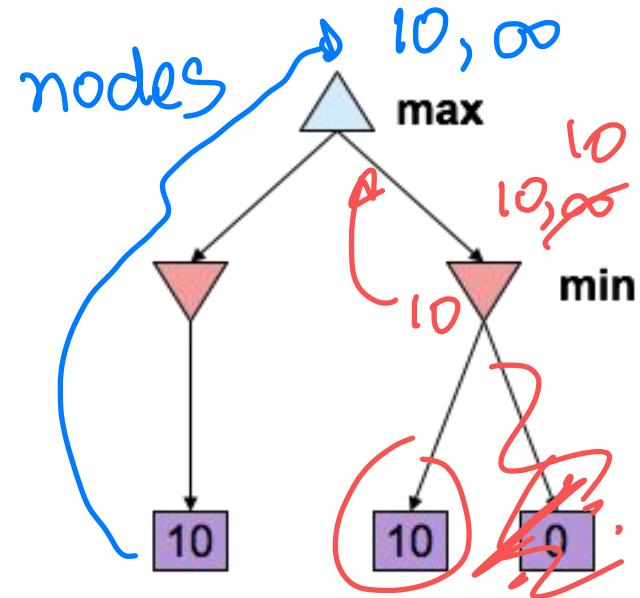
≤ 10



Alpha-Beta Search Properties

1. Return the same action as minimax search.

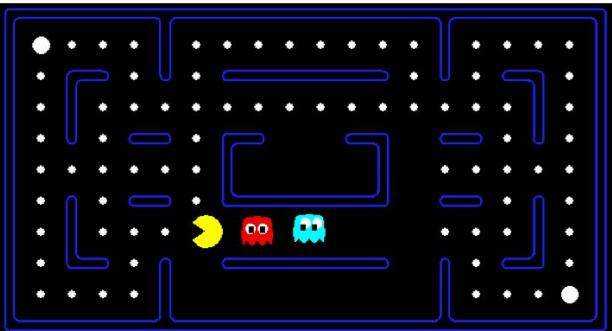
2. The values of non-root nodes might not be the minimax values.



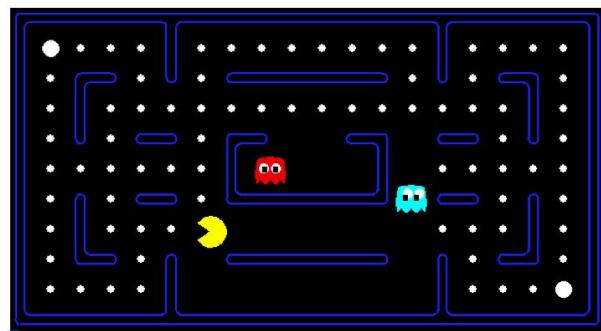
We need to be faster → Use heuristics!

$$\text{eval}(B) > \text{eval}(A) > \text{eval}(C) = \text{eval}(D)$$

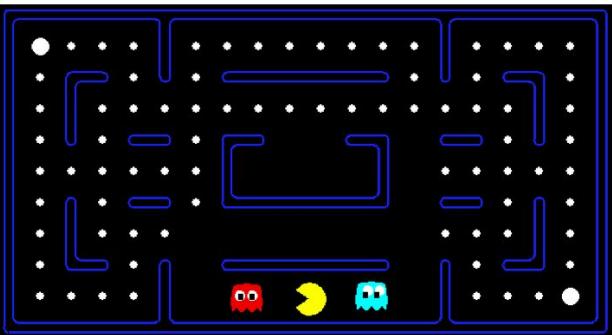
A



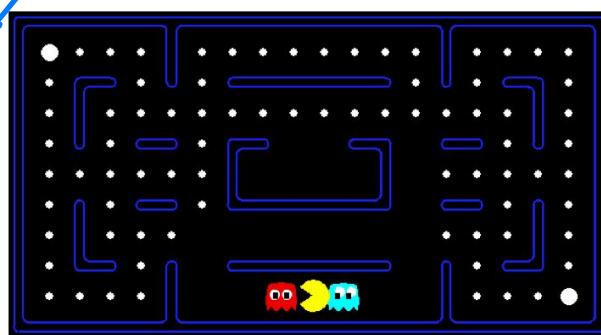
B



C



D



Poll: Sort the heuristic values
e.g. A > B > C > D

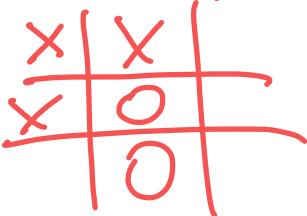
Depth-Limited Search + Evaluation Function

run minmax or alpha-beta search

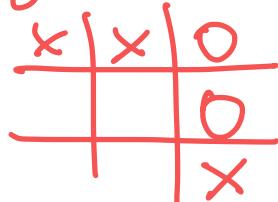
but if the depth-level reaches

a limit, return $\text{eval}(s)$ value.

we are playing O



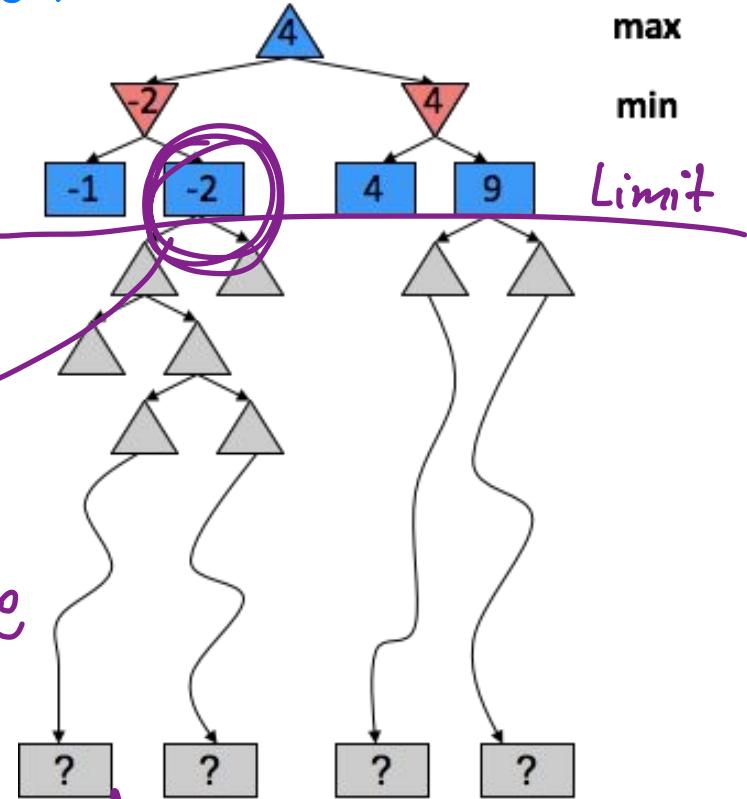
A



B

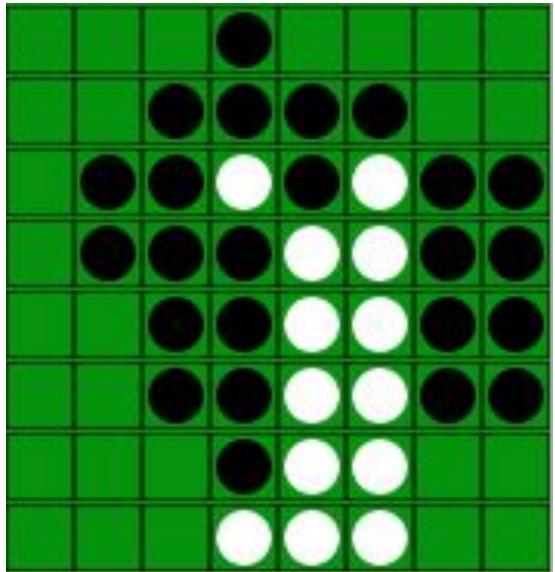
$\text{eval}(A) < \text{eval}(B)$

we need to
approximate the
utility of
non-terminal nodes



Example: Othello (Reversi)

$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \dots + w_n f_n(s)$$



- $f_1(s) = \# \text{white legal moves}$
- $f_2(s) = \# \text{white} - \# \text{black}$
- ...

	a	b	c	d	e	f	g	h
1	100	-20	10	5	5	10	-20	100
2	-20	-50	-2	-2	-2	-2	-50	-20
3	10	-2	-1	-1	-1	-1	-2	10
4	5	-2	-1	-1	-1	-1	-2	5
5	5	-2	-1	-1	-1	-1	-2	5
6	10	-2	-1	-1	-1	-1	-2	10
7	-20	-50	-2	-2	-2	-2	-50	-20
8	100	-20	10	5	5	10	-20	100

The Depth-Limited Alpha-Beta Search algorithm

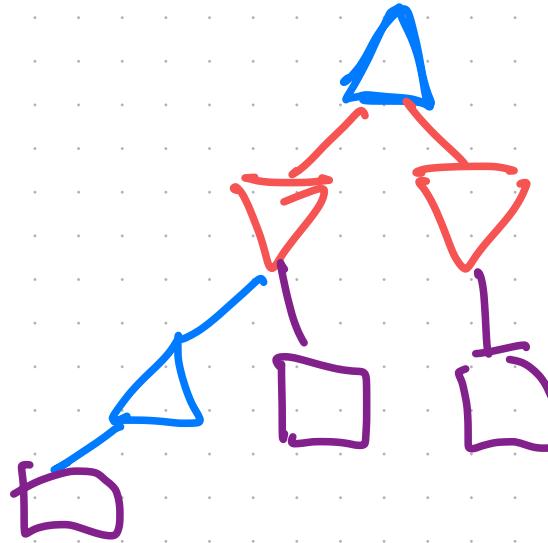
```
function ALPHA-BETA-SEARCH(state) returns an action  
  v  $\leftarrow$  MAX-VALUE(state,  $-\infty$ ,  $+\infty$ )  
  return the action in ACTIONS(state) with value v
```

```
function MAX-VALUE(state,  $\alpha$ ,  $\beta$ ) returns a utility value  
  if TERMINAL-TEST(state) then return UTILITY(state)  
  v  $\leftarrow -\infty$   
  for each a in ACTIONS(state) do  
    v  $\leftarrow$  MAX(v, MIN-VALUE(RESULT(s,a),  $\alpha$ ,  $\beta$ ))  
    if v  $\geq \beta$  then return v  
     $\alpha \leftarrow \text{MAX}(\alpha, v)$   
  return v
```

```
function MIN-VALUE(state,  $\alpha$ ,  $\beta$ ) returns a utility value  
  if TERMINAL-TEST(state) then return UTILITY(state)  
  v  $\leftarrow +\infty$   
  for each a in ACTIONS(state) do  
    v  $\leftarrow$  MIN(v, MAX-VALUE(RESULT(s,a),  $\alpha$ ,  $\beta$ ))  
    if v  $\leq \alpha$  then return v  
     $\beta \leftarrow \text{MIN}(\beta, v)$   
  return v
```

Summary.

1.  max  min



2. Optimal action

= a action that leads to an optimal value child node

3. Adversarial Search Problem → Formulation

4. minimax algorithm

5. Alpha - Beta pruning

6. Depth - limit + evaluation function.

minimax value
 $V(S) \{ \begin{array}{l} \max V(S') \\ \min V(S') \end{array} \}$

$V(S) = \text{Utility}(S)$
if S is terminal