



Artificial and Computational Intelligence AIMLCZG557

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M1: Introduction to Al

M2: Problem Solving Agent using Search

BITS Pilani

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Artificial and Computational Intelligence

Disclaimer and Acknowledgement



- Few content for these slides may have been obtained from prescribed books and various other source on the Internet
- I hereby acknowledge all the contributors for their material and inputs and gratefully acknowledge people others who made their course materials freely available online.
- I have provided source information wherever necessary
- This is not a full fledged reading materials. Students are requested to refer to the textbook w.r.t detailed content of the presentation deck that is expected to be shared over e-learning portal - taxilla.
- I have added and modified the content to suit the requirements of the class dynamics & live session's lecture delivery flow for presentation
- Slide Source / Preparation / Review:
- From BITS Pilani WILP: Prof.Raja vadhana, Prof. Indumathi, Prof.Sangeetha
- From BITS Oncampus & External: Mr.Santosh GSK

Course Plan

M1	Introduction to Al
M2	Problem Solving Agent using Search
M3	Game Playing
M4	Knowledge Representation using Logics
M5	Probabilistic Representation and Reasoning
M6	Reasoning over time
M7	Ethics in Al

Learning Objective

At the end of this class, students Should be able to:

- 1. Identify dimensions of TASK environment
- 2. Design problem solving agents
- 3. Create search tree for given problem
- 4. Apply uninformed search algorithms to the given problem

Dimensions of Task Environment

Sensor Based:

Observability : Full Vs Partial

Action Based:

Dependency : Episodic Vs Sequential

State Based:

No.ofState : Discrete Vs Continuous

Agent Based:

> Cardinality : Single Vs MultiAgent

Action & State Based:

- State Determinism : Deterministic Vs Stochastic | Strategic
- Change in Time : Static Vs Dynamic



Task Environment



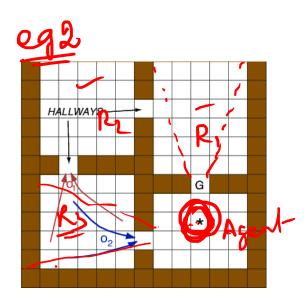
A rational agent is built to solve a specific task. Each such task would then have different environment which we refer to as Task Environment

Based on the applicability of each technique for agent implementation its task environment design is determined by multiple dimension

Sensor Based:

Observability : Full Vs Partial





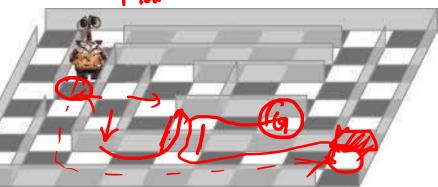
innovate achieve lead

Task Environment

Action Based:

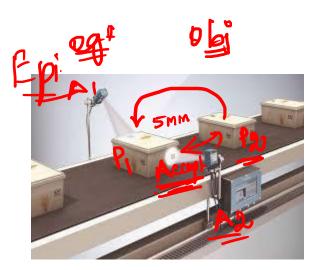
Dependency: Episodic Vs Sequential







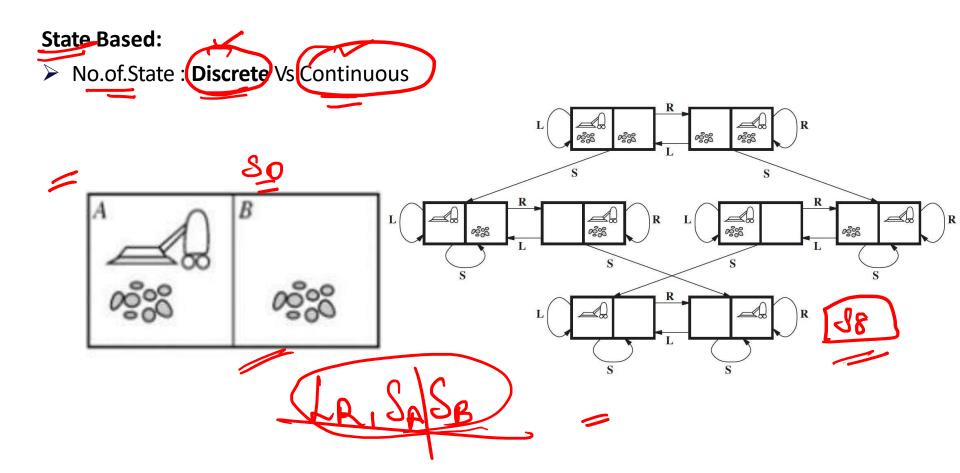
Sog, of Movel





A Rejected

Task Environment

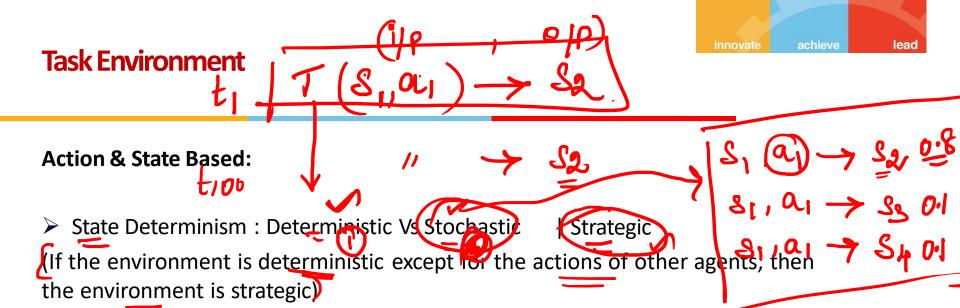


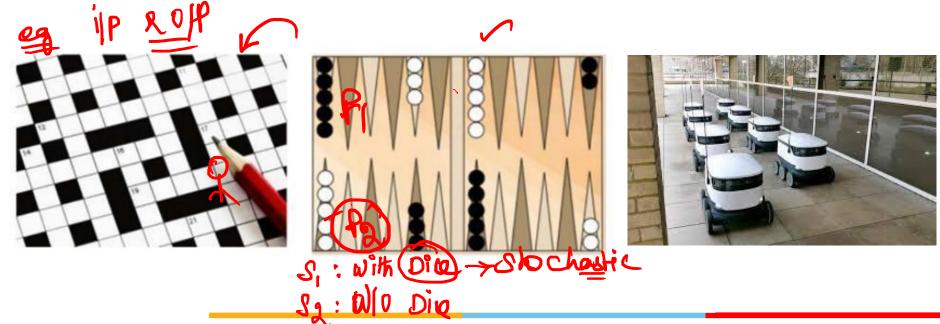
Task Environment

State Based:

No.of.State : Discrete Vs Continuous

VS.





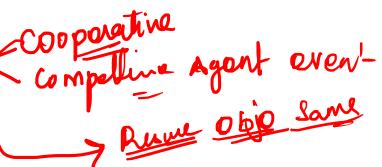
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Task Environment

Agent Based:

> Cardinality : Single Vs MultiAgent







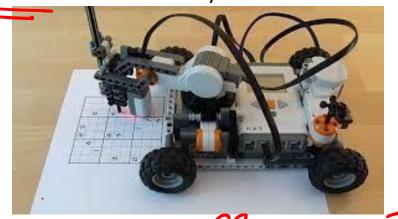


Task Environment

Action & State Based:

- ➤ Change in Time : Static Vs Dynamic
- >(The environment is semi dynamic) f the environment itself does not change with the passage of time but the agent's performance score does)





8th attentioners

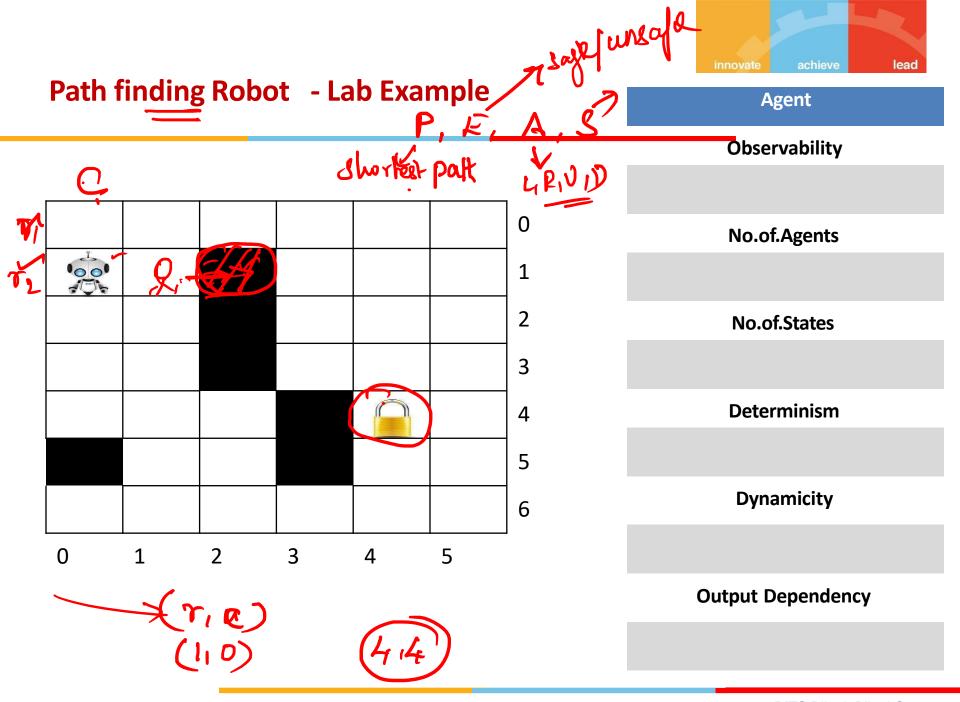
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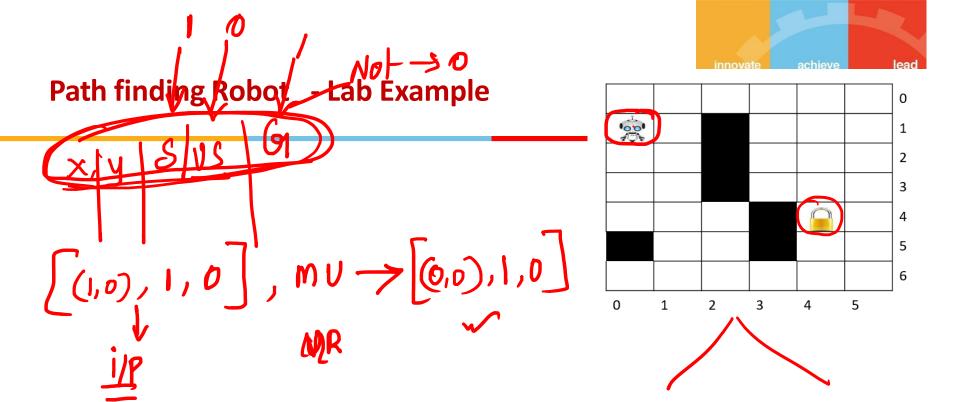
604.



Task Environment

	ask nvironment	Fully vs Partially Observable	Single vs Multi- Agent	Deterministic vs Stochastic	Episodic vs Sequential	Static vs Dynamic	Discrete vs Continuous
g d	1edical iagnosis ystem	Partially 	Single —	Stochastic	Sequential	Dynamic =	Continuous
A	atellite Image nalysis ystem	Fully	Single	Deterministic	Episodic	Static	Continuous
	nteractive nglish tutor	Partially	Multi	Stochastic	Sequential	Dynamic	Discrete







Path finding Robot - Lab Example

Agent

Observability



No.of.Agents



No.of.States



Determinism

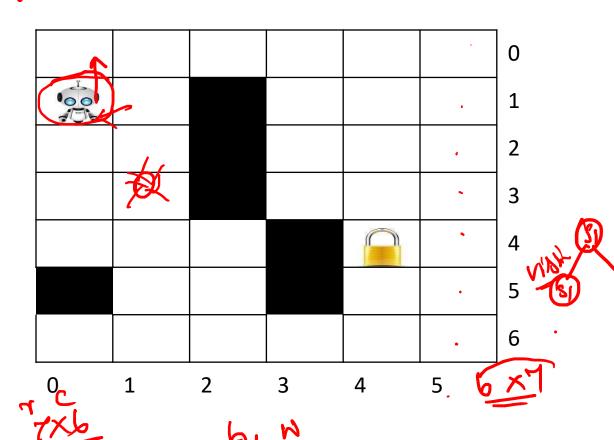


Dynamicity



Output Dependency







What the world is like now

What action I

should do now

Actuators

Simple Reflex Agent

Condition-action rules

Agent

function SIMPLE-REFLEX-AGENT(percept) returns an action

persistent: rules, a set of condition-action rules

state←INTERPRET-INPUT(percept)

rule←RULE-MATCH(state, rules)

action ←rule.ACTION

return action

function REFLEX-VACUUM-AGENT([location, status]) returns an action

if status = Dirty then return Suck

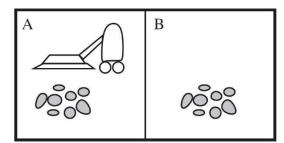
else if location = A then return Right

else if location = B then return Left

Fully Observable

Simple Reflex Agents

D-> cl such



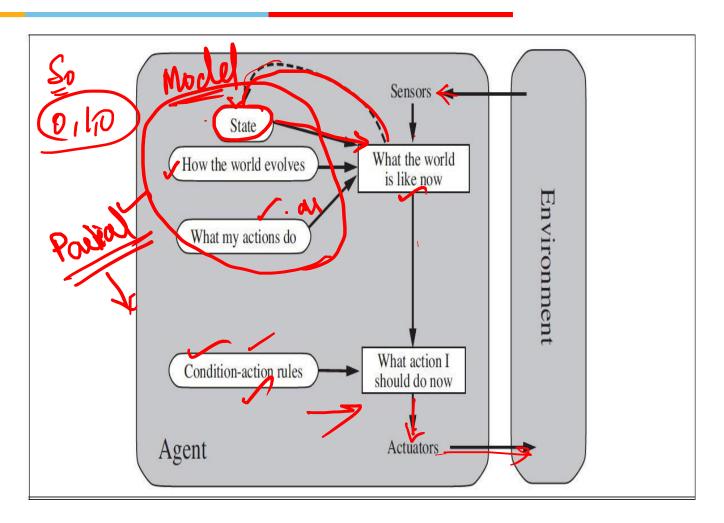
Environment



Model based Agent









Model based Agent

function MODEL-BASED-REFLEX-AGENT(percept) returns an action

persistent: state, the agent's current conception of the world state

transition model, a description of how the next state depends on the current state and action sensor model, a description of how the current world state is reflected in the agent's percepts rules, a set of condition-action rules action, the most recent action, initially none

state←UPDATE-STATE(state, action, percept, transition model, sensor model)

rule←RULE-MATCH(state, rules)

action ←rule.ACTION

return action



Goal based Agent



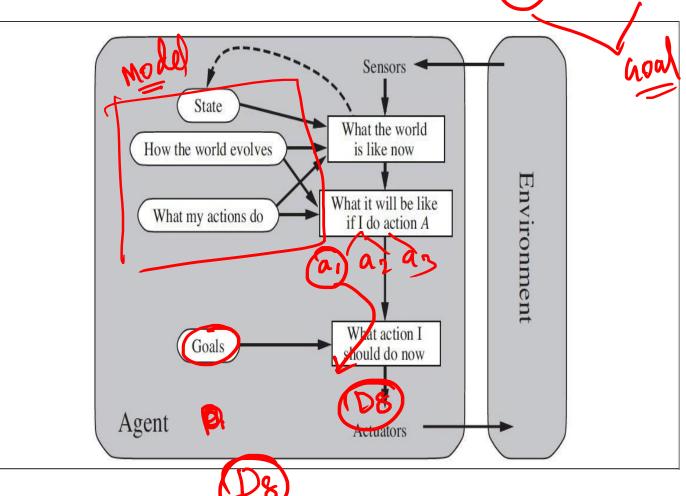
Simple Reflex Agents



Model Based Agents

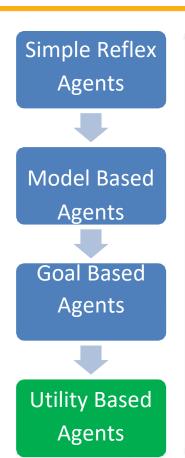


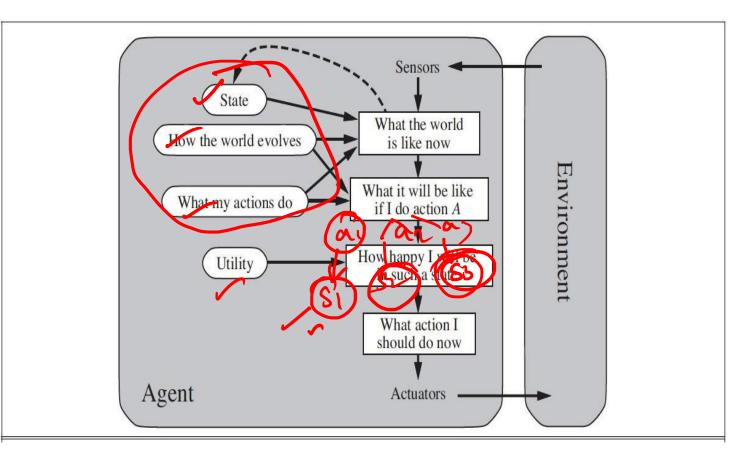
Goal Based Agents



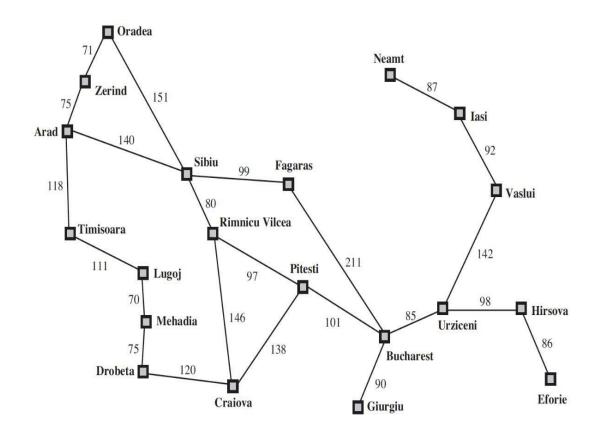


Utility based Agent





Learning Agent





Learning Agent

Simple Reflex Agents



Model Based Agents



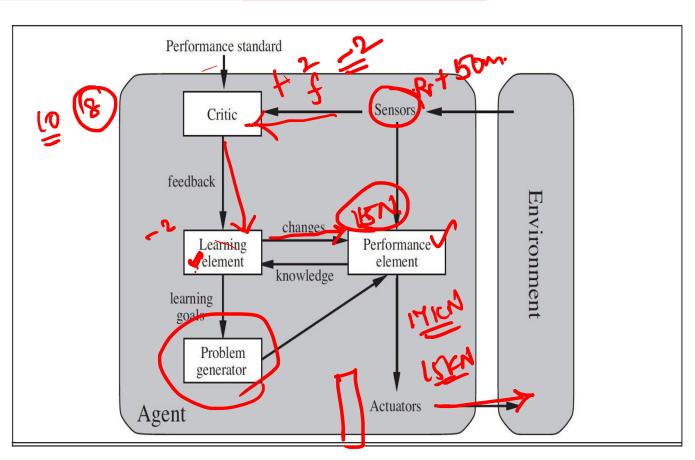
Goal Based Agents



Utility Based Agents



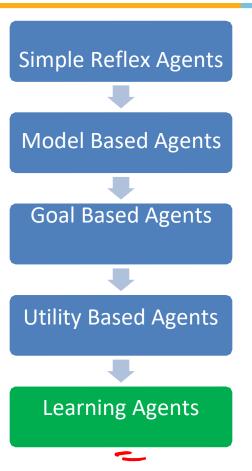
Learning Agents







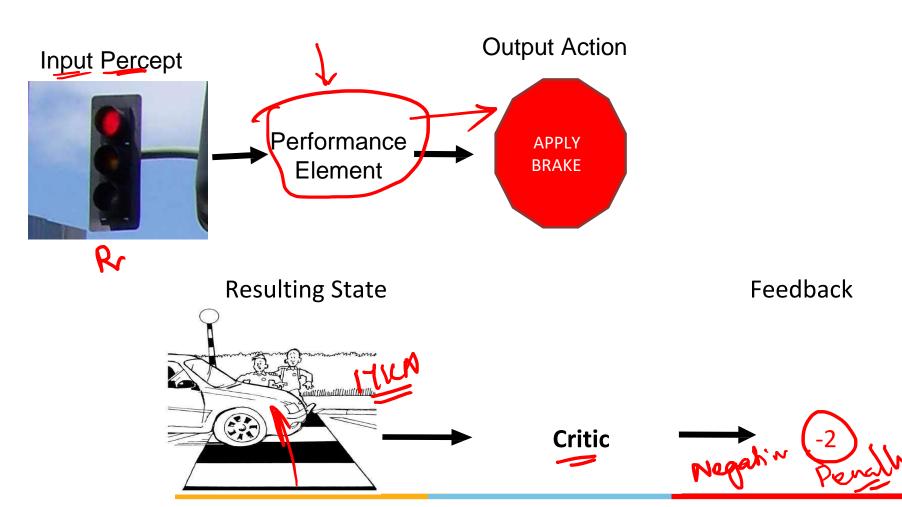
Learning Agent



- **Performance Element** taking a decision of action based on percepts
- **Learning Element** Make the performance element select better actions such that the utility function is optimized
- **Critic** − Provides feedback on the actions taken
- **Problem Generator** Make the Performance Element select sub-optimal actions such that you would learn from unseen actions



Agents that improve their performance by learning from their own experiences

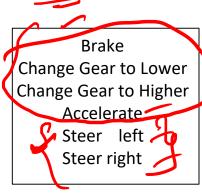




Input Percept



Possible Actions





Random

Selected Action

Change Gear to Lower



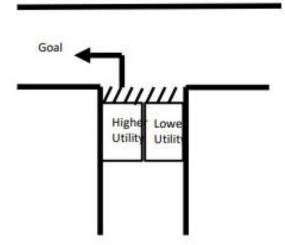
Performance Element – Takes decision on action based on percept

```
f(red \ signal, \ distance) = 15k \ N \ brake

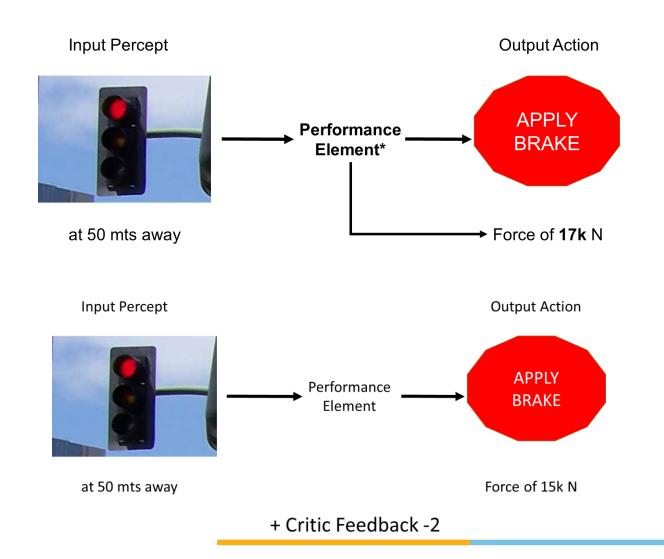
distance = f'(percept \ sequence)

f(percepts, distance, raining)
```

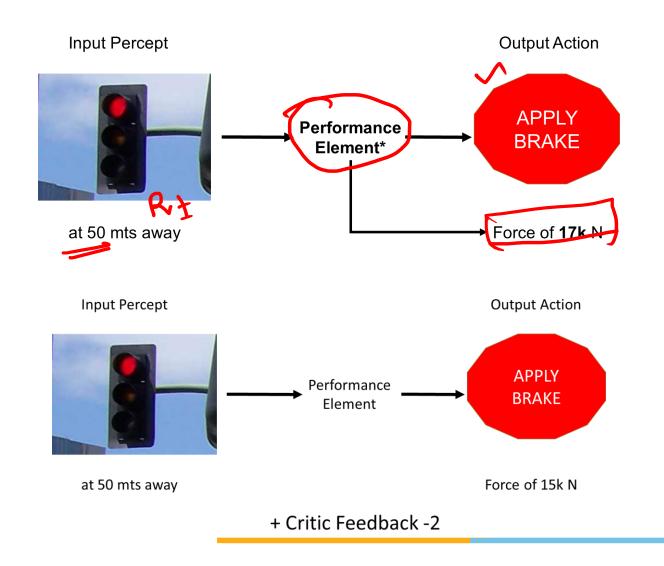
- $f(state_0, actionA) = 0.83,$
- $f(state_0, actionB) = 0.45$



Learning: Supervised Vs Unsupervised Vs Reinforcement



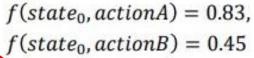
Learning: Supervised Vs Unsupervised Vs Reinforcement

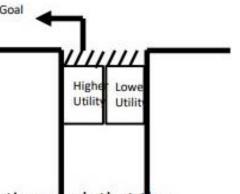


Performance Element - Takes decision on action based on percept



```
f(red signal, distance) = 15k N brake
distance = f'(percept sequence)
f(percepts, distance, raining)
```





Learning Element – Make the performance element select better actions such that the utility function is optimized

Critic - Provides feedback on the actions taken

<u>Problem Generator</u> – Make the Performance Element select sub-optimal actions such that you would learn from unseen actions

Required Reading: AIMA - Chapter #1, 2, 3.1, 3.2, 3.3

Thank You for all your Attention

Note: Some of the slides are adopted from AIMA TB materials