



COL778: Principles of Autonomous Systems

Semester II, 2023-24

Course Introduction

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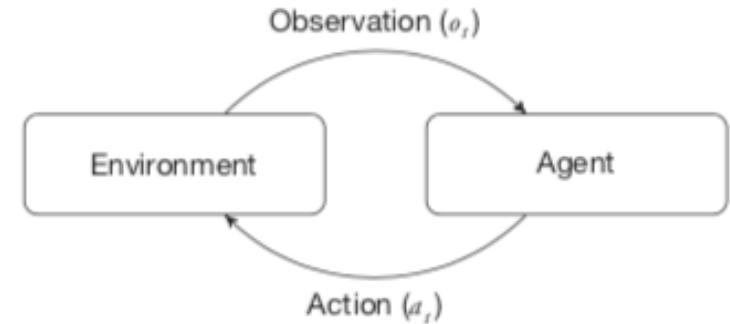


Today's lecture

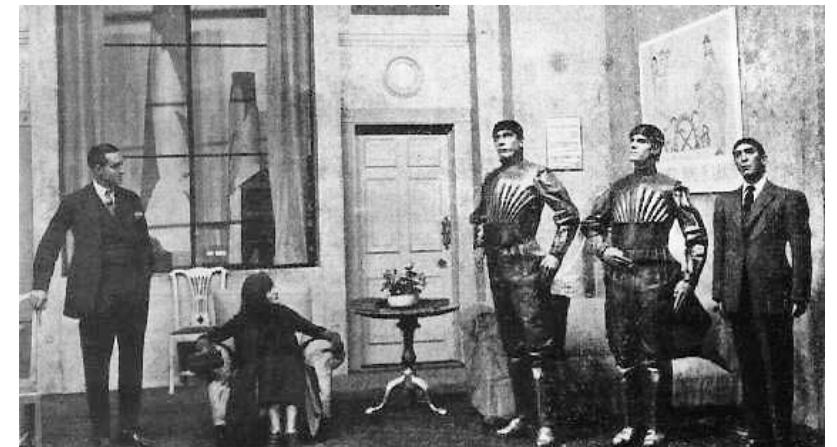
- Last Class
 - Course Organization
- This Class
 - Introduction
 - What is embodied AI?
 - Core challenges: Estimation and Planning

Intelligent Robotic Systems

- Intelligent agents that can perform tasks in the physical world.
- Platforms that can carry a payload, sense the environment and take actions.
- Perform goal-directed tasks in the real world.
- Human interaction – task specification, resolving ambiguity etc.
- Various names: Embodied AI, autonomous systems, robot intelligence.
- The word “Robot” means “labour” in Czech by Karl and Joseph Kapek (1920s).



At a basic level, an embodied AI agent takes observations from the environment and synthesizes goal-directed actions.



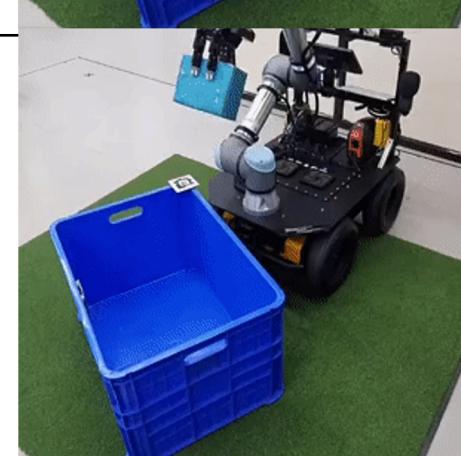
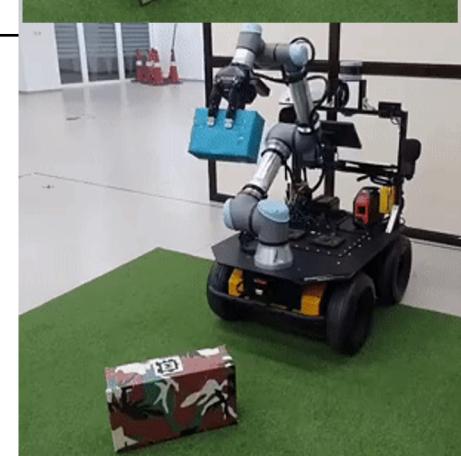
A scene from "Rossum's Universal Robots," showing three robots,
<https://www.sciencefriday.com/segments/the-origin-of-the-word-robot/>

Let's take an example: Intelligent Manipulation

Pick



Place



Manipulation with Planning

Partial Observability is a key problem



Planning a Sequence of Actions

Generates the sequence of actions to take the robot from the initial state to the desired goal state.



$$\pi = [a_0, a_1, a_2, \dots, a_{n-1}]$$

$$s_0 \xrightarrow{a_0} s_1 \xrightarrow{a_1} s_2 \xrightarrow{a_2} \dots \xrightarrow{a_{n-2}} s_{n-1} \xrightarrow{a_{n-1}} s_n$$

$$\tau(s_i, a_i) \rightarrow s_{i+1}$$

$$g_t \subseteq s_n$$

τ : transition function

π : plan

a_i : action at timestep i

s_i : state at timestep i

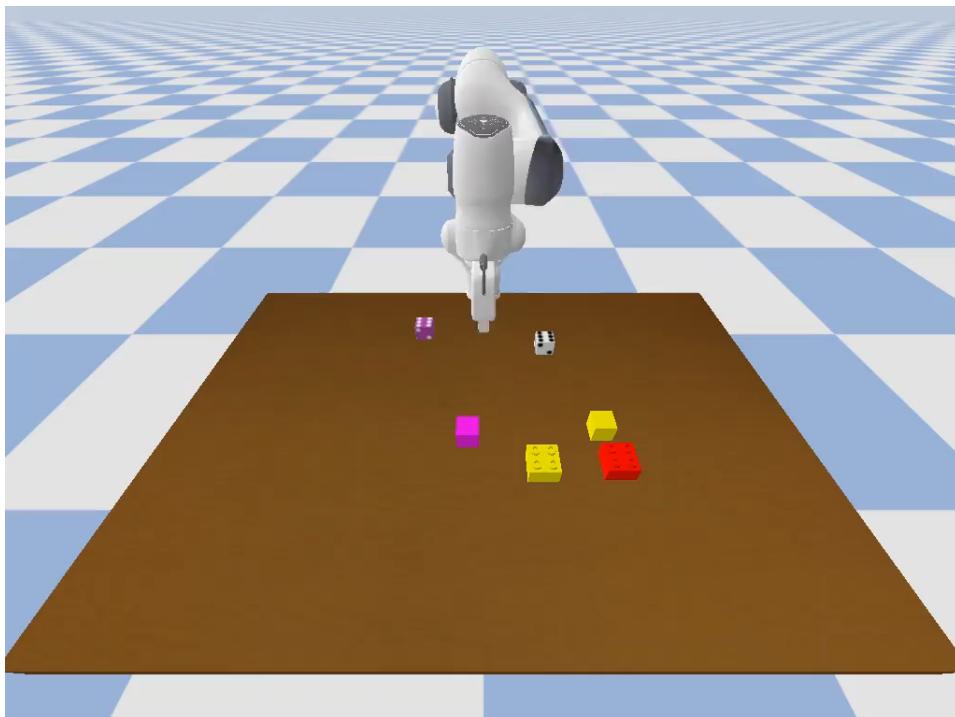
g_t : goal state

```
(:action pick
  :parameters (?obj - item ?loc - region)
  :precondition (and (gripperFree) (at ?obj ?loc)
    (clear ?obj)
    (onGround
      ?obj))
  :effect(and (not (at ?obj ?loc))
    (not (gripperFree))
    (not (onGround ?obj))
    (holding ?obj))

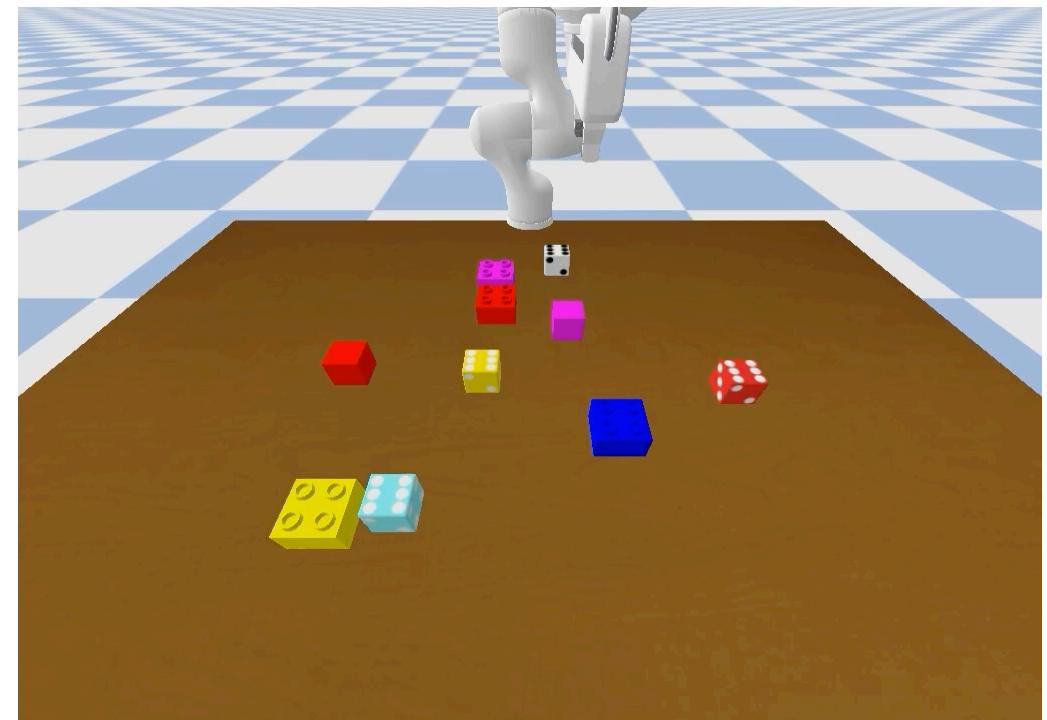
(:action place )
  :parameters (?obj - item ?loc - region)
  :precondition (holding ?obj)
  :effect(and (at ?obj ?loc)
    (gripperFree)
    (not (holding ?obj))
    (onGround ?obj)))
```

Reasoning and Planning

"Put the white dice above the yellow lego object and move the yellow cube on top of the white dice"



"Place the magenta cube to the left of red cube"
Sensor errors happen all the time!



Autonomous systems need human data

Data Collection Interface

The interface consists of two main panels. The left panel, titled 'List of Symbolic Objects', shows a grid of objects with their IDs: apple, ball, banana, big_tray, bigger_table, book, bottle_blue, bottle_gray, bottle_red, cupboard, dirt, chair, couch, cube_gray, cube_red, cube_green, cube_silver, deer, dumper, floor, glue, ledge, light, milk, mop, orange, paper, paper2, paper3, shelf, smaller_table, sponge, stool, tap, tray, vacuum, wall. Below this is a 'Task Description (Goal to achieve)' section with the goal 'Place fruits in the cupboard' and a timer at 09:57. An 'Instruction Input' field is present, along with 'Execute Move', 'Undo Move', and 'Report Process' buttons. A red arrow points to the 'Goal' text. The right panel, titled 'Virtual Mobile Manipulator', shows a 3D simulation of a robot arm in a room with a brick wall, a table, and various objects. A red arrow points to the robot arm. Below the simulation is a 'Scene with interactable objects' section and a 'General Instructions' list:

- Please take a look at the simple example which has been provided before starting.
- Keep in mind the weight, feel and physical properties. We have tried to simulate the real world.
- Please refrain from giving instructions not possible in the real world. However we support creativity.

Annotations on the left side of the interface include:

- List of Symbolic Objects**: Points to the grid of objects.
- Goal**: Points to the 'Place fruits in the cupboard' text.
- Human Instructed Robot Plans**: Points to the 'Move list' button.

- A human teacher selects a goal (a high-level task) and specifies a symbolic plan for the robot.
- A coarse simulation is performed for each symbolic action in sequence.
- The world state, the goal and the instructed plan forms a datum for training.

Learning from human demonstration

Plan Execution Example - I

Training



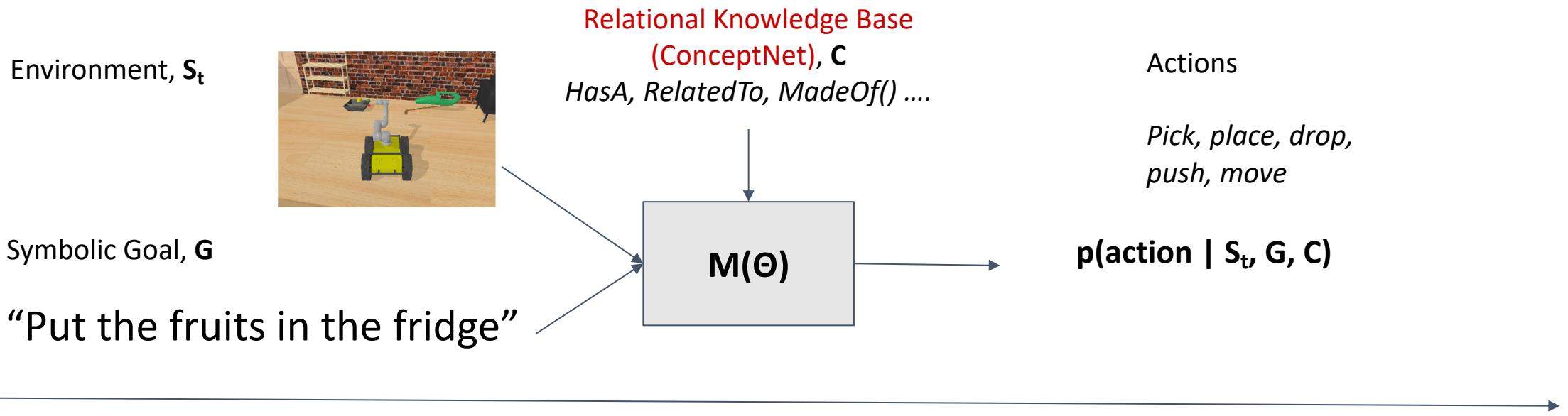
The human demonstrates the use of a tray for transporting items to the cupboard.

Inference



The model infers the utility of the box for the transporting task. The box-type object was not seen in training.

Learning from Demonstration

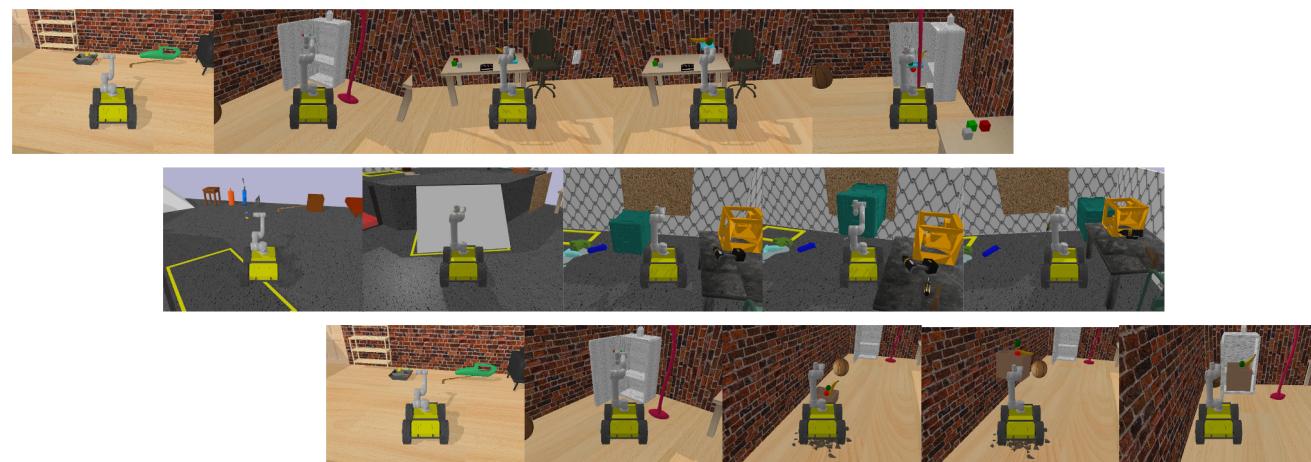


$$< s_0^0, a_0^0, s_1^0, a_1^0, \dots, s_g^0 >$$

$$< s_0^1, a_0^1, s_1^1, a_1^1, \dots, s_g^1 >$$

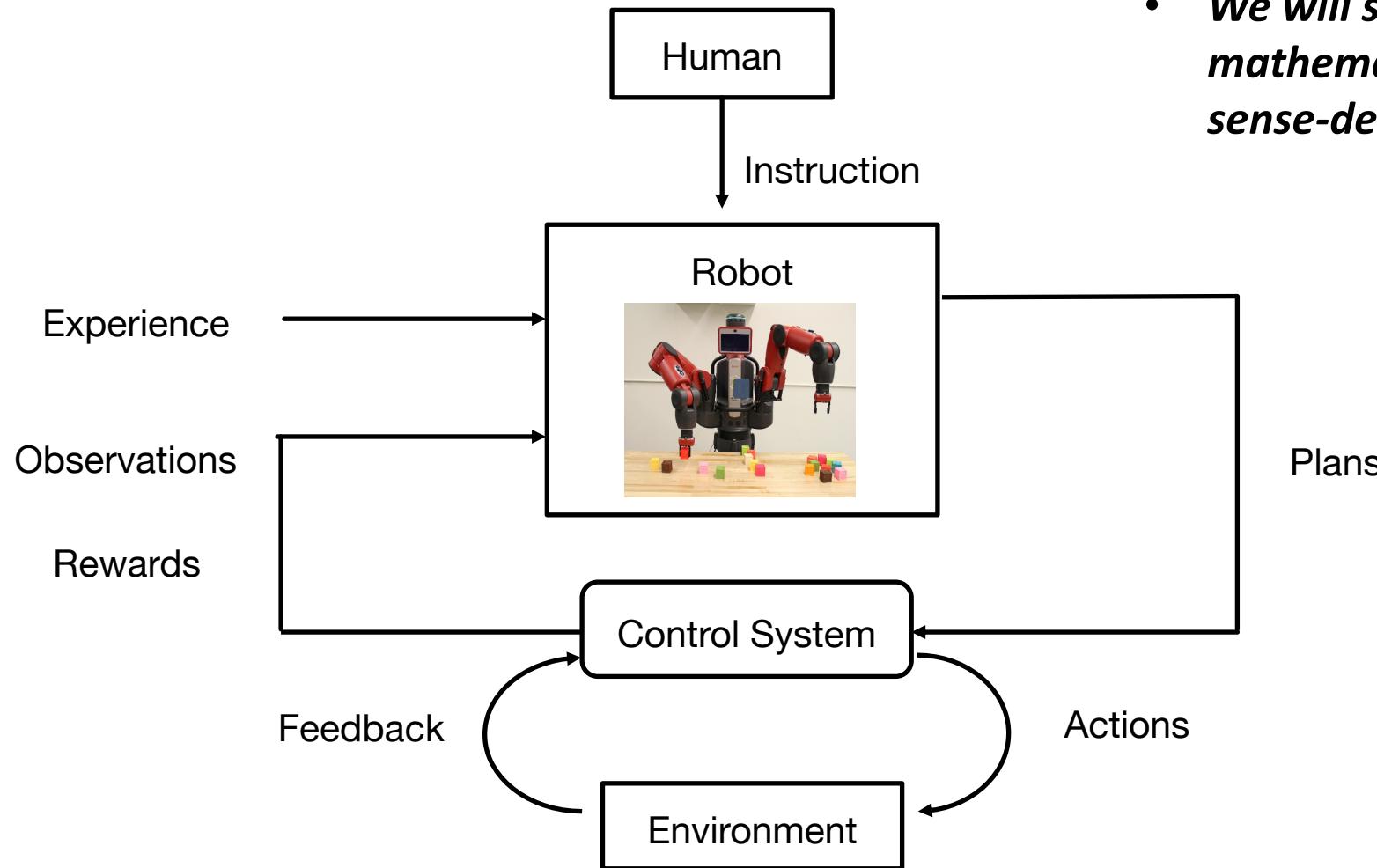
$\vdots \quad \vdots \quad \vdots$

$$< s_0^n, a_0^n, s_1^n, a_1^n, \dots, s_g^n >$$



What is the core problem?

- *Needs many aspects of AI and Learning to come together!*
- *We will study the core mathematical formalisms for sense-decide-act cycle.*



An estimation task:

$$p(\text{plans} \mid \text{observations, instruction, experience})$$

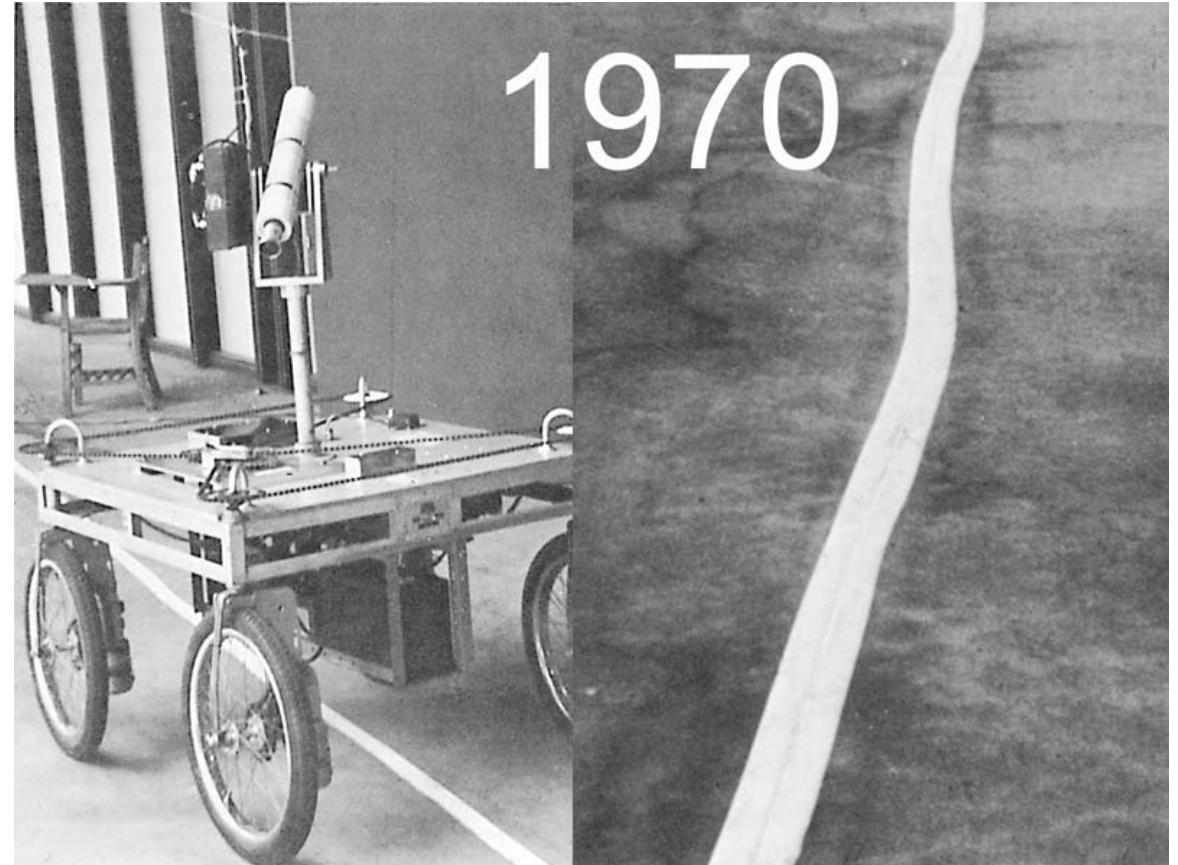
Historical Perspective

- Quest to create artificial agents that can sense, reason and act intelligently in the world.
- Stanford's Cart (Hans Moravec) following a line.

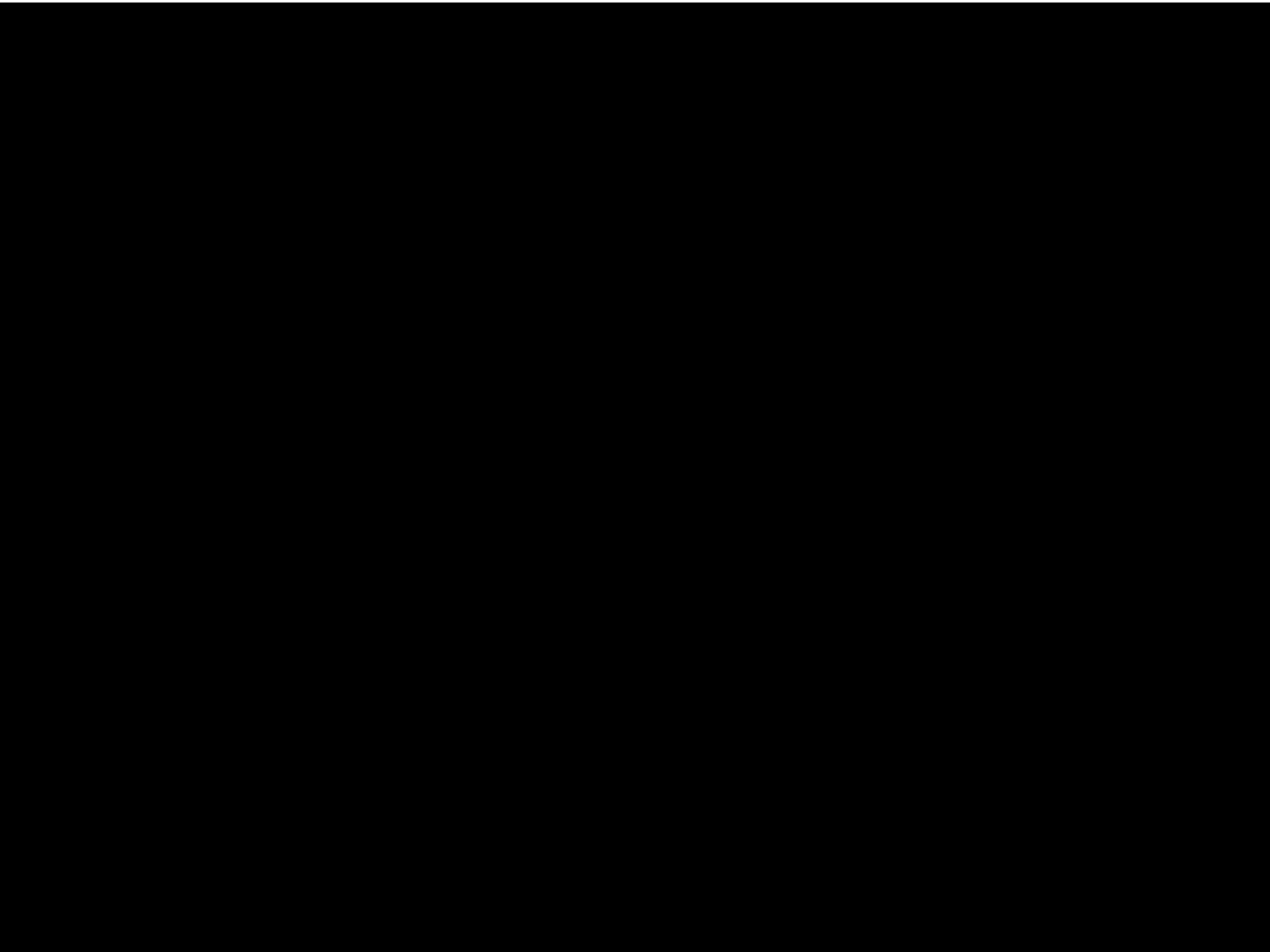


Obstacle avoidance and navigation in the real world by a seeing robot rover

Responsibility by Hans Peter Moravec.
Imprint 1980.
Physical description vii, 170 leaves, bound : ill. ; 28 cm.

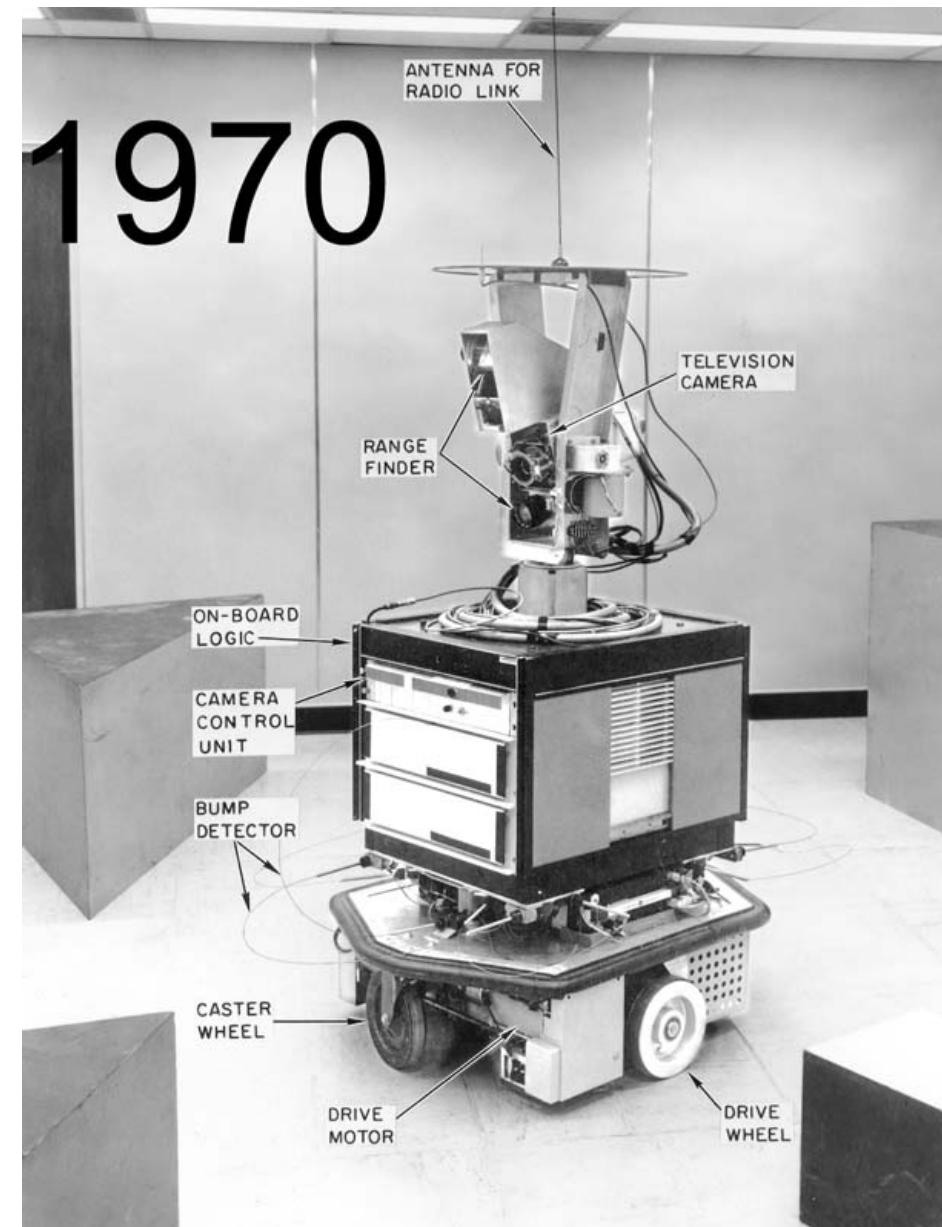


<https://youtu.be/8Mxk2L3lu9Q>

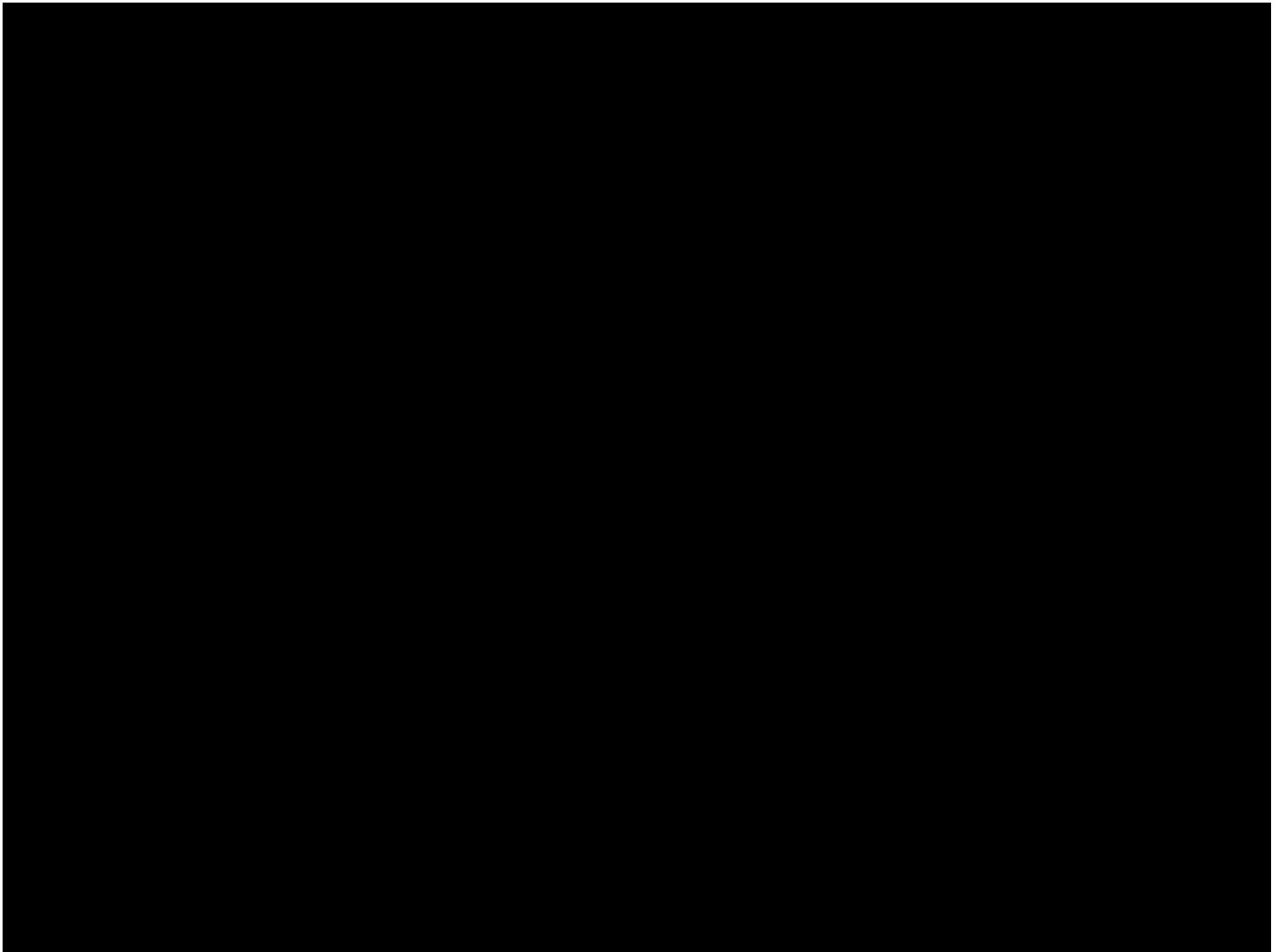


Historical Perspective

- Lab Experiments
 - Create artificial agents that take high-level goals and move in the environment
- Shakey
 - Stanford Research Institute (SRI)
 - The A* planner (Nils Nilsson) emerged from this research project



<https://youtu.be/GmU7SimFkpU>



Industry Automation

- Manufacturing Section
 - Precision
 - Speed
 - Sectors: semi-conductor, heavy engineering (engines), automotive.
- Factory robots
 - Computer controlled devices.
 - Pre-programmed trajectories.
 - Limitation
 - Very limited reasoning and hence cannot adapt easily.



Example: Orangewood Robotics
<https://twitter.com/i/status/1685310025802432518>

Robot: PickUp(1.5), Weld(2s), Put(2.0), ... Repeat

Ware house Automation



Amazon Robotics



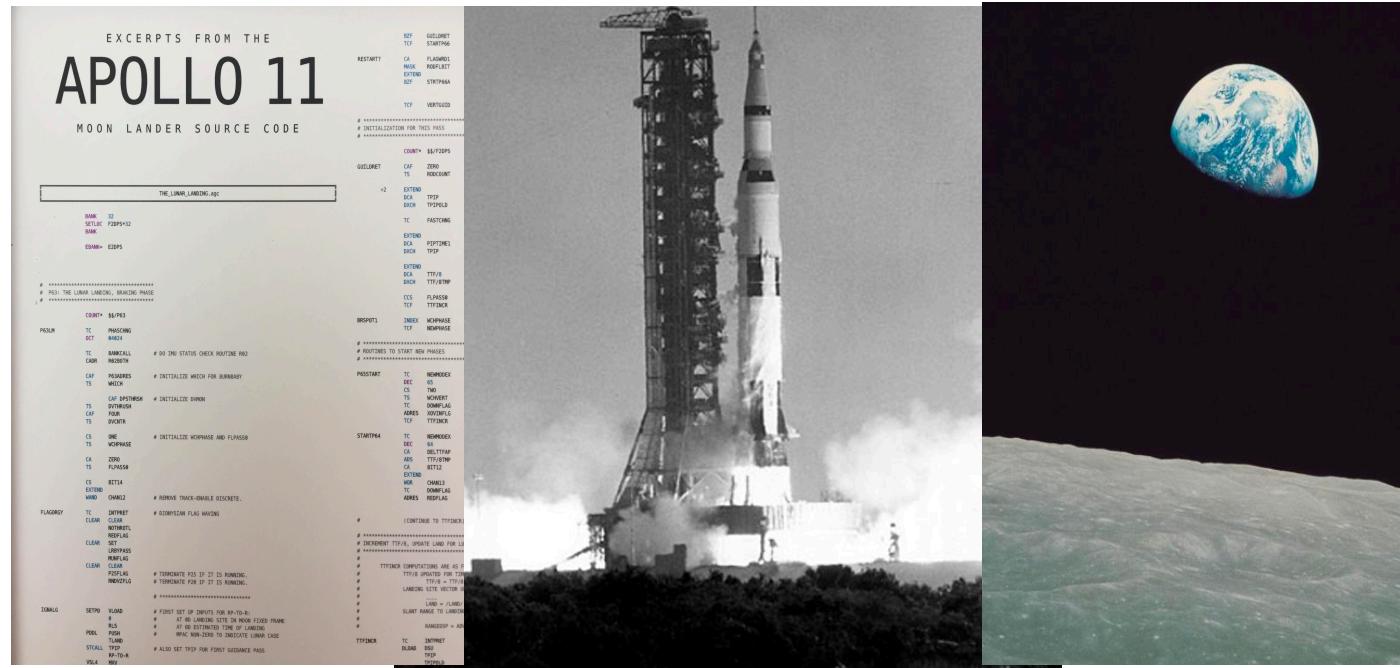
Add verb Automation



Grey Orange Robotics

Precision Guidance and Navigation

- Computer Guidance
 - 1960s.
 - Computers controlling systems
- Task
 - Fuse all the sensor data,
 - Determine the system state and take actions
- Demonstration
 - Apollo program
 - Computers performed that allow precise state estimation and guided navigation.
- Key Innovation
 - Kalman Filtering (later in the course)
 - Advances in handling uncertainty in measurements and actions.



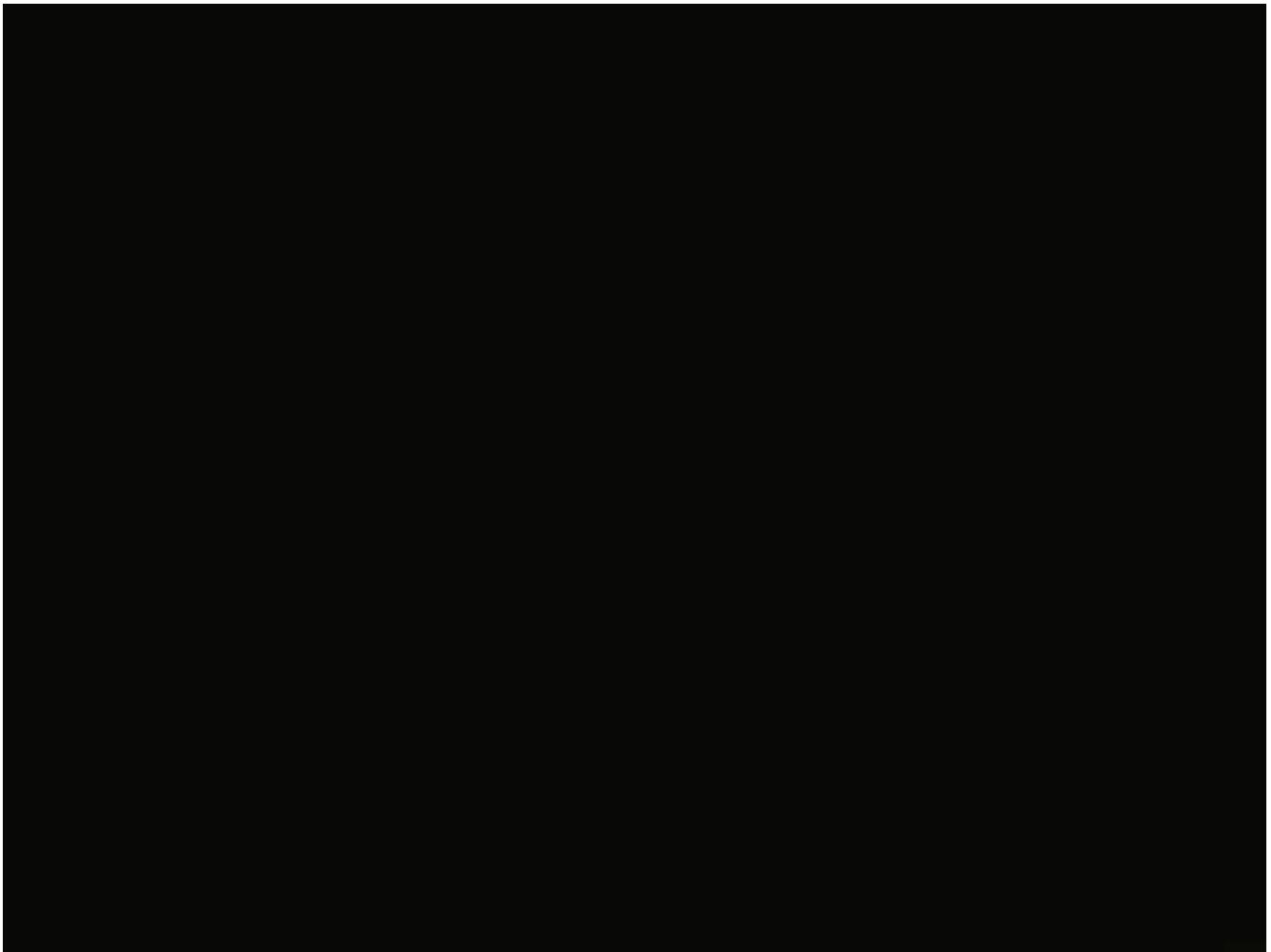
Modern Examples: Autonomous Driving

- Vehicles capable of detecting roads, people, traffic signs, following lanes, avoiding collisions etc.



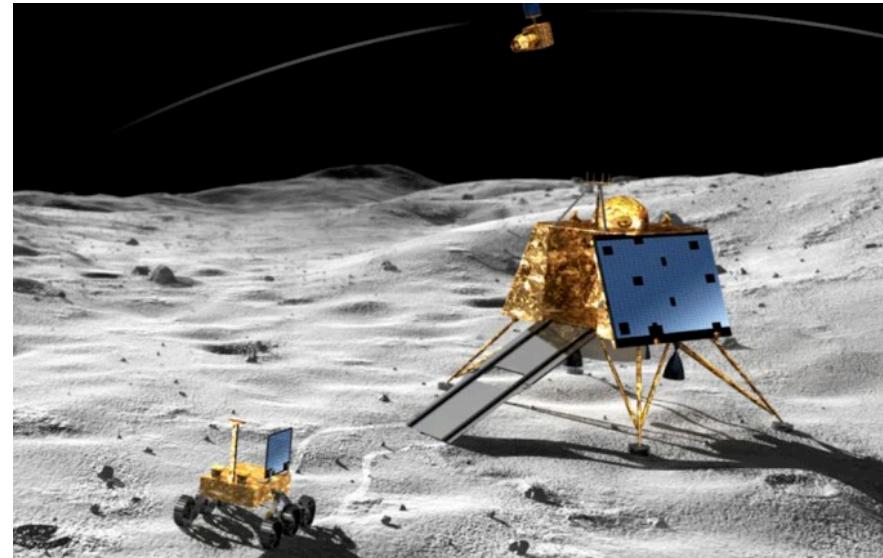
Darpa Grand Challenge (2005)
<https://www.youtube.com/watch?v=M2AcMnfzpNg>





Other Examples

- Complex operations in remote and hazardous environments.

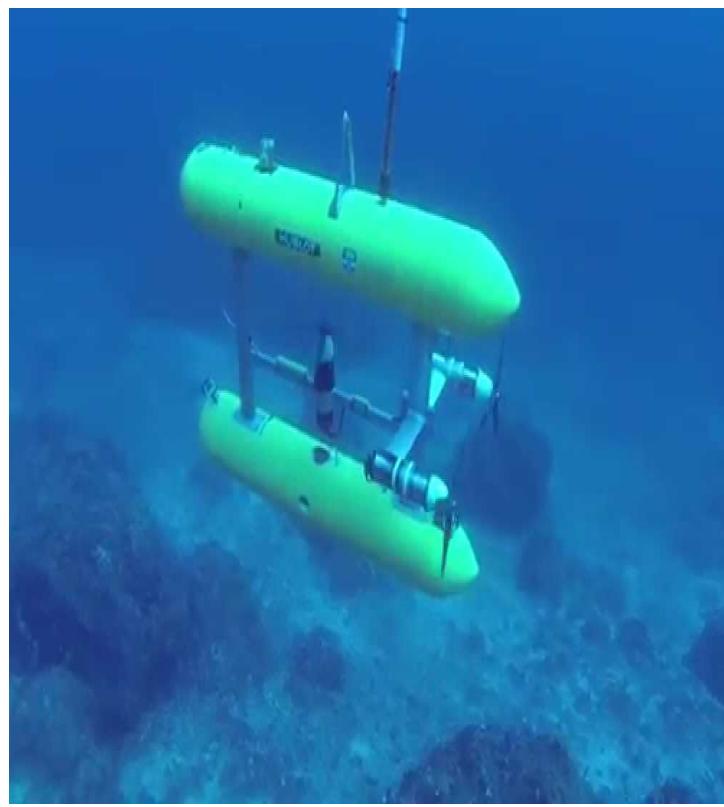


<https://www.youtube.com/watch?v=N9hXqzkH7YA>

Other Examples



Aerial platforms



Sub-sea unmanned vehicles



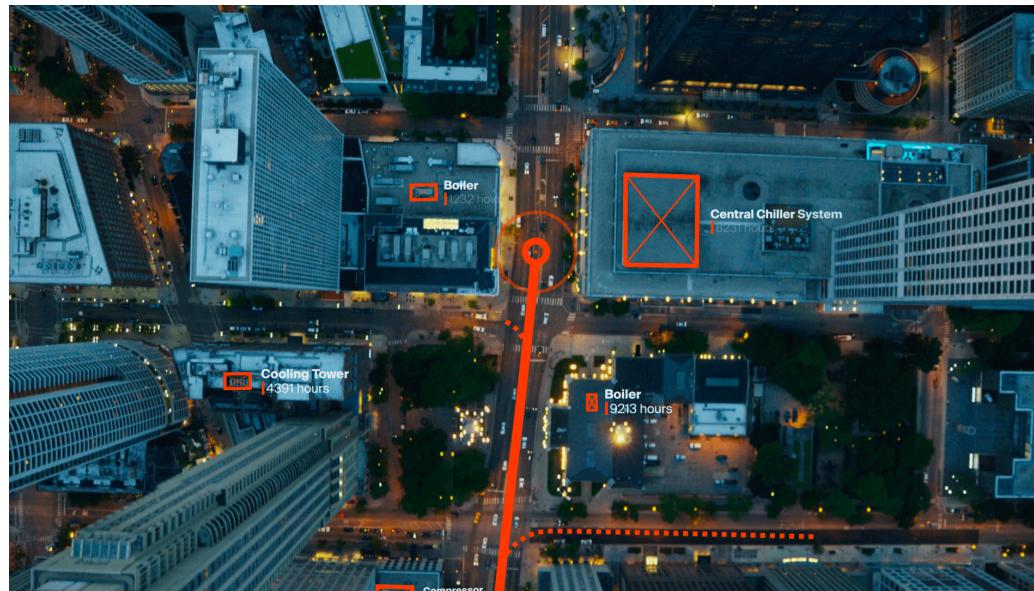
Persistent monitoring land vehicles

<https://www.indiatimes.com/technology/news/5-ways-india-is-boosting-its-drone-industry-and-why-its-good-for-everyone-549715.html>

Other Embodied AI Systems



Assistive devices



Monitoring power equipment
<https://www.tagup.io/>



Traffic Alert and Collision
Avoidance Systems

Need for reasoning

Vehicle on the road that can detect and avoid obstacles.

Factory robot that can pick and place tools.

A robot in the hospital that can deliver samples.

A remote operated vehicle that can relay images.

Vehicle that can understand that a ball coming on the road may be followed by a child.

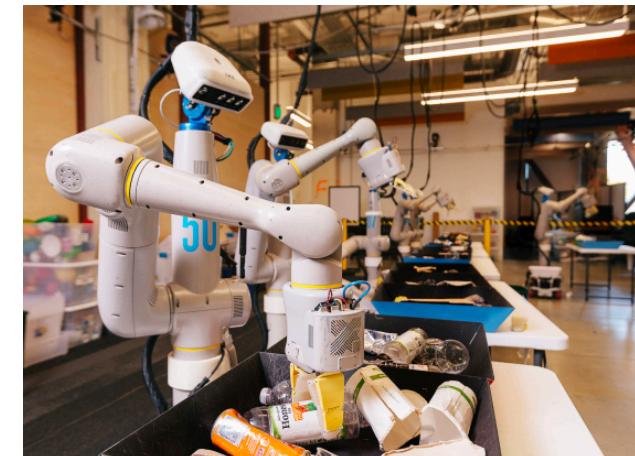
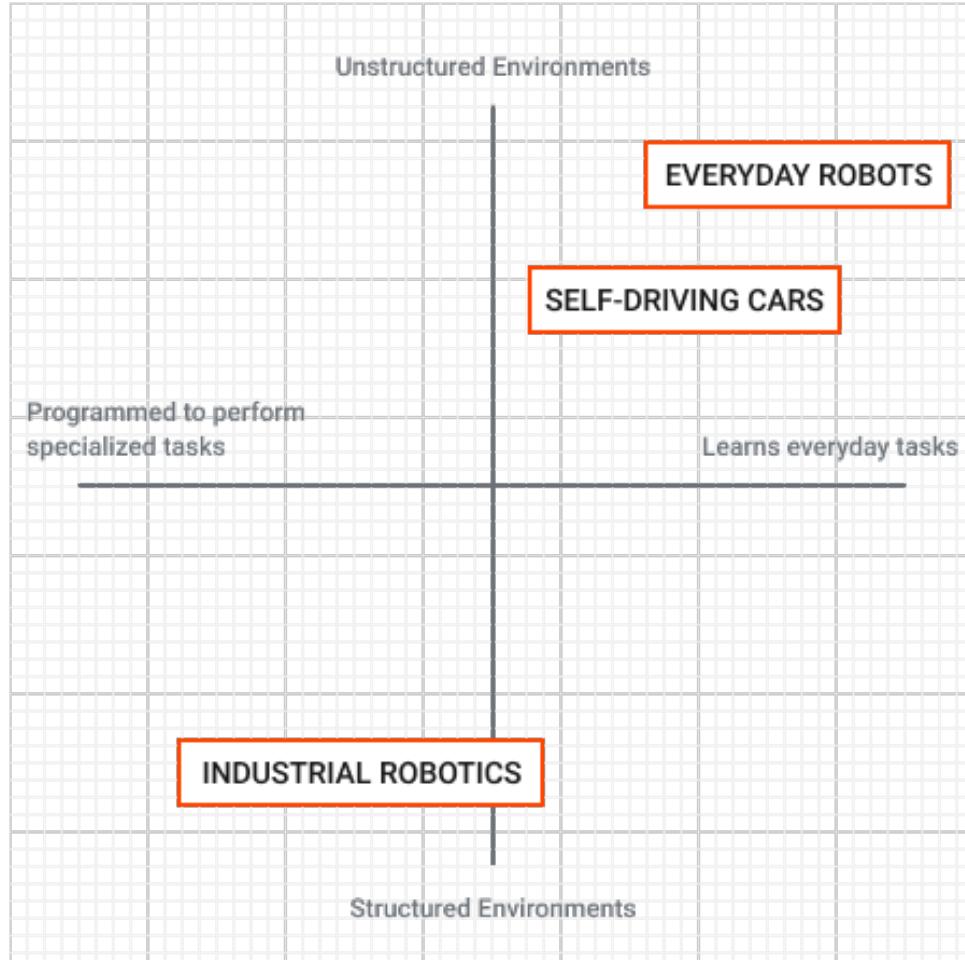
Factory robot that can be instructed to assemble a solar panel

A robot that can assist the surgeon by watching the surgery and providing tools, responding to contingencies.

A vehicle that can be commanded to survey behind the wall, inform if there is a person, deliver supplies.

Writing explicit rules is going to be challenging..... *Uncertainty*
Reason about long-term consequence of actions *Planning*

Performing General Purpose Tasks



<https://x.company/projects/everyday-robots>

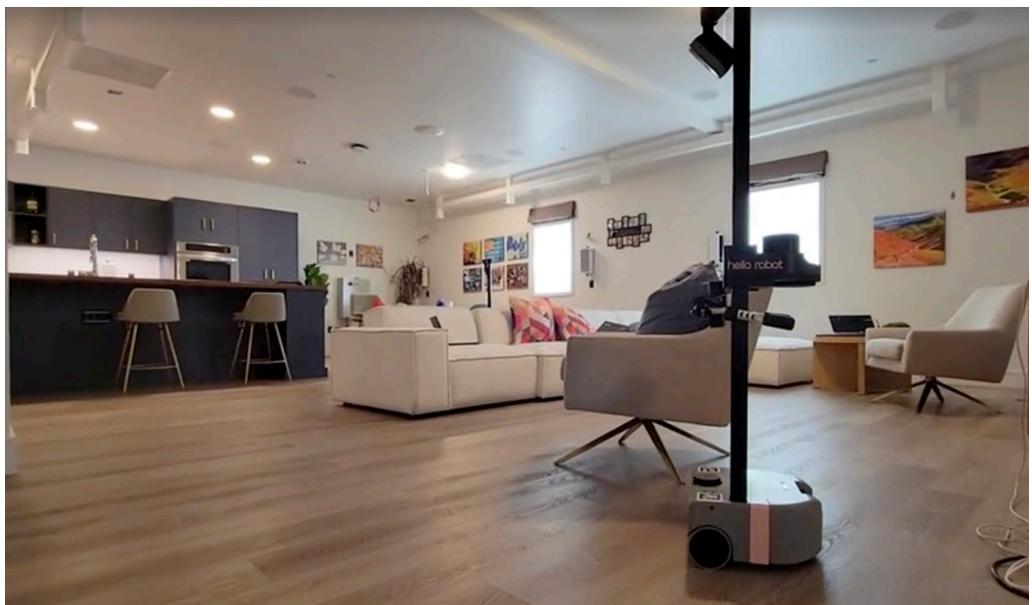
Example

Google Robotics Research

<https://sites.research.google/palm-saycan>

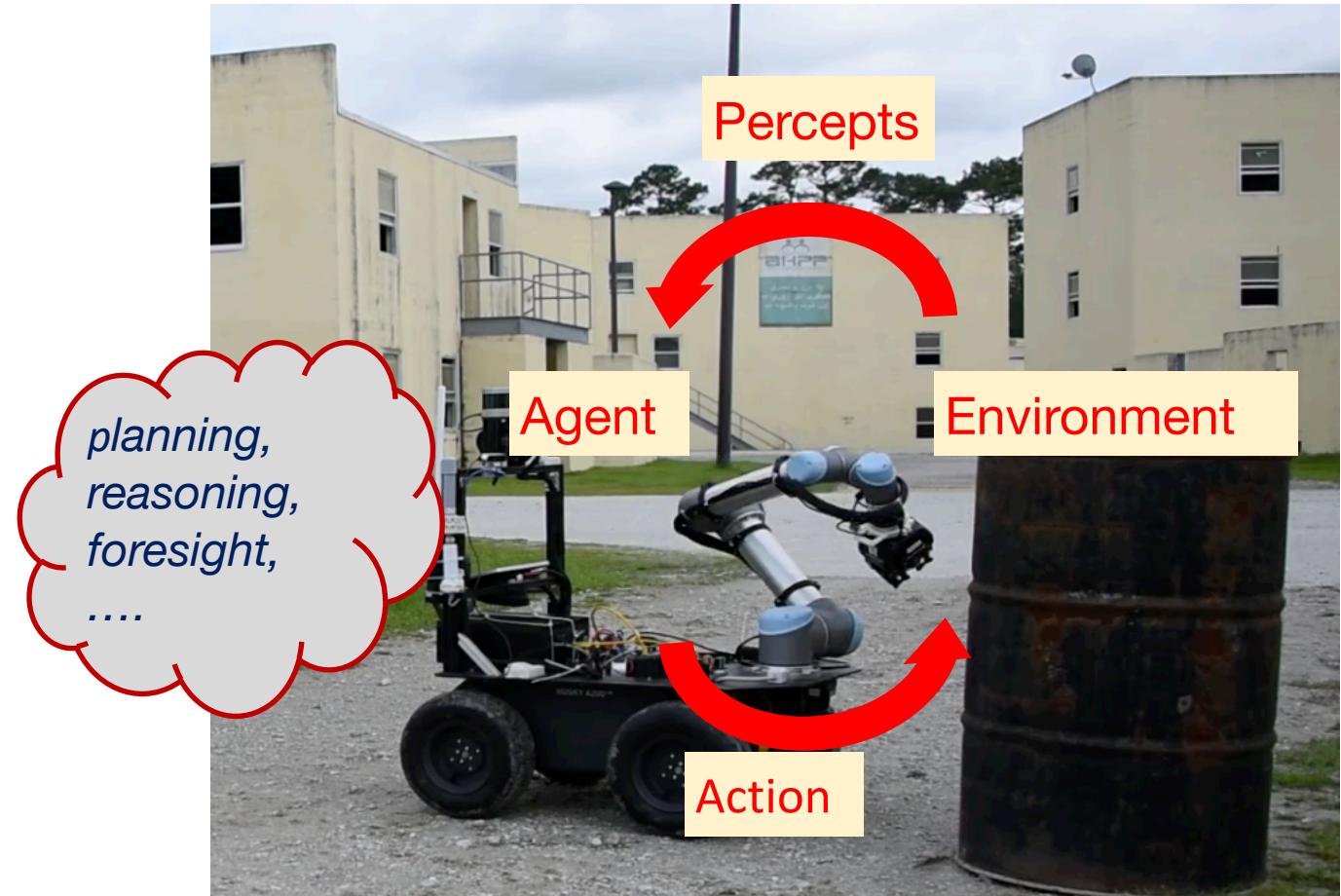
Facebook AI Research

https://aihabitat.org/challenge/2023_homerobot_ovmm/



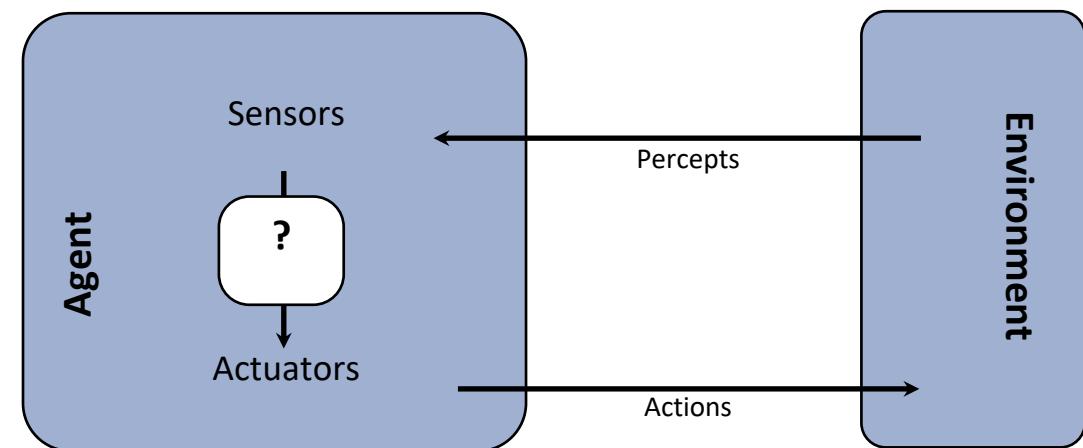
Agent Representation

- Observations
 - Sensor takes observations from the environment.
- Goal
 - Need for goal directed actions.
- Actions
 - Behavioral abstraction for actions. Pick, place, push
 - ...



Agent view is popular in AI

- An agent is anything that can be viewed as perceiving its environment through sensors and acting upon the environment through actuators.
- Examples (from Russell and Norvig)
 - Alexa
 - Robotic system
 - Refinery controller
 - Question answering system
 - Crossword puzzle solver
 -
- *How is intelligence measured?*

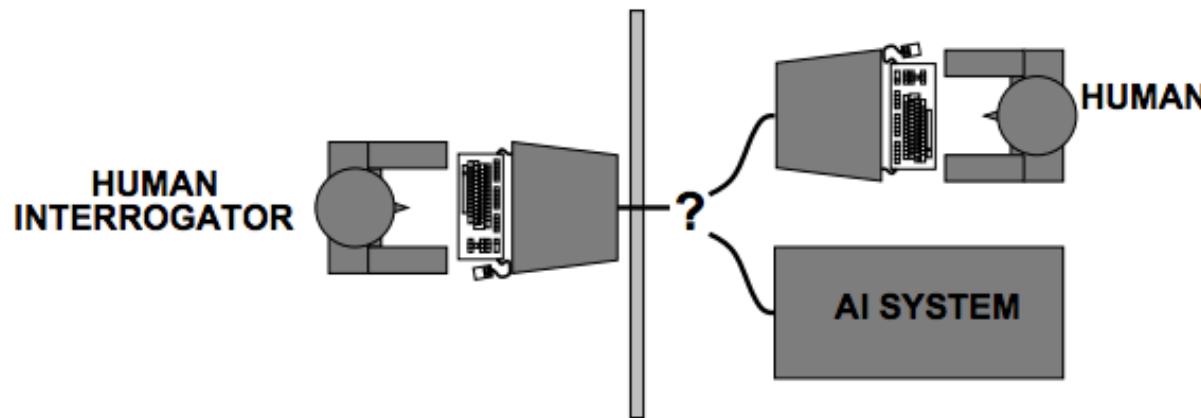


In this class we are concerned with agents that operate in the physical environment.

Acting Humanly: The Turing Test

Turing (1950) "Computing machinery and intelligence":

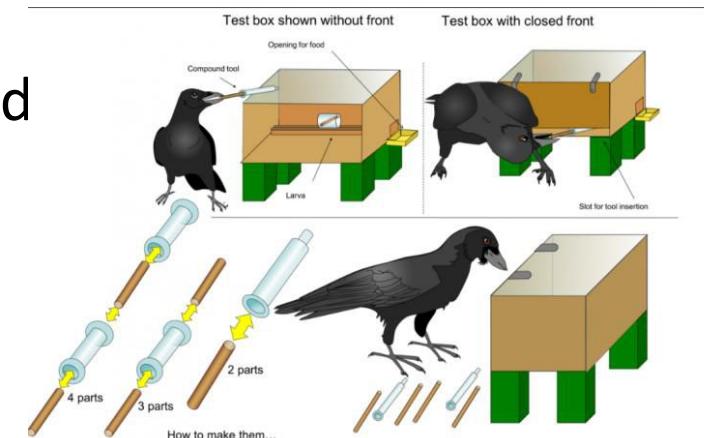
- ◊ "Can machines think?" → "Can machines behave intelligently?"
- ◊ Operational test for intelligent behavior: the Imitation Game



Alan Turing

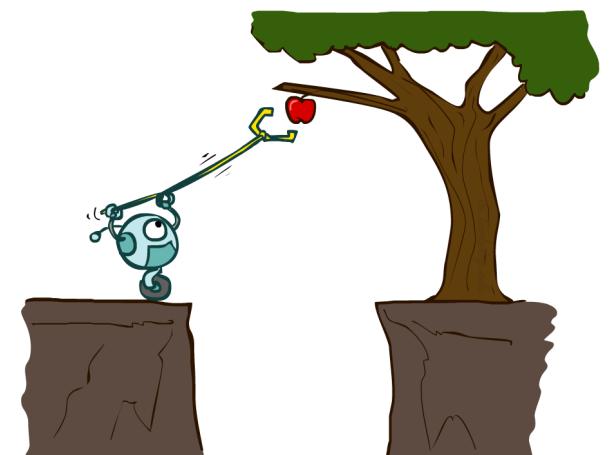
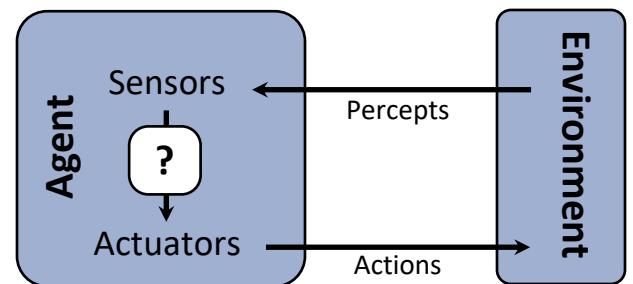
Thinking Humanly

- Cognitive Science
 - Hard to understand how humans think
- Efforts to build cognitive models of human reasoning.
- Understanding:
 - How humans or animals perceive and act in the world
- Applications
 - Human computer interaction



Acting Rationally: Maximizing Expected Utility

- An **agent** is an entity that *perceives* and *acts*.
- A **rational agent** selects actions that maximize its (expected) **utility**.
- Characteristics of the **percepts**, **environment**, and **action space** dictate techniques for selecting rational action.



Slide adapted from D. Klein

Various Definitions for AI Agents

Embodied AI agents can be viewed similarly.

Thinking Humanly <p>“The exciting new effort to make computers think . . . <i>machines with minds</i>, in the full and literal sense.” (Haugeland, 1985)</p> <p>“[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . .” (Bellman, 1978)</p>	Thinking Rationally <p>“The study of mental faculties through the use of computational models.” (Chamiak and McDermott, 1985)</p> <p>“The study of the computations that make it possible to perceive, reason, and act.” (Winston, 1992)</p>
Acting Humanly <p>“The art of creating machines that perform functions that require intelligence when performed by people.” (Kurzweil, 1990)</p> <p>“The study of how to make computers do things at which, at the moment, people are better.” (Rich and Knight, 1991)</p>	Acting Rationally <p>“Computational Intelligence is the study of the design of intelligent agents.” (Poole <i>et al.</i>, 1998)</p> <p>“AI . . . is concerned with intelligent behavior in artifacts.” (Nilsson, 1998)</p>
Figure 1.1 Some definitions of artificial intelligence, organized into four categories.	

Other notions to know about

- Weak AI Hypothesis
 - Machines could act as if they were intelligent. They may be simulating.
- Strong AI Hypothesis
 - Machines that act intelligently not just by simulating but actually by thinking.

Agent Representation

- Agent Type
- Performance Measure
- Environment
- Actuators
- Sensors

Embodied AI agents can be viewed similarly.

Agent Type	Performance Measure	Environment	Actuators	Sensors
Medical diagnosis system	Healthy patient, reduced costs	Patient, hospital, staff	Display of questions, tests, diagnoses, treatments, referrals	Keyboard entry of symptoms, findings, patient's answers
Satellite image analysis system	Correct image categorization	Downlink from orbiting satellite	Display of scene categorization	Color pixel arrays
Part-picking robot	Percentage of parts in correct bins	Conveyor belt with parts; bins	Jointed arm and hand	Camera, joint angle sensors
Refinery controller	Purity, yield, safety	Refinery, operators	Valves, pumps, heaters, displays	Temperature, pressure, chemical sensors
Interactive English tutor	Student's score on test	Set of students, testing agency	Display of exercises, suggestions, corrections	Keyboard entry

Figure 2.5 Examples of agent types and their PEAS descriptions.

Domain Characteristics Can Vary

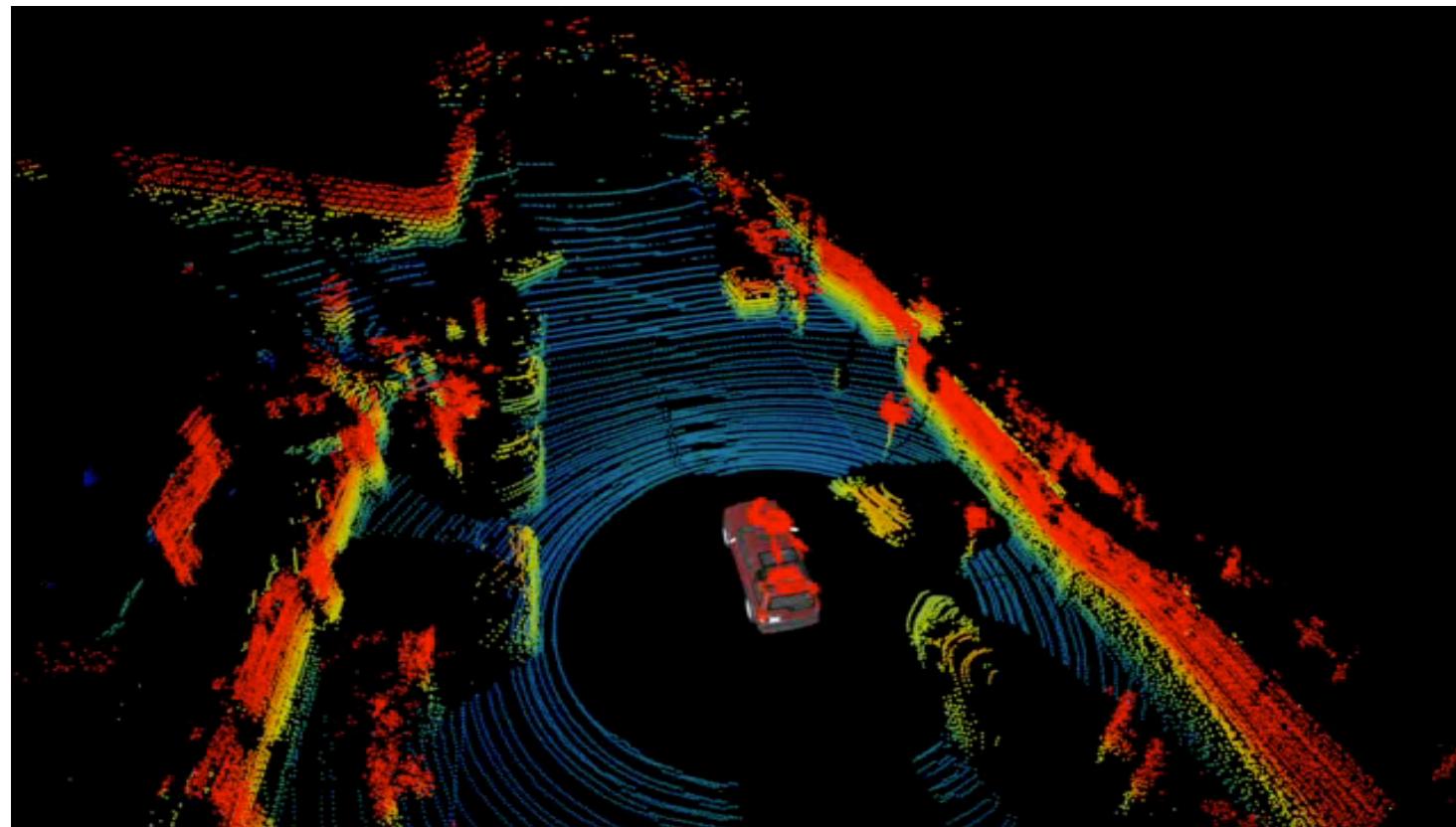
- Fully or Partially observed
- Single vs. Multiple Agents
- Deterministic or Stochastic
- Episodic or Sequential
- Static or dynamic
- Discrete or Continuous



Domain characteristics of this agent?

Challenge I: Observations are Noisy

- The agent observes the environment via sensors
- Noisy and uncertainty
 - Give a noisy and incomplete picture of the real world
- Inference task
 - Given observations estimated the true world state.



Challenge II: Partial-Observability

- Task Planning
 - In order to execute a task, we need to know some properties of the environment.
- Problem
 - Some of these properties are not directly observed.
 - Formally, some variables in the robot's state are not directly observed.
 - Example: the internal state of the barrel, inside of cupboards/boxes.
- Partial-observability
 - Formally, some variables in the robot's state are not directly observed.
 - Decision-making models must take this into account. Typically done by “exploration or information gathering actions”
 - Tools such as POMDP, information-theoretic planning



Intelligent Interaction with the World

Experiment #2

A mobile manipulator is tasked with picking up a heavy case and is given correct information, incorrect information, and no information. The robot estimates the state of each object online until it converges to a solution. The natural language understanding model allows the robot to acquire the object given correct information more quickly but is also robust to incorrect information.

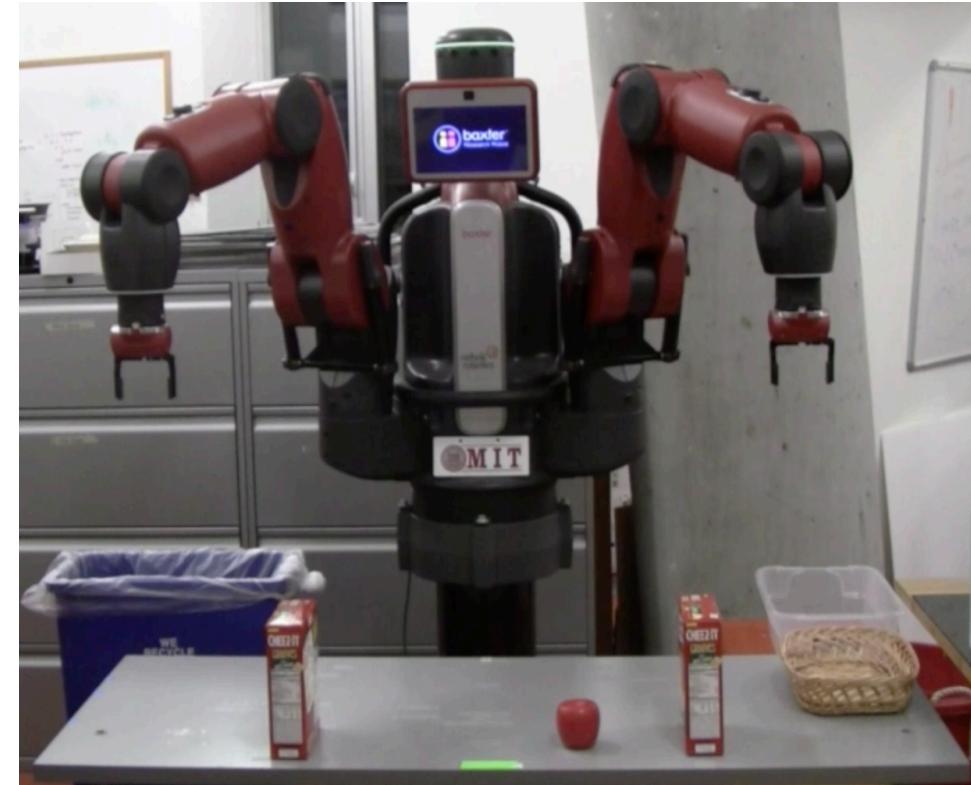
Active interaction with the environment to gather information for planning



Determining push ability of objects and moving

Challenge III: Common sense knowledge

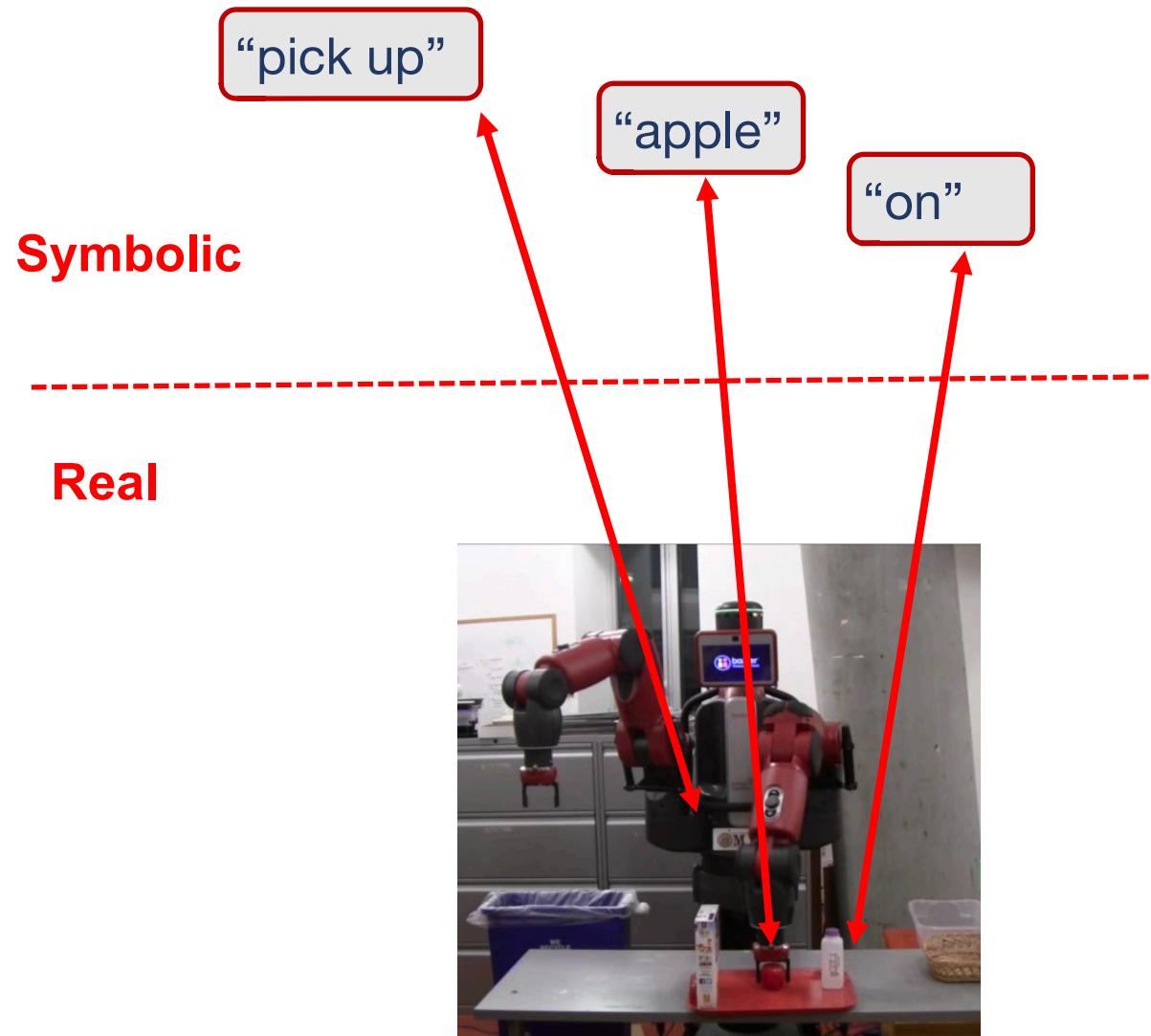
- We acquire a lot of knowledge from experience.
- AI agents often lack such knowledge.
- Examples:
 - To put an object inside the box, the lid must be removed.
 - Milk is an edible food item.
- You may have tried speaking to a Google home or automated reservation system and faced this issue.
 - Common problem in related dialogue systems also.





Challenge IV: Human Interaction

- Interpretable AI
 - Strong push towards AI system that are not black box.
 - Can explain their decision.
- Embodied AI context
 - The agent should be able to interact with a human.
- Computational problem
 - How can a program acquire the same semantic representation as a human.
 - Notions of objects, regions, interactions.
 - Also called “symbol grounding” problem



Challenge IV: Human Interaction



Embodied Agents to support the elderly

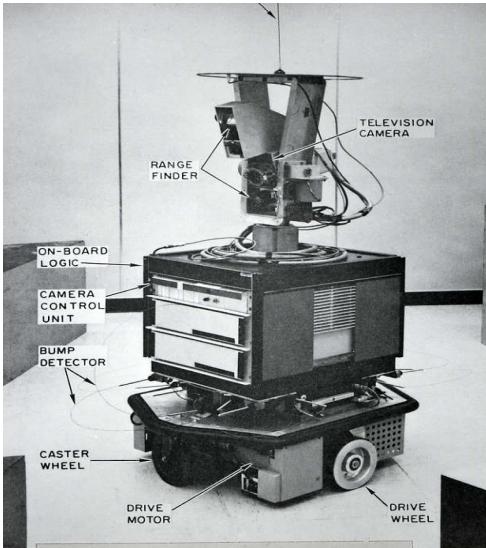


Computer controlled wheel chairs.



Intelligent agents to support persons with limitations

Closely connected algorithmic developments



Visual recognition
Path planning
 A^* planner



Kalman filtering
State estimation

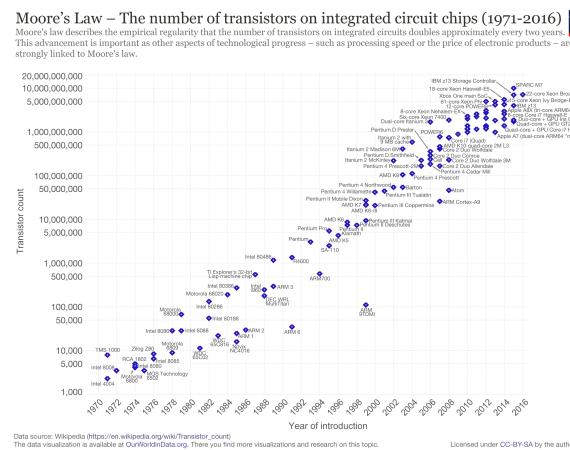
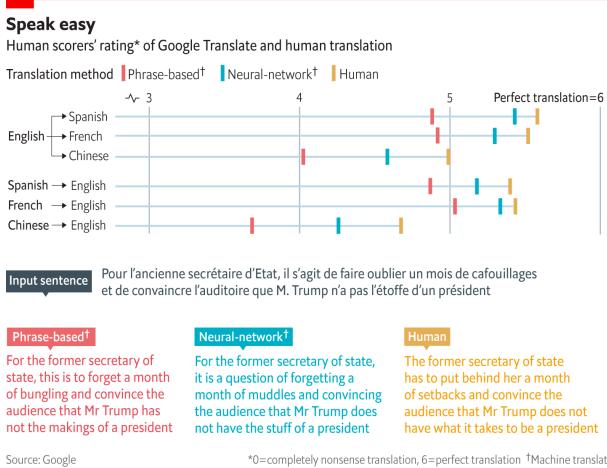
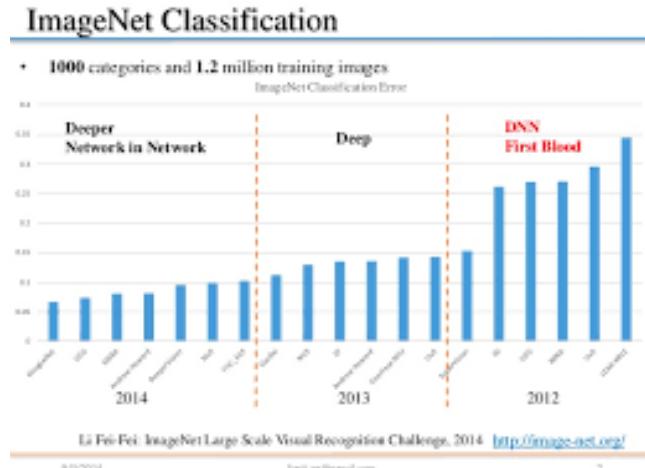


Localization /mapping,
Deep Learning for
perception



Inverse
reinforcement
Learning

Recent AI Progress: Largely domain specific



Embodied AI systems confront many problems together.
Require general-purpose intelligence.

Intelligence measures an agent's ability to achieve goals in a wide range of environments

$$\Upsilon(\pi) := \sum_{\mu \in E} 2^{-K(\mu)} V_\mu^\pi.$$

Measure of Intelligence Complexity penalty Value achieved
Sum over environments

Universal Intelligence: A Definition of Machine Intelligence, Legg & Hutter

Next Time

- This Class
 - Course Introduction
- Next Class
 - Agent Representation