TDDE19 Advanced Project Course - AI and Machine Learning

AI Projects (technical perspective)

Mattias Tiger (PhD, AI Researcher)

AI and Integrated Computer Systems (AIICS),
Department of Computer Science

mattias.tiger@liu.se

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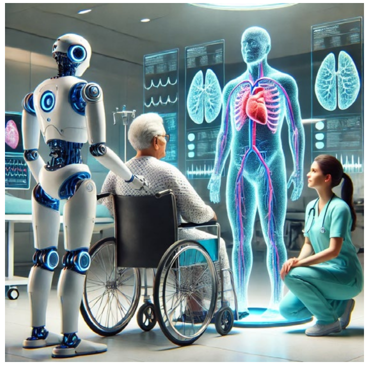
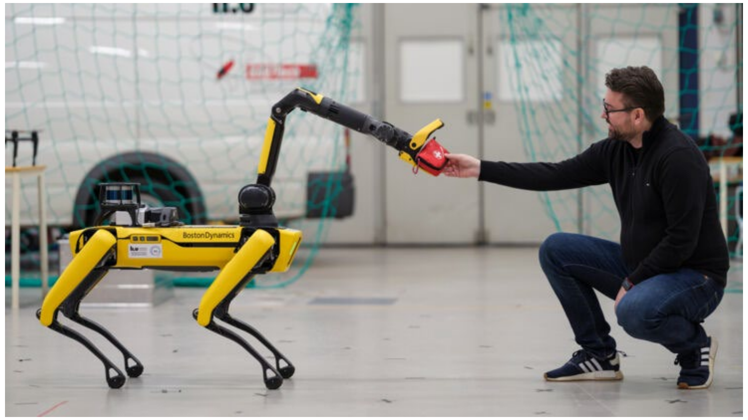
What can AI do?

- **Draw conclusions**, e.g. perform logical reasoning.
- **Classify**, e.g. recognize an object.
- **Predict**, e.g. anticipate future events.
- **Create**, e.g. create images from a text.
- **Act**, e.g. control a robot.





AI and Technology

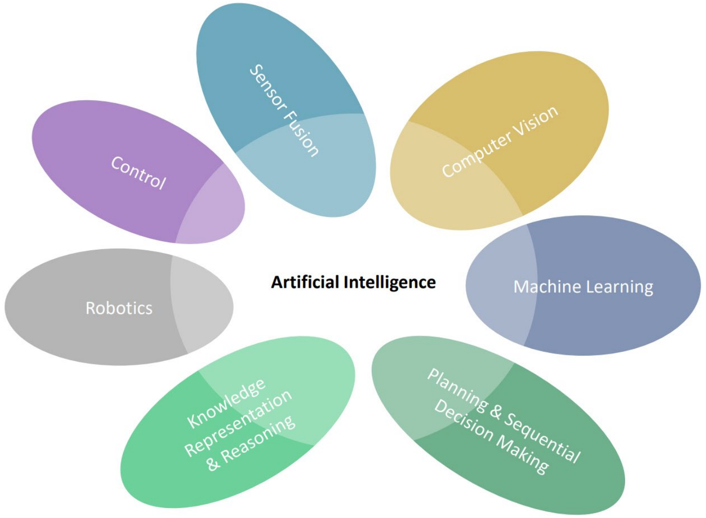
Tools that can act on their own (autonomy)

AI and Technology

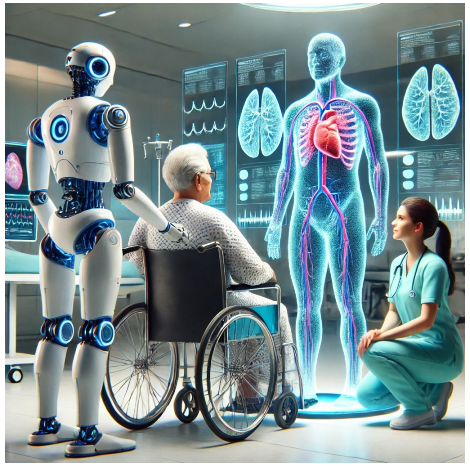
- **AI is *meta-technology***
  - How to describe/realize technology that on its own can create (or help us create) *new technology*
  - How to describe/realize problem-solving *through computers*

Why AI?

- Automated Problem Solving
- Enhanced Capabilities
- Augmented Intelligence



Bring clarity and control to an increasingly complex and uncertain world



The AI Toolbox

Approaches to automated problem solving

- **MIP** (Simplex, Gurobi)
  - Assumes smoothness in the search space
- **Search** (A*, BestFirst)
  - Assumes effective heuristics
- **Sampling** (Random)
  - Assumes calibrated probability distributions & efficient sampling schema
- **Approximated** (ML, RL, Algorithmic)
  - Assumes sufficiently good approximation. For ML: assumes *representative* training data, sufficient capacity and sufficient training time.
- **Hybrid** (MCTS, DL+A*)
  - Assumes effective integration of different techniques

The AI Toolbox

Approaches to automated problem solving

Simplex, Gurobi → MIP

A*, BestFirst → Search

Random → Sampling

ML, RL, Algorithmic → Approximated

MCTS, DL+A* → Hybrid

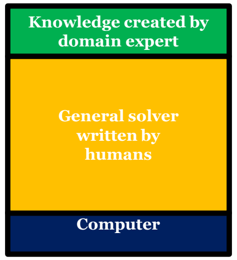
Solver: MIP, Search, Sampling

Learner: Approximated

- MIP: Assumes smoothness in the search space
- Search: Assumes ... heuristics
- Sampling: Assumes calibrated probability distributions & efficient sampling schema
- Approximated: Assumes ...ood ...on. For ML: assumes *representative* training data, sufficient capacity and sufficient training time.
- Hybrid: Assumes effective integration of different techniques

The Big Picture| Applied AI

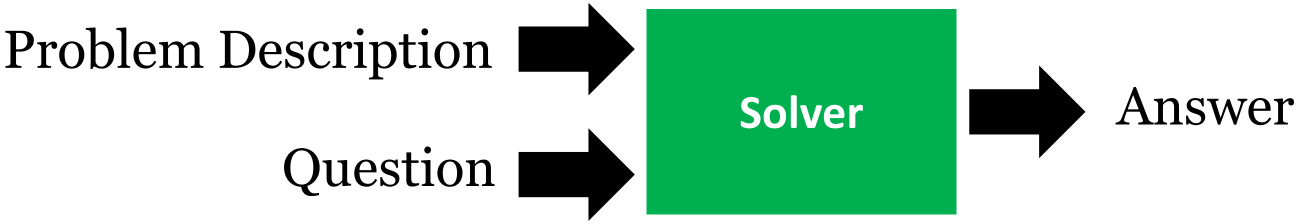
Algorithms, solvers and learners

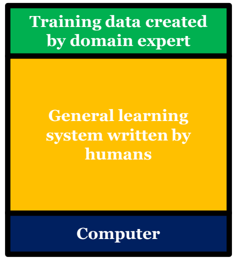


Knowledge-based

Solver

- Capable of solving **different types** of problems
- Optimal in some sense
- The answer is **guaranteed** to be the solution to the problem

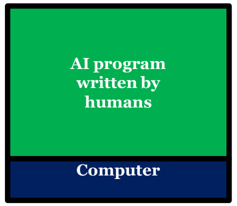




Learning-based

Learner

- The problem is given indirectly **through data**
- Characteristics depend on the chosen technique
- Sometimes gives **incorrect answers**.



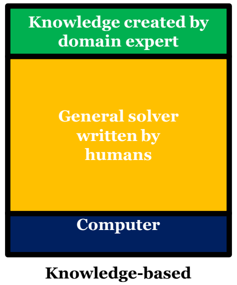
Algorithmic

Algorithm

- Solves a specific problem

The Big Picture| Applied AI

Algorithms, solvers and learners



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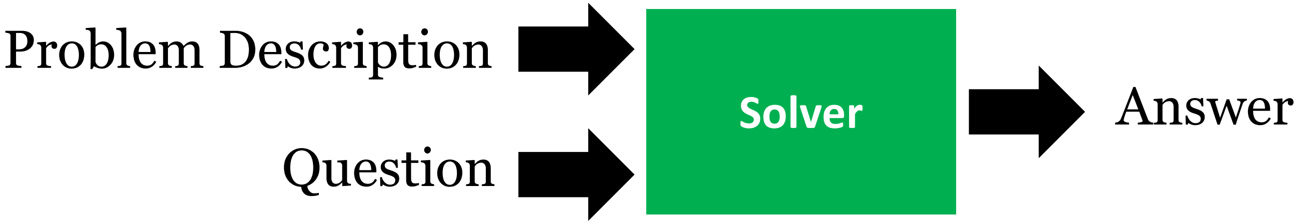

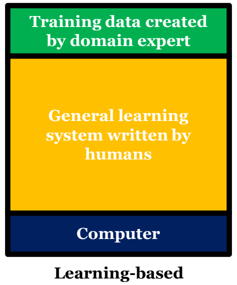

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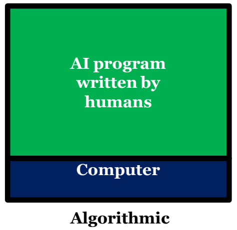

Algorithm

- Solves a specific problem

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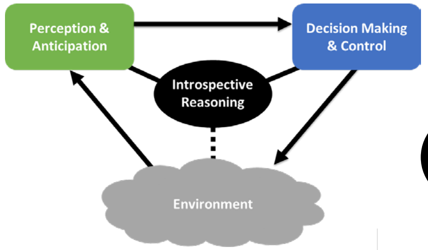
Examples: Motion-planning (Safe, Adaptive, Trustworthy)

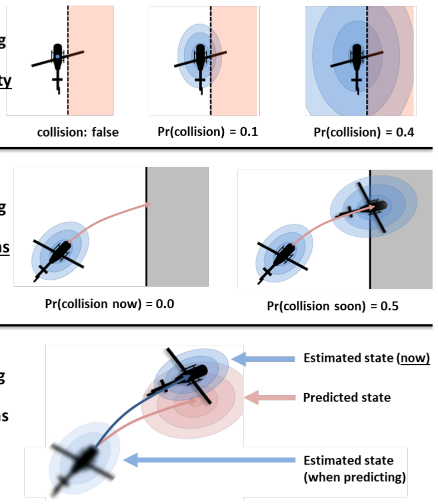
Solver

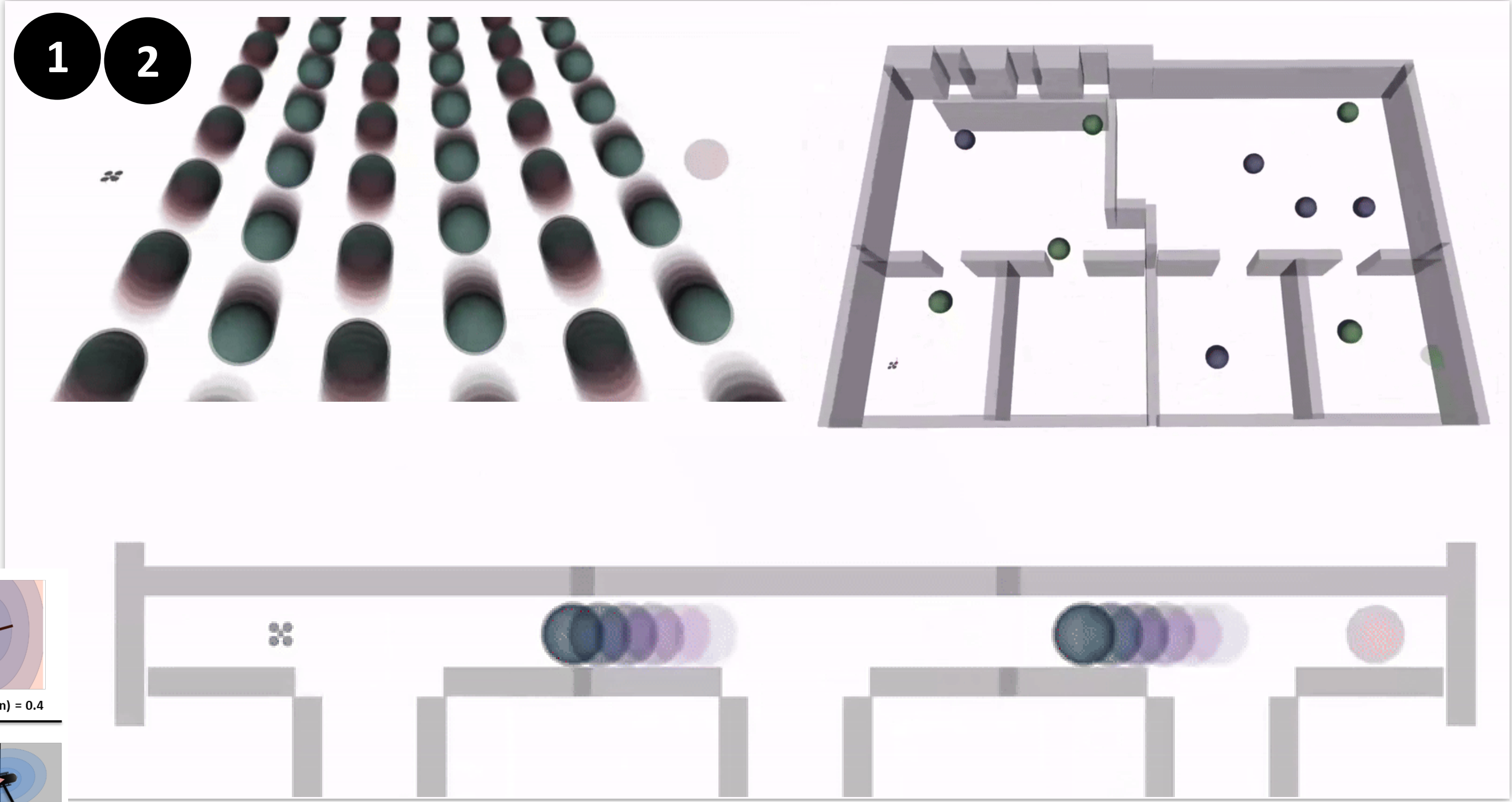
1. Safe Motion Planning
2. Safe Motion Execution
3. Safety-Aware Introspection (Anomaly Detection)

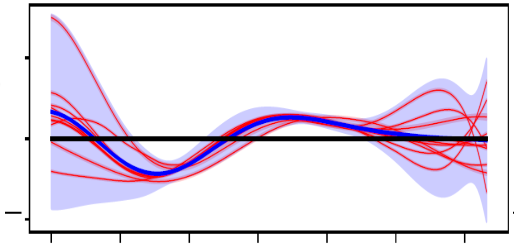


3

- Probabilistic
  - Is the robot inside the no-go-zone?
- Anticipatory
  - Will the robot be colliding in the near future?
- Introspective
  - Is the prediction similar to the realization?







3

Probabilistic Logic: For what we can write down
Robust ML: For what we can't express with words

Learner

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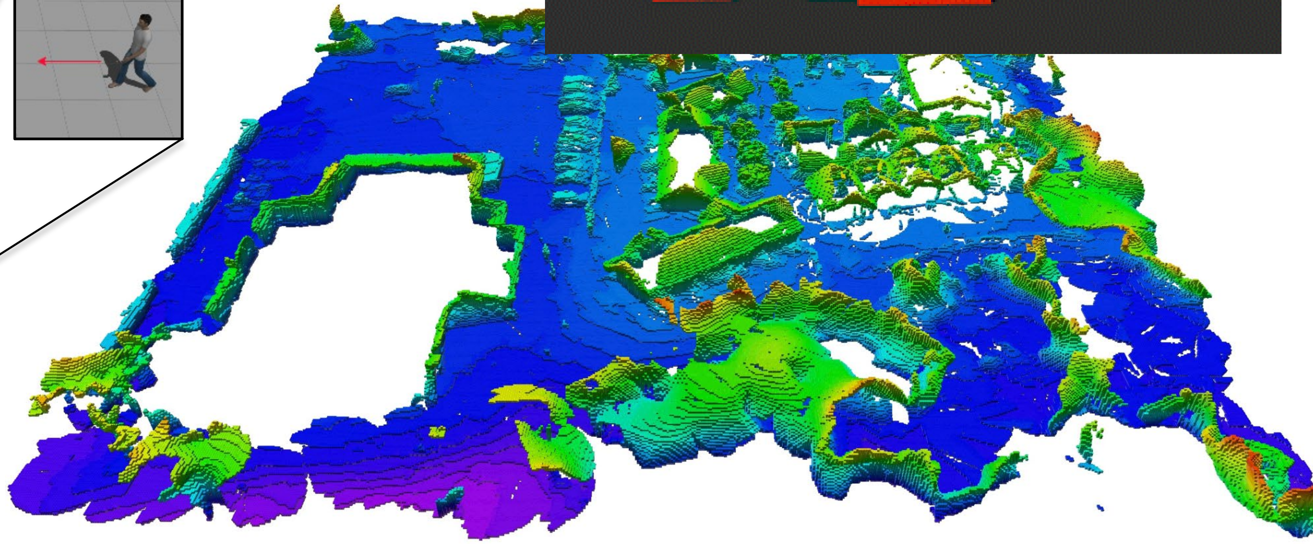
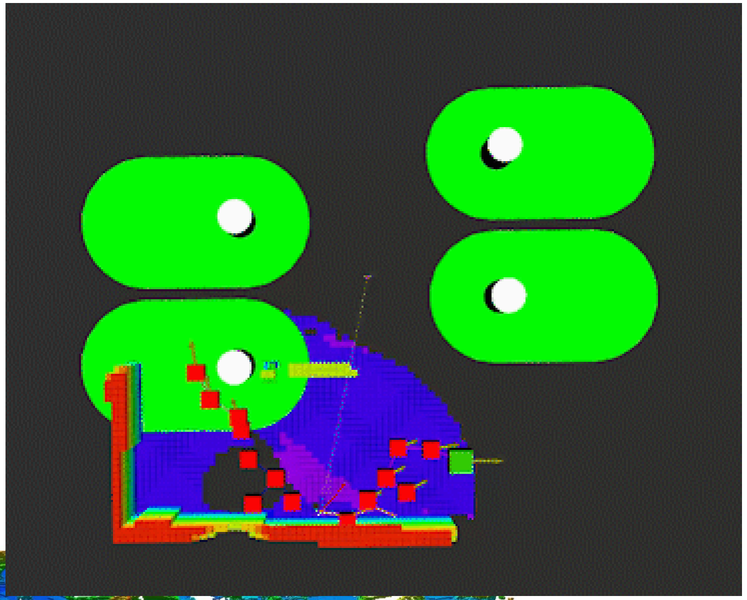
[6] **Tiger, M.**, and Heintz, F. *Incremental reasoning in probabilistic signal temporal logic*. International Journal of Approximate Reasoning, 2020.
[7] **Tiger, M.**, Bergström, D., Norrstig, A., & Heintz, F. *Enhancing lattice-based motion planning with introspective learning and reasoning*. IEEE RA-L, 2021.
[8] Wiman, E., **Tiger, M.** *Safe lattice motion planning for motion planning with dynamic obstacles*. IROS 2025.

Examples: Autonomous 3D-exploration planning

Solver

4. *3D exploration methods for systems to perform* ***effective 3D exploration tasks*** *in* ***uncertain***, ***dynamic***, *and potentially* ***crowded environments***.





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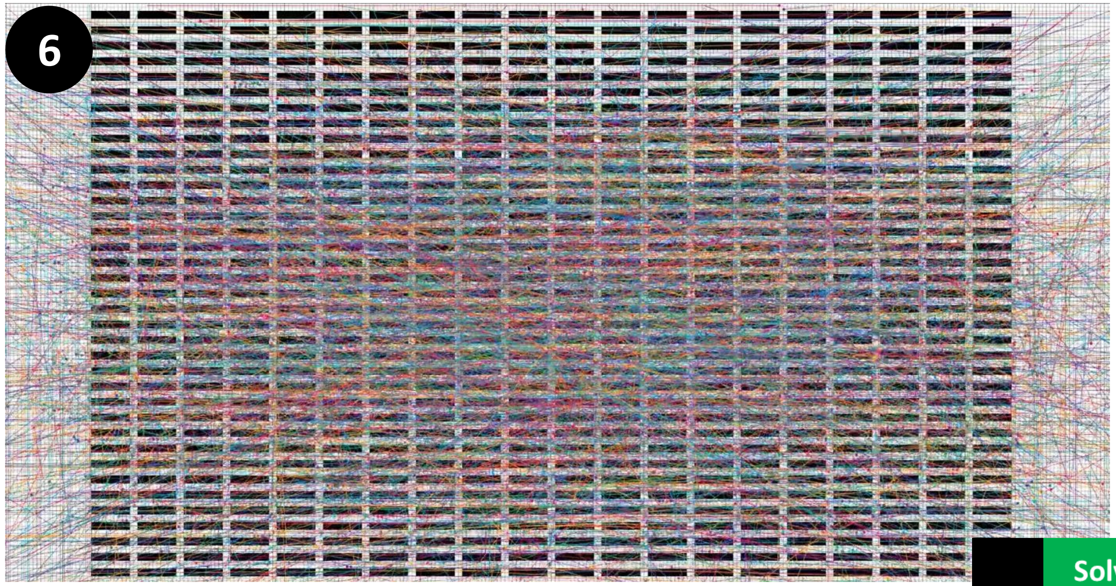
[9] Wiman, E., Widén, L., **Tiger, M.,** & Heintz, F. Autonomous 3D exploration in large-scale environments with dynamic obstacles, ICRA, 2024.

Examples: Multi-agent Exploration | Path Planning | Order Picking

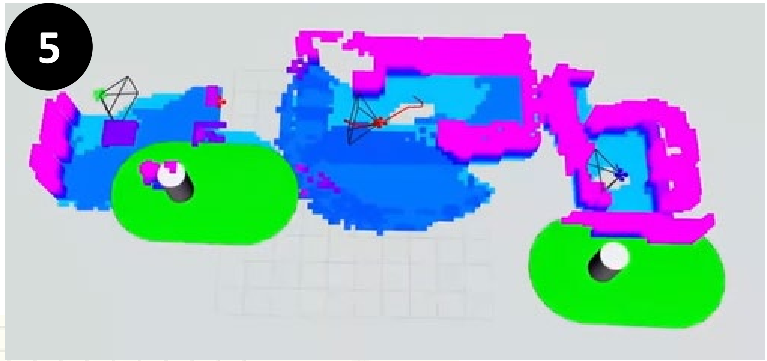
Solver

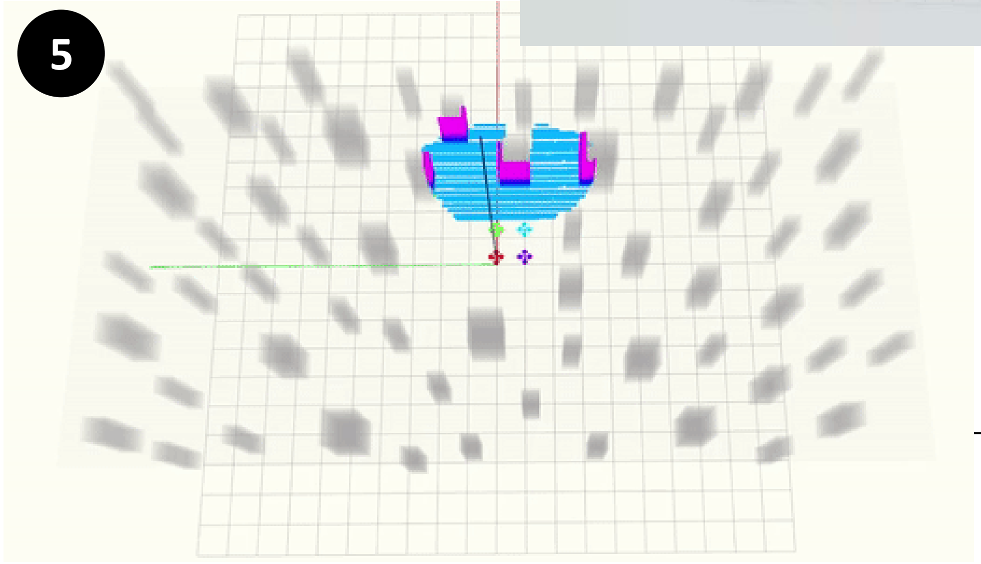
[Work with Amath Sow, Emil Wiman, David Bergström]

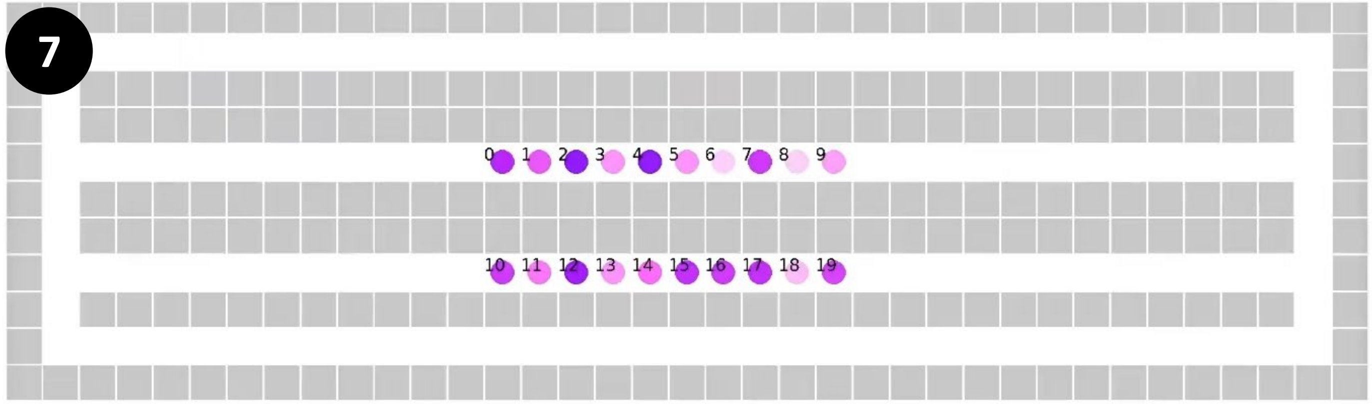
5. Multi-agent Exploration (IROS25)
6. Multi-agent Path Planning (AAMAS26?)
7. On-demand Multi-agent Order Picking (ICRA23)



AI
Solver
Heuristic







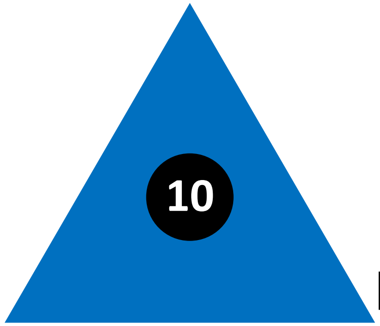
Examples: Multi-agent Coordination | Situation Awareness | U-Space

Solver

AI | Solver | Heuristic

8. DyMuDRoP (Dynamic Multi-Drone Route Planning)
9. SymbiCloud [a]
   (Distributed world model
   & situation awareness)
10. Delegation [b]
   (Distributed self-organizing
   autonomous organization)

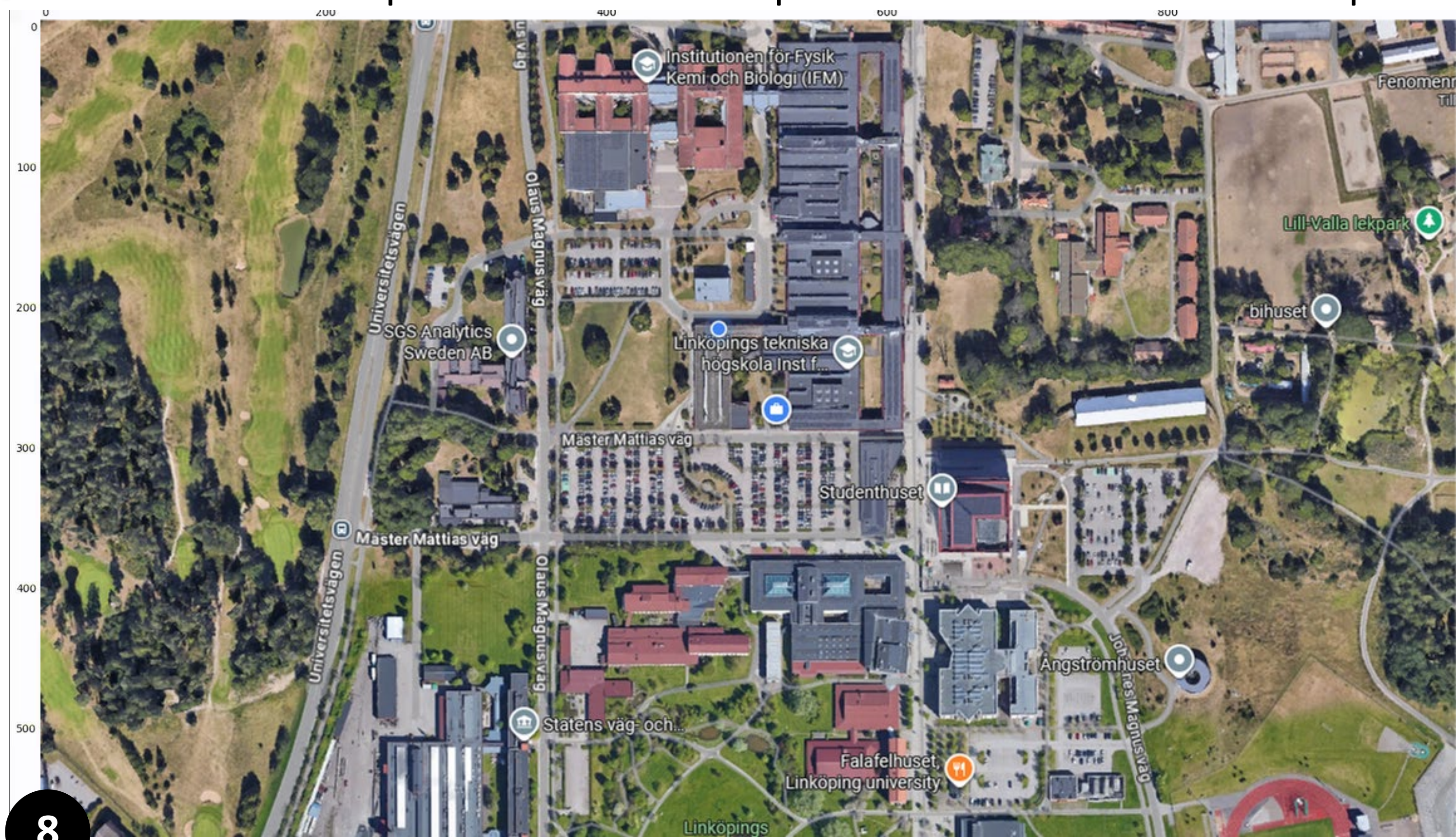
Delegation



Sliding Autonomy

Mixed-Initiative Interaction

Near-optimal collision-free paths for 800 drones: 1 sec to plan



8

[Work with Amath Sow]

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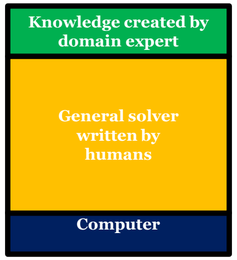
[a] Doherty, Patrick, et al. "Hastily formed knowledge networks and distributed situation awareness for collaborative robotics." Autonomous Intelligent Systems 1.1 (2021): 16.
[b] Doherty, Patrick, Fredrik Heintz, and Jonas Kvarnström. "High-level mission specification and planning for collaborative unmanned aircraft systems using delegation." *Unmanned Systems* 1.01 (2013): 75-119.

The Big Picture| Applied AI

Algorithms, solvers and learners



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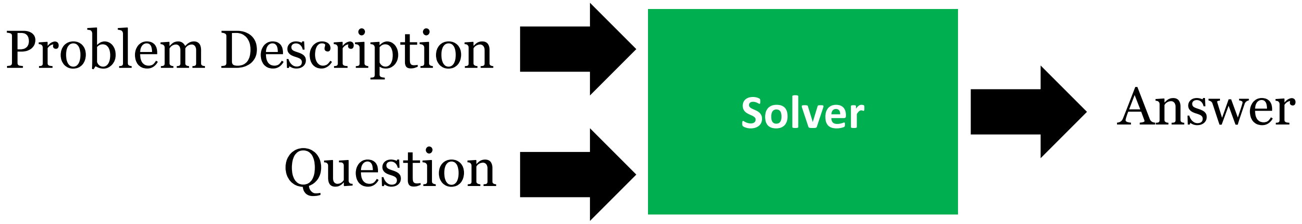

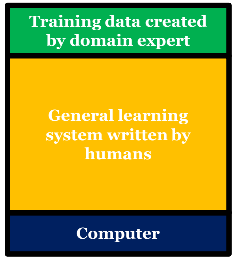

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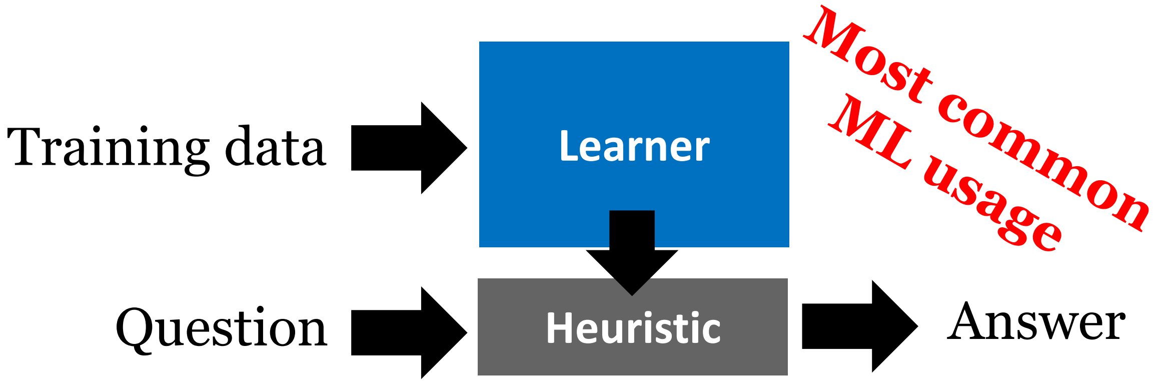
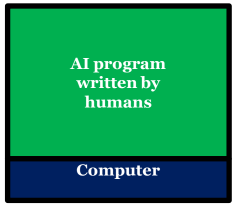




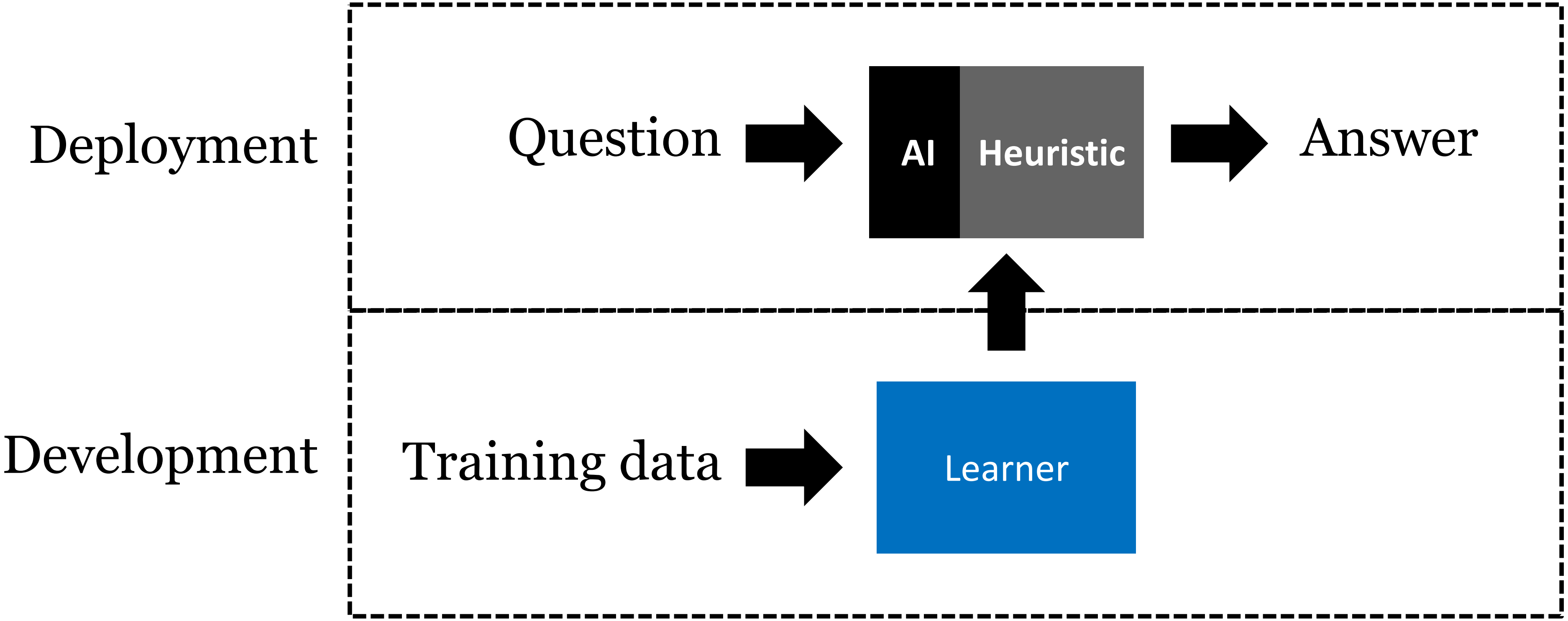
Algorithmic

Algorithm

- Solves a specific problem

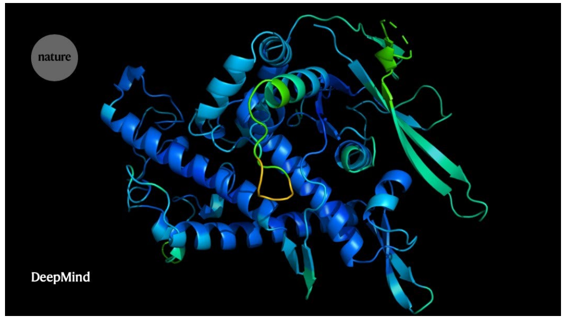
Applied AI | ML (Machine Learning)

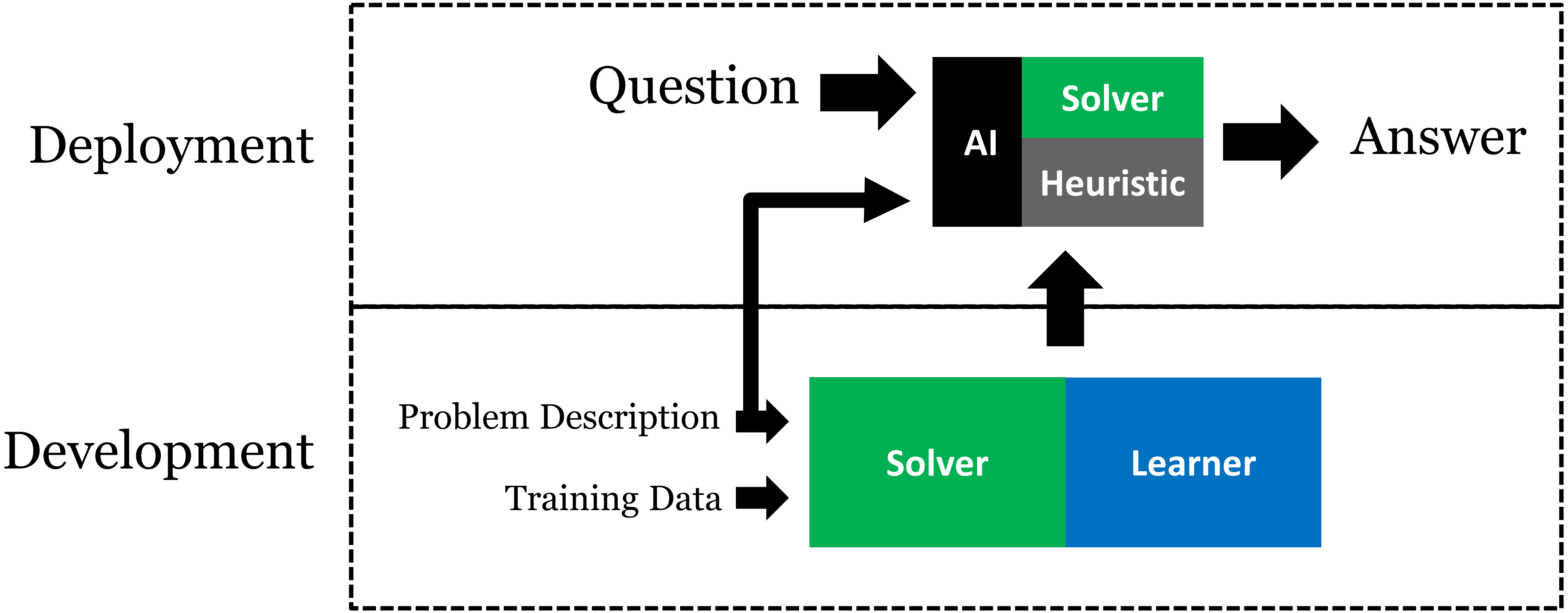
- ML in practice (image, audio, text, …):

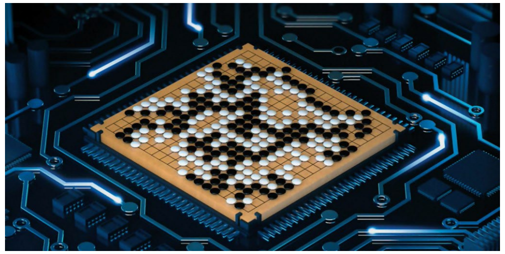


Applied AI | Hybrid AI (offline learning)

- Hybrid AI
  - ➢ *Combining systematic and approximate AI (Knowledge-based and artifacts from Learning-based)*







deepseek R1

ChatGPT o

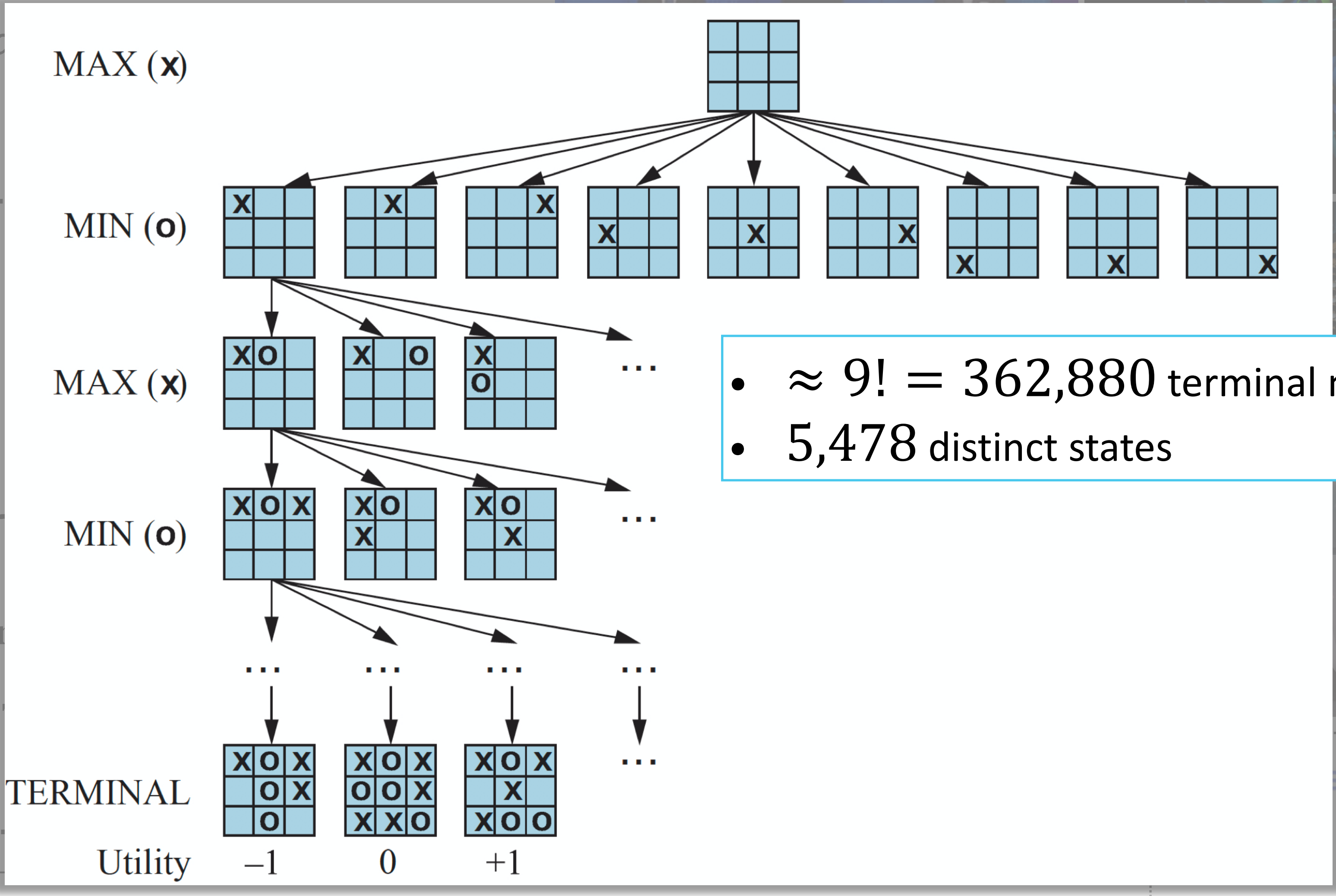
“Thinking” + tools

Systematic AI (illustration)

Tic-Tac-Toe

Heuristic search:
Use a heuristic to decide on *the order* in which to try different actions

Heuristic:
How likley is a win if picking action *a*?



- $\approx 9! = 362{,}880$ terminal nodes
- $5{,}478$ distinct states

Applied AI | Hybrid AI (offline learning)

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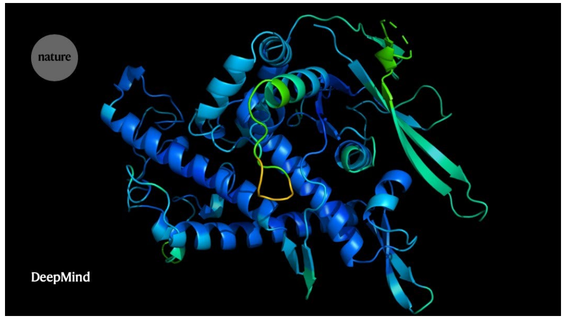

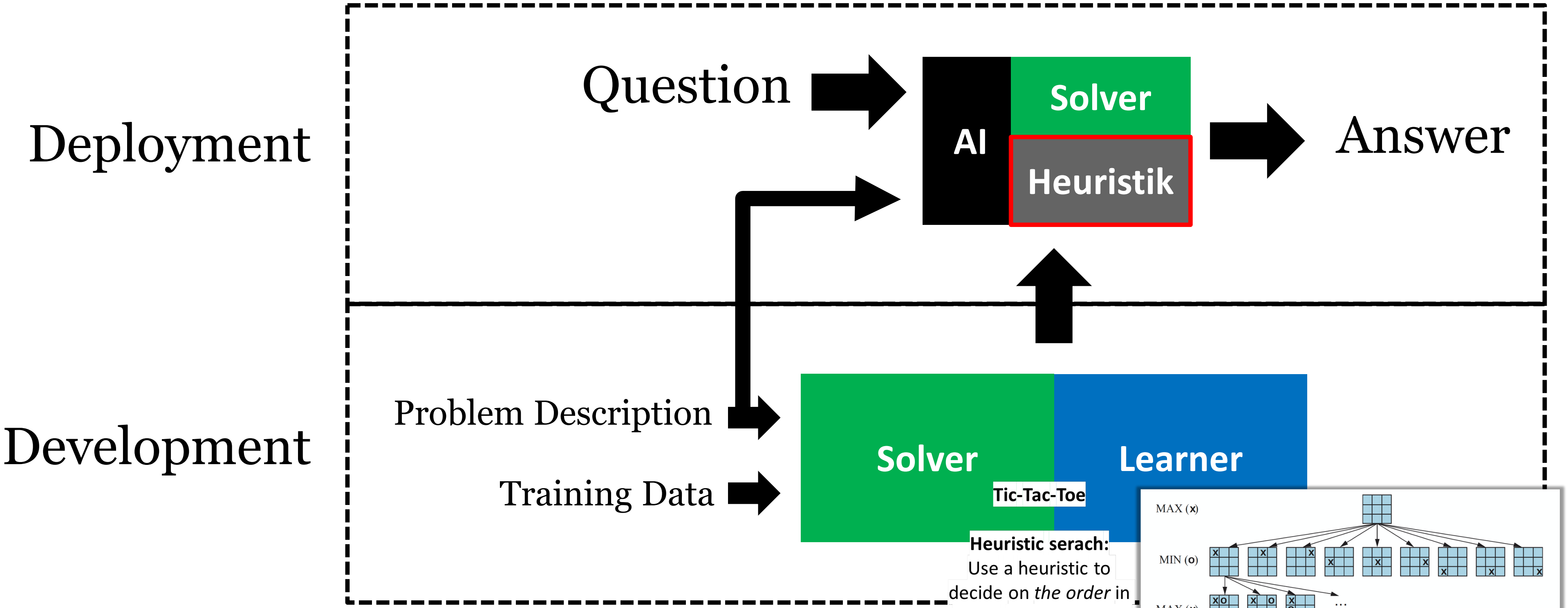

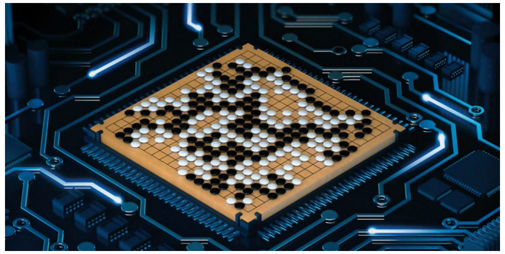

Tic-Tac-Toe

Heuristic serach: Use a heuristic to decide on *the order* in which to try different actions

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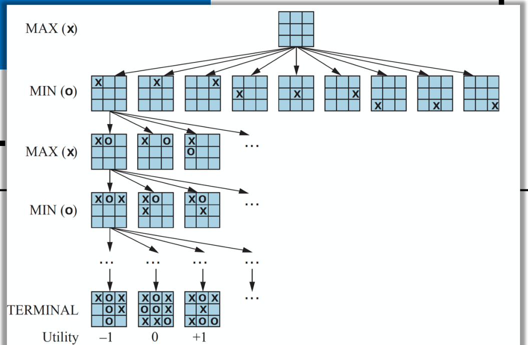

deepseek R1

ChatGPT o

"Thinking" + tools

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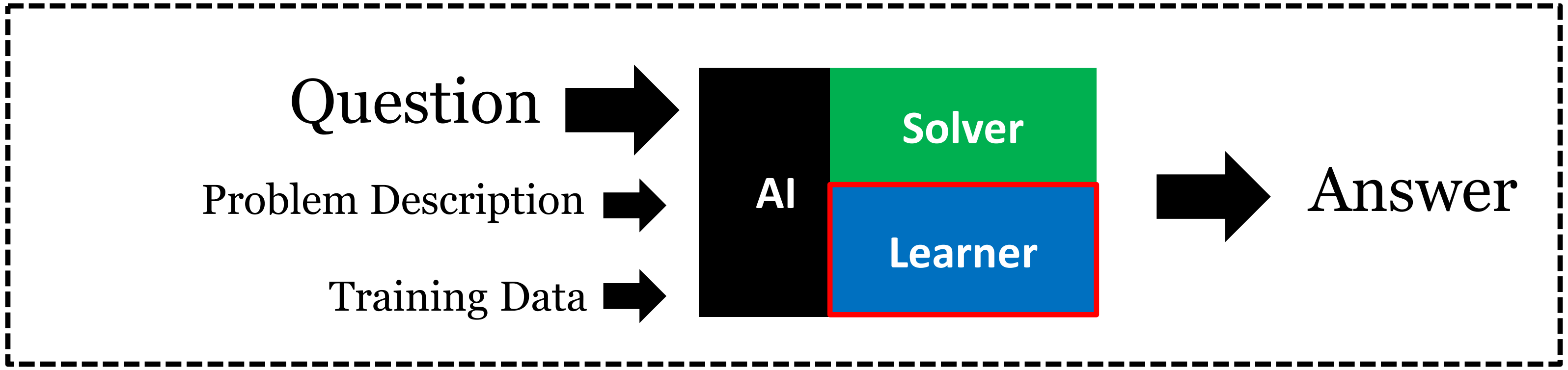
Applied AI | Hybrid AI (online learning)

- Hybrid AI
  - ➢ *Combining systematic and approximate AI (Knowledge-based and Learning-based)*

Deployment



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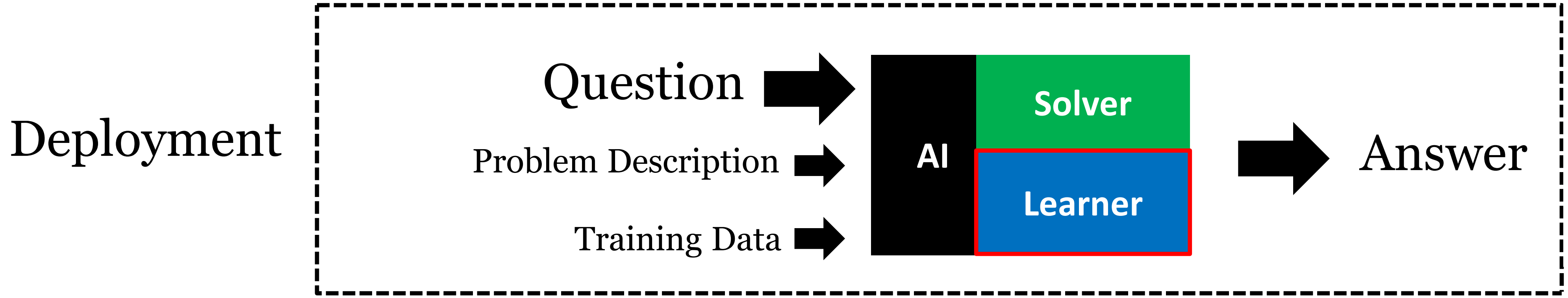
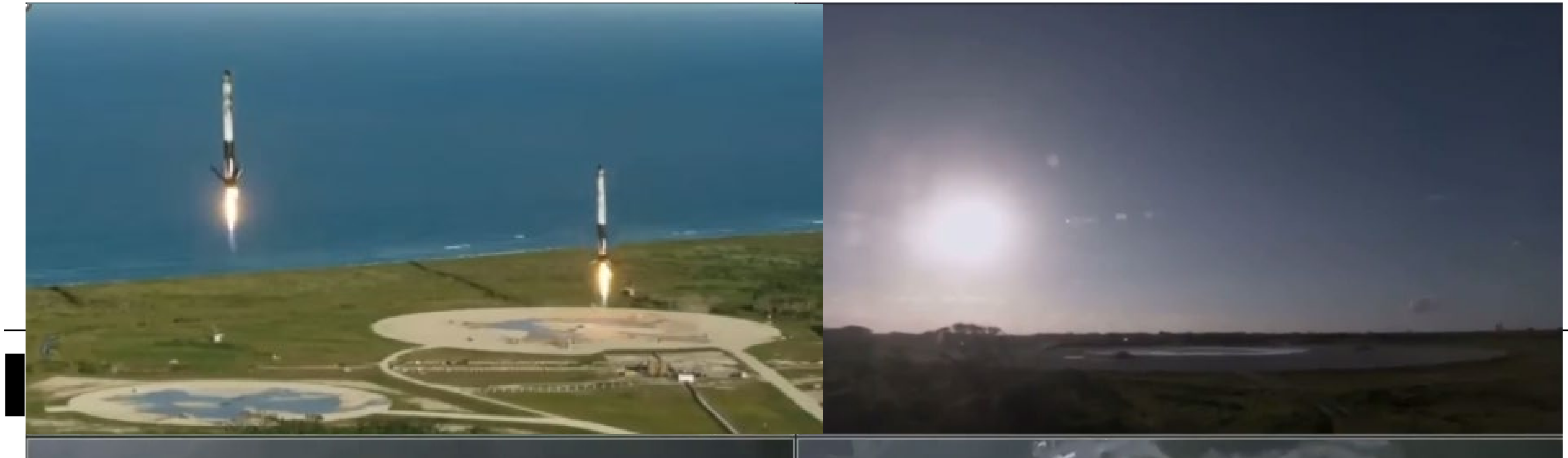


Solver
Model Predictive Control



Learner
Bayesian State Estimation

ML | Categorization of Approaches

Probabilistic ML (Bayesian Learning, Grounded ML, Casual ML)

- **Examples:** Graphical models, Gaussian processes, BNNs*, …
- **SOTA**: Automatic decision making, safety-critical systems, building understanding (automated research)

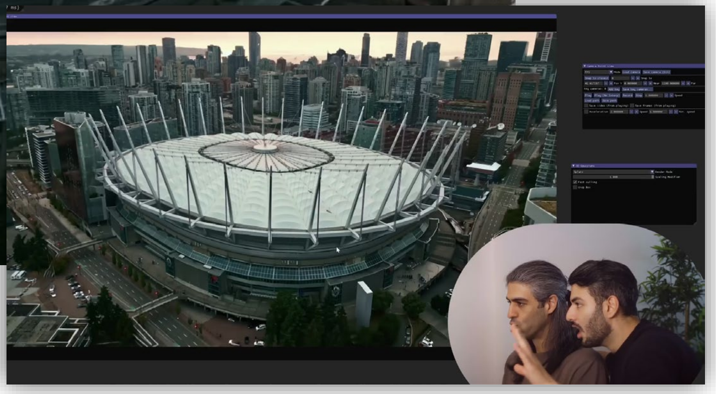
Deep Neural Networks

- **Examples:** FNN, CNN, RNN, GNN, ResNET, Transformer, …
- **SOTA:** Image, Video, Sound, Text, … (unstructured, high-dimensional)

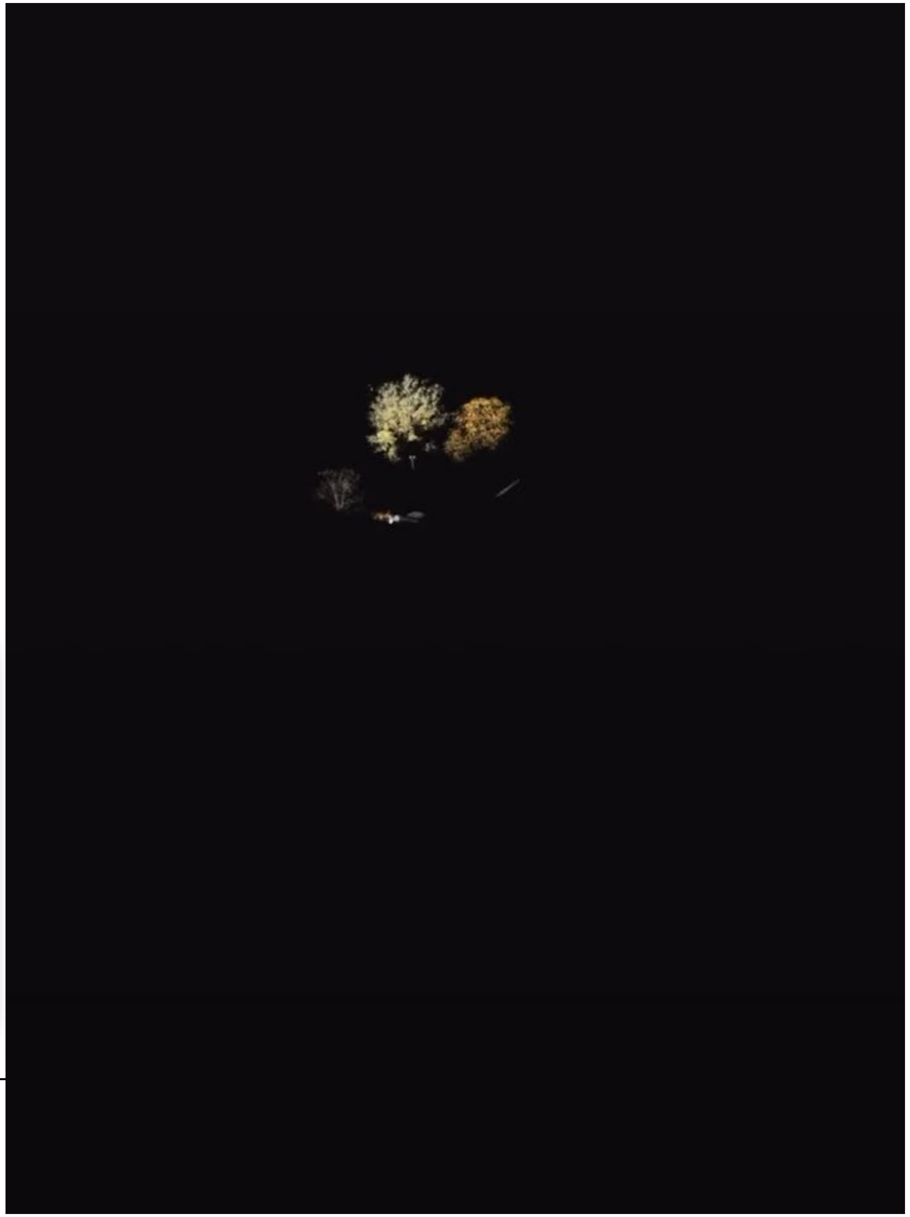
Gradient Boosting Decision Trees

- **Examples:** XGBOOST, CatBoost, Light GBM
- **SOTA:** Tabular data (structured data)

Example: Probabilistic ML (Gaussian Splatting)



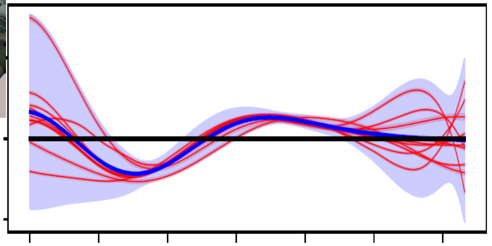
8 second
drone video



ML | Categorization of Approaches

Probabilistic ML (Bayesian Learning, Grounded ML, Casual ML)

- **Gold standard**
  - The full learning problem with uncertainty can be stated (then often approximated for efficiency…).
  - Integrate domain knowledge (i.e. from physics) directly into the ML models
  - Online learning, Sample-efficient learning, *understanding*, Guarantees, …



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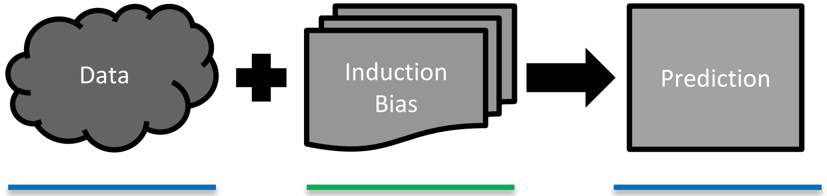
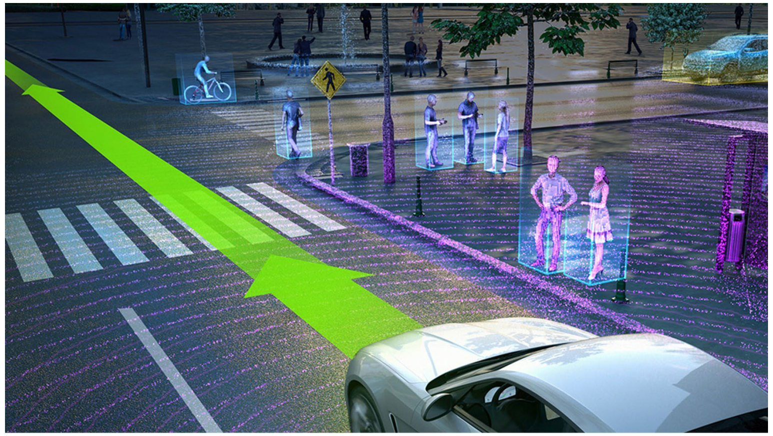


What is needed for effective ML in the wild

- We need Probabilistic ML – But it does not scale
- DL (etc.) scale – But it has none* of the necessary properties
- ➢ We need to effectively combine both

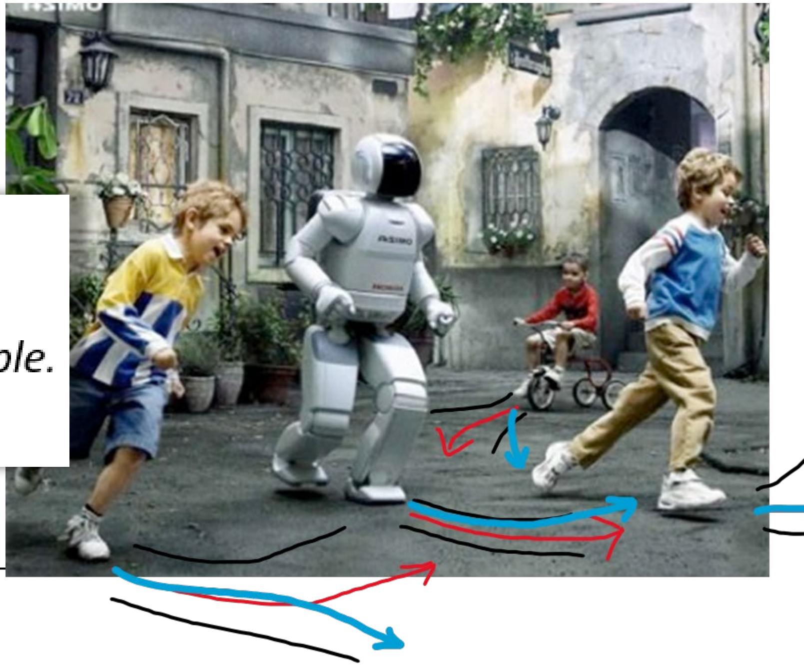


Deep Neural Networks

- **Examples:** FNN, CNN, RNN, GNN, ResNET, Transformer, …
- **SOTA:** Image, Video, Sound, Text, … (unstructured, high-dimensional)

+

- **Gold standard**
  - Trust, transparency, reliability, explicit uncertainty/probabilities, guarantees…
  - *Induction bias* is explicit, *prediction uncertainty* well founded, model is *explainable*.
  - Explicit separation (and estimation) of **Epistemic** and **Aleatoric** uncertainty.



Bridging academia and industry

Industry (and society)

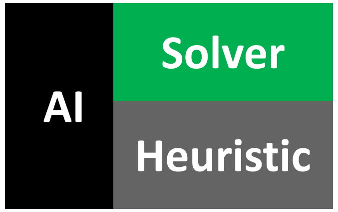
- Makes AI **concrete** through **usability** and **societal impact**
- Possesses resources and expertise in **production** and **deployment**
- Has access to **socio-strategic**, **industry-tactical**, and **immediate perspectives** and **needs**

Academia (basic research in AI)

- Offers a vast toolkit of **general-purpose methods** adaptable to many specific applications
- Provides **knowledge on enabling technologies** for the next (next-next) gen. of tech (**2-10 years ahead**)
- Contributes **strategic** and long-term **perspectives** on **capabilities** and impact

<u>**Current dynamics**</u>

➢ **AI research** now traverses Technology Readiness Levels (TRLs) **at unprecedented speed**: what once took 5-10 years can now happen within 3-12 months.



➢ With sufficient resources, **we can build a demo of almost anything** today.

➢ Building something reliable, however, remains far more challenging. **It requires safety and adaptivity by design**.

AI projects

AI projects vs other kinds of projects?

- Competence?
- Uncertainty?
- Resources?
- Input?
- Verification and Validation?
- Users?
- Legal?
- Ethics?

Mattias Tiger

AI och Integrerade Datorsystem (AIICS),
Institutionen för Datavetenskap

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ARTIFICIAL INTELLIGENCE AND INTEGRATED COMPUTER SYSTEMS
AIICS

TAILOR
Foundation of Trustworthy AI:
Integrating Learning, Optimisation and Reasoning

WASP
WALLENBERG AI,
AUTONOMOUS SYSTEMS
AND SOFTWARE PROGRAM