

Mind everywhere, AI of Things, and the future of engineering

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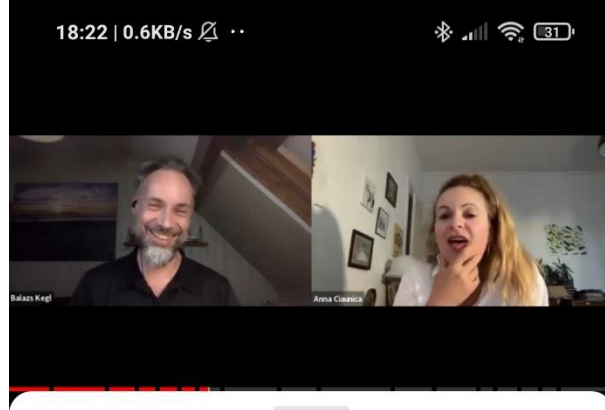
Part I

AI in engineering systems

AI Embodiment Through 6G: Shaping the Future of AGI

Lina Bariah and Mérouane Debbah

- Additionally, the paper examines **the limitations of current AI models**, particularly Large Language Models (LLMs), in achieving true AGI.
- It argues that while LLMs have made significant strides in natural language understanding, they still **lack the depth of knowledge representation and reasoning** required for AGI.
- The authors suggest that **sensory grounding in the real world is necessary** but not sufficient for LLMs to achieve robust understanding.
- They propose that a blend of technologies, including **generative language models, internet-of-senses, reinforcement learning, and edge intelligence**, integrated harmoniously via 6G networks, will be pivotal in realizing the vision of AGI.



Description



#7 Anna Ciaunica: embodied cognition and depersonalization

8

Likes

139

Views

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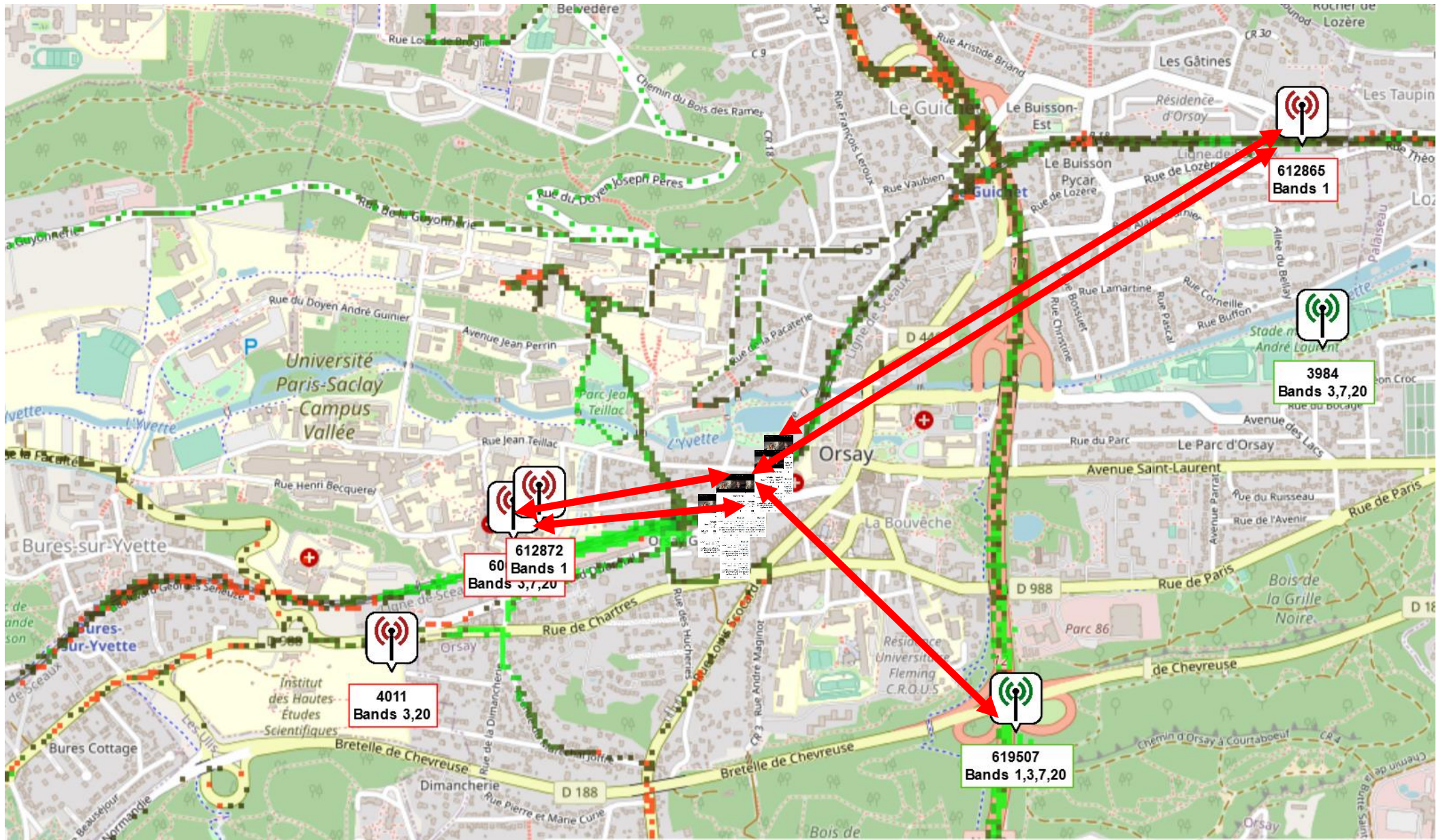
2023

I, Scientist

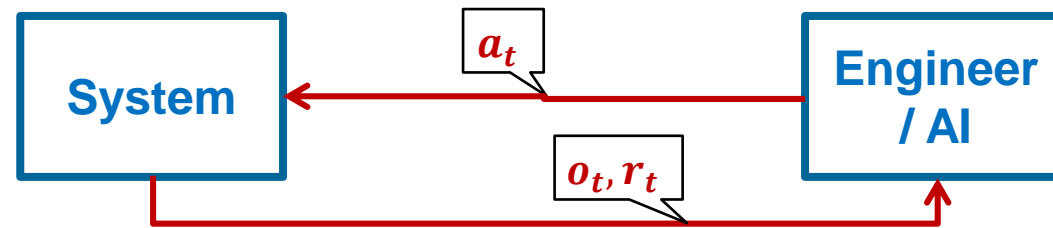
[00:00:00](#) Intro: empirical vs armchair philosopher. Visual vs tactile understanding.

[00:06:08](#) How subjective experience rises from physical matter. Entering wine into your body vs seeing a





A typical engineering control system



Engineer or AI observes
system states and **performance indicators**,
tunes some parameters time to time,
to **optimize the performance indicators**

Engineering systems = ~\$10s of trillions per year



Our use cases

■ Self-driving engineering systems

- › Wireless parameter tuning
- › Wi-Fi parameter tuning
- › Data center cooling
- › Energy, smart cities, etc.

■ Making them

- › Safer, better, more reliable, more energy efficient

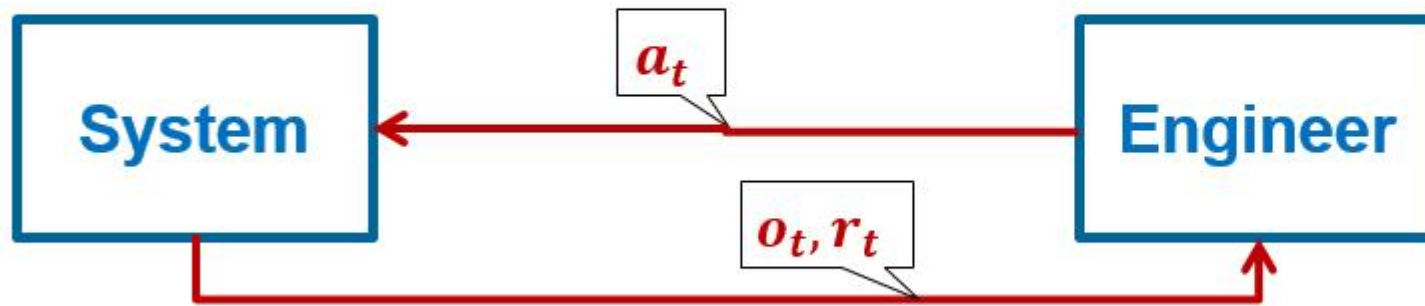
■ These are only the **tip of the iceberg**



What is AI (in this context)?

Learn the system behavior
based on **historical data**
and use it for better control

Controlled engineering system: organizational constraints

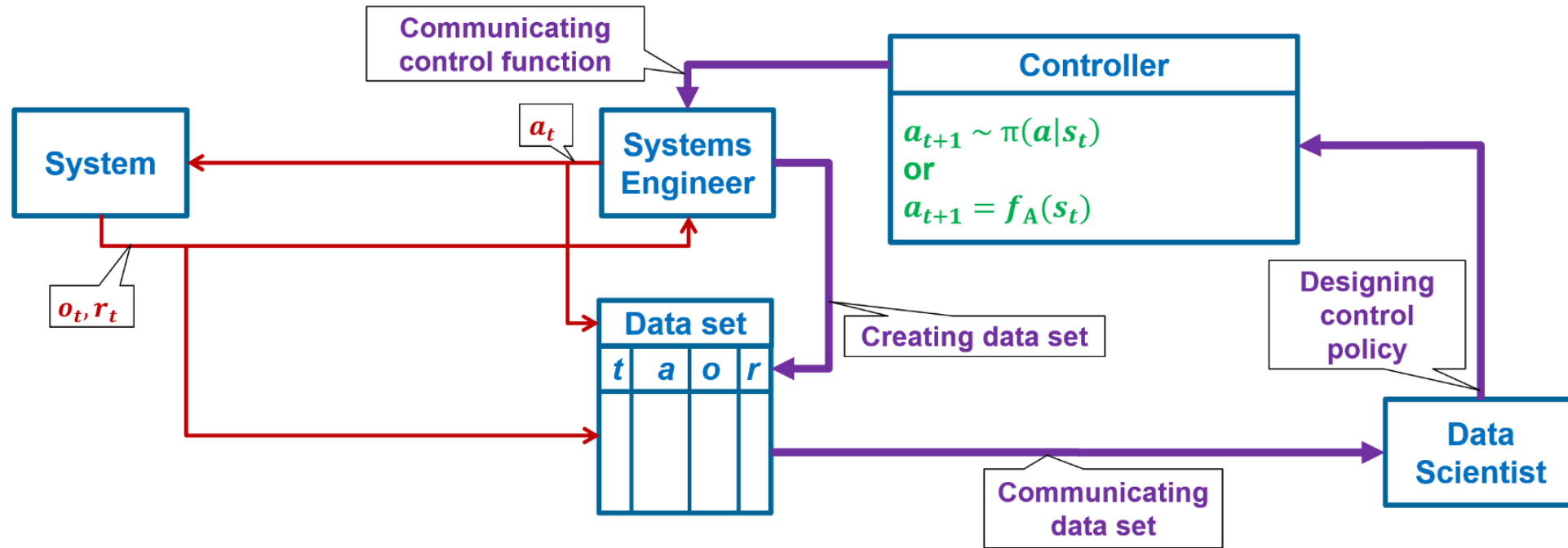


- **Offline (batch):** system traces (logs)
- **Micro-data:** physical systems, slow white-box simulators
- **Safety:** we cannot "lose" while learning
- **Multi-agent:** multiple interdependent copies of the same system

Part II

Single-agent intelligence

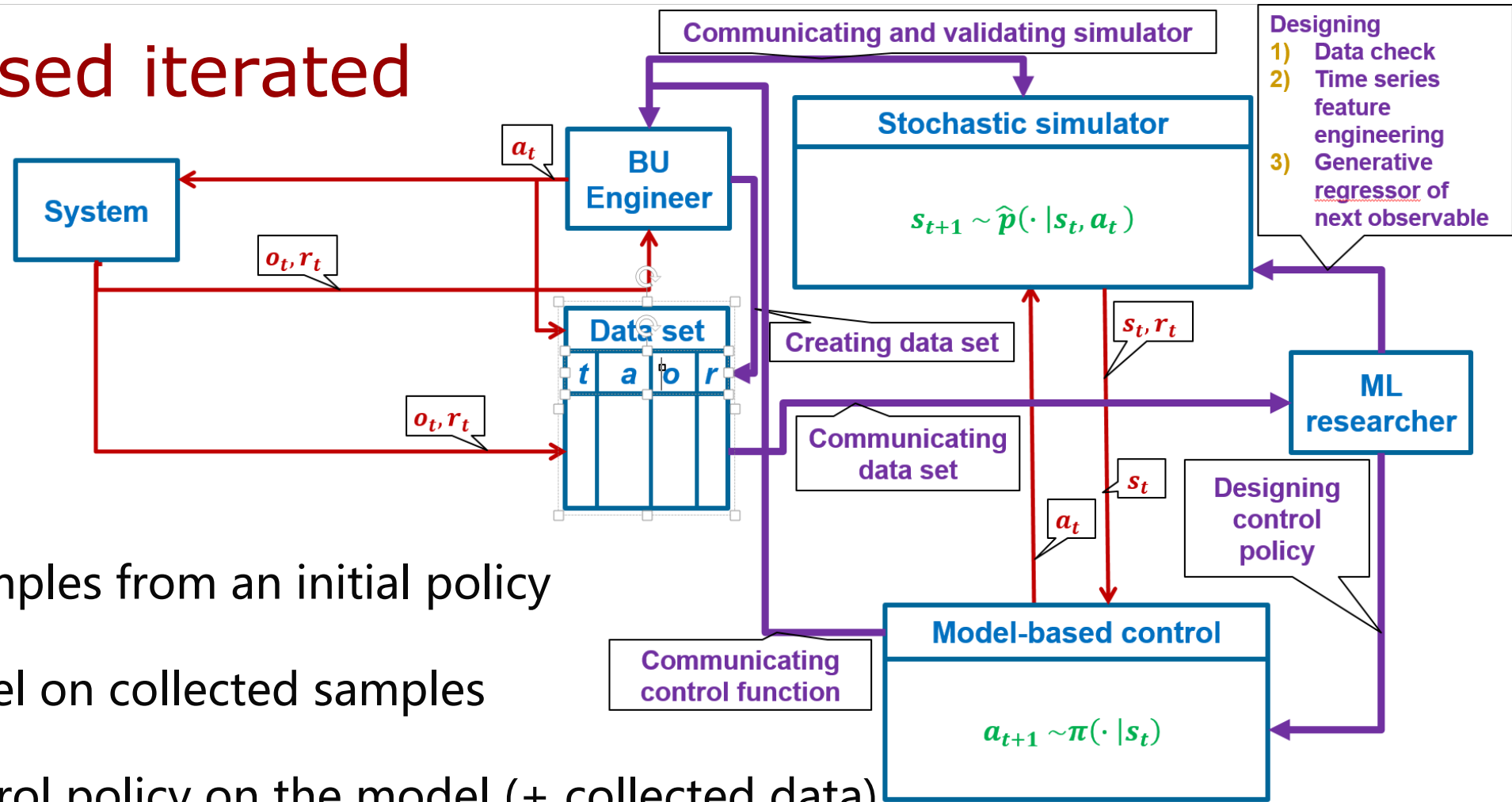
Iterated offline/batch RL



■ Realistic:

- › **Fits the organizational scenario** we can hope to implement
- › **Technically doable**
- › **Not well-studied** in research (cf trillion dollar market)

Model-based iterated batch RL



1. **Collect** samples from an initial policy
2. **Train** model on collected samples
3. **Learn** control policy on the model (+ collected data)
4. **Apply** control policy on real system and collect the data, go back to 2.

System model
=
multi-output
probabilistic (generative)
time series forecaster

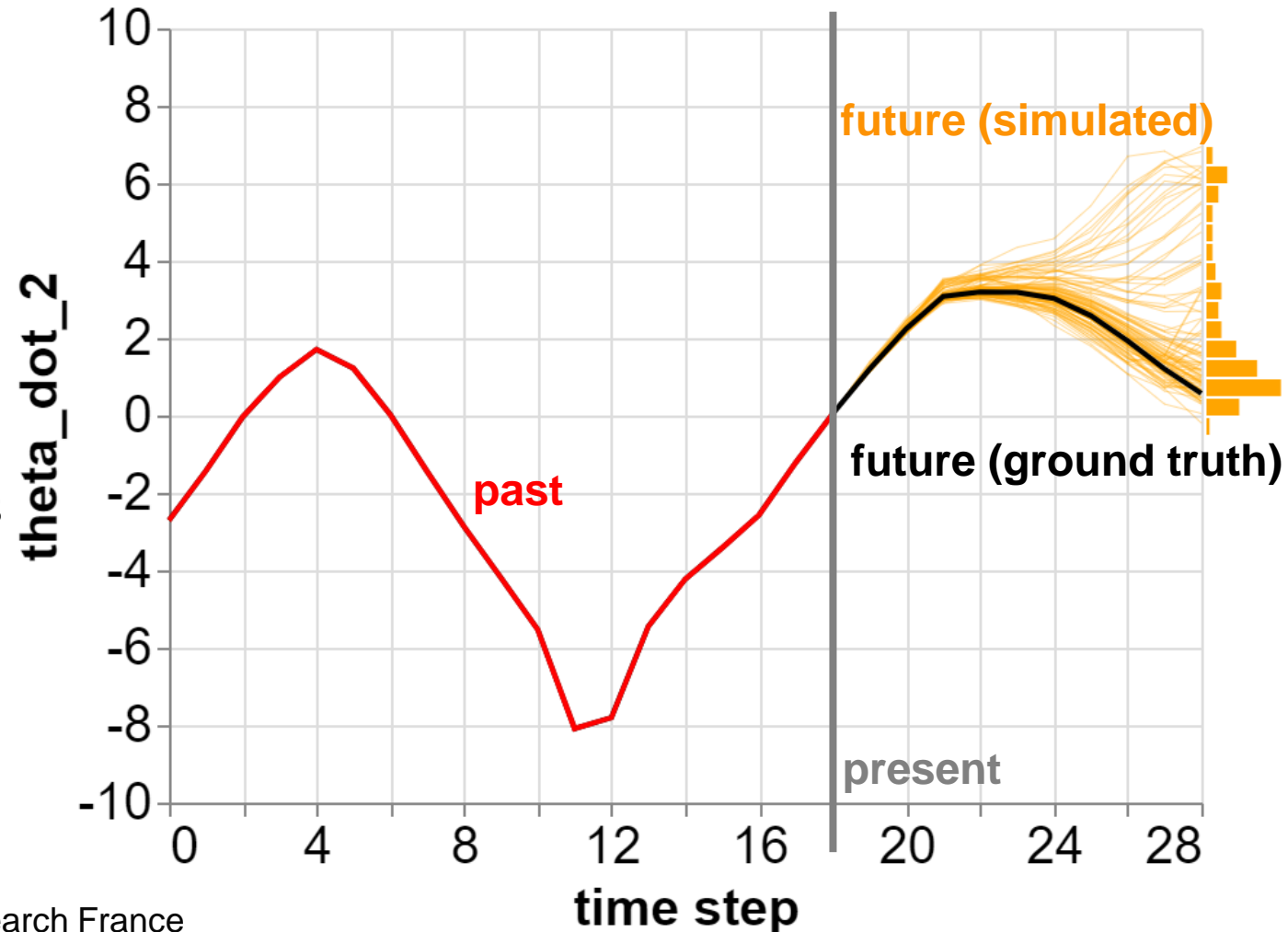
System model = multi-output time series forecaster

- Predict (random) future from history of system observables and control

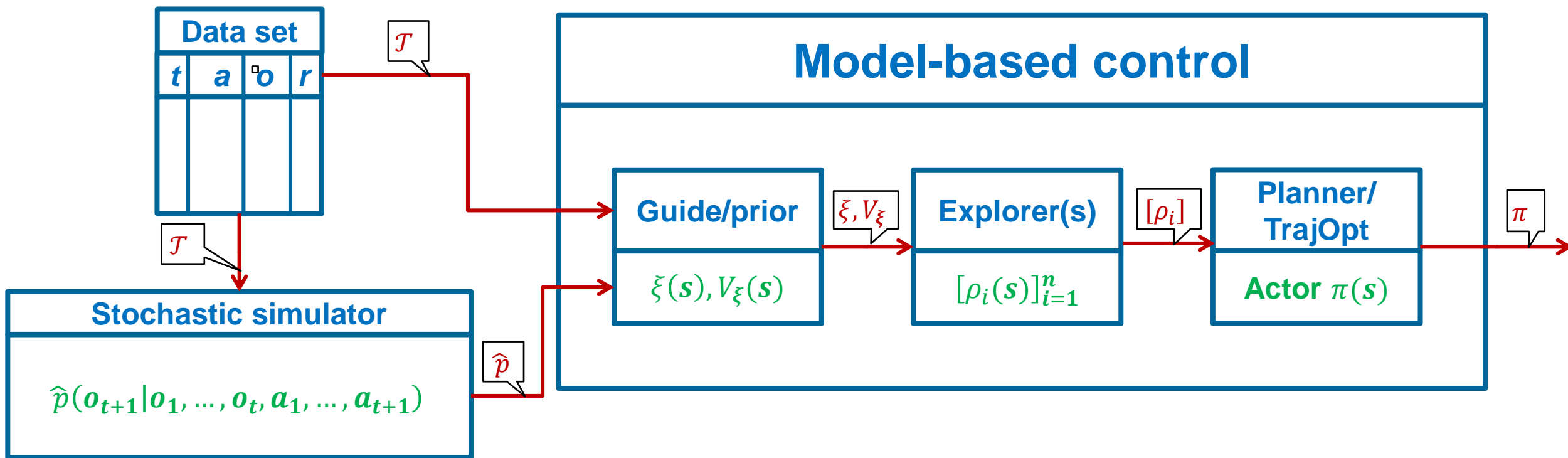
actions:

$$o_{t+1} \sim p\left(\underbrace{y}_{o_{t+1}} \mid \underbrace{x}_{(o_1, a_1), \dots, (o_t, a_t)}\right)$$

- › We want to **simulate multiple futures** from the model
- › **Density Nets**: output the parameters of a distribution by a neural net
 - » Typically **μ and σ of a Gaussian**
- › Learned on single-step transitions



What to do with a good model (simulator)?



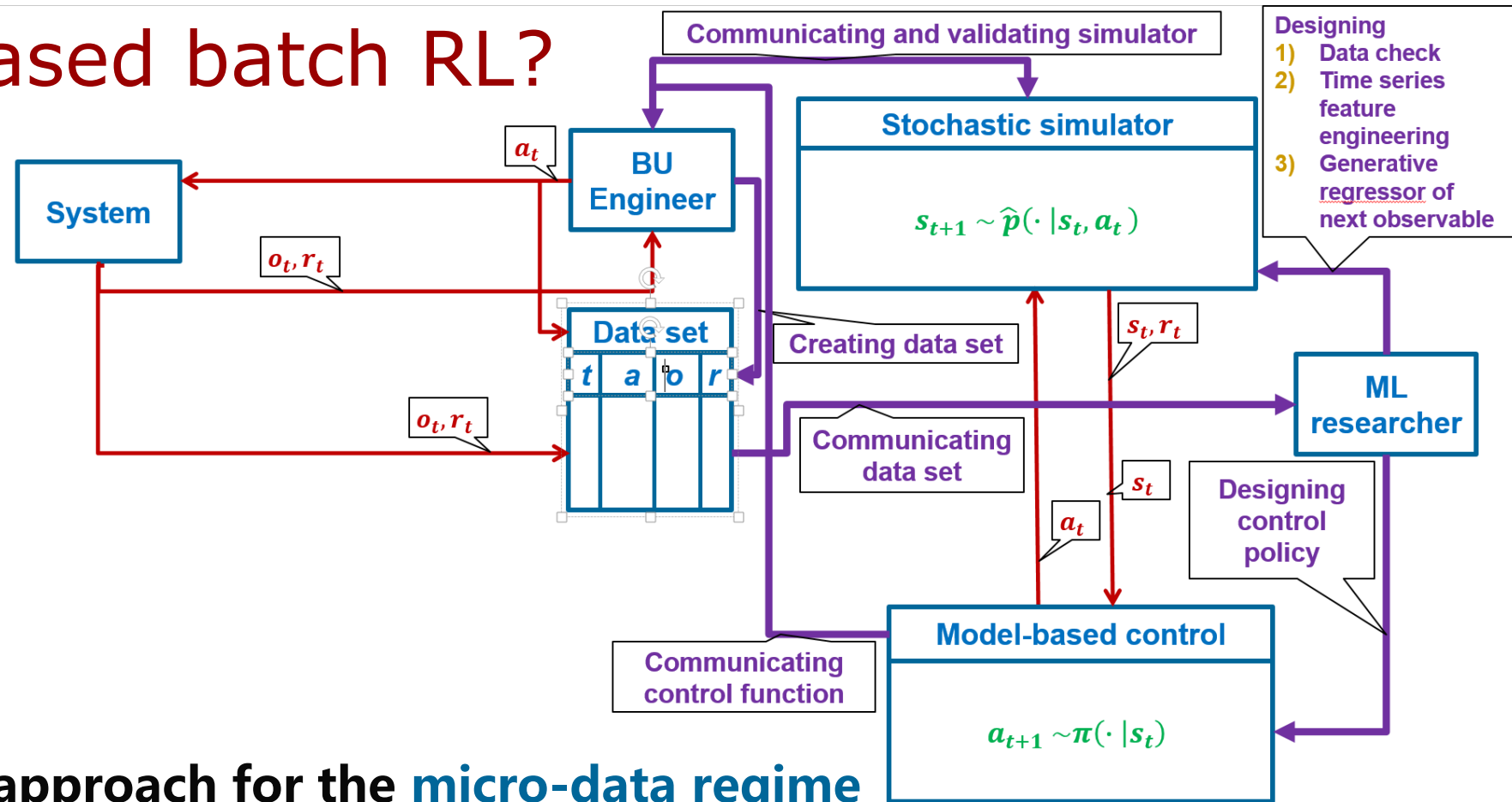
- **Learn a model-free policy** (pure Dyna-style)
- Add **exploration** (*iterated* batch)
- Use it to guide **planning**

Under review as a conference paper at ICLR 2023

THE GUIDE AND THE EXPLORER: SMART AGENTS FOR RESOURCE-LIMITED ITERATED BATCH REINFORCEMENT LEARNING

Anonymous authors
Paper under double-blind review

Why model-based batch RL?

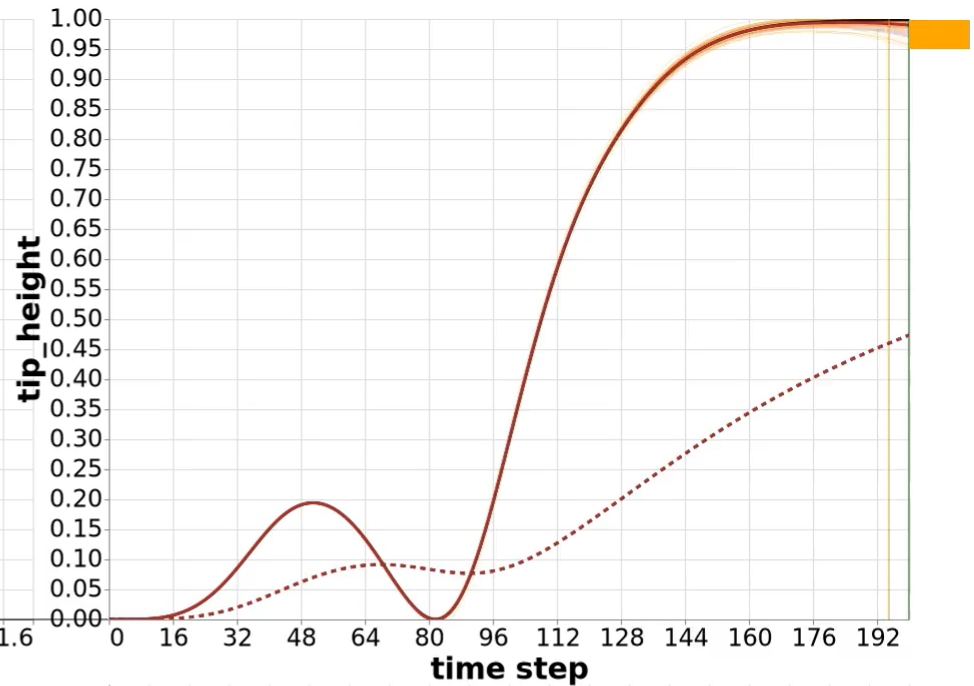
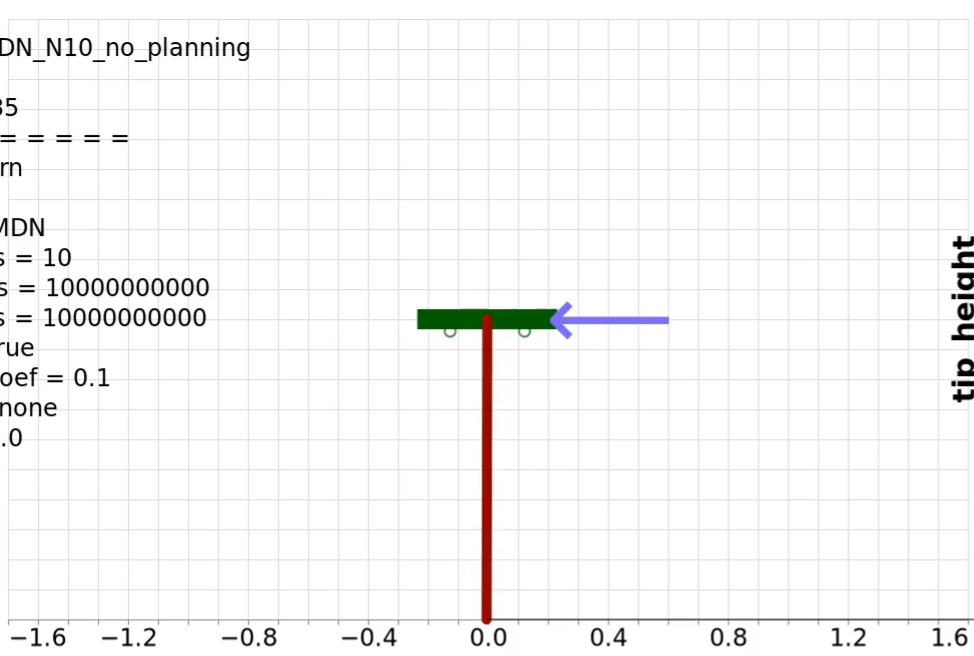


- Considered the best approach for the **micro-data regime**

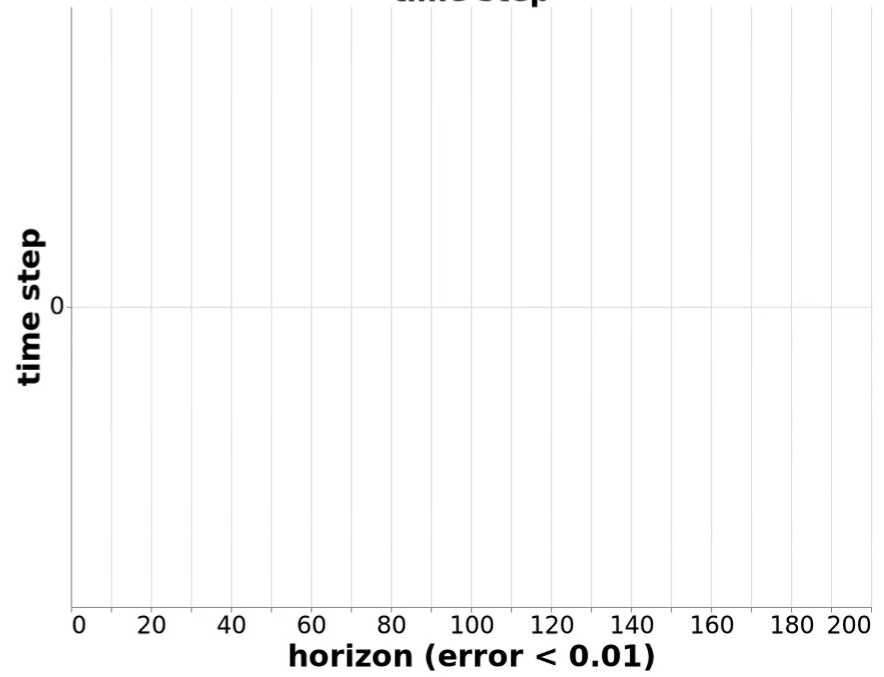
```

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legend = MDN_N10_no_planning
seed = 28
episode = 35
=====
model = darn
actor = sac
nn_type = MDN
n_gaussians = 10
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last_n_steps = 10000000000
is_valid = True
bootstrap_coef = 0.1
planning = none
gamma = 1.0

```



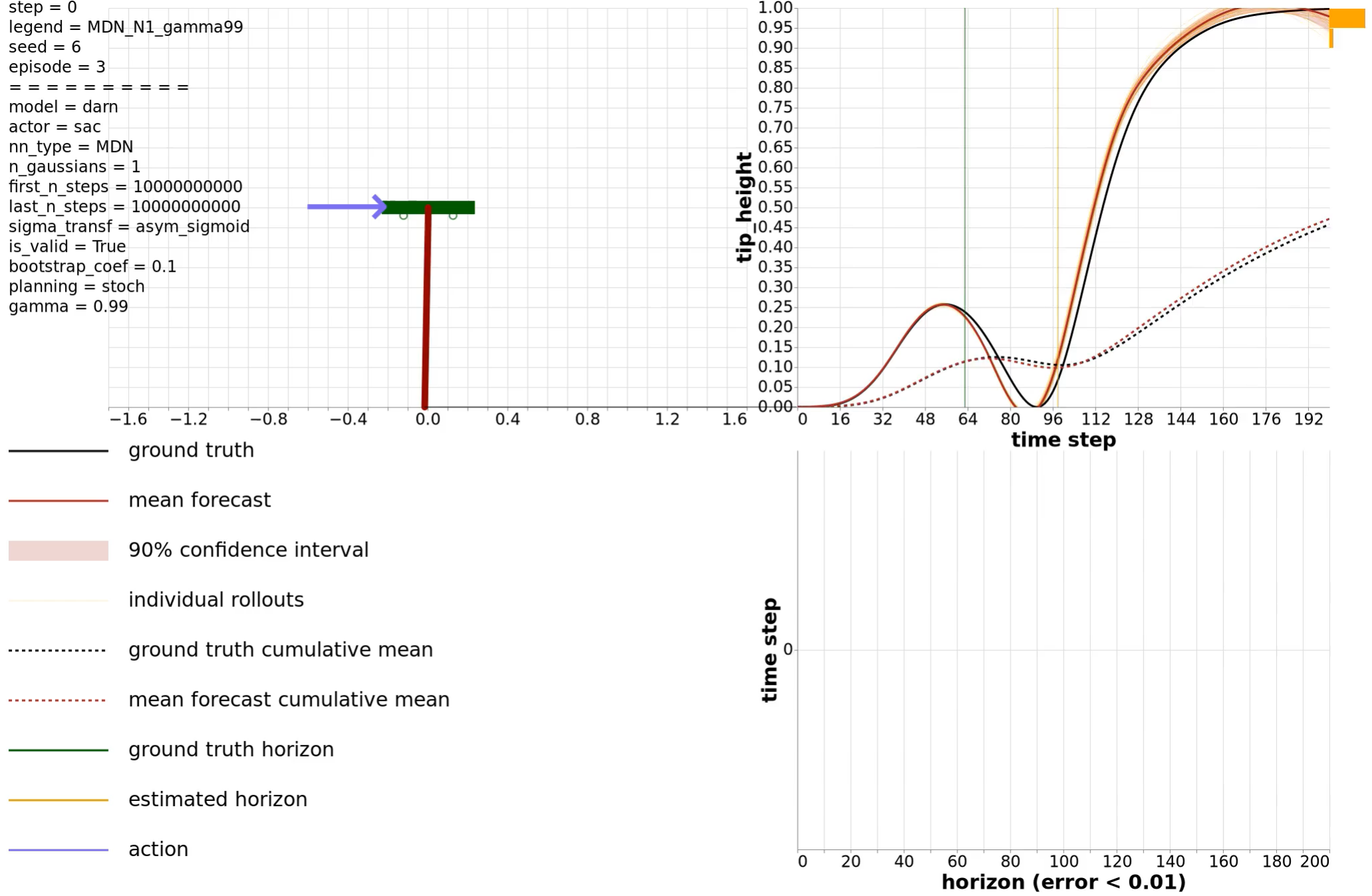
- ground truth
- mean forecast
- 90% confidence interval
- individual rollouts
- ground truth cumulative mean
- mean forecast cumulative mean
- ground truth horizon
- estimated horizon
- action



```

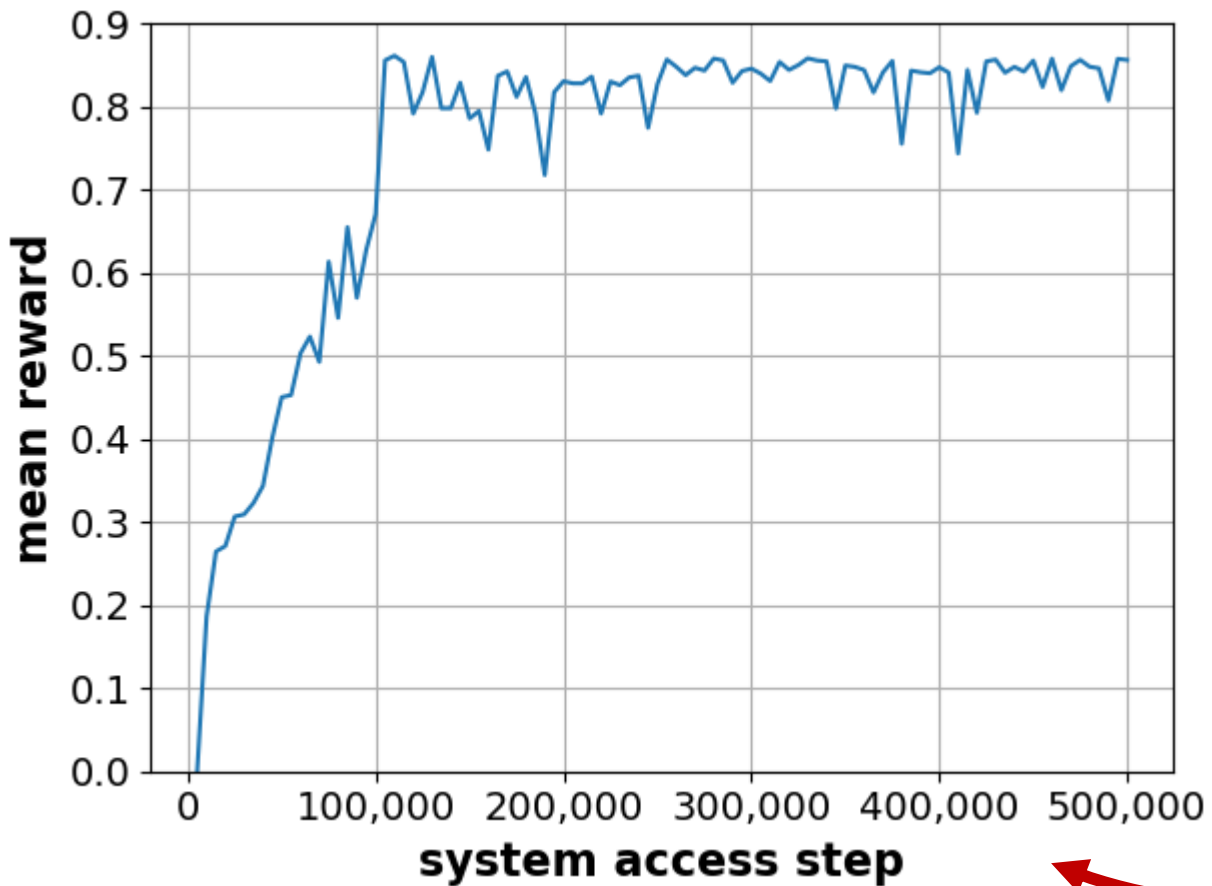
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legend = MDN_N1_gamma99
seed = 6
episode = 3
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actor = sac
nn_type = MDN
n_gaussians = 1
first_n_steps = 10000000000
last_n_steps = 10000000000
sigma_transf = asym_sigmoid
is_valid = True
bootstrap_coef = 0.1
planning = stoch
gamma = 0.99

```

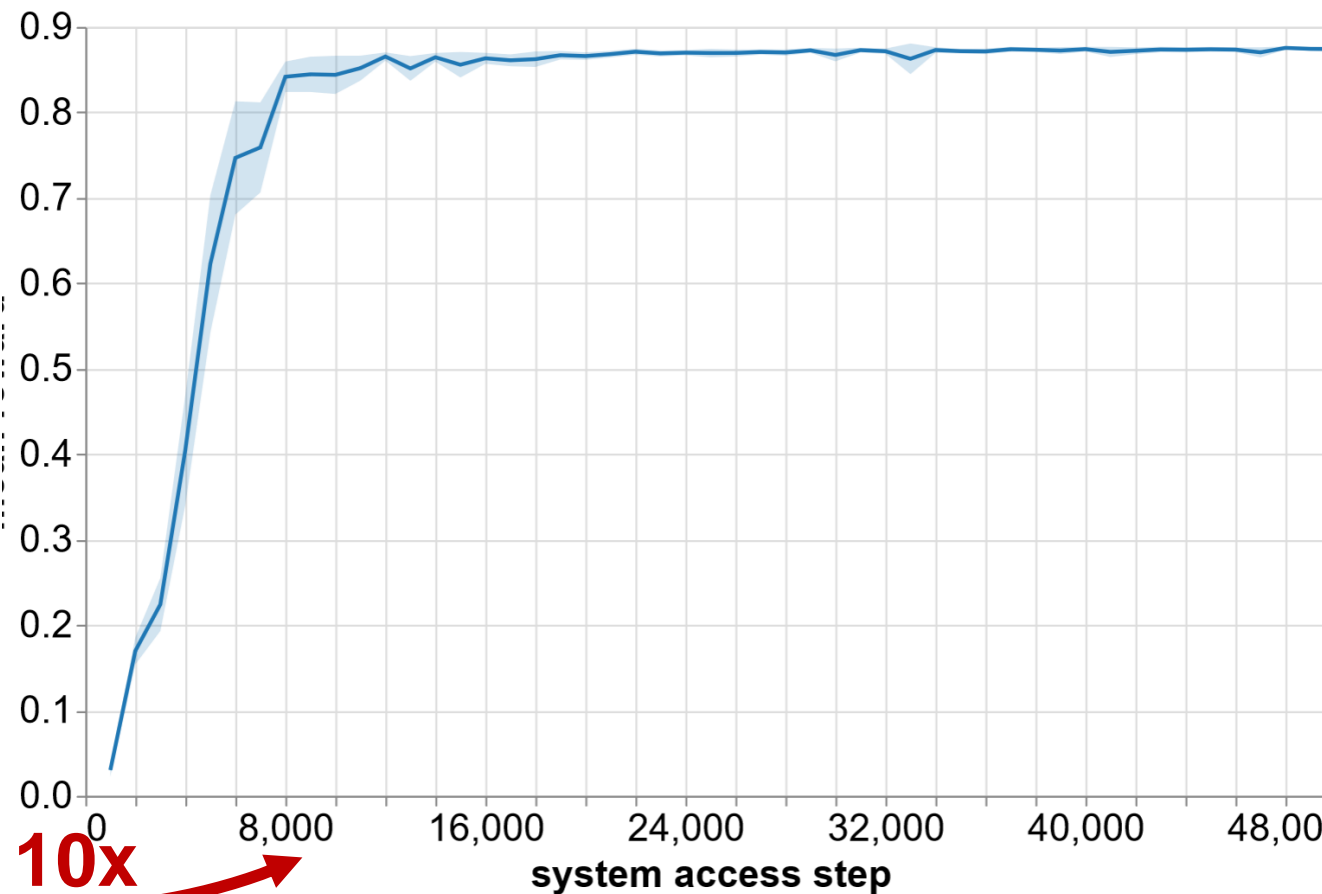


Cartpole

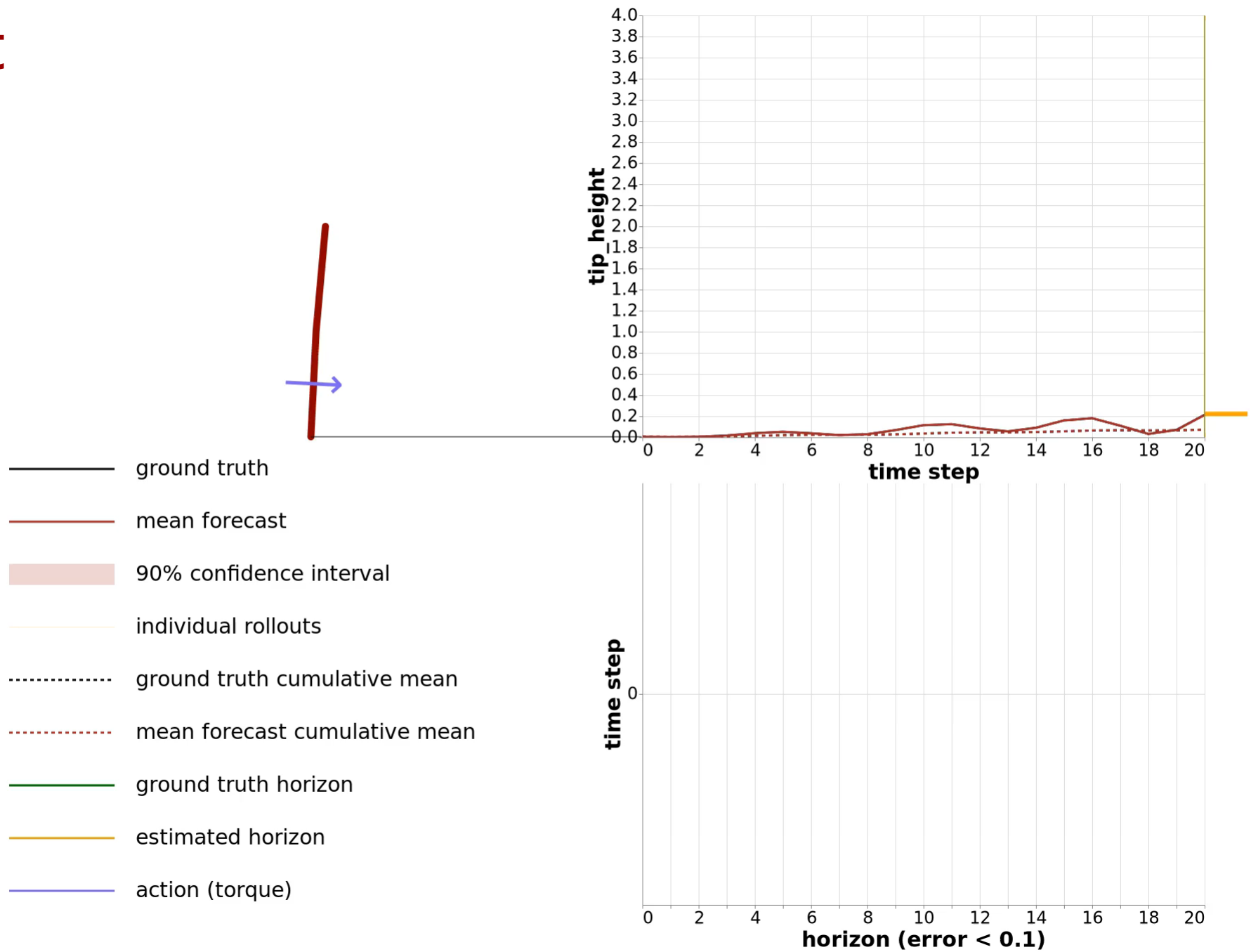
Model-free (SAC)



Model-based (Dyna + planning)

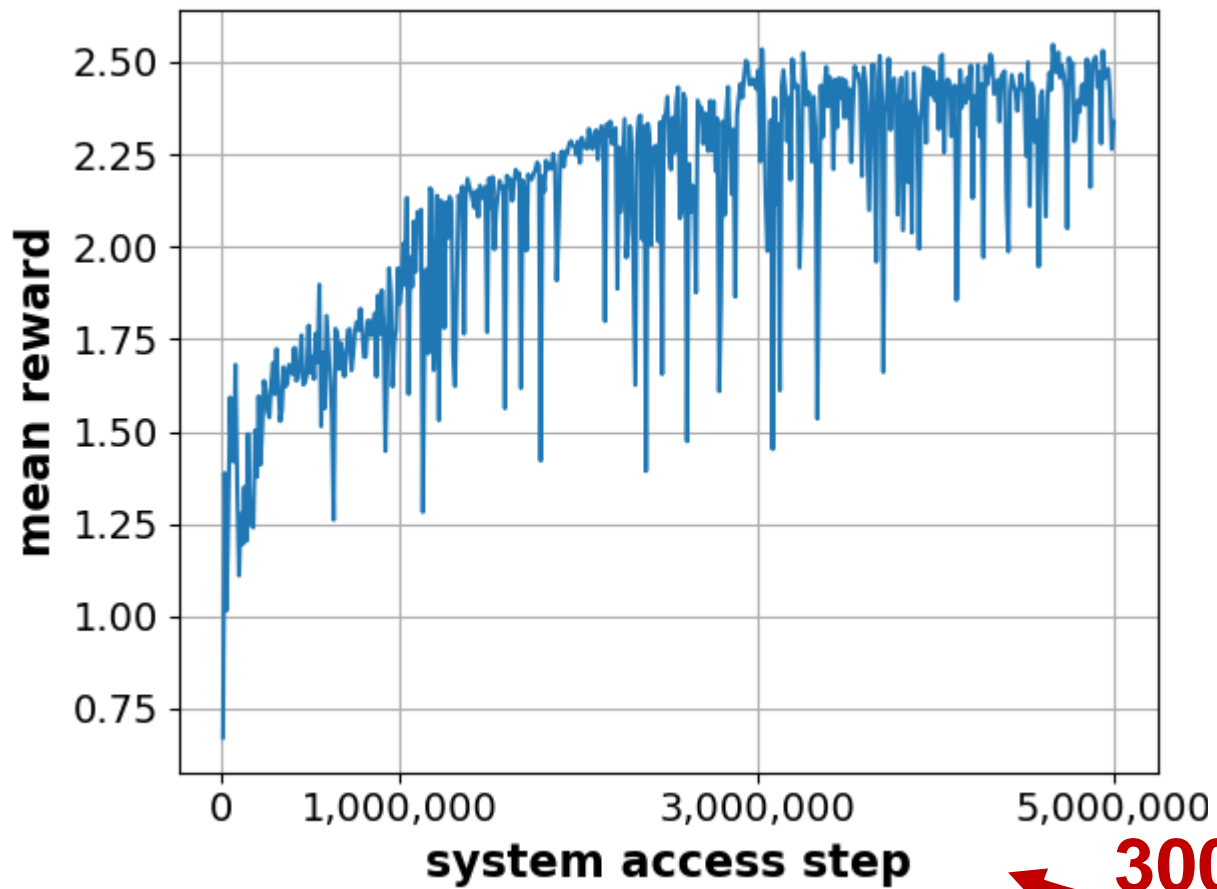


Acrobot

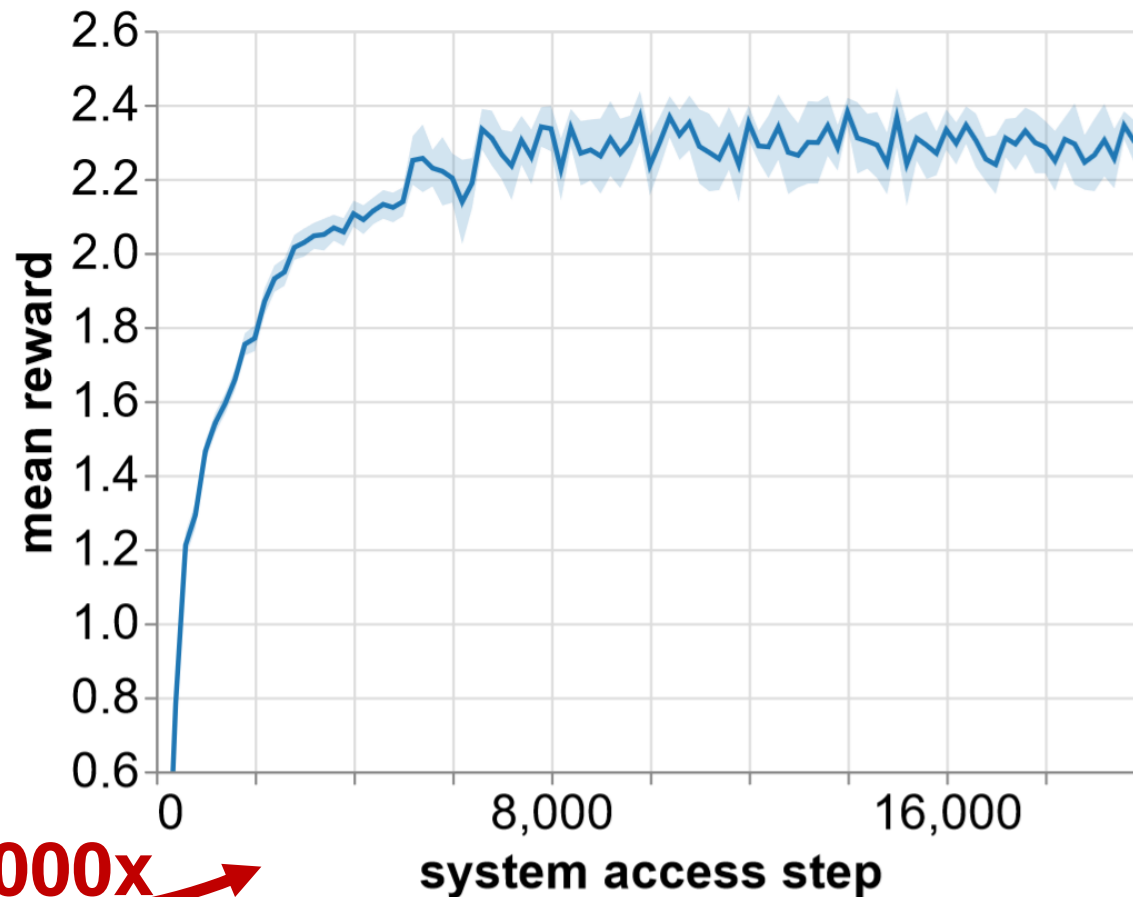


Acrobot

Model-free (DQN)

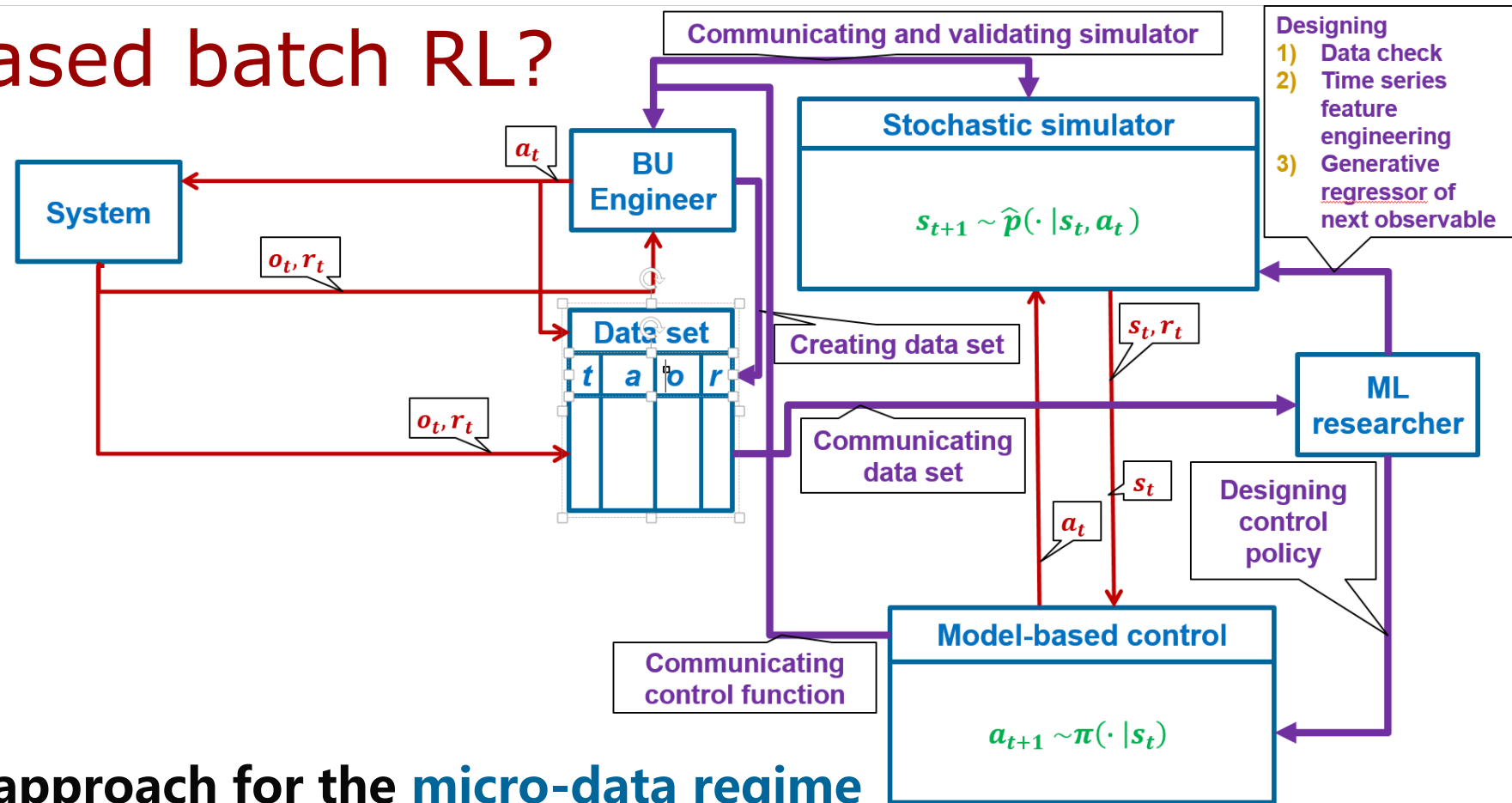


Model-based (Dyna + planning)



30000x

Why model-based batch RL?



- Considered the best approach for the **micro-data regime**
- We do **not waste predictive power** (unlike, e.g., on images)
- System models (**simulators or digital twins**) are **useful on their own**
- **Self-supervision** (learning without human labeling) in RL

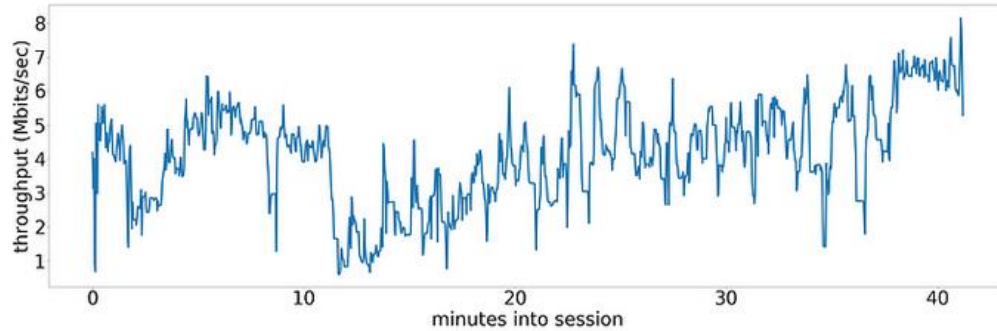
Part III

Mind Everywhere

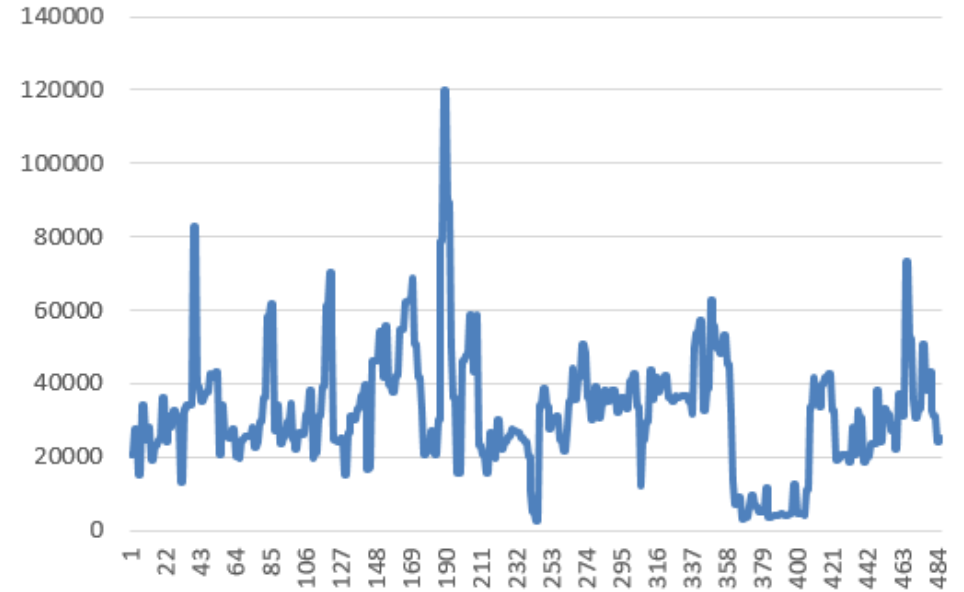
Review of throughput for video streaming

traffic(kbps) video2

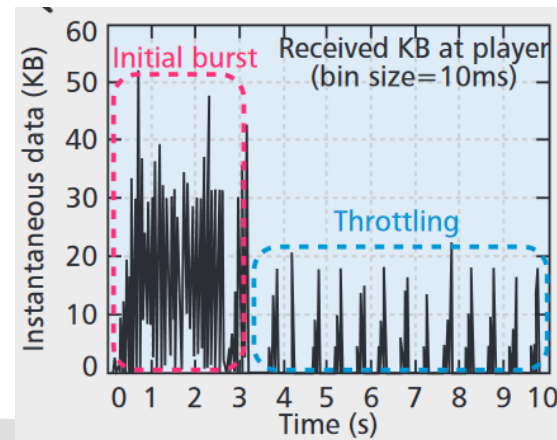
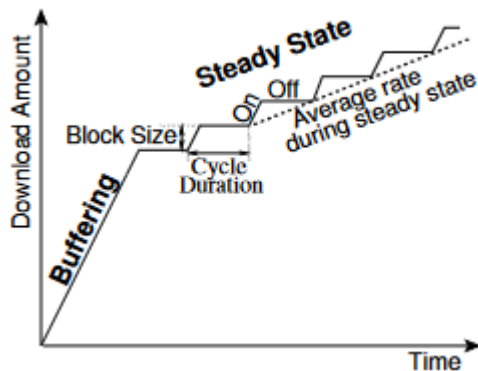
- Unstable throughput in the experiments
- From a Netflix blog post, similar behavior



Examples of network throughput traces measured from real viewing sessions.



- Typical behavior (Netflix, Youtube): initial buffering then on-off cycles triggered by thresholds on the buffer size



Mind everywhere

■ Phones are **agential**, not passive machines

- › Intelligent buffering: a (future) video app uses AI to predict the video, the behavior of its owner and the available throughput from the base station
- › They learn and self-update
- › They cannot be fully controlled by the base station

■ Base stations are not fully in control

- › They can vary the response to the phone requests
- › Create a landscape of states and rewards
- › Want to avoid arms races and deadlocks, for the common good

■ The body analogy

- › Phones are cells with their own monocellular goals
- › Base station – set of phones organism is a higher level multi-cellular organism
- › Emergence and emanation

Mind everywhere

■ Thesis

- › Future intelligent systems will look more like **biological bodies** than classical control systems
- › So their design should be inspired by the latest research in **distributed cognition** and **multi-layer developmental system biology**
- › Understanding and creating these embodied systems will complement language-based narrow AI on the **road to AGI**

■ Inspirations

- › Michael Levin: Technological Approach to Mind Everywhere
- › Mark Solms: The Hidden Spring, affect-based dual-aspect monistic view of consciousness
- › Lina Bariah and Merouane Debbah: AI embodiment through 6G: shaping the future of AGI
- › John Vervaeke: Artificial Intelligence, The Meaning Crisis, & The Future of Humanity (YouTube)

Mind everywhere

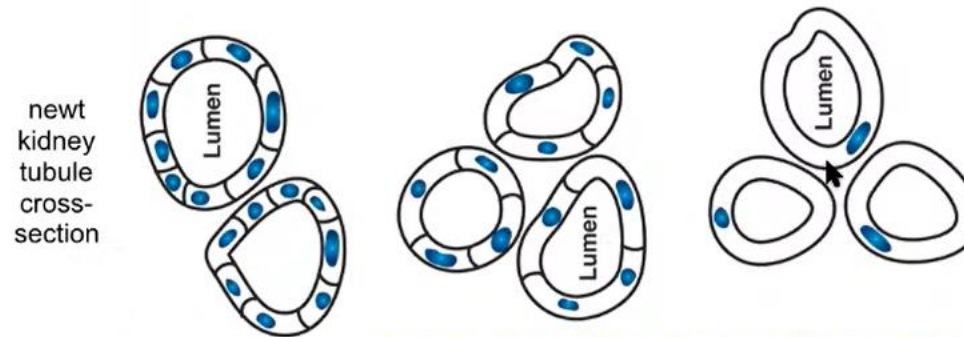
■ Intelligence by William James:

Solving a higher-level problem through *whatever* lower-level mechanism is available.

■ Top-down causation

Same anatomy, despite perturbations

- get to the same outcome
 - despite perturbations (external and internal)
 - from diverse starting positions
 - via different paths



Fankhauser, 1945, J. Exp. Zool., 100(3): 445-455

Changing the size of cells still enable large-scale structures to form, even if they have to utilize different molecular mechanisms = top-down causation

As a newt-to-be, you can't count on # of chromosomes, cell number, cell size, etc. - Play the Hand you're Dealt



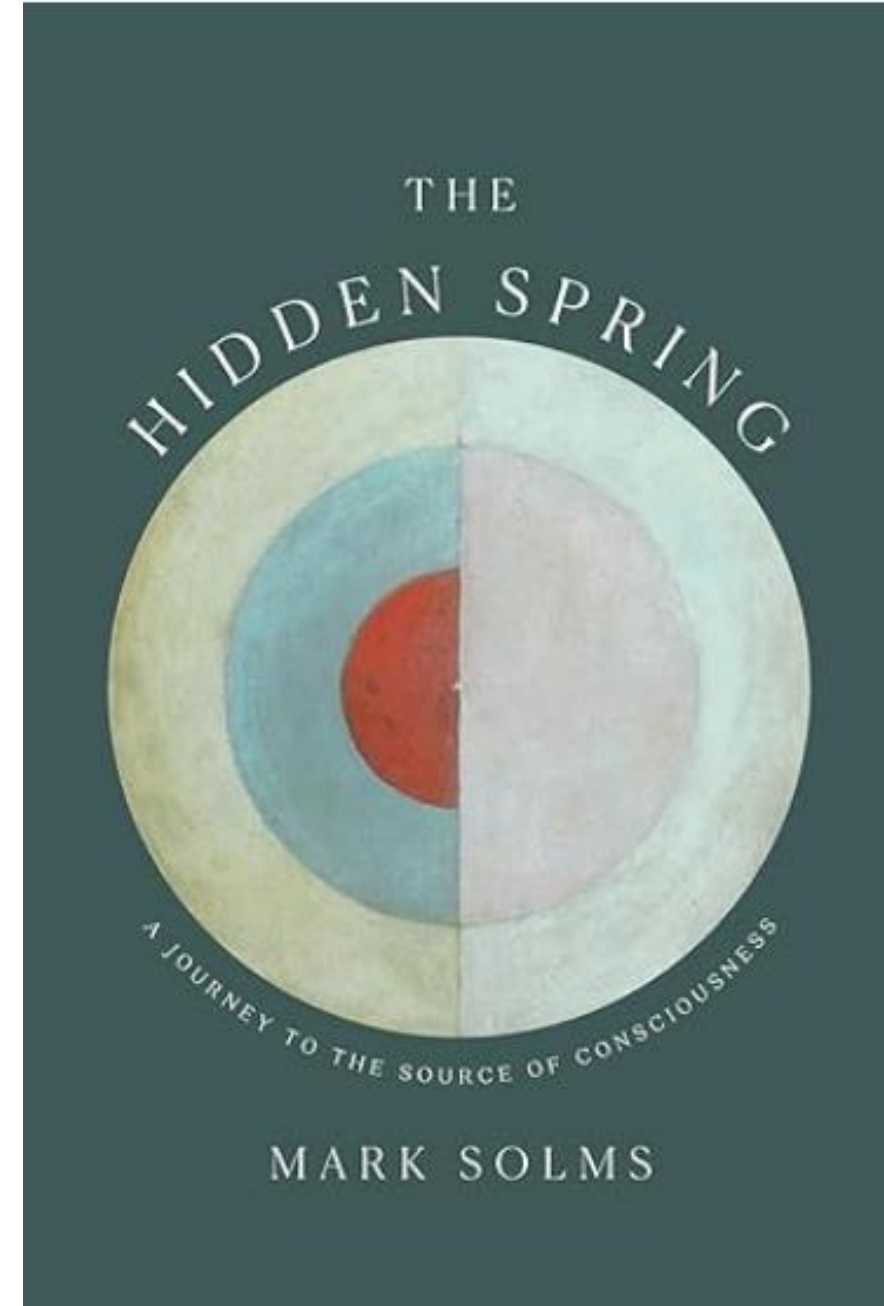
Michael Levin

Powered by Zoom



Conditions for consciousness

- **Autonomous, self-organizing, auto-poietic systems**
- **Separated from their environment by a **Markov blanket: sensors** for extero and interoception**
- **Responsible for their **persistence**: maintaining and optimizing vital internal states**
 - › Modelling future states and recording predictive errors
 - › Feeling, affect = feedback signal: how well am I doing?
 - › Actions: what to do to improve?
- **More than one vital dimensions which require arbitration at the organism level, cannot be automated because of unknown unknowns in the environment**



How will engineering systems look like?

- They will consist of **intelligent parts** that all **build predictive models**
- They will act to satisfy and optimize **multiple key performance indicators**
 - › Which are often contradictory
- They will act to safely **explore, collect data, and learn** about the world
- They will be **hierarchical and multi-agent**
 - › Horizontal and vertical channels
- They will **not be in full control** of their parts
 - › Request, persuasion, shaping states and rewards, hierarchical adaptation
- They will **individuate**
 - › Old hardware will need to teach new hardware
- They will **communicate, partially through language**
 - › They will talk to us, and maybe to each other

The four pillars of embodied AIoT

■ World models and digital twins

- › **Data efficient**
- › **Self-calibrated**: will know about their own uncertainties
- › Consistently **multi-timestep and multi-timescale**
- › Robust and **auto-tuning**

■ Model-based control

- › **Data efficient** and **safe**
- › **Continual learning** and deployment
- › Combining model-based, model-free control and planning

■ Communication through LLMs

- › **Episodic memory**: each device will remember its experience

■ Hierarchical multi-agent systems

- › **Collective intelligence**, persuasion, reward and state-shaping, emergence and emanation

<https://balazskegl.medium.com/mind-everywhere-embodied-ai-of-things-and-the-future-of-engineering-124e1b3a35e7>

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