Summer Meetings on Joint Inference and Control

- Agenda:
  - **[12:00pm, 12:10pm]: grab lunch**
  - [12:10pm, t_0] : presentation
  - [t_0, 2pm]: discussion/brainstorming
- Today: Andrea Censi (MIT)
  "Joint Inference and Control: Opportunities and Challenges from the Robotics perspective"
- Next week:
  - Josh Hernandez (grad, UCLA)
- Next meetings, up to a permutation:
  - Alex Gorodetsky (grad, MIT)
  - Pratik Chaudari (grad, MIT)
  - Vasiliy Karasev (grad, UCLA)
  - Ali Agha (postdoc, MIT)
  - Dmitry Yershov (postdoc, MIT)
  - Chris Amato (postdoc, MIT)
  - you? we can add a couple of slots
- Website:
  sites.google.com/site/jointinferencecontrol
- Join the mailing list! (if it works)
  joint-inference-and-control-join@mit.edu
- Who's here:
  - people from Frazzoli's group
    thanks Emilio for the food!
  - people from Soatto's (UCLA) group
  - people from Youssef's (AA) group
  - people from Leslie's (CSAIL) group
  - other from LIDS/CSAIL?
- Who's spatiotemporally displaced:
  Emilio, Stefano, other UCLA people, random people from BU, Berkeley, UPenn.
- Presentations will be recorded
  (if it works)

Agenda

- ✓ Grab lunch
- ✓ Logistics
- Presentation: "**Joint Inference and Control: Opportunities and challenges from the robotics perspective**"
  - Robotics in 5 minutes
  - "Joint inference and control" seen as competition for limited available resources
  - Some formalizations of the joint problem.
  - Challenges: death by generality, death by abstraction.
- Discussion
  - *The best way to have a good idea is to have lots of ideas.*

The big picture for robotics and autonomous systems

past

civilian

"autonomous"
ground vehicles

military

Lockheed D-21 (1966)

The big picture for robotics and autonomous systems

past → **present (deployed)**

civilian

Mint floor cleaner

JPL Mars rovers

"autonomous" ground vehicles

Kiva's robotic warehouse

military

Lockheed D-21 (1966)

AAI RQ-7 (recon)

GA MQ-9 (strike)

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better sensors

more computation power

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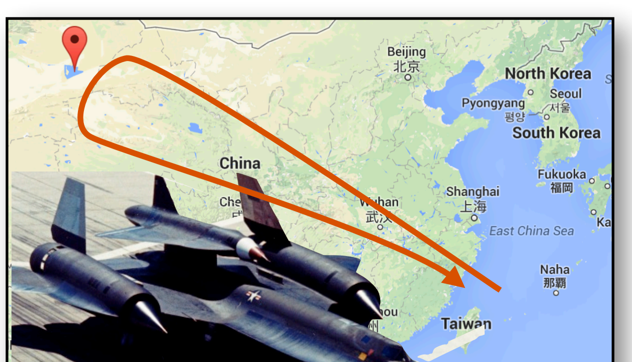

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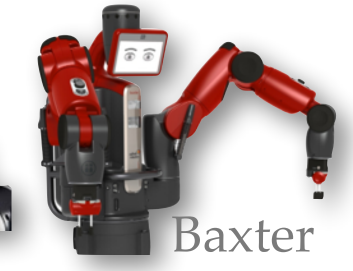
PR2



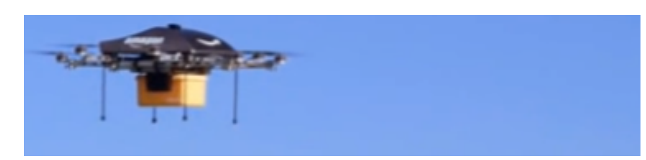
Baxter

multipurpose assistants

autonomous driving

“autonomous” ground vehicles

Kiva’s robotic warehouse



amazon Prime Air

autonomous delivery

military

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BAE Systems “Mantis” (autonomous combat)

The big picture for robotics and autonomous systems

past → **present (deployed)** → **future (?)**

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better sensors

more computation power

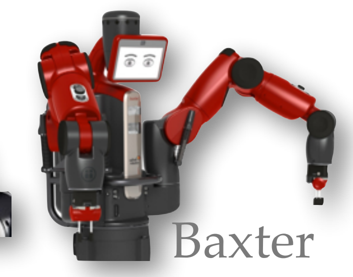
Mint floor cleaner

JPL Mars rovers

“reduce design effort”

“make things robust”

PR2



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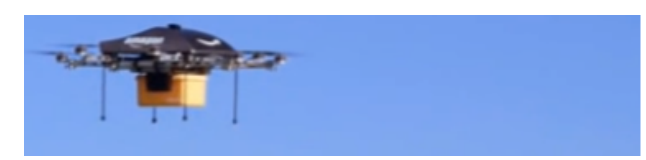

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Jobs that will disappear in *N* years

for N varying according to one's optimism level

What is a robot?

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- A robot is an interconnection of **sensors** and **actuators** interacting with the physical world.

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A

B

C

D

E

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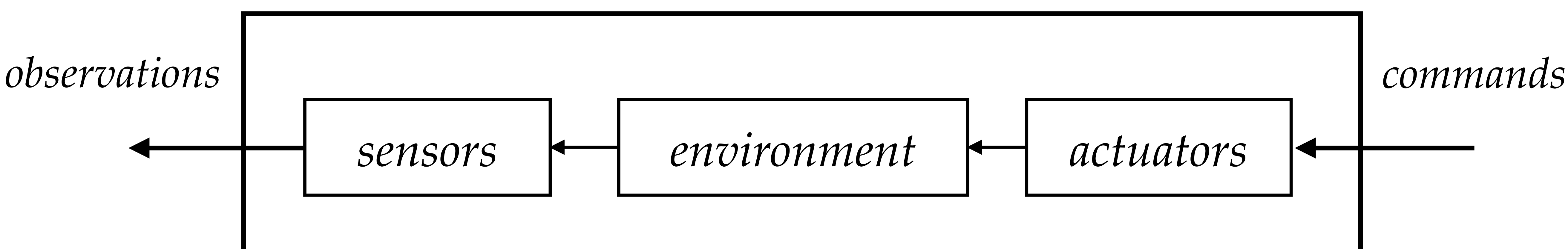
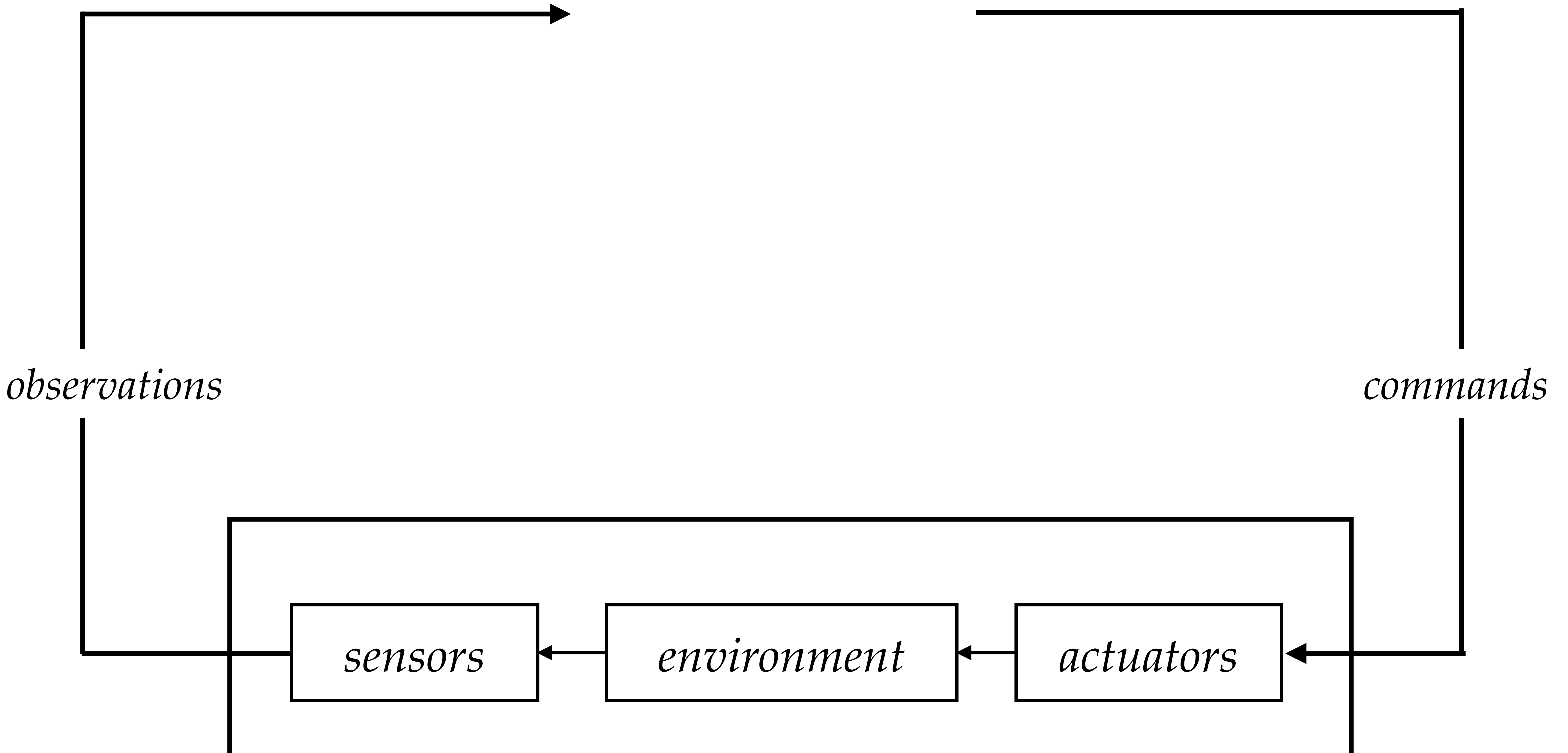
A **B** **C** **D** **E**



Agent vs Robot



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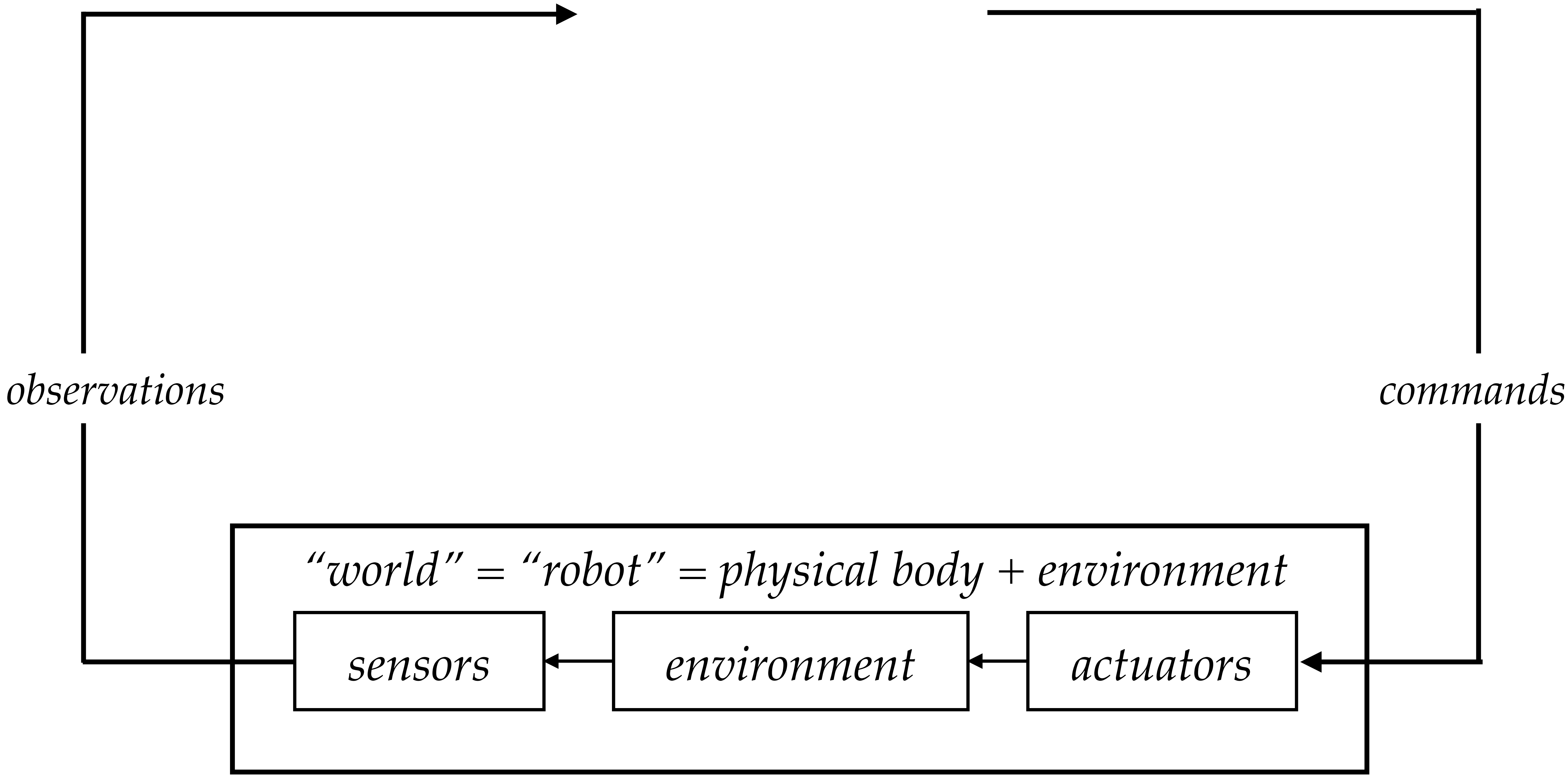

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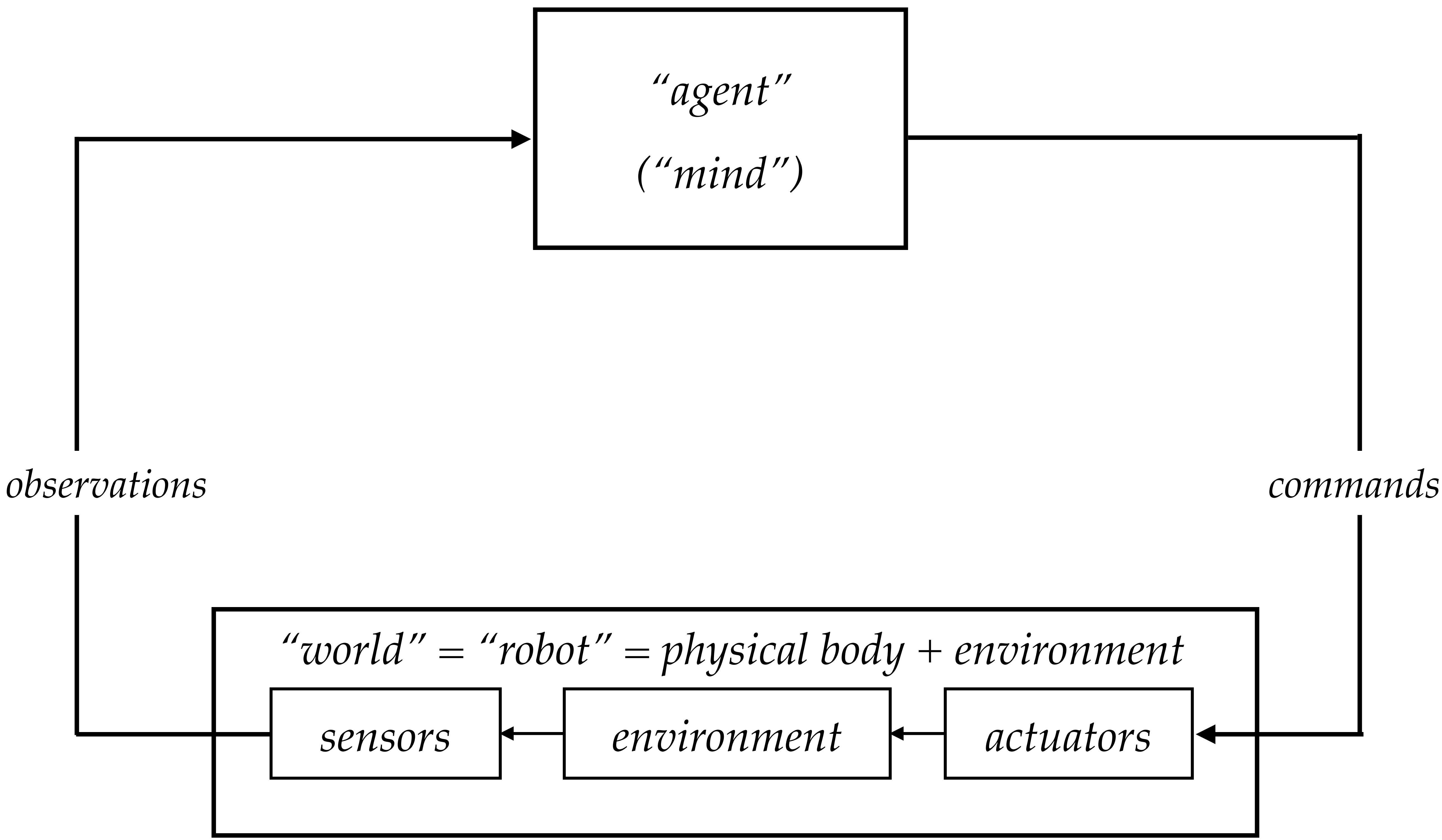
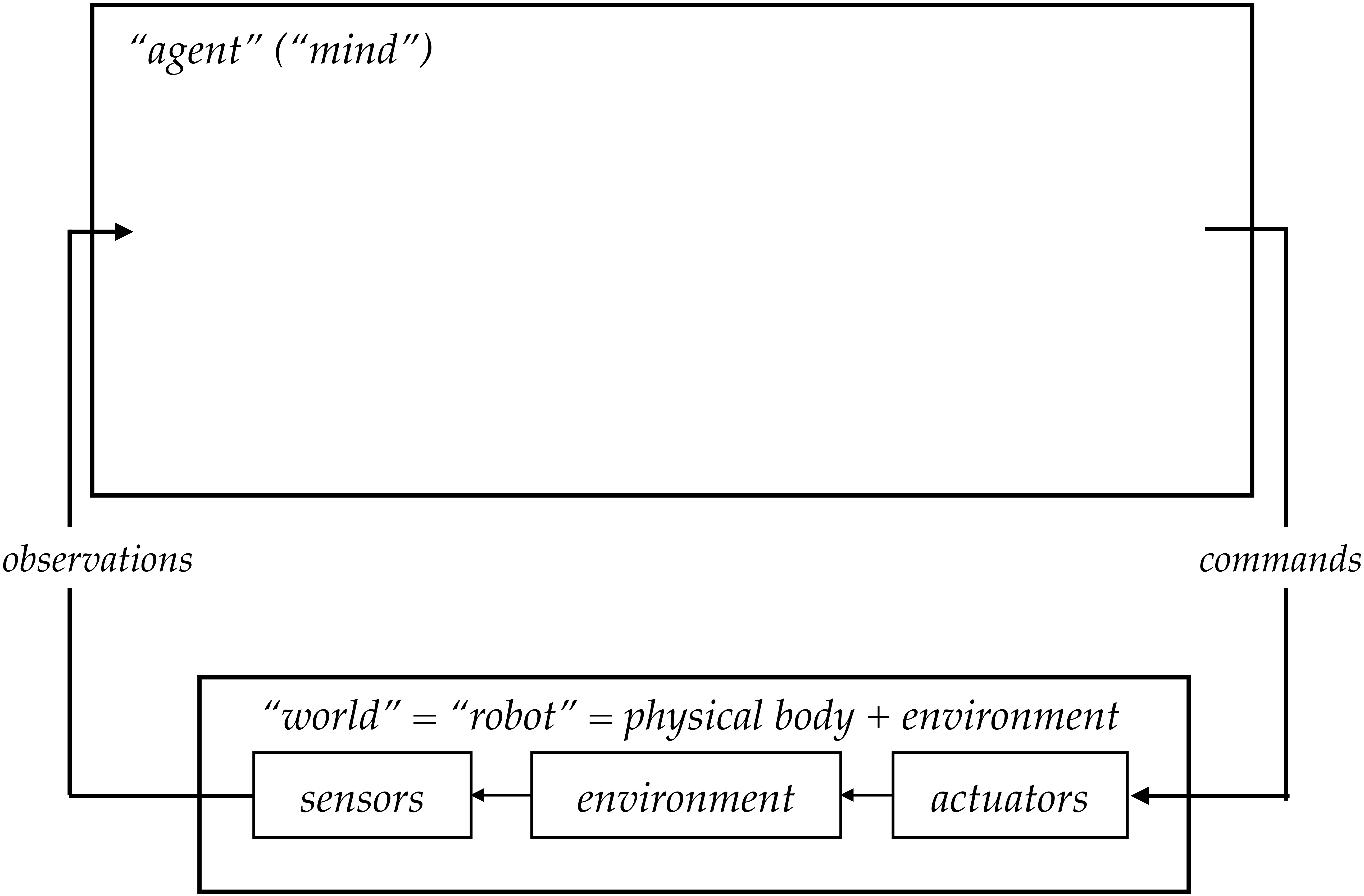


Simple example of control architecture for navigation



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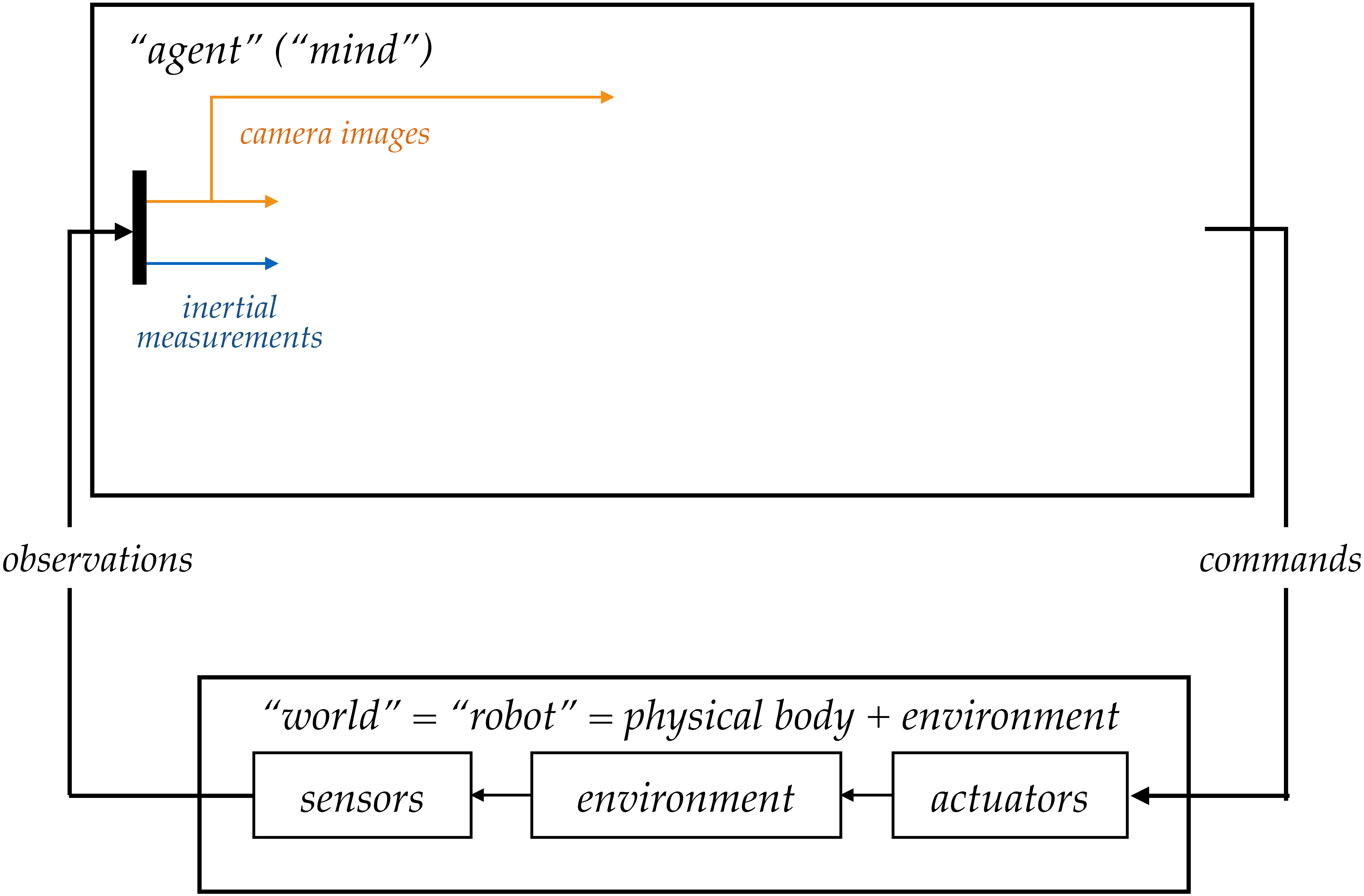

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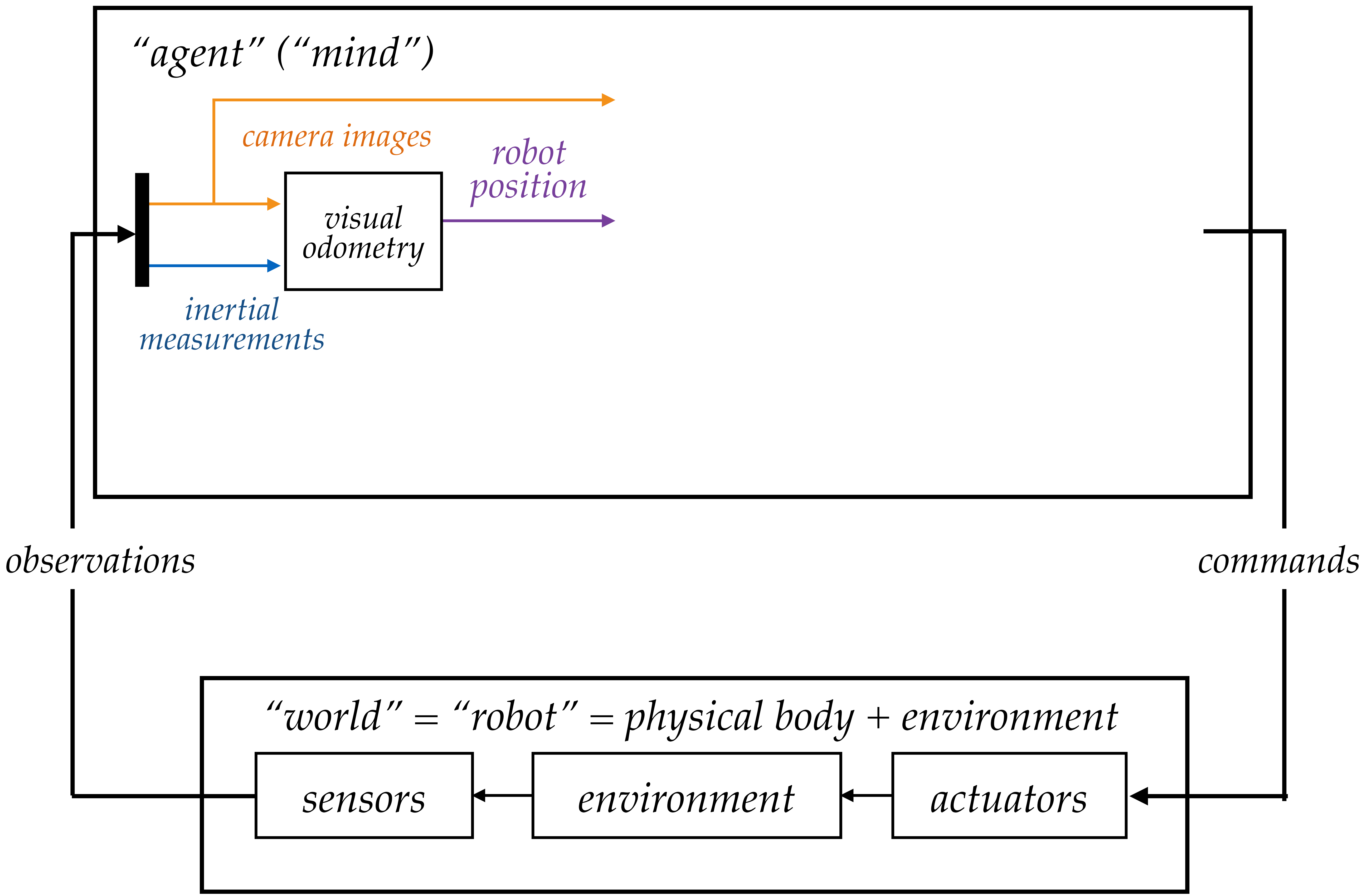

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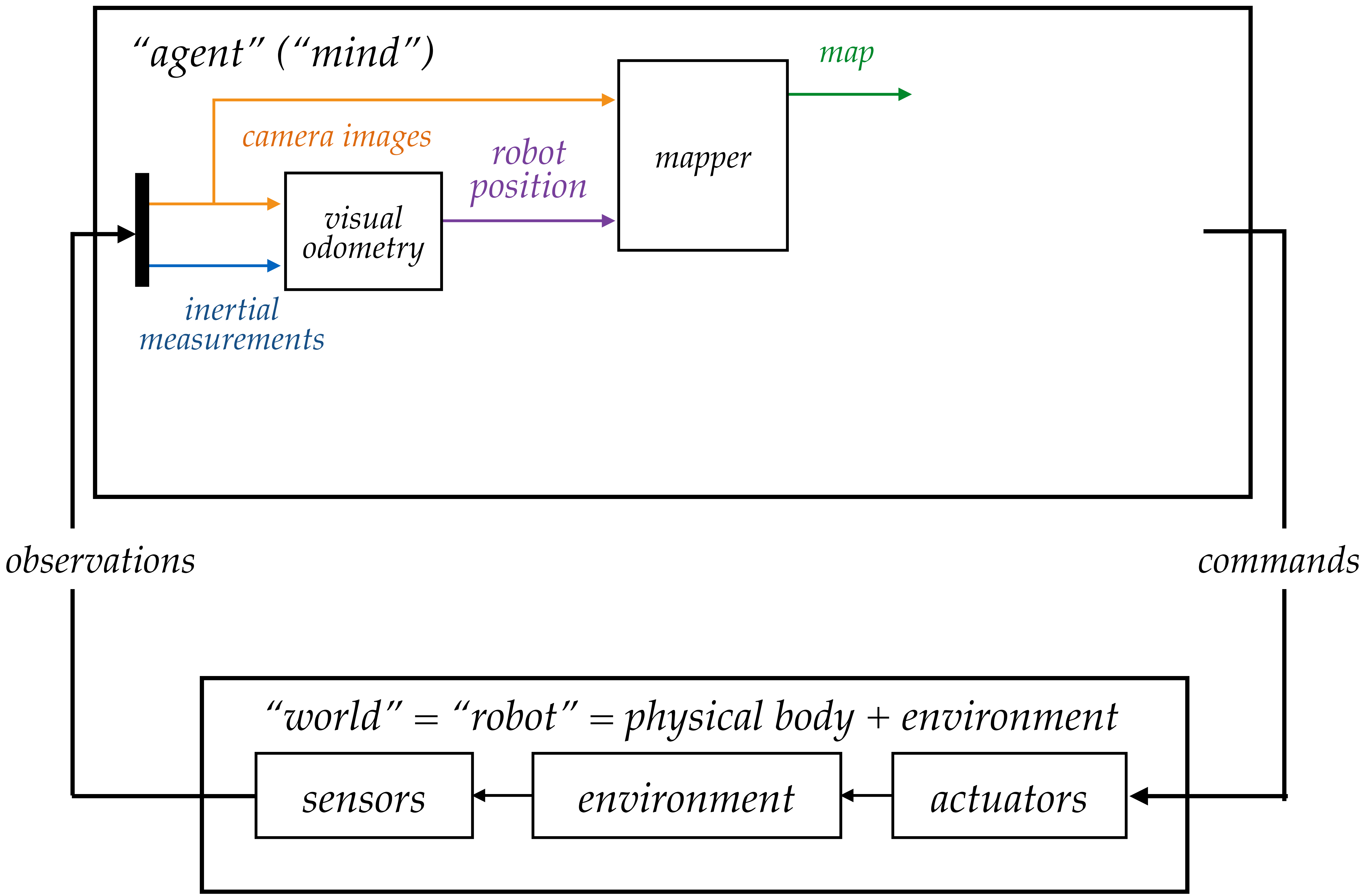

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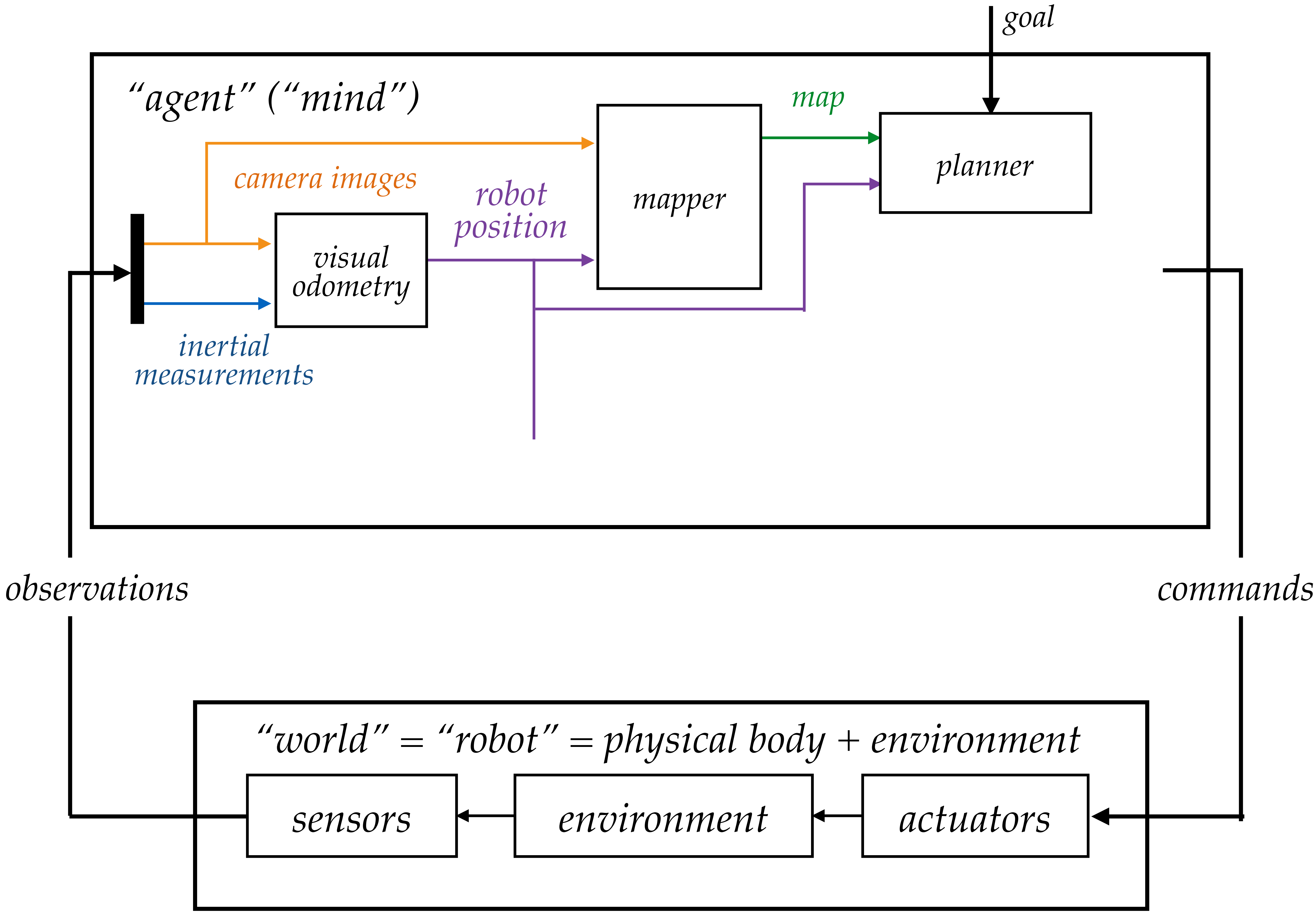

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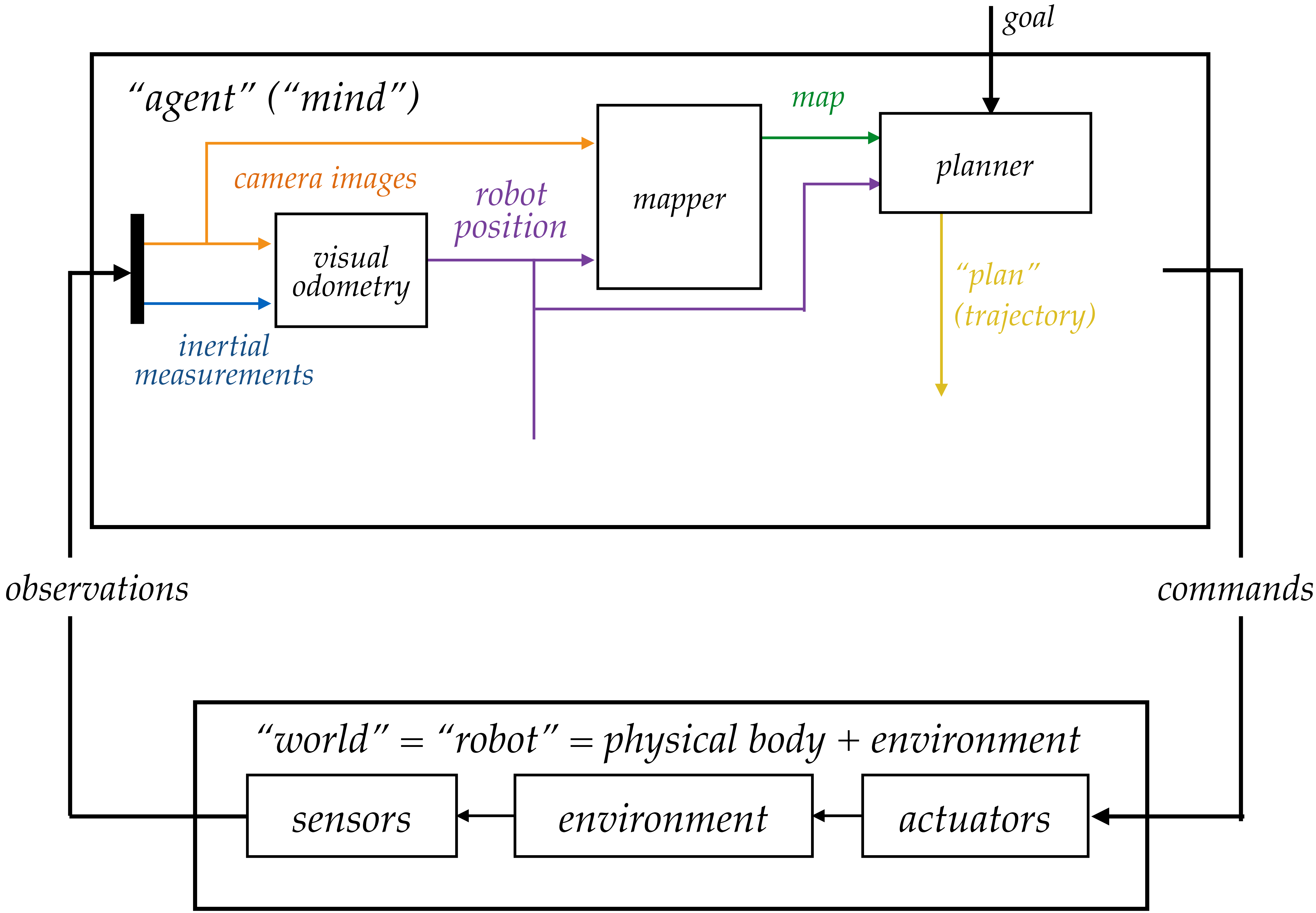

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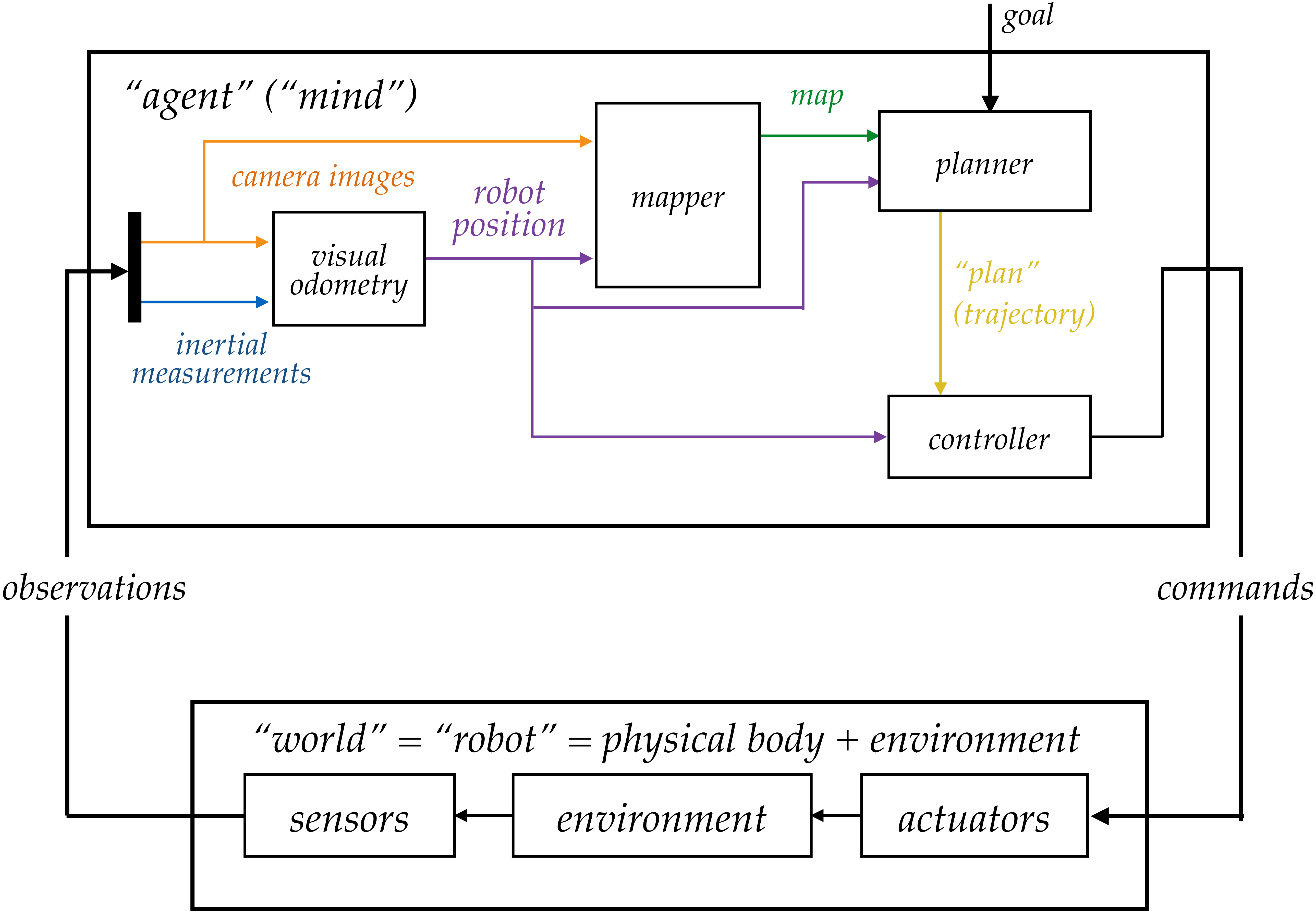
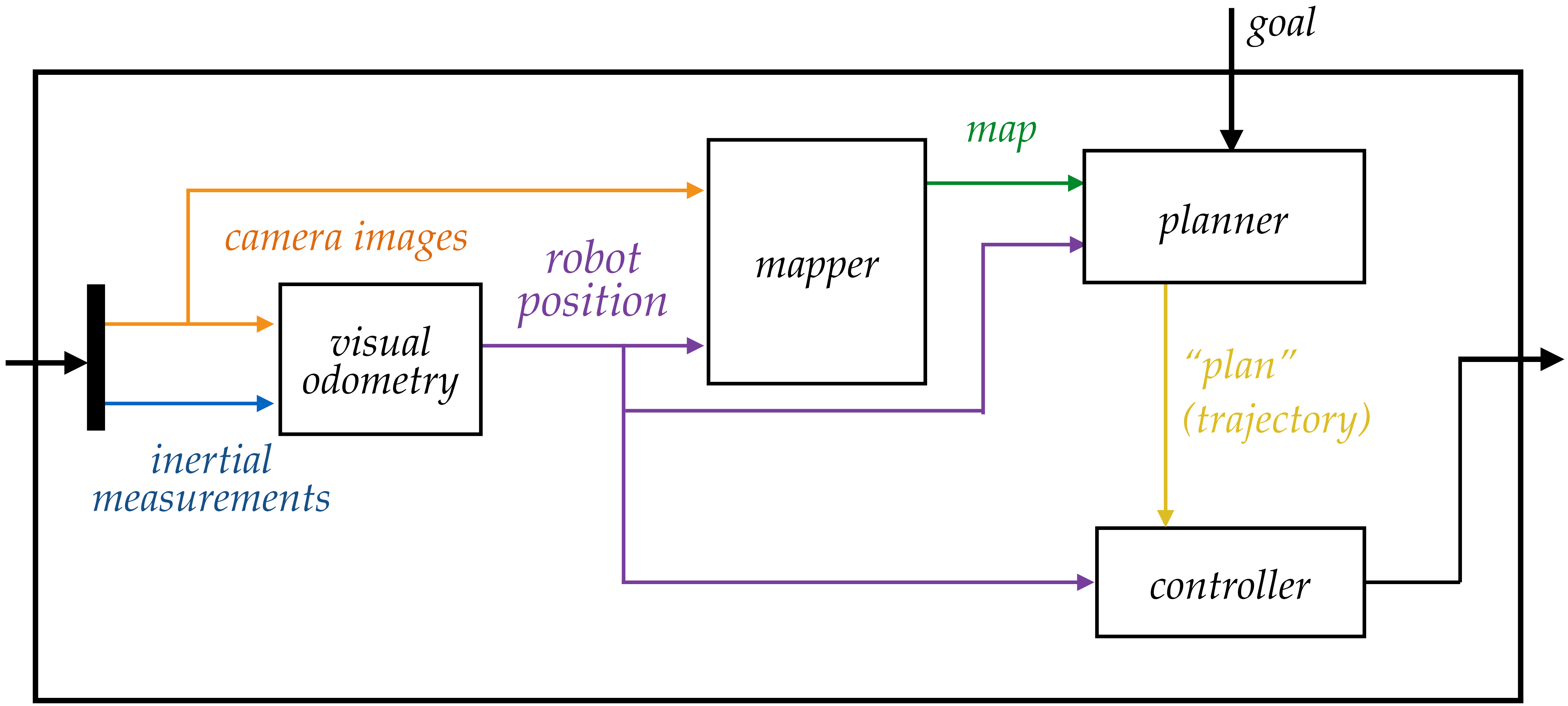
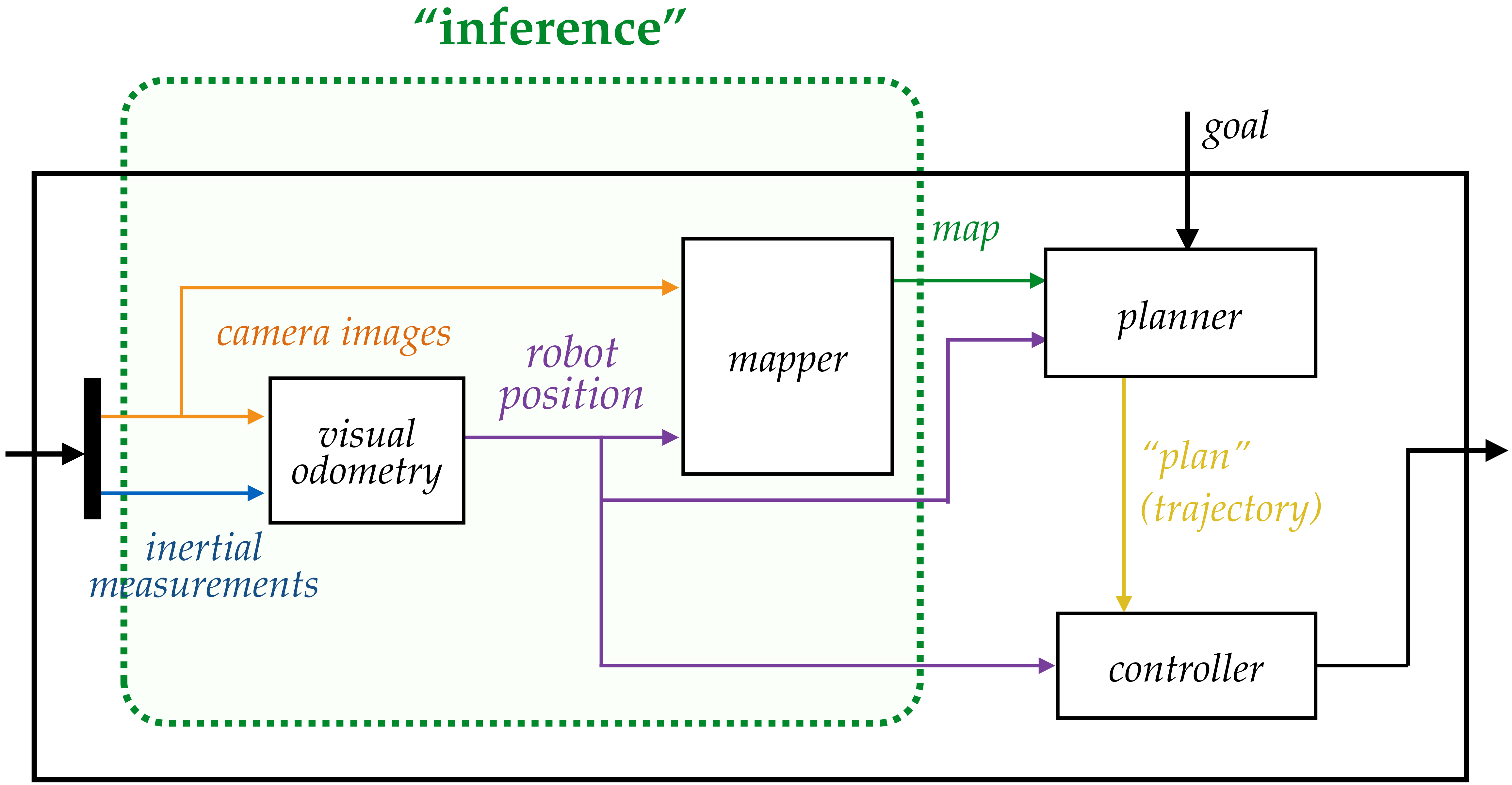




goal
map
planner
camera images
robot
position
mapper
visual
odometry
"plan"
(trajectory)
inertial
measurements
controller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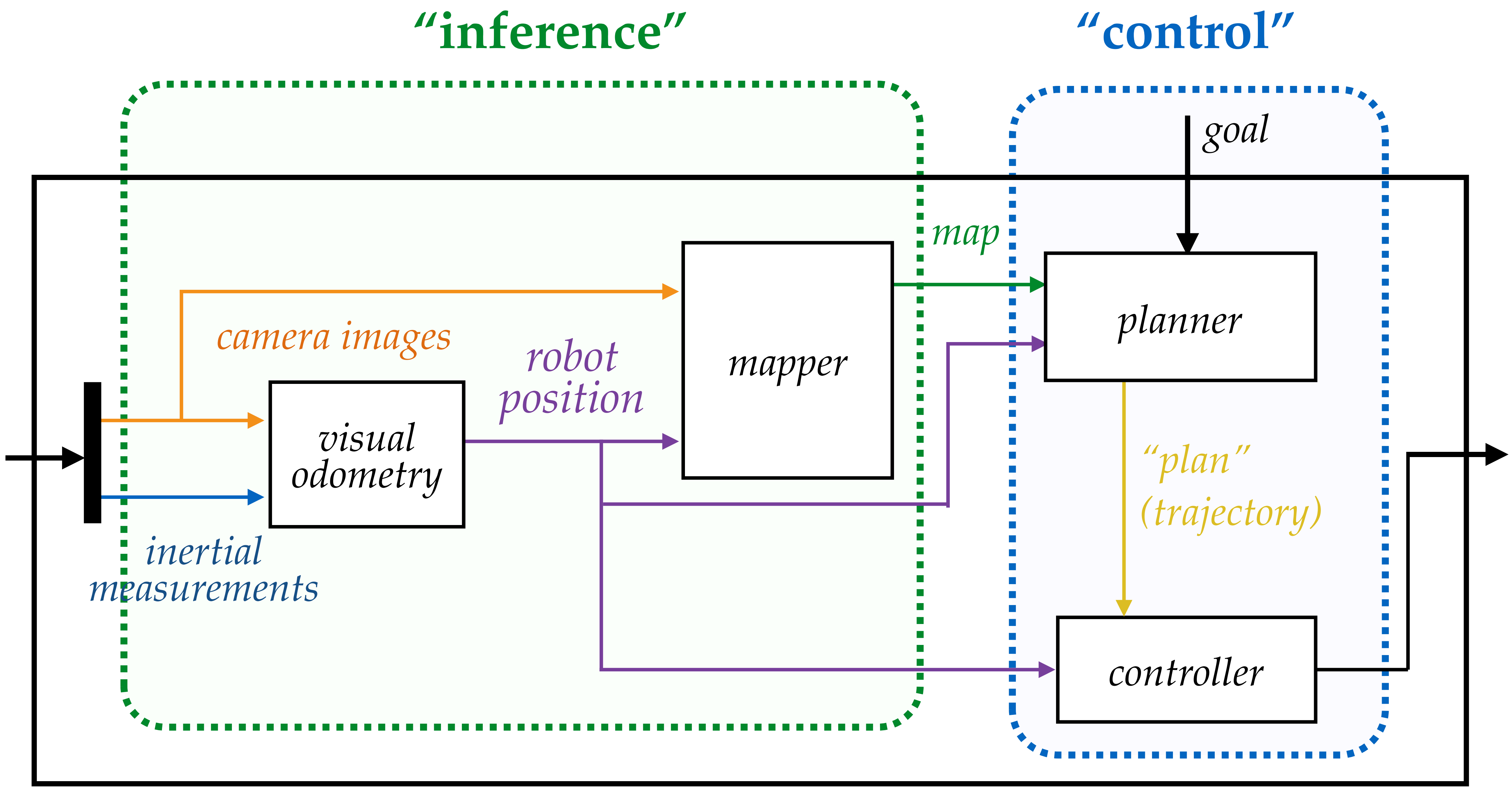
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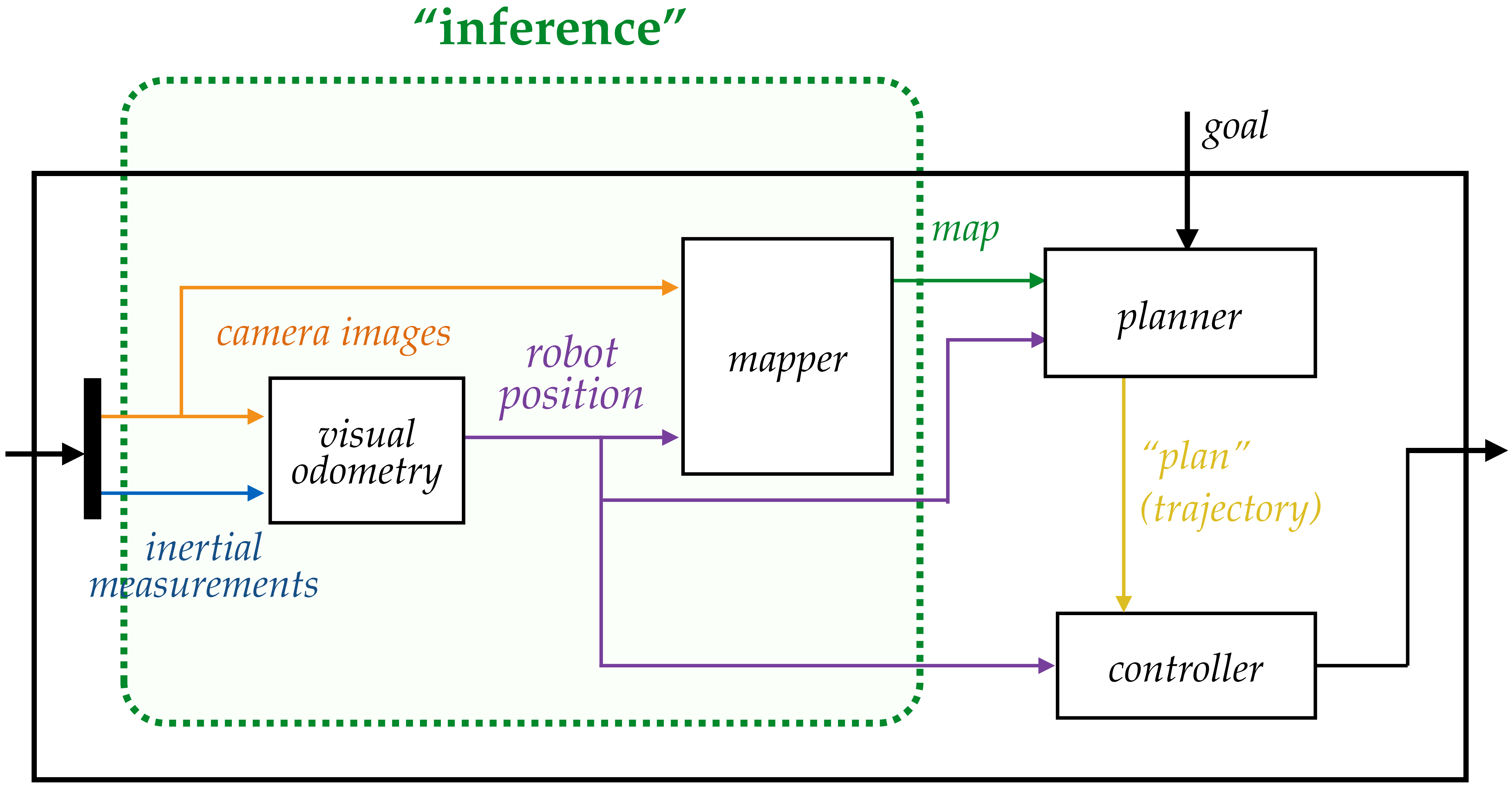
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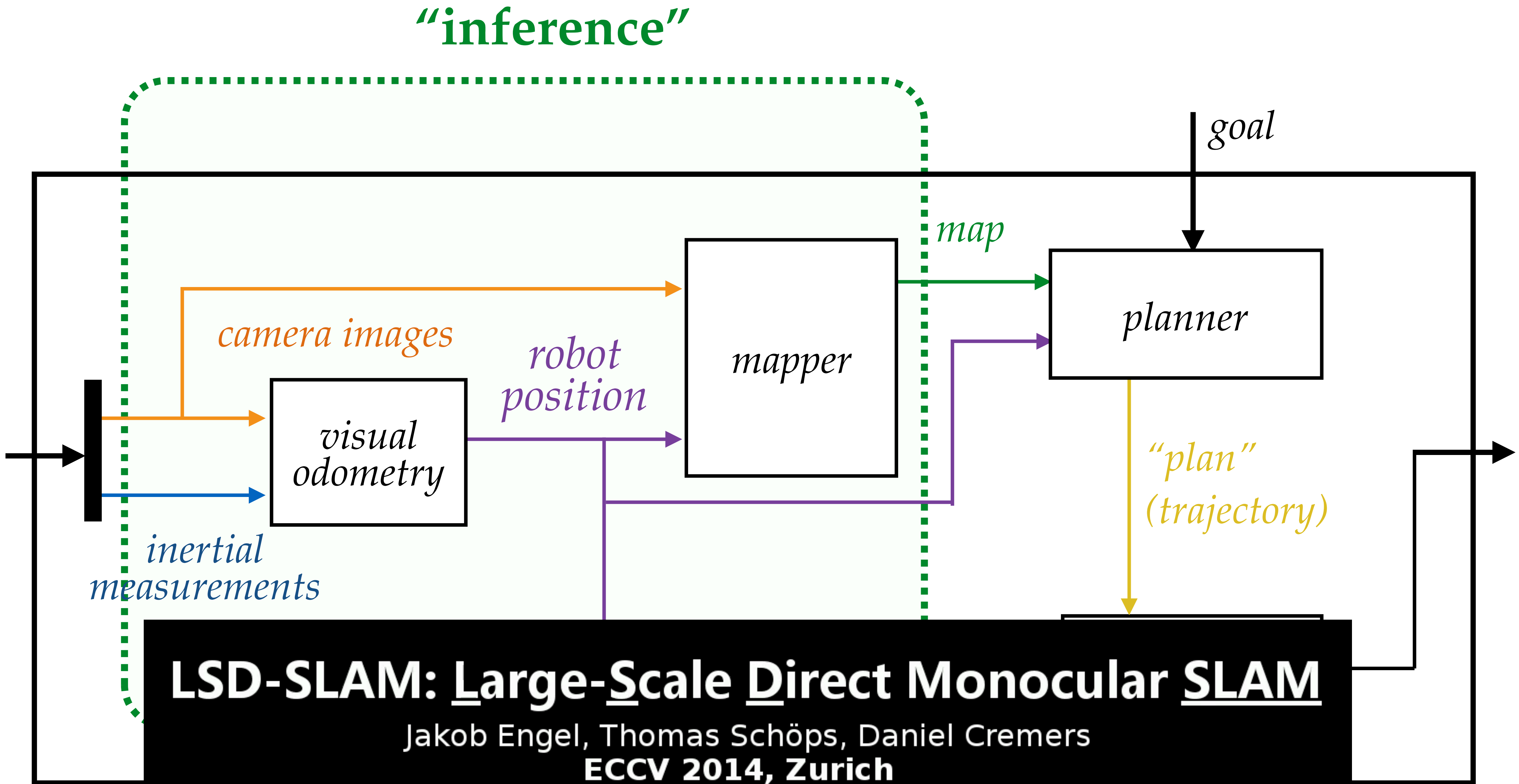

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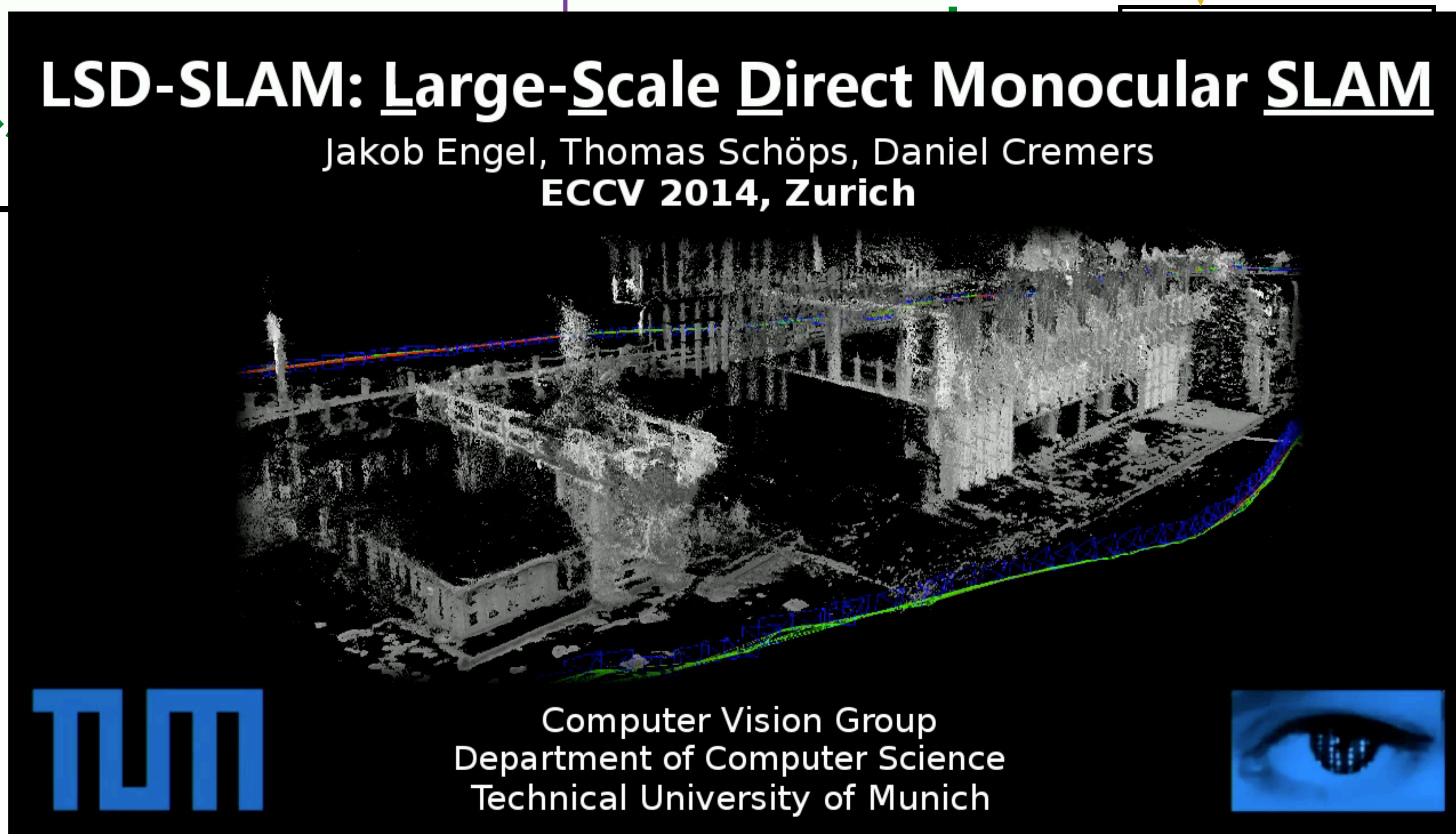
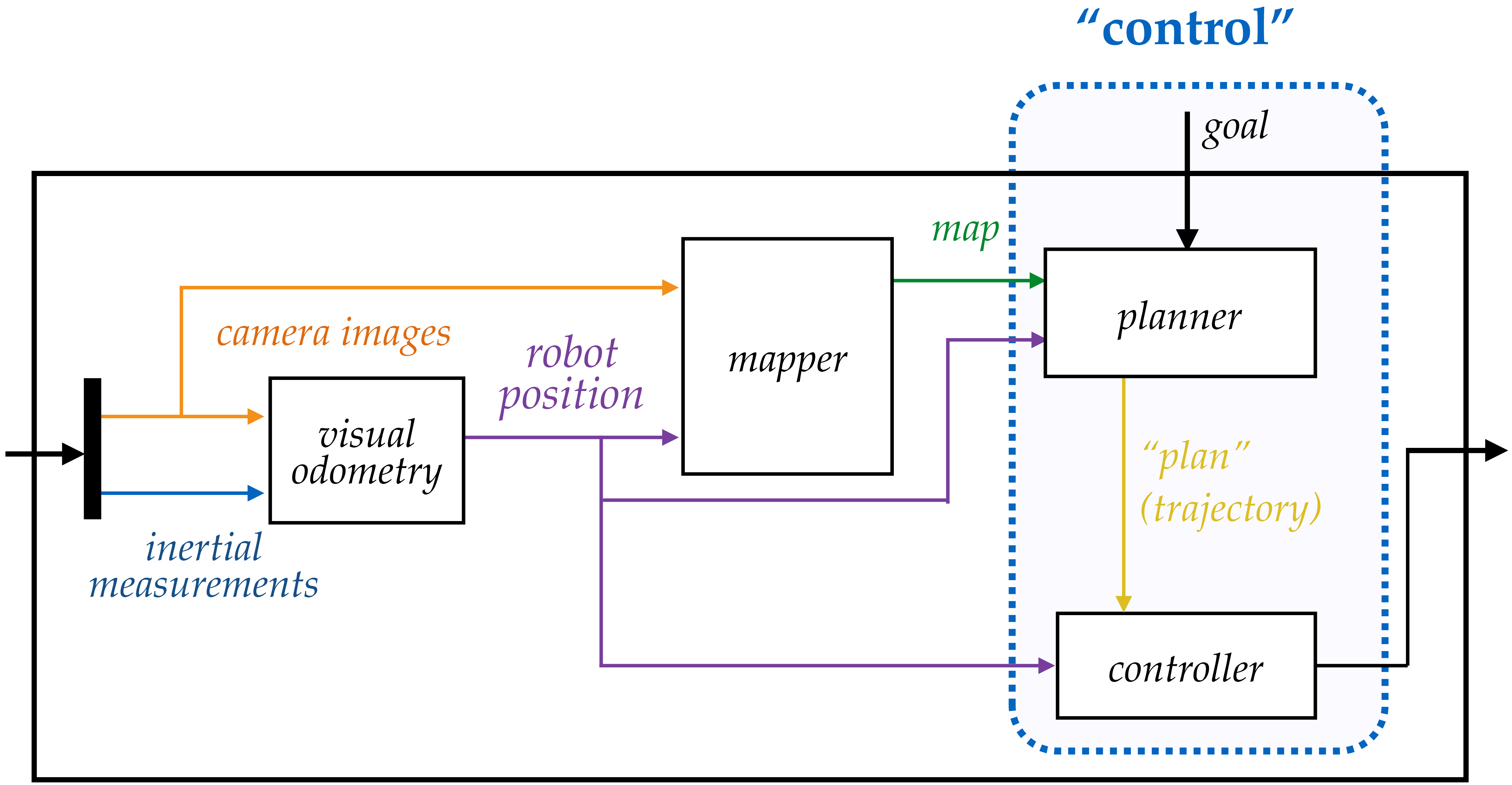


LSD-SLAM: Large-Scale Direct Monocular SLAM
Jakob Engel, Thomas Schöps, Daniel Cremers
ECCV 2014, Zurich
Computer Vision Group
Department of Computer Science
Technical University of Munich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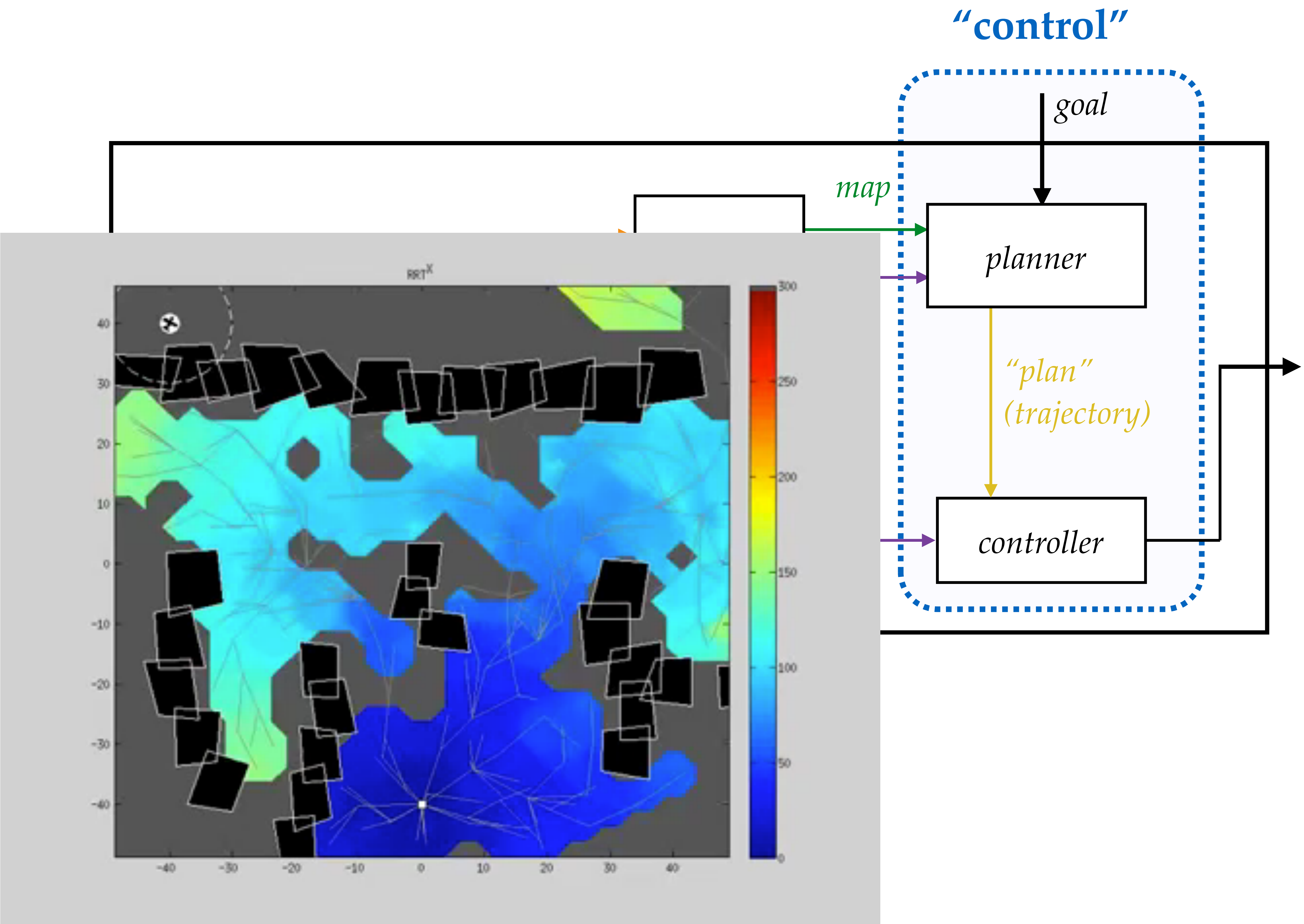
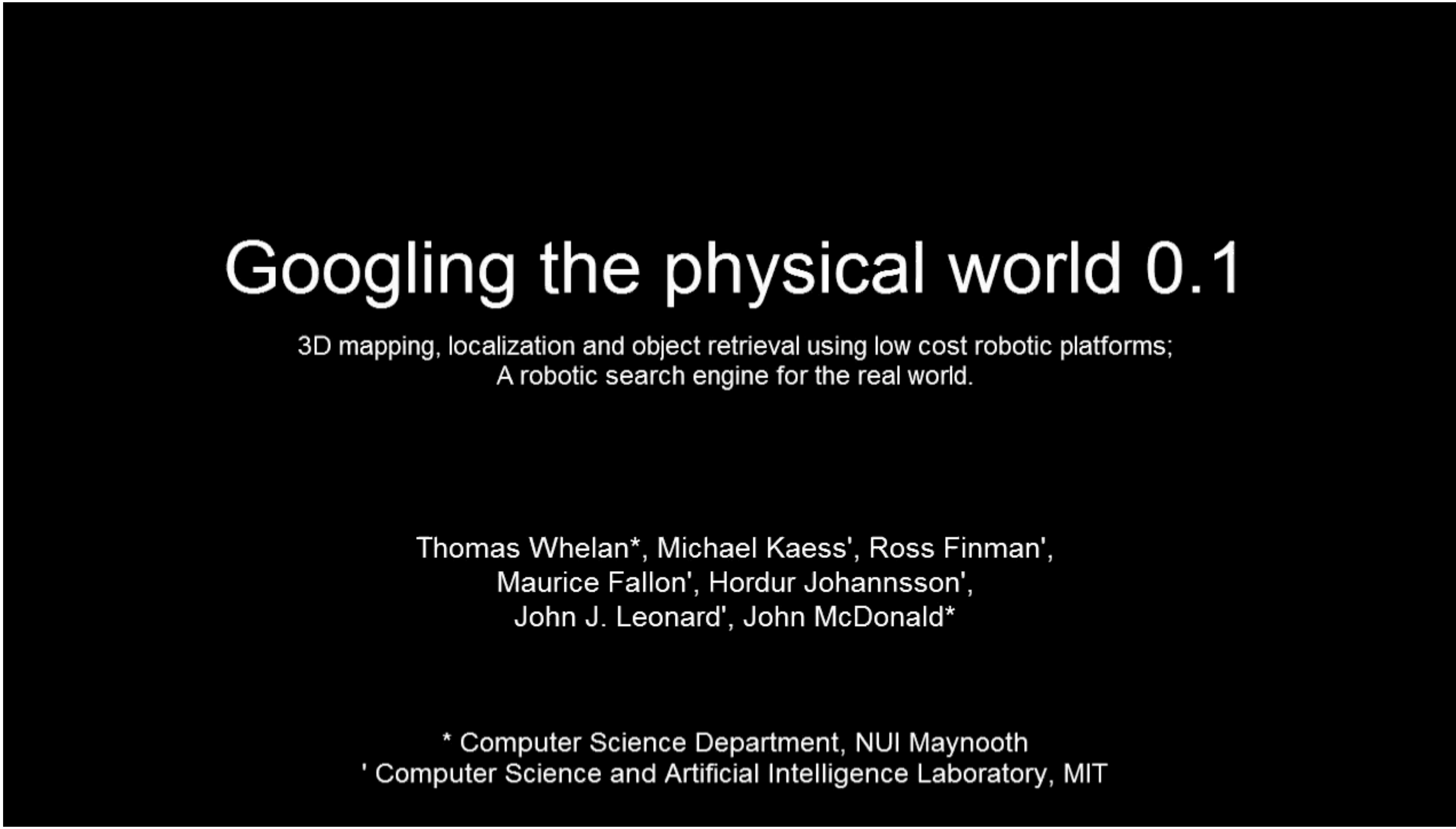


Otte, RRTX for Dubin's vehicle in a dynamic environment

A demo of a complete system

A demo of a complete system



Perception is solved!

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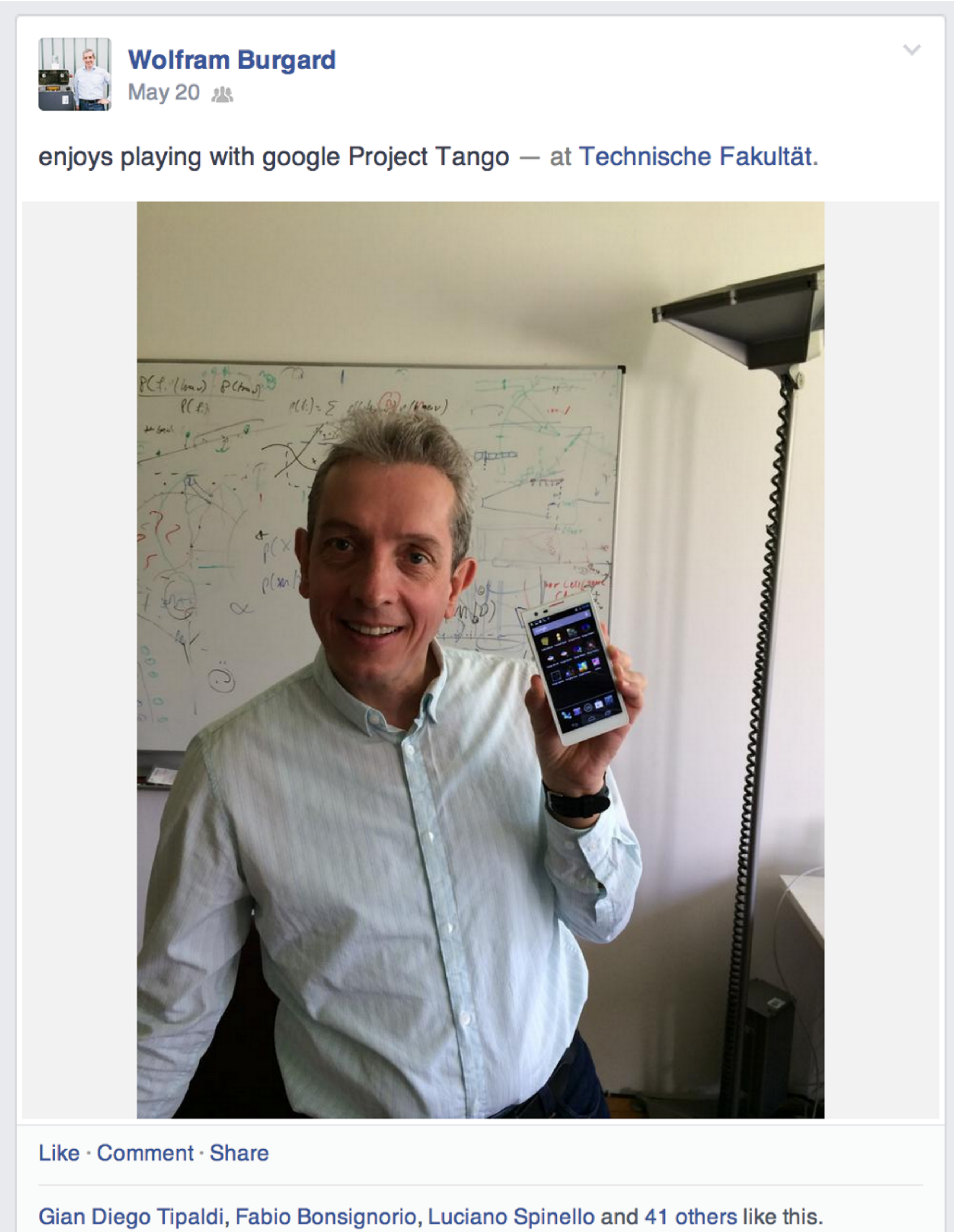

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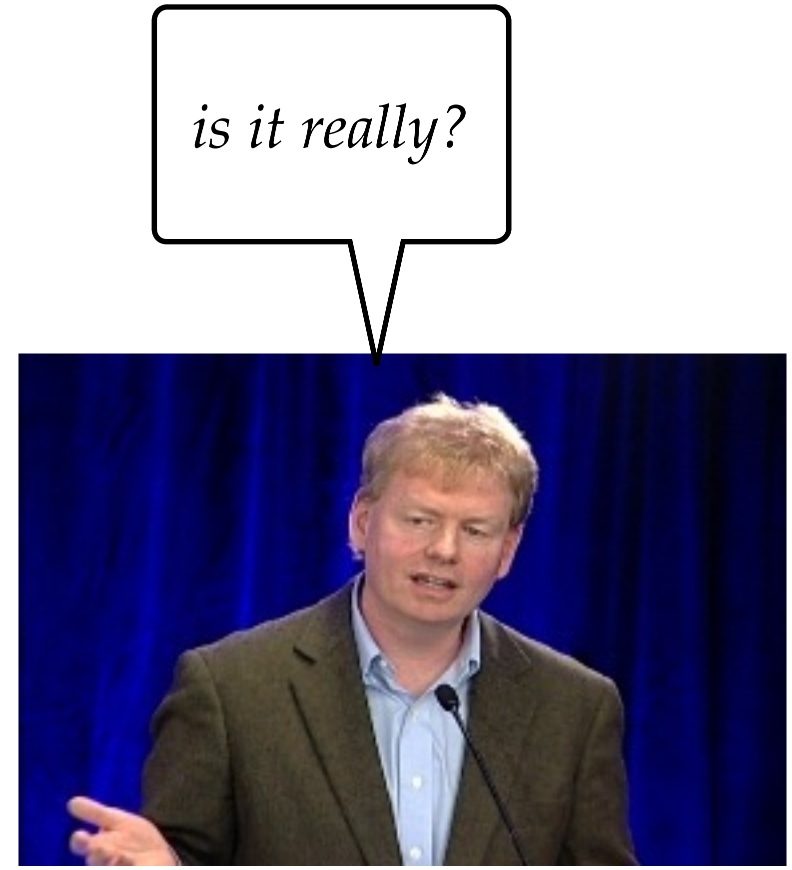

Perception is solved!

is it really?

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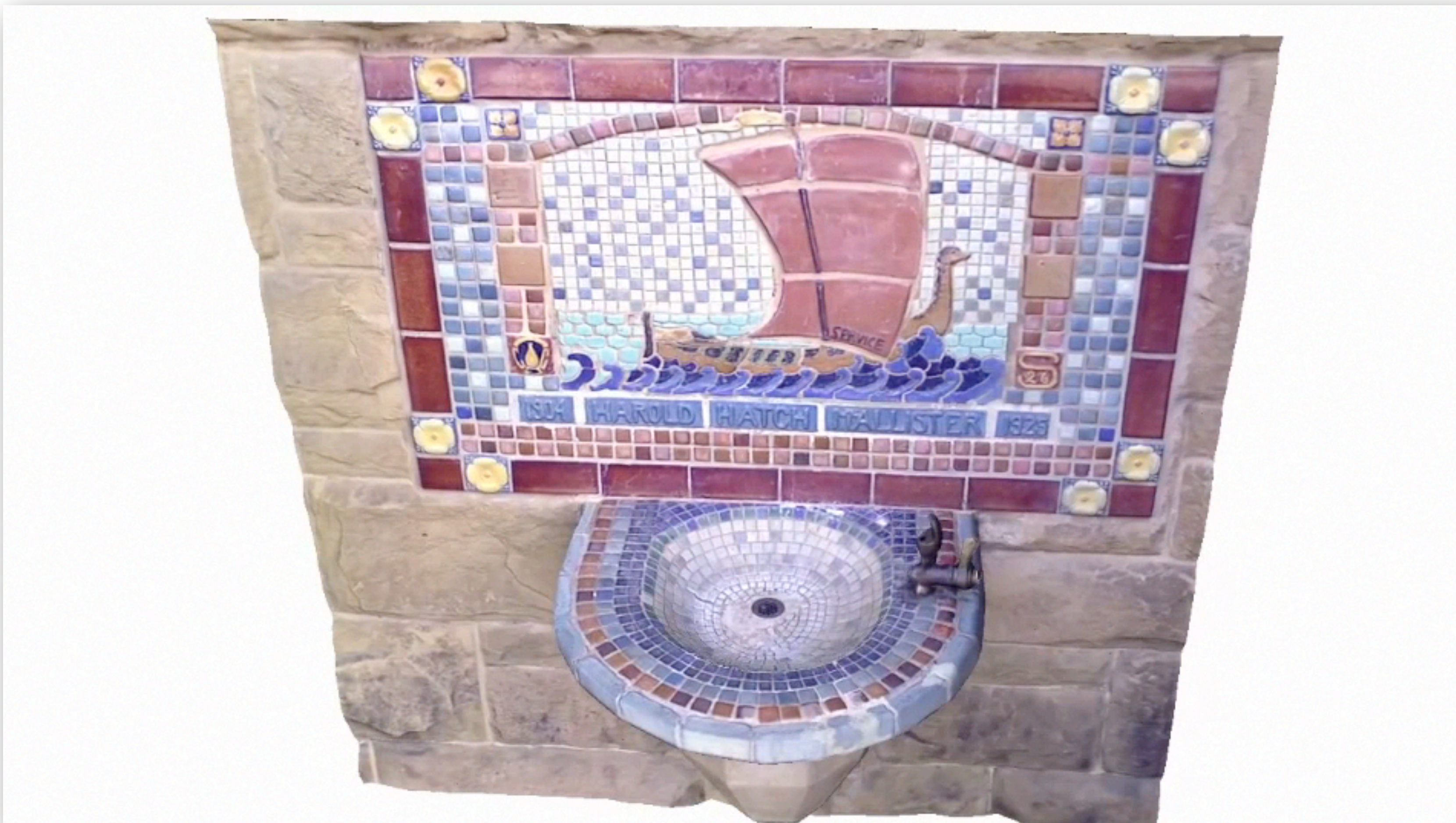

Zhou, Koltun. *Color Map Optimization for 3D Reconstruction with Consumer Depth Cameras,* SIGGRAPH 2014.

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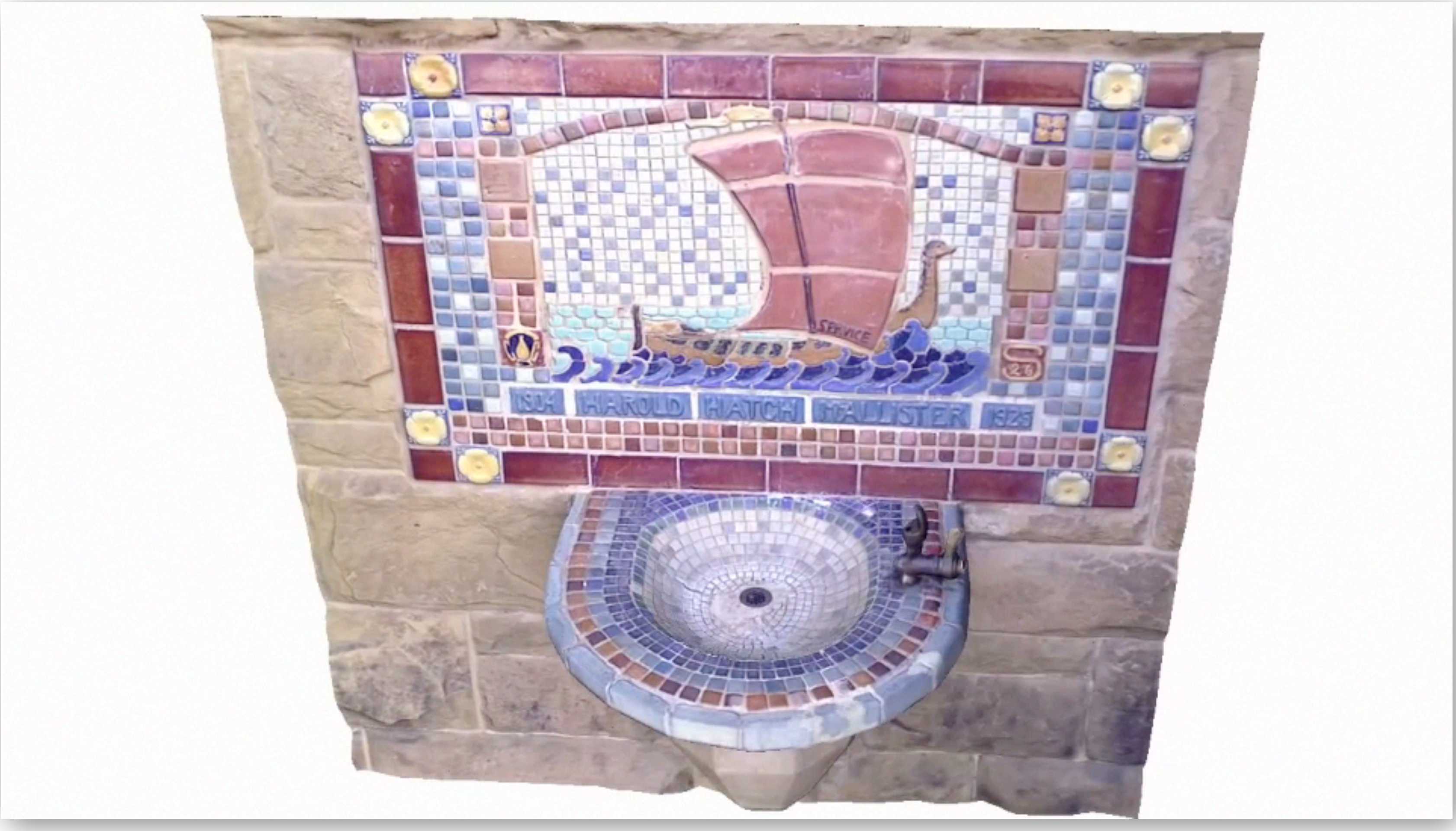

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perception **in** robotics

perception **in** robotics

↓

perception **for** robotics

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1. The business of adapting cool techniques in other fields to obtain a cute demo with a robot.

What is Robotics?

1. The business of adapting cool techniques in other fields to obtain a cute demo with a robot.
2. The scientific quest of understanding and replicating embodied intelligence.

What's embodied intelligence about?

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- It’s (also) about doing well in the world using **limited resources.**

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agent resources

power

computation

memory

bandwidth

latency budget

What's embodied intelligence about?

- It's (also) about doing well in the world using **limited resources.**

designer resources
("offline" resources)

design effort

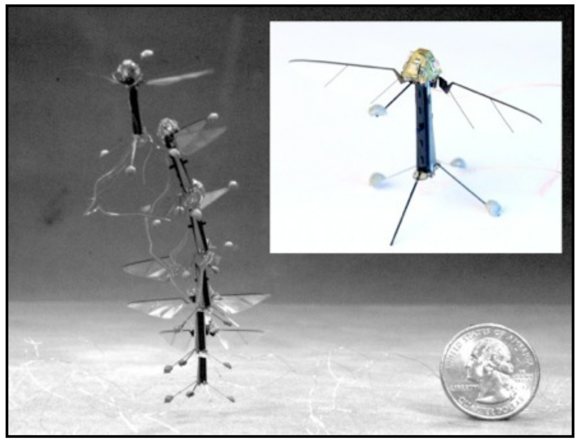
prior knowledge

agent resources

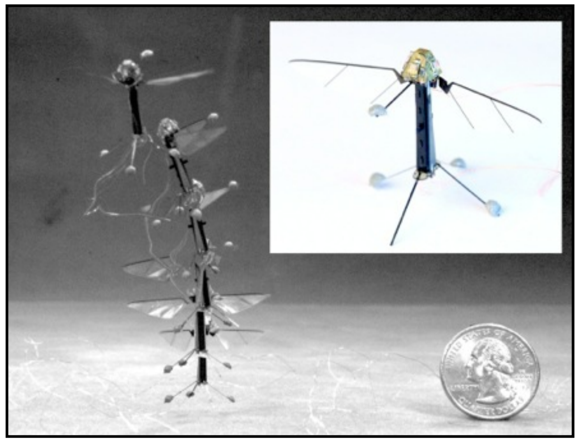
power
computation
memory
bandwidth
latency budget

complexity

complexity



complexity



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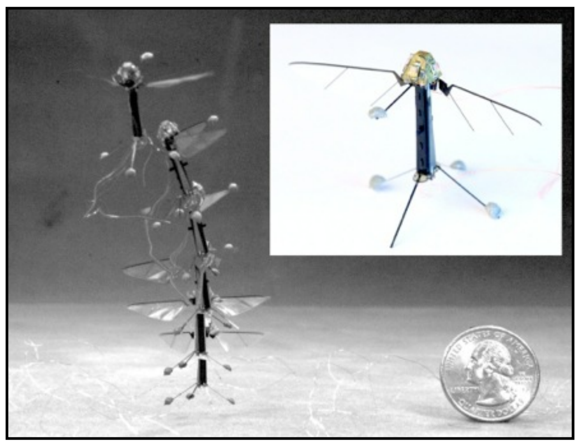

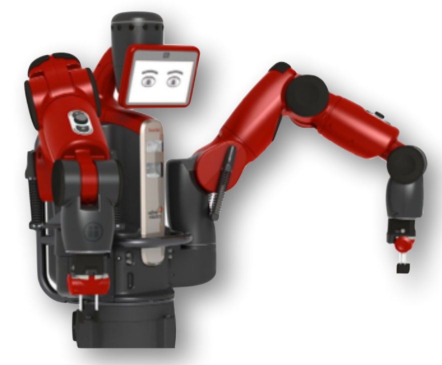

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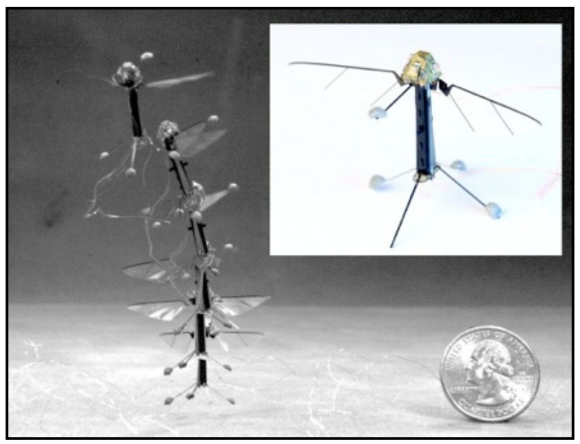

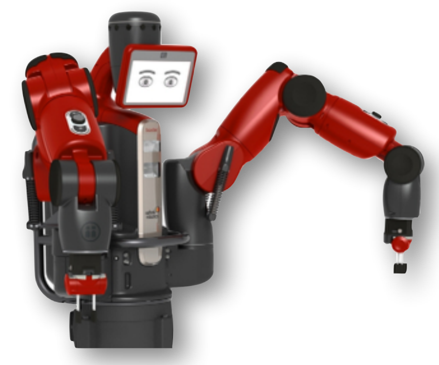

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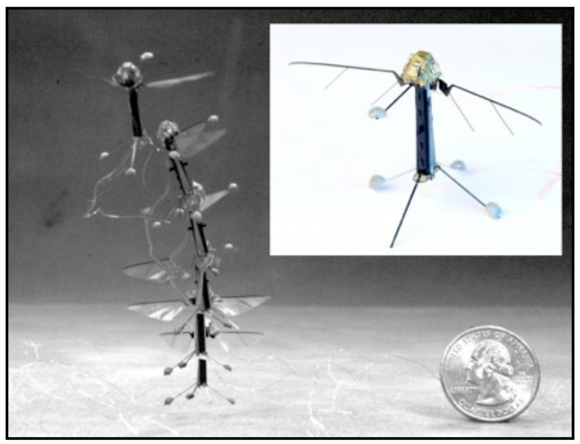

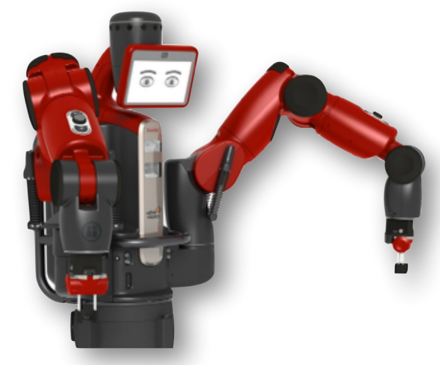

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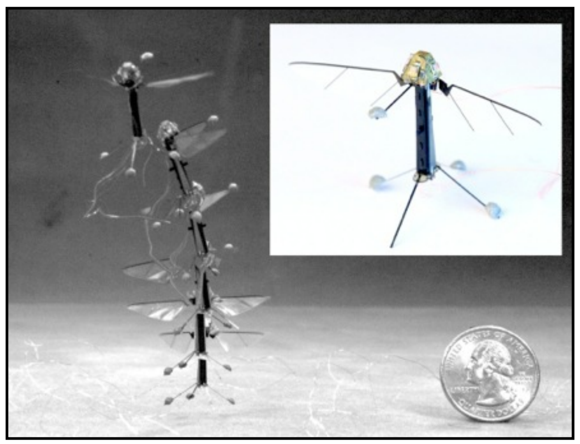

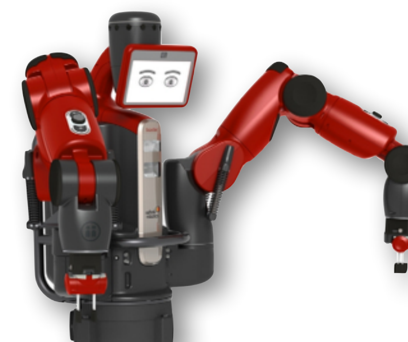


Doing well with limited resources

Doing well with limited resources

- Here's a task T; X watts of power; and Z bytes of memory. Design an agent that gives a reasonable answer in Y seconds with minimum obtained performance P.

Some control theory pride

Some control theory pride

a textbook example of a formal design problem

11.15 (Stabilization of an inverted pendulum with visual feedback) Consider stabilization of an inverted pendulum based on visual feedback using a video camera with a 50-Hz frame rate. Let the effective pendulum length be l. Assume that we want the loop transfer function to have a slope of $n_{gc} = -1/2$ at the crossover frequency. Use the gain crossover frequency inequality to determine the minimum length of the pendulum that can be stabilized if we desire a phase margin of 45°.

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textbook: Åström, Murray Feedback Systems (available online)

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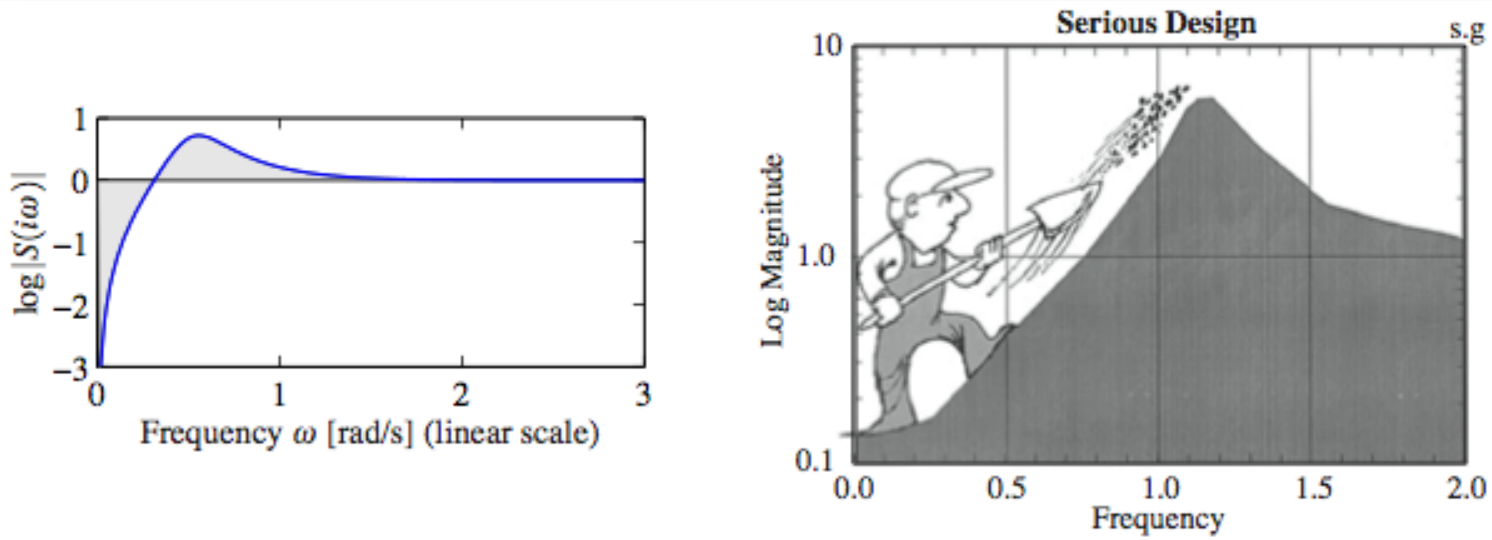
a textbook example of a trade-off between design objectives



(a) Bode integral formula

(b) Control design process

Figure 11.14: Interpretation of the *waterbed effect*. The function $\log |S(i\omega)|$ is plotted versus ω in linear scales in (a). According to Bode's integral formula (11.19), the area of $\log |S(i\omega)|$ above zero must be equal to the area below zero. Gunter Stein's interpretation of design as a trade-off of sensitivities at different frequencies is shown in (b) (from [Ste03]).

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$X = 500\ W$

$Y = 100\ milliseconds$

Doing well with limited resources

- Here's a task T; X watts of power; and Z bytes of memory. Design an agent that gives a reasonable answer in Y seconds with minimum obtained performance P.

$X = 1\ \mu W$

$Y = 1$ *millisecond*

$X = 500\ W$

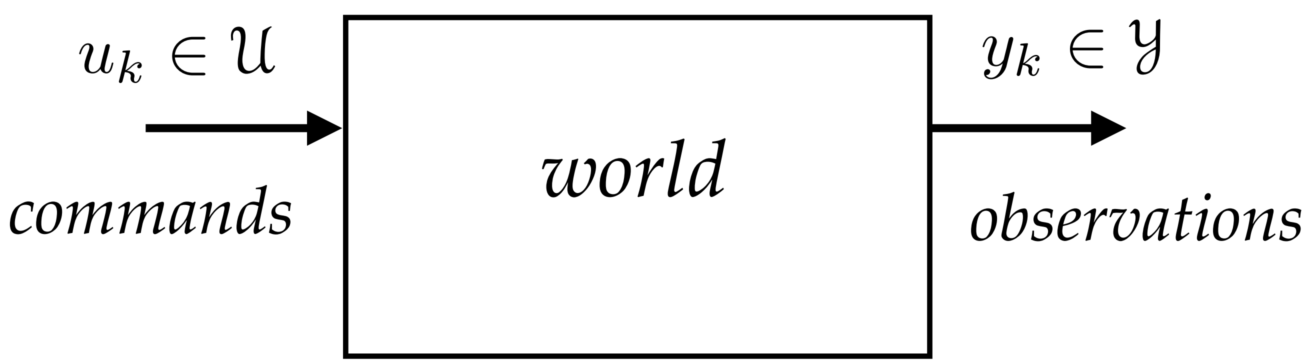
$Y = 100$ *milliseconds*

Joint inference and control: opportunities and challenges

Joint inference and control: opportunities and challenges

solving the joint problem
is more resource-efficient

- The world / plant is
  a causal black box from $\boldsymbol{u}$ to $\boldsymbol{y}$.



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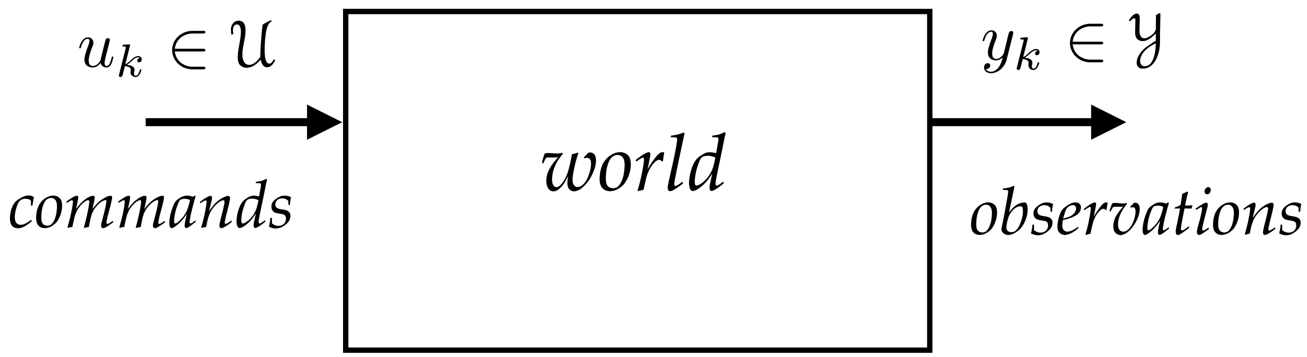
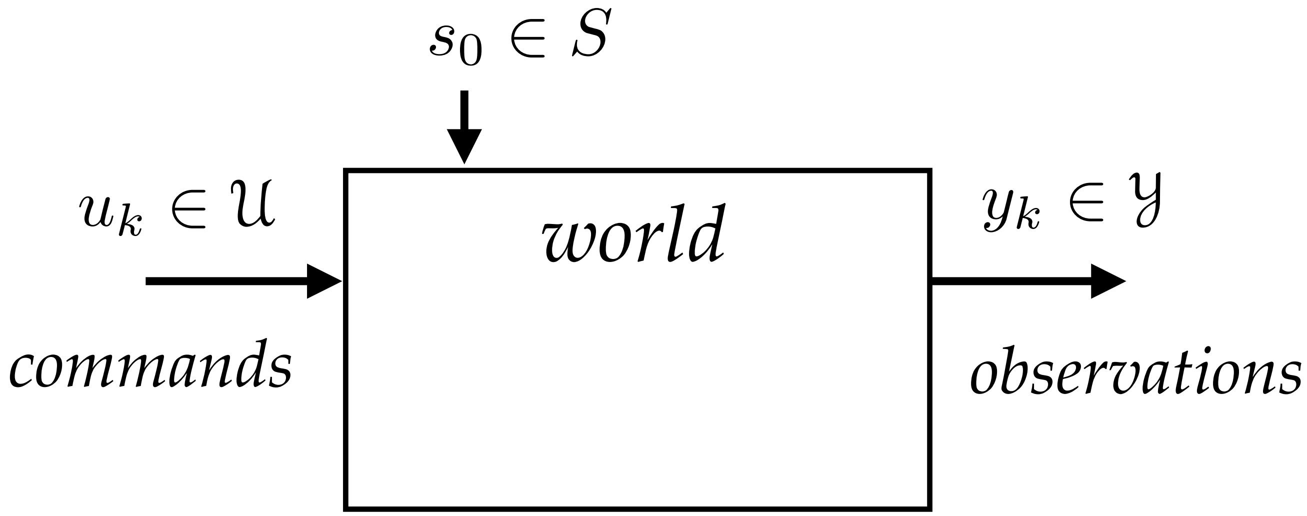


- We need to design an agent / controller
  as a causal black box from $\boldsymbol{y}$ to $\boldsymbol{u}$.

- Markov assumption:
  S are the states



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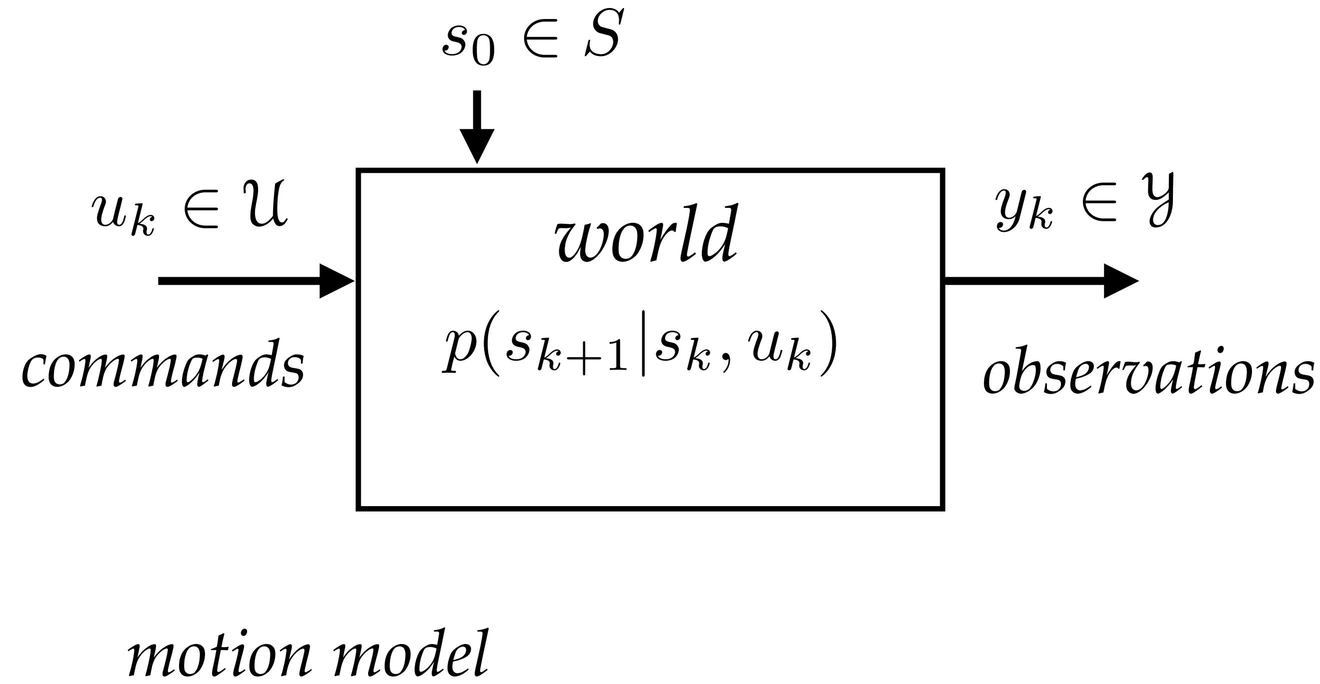

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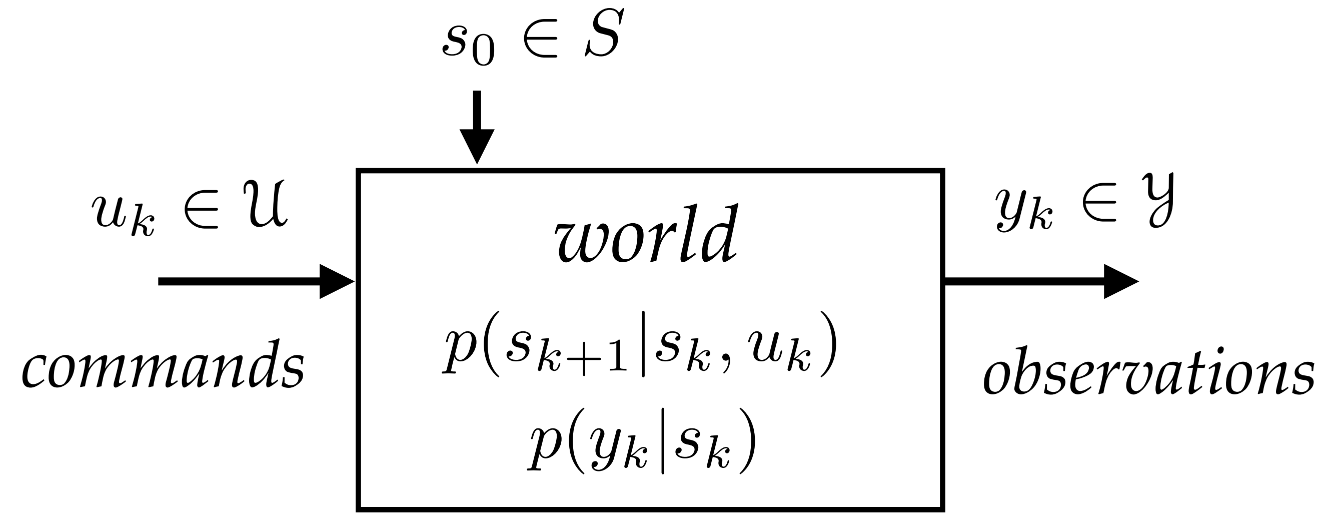
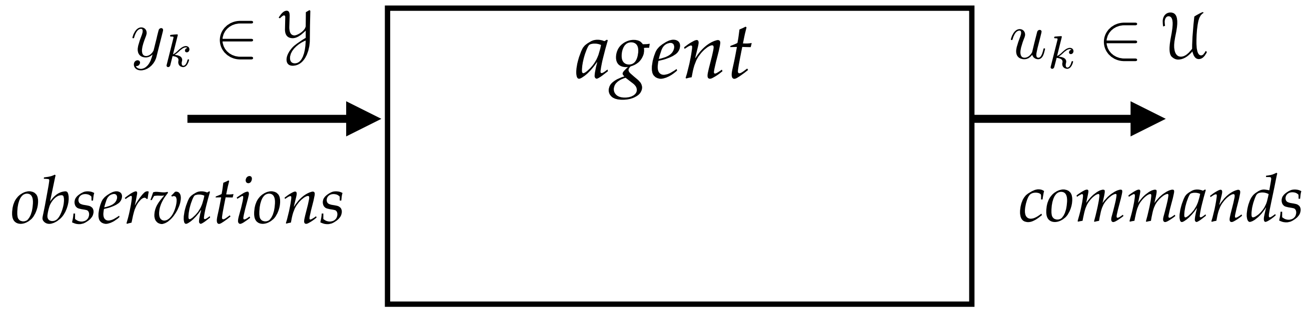
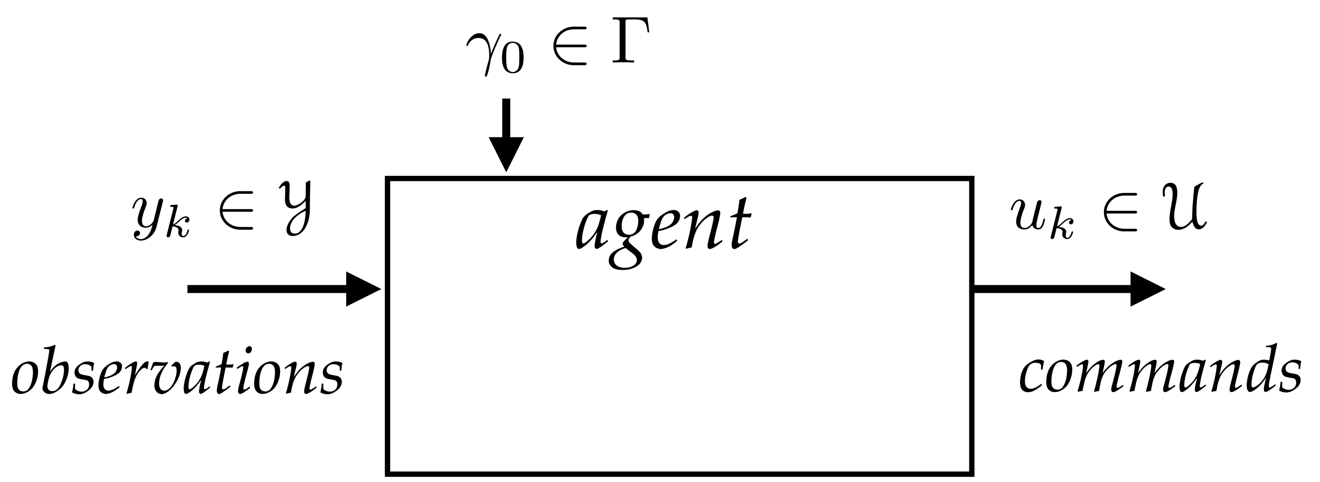


motion model *observation model*

- A **(deterministic) agent** is a tuple $\langle \Gamma, f, g \rangle$



- A **(deterministic) agent** is a tuple $\langle \Gamma, f, g \rangle$
  where Γ is any set representing the agent memory;



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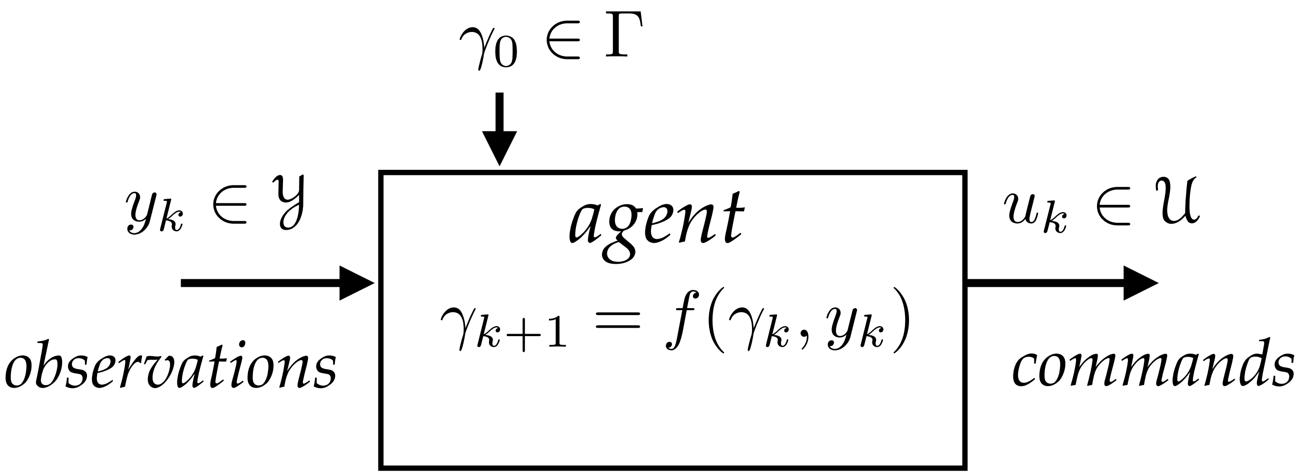

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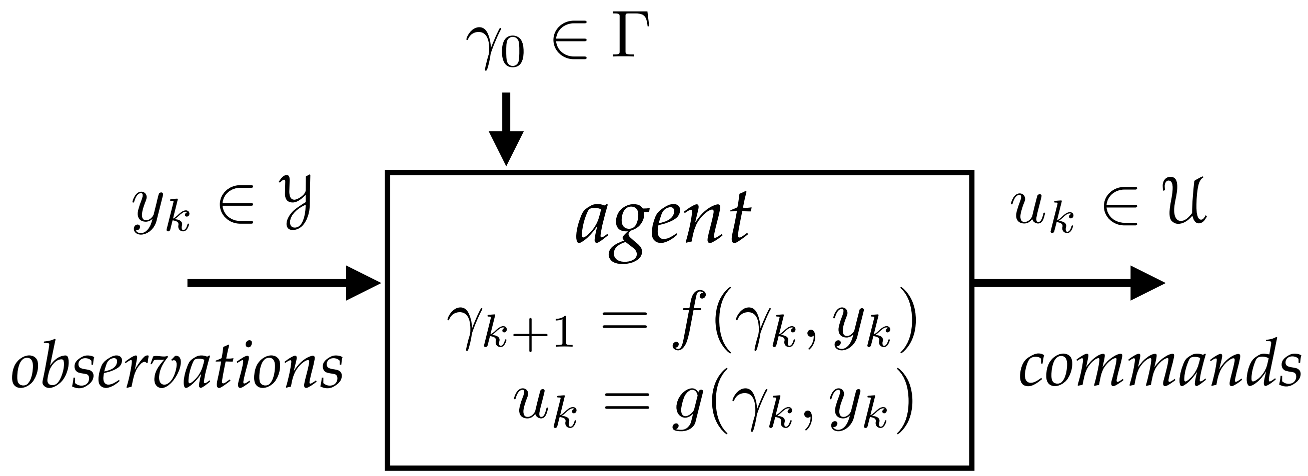
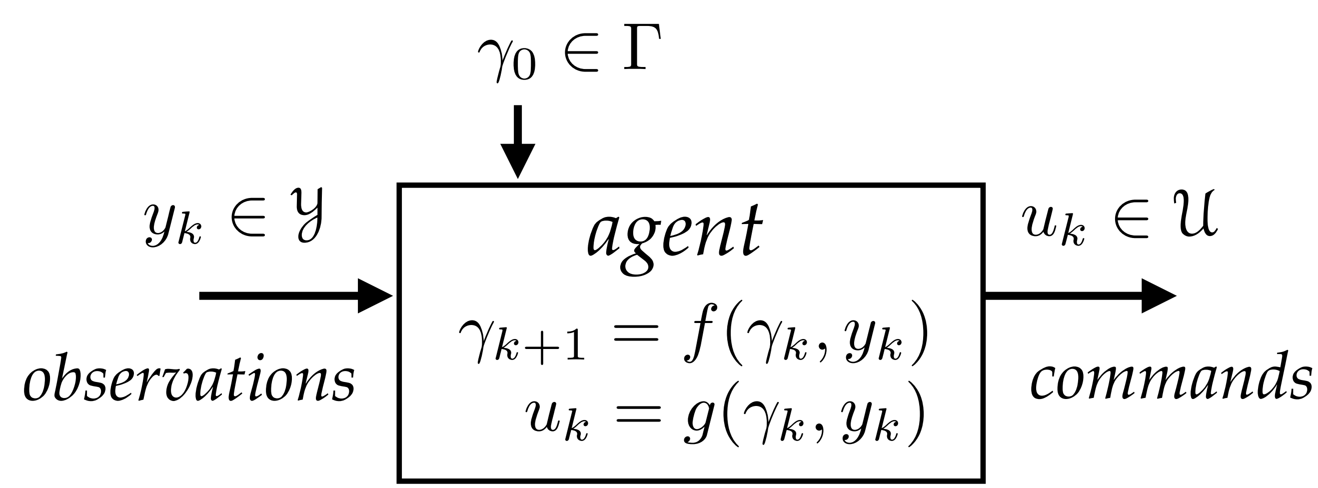
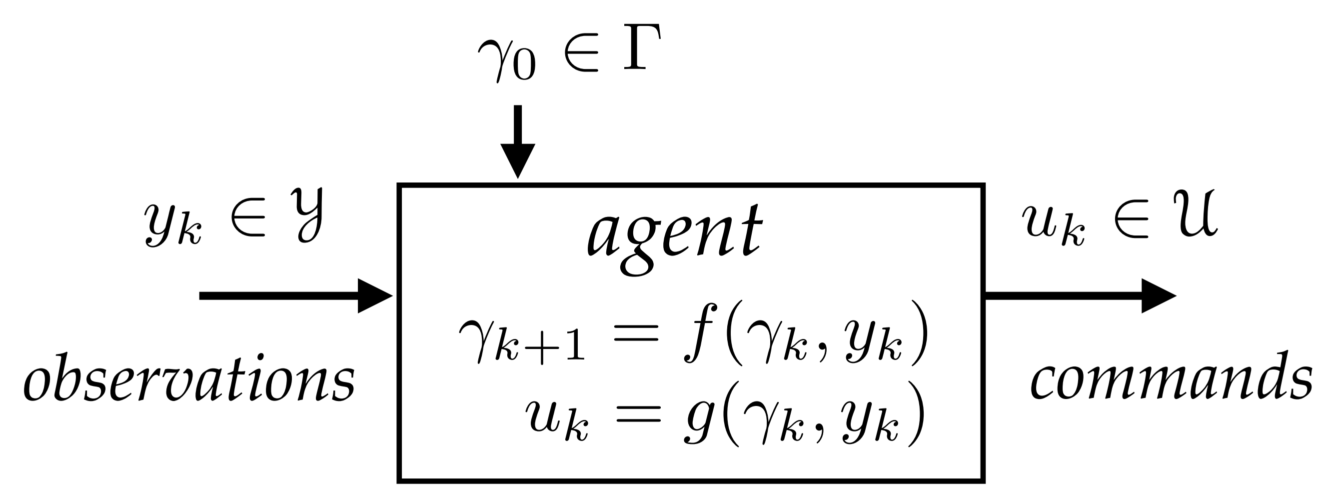


- The **"canonical" probabilistic agent:**



- The **“canonical” probabilistic agent:**

$$\Gamma \quad = \quad \textit{beliefs (probability distributions on world's state)}$$



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Γ = *beliefs (probability distributions on world's state)*

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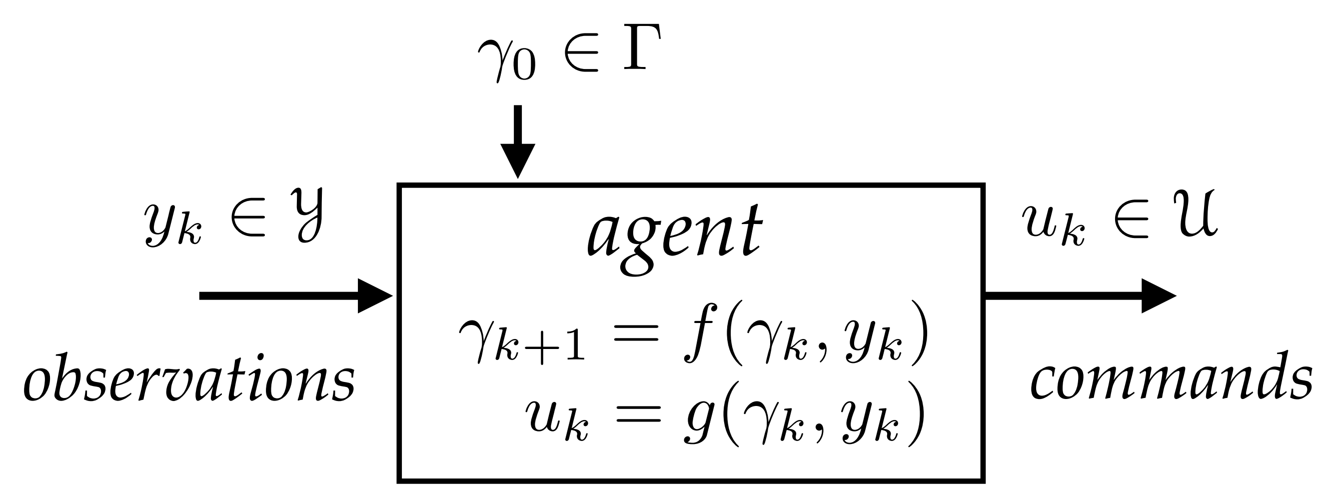

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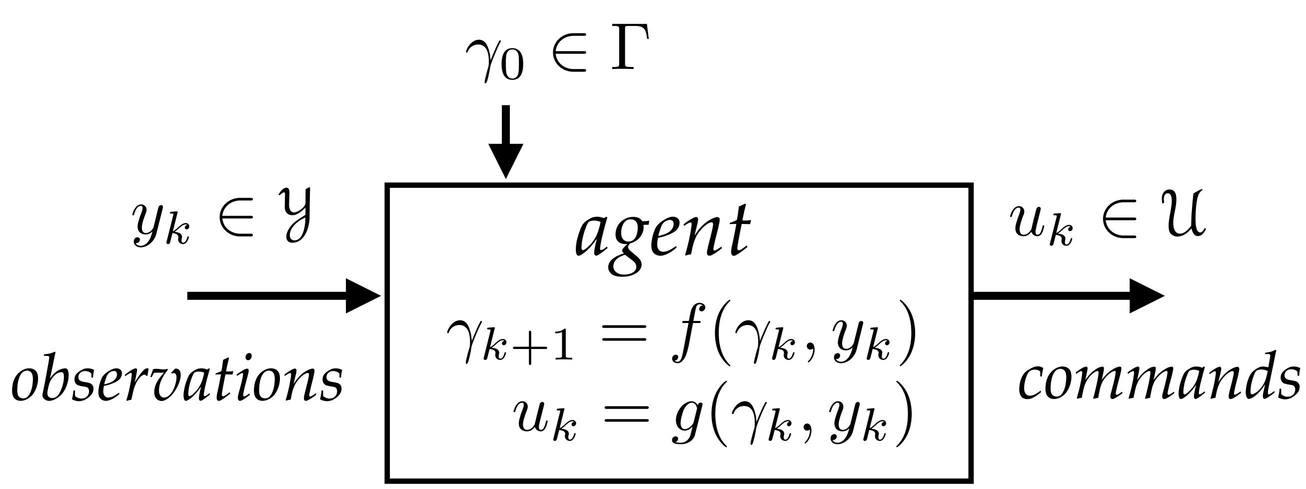

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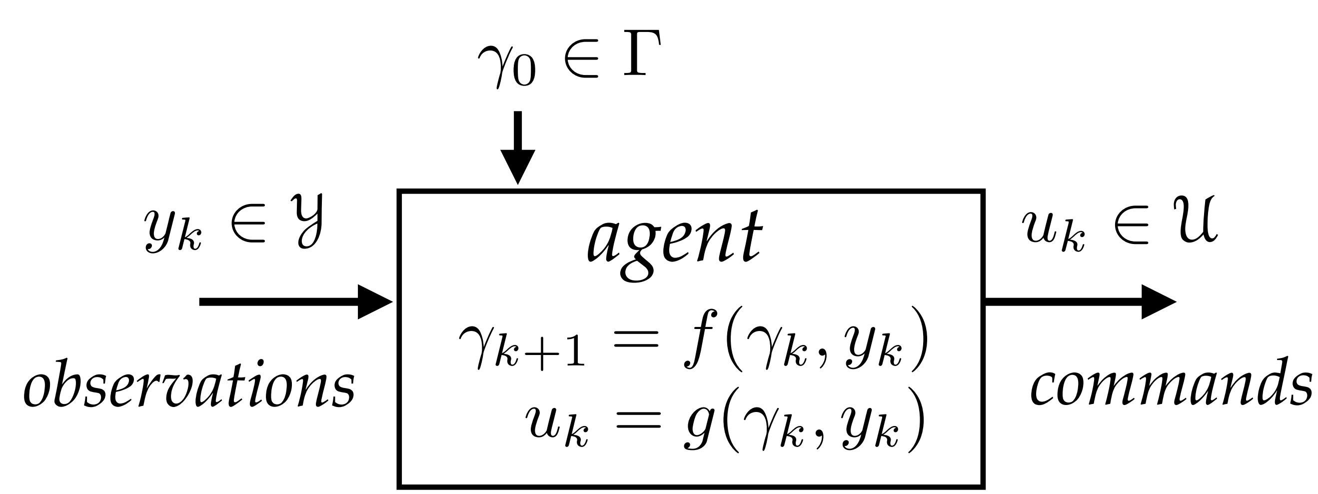

- The "~~canonical~~" realistic **probabilistic agent:**

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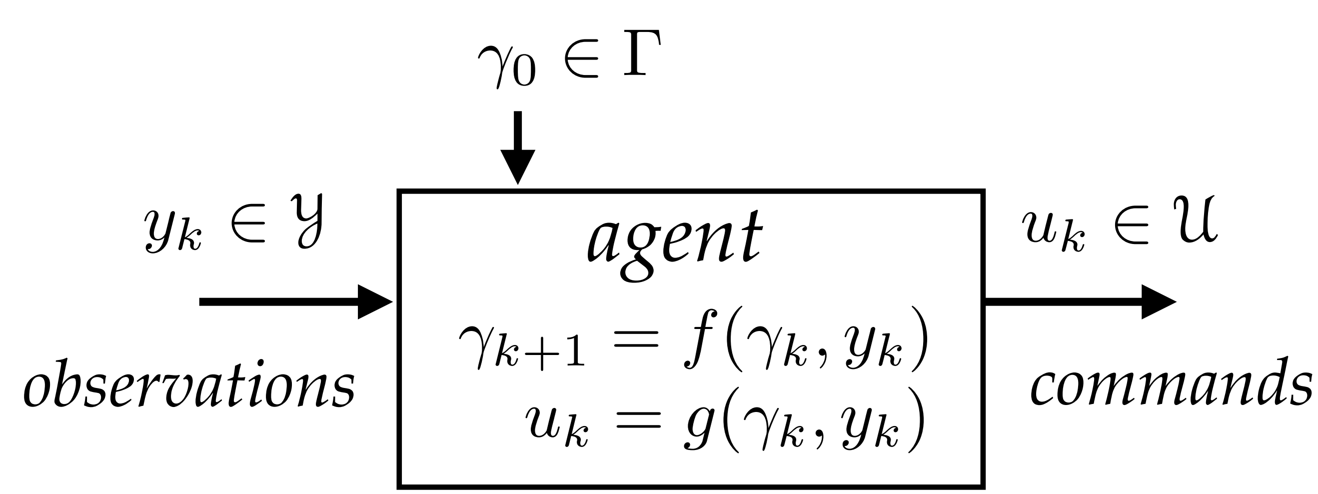

- The **“~~canonical~~” probabilistic agent:** realistic

Γ = *beliefs (probability distributions on world's state)*

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f = approximated *Bayesian filter*

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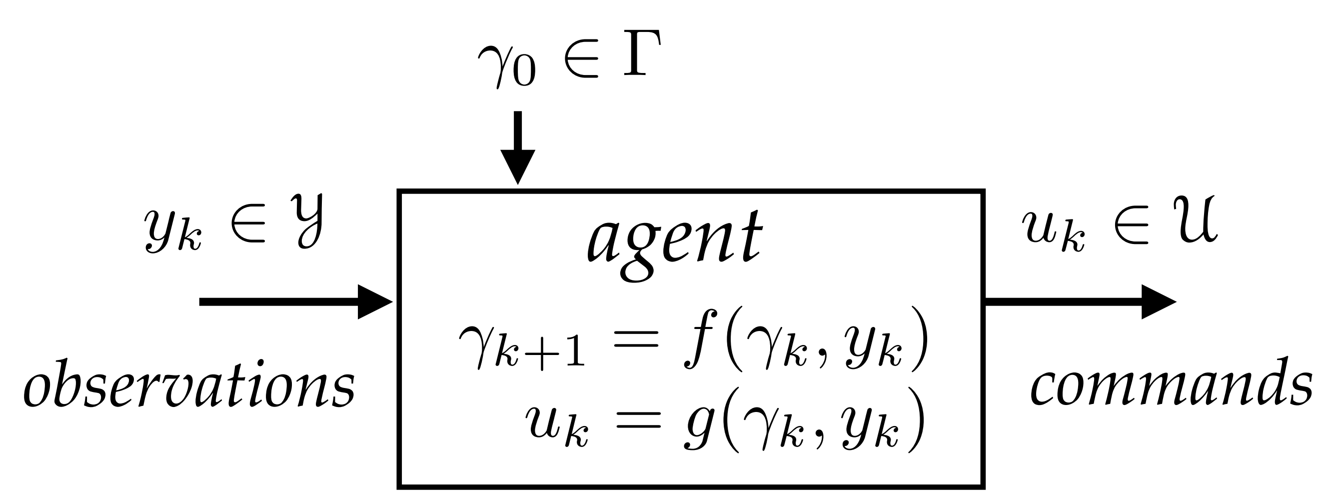

realistic

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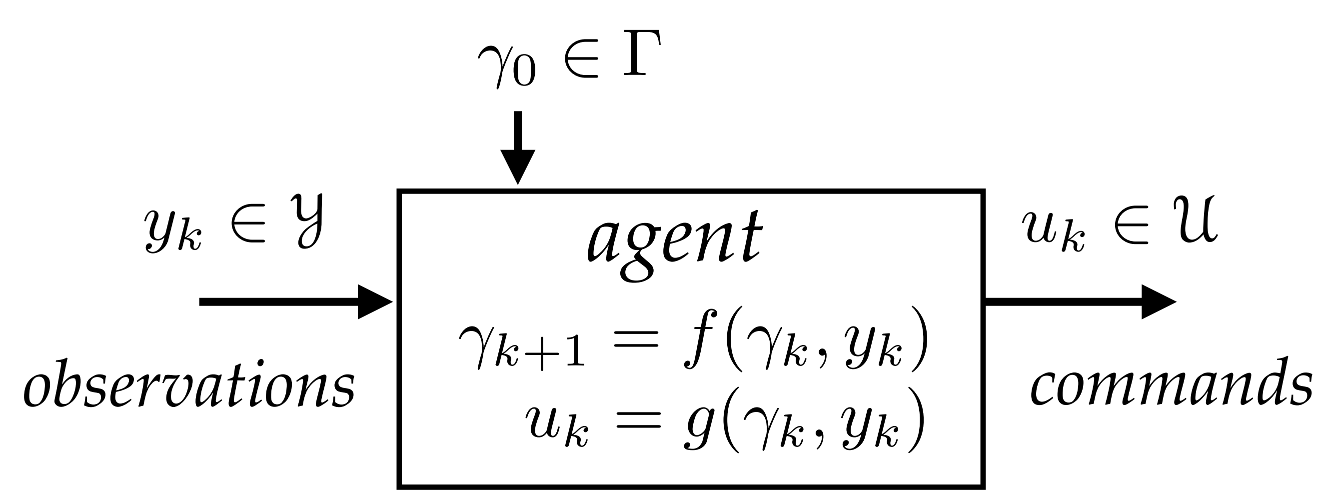
approximated

g = *solver of a POMDP*

approximated



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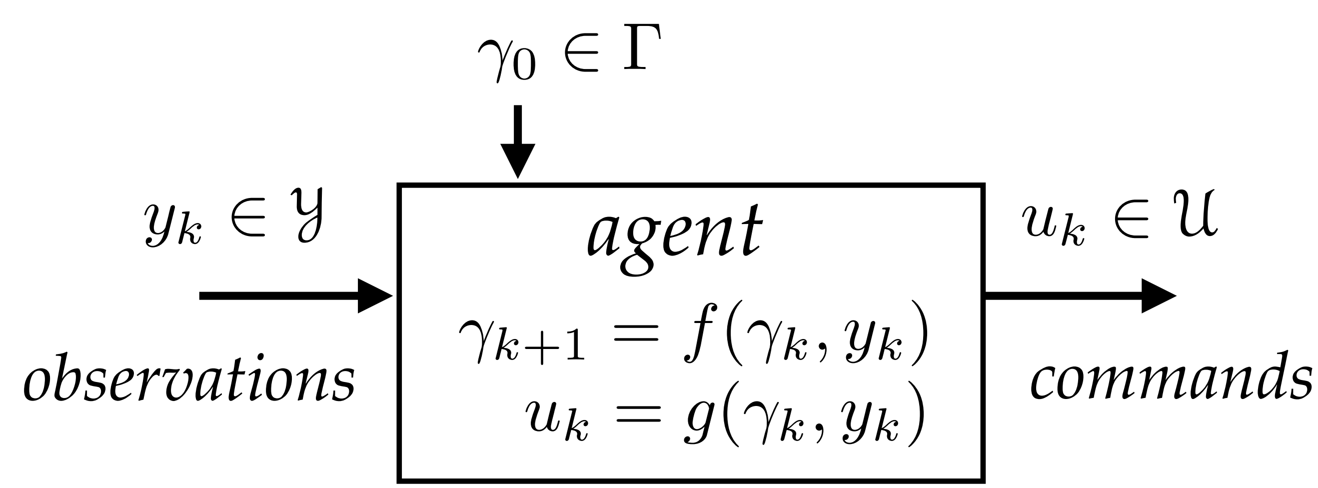

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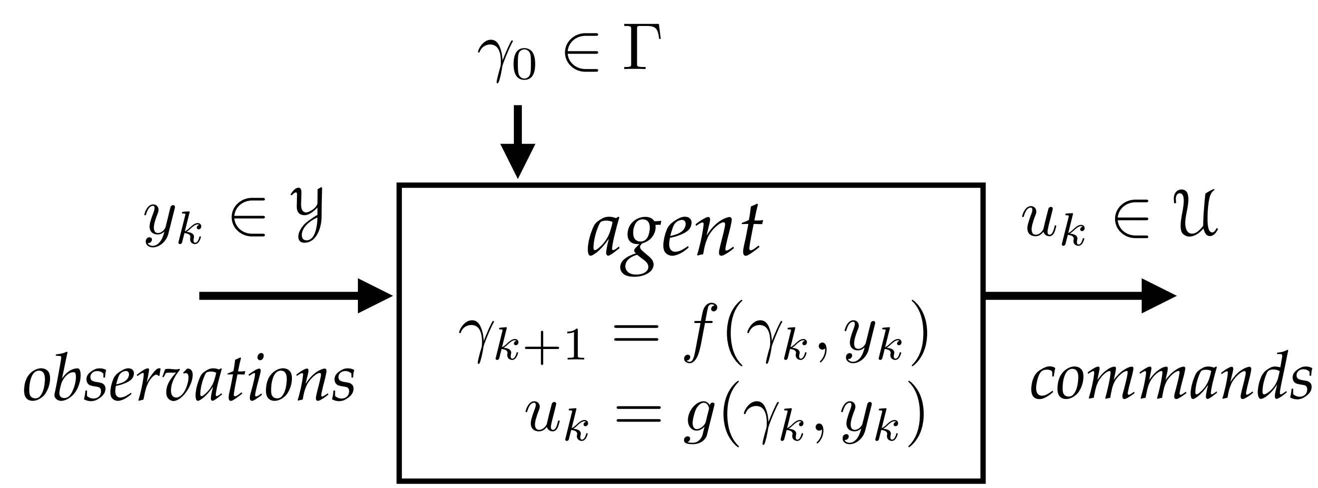

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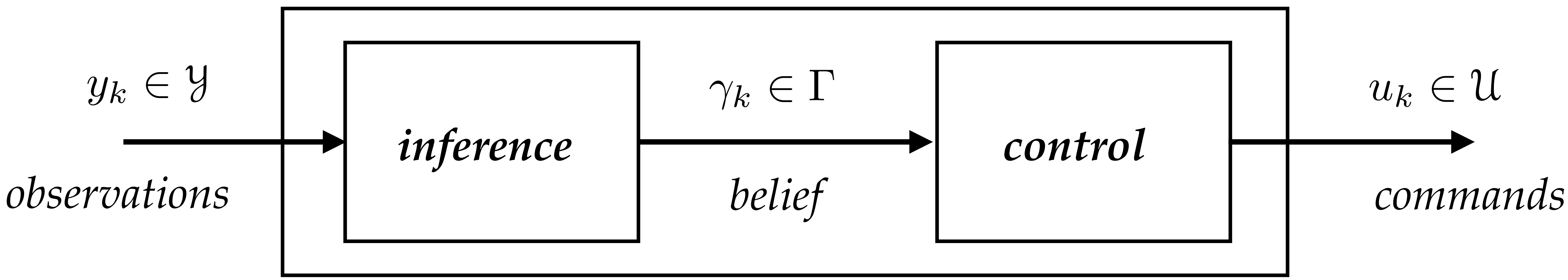

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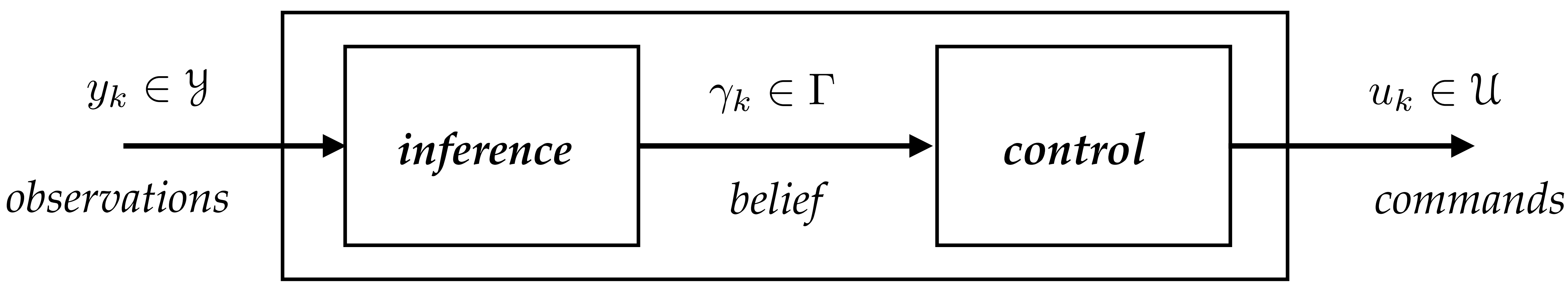

what's beyond this?

Joint inference and control: opportunities and challenges

solving the joint problem
is more resource-efficient

Joint inference and control: opportunities and challenges

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There are many formalizations
(only partially compatible)

Joint inference and control: opportunities and challenges

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1. …
2. …
3. …
4. …
5. …

Doing well with limited resources

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1. Find an **optimal agent**
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Doing well with limited resources

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2. Find a **suboptimal agent**
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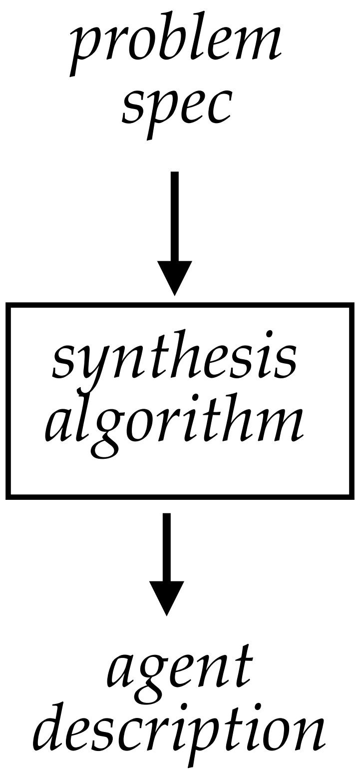
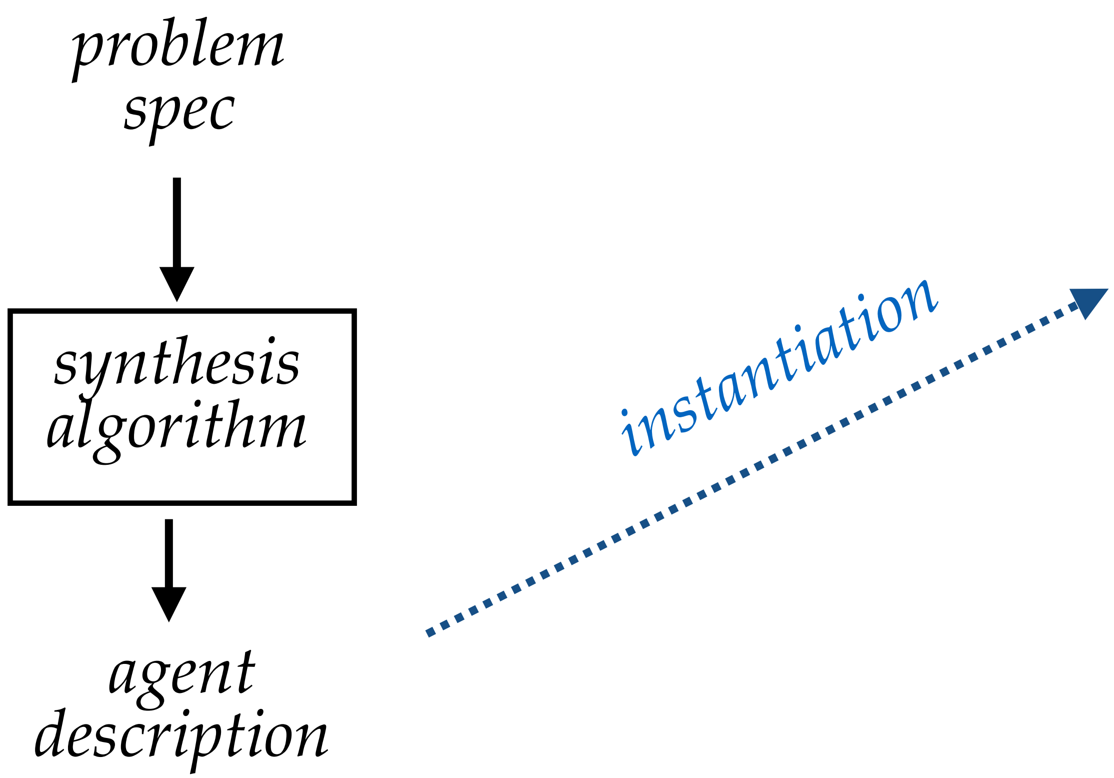
Offline design vs online execution

Offline design vs online execution



Offline design vs online execution



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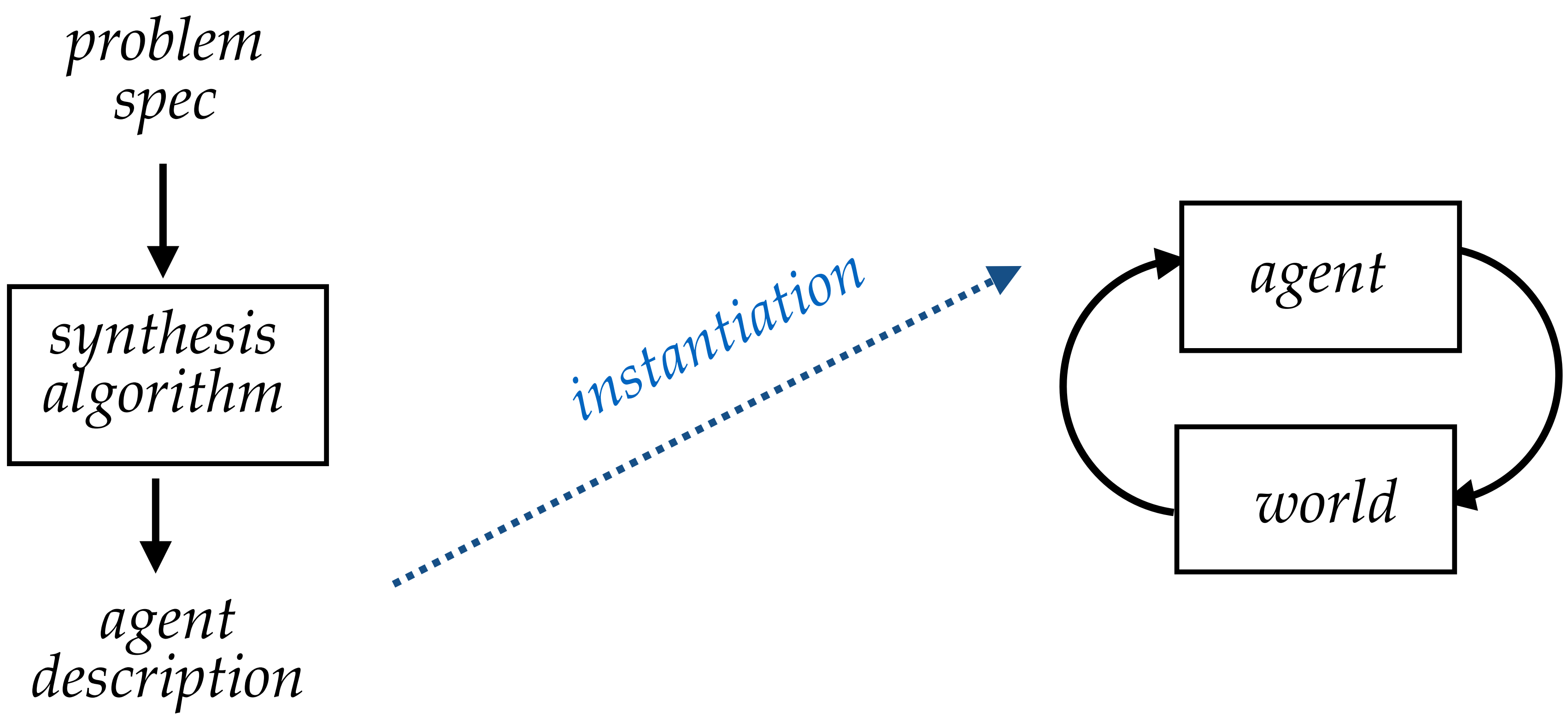
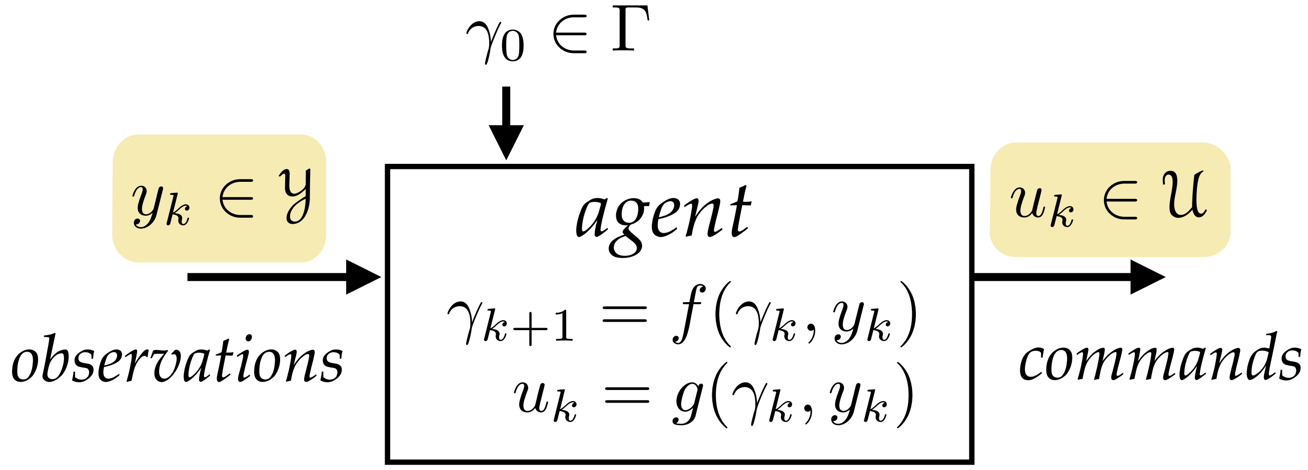
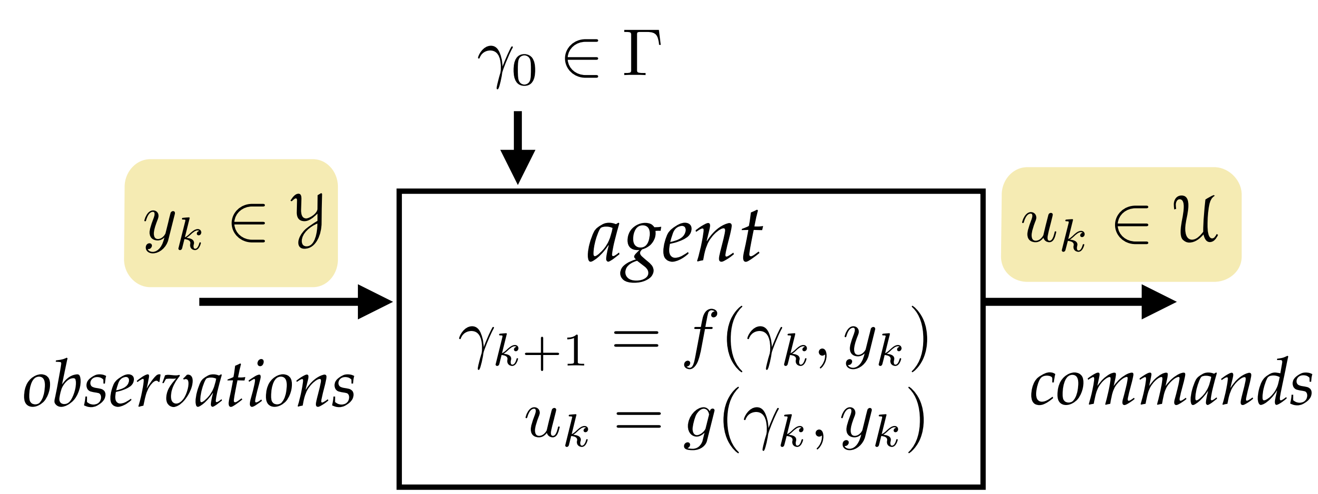


1. Minimality of sensing / control



1. Minimality of sensing / control

- What can you do with minimal sensing / control?



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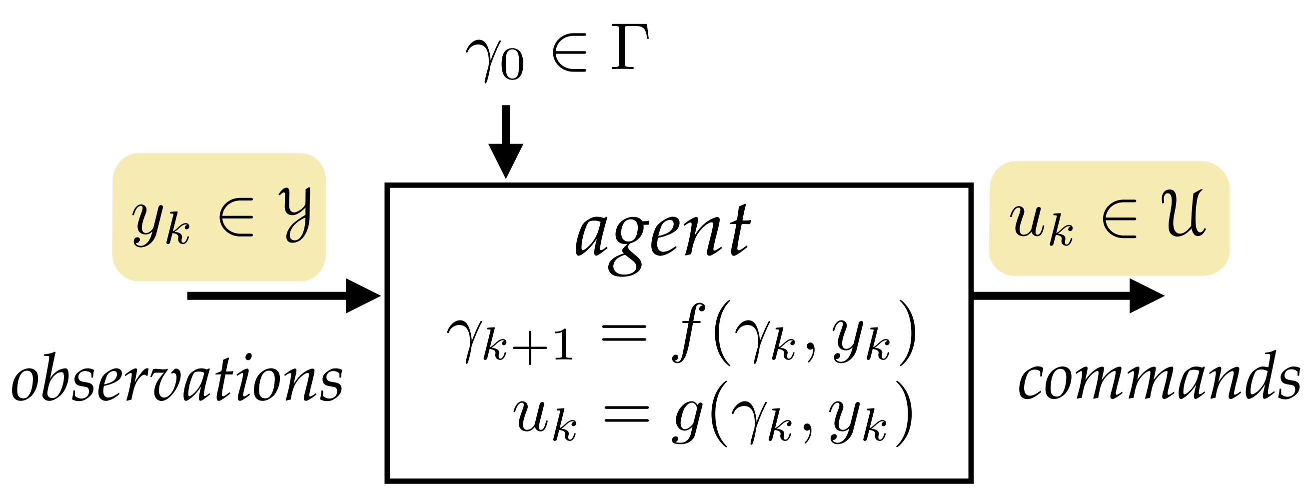

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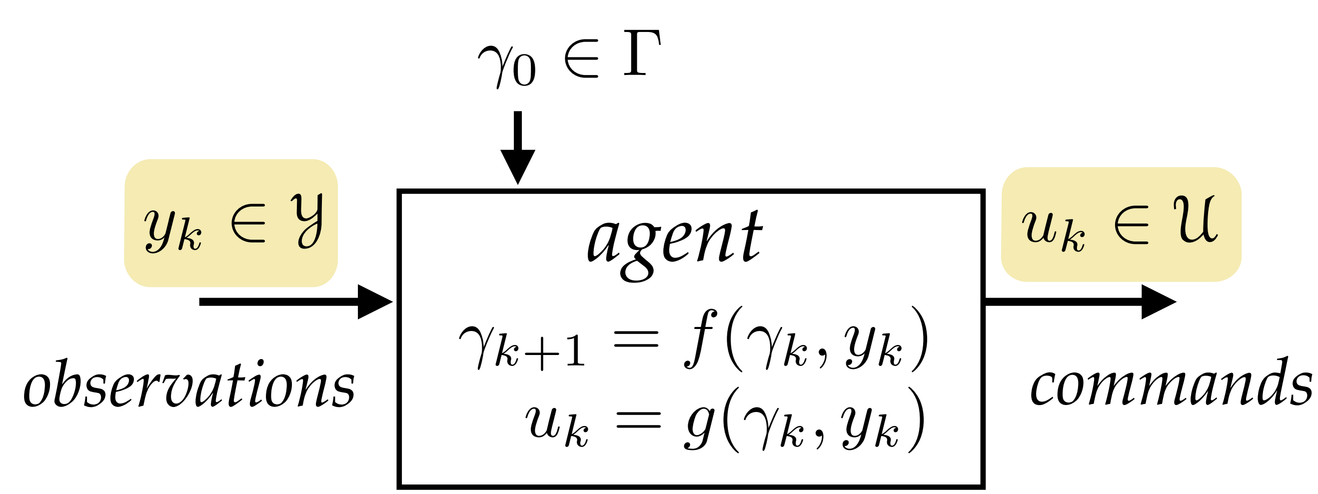

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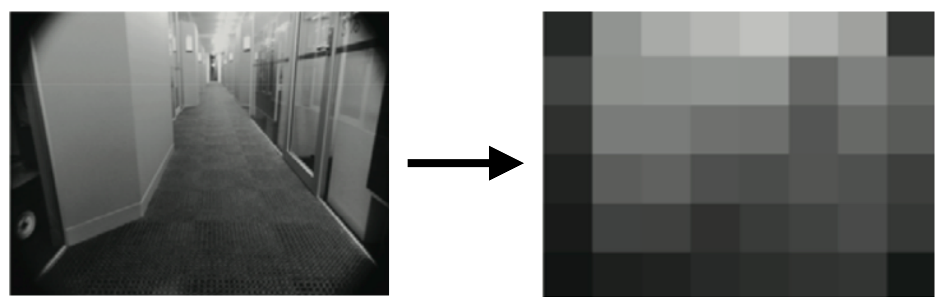
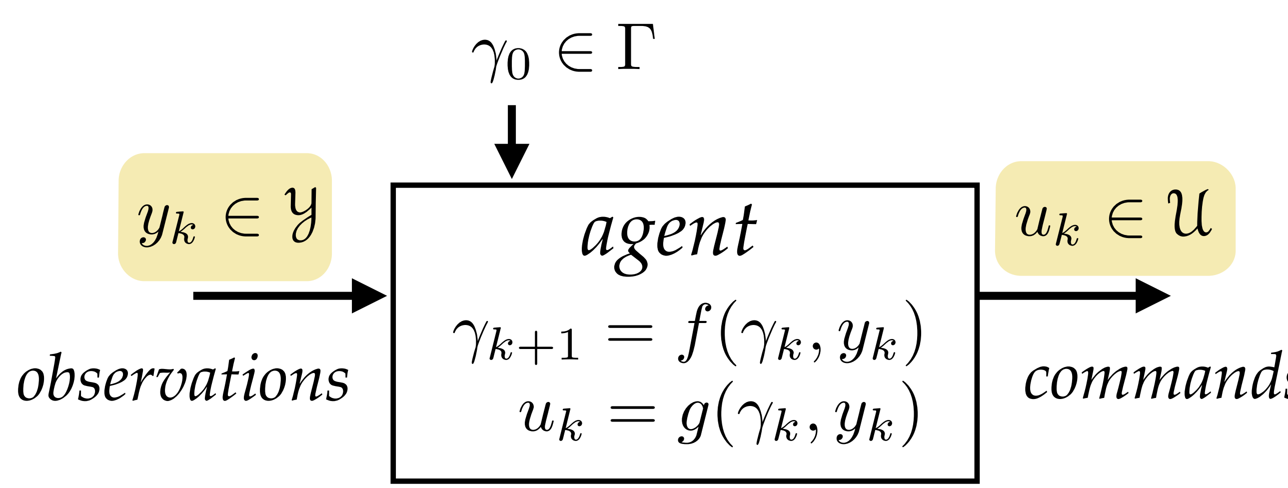
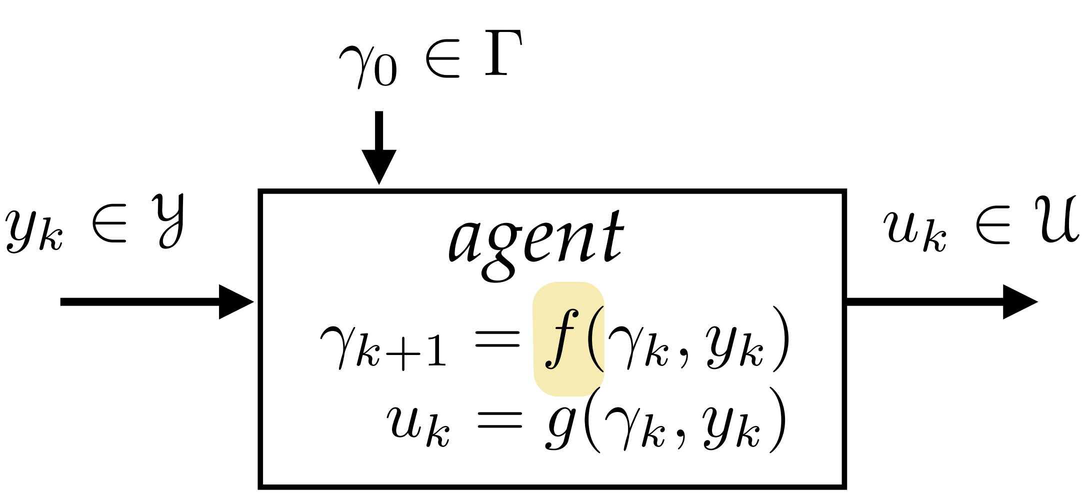


Milford. *Vision-based place recognition: how low can you go?* IJRR 2013



2. Penalizing the cost of computation

Ortega, Braun. *Thermodynamics as a theory of decision-making with information-processing costs*, 2013
Braun, Ortega, Theodorou, Schaal. *Path Integral Control and Bounded Rationality*, 2011



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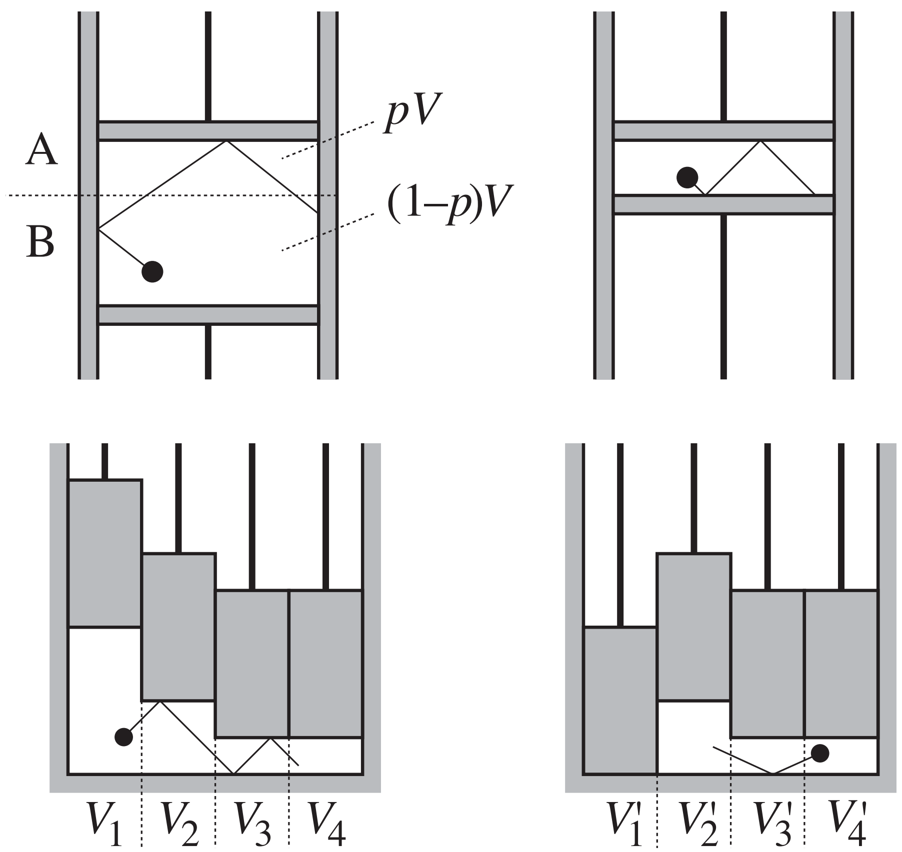
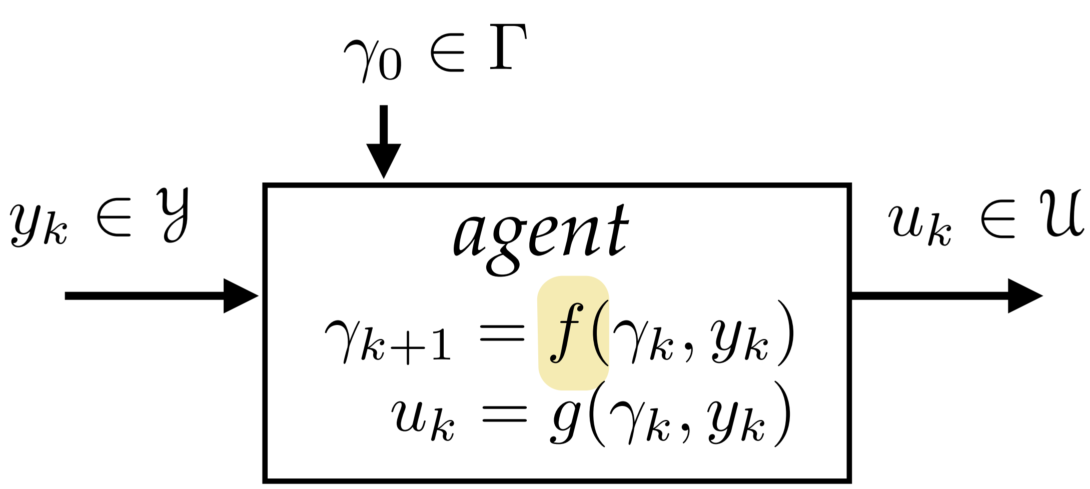


updating information state takes work
(physical work)

↓

variational problem



3. Penalizing the control information

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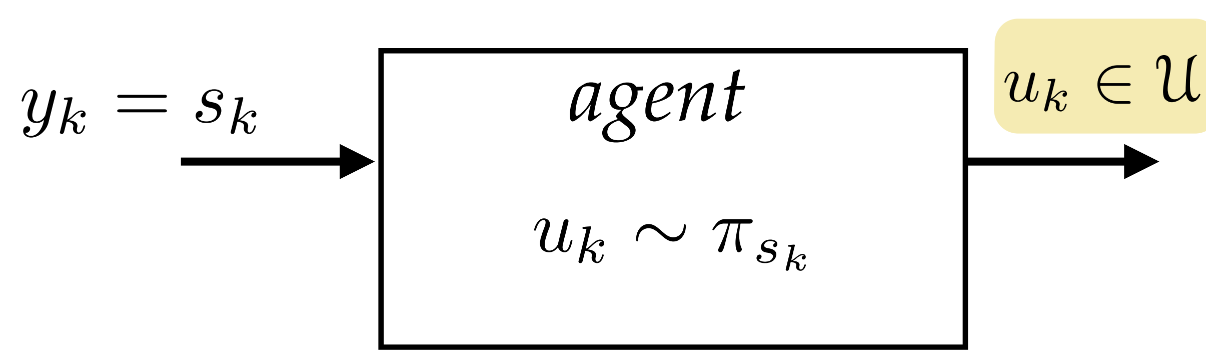

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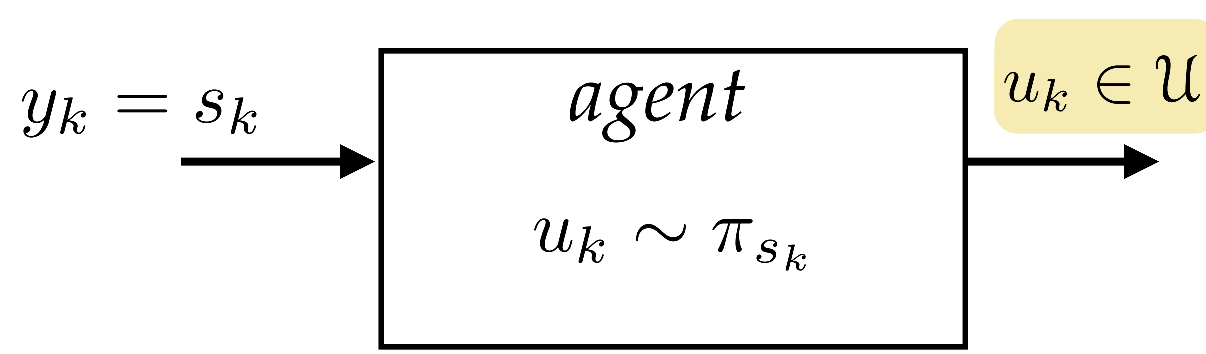
Rubin, Shamir, Tishby. *Trading value and information in MDPs*. 2010



3. Penalizing the control information

= *deviation from random policy* =

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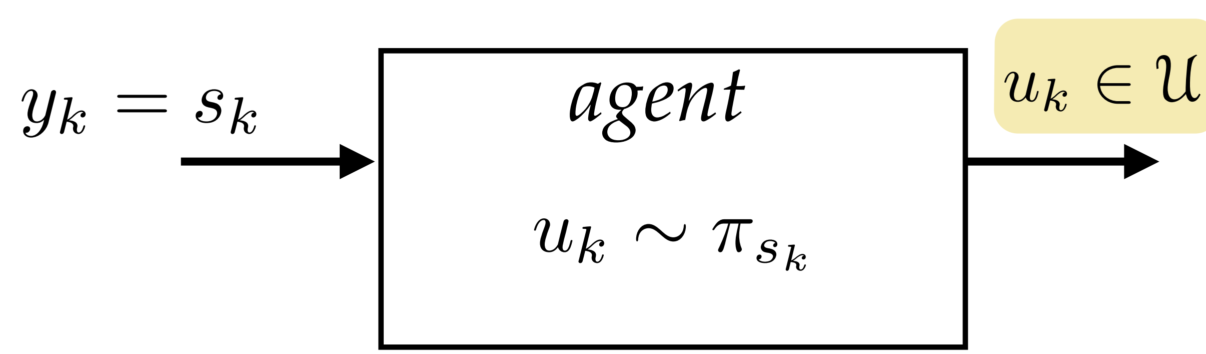

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$$= \textit{deviation from random policy} = \qquad \mathbb{E}\left\{\log \frac{\pi_s(u)}{\hat{\rho}(u)}\right\}$$

policy

a blind random policy

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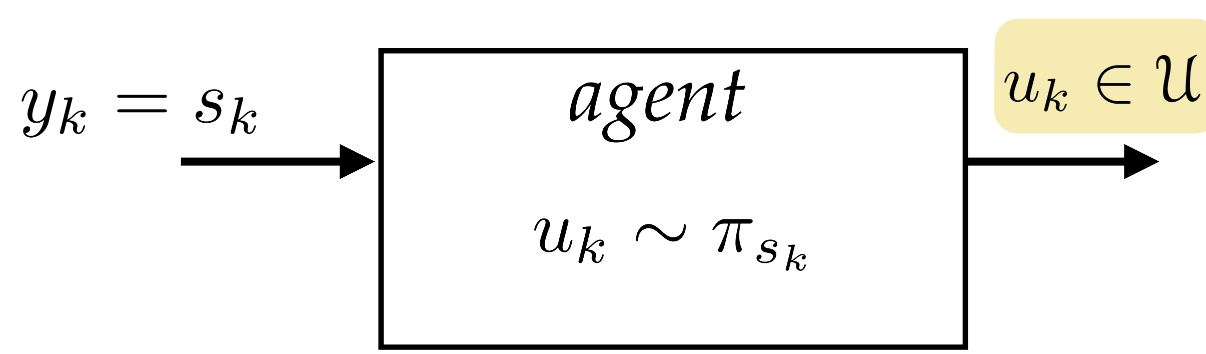

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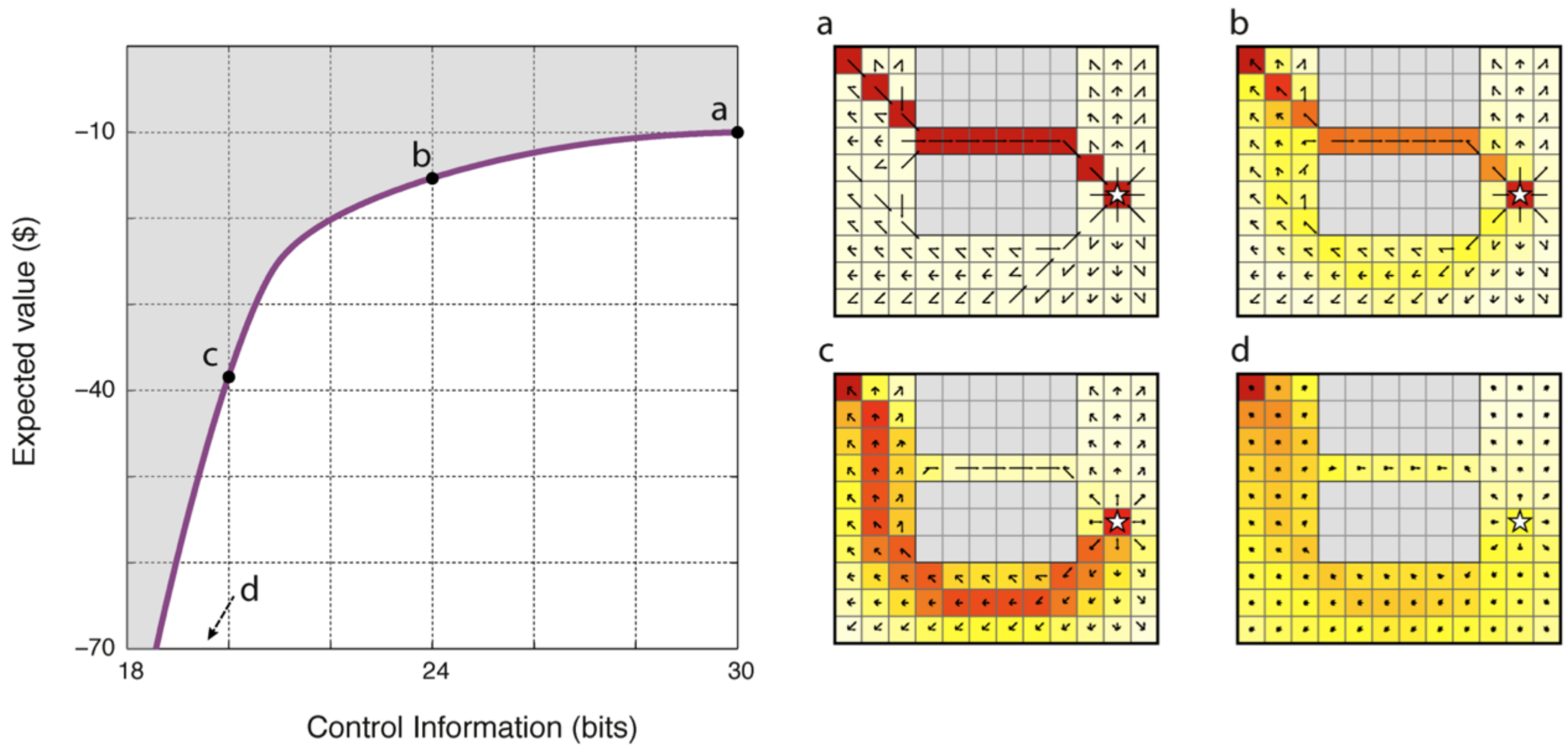

Rubin, Shamir, Tishby. *Trading value and information in MDPs.* 2010

$y_k = s_k$

agent

$u_k \sim \pi_{s_k}$

$u_k \in \mathcal{U}$

4. Minimizing the agent-world bandwidth

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P1

P2

4. Minimizing the agent-world bandwidth

P1

P2

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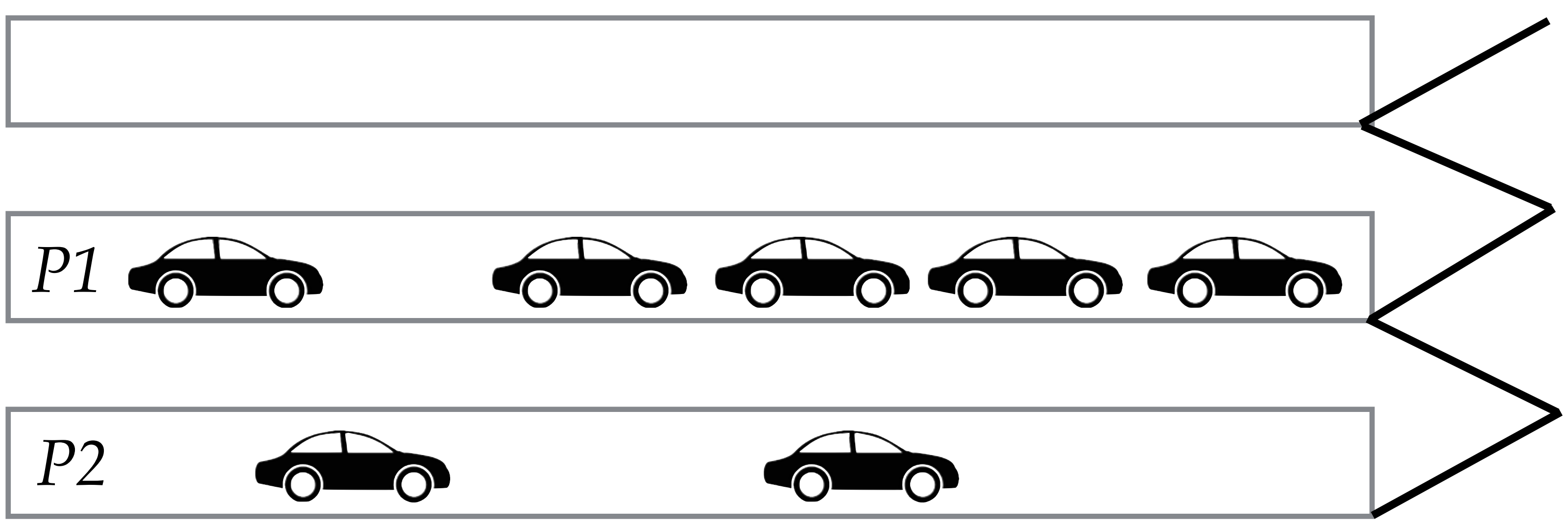

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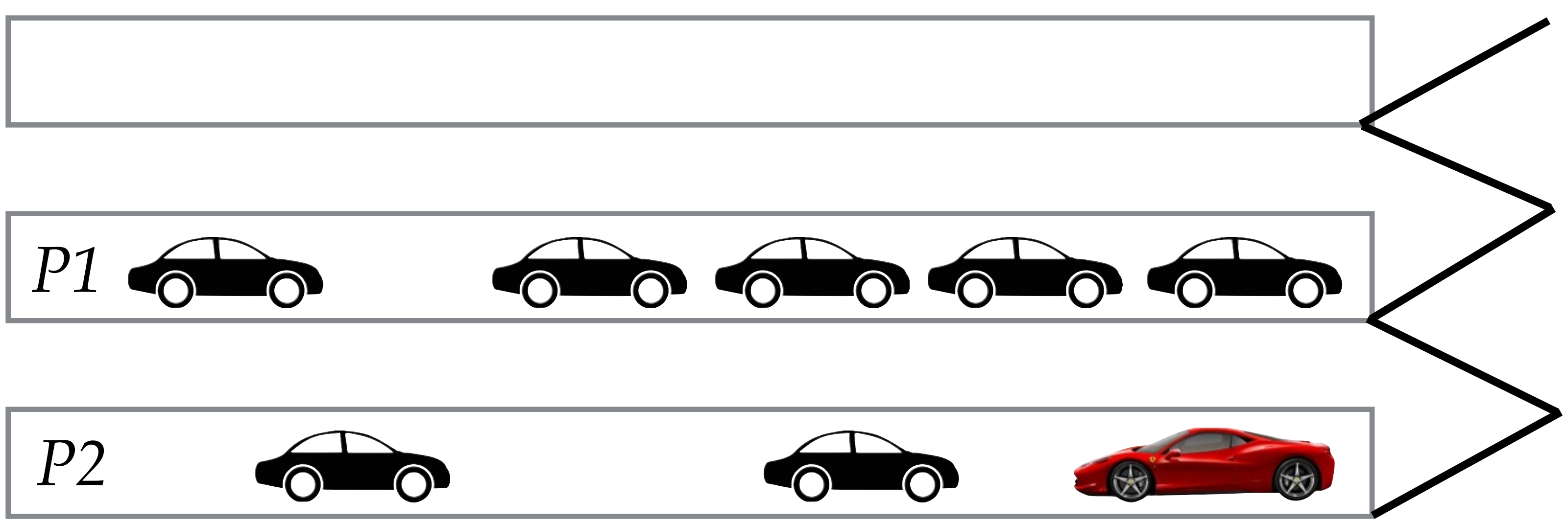

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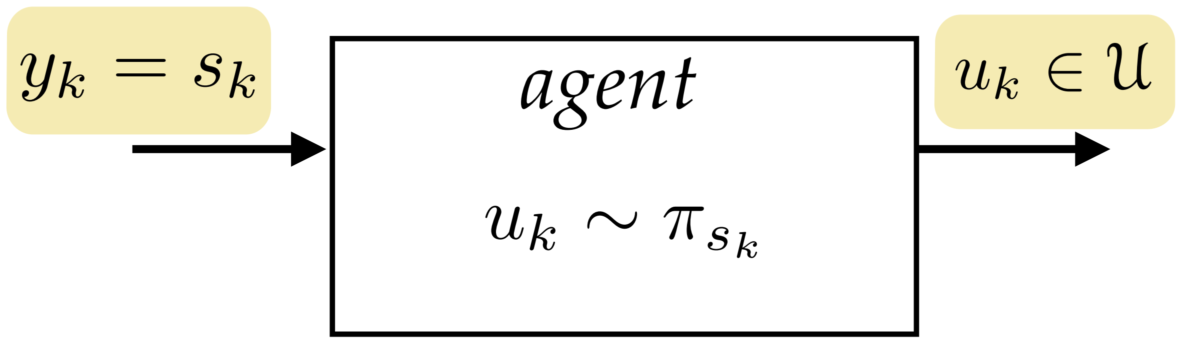

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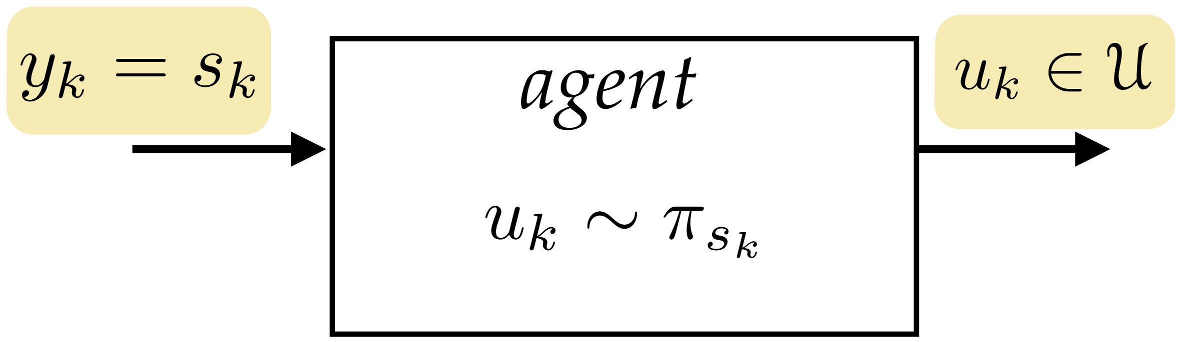
Tishby, Polani. *Information Theory of Decisions and Actions.* 2011



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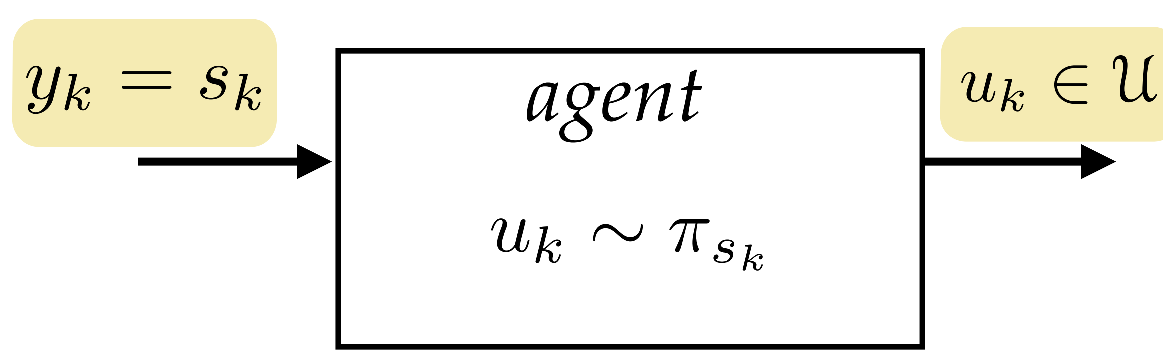
"information to go" =



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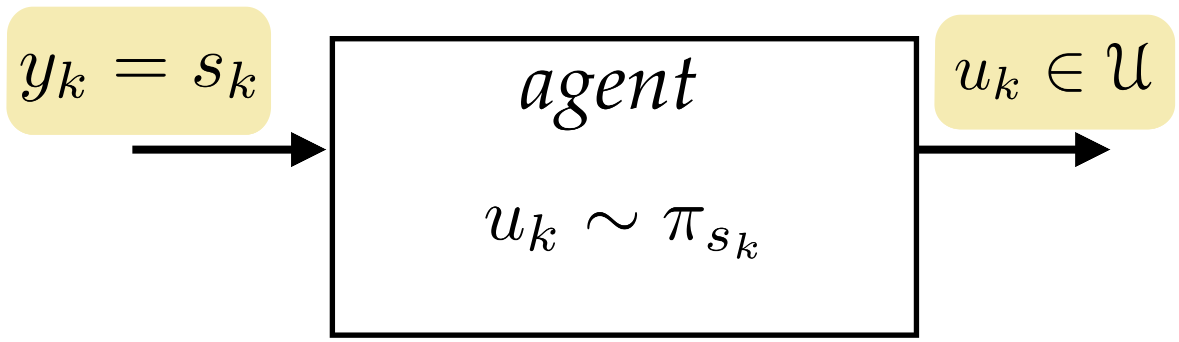
"information to go" = $D_{\mathrm{KL}}(p_\pi \;||\; \hat{p})$



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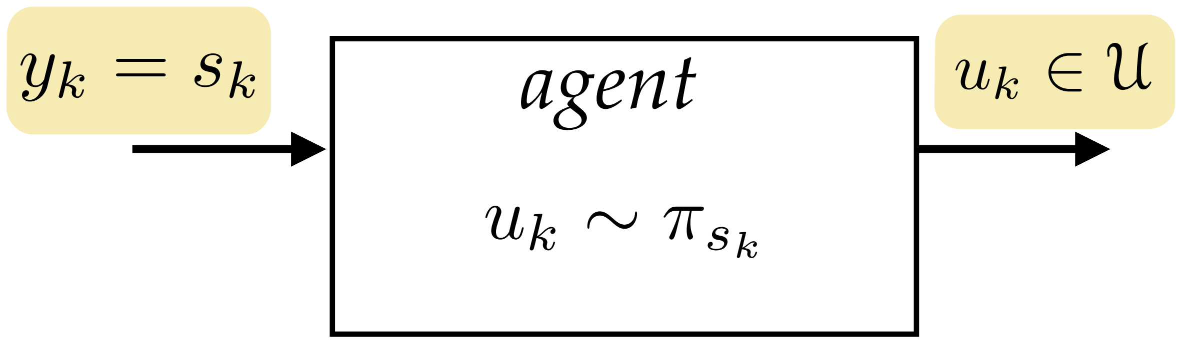
distribution of states, actions under random policy



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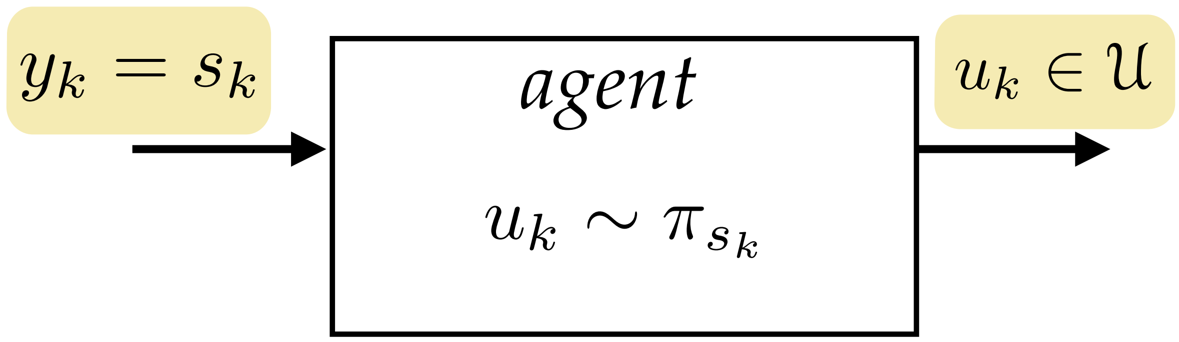

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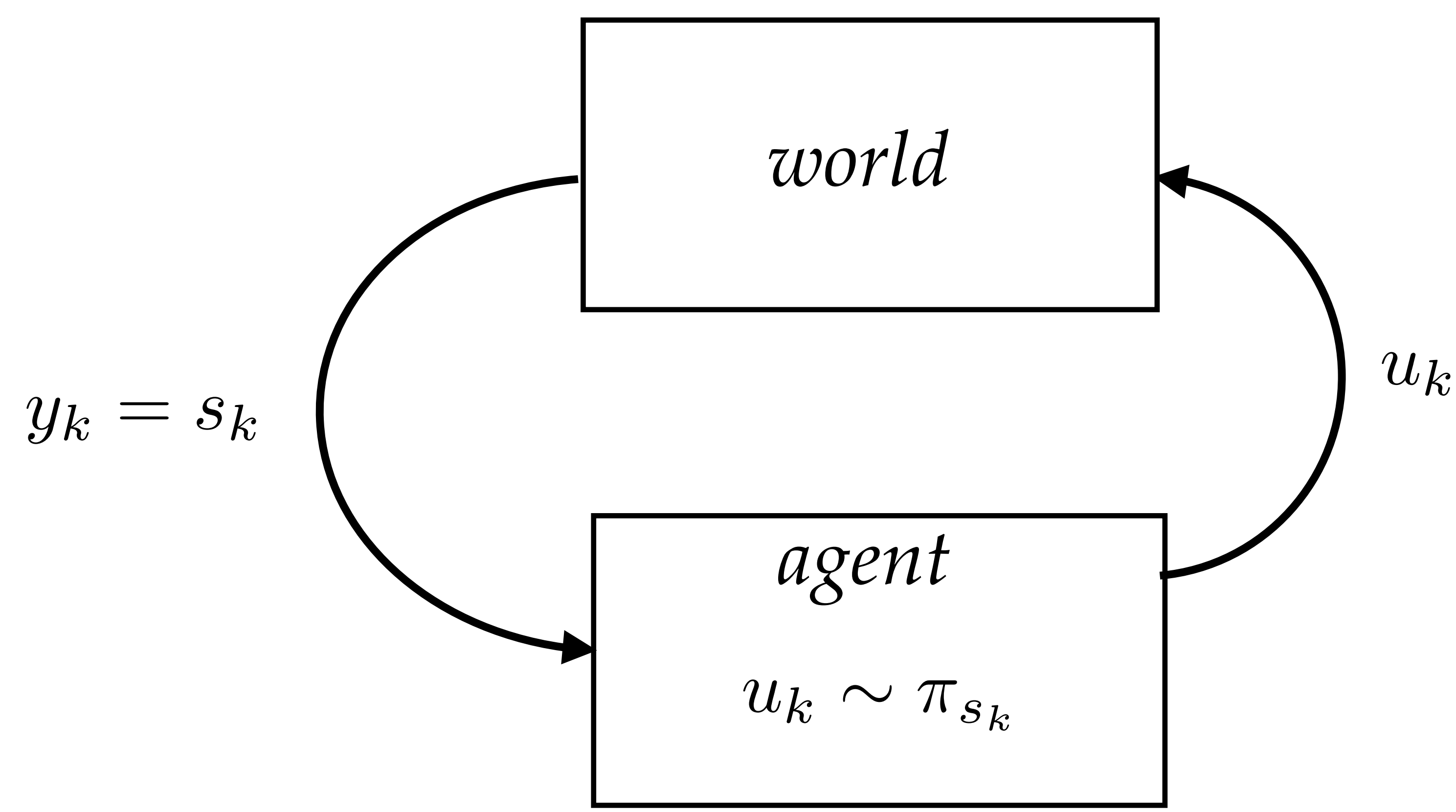

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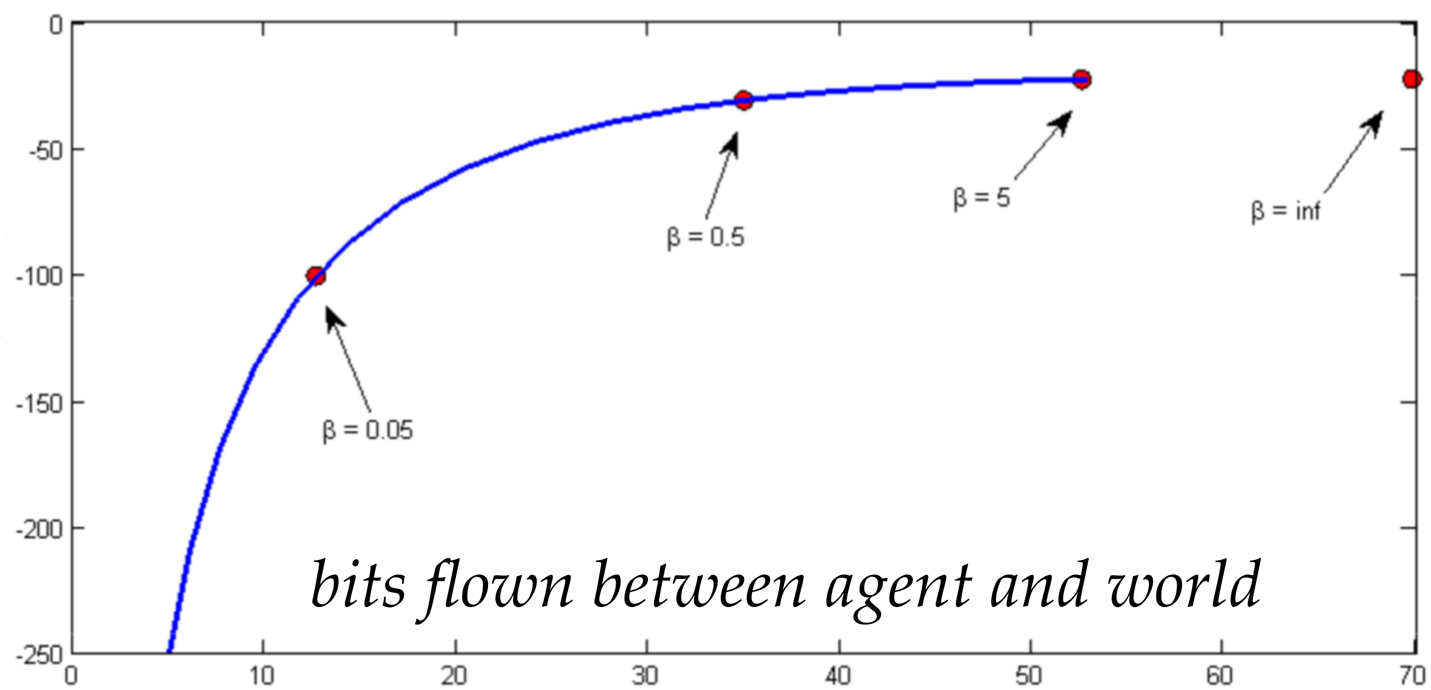
reward



bits flown between agent and world

4. Minimizing the agent-world bandwidth

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distribution of states, actions under random policy

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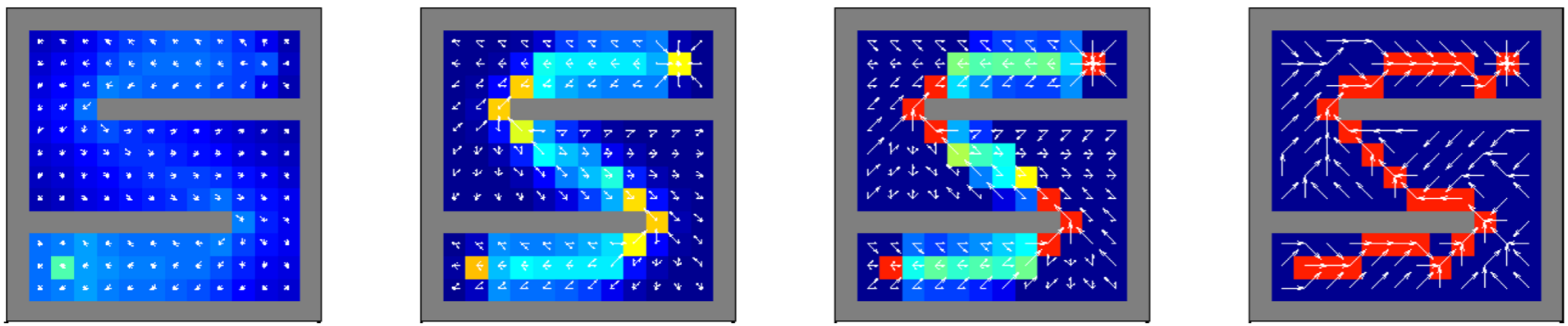

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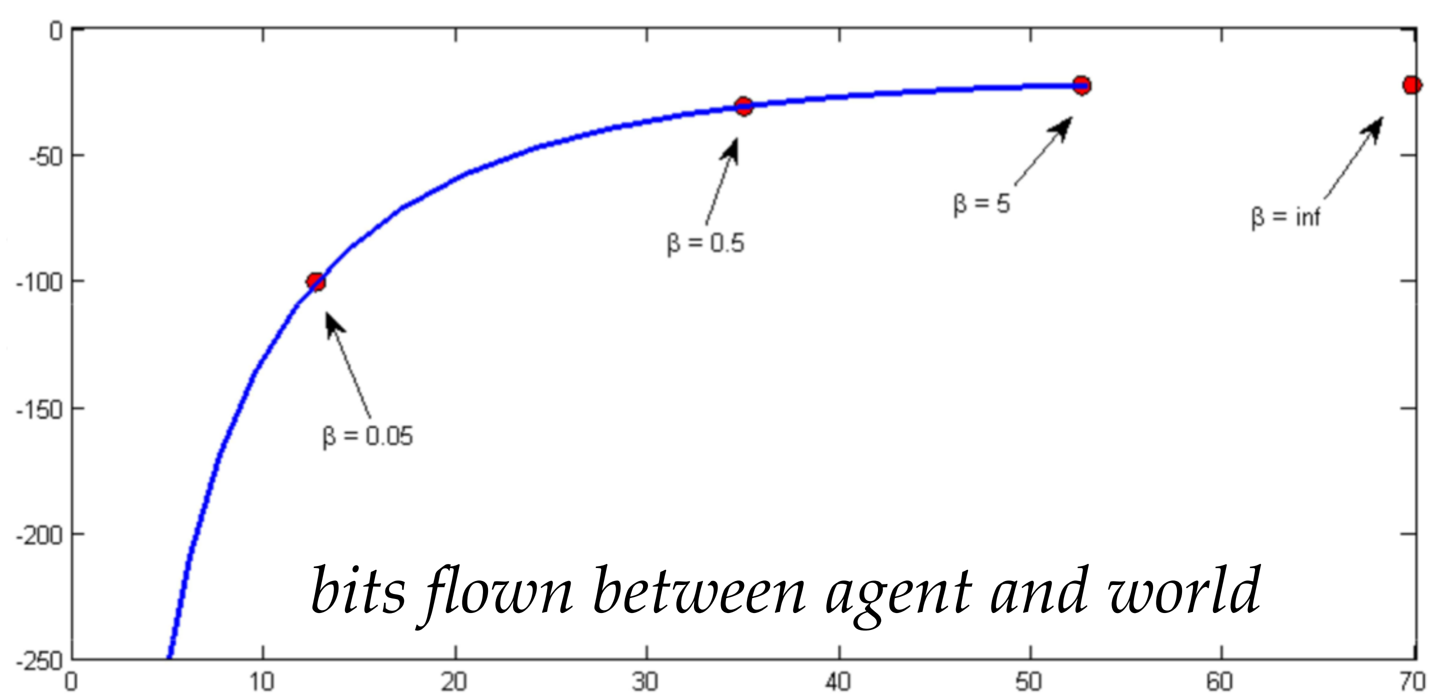
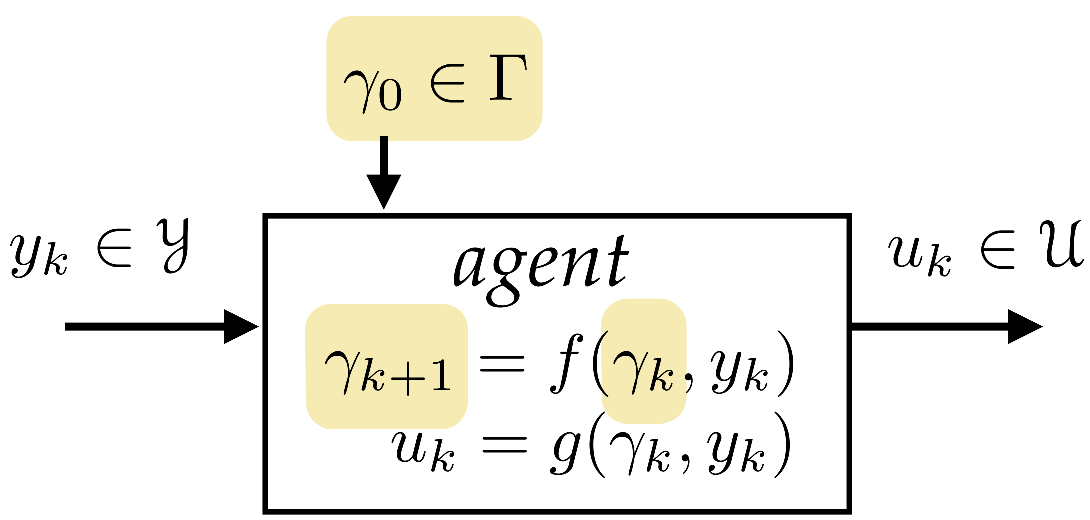


5. Minimality of representation (size of agent state)

- Most of the computation cost
  is in updating the representation.

- Penalize size of representation:

$$\min |\Gamma|$$



5. Minimality of representation (size of agent state)

1. Find an **optimal agent** that uses the **fewest resources**.
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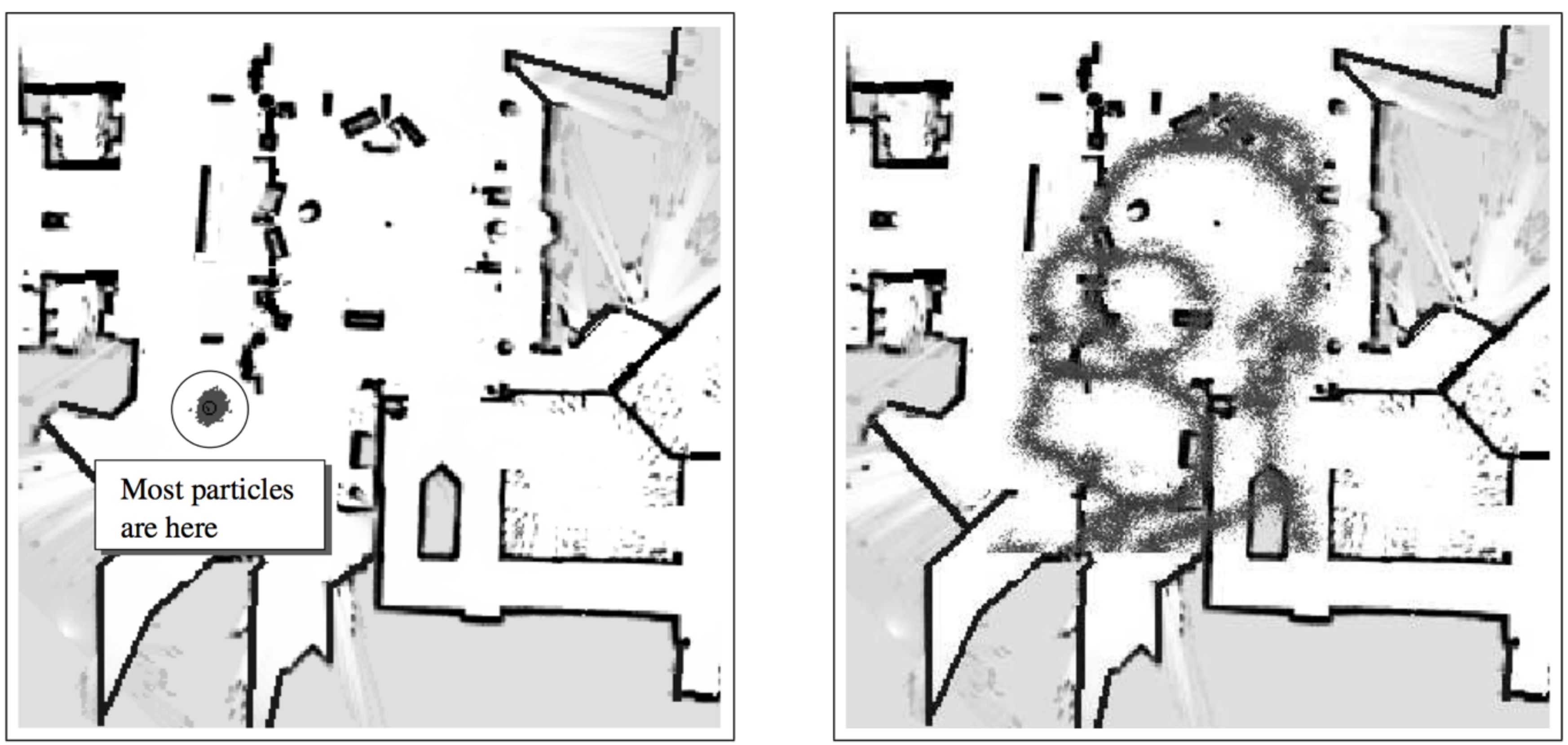
Roy, Gordon, Thrun. *Finding Approximate POMDP Solutions Through Belief Compression*. JAIR 2005



(a) A common belief

(b) An unlikely belief

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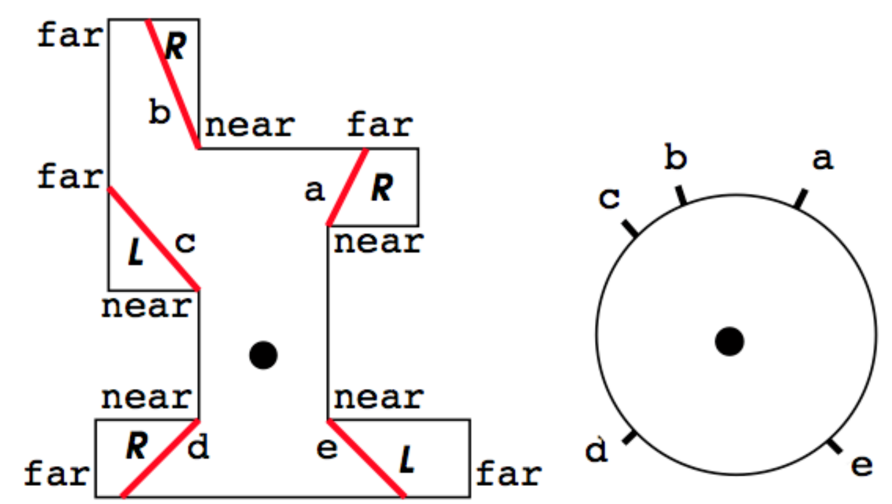
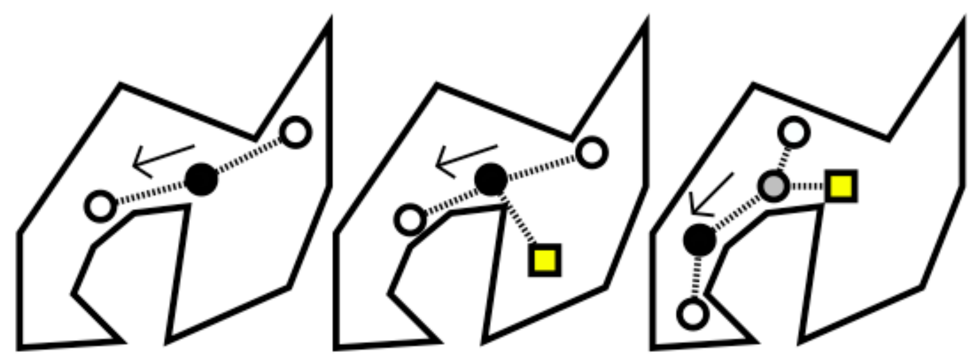
5. Minimality of representation

Tovar, Guilamo, LaValle *Gap Navigation Trees: Minimal Representation for Visibility-based Tasks*. WAFR 2004

- A range-finder can be abstracted as a "gap sensor"



- Map can be represented as graphs ("gap navigation trees") encoding the topology and visibility constraints



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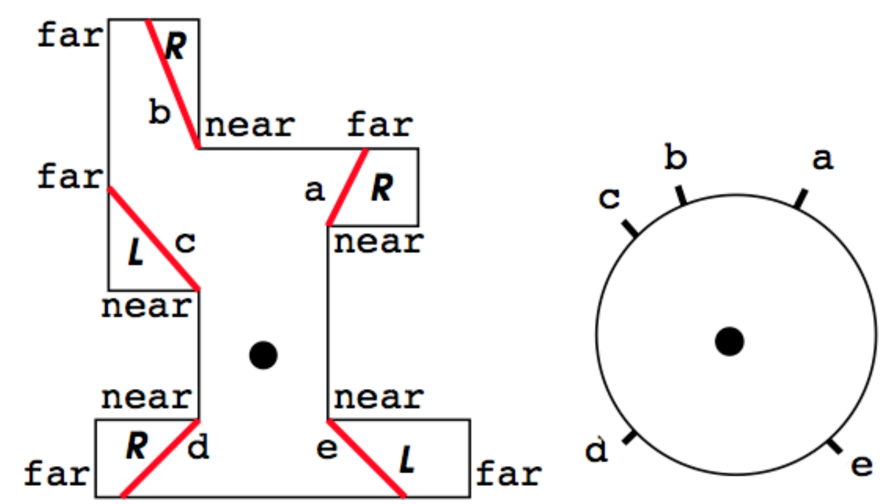

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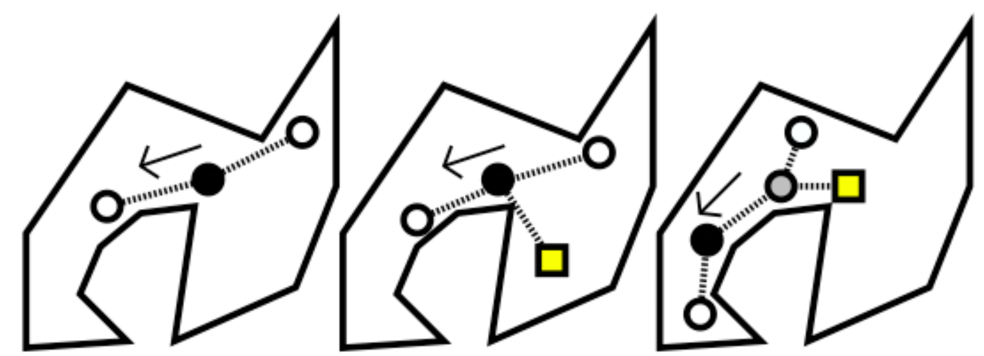
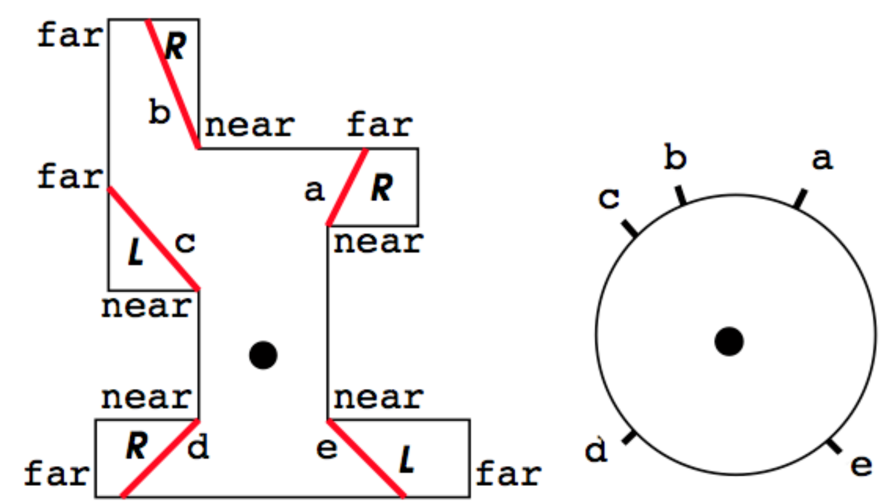


Q: Can we automatically synthesize the minimal representation?

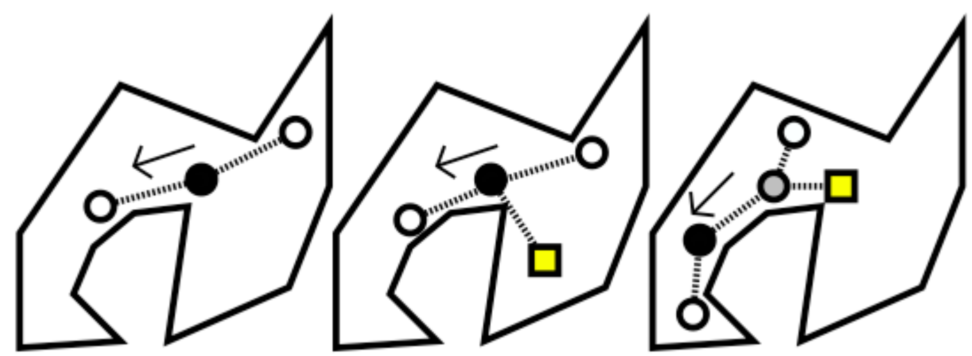
5. Minimality of representation

Tovar, Guilamo, LaValle *Gap Navigation Trees: Minimal Representation for Visibility-based Tasks*. WAFR 2004

- A range-finder can be abstracted as a "gap sensor"



- Map can be represented as graphs ("gap navigation trees") encoding the topology and visibility constraints

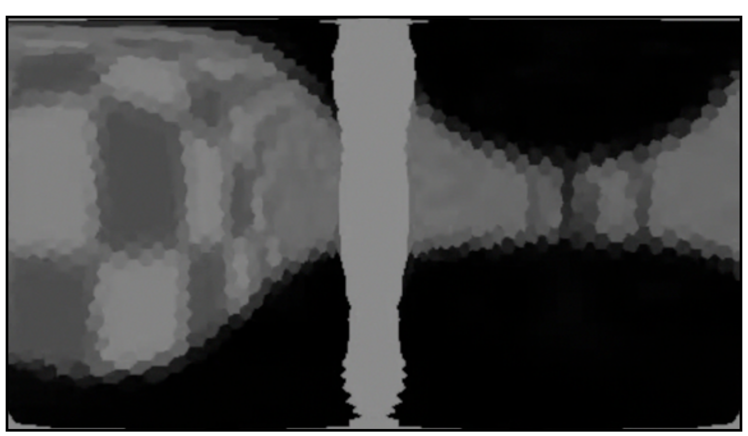


Q: Can we automatically synthesize the minimal representation?

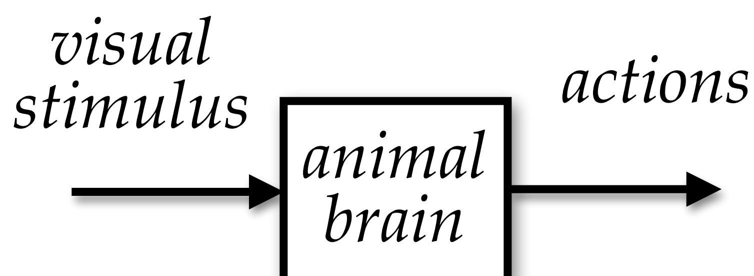
Josh will tell us the answer next week!

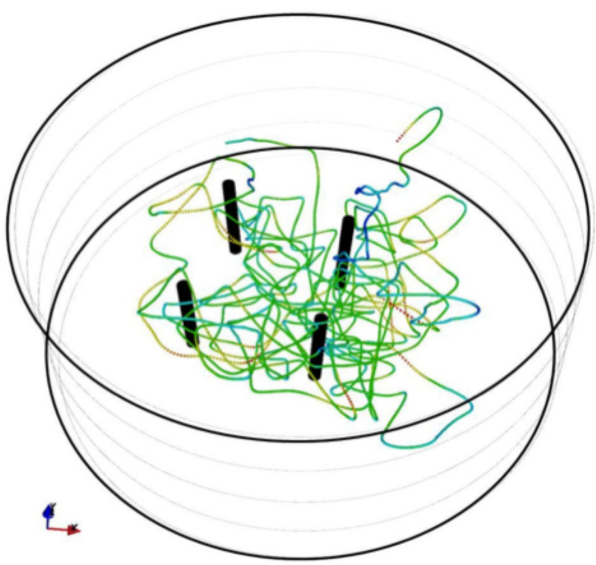
5. Minimality of representation

- "What is the simplest neural process that realizes the observed behavior?"



reconstructed stimulus





tracked trajectories

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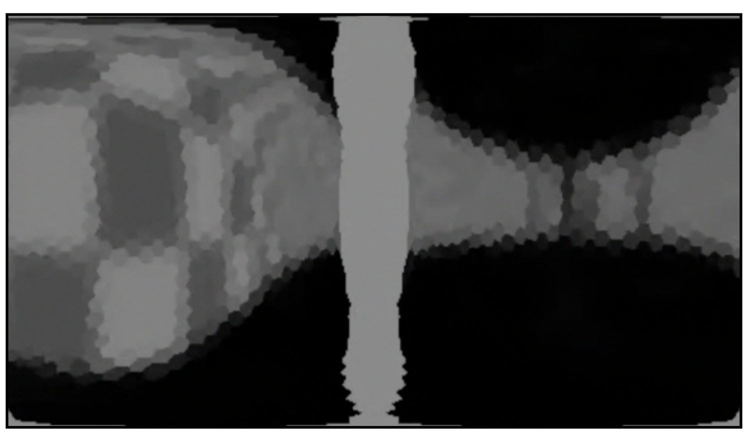

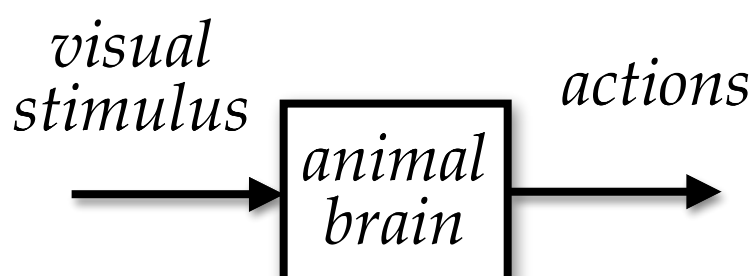

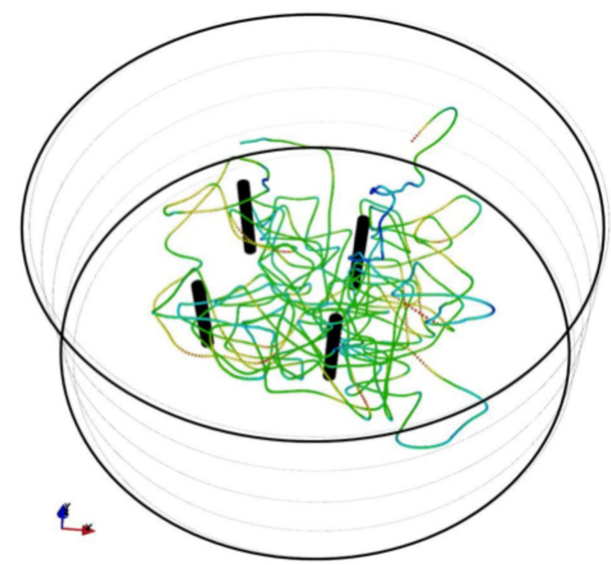

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Joint inference and control: opportunities and challenges

Joint inference and control: opportunities and challenges

- Death by generality
- Death by specificity
- Death by abstraction

Death by Generality

Death by Generality

or: the formalization fetish

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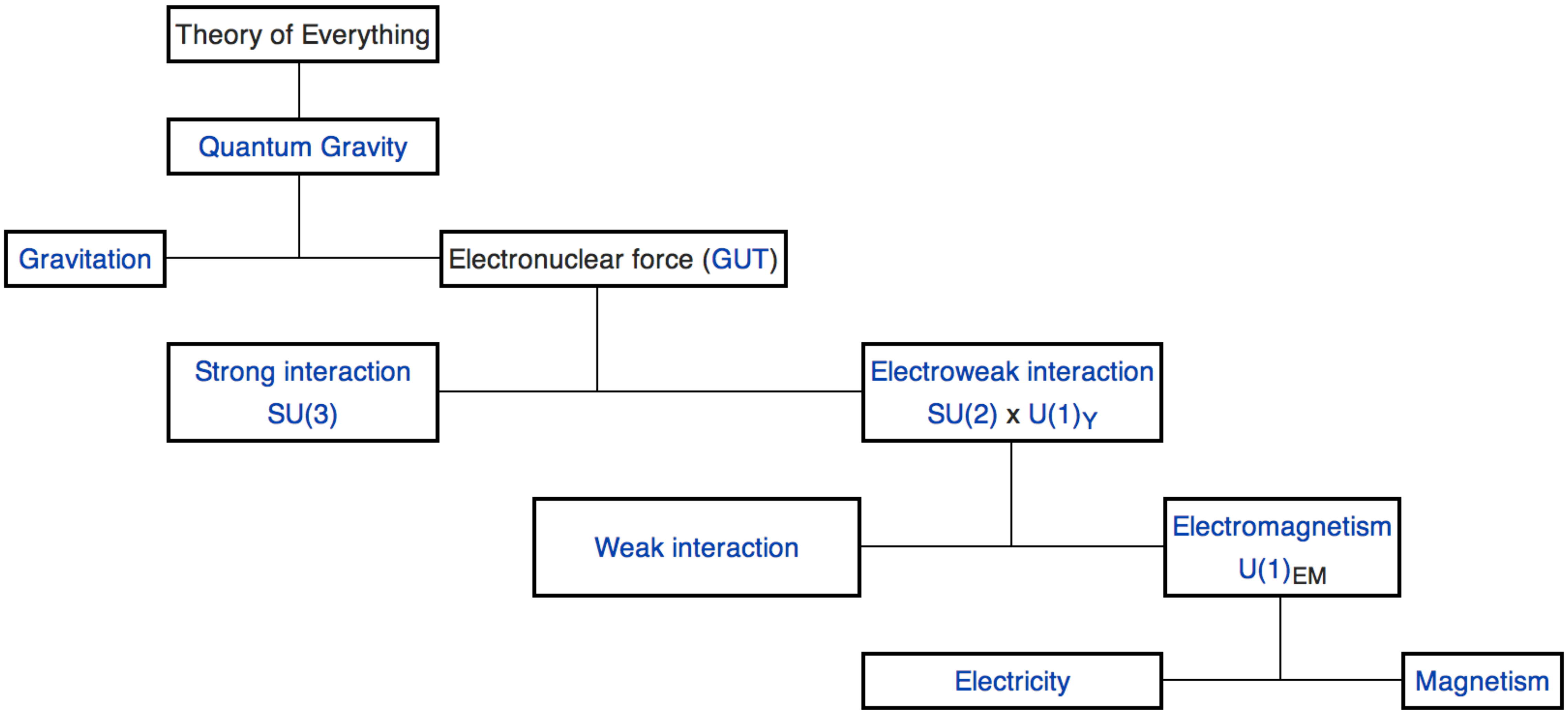

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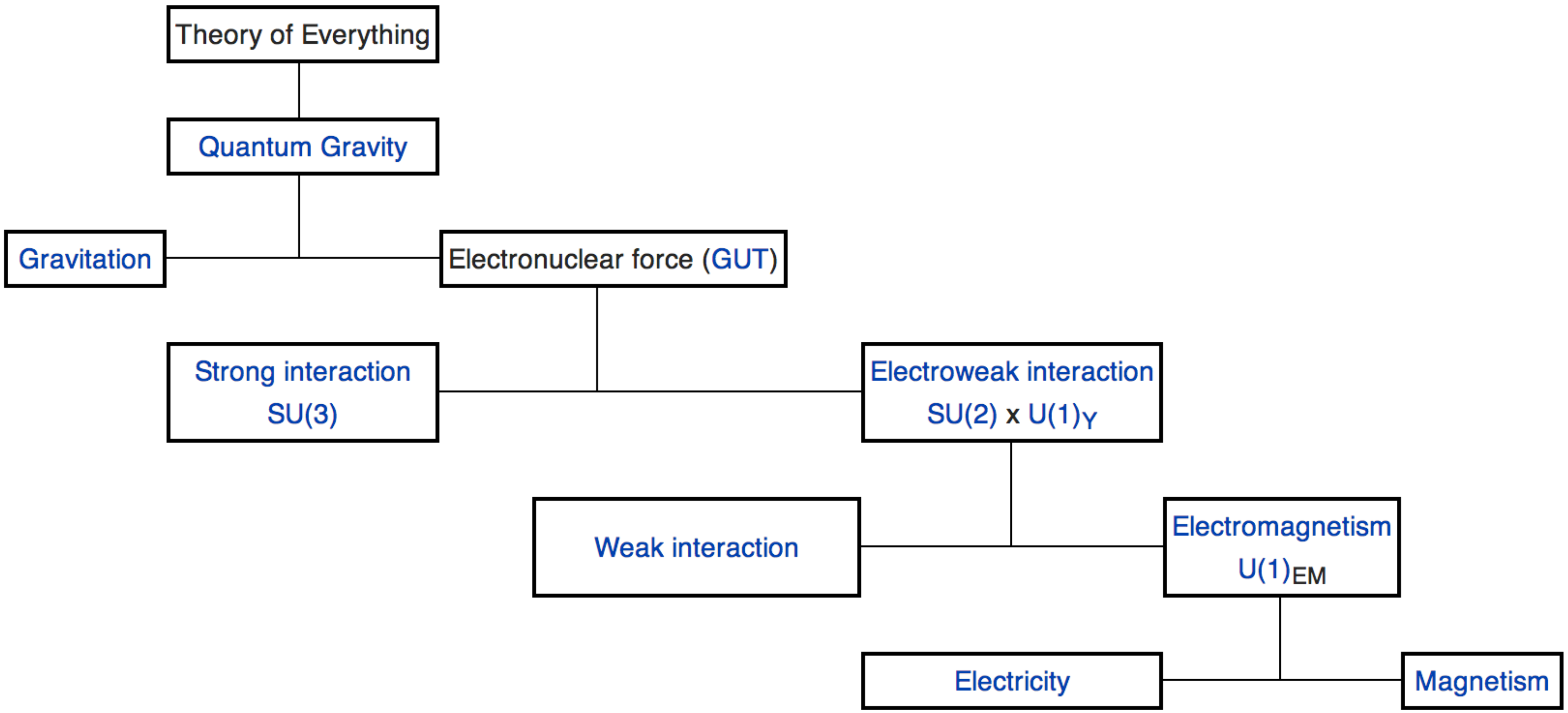

pure science question: What does the theory predict?

Death by Generality

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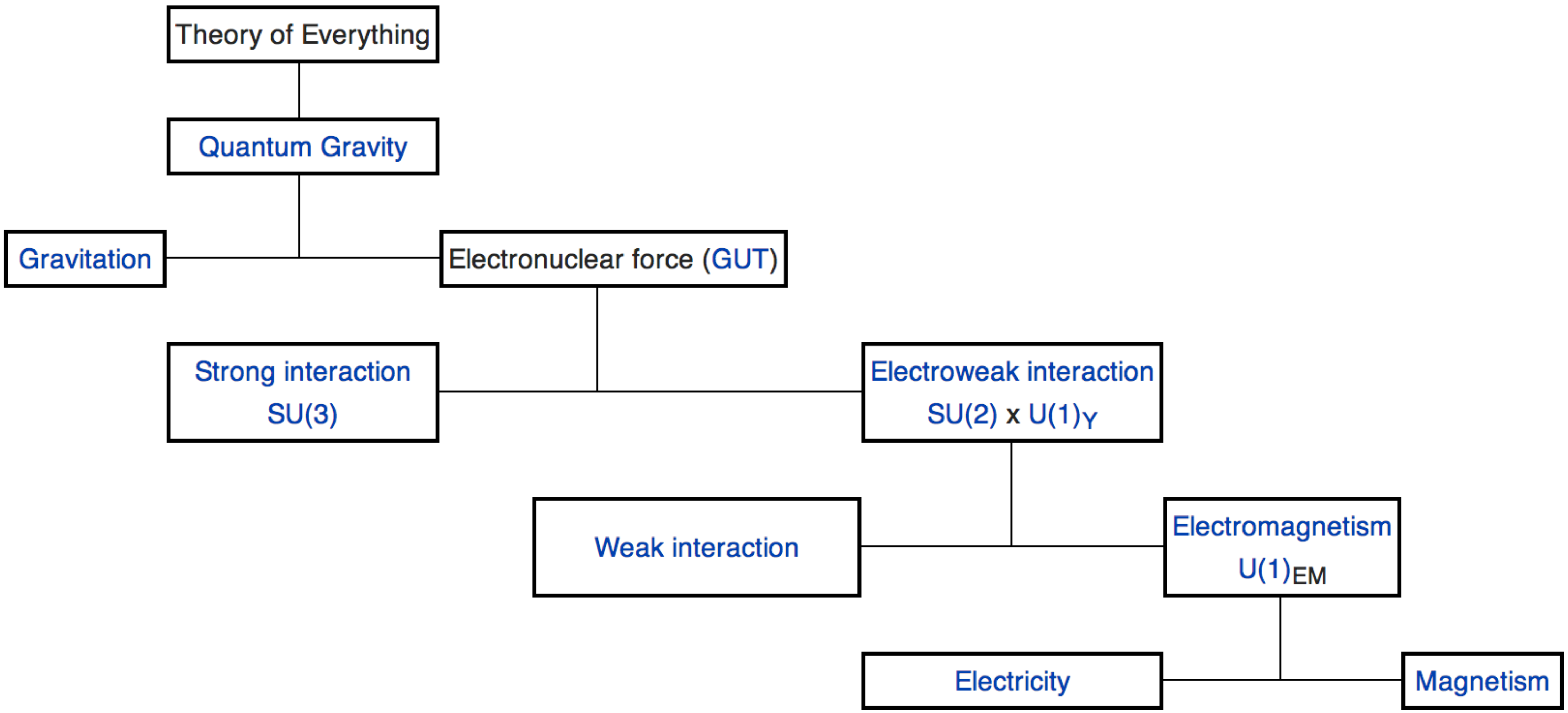

pure science question: *What does the theory predict?*

pure math question: *How beautiful is it?*

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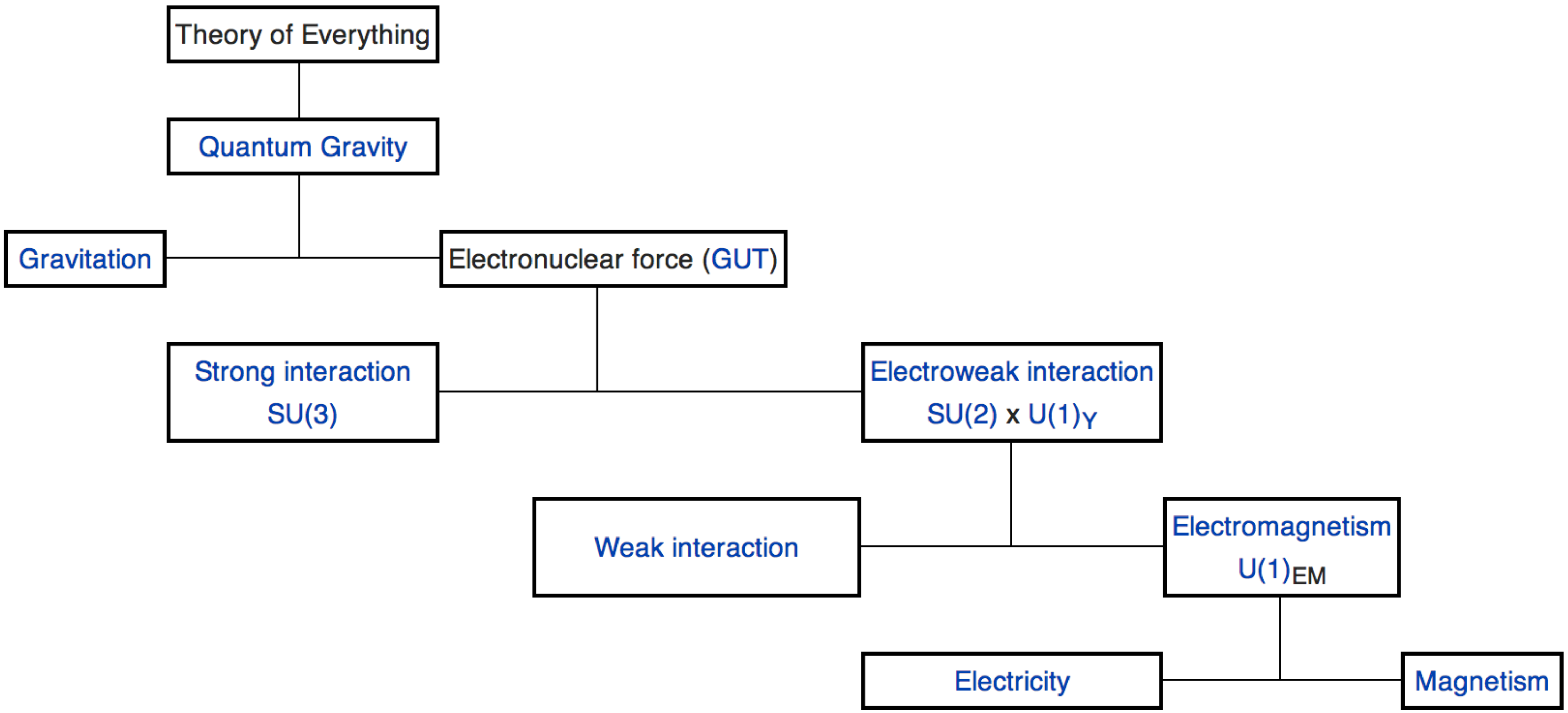
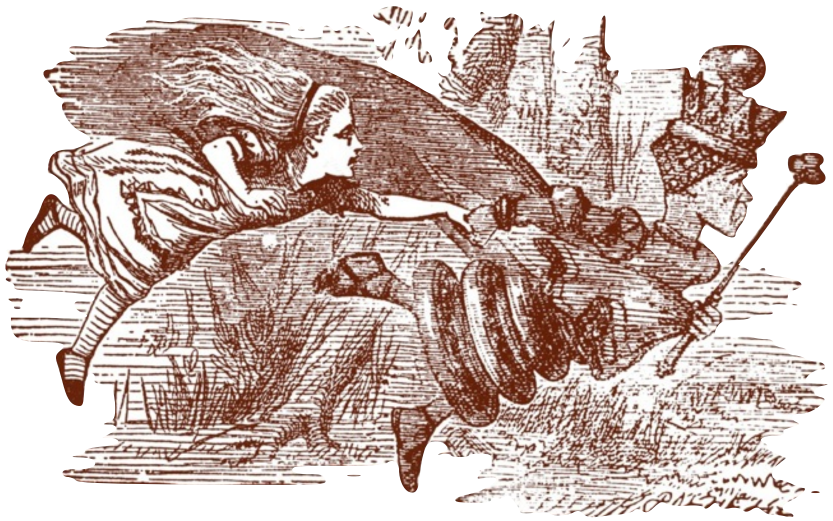


pure science question:	*What does the theory predict?*
pure math question:	*How beautiful is it?*
engineering research question:	*What can we do with it?*

Death by Specificity

Death by Specificity

or: the Red Queen's race



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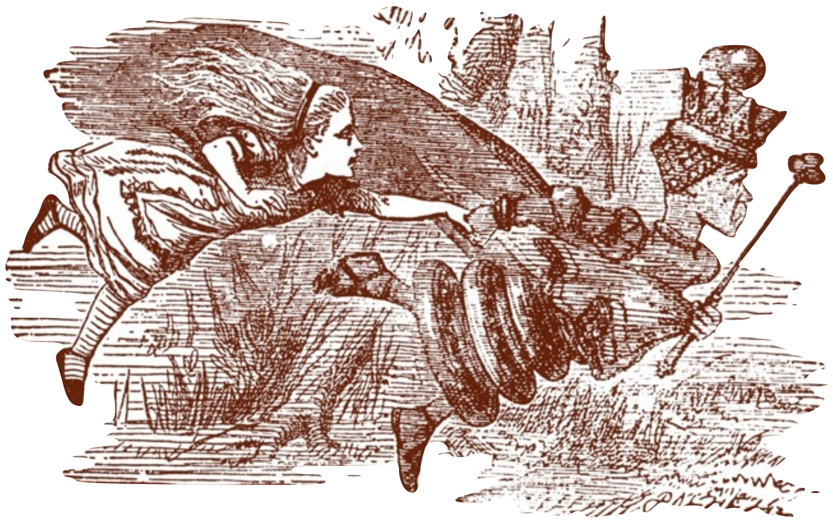

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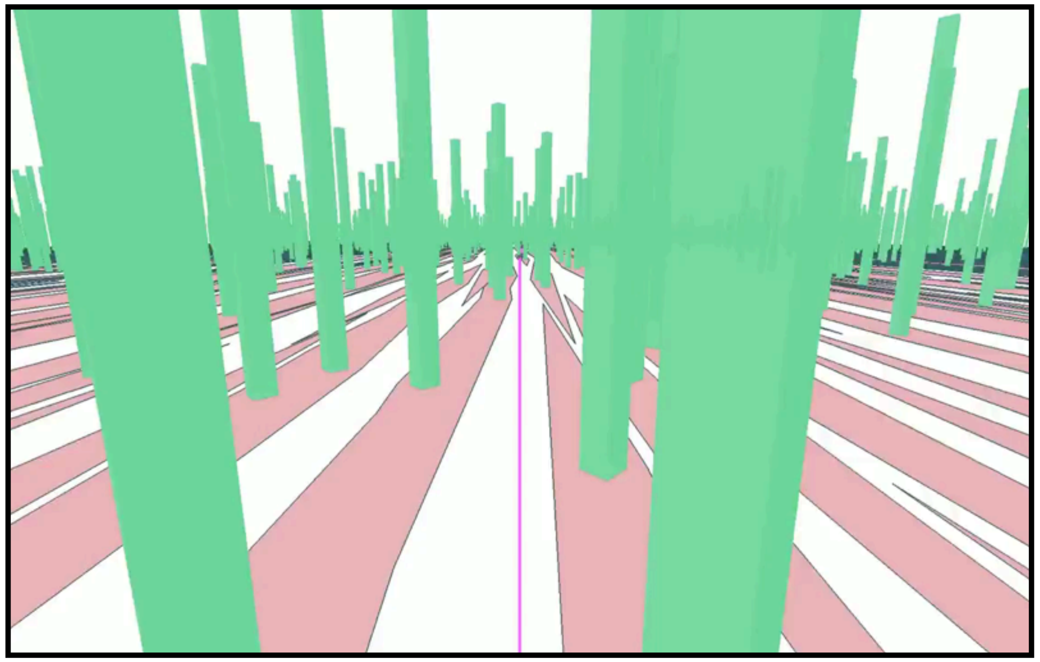

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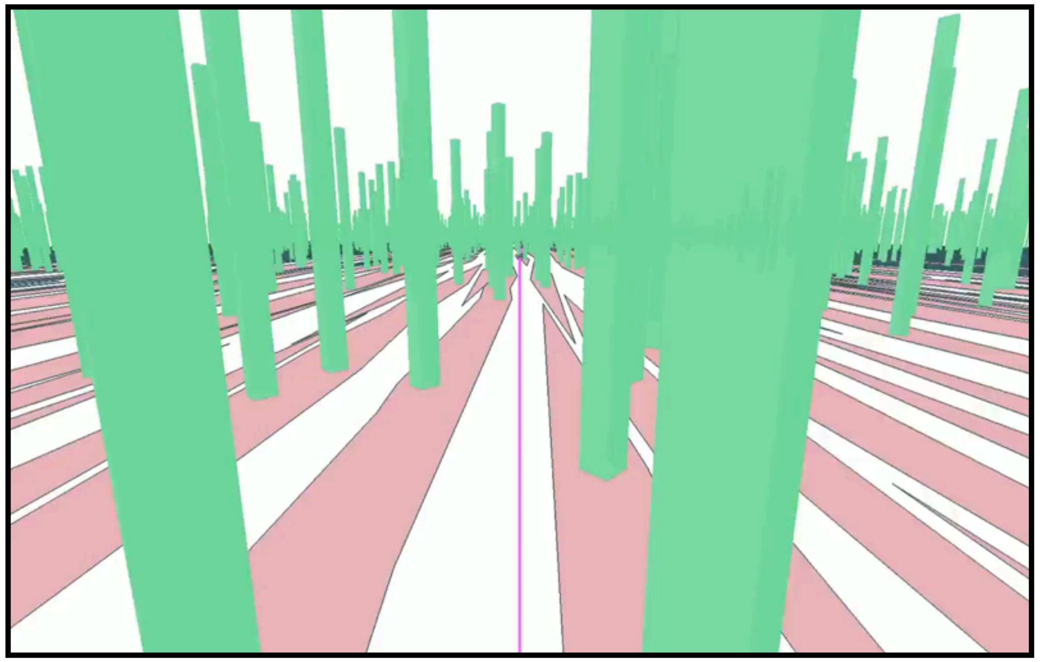

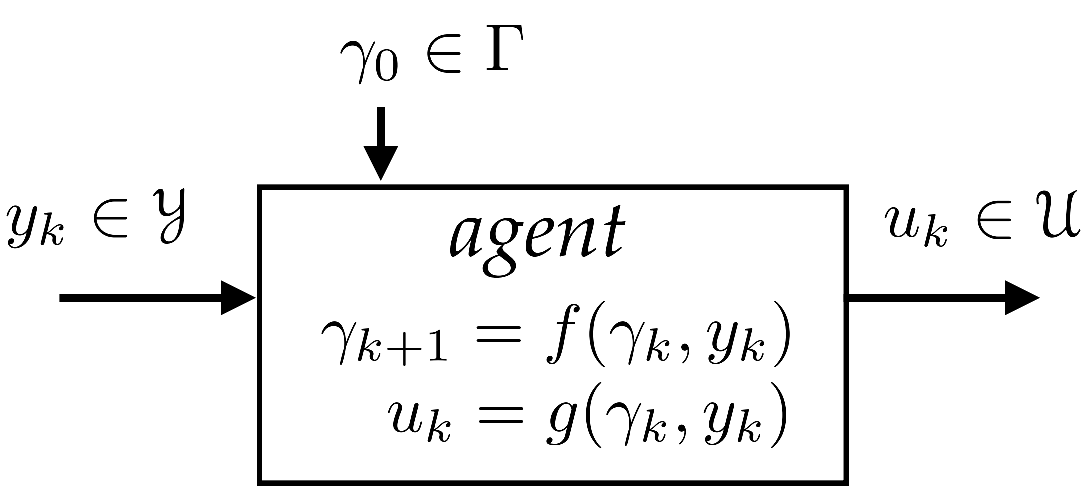

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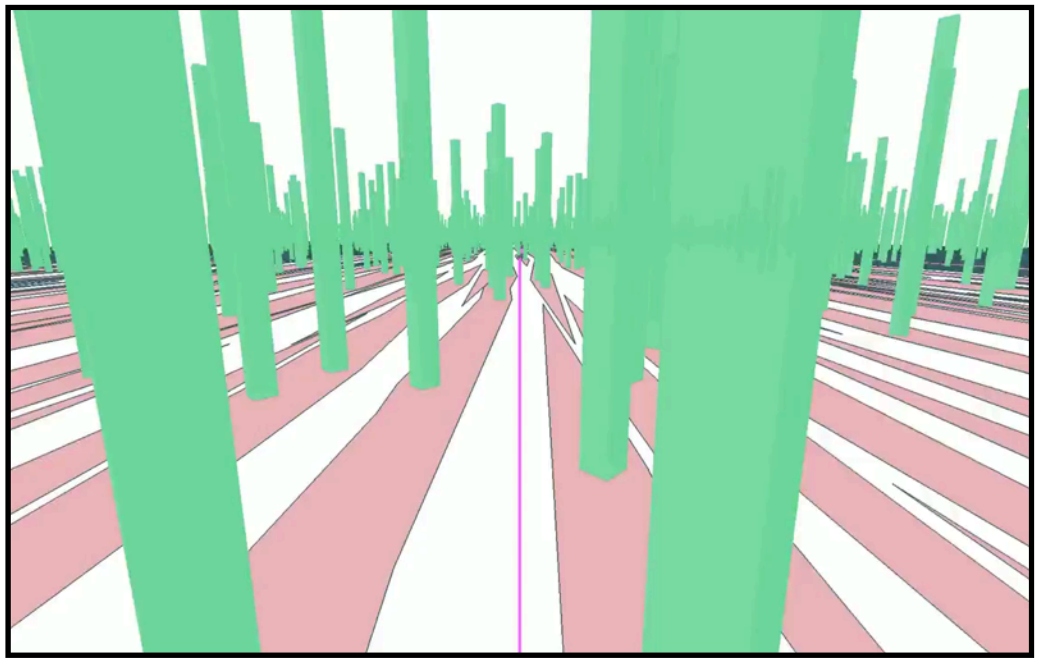

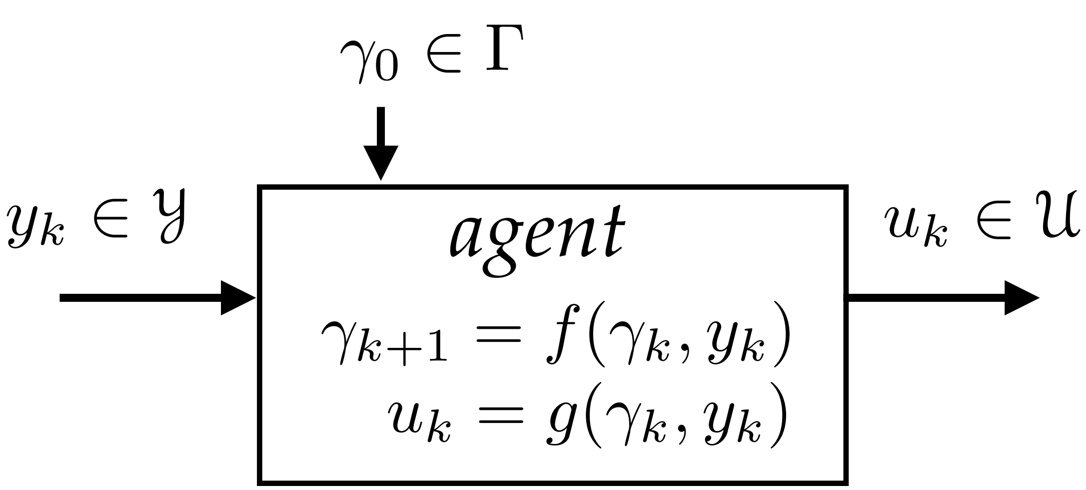

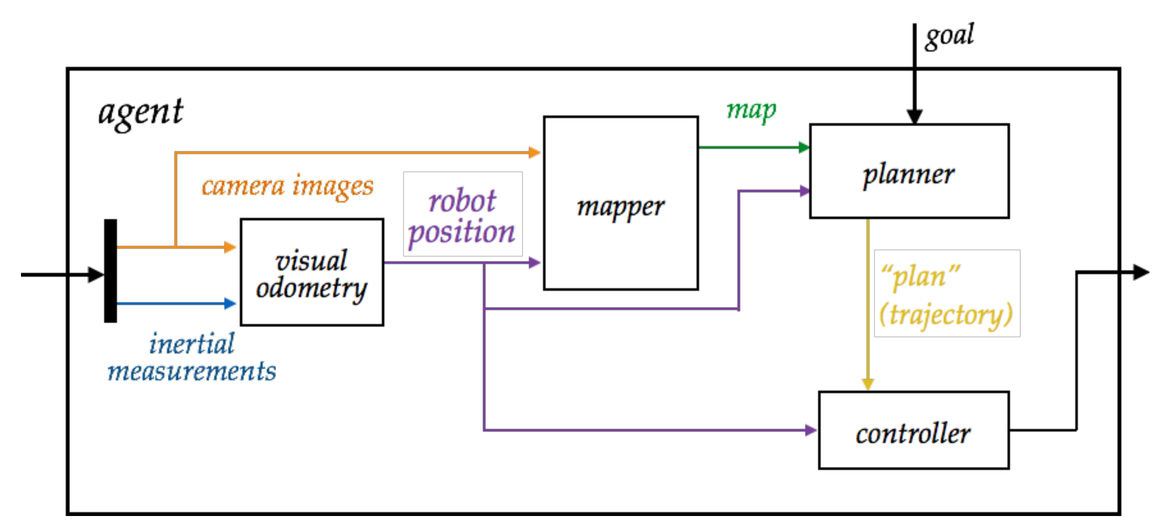

Joint inference and control:

Joint inference and control: opportunities

solving the joint problem
is more resource-efficient

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There are many formalizations
(only partially compatible)

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1. Minimality of sensing / control
2. Penalizing computation
3. Penalizing control information
4. Penalizing agent-world bandwidth
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Joint inference and control: opportunities and challenges

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Death by generality

Q: What is robotics?

Q: What's special about embodied intelligence?

Death by specificity

Q: Does it generalize?

Death by abstraction

Q: What can we integrate within realistic architectures?

Some Questions for the Discussion

- Is your idea of "Joint Inference and Control"
  not captured by any of the formalizations presented today?

- What formalization fits better the needs of field *X*?
- What formalization is easier to solve?

- How to avoid death by generality / specificity?
- How to avoid death by abstraction?

- Questions suggested by remote speakers?