

Introduction

What is learning?

What is learning?

- **Question.** How do human learn?

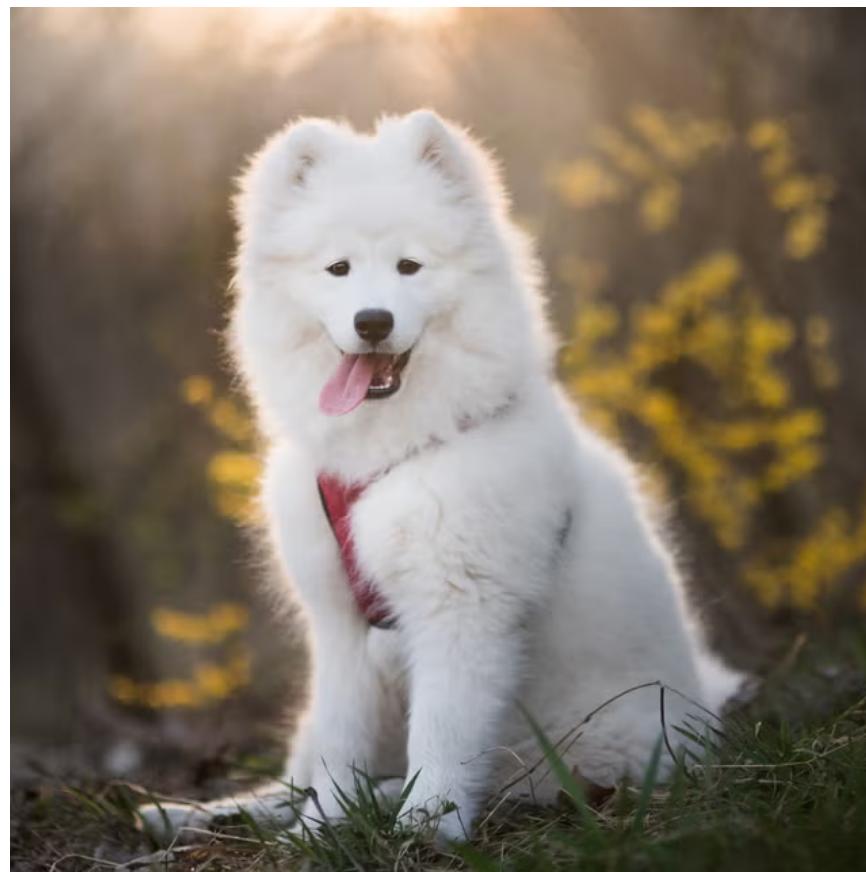
What is learning?

- **Question.** How do human learn?
- Toddlers like to call the names of many things
 - Learning “concepts” – associations of visual and linguistic signals



What is learning?

- Toddlers learn concepts from many **samples**
 - Images of dogs, and images of non-dogs



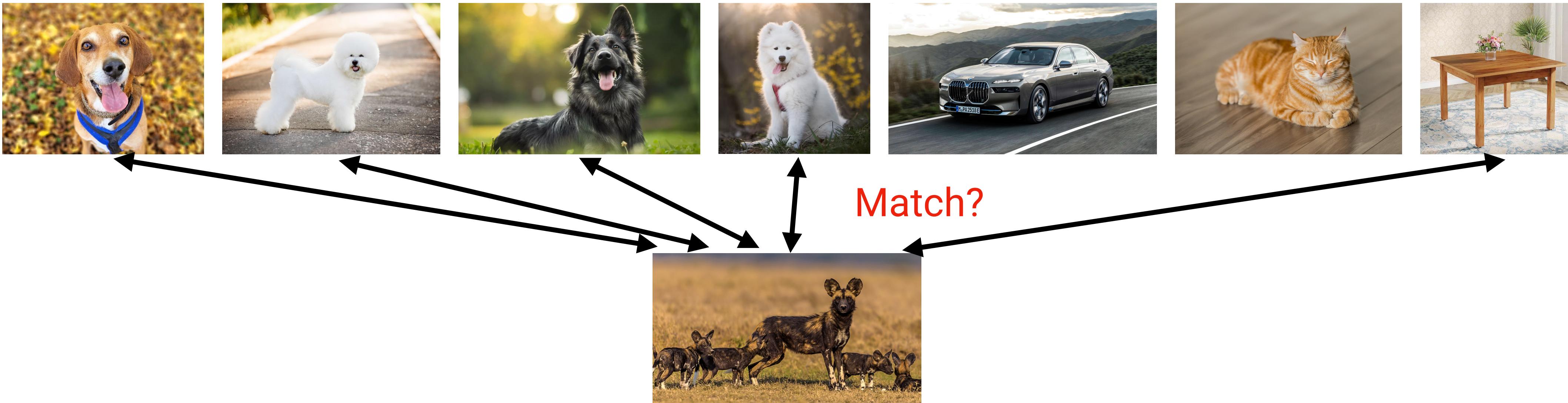
What is learning?

- Importantly, the learned knowledge should be **generalizable**
 - Applicable to the data that have not been observed yet



What is learning?

- Why? We simply can't **memorize** everything
 - Limited data: Cannot observe everything
 - Limited memory: Cannot remember everything
 - Limited compute: “Recalling” requires loading and comparing with all the data we have seen and remembered, which is extremely slow



What is learning?

- To generalize, we want to find **patterns** from the observed samples
 - Simple yet widely applicable rule



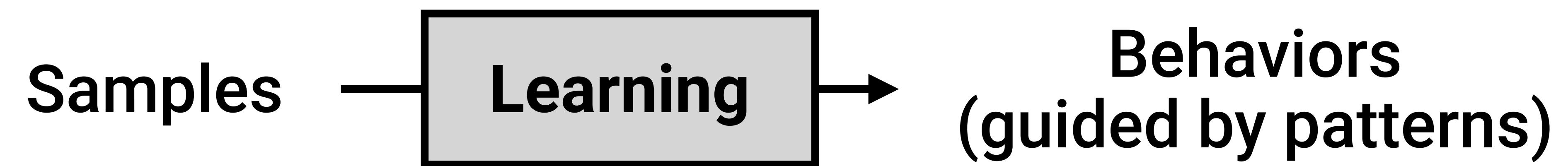
What is learning?

- Based on the patterns learned, human **behaves**:
 - Predictions, Decisions, Actions



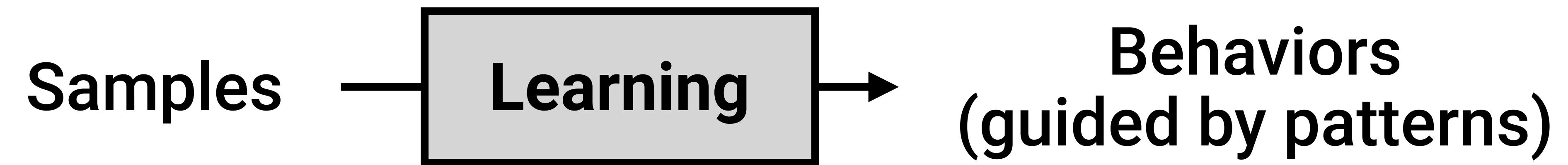
What is learning?

- Summing up, learning is the process of extracting and utilizing the patterns from the samples

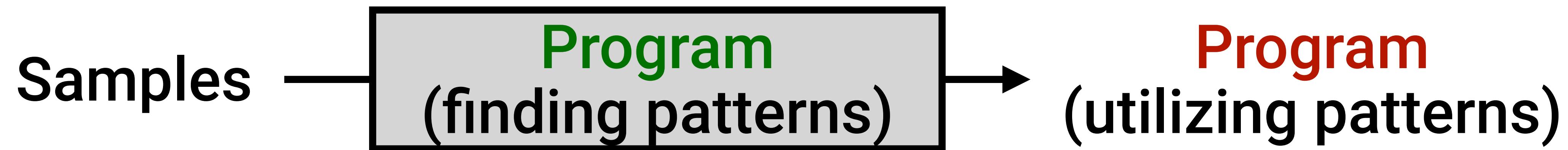


What is learning?

- Summing up, learning is the process of extracting and utilizing the patterns from the samples



- Machine Learning. Letting a machine do this



Machine learning



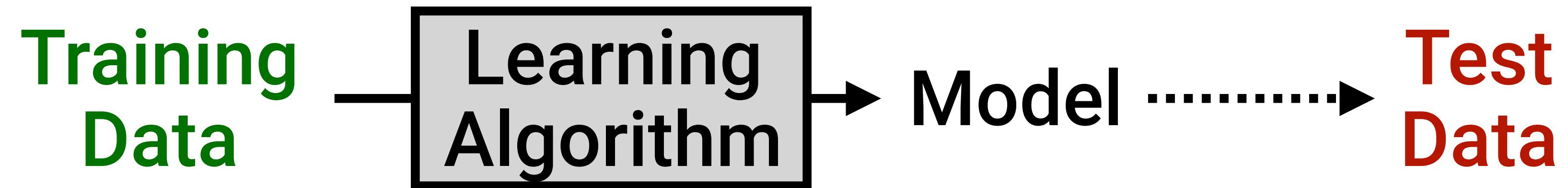
- Two programs in action:
 - **One** utilizes patterns
 - The program is called “model” (or “predictor” or “hypothesis”)
 - Running the program is called “inference” (or “prediction”)

Machine learning



- Two programs in action:
 - One utilizes patterns
 - The program is called “model” (or “predictor” or “hypothesis”)
 - Running the program is called “inference” (or “prediction”)
 - **Another** finds patterns from samples
 - The program is called “learning algorithm”
 - Running the program is called “training”

Machine learning



- The data that learning algorithm sees is called **training data**
 - The samples from which the patterns are discovered
- The data that model sees is called **test data**
 - Never observed during the training
 - The ultimate goal is to do well on this data!

**Why machine learning?
(instead of human learning)**

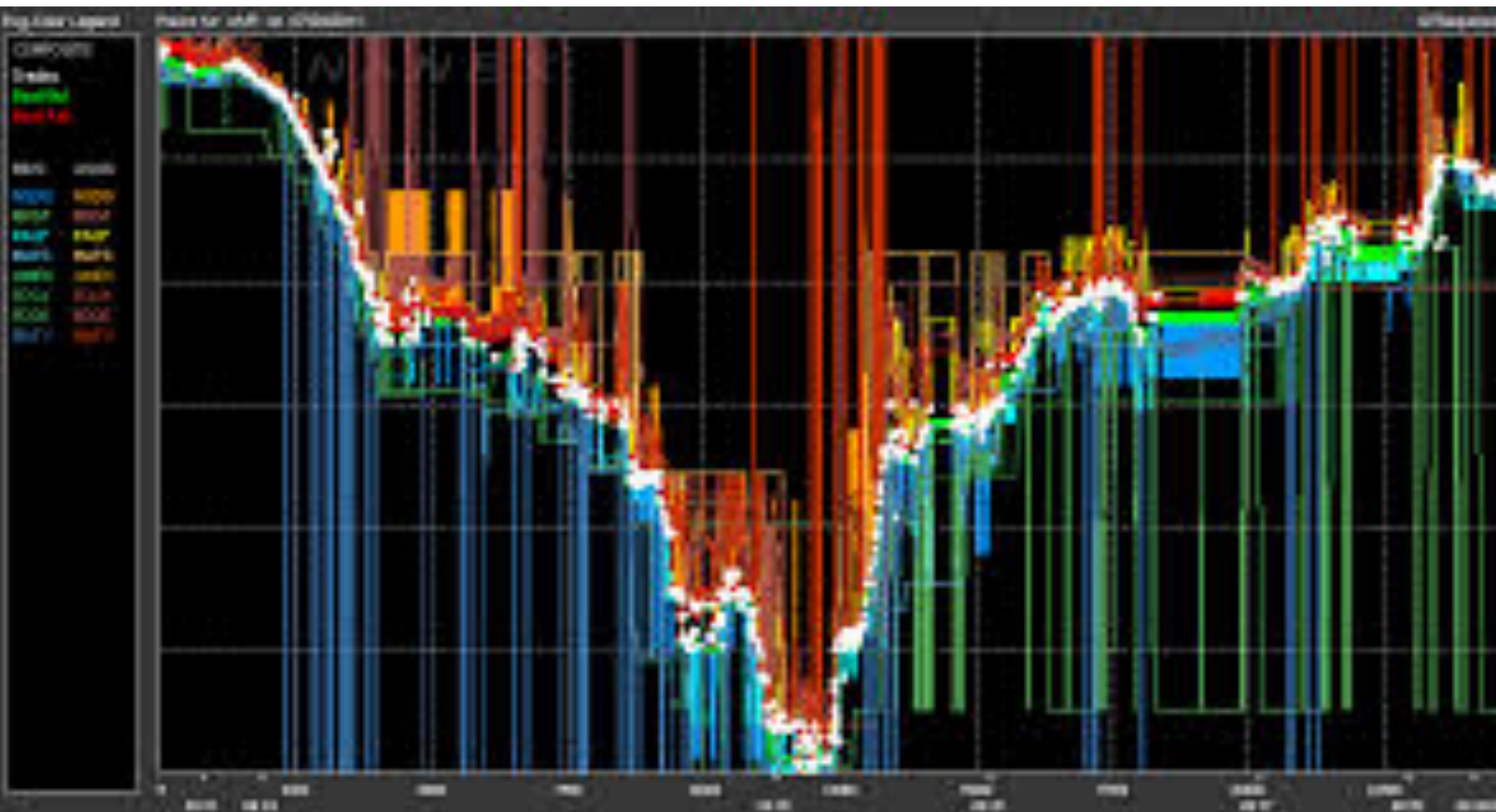
Why machine learning?

- In principle:
 - Machines are better at **utilizing** patterns (inference)
 - Machines are better at **finding** patterns (training)

(Caveat: it takes much effort to make this advantage happen)

Machine for inference

- Humans are slow (e.g., high-frequency trading)



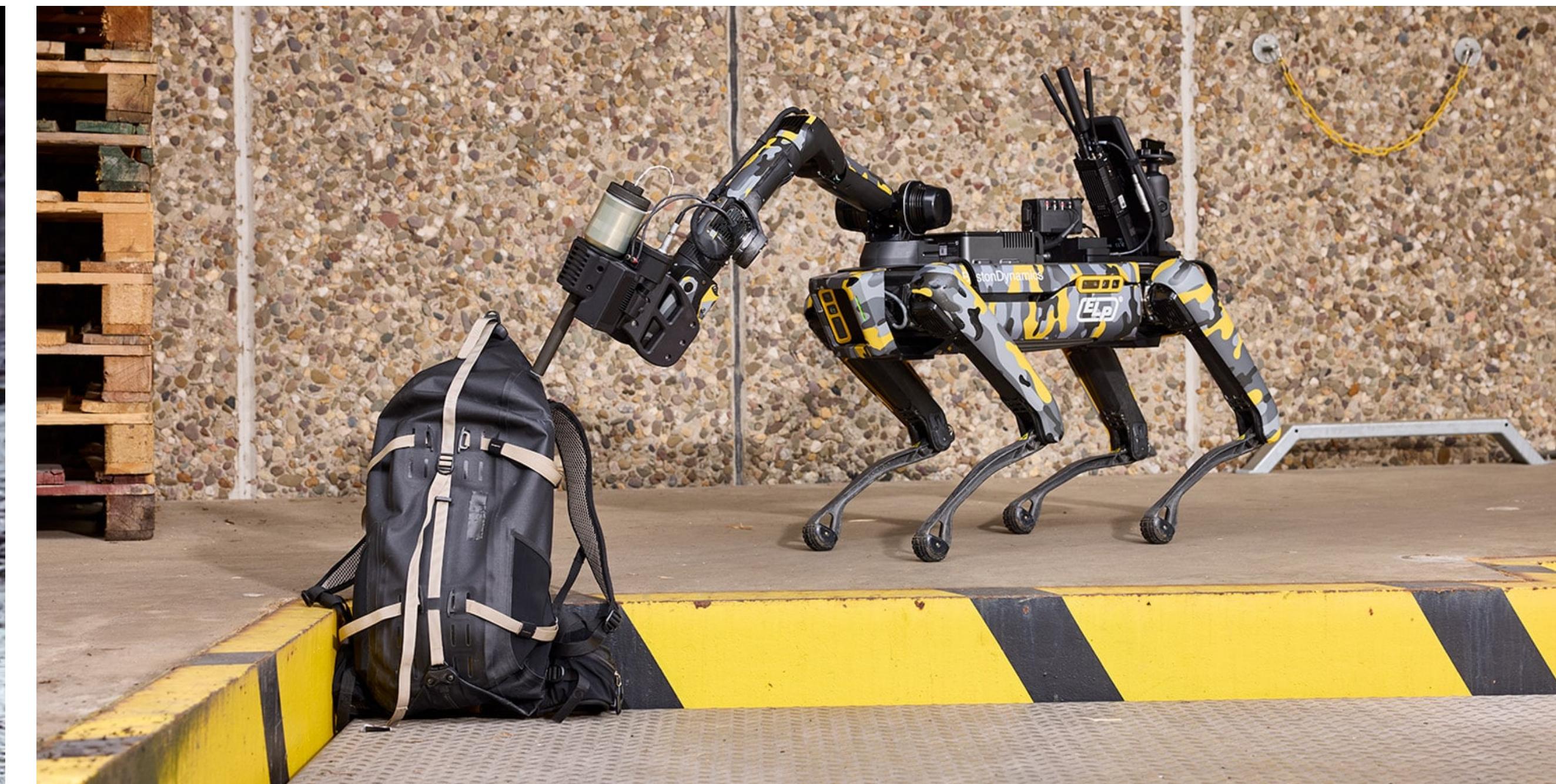
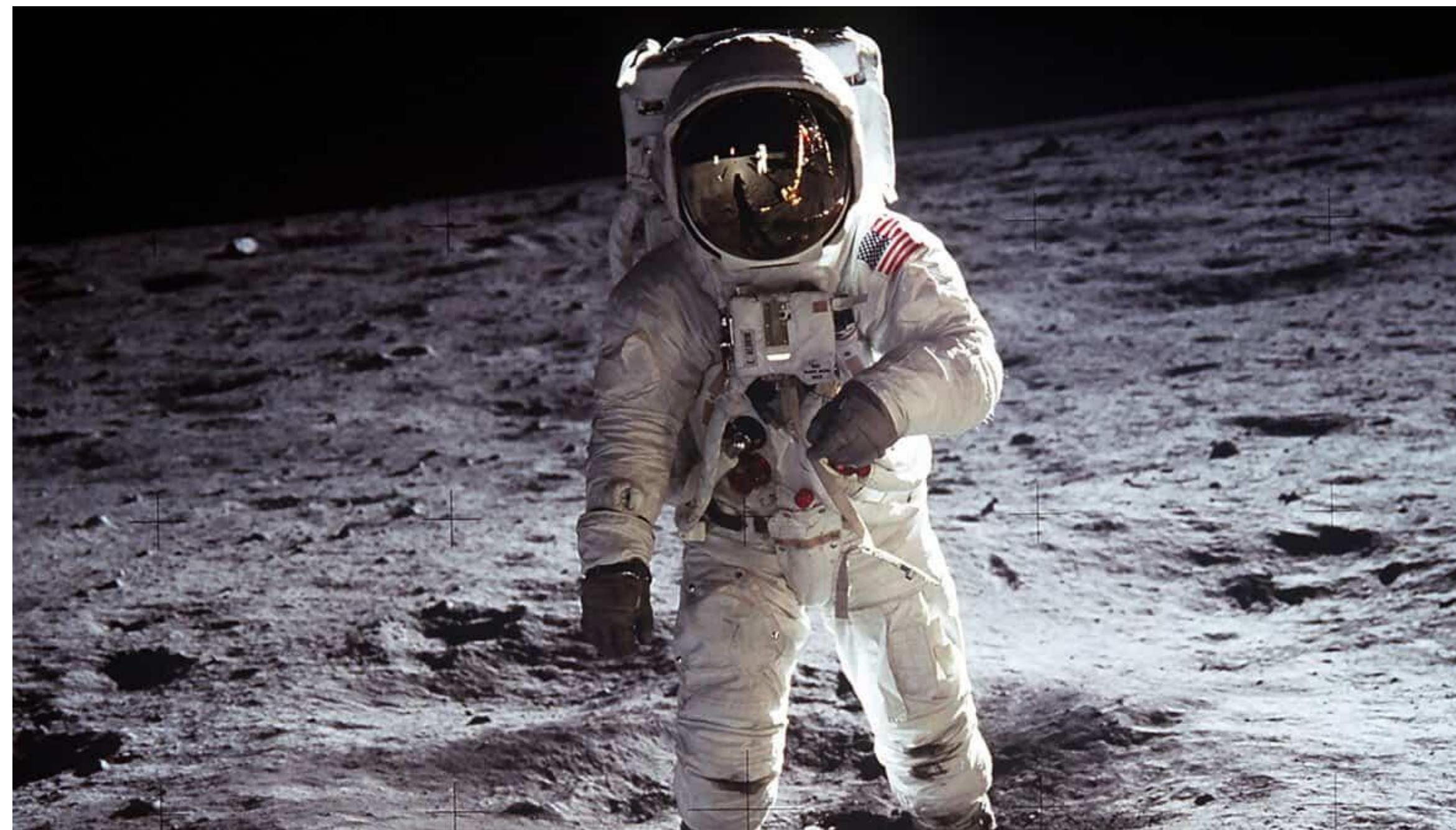
Machine for inference

- Human has limited or inconsistent sensory capabilities (e.g., self-driving)



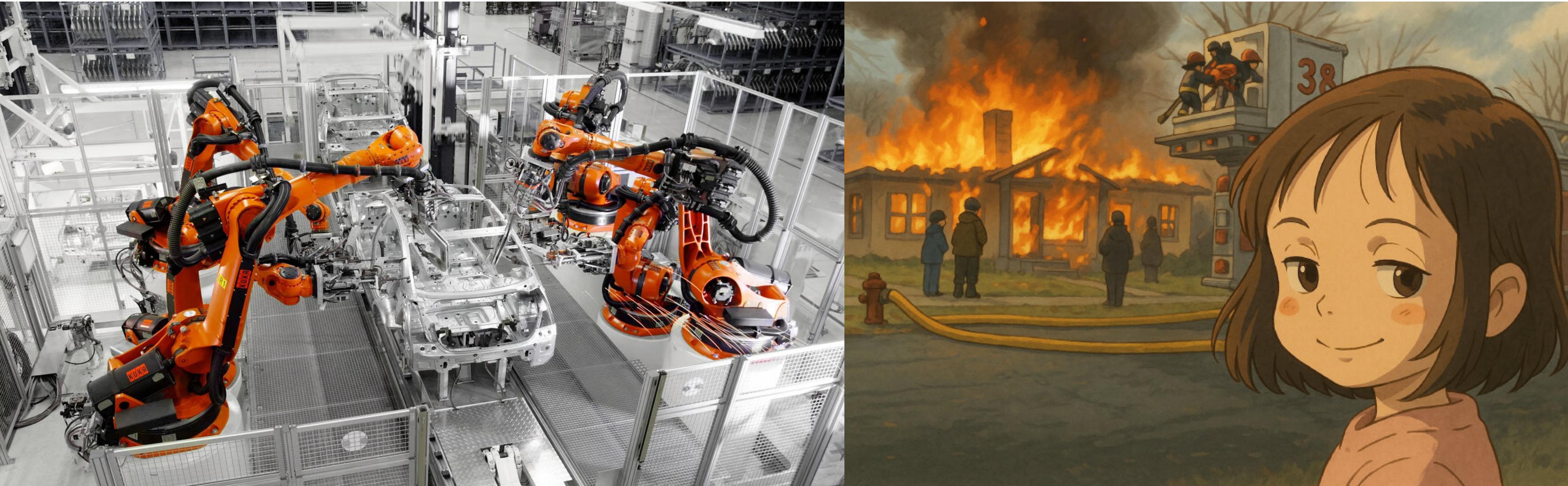
Machine for inference

- Human are vulnerable (e.g., space mission / explosive disposal)



Machine for inference

- Human are expensive (e.g., manufacturing or drawing)



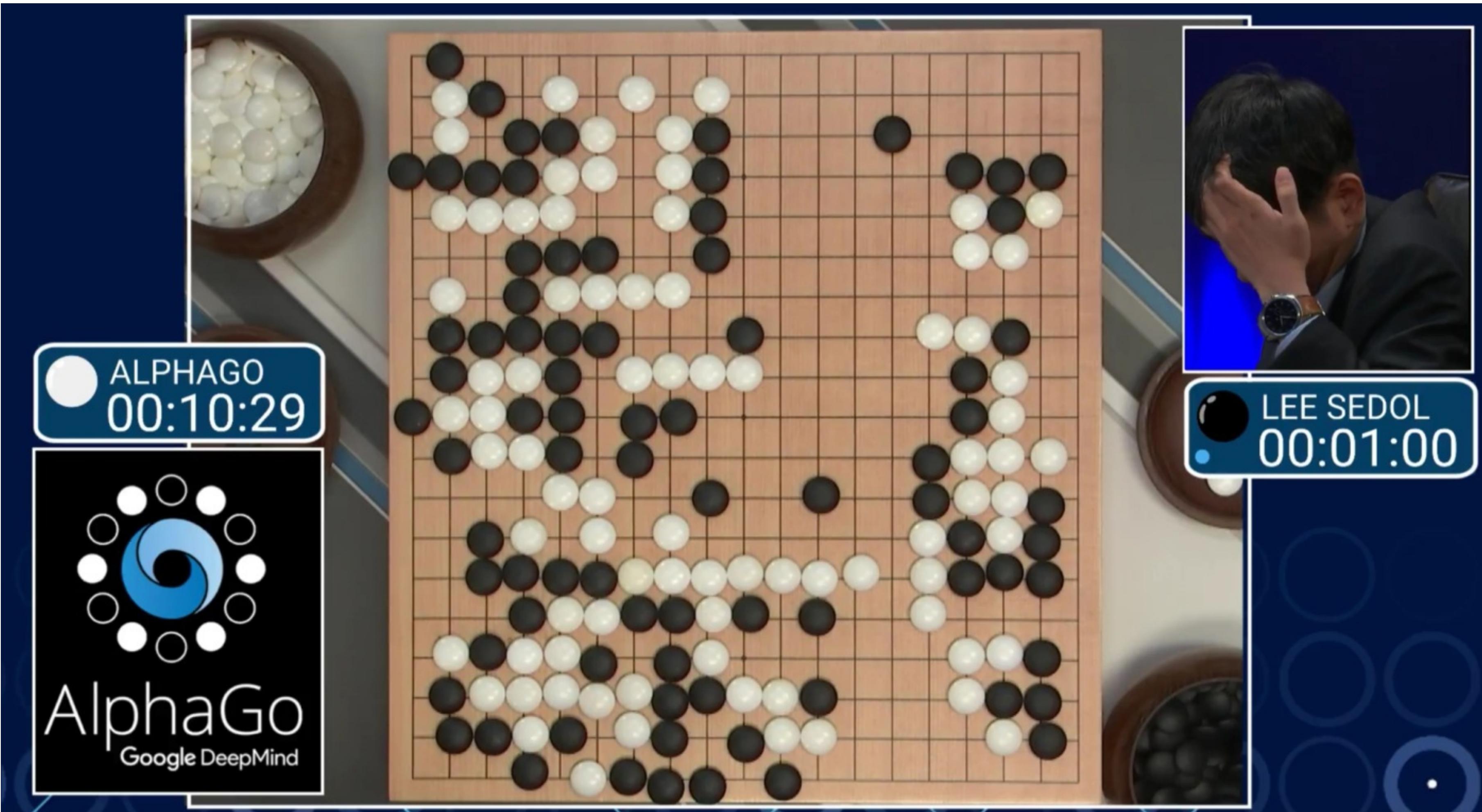
Machine for training

- Dataset is too big to be learned by a human (e.g., machine translation)



Machine for training

- Human are often guided by prejudice (e.g., AlphaGo)



Machine for training

- Even when human can find better patterns, difficult to write it as a code:
 - How would you code up a “dog classifier?”

```
def classify_dog(pixels):  
    if pixels[0] == 'gray':  
        return 'Siberian Husky'  
    elif pixels[1] == 'yellow':  
        return 'Golden Retriever'  
    else:  
        return 'Beagle'  
    else  
,
```

Why machine learning?

- Summing up, ML is useful because it can **scale up intelligence**
 - Super-human intelligence
 - using massive datasets
 - Massive deployment
 - inexpensive, consistent and robust
 - Can utilize massive sensory inputs
 - e.g., multiple sensors

“Human” in Machine Learning

- One thing to remember is that we **DON'T** expect

machine intelligence = human intelligence

- Different sensory inputs
 - e.g., still don't have sensors as dense as human
- Machine should be better than human

“Human” in Machine Learning

- Rather, human is:
 - **Proof-of-concept.** that some tasks are indeed solvable
 - e.g., self-driving is solvable with pure vision, not radar
 - **Source of data / supervision.** a black-box we want to approximate
 - e.g., chatbots generating human-like responses
 - **End-user.** Someone who machine wants to assist and make happy
 - e.g., robotic pet



In this course

In this course...

- Study the **basics of machine learning**
 - Basic framework
 - Tasks, dataset, and mathematical theories
 - Algorithms
 - Classic algorithms (e.g., linear models)
 - Deep learning
 - Hands-on experiences
 - Frontiers
 - Application on specific domains (vision, language, robotics)
 - Challenges to be solved

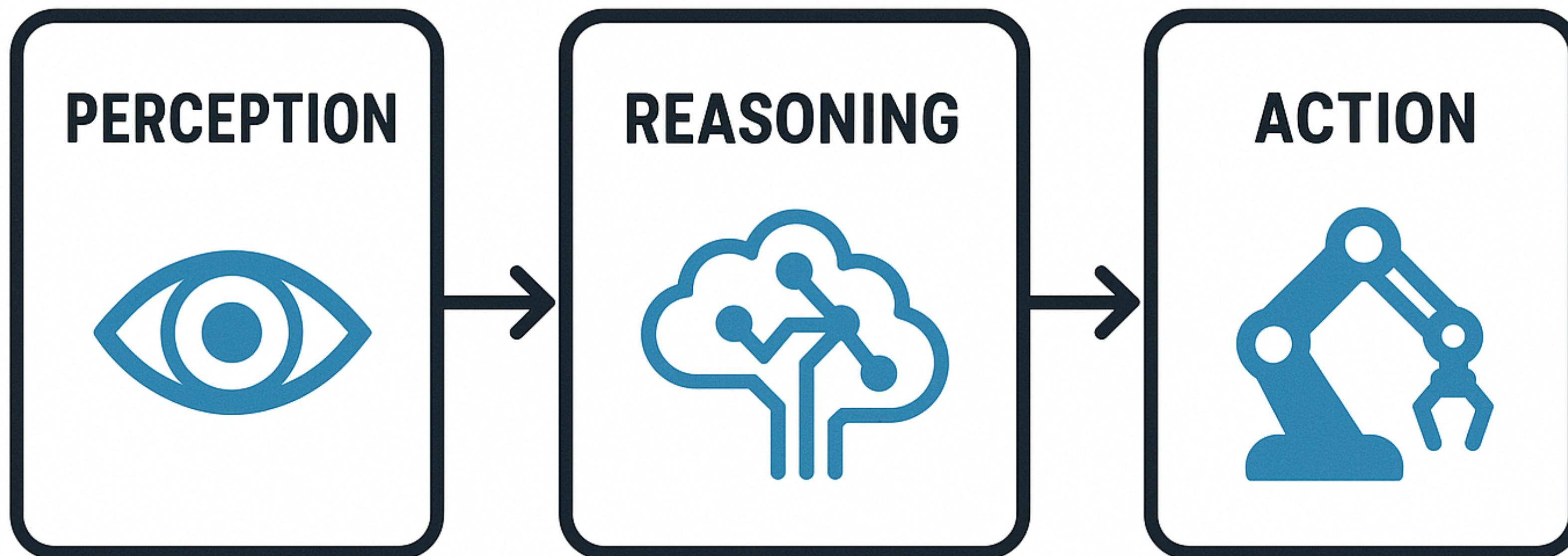
Week-by-week

- Let's see the webpage:

<https://jaeho-lee.github.io/docs/teaching/fall25ml/>

Broader scope

- Machine intelligence can be broken down into three parts:
 - **This course (ML).** Reasoning + Little bit of everything (Me)
 - **Computer Vision.** Perception (Prof. Kwang In Kim)
 - **Robot Learning.** Action (Prof. Hyemin Ahn)



Administrivia

Instructor

- Jaeho Lee 이재호
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- **Positions**
 - Assistant Professor @ POSTECH EE 22.03–Present
 - Research Scientist @ Google 23.09–25.08
 - Ph.D. @ University of Illinois Urbana-Champaign
- **Roles**
 - Lectures, Q&A

Teaching Assistant

- Minseok Kim 김민석
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 - M.S. candidate in EE
- Taesun Yeom 염태선
 - tsyeom@postech.ac.kr
 - Ph.D. candidate in AI
- **Roles**
 - Attendance, Grading, Assignments

Attendance

- Please use the **electronic attendance** system.
 - Counted begins on September 11.
- You'll get an **F** if you miss **more than 3** classes
 - “I forgot to ... ” doesn't mean it's okay
 - “I made mistakes in electronic attendance” does not count
 - Your research group's business doesn't mean it is okay to miss

Location & Hours

- **Lectures**
 - LG Hall 105
 - Mondays & Wednesdays, 9:30AM – 11:00AM
- **Office Hours**
 - GoAround Coffee, RIST
 - Wednesdays, 5:00PM – 6:00 PM
- **Materials**
 - <https://jaeho-lee.github.io>
Lecture notes
 - PLMS
Assignments

Prerequisites

- I'll assume that you know:
 - Calculus
 - Basic linear algebra
 - Basic probability & random variables
 - Signals & Systems
 - Python programming

Textbook

- **Main**
 - Lecture slides
- **Supplementary**
 - Mathematics for Machine Learning <https://mml-book.github.io/>
 - Understanding Deep Learning <https://udlbook.github.io/udlbook/>
 - Patterns, Predictions, and Actions <https://mlstory.org/>
 - Dive into Deep Learning <https://d2l.ai/>

Grading

- **Attendance (10%)**
 - Use electronic attendance system
 - **Assignments (30%)**
 - Planning to give you at least 3 homeworks
 - **Mid-Term (30%)**
 - **Final Project (30%)**
 - Deep learning project
- * Graduate students are graded separately
- * QE sit-ins will be evaluated against UGs

Final Project

- Local Kaggle Competition <https://www.kaggle.com/competitions>
 - Presentations in the final week

Competitions

Search competitions Filters

Featured X

Results Recently Launched ▾ grid

 NeurIPS - Ariel Data Challenge 2025 Derive exoplanet signals from Ariel's optical instruments Featured · Code Competition · 51 Teams · 3 months to go	\$50,000	...
 Google - The Gemma 3n Impact Challenge Explore the newest Gemma model and build your best products for a better world Featured · 0 Teams · A month to go	\$150,000	...
 NeurIPS - Open Polymer Prediction 2025 Predicting polymer properties with machine learning to accelerate sustainable materials research. Featured · Code Competition · 794 Teams · 3 months to go	\$50,000	...
 CMI - Detect Behavior with Sensor Data Predicting Body Focused Repetitive Behaviors from a Wrist-Worn Device Featured · Code Competition · 1386 Teams · 2 months to go	\$50,000	...

Honor codes

- You'll get **F** if:
 - Sharing solutions
 - Copying solutions
 - “Collaborating” with your friends for homework
 - Use me & TA, instead
 - Using GPT for homework
 - Miss more than 3 classes