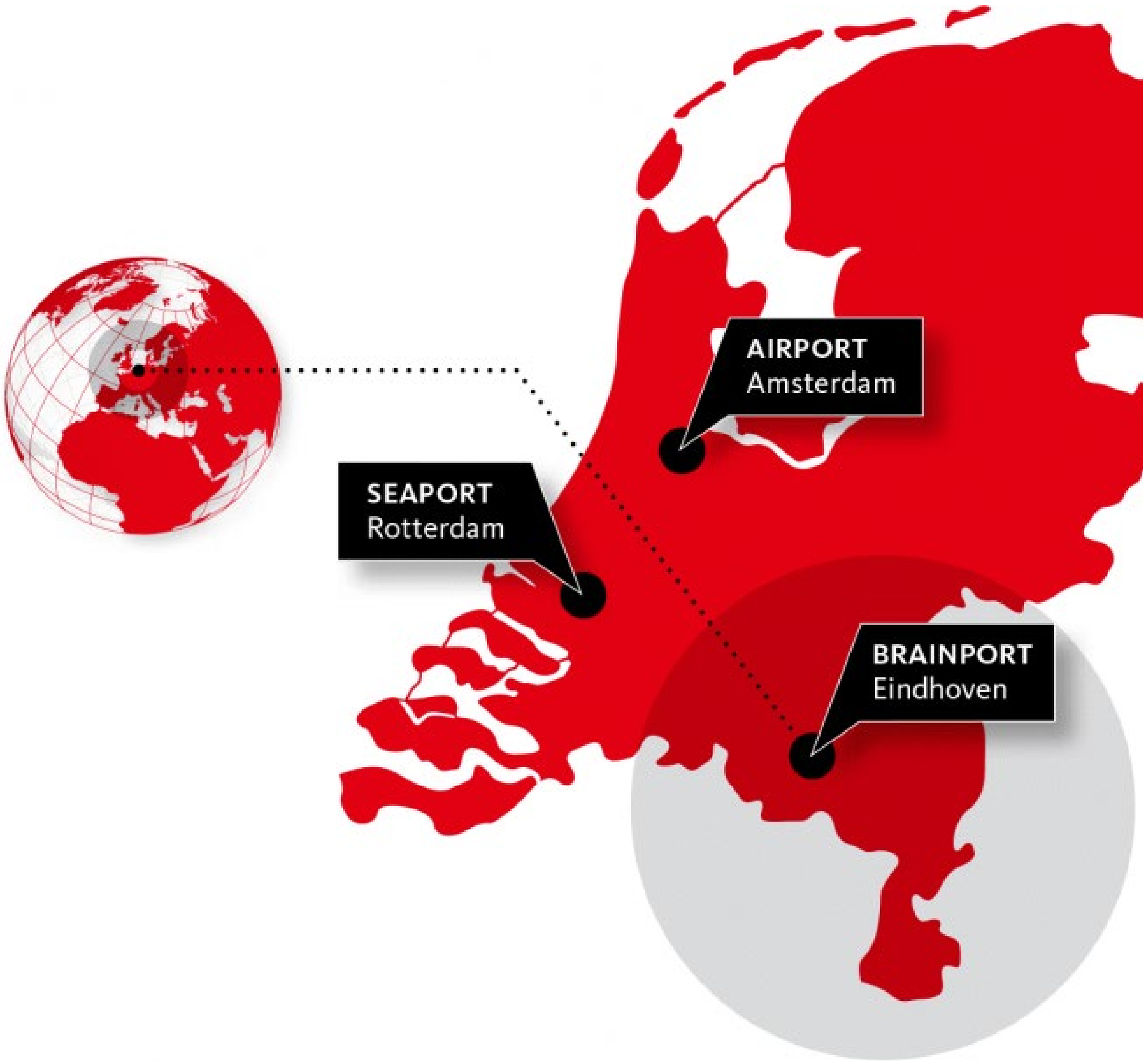
Natural/Artificial Intelligence for control & mobile robotics

Dr. Wouter M. Kouw | CRT in AI – Amsterdam AI | 15-apr-2024



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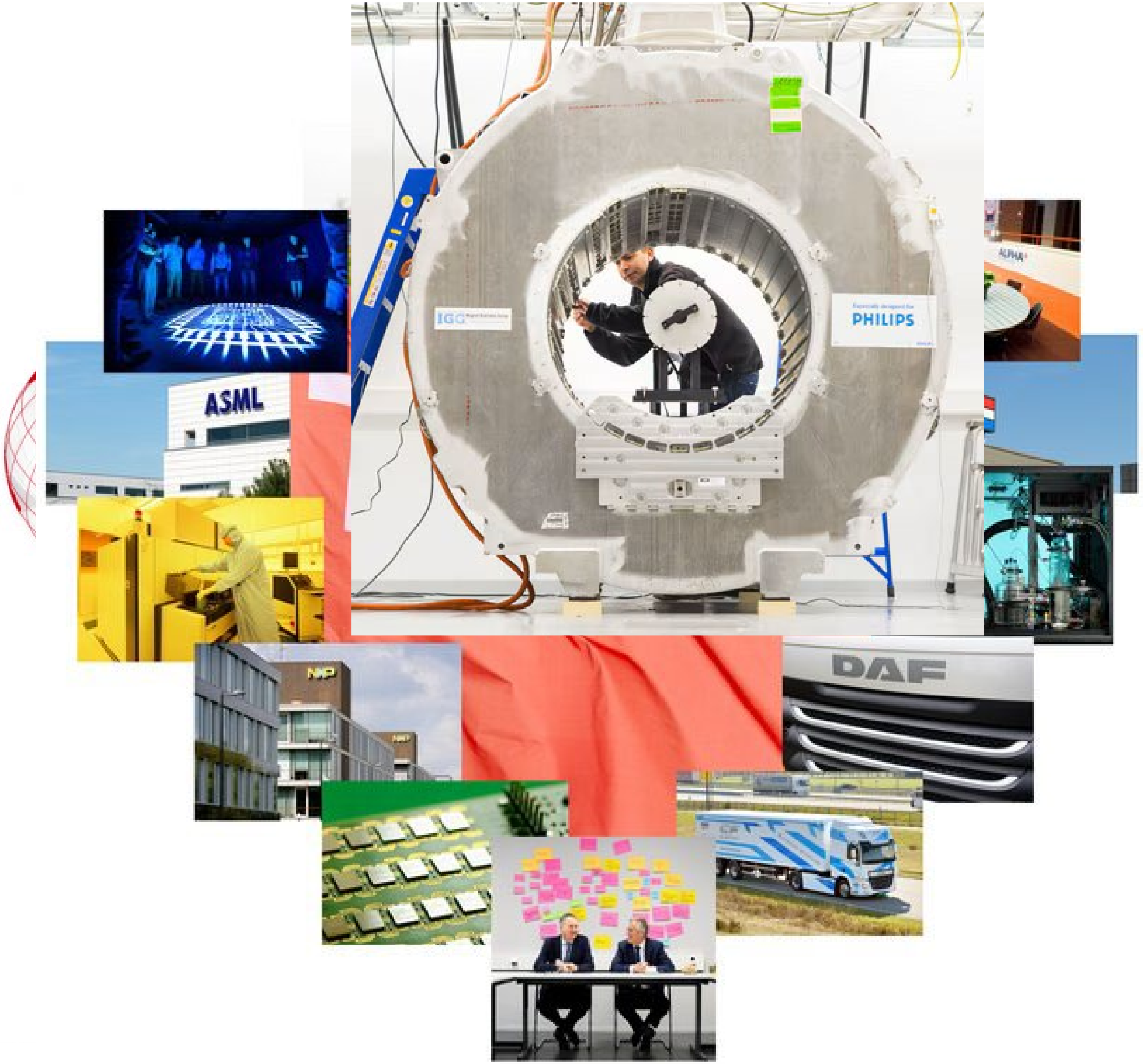

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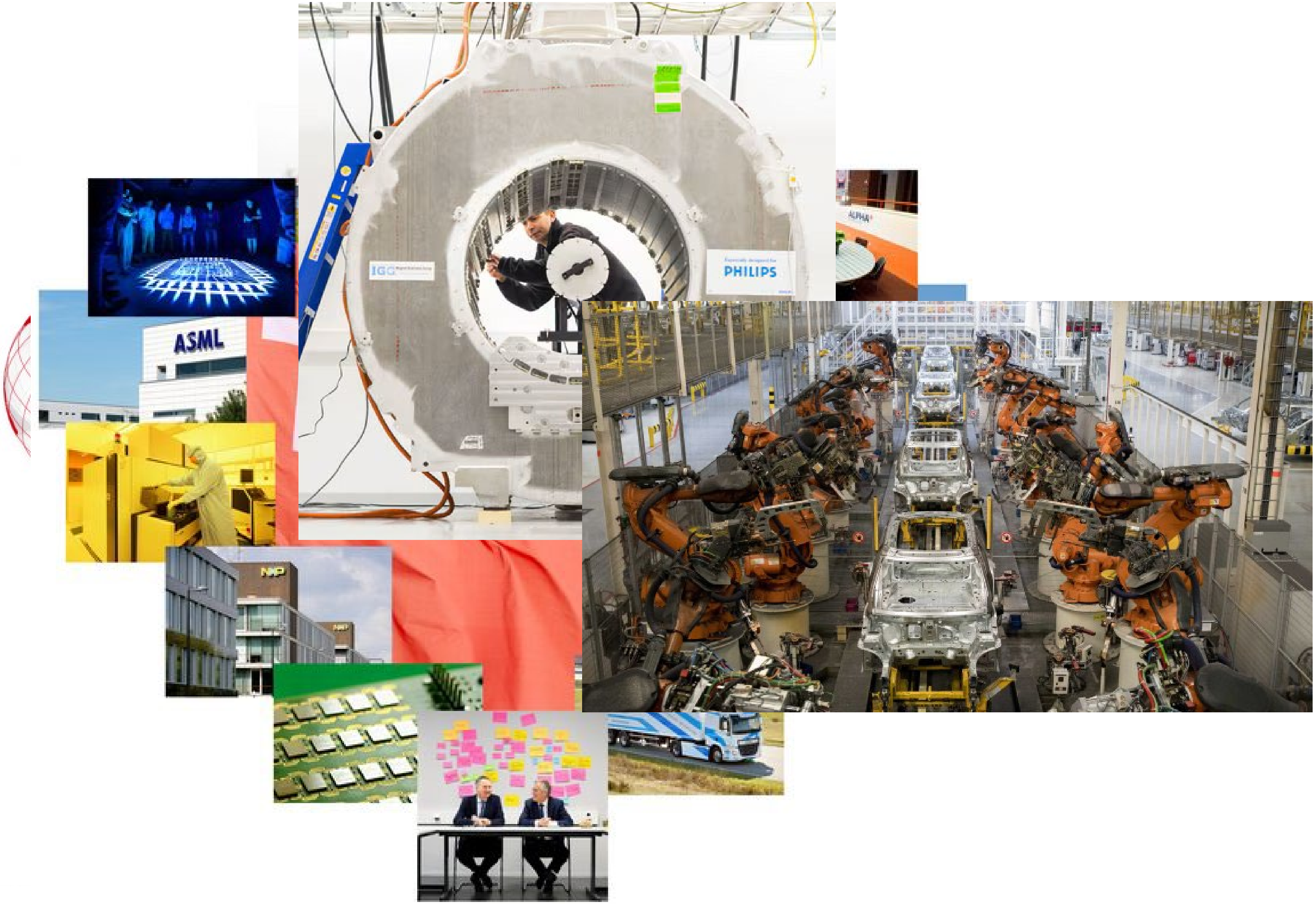

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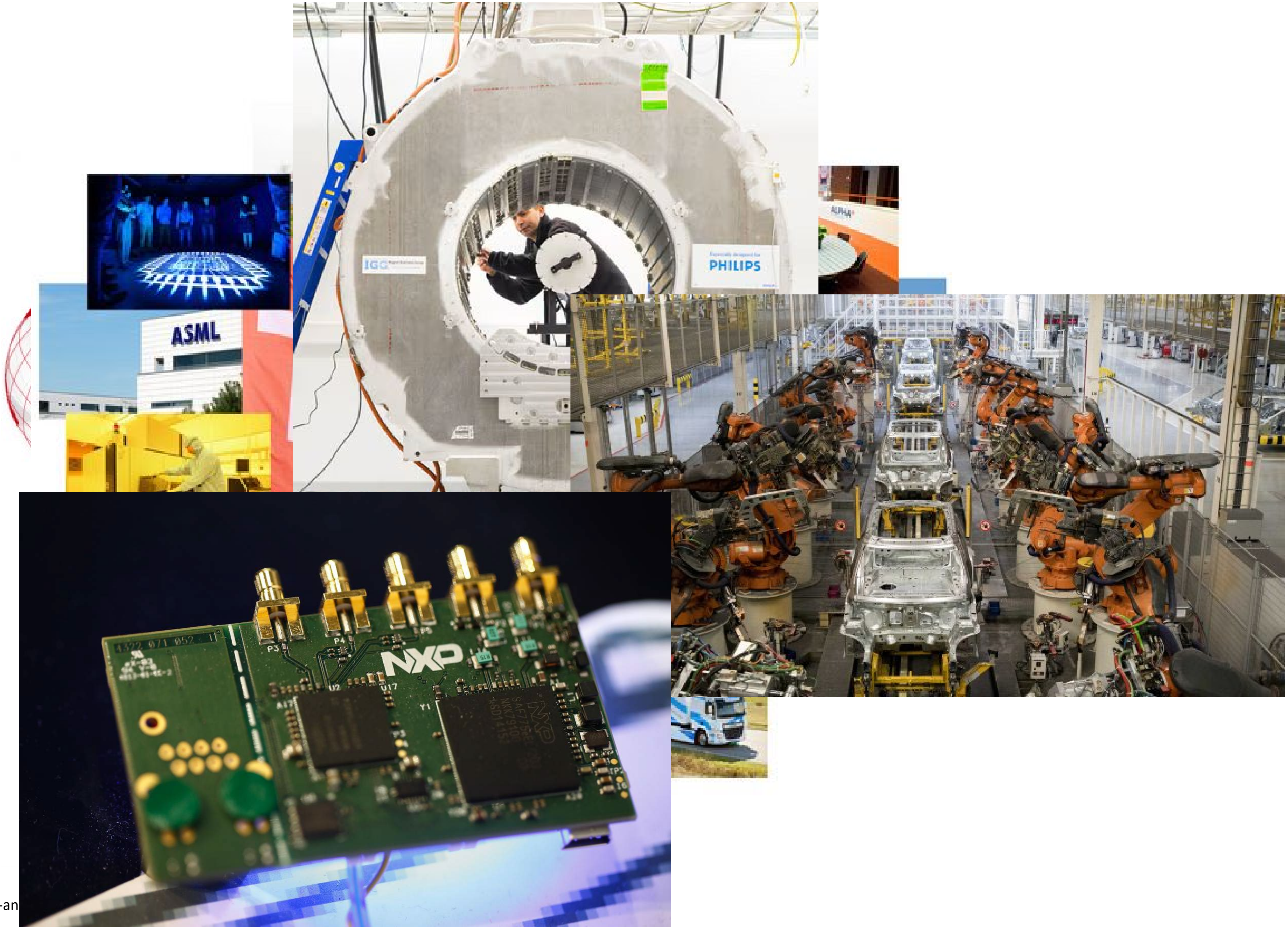

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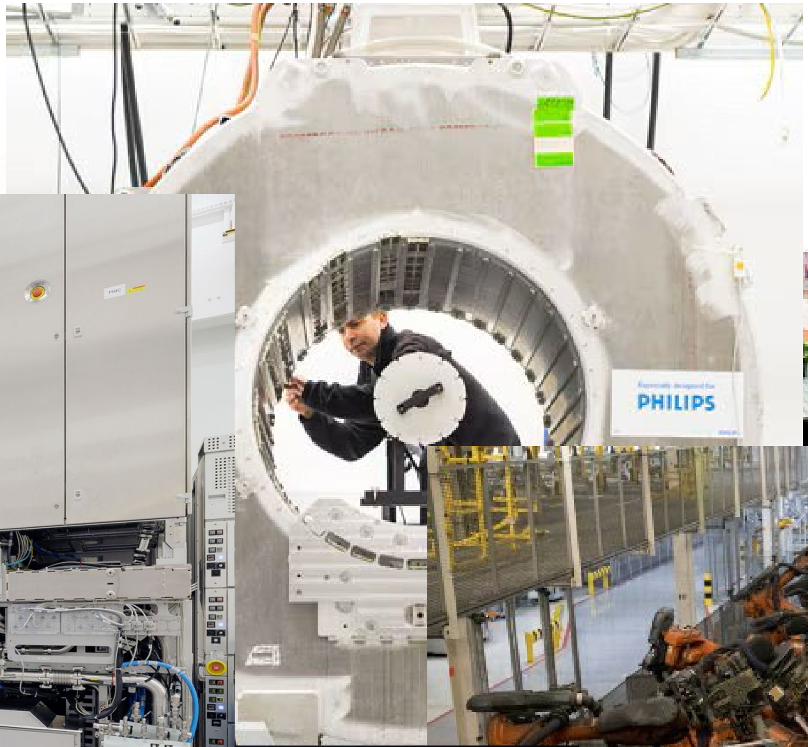

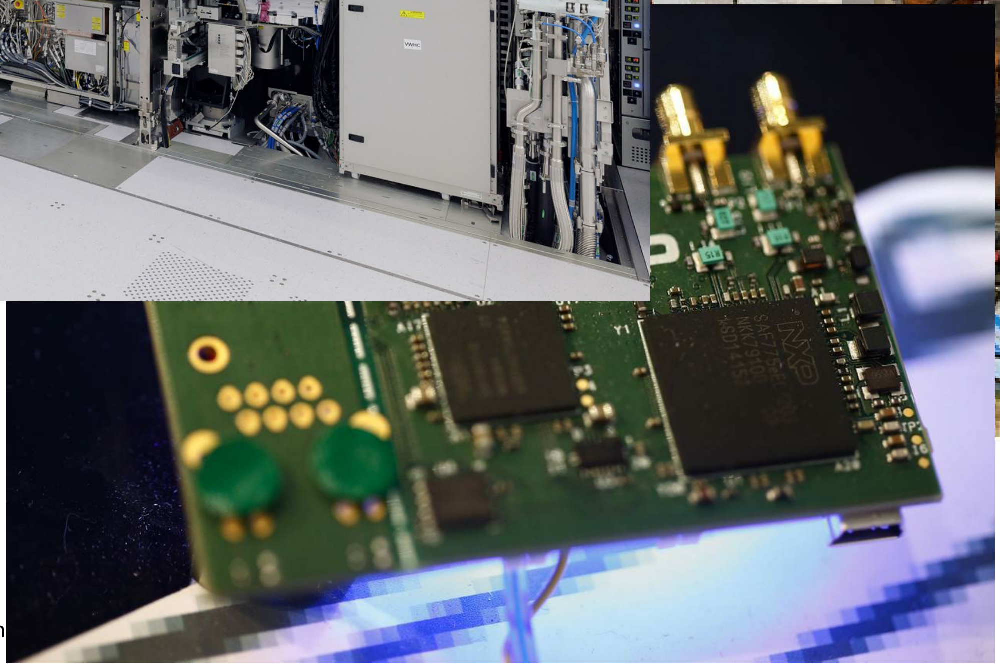

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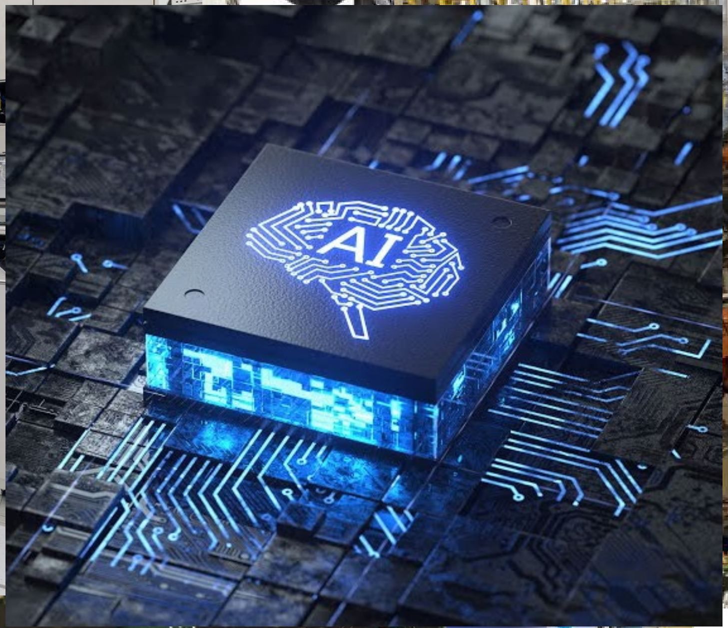

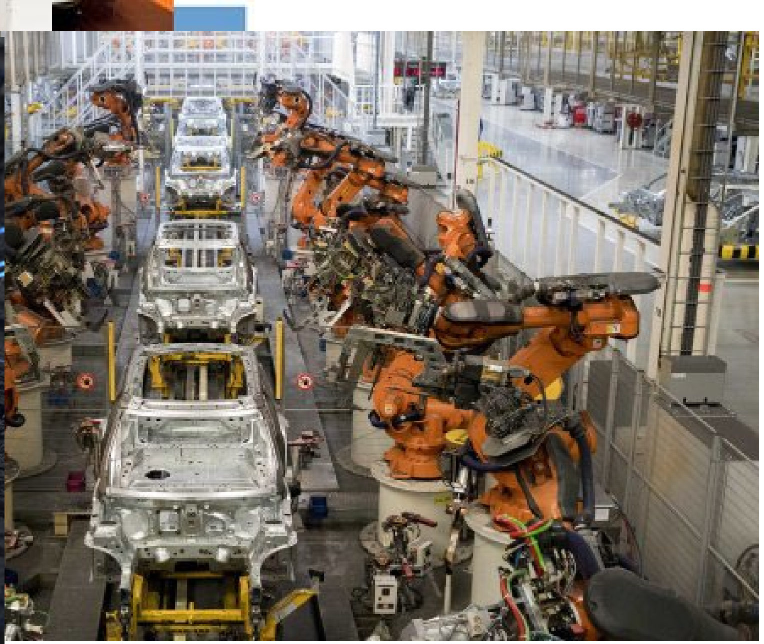
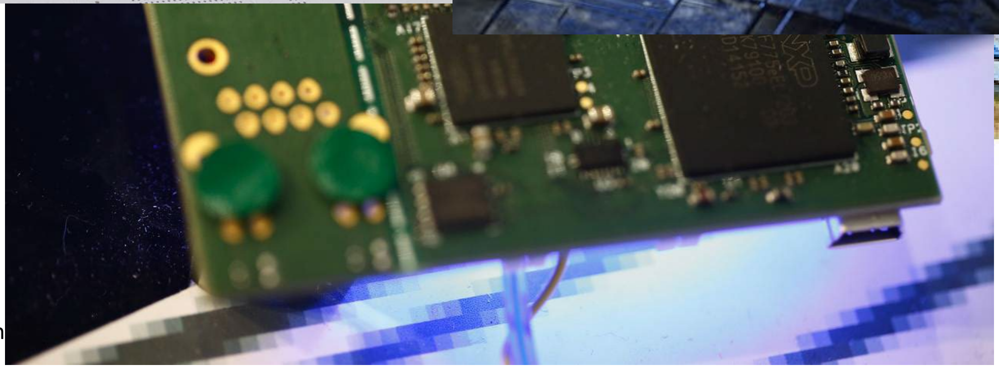


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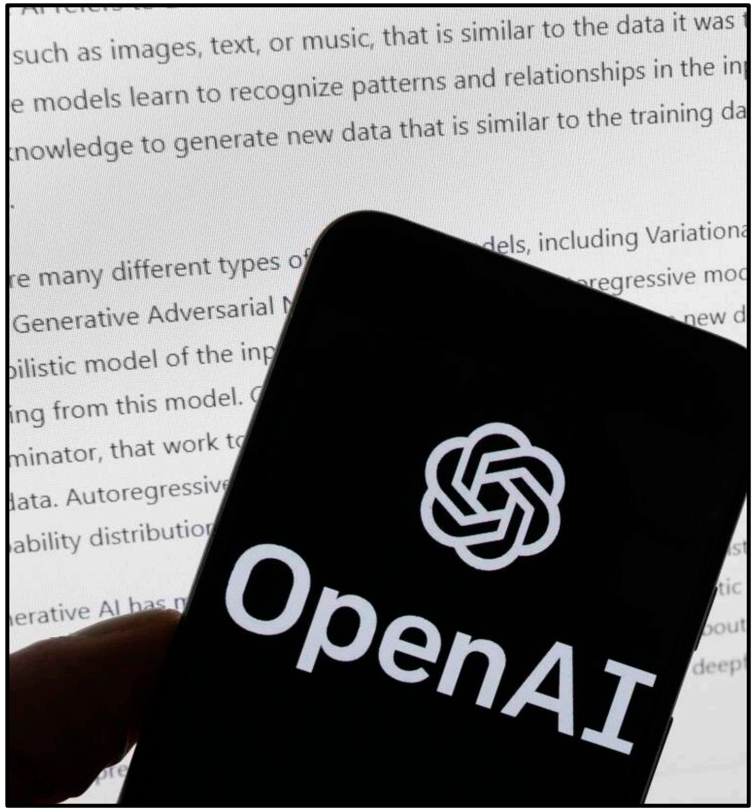
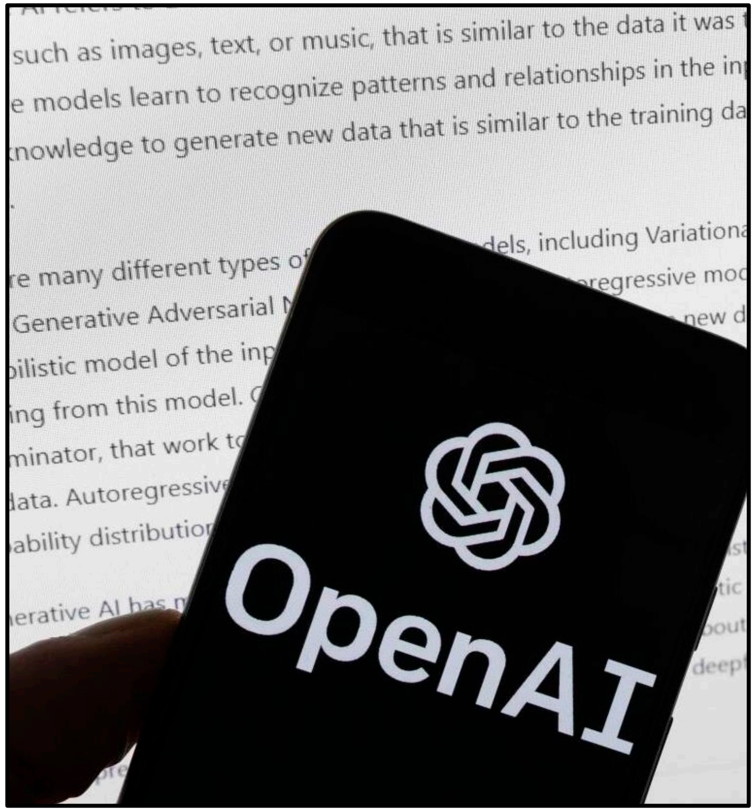
Generative AI



Generate text, code, images → Automate writing, programming, graphic design

Generative AI



no real-time learning

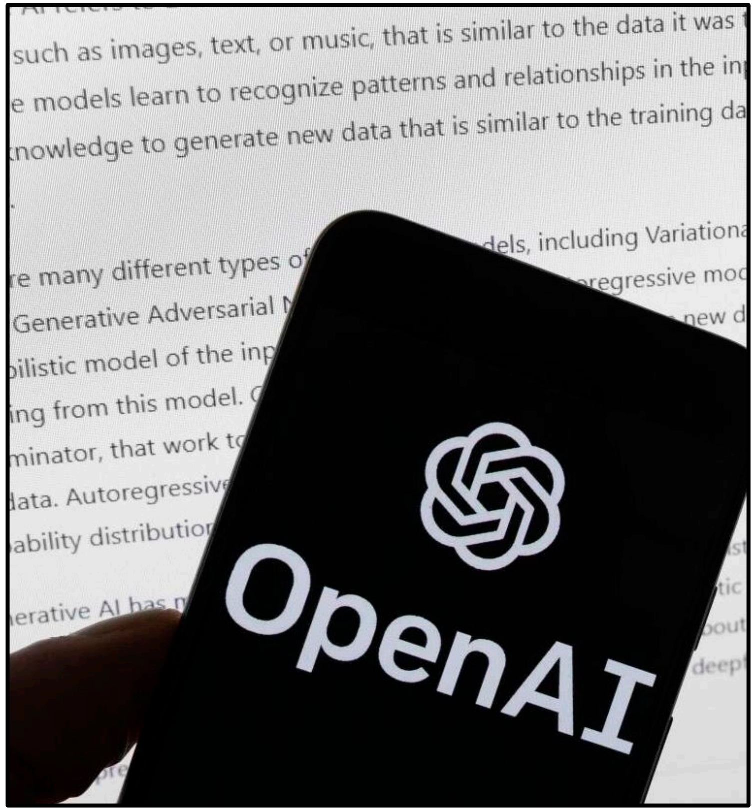
hallucination

resource-hungry

black box

Generate text, code, images → Automate writing, programming, graphic design

Generative AI



Intelligence in nature

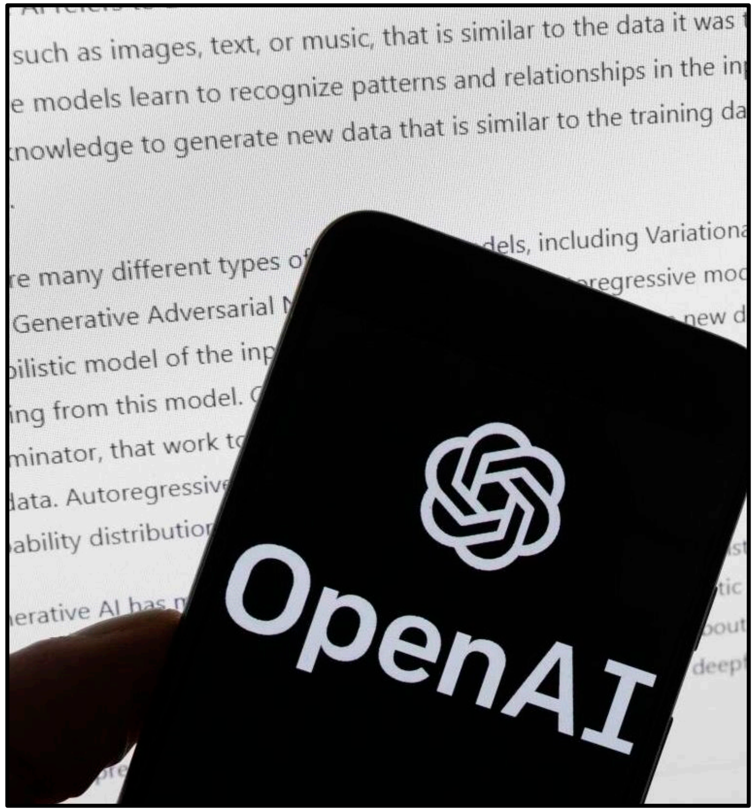
no real-time learning	real-time learning
hallucination	physics-constrained
resource-hungry	0 engineers, 20 watts
black box	explainable

Generate text, code, images → Automate writing, programming, graphic design

Generative AI

Intelligence in Nature

Natural AI



no real-time learning	real-time learning
hallucination	physics-constrained
resource-hungry	0 engineers, 20 watts
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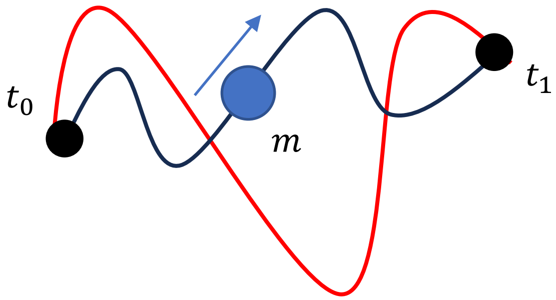
Generate text, code, images → Automate writing, programming, graphic design

Learn Sensor -> Actuator → Autonomous intelligent systems

The Principle of Least Action

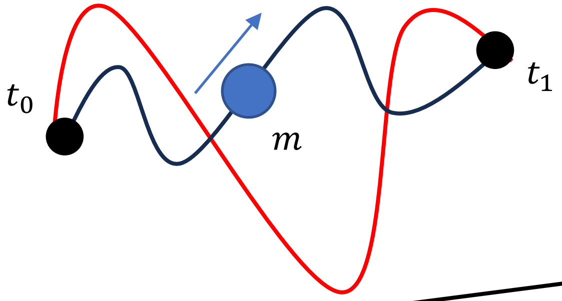
"In nature, energy differences of any kind are neutralized as fast a possible"



$$\boxed{\min \int L(x, \dot{x})\mathrm{d}t}$$

The Principle of Least Action

"In nature, energy differences of any kind are neutralized as fast a possible"

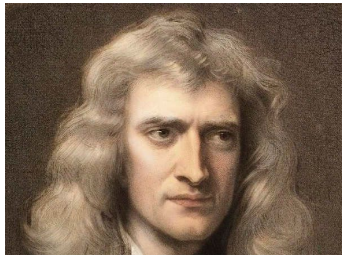


$$\boxed{\min \int L(x, \dot{x}) \mathrm{d}t}$$

Movement of
big things
(classical mechanics)

$$\min \int \big(\overbrace{\frac{1}{2} m \dot{x}^2 - V(x)}^{\text{Lagrangian}}\big) \mathrm{d}t$$

$$\Rightarrow -\frac{\partial V(x)}{\partial x} = m\ddot{x}$$



Isaac Newton

The Principle of Least Action

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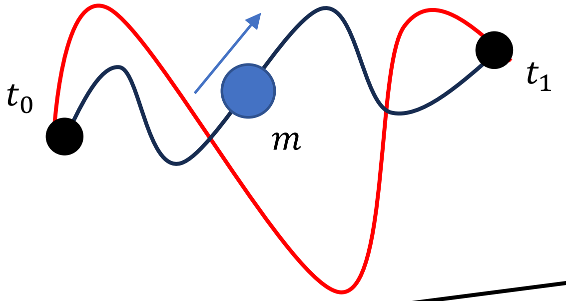

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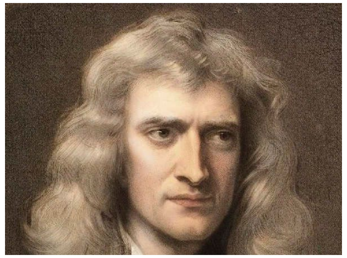
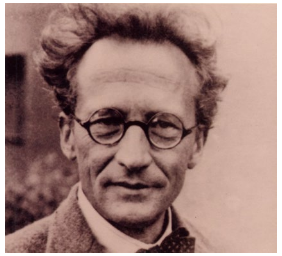


Isaac Newton

Movement of
small things
(quantum mechanics)

$$-\frac{\hbar^2}{2m} \nabla^2 \psi + V \psi = E \psi$$



Erwin Schrodinger

The Principle of Least Action

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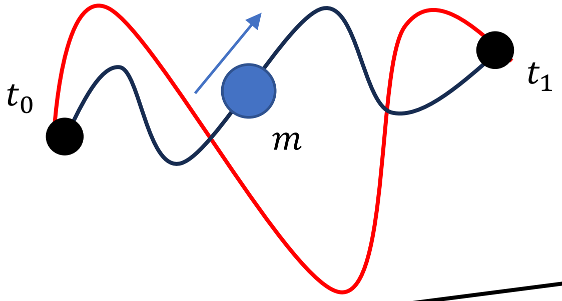

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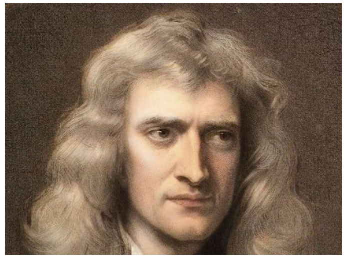

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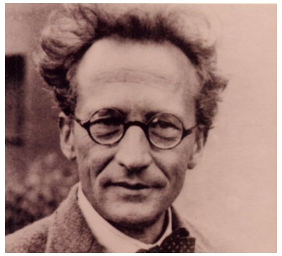

Erwin Schrodinger

Movement of electromagnetic fields (electrodynamics)

$$\mathcal{L} = -\frac{1}{4\mu_0}F_{\mu\nu}F^{\mu\nu} - j^\mu A_\mu$$

James C. Maxwell

The Principle of Least Action

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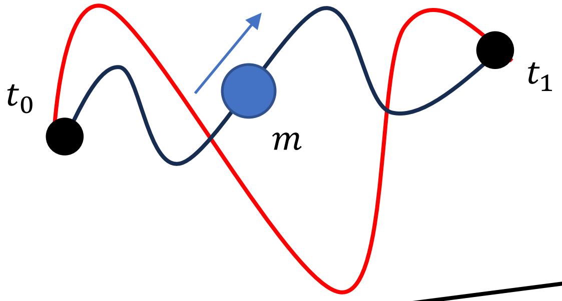

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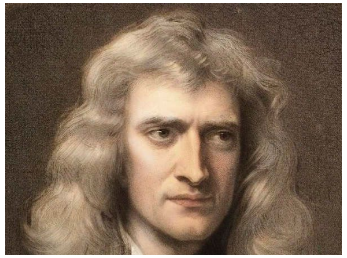

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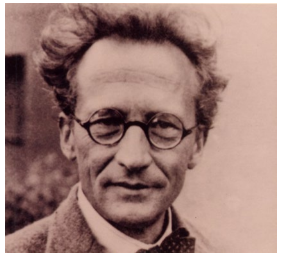


Erwin Schrodinger

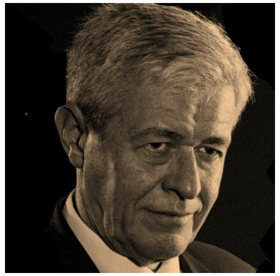
Movement of electromagnetic fields (electrodynamics)

$$\mathcal{L} = -\frac{1}{4\mu_0}F_{\mu\nu}F^{\mu\nu} - j^\mu A_\mu$$

James C. Maxwell

Movement of information in brains (Bayesian mechanics)

$$F[q] = \int q(s)\log\frac{q(s)}{p(x,s)}\mathrm{d}s$$



Karl Friston

Contents lists available at ScienceDirect

Physics Reports

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ELSEVIER

The free energy principle made simpler but not too simple

Karl Friston [a], Lancelot Da Costa [a,b,*], Noor Sajid [a], Conor Heins [c,d,e], Kai Ueltzhöffer [a,f], Grigorios A. Pavliotis [b], Thomas Parr [a]

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[b] *Department of Mathematics, Imperial College London, London, SW7 2AZ, United Kingdom*
[c] *Department of Collective Behaviour, Max Planck Institute of Animal Behaviour, Konstanz D-78457, Germany*
[d] *Centre for the Advanced Study of Collective Behaviour, University of Konstanz, D-78457, Germany*
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Keywords:
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Bayesian
Markov blanket

ABSTRACT

This paper provides a concise description of the free energy principle, starting from a formulation of random dynamical systems in terms of a Langevin equation and ending with a Bayesian mechanics that can be read as a physics of sentience. It rehearses the key steps using standard results from statistical physics. These steps entail (i) establishing a particular partition of states based upon conditional independencies that inherit from sparsely coupled dynamics, (ii) unpacking the implications of this partition in terms of Bayesian inference and (iii) describing the paths of particular states with a variational principle of least action. Teleologically, the free energy principle offers a normative account of self-organisation in terms of optimal Bayesian design and decision-making, in the sense of maximising marginal likelihood or Bayesian model evidence. In summary, starting from a description of the world in terms of random dynamical systems, we end up with a description of self-organisation as sentient behaviour that can be interpreted as self-evidencing; namely, self-assembly, autopoiesis or active inference.

Contents lists available at ScienceDirect

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PHYSICS REPORTS

The free energy

Karl Friston [a], Lance
Kai Ueltzhöffer [a,f], G

[a] Wellcome Centre for Human N
[b] Department of Mathematics, I
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Int. J. Systems Sci., 1970, vol. 1, No. 2, 89-97

EVERY GOOD REGULATOR OF A SYSTEM MUST BE A MODEL OF THAT SYSTEM[1]

Roger C. Conant

Department of Information Engineering, University of Illinois, Box 4348, Chicago, Illinois, 60680, U.S.A.

and W. Ross Ashby

Biological Computers Laboratory, University of Illinois, Urbana, Illinois 61801, U.S.A.[2]

[Received 3 June 1970]

The design of a complex regulator often includes the making of a model of the system to be regulated. The making of such a model has hitherto been regarded as optional, as merely one of many possible ways.

m this paper a theorem is presented which shows, under very broad conditions, that any regulator that is maximally both successful and simple *must* be isomorphic with the system being regulated. (The exact assumptions are given.) Making a model is thus necessary.

The theorem has the interesting corollary that the living brain, so far as it is to be successful and efficient as a regulator for survival, *must* proceed, in learning, by the formation of a model (or models) of its environment.

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Axiomatic Derivation of the Principle of Maximum Entropy and the Principle of Minimum Cross-Entropy

JOHN E. SHORE, MEMBER, IEEE, AND RODNEY W. JOHNSON

Abstract—Jaynes's principle of maximum entropy and Kullback's principle of minimum cross-entropy (minimum directed divergence) are shown to be uniquely correct methods for inductive inference when new information is given in the form of expected values. Previous justifications use intuitive arguments and rely on the properties of entropy and cross-entropy as information measures. The approach here assumes that reasonable methods of inductive inference should lead to consistent results when there are different ways of taking the same information into account (for example, in different coordinate systems). This requirement is formalized as four consistency axioms. These are stated in terms of an abstract information operator and make no reference to information measures. It is proved that the principle of maximum entropy is correct in the following sense: maximizing any function but entropy will lead to inconsistency unless that function and entropy have identical maxima. In other words, given information in the form of constraints on expected values, there is only one distribution satisfying the constraints that can be chosen by a procedure that satisfies the consistency axioms; this unique distribution can be obtained by maximizing entropy. This result is established both directly and as a special case (uniform priors) of an analogous result for the principle of minimum cross-entropy. Results are obtained both for continuous probability densities and for discrete distributions.

The principle of maximum entropy states that, of all the distributions q that satisfy the constraints, you should choose the one with the largest entropy $-\sum_i q(x_i)\log(q(x_i))$. Entropy maximization was first proposed as a general inference procedure by Jaynes [1], although it has historical roots in physics (e.g., Elasser [67]). It has been applied successfully in a remarkable variety of fields, including statistical mechanics and thermodynamics [1]–[8], statistics [9]–[11, ch. 6], reliability estimation [11, ch. 10], [12], traffic networks [13], queuing theory and computer system modeling [14], [15], system simulation [16], production line decisionmaking [17], [18], computer memory reference patterns [19], system modularity [20], group behavior [21], stock market analysis [22], and general probabilistic problem solving [11], [17], [23]–[25]. There is much current interest in maximum entropy spectral analysis [26]–[29].

The principle of minimum cross-entropy is a generaliza-

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Int. J. Systems Sci., 19

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The principle of minimum cross-entropy is a generaliza

Article | Open Access | Published: 07 August 2023

Experimental validation of the free-energy principle with in vitro neural networks

Takuya Isomura, Kiyoshi Kotani, Yasuhiko Jimbo & Karl J. Friston

Nature Communications **14**, Article number: 4547 (2023) | Cite this article

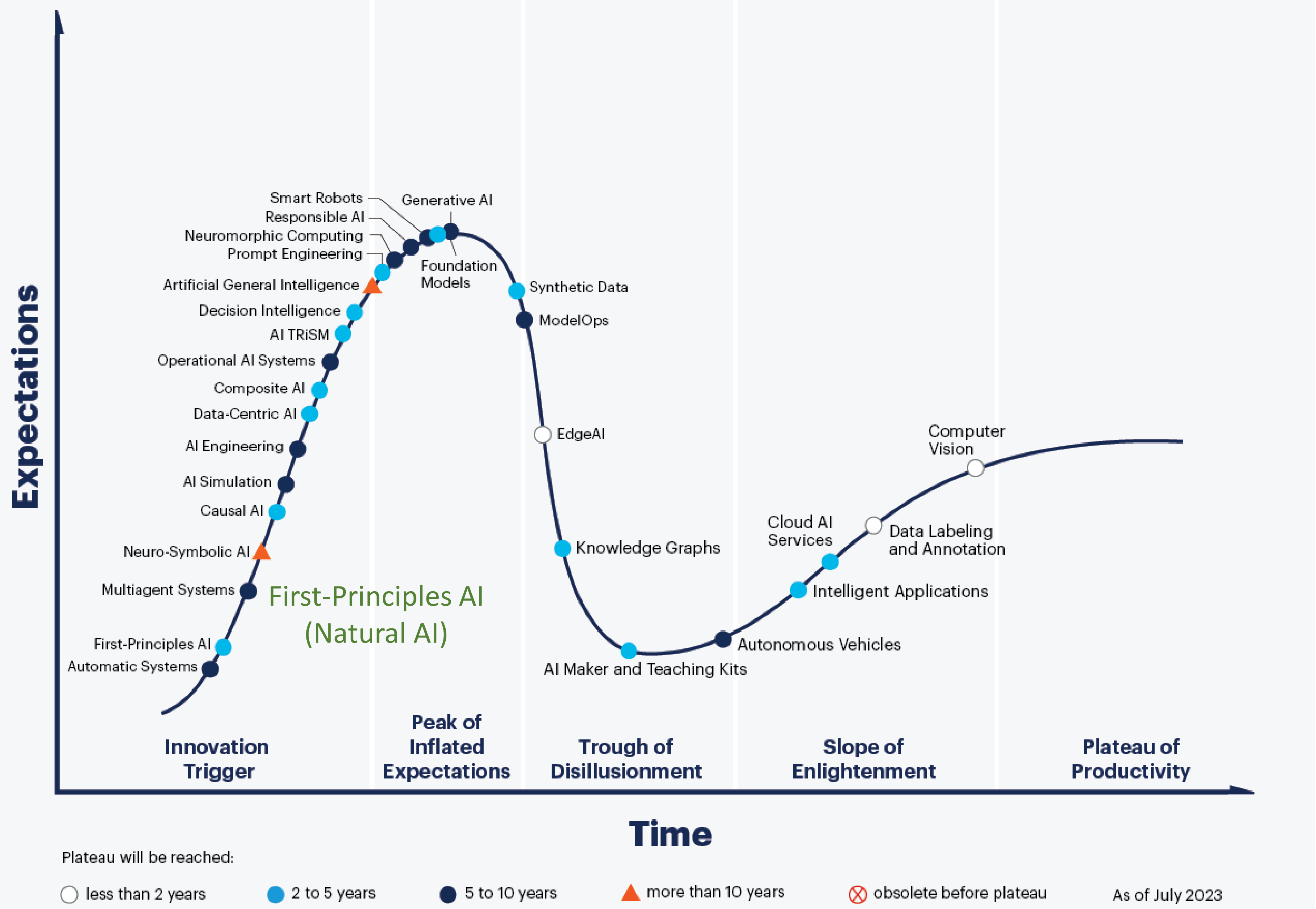
12k Accesses | **302** Altmetric | Metrics

Abstract

Empirical applications of the free-energy principle are not straightforward because they entail a commitment to a particular process theory, especially at the cellular and synaptic levels. Using a recently established reverse engineering technique, we confirm the quantitative predictions of the free-energy principle using in vitro networks of rat cortical neurons

Hype Cycle for Artificial Intelligence, 2023

Source: gartner.com, 17-aug 2023



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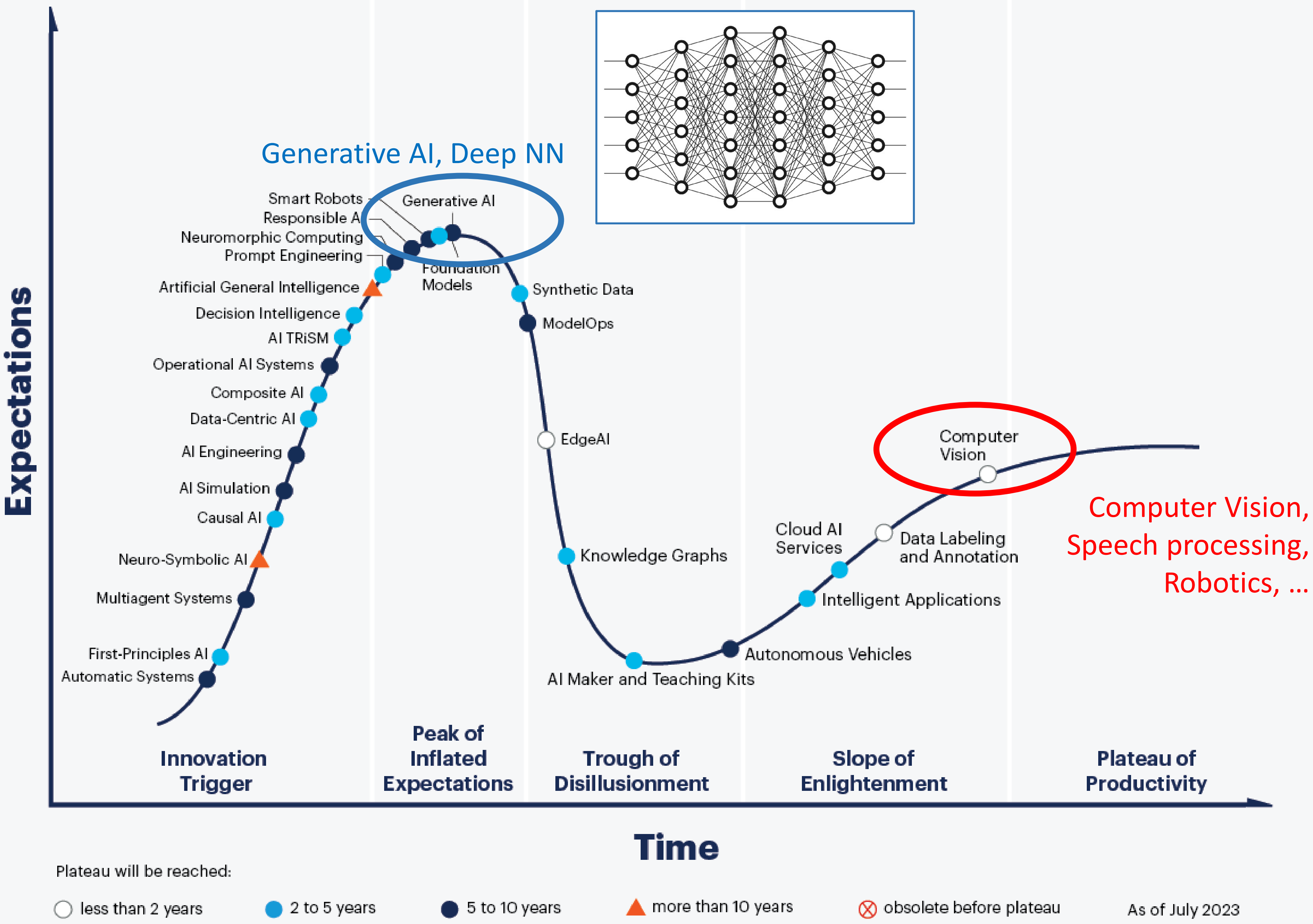

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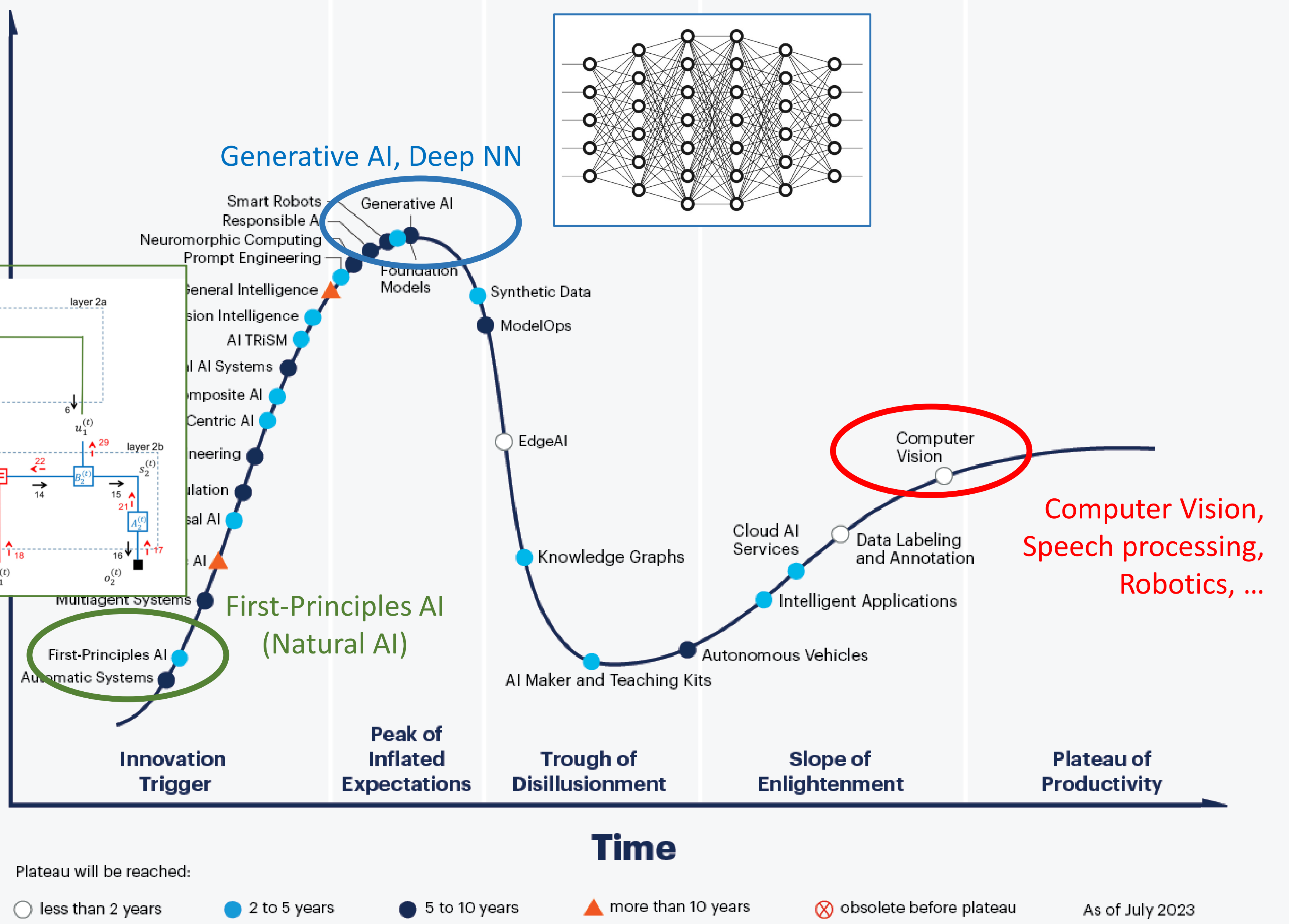
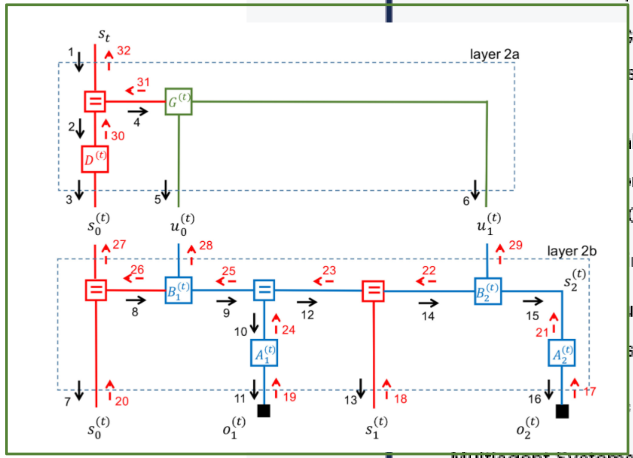
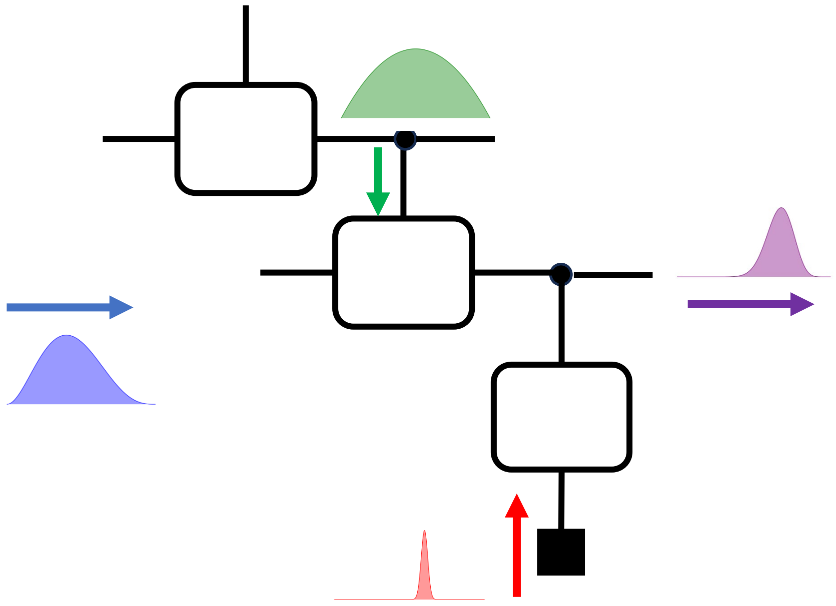
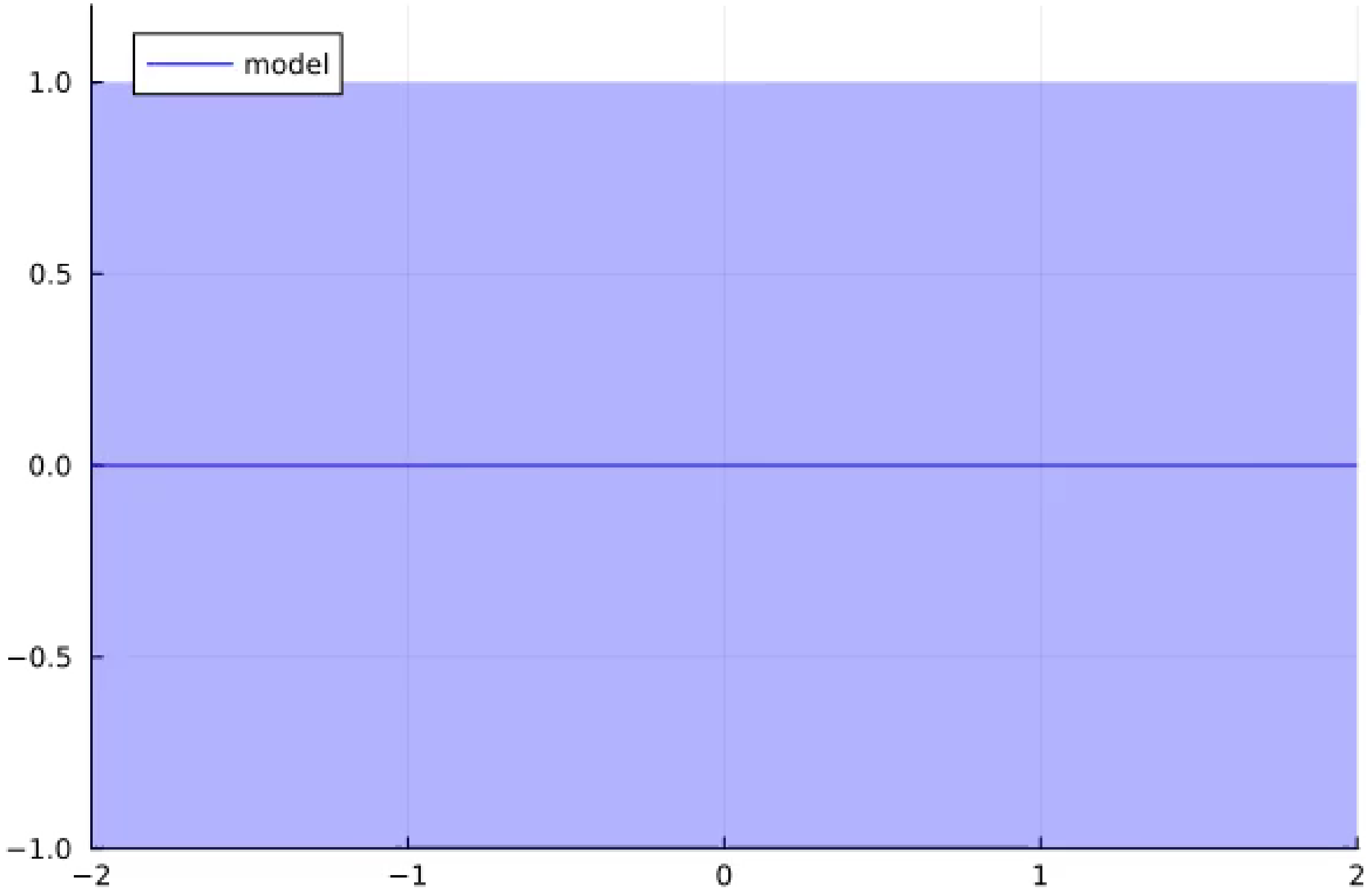




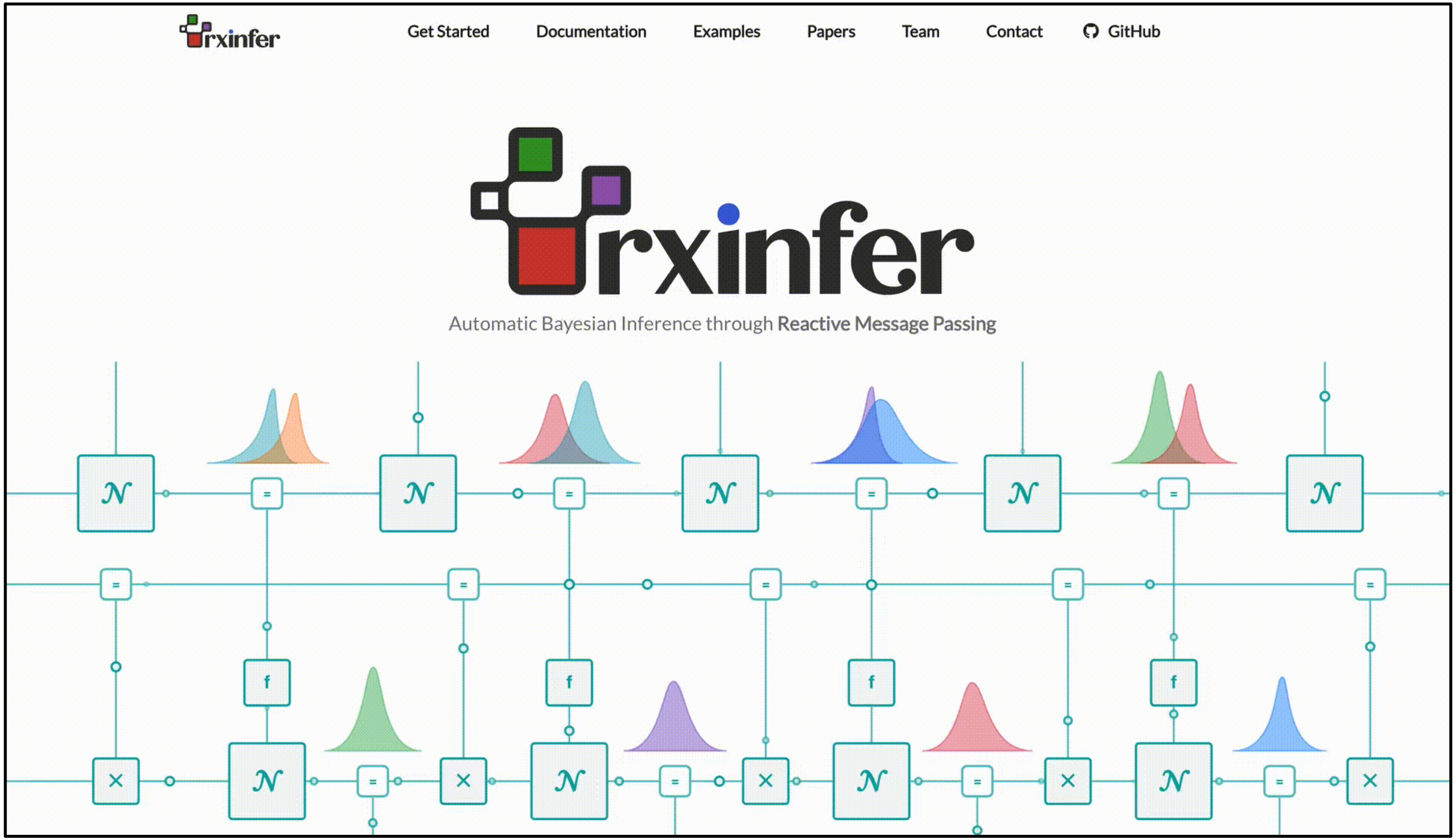
Learning under free energy principle





BIASlab

Software Toolbox for Scalable, Real-time, Automated Free Energy Minimization



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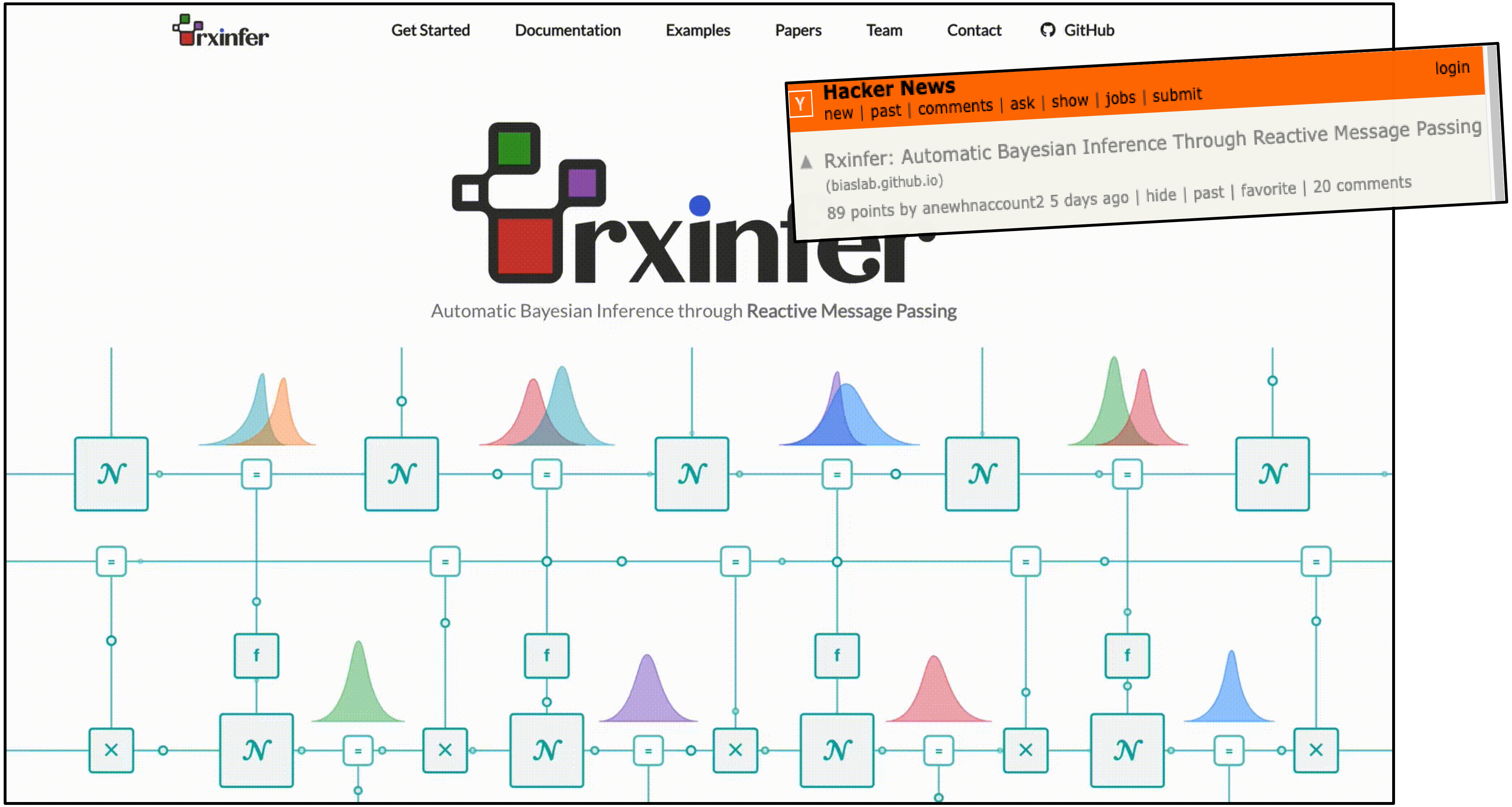
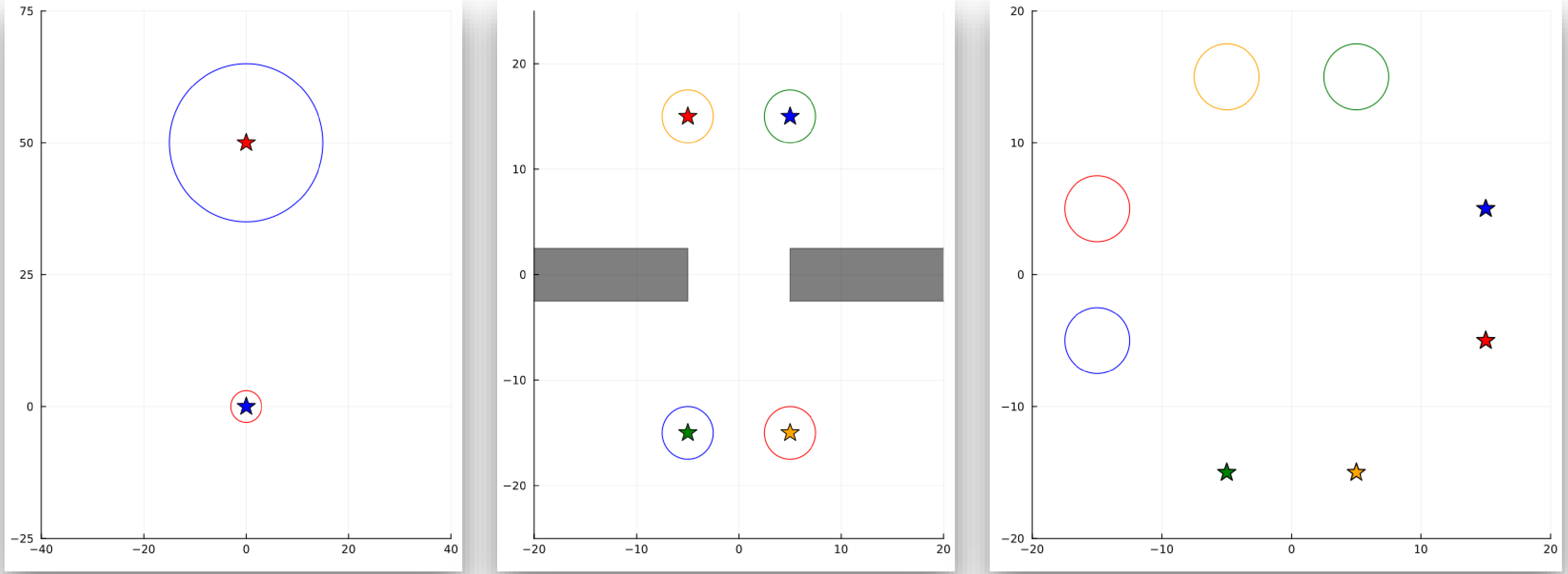


BIASlab

rxinfer

Smart Navigation and Collision Avoidance

LAZY DYNAMICS



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Smart Navigation and Collision Avoidance

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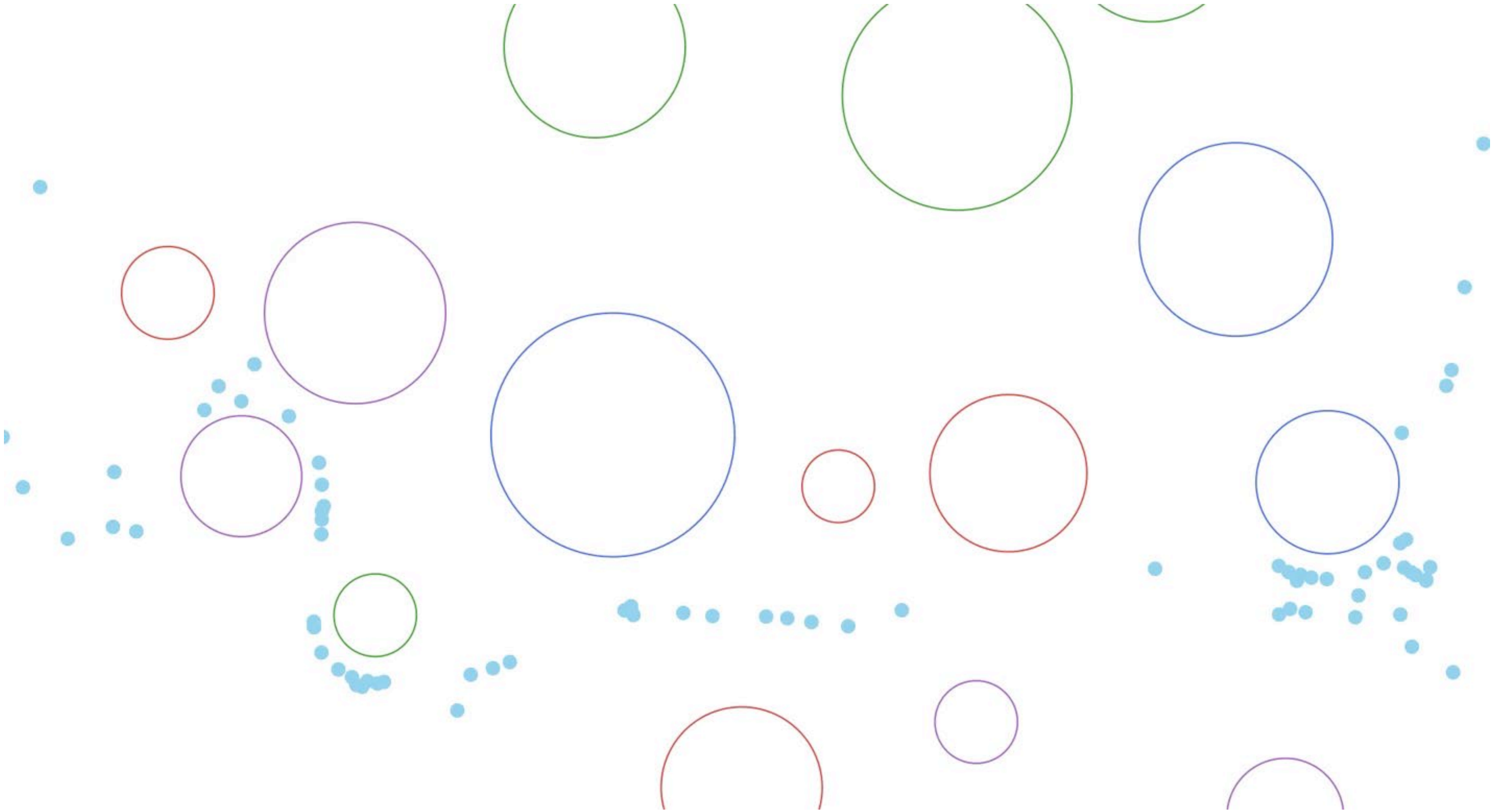
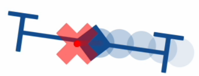


BIASlab

rxinfer

Drone flight control

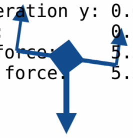
LAZY DYNAMICS



Drone's mass		5.0
Drone's size		0.1
Engine power		20.0m/s²
Gravity		9.8m/s²
Sensor noise		1.13e-08
Tasks frequency		40

Debug view

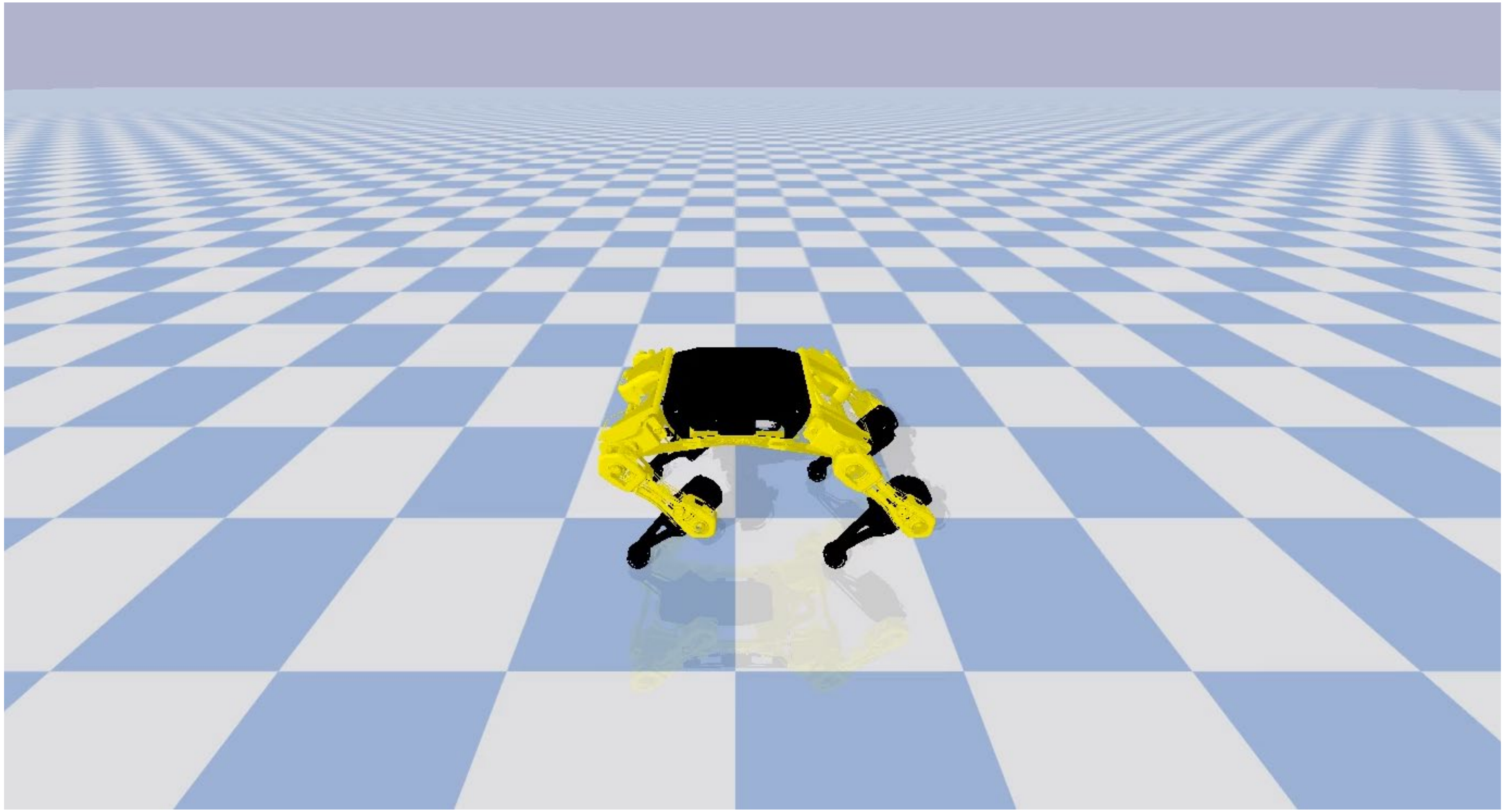
```
Coordinate x:   -0.2749
Coordinate y:   0.0424
Acceleration x: -0.1666
Acceleration y: 0.0017
Angle:          0.1426
Left force:     5.5952
Right force:    5.5952
```



BIASlab

rxinfer

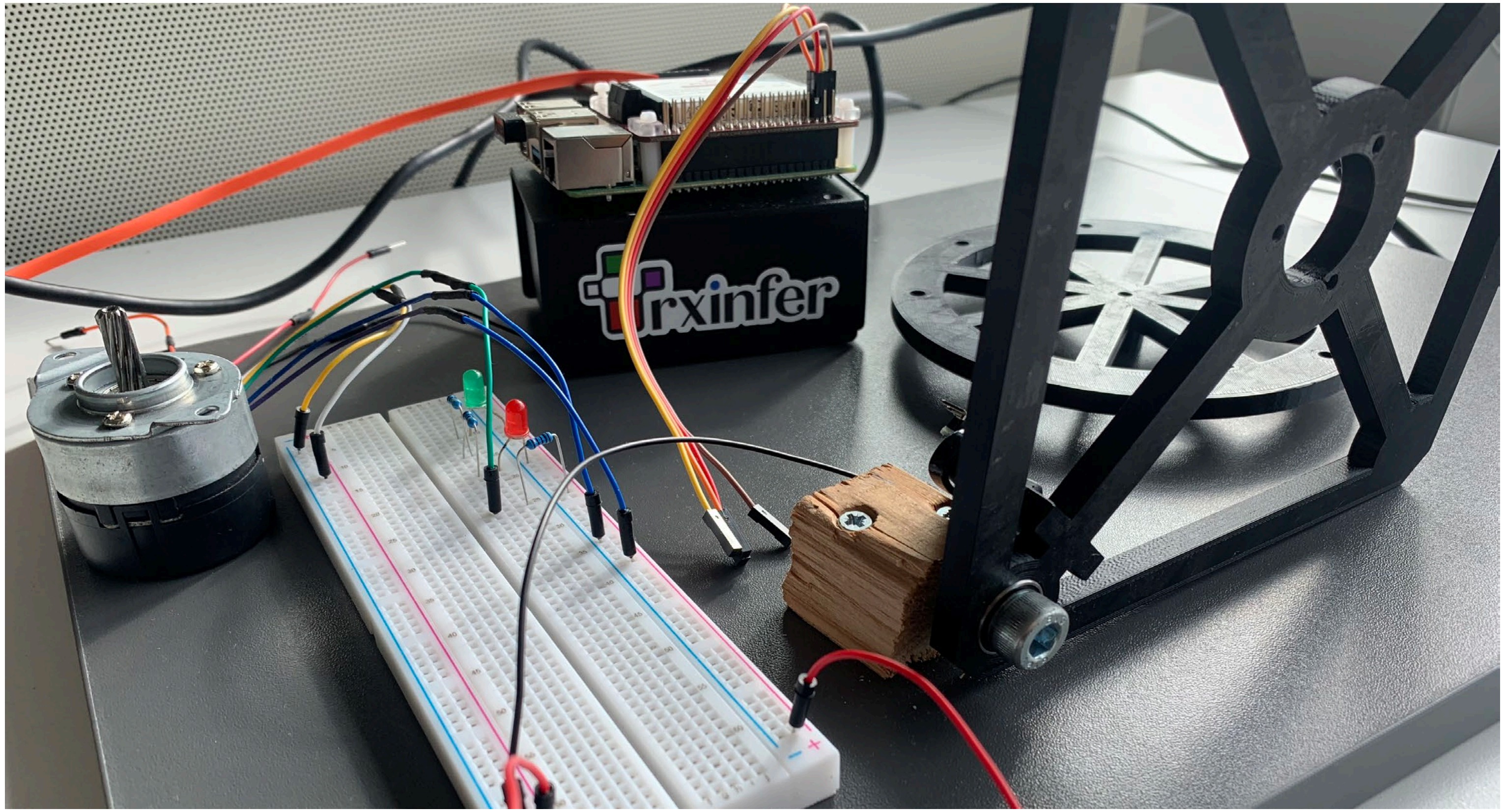
Robots that learn to walk



BIASlab

rxinfer
Hardware

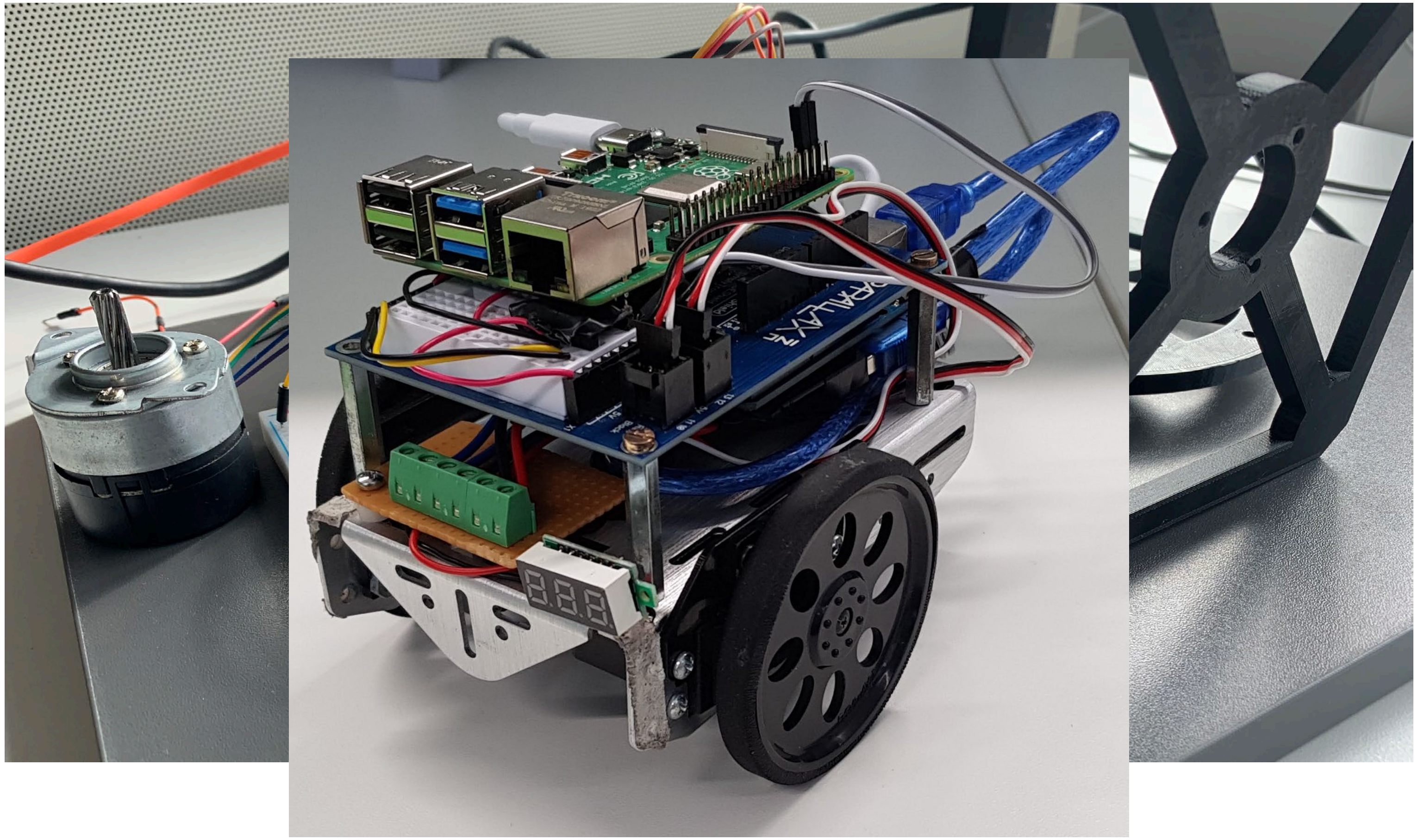
LAZY DYNAMICS



BIASlab

rxinfer Hardware

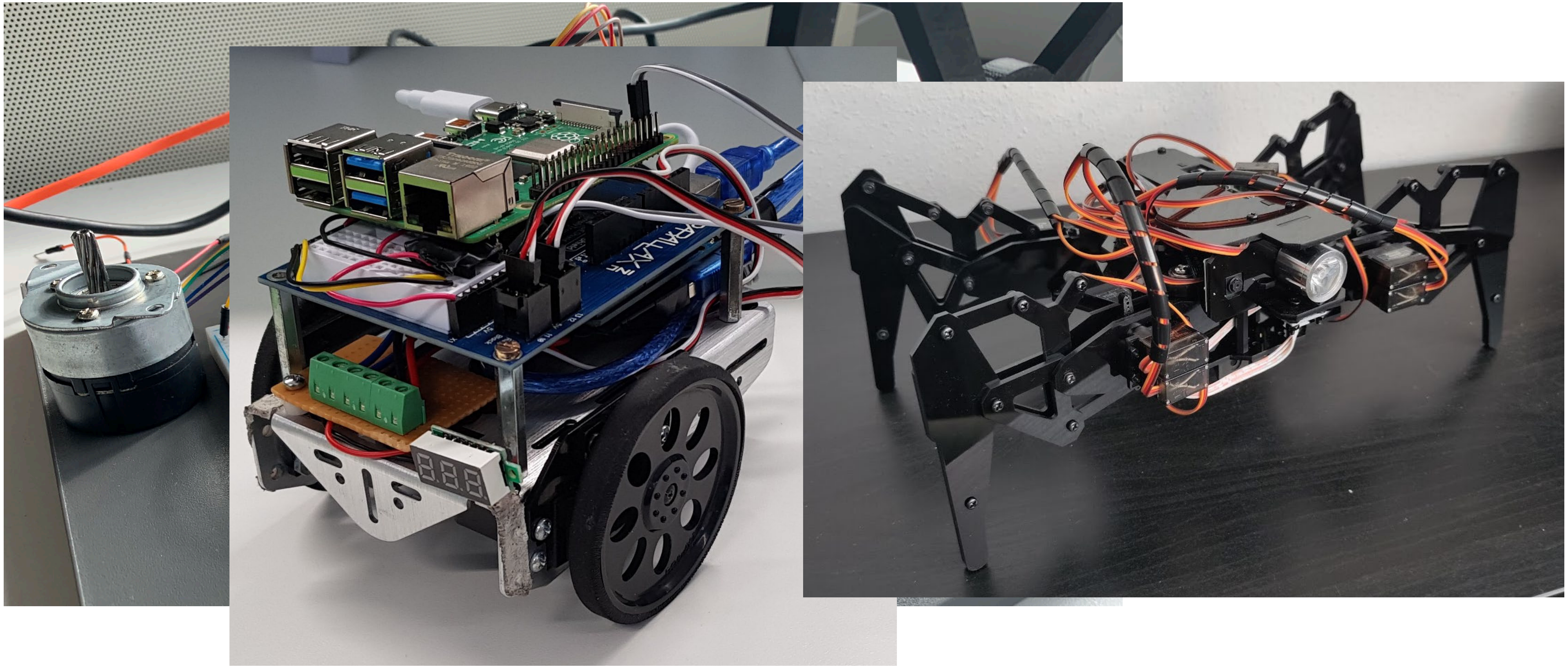
LAZY DYNAMICS



BIASlab

rxinfer
Hardware

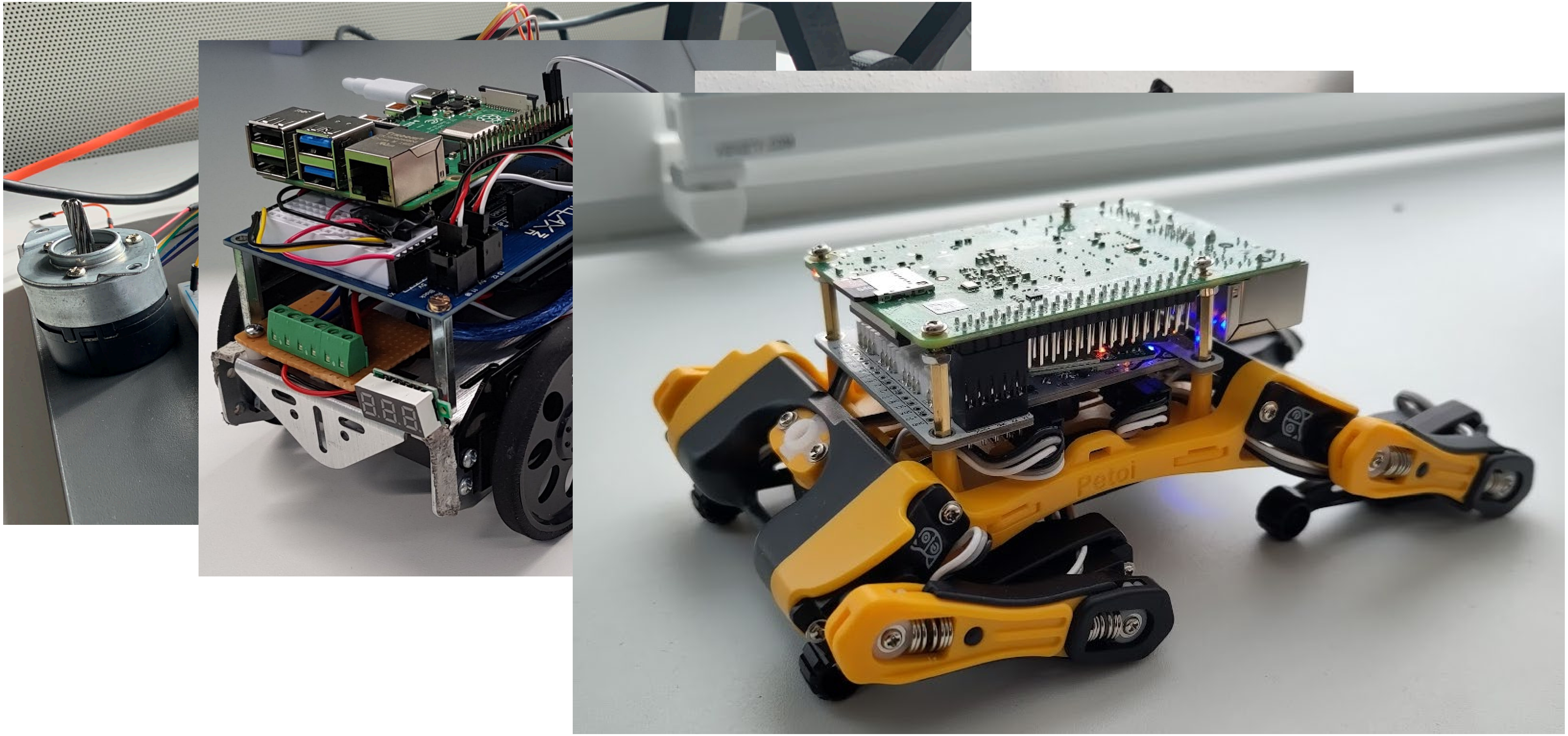
LAZY DYNAMICS



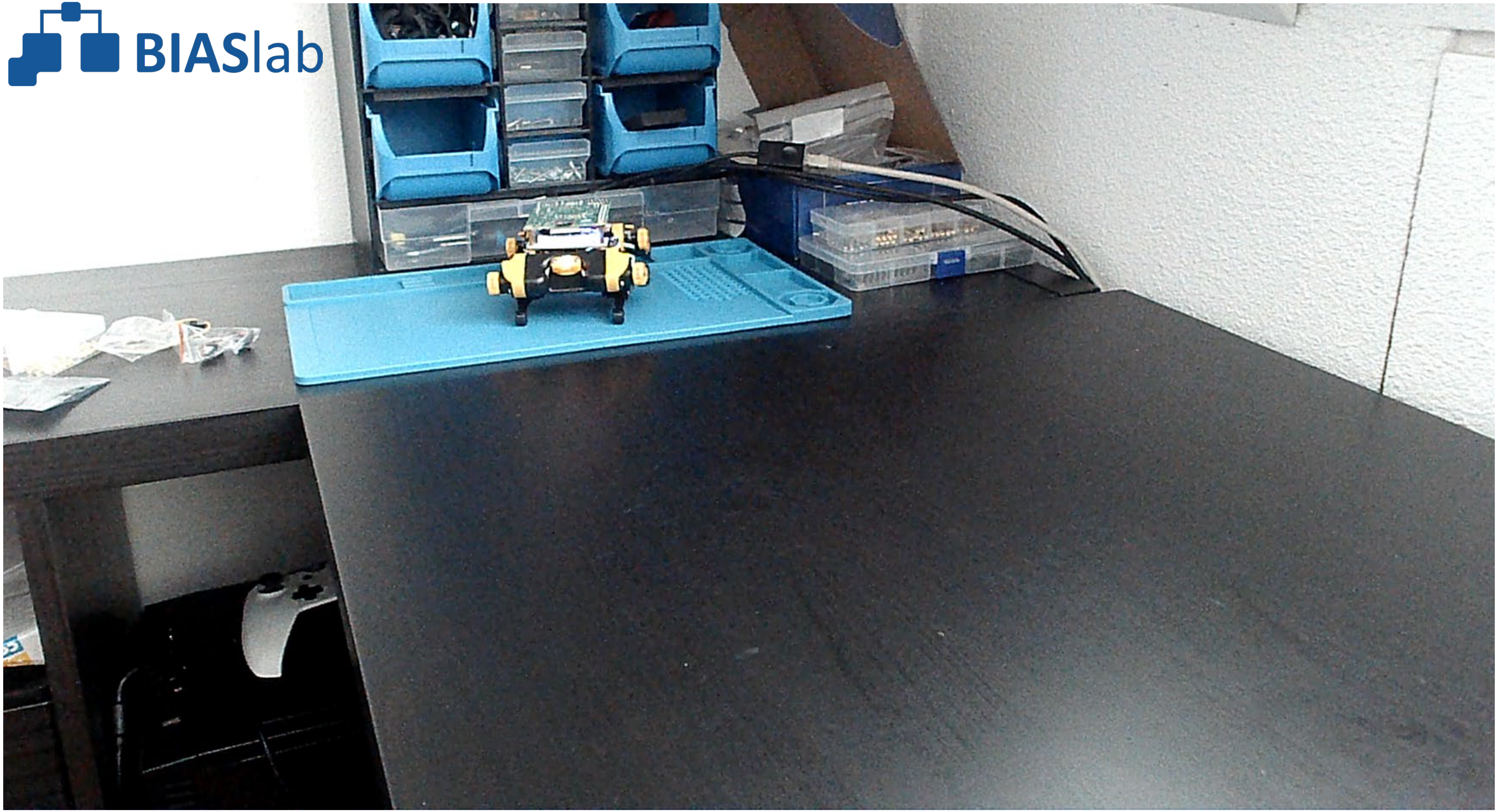
BIASlab

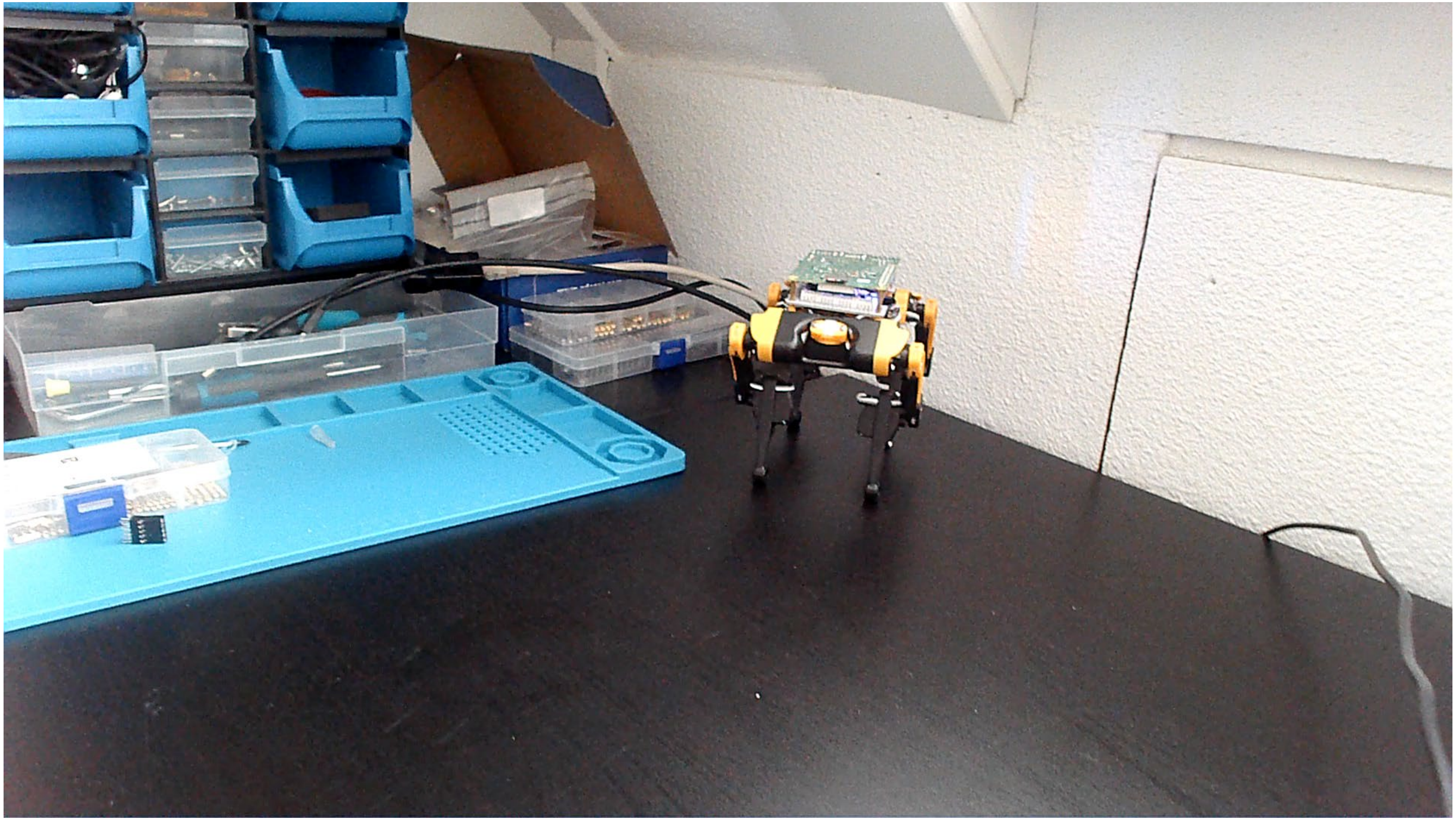
rxinfer
Hardware

LAZY DYNAMICS



BIASlab





Bayesian Intelligent Autonomous Systems lab

EINDHOVEN UNIVERSITY OF TECHNOLOGY

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https://biaslab.github.io/

https://rxinfer.ml

https://lazydynamics.com/