Co-Design of Embodied Intelligence: A Structured Approach

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The pain of engineering complex systems

So many **components** (hardware, software, ...), so many choices to make!

Nobody can understand the **whole** thing!

We forget why we made some **choices**, and we are afraid to make **changes**...

These "computer" thingies are not helping us that much for design...

anthropomorphization of 21st century engineering malaise

"My dear, it's simple: you lack a proper theory of co-design!"

Co-design of autonomous systems: from hardware selection to control synthesis

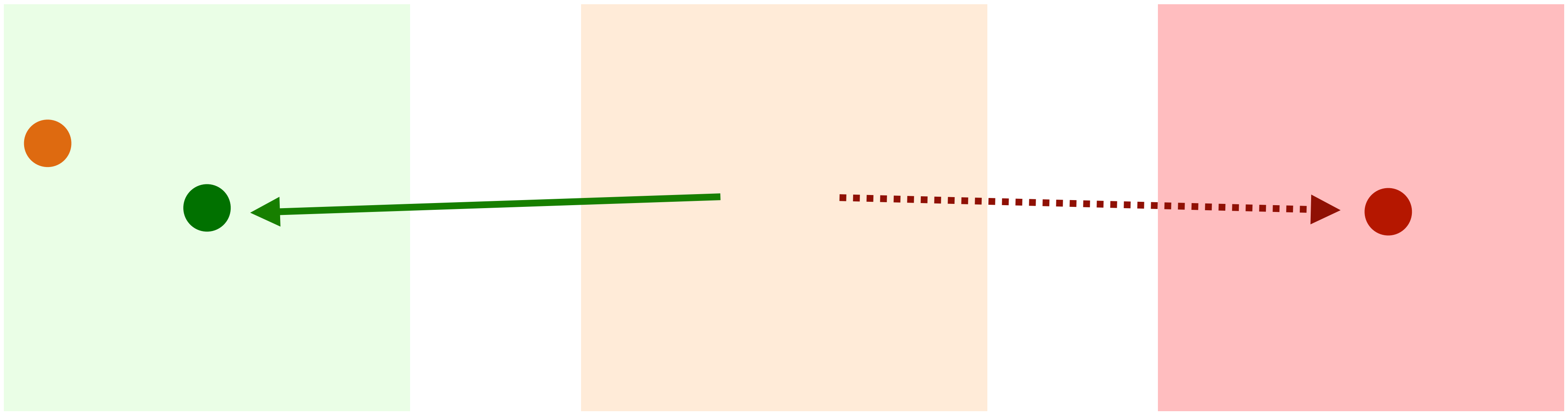
An autonomous robot =

software behavior coordination hardware actuation localization planning social sensing interaction acceptance control computation learning mapping liability perception energetics communication regulations

- **Takeways** of this talk**:**
  - Using co-design, it is easy to **hierarchical embodied intelligence models**
  - Very **intuitive** modeling approach (no “acrobatics” needed)
  - **Rich modeling capabilities**: analytic models, catalogues, simulations
  - **Compositionality** and **modularity** allow **interdisciplinary collaboration**
  - Co-design produces **actionable information** for designers to **reason** about their problems

An abstract view of design problems

- Across fields, design or synthesis problems are defined with 3 spaces:
  - **implementation space**: the options we can choose from;
  - **functionality space**: what we need to provide/achieve;
  - **requirements/costs space**: the resources we need to have available;



functionality *(provided)*	***implementations***	***costs, resources*** *(required)*
desired behavior	*choices*	
specifications	*plans*	*requirenents*
objectives	*blueprints*	*dependencies*
guarantees	*decision variables*	
“function”	*“form”*	*“function”*
“conclusions”	*“proof”*	*“assumptions”*

An abstract view of design problems

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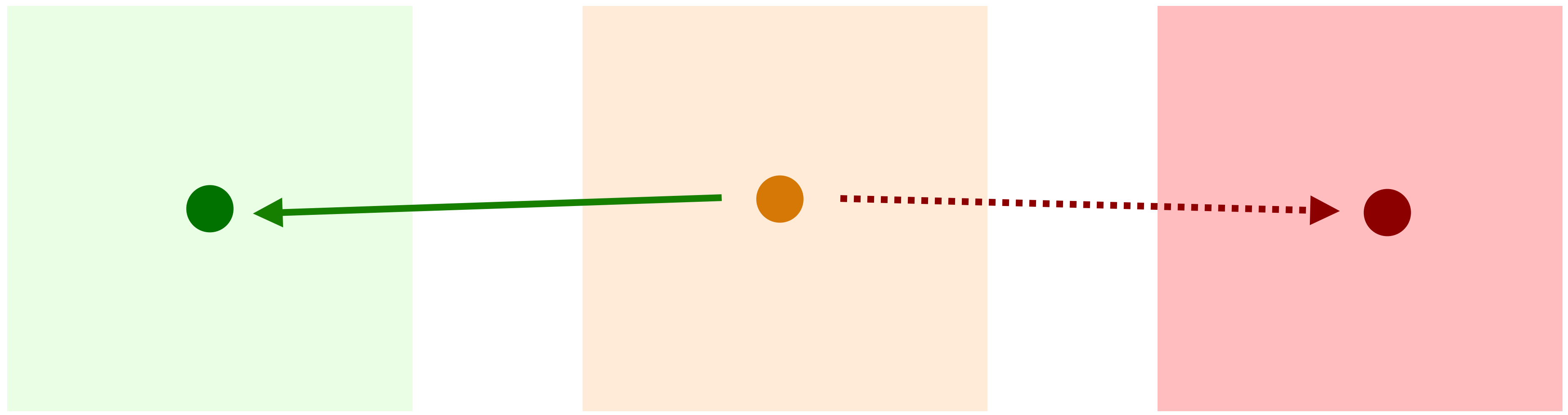


choices

Partially ordered sets

to maximize $\langle \mathbf{F}, \preceq_{\mathbf{F}} \rangle$

to minimize $\langle \mathbf{R}, \preceq_{\mathbf{R}} \rangle$

Partial orders allow to model various trade-offs

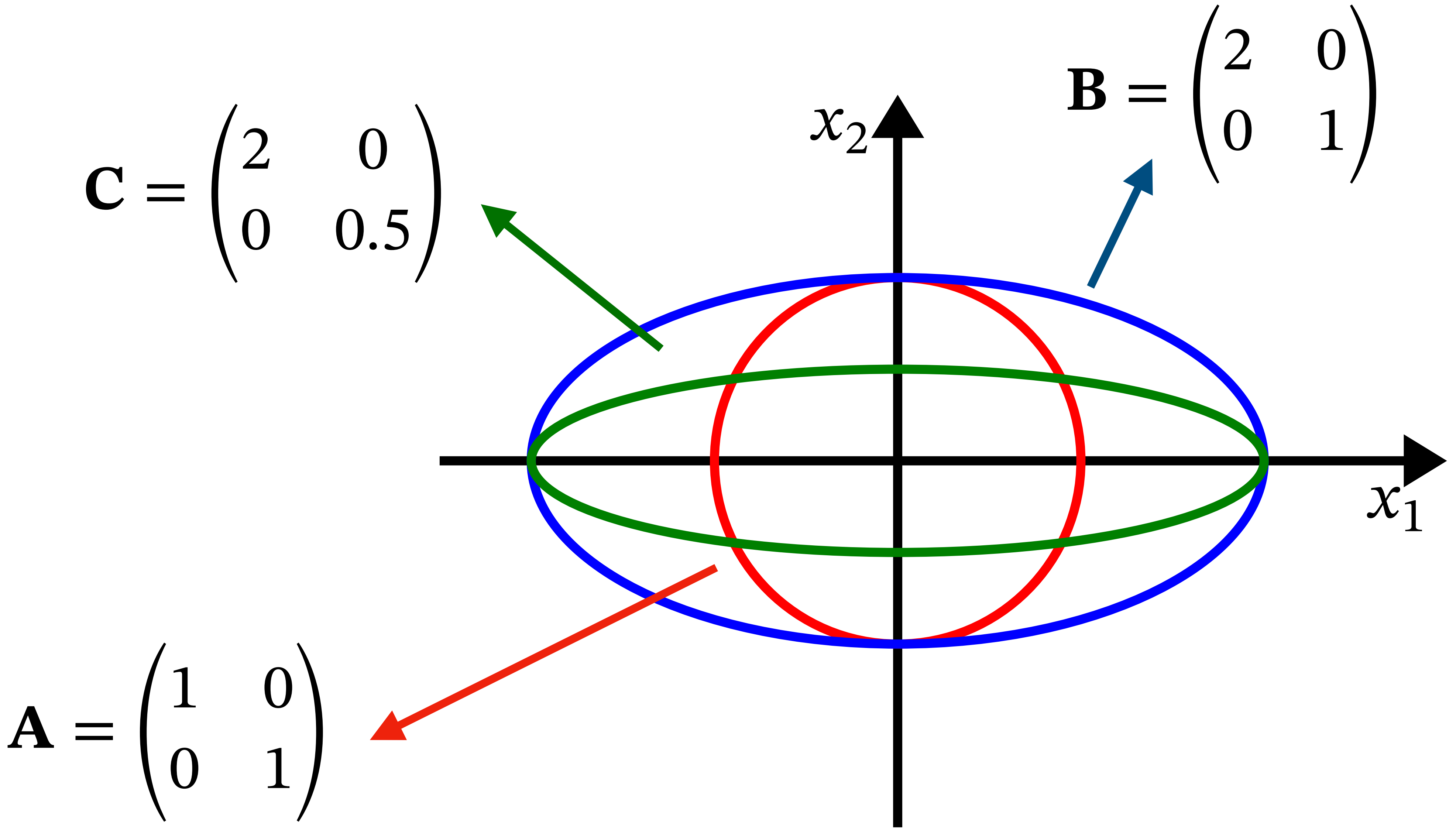
> **Definition.** A *poset* is a tuple $\langle P, \preceq_P \rangle$, where P is a set and $\preceq_P$ is a partial order, defined as a reflexive, transitive, and antisymmetric relation.

- All **totally ordered sets** are particular cases of **partially ordered sets:** $\langle \mathbb{R}_{\geq 0}, \leq \rangle$ $\langle \mathbb{N}, \leq \rangle$

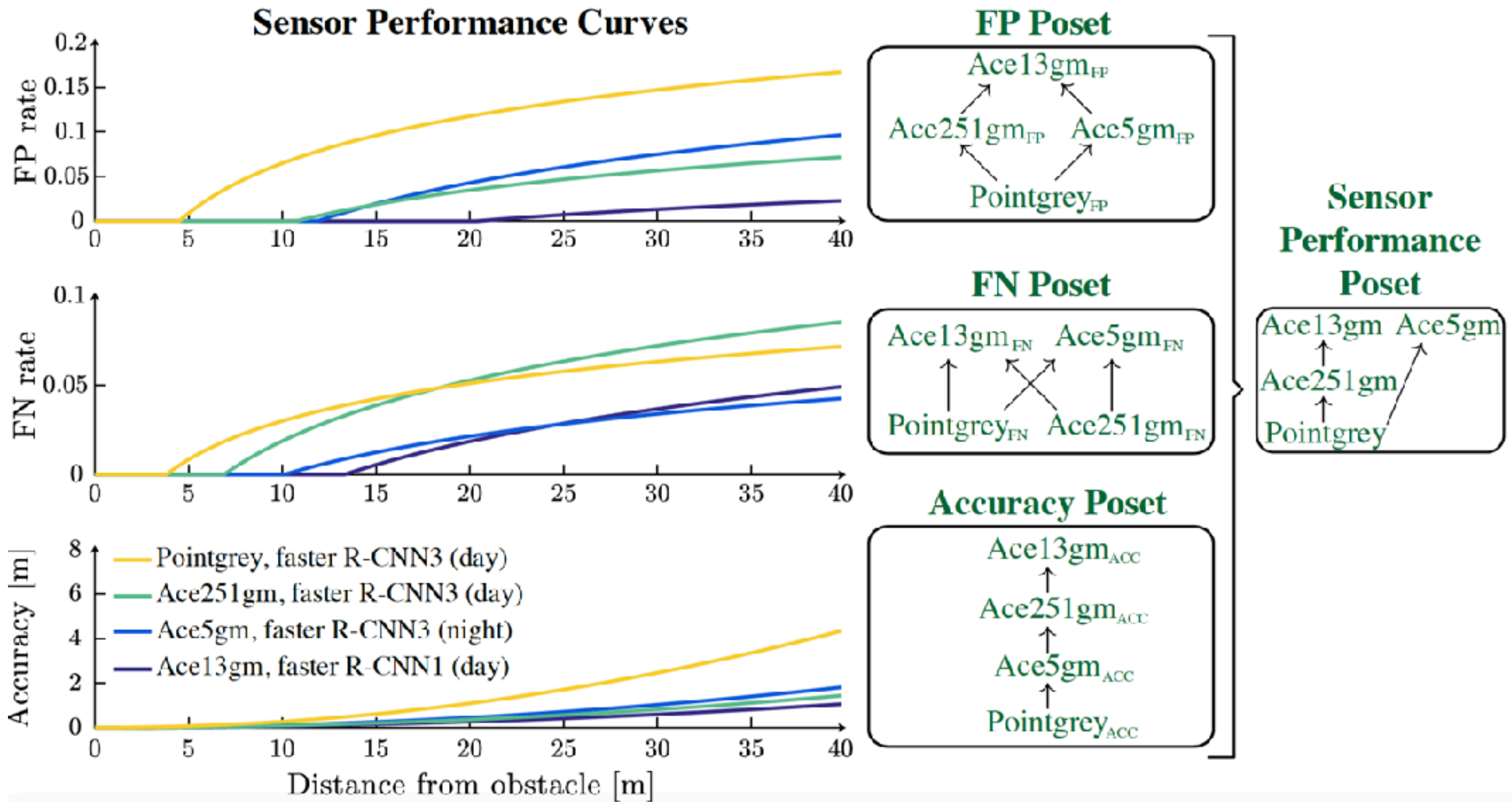
- In this work, among others, we consider

A poset of positive semi-definite matrices

$$\mathbf{A} \preceq \mathbf{B} \Leftrightarrow (\mathbf{A} - \mathbf{B}) \in \mathcal{P}^n, \quad \mathbf{A}, \mathbf{B} \in \mathcal{P}^n$$



A poset of sensors



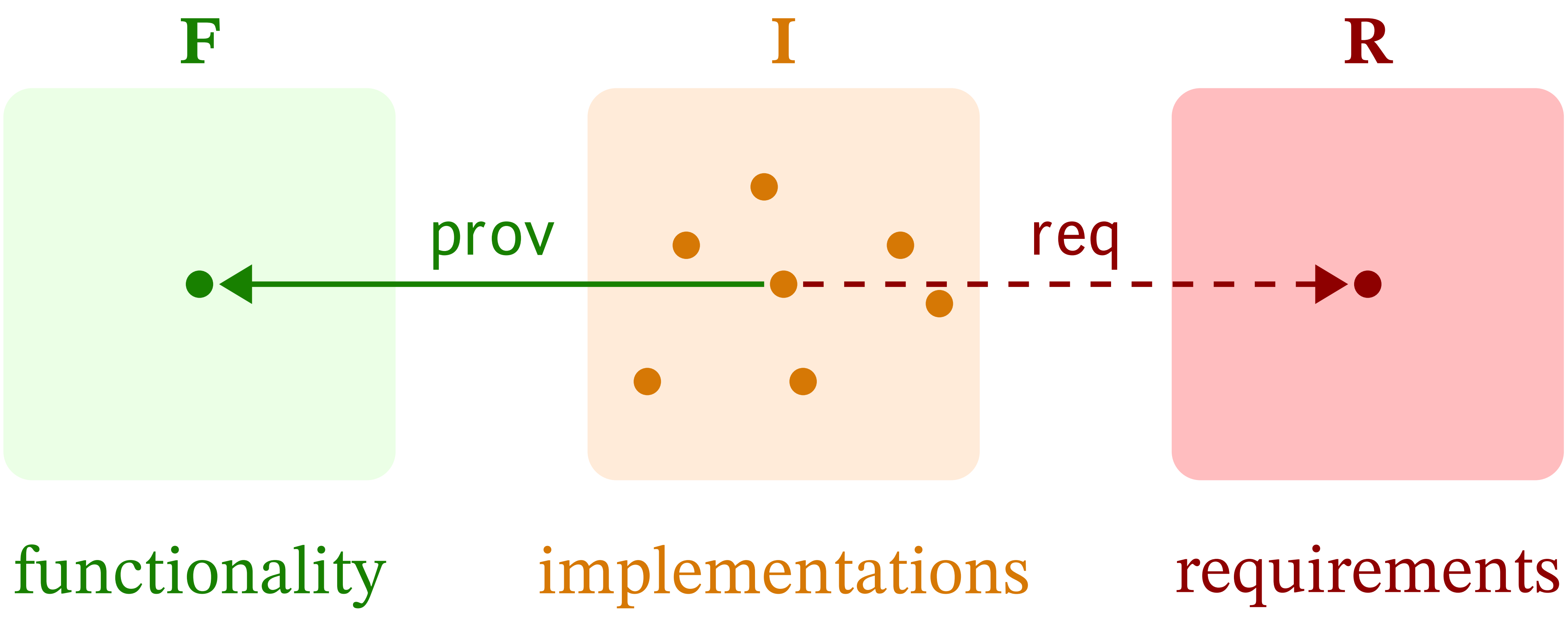
Design problem with implementation (DPIs)

Definition (Design problem with implementation). A *design problem with implementation* (DPI) is a tuple

$$\langle \mathbf{F}, \mathbf{R}, \mathbf{I}, \mathtt{prov}, \mathtt{req} \rangle,$$

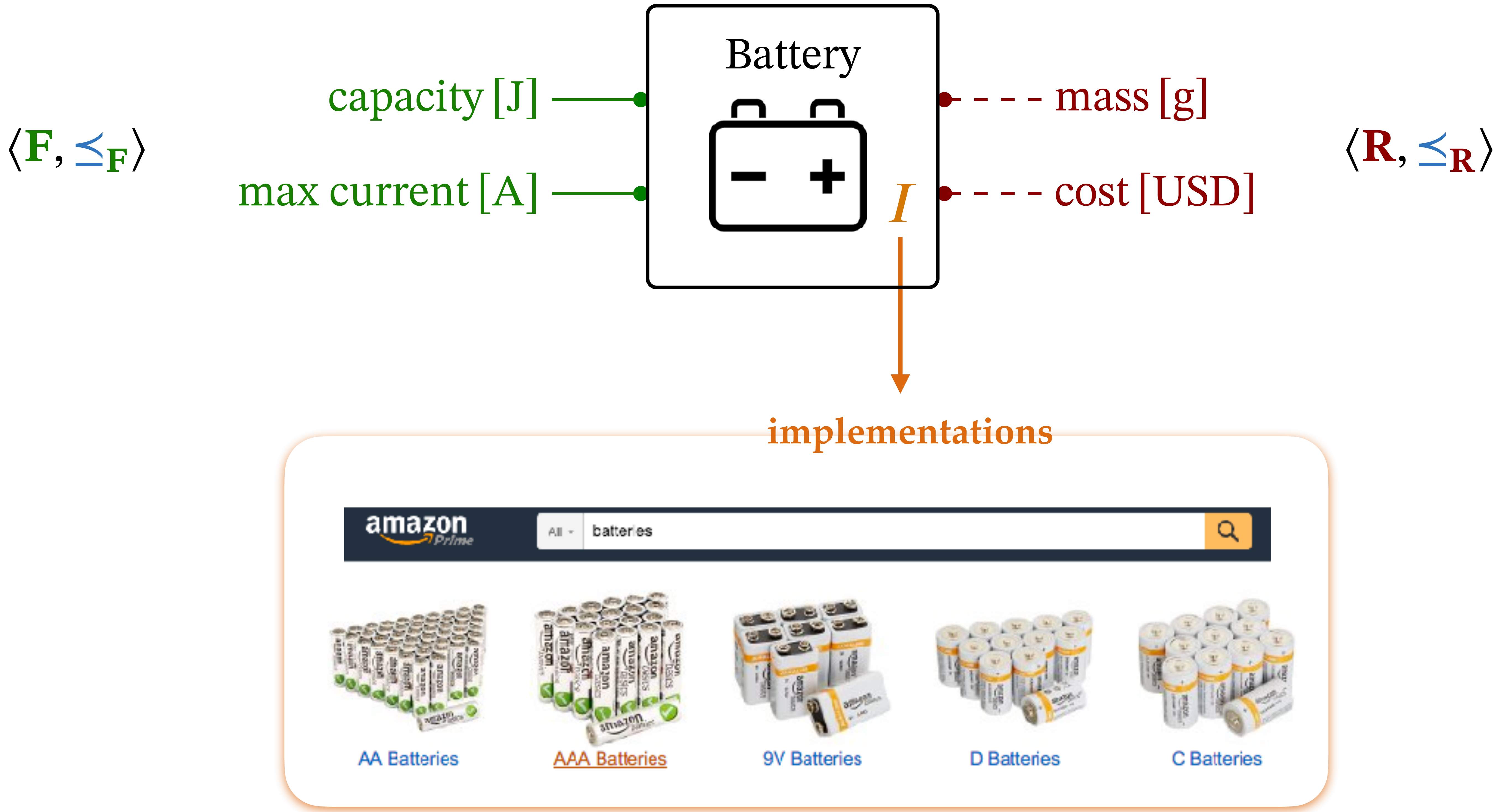
where:

- $\mathbf{F}$ is a poset, called *functionality space*;
- $\mathbf{R}$ is a poset, called *requirements space*;
- $\mathbf{I}$ is a set, called *implementation space*;
- the map $\mathtt{prov} : \mathbf{I} \to \mathbf{F}$ maps an implementation to the functionality it provides;
- the map $\mathtt{req} : \mathbf{I} \to \mathbf{R}$ maps an implementation to the resources it requires.



Graphical notation for DPIs

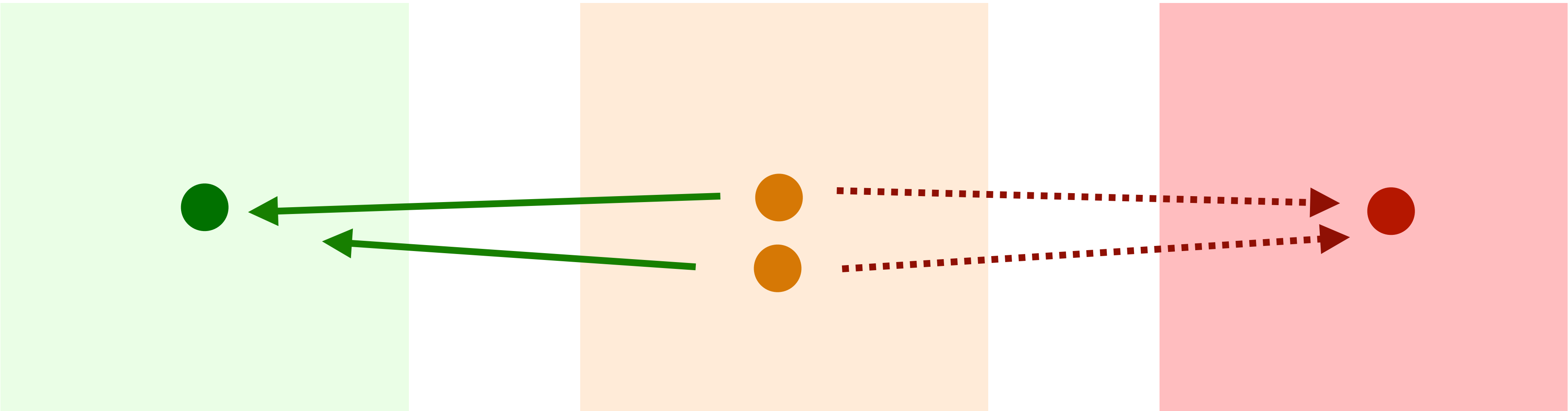
- We use this graphical notation:
  - functionality: **green continuous wires** on the left
  - requirements: **dashed red wires** on the right.



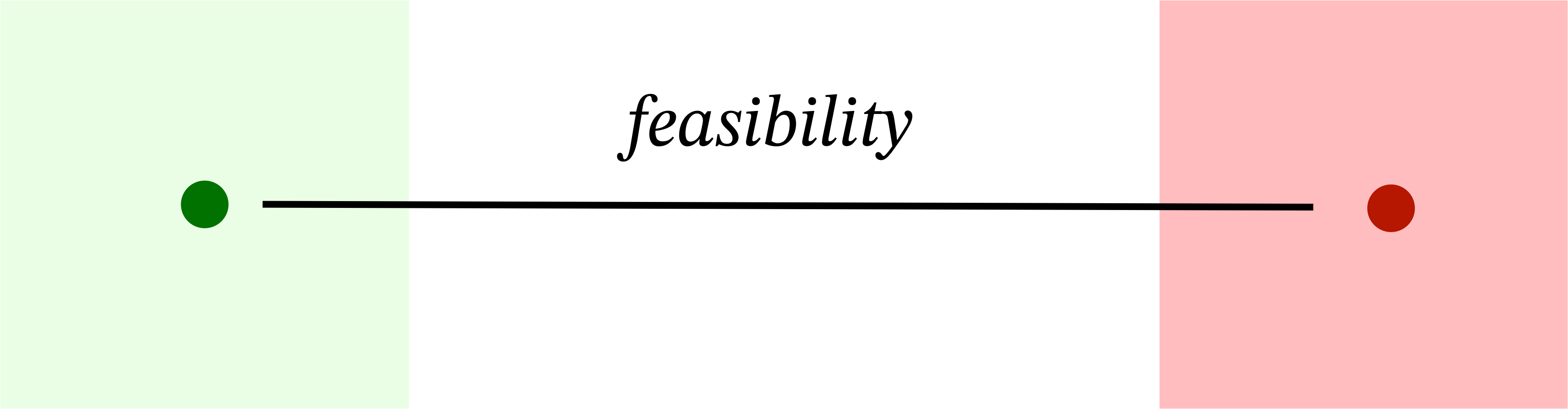
Engineering is constructive

- For the purpose of design, we **need to know how something is done**, not just that it is possible to do something: **engineering is constructive**.

- We need to know what are the implementation(s), if any, that relate functionality and costs.



- For the algorithmic solution of co-design problem, **it is useful to consider a direct feasibility relation** from functionality to costs.



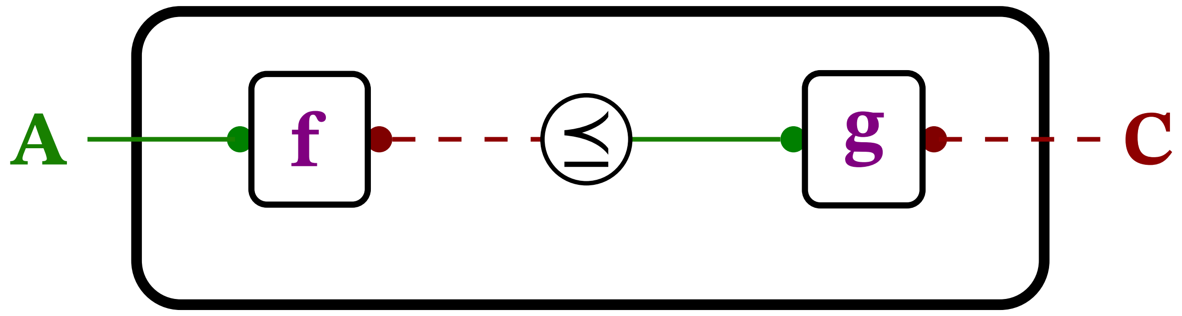
$$\mathbf{d} : \mathbf{F}^{\mathrm{op}} \times \mathbf{R} \to_{\mathbf{Pos}} \mathbf{Bool}$$

$$\langle f^*, r \rangle \mapsto \exists i \in \mathbf{I} : (f \preceq_{\mathbf{F}} \mathsf{prov}(i)) \wedge (\mathsf{req}(i) \preceq_{\mathbf{R}} r)$$

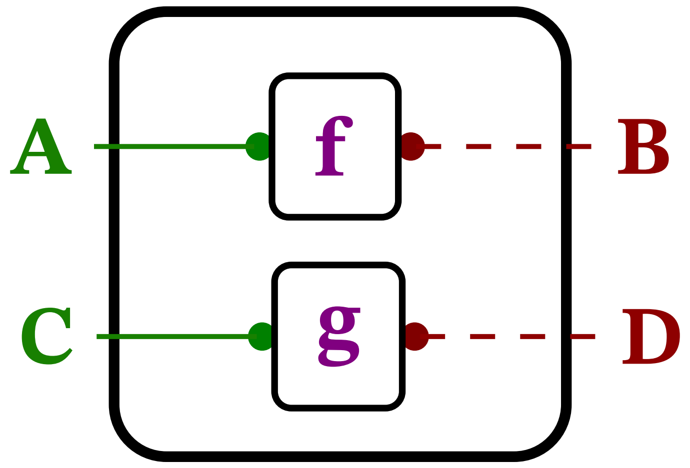
- **Monotone** map: **Lower functionalities** does **not** require **more resources**, **higher resources** do not provide **less functionalities**

Composition operators

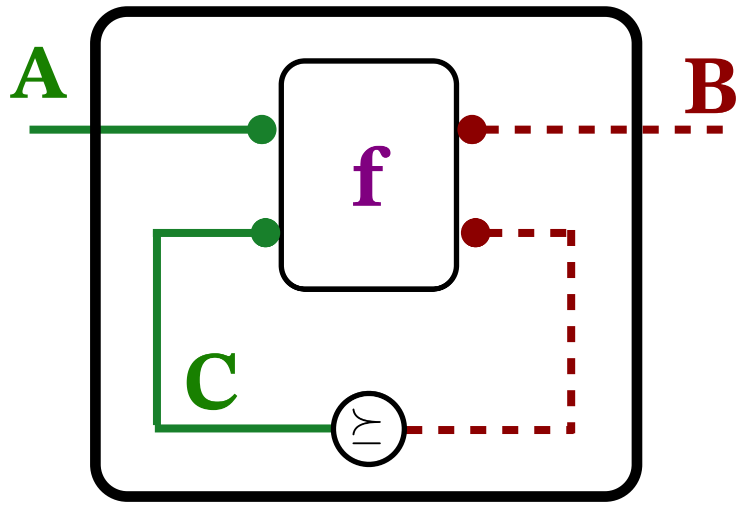
"series"



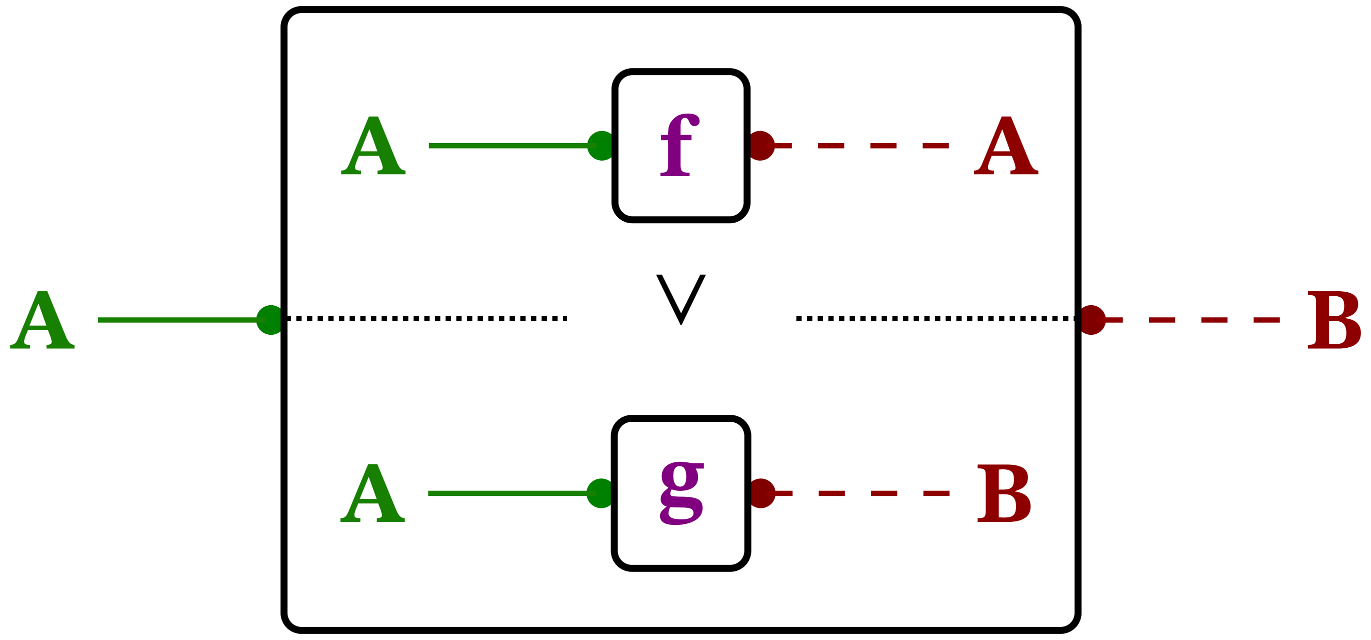
"parallel"



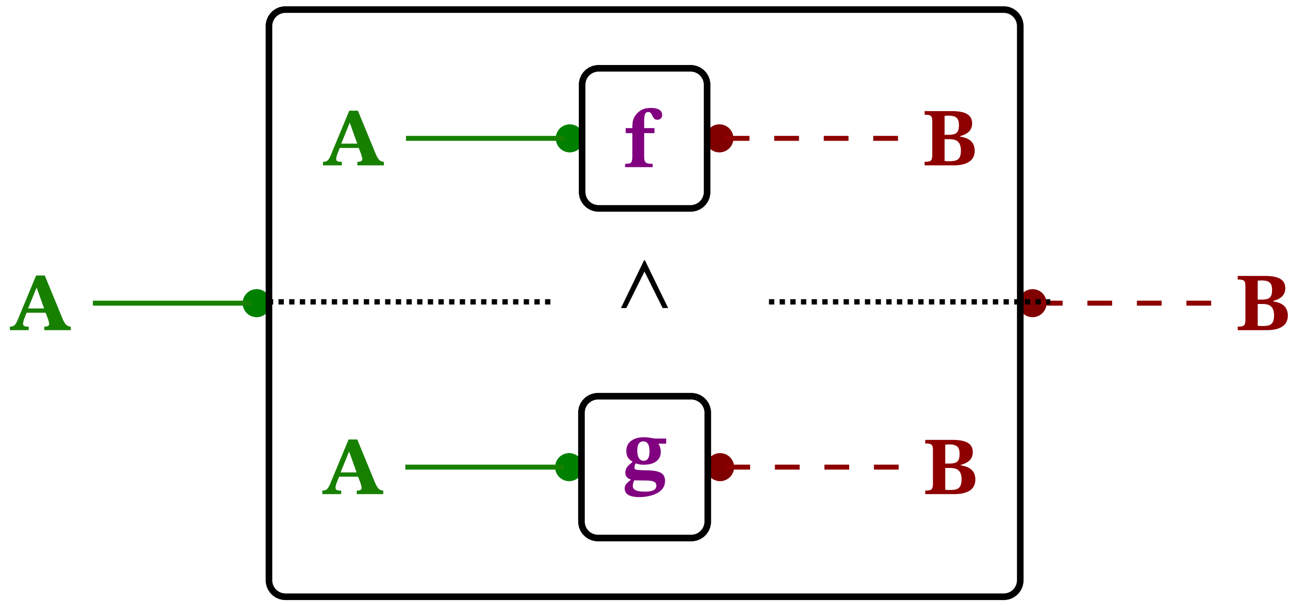
"feedback"



"choose between two options"



"convince two experts"



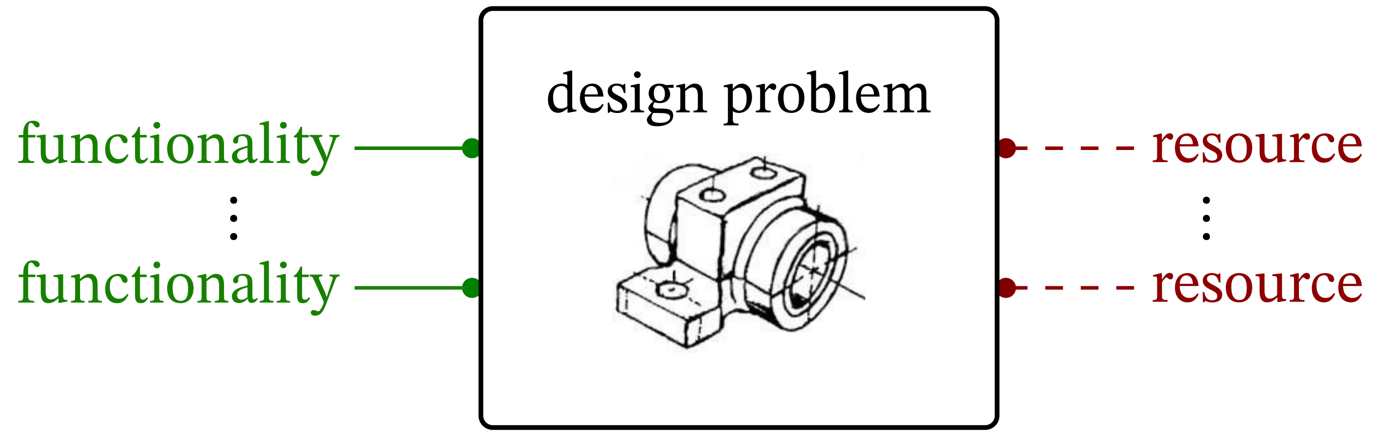
- The **composition** of any two **DPs** returns a **DP** (closure)
- Very practical tool to **decompose** large **problems** into **subproblems**

Design queries

- Two basic design queries are:
  - **FixFunMinReq**: Fixed a lower bound on functionality, minimize the resources.
  - **FixReqMaxFun**: Fixed an upper bound on the resource, maximize the functionality

Given the functionality to be provided,
what are the **minimal resources** required?

FixFunMinReq →



← **FixReqMaxFun**

Given the resources that are available, what is
the **maximal functionality** that can be provided?

Design queries

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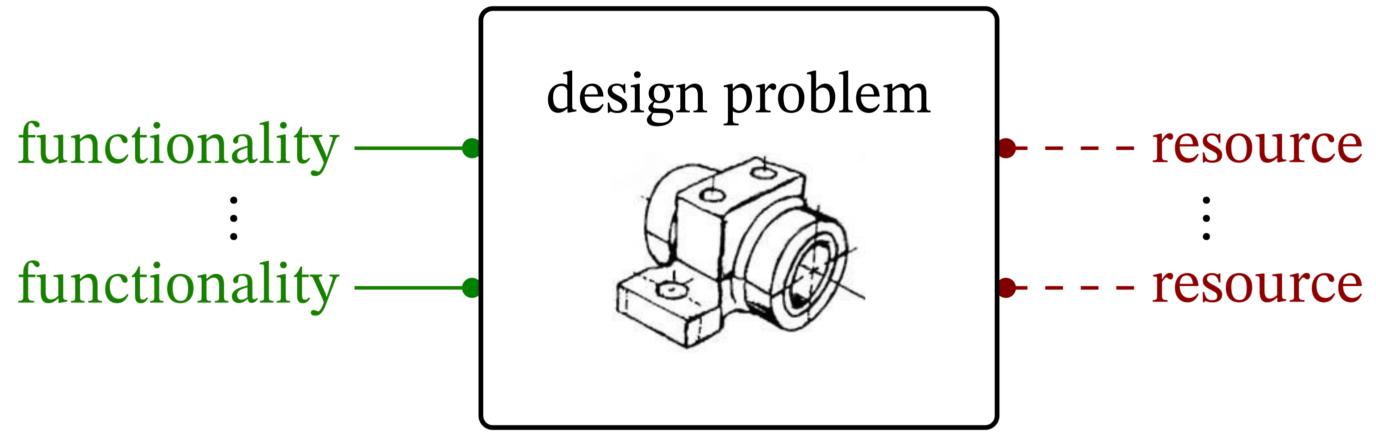
FixFunMinReq



FixReqMaxFun

Given the resources that are available, what is
the **maximal functionality** that can be provided?

- The two problems are **dual**
- From the solutions, one can retrieve the **implementations** (design choices)

Design queries

- Two basic design queries are:
  - **FixFunMinReq**: Fixed a lower bound on functionality, minimize the resources.
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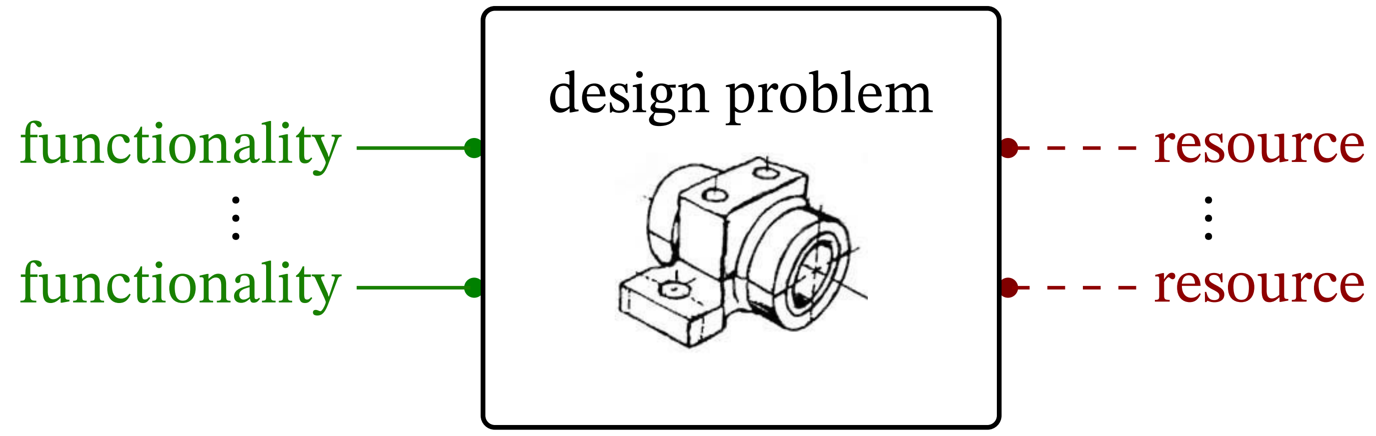
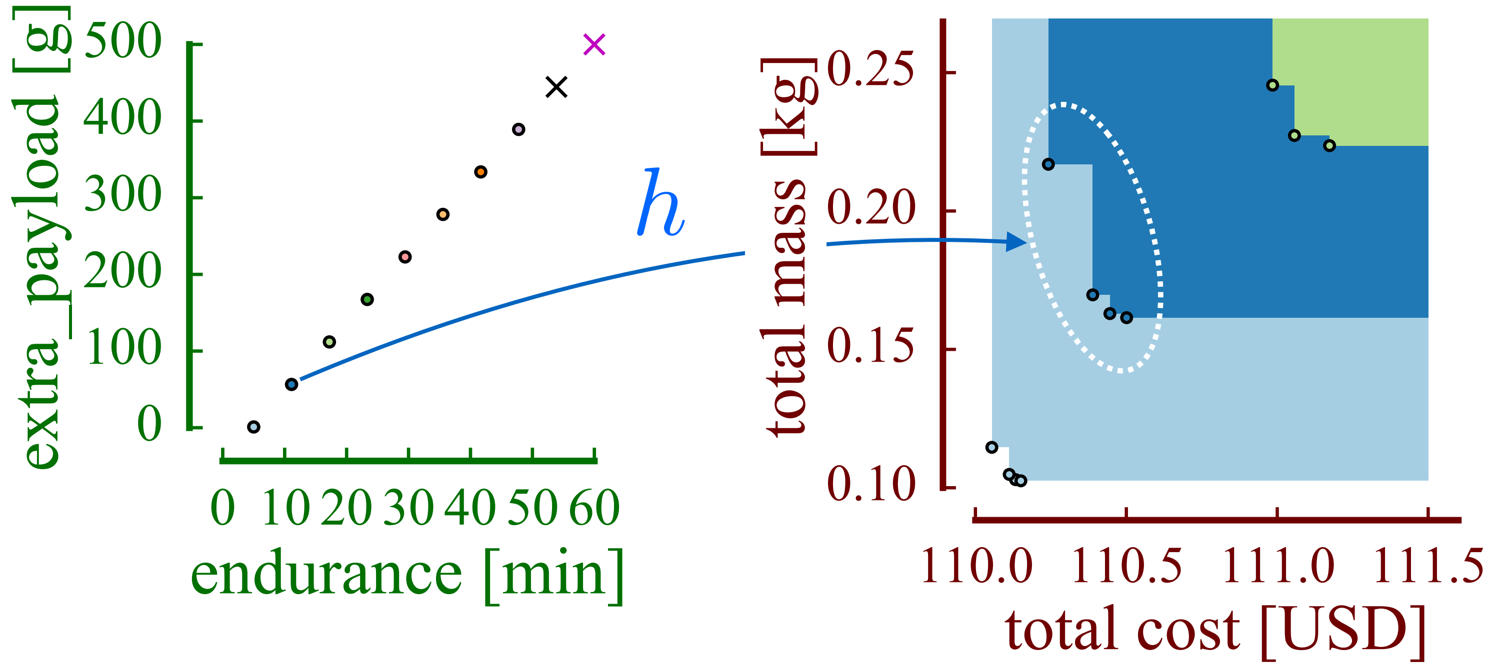
FixFunMinReq →



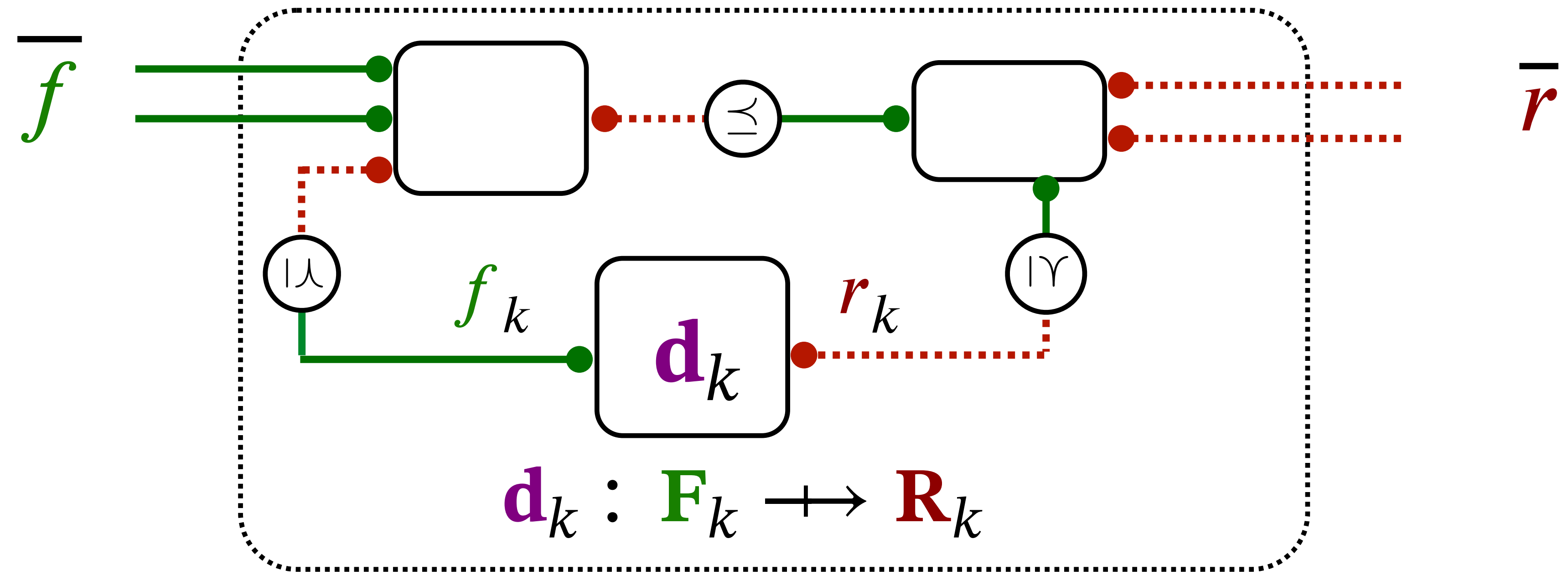
- We are looking for:
  - A map from functionality to upper sets of feasible resources: $h : \mathbf{F} \to \mathcal{U}\mathbf{R}$
  - A map from functionality to antichains of minimal resources: $h : \mathbf{F} \to \mathcal{A}\mathbf{R}$



Optimization semantics

- This is the semantics of **FixFunMinReq** as a **family of optimization problems.**

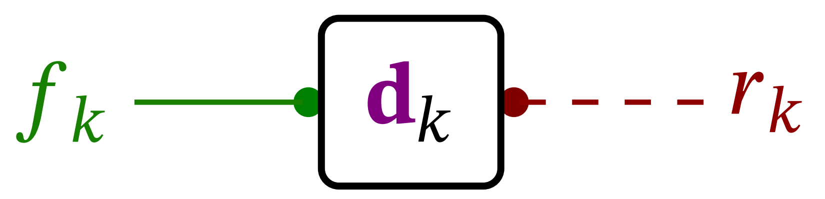
chosen by user

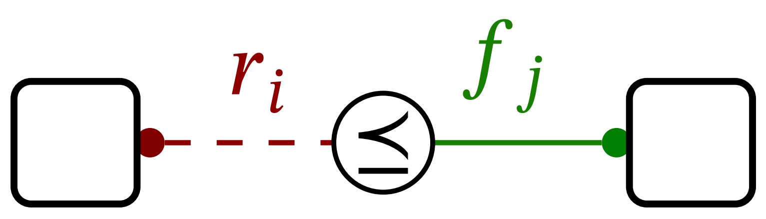


to minimize

variables $r_k \in \langle \mathbf{R}_k, \preceq_{\mathbf{R}_k} \rangle$ $\quad f_k \in \langle \mathbf{F}_k, \preceq_{\mathbf{F}_k} \rangle$

constraints *for* ***each node:*** *for* ***each edge:***





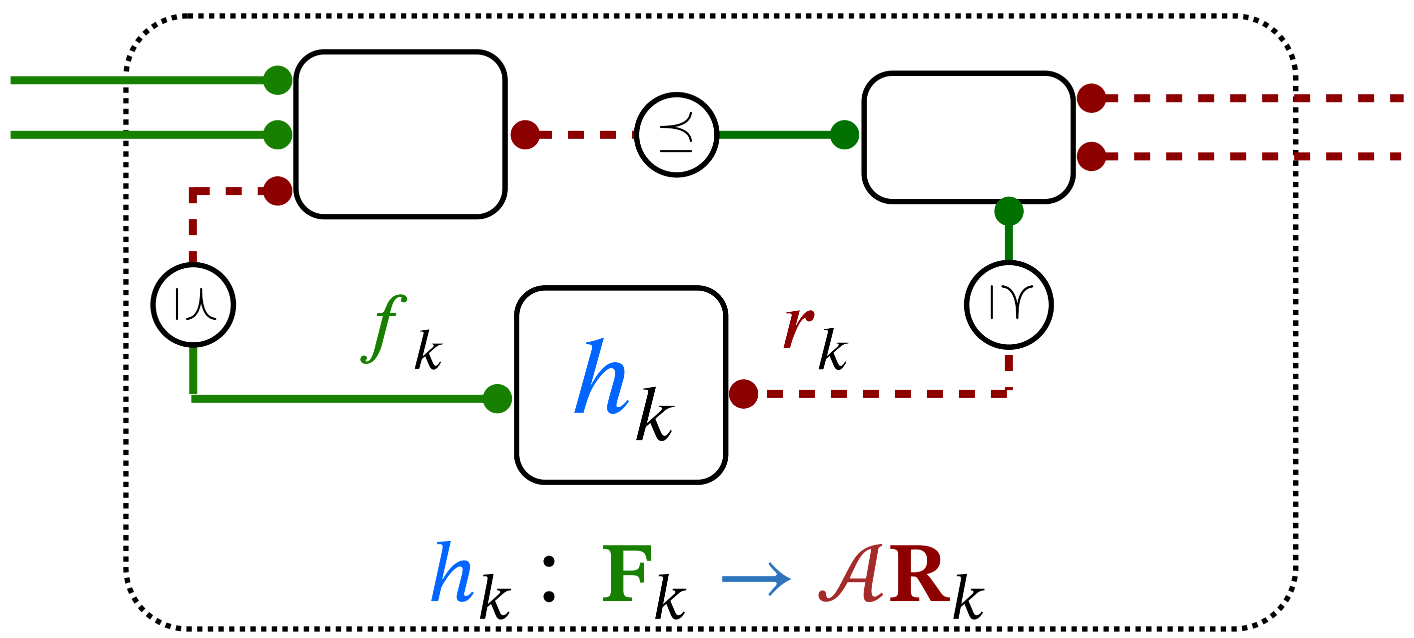
$$\mathbf{d}_k(f_k^*, r_k) = \top \qquad r_i \preceq f_j$$

objective $\underset{\preceq}{\mathrm{Min}}\, \overline{r}$

- ! not convex
- ! not differentiable
- ! not continuous
- ! not even defined on continuous spaces

Solving DP queries

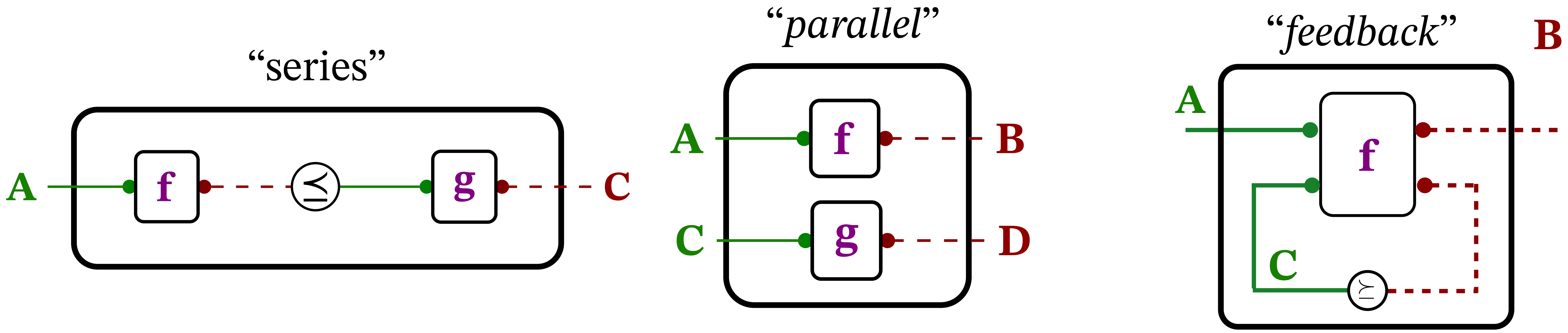
- Suppose we are given the function $h_k : \mathbf{F}_k \to \mathcal{A}\mathbf{R}_k$ for all nodes in the co-design graph.



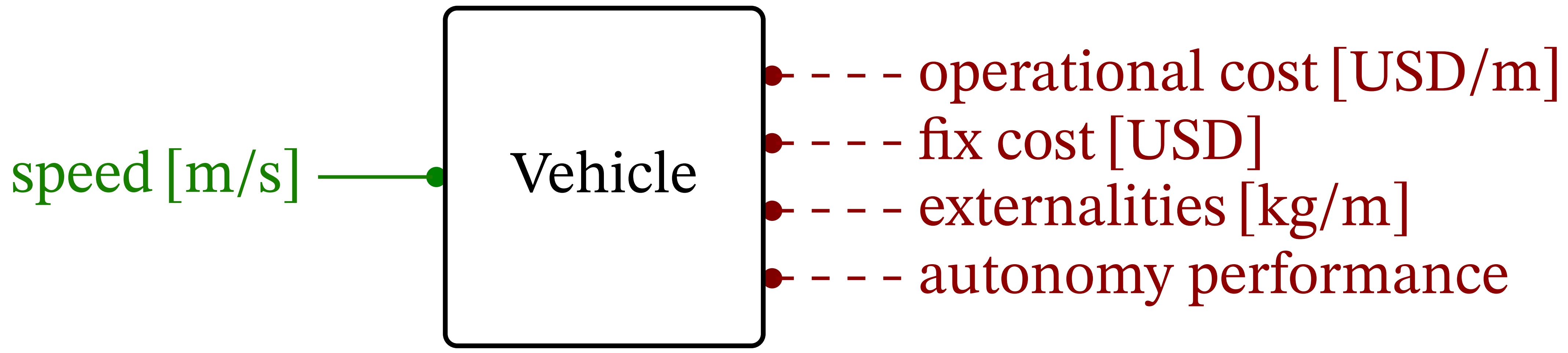
- Can we find the map $h : \mathbf{F} \to \mathcal{A}\mathbf{R}$ for the entire diagram?

- **Recursive approach:** We just need to work out the the composition formulas for all operations we have defined

- The set of **minimal** feasible resources can be obtained as the **least fixed point** of a monotone function in the space of anti-chains.



Co-design of embodied intelligence



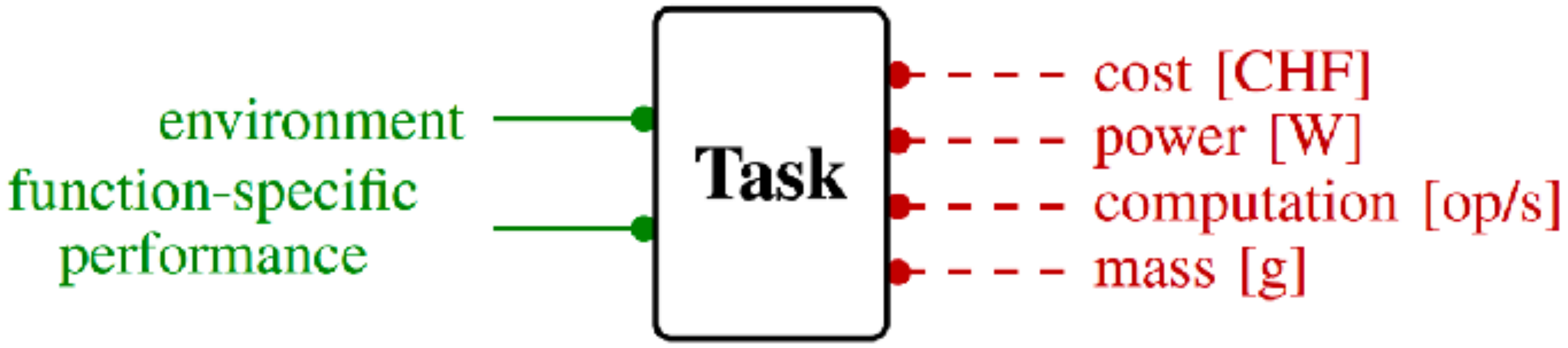
- We propose a **structured** approach to **model** and **solve embodied intelligence** co-design problems
- We take the proxy of **AV design**, from the perspective of the **developers:**
  - The methodology can be applied to other autonomous systems
  - *Proof of concept* implementation

- **Modeling approach:**
  - **Task -** *what do we need to do?*
  - **Functional decomposition -** *how to decompose the system?*
  - **Find components -** *decompose until you find components* (hardware and software)
  - **Find common resources** - In robotics, **size**, **weight**, **power**, **computation**, **latency**

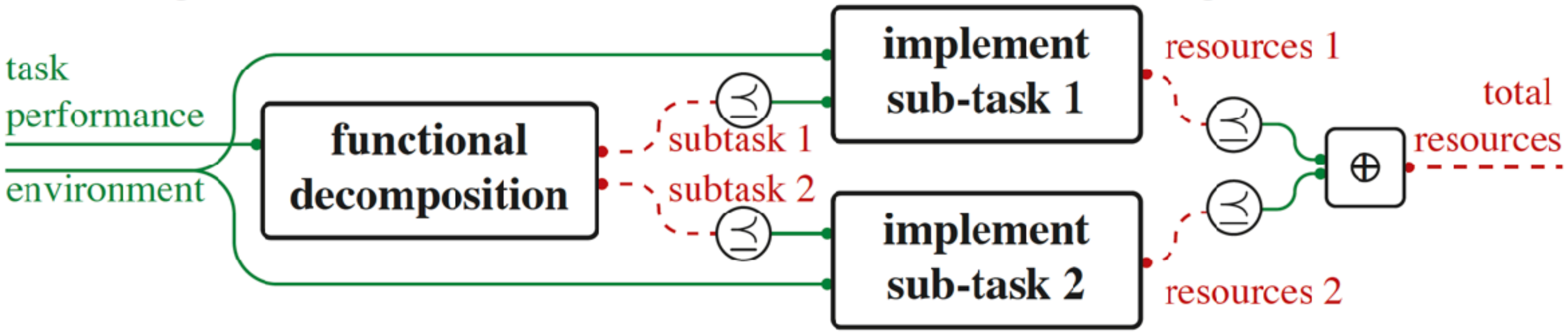
- **Implementation:**
  - **Skeleton** - *write the structure using the formal language and the found dependencies*
  - **Fill-in the holes** - *catalogues, analytic models, simulations*

Task abstraction and functional decomposition in autonomy

- Embodied intelligence tasks can be usually characterized as a **design problem:**

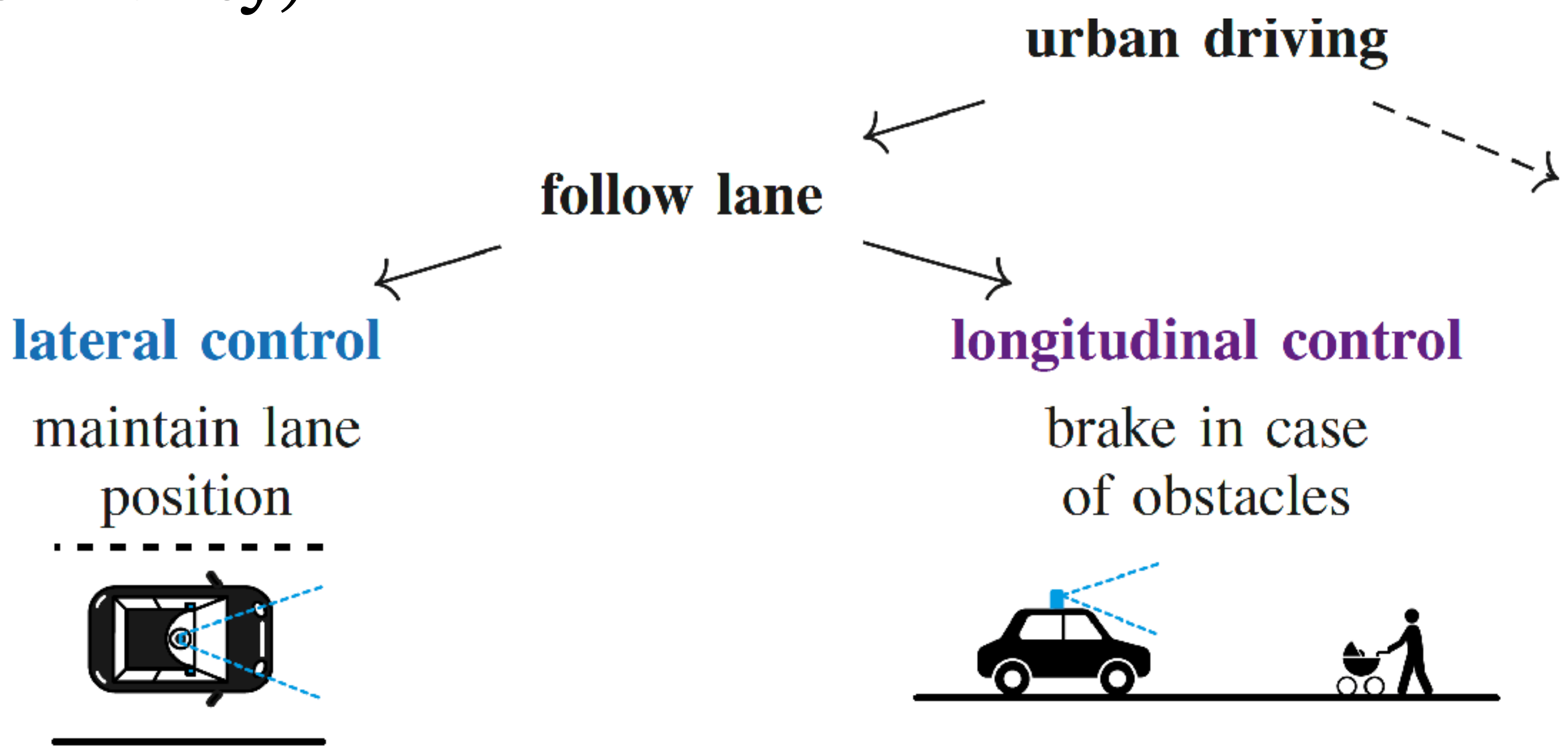


- Given **sub-tasks**, one can interconnect them:



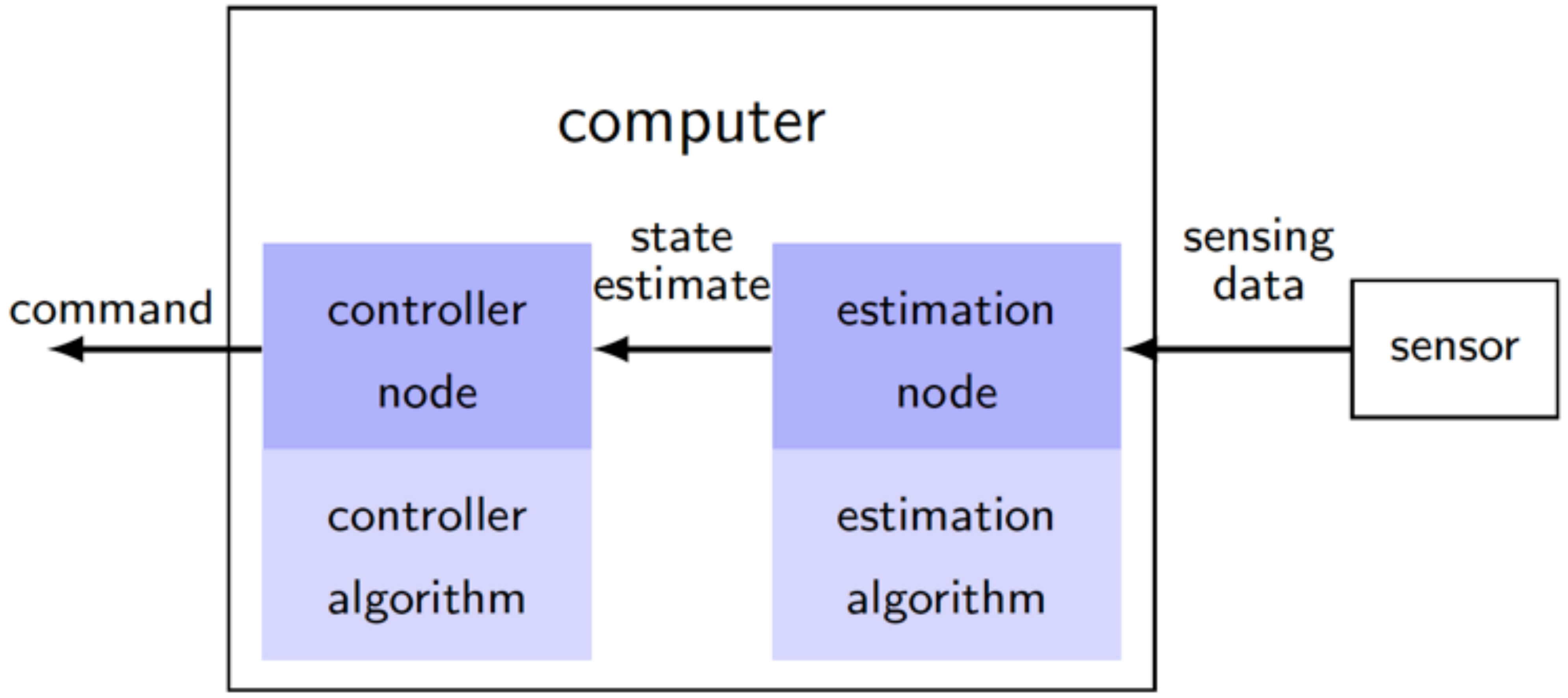
- Note that **composing** tasks returns a **task** (**compositionality**)

- For instance, in **urban driving**:



Finding components: Data flow vs. Logical dependencies

- In robotics, we are used to think about **data flow:**



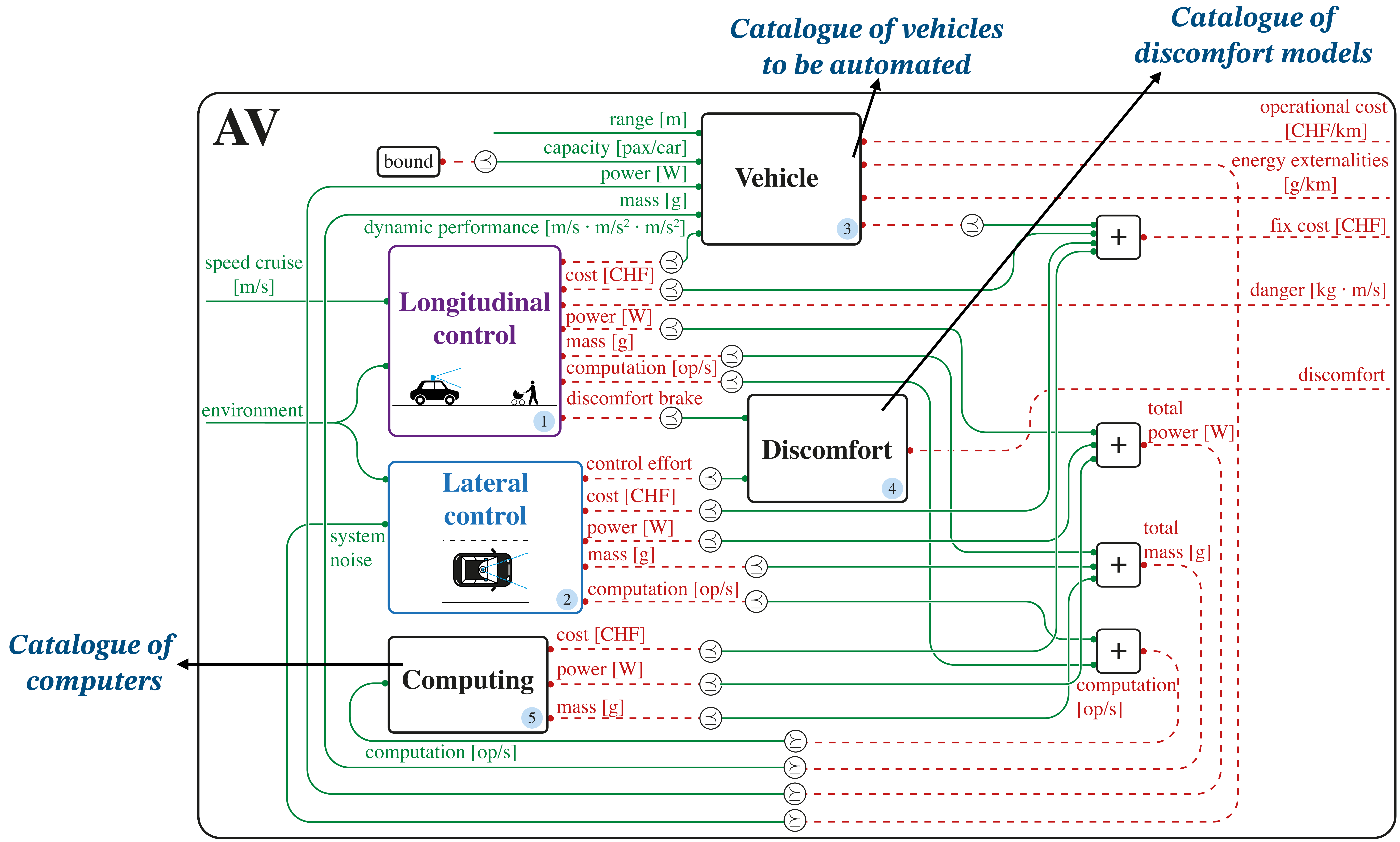
- To find **components**, it helps to reason about **logical dependencies**:

Decision making $\xrightarrow{\text{requires}}$ *State estimation* $\xrightarrow{\text{requires}}$ *Sensing data* $\xrightarrow{\text{requires}}$ *Sensor*

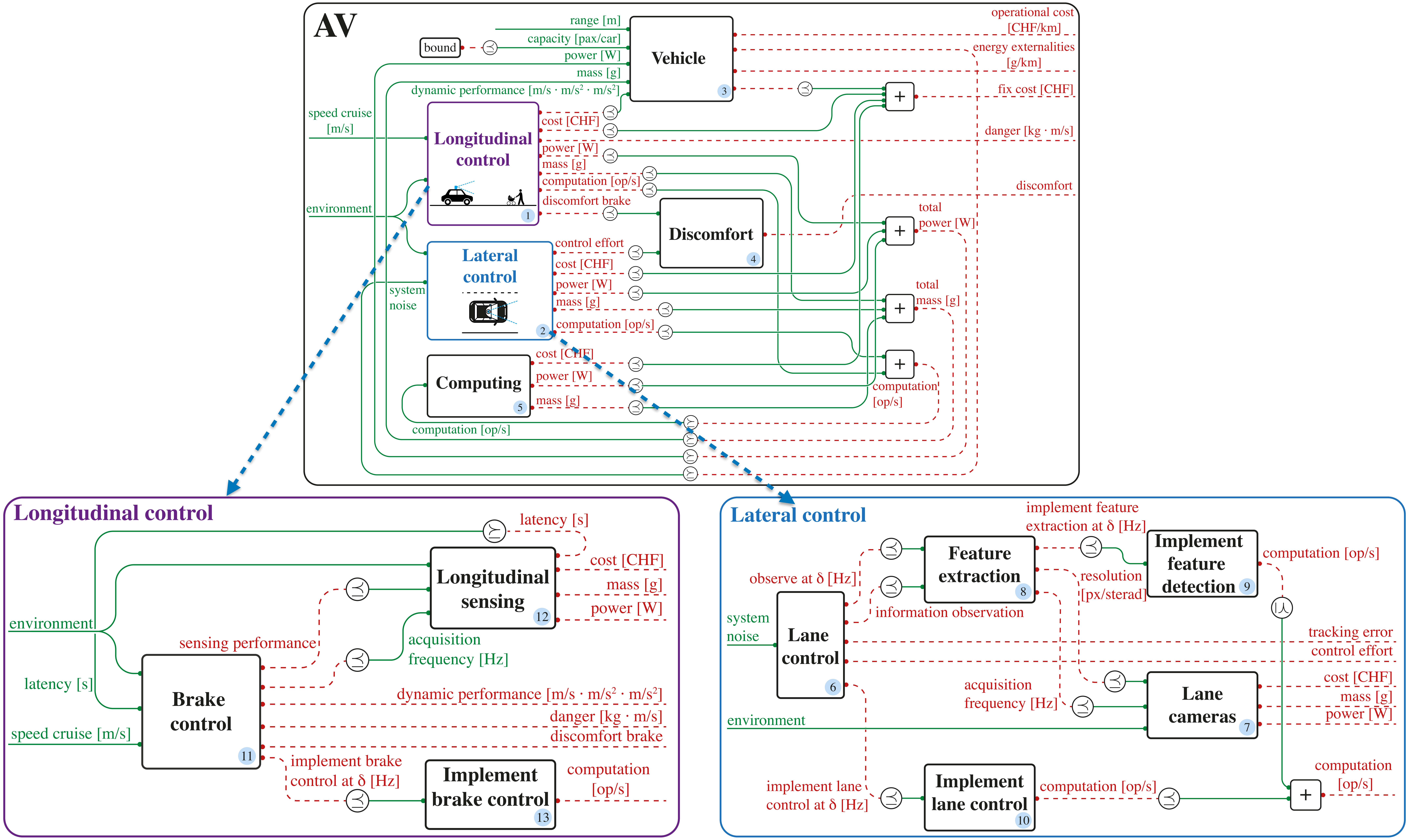
State estimation $\xrightarrow{\text{requires}}$ *algorithm*

State estimation $\xrightarrow{\text{requires}}$ *computation* $\xrightarrow{\text{requires}}$ *Computer*

Co-design of an autonomous vehicle

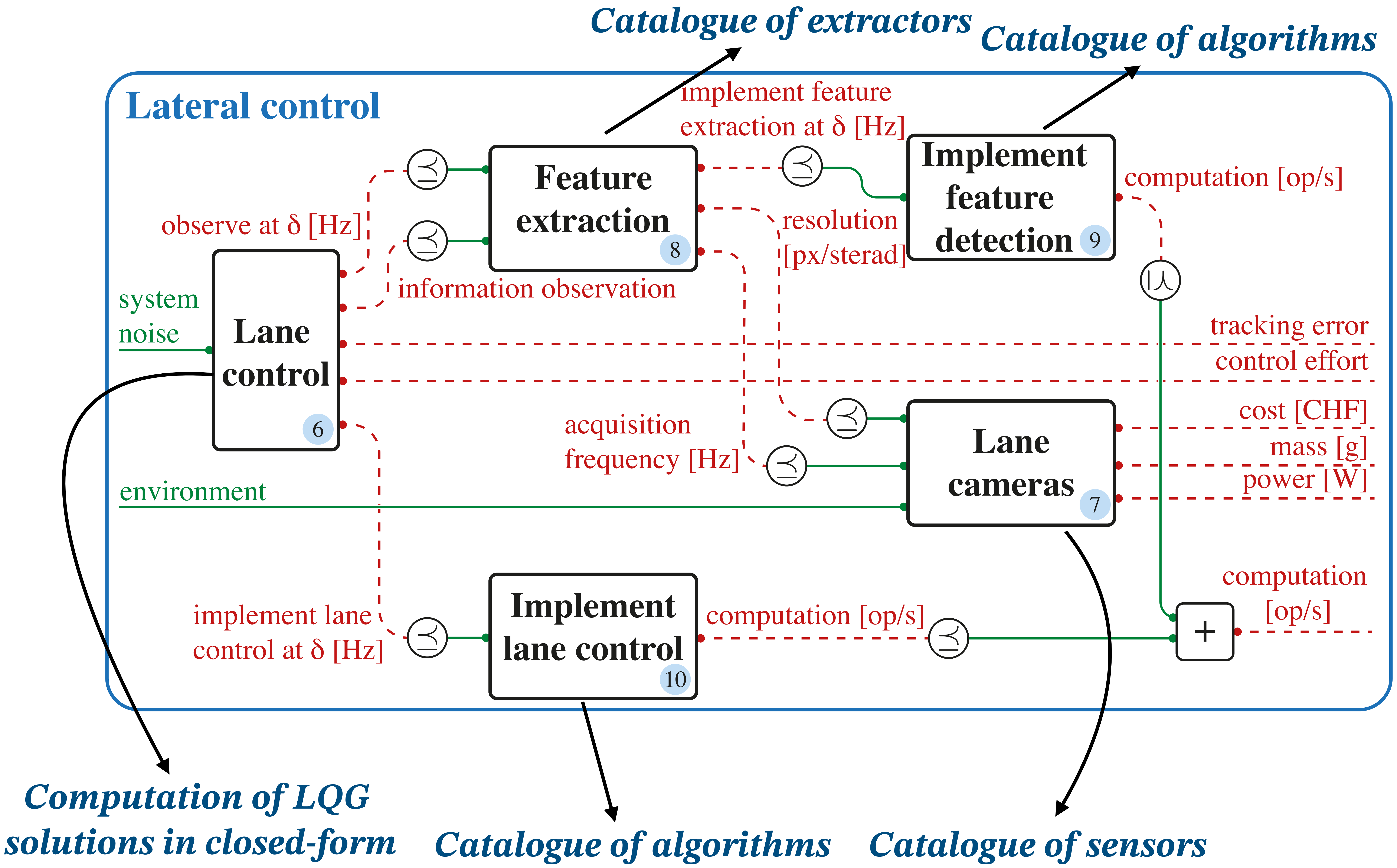


Encapsulating co-design models via functional decomposition



Co-design of lateral control: Closed-form simulations

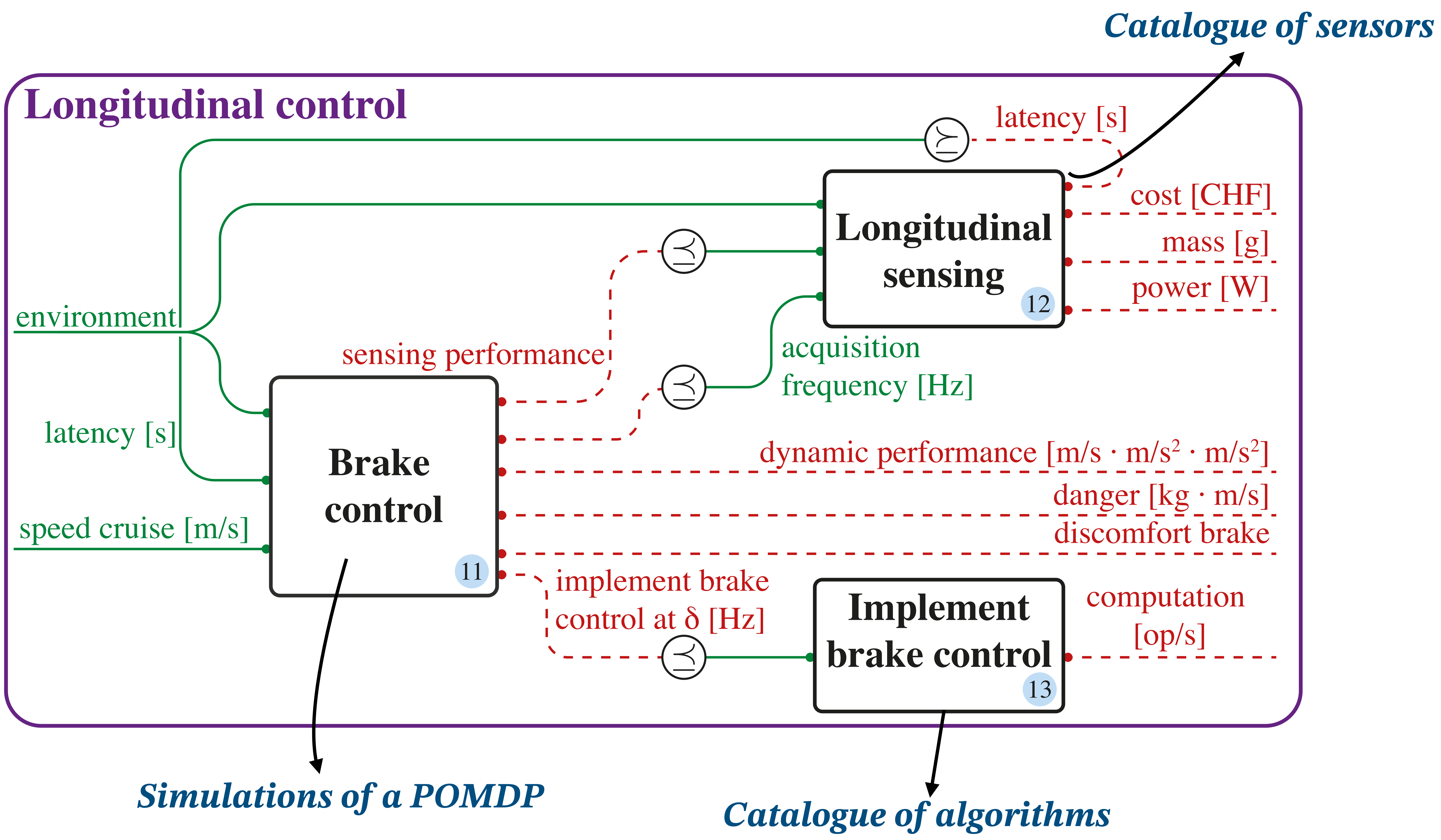
- Lateral control itself can decomposed in **sub-tasks:**



Zardini, Censi, Frazzoli, Co-design of Autonomous Systems: From Hardware Selection to Control Synthesis, *ECC 2021*

Co-design of longitudinal control: Simulations of POMDPs

- Longitudinal control can be decomposed in **sub-tasks**:



User friendly interface to solve complex optimization problems

- The theory comes with a **formal language** and a **solver (MCDP)**
- Very intuitive to use:

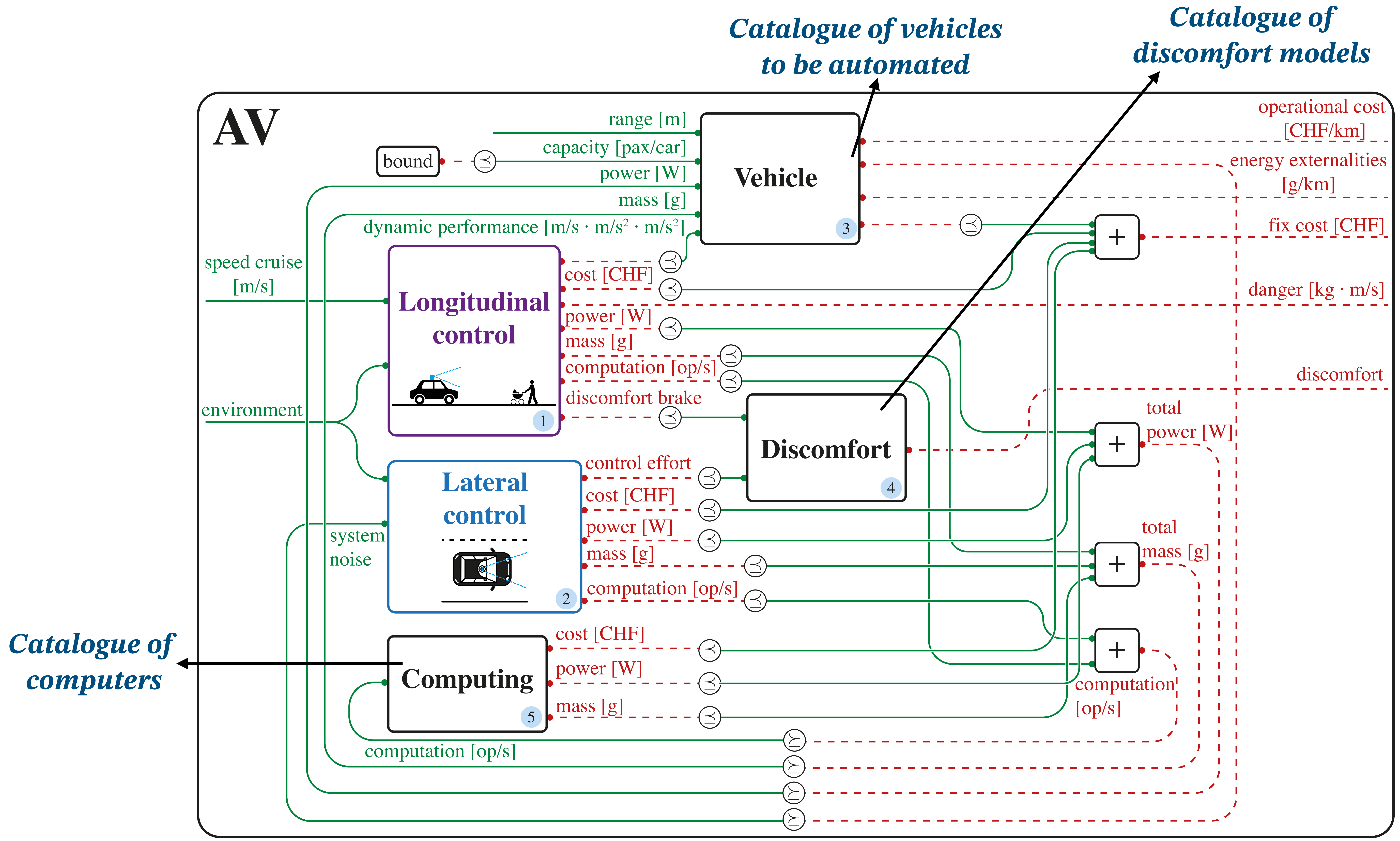
```
mcdp {
    provides computation [op/s]
    requires cost [CHF]
    requires mass [g]
    requires power [W]

}
```

```
choose(
        SedanS: (load Car_SedanS),
        SedanM: (load Car_SedanM),
        SedanL: (load Car_SedanL),
        SUVS: (load Car_SuvS),
        SUVM: (load Car_SuvM),
        Minivan: (load Car_Minivan),
        Shuttle: (load Car_Shuttle),
        Hybrid: (load Car_Hybrid),
        BEV: (load Car_BEV)
)
```

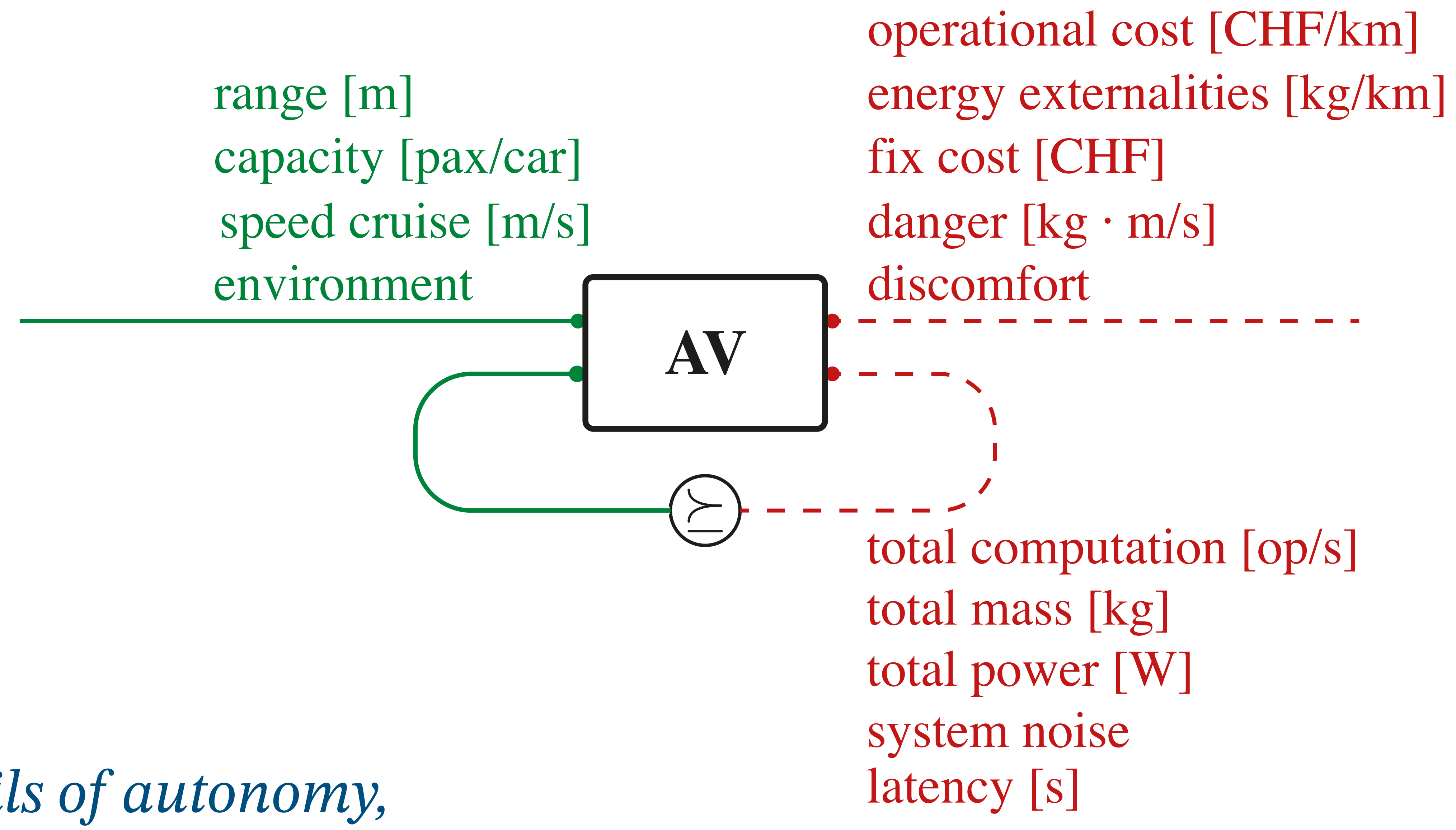
Choose query type:

- Fixed the functionality, minimize the resources.
- Fixed the resources, maximize the functionality.
- Given an implementation, evaluate functionality/resources. [UI not implemented]
- Given min functionality and max resources, determine if there is a feasible implementation. [UI not implemented]
- Given min functionality and max resources, find a feasible implementation. [UI not implemented]
- "Solve for X": find the minimal component that makes the co-design problem feasible. [UI not implemented]

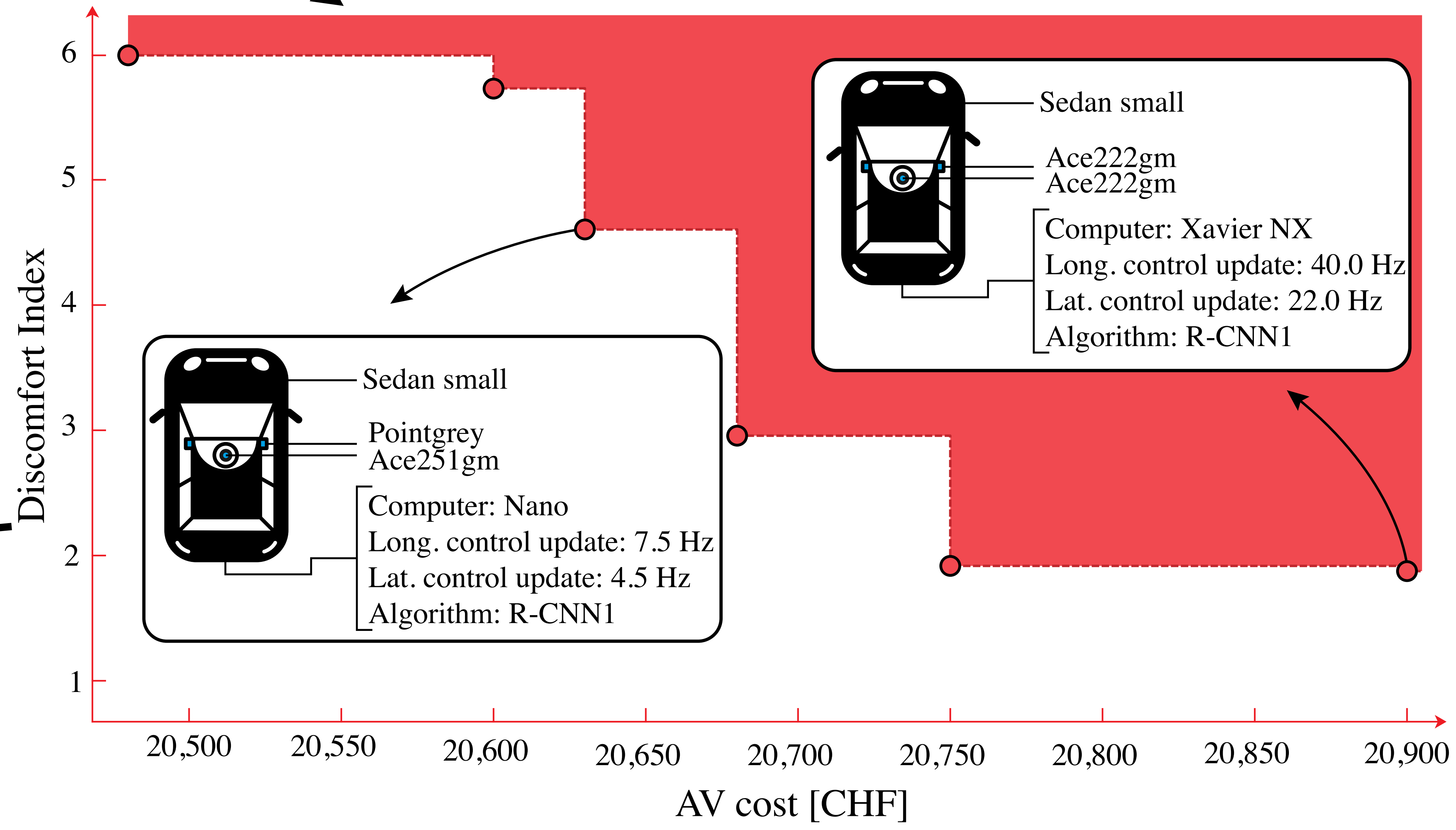
Co-design of an autonomous vehicle



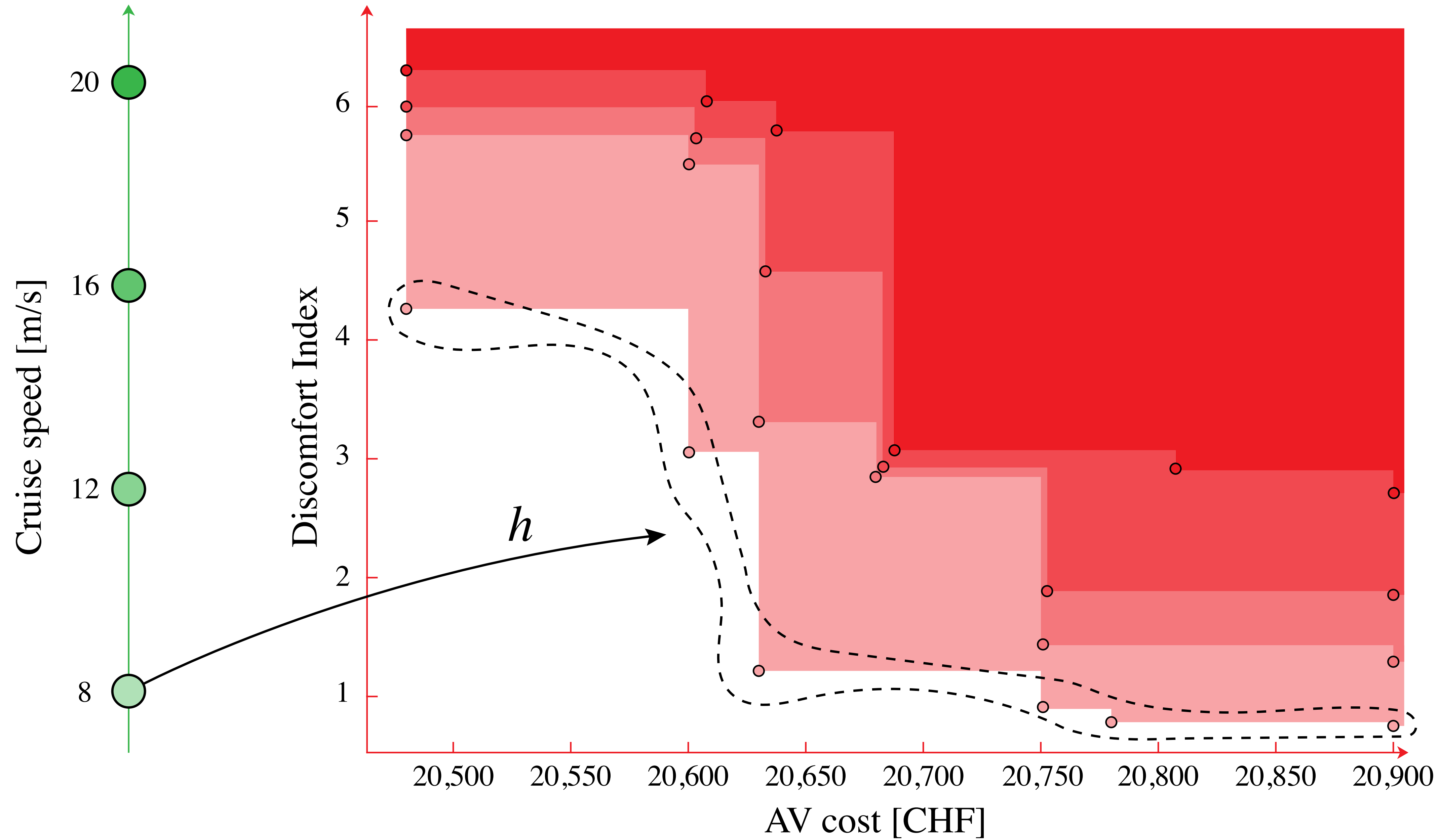
Solution of DPs



Fix **functionalities**, look at minimal **cost** and **discomfort**



*Details of autonomy, both **hardware** and **software***



***Monotonicity:** Higher achievable speeds will not require **less** resources*

Takaways

- Using co-design, it is **easy** to formalize **hierarchical models** (never possible before)
  We formalized AVs all the way from sensor selection to control and perception algorithms

- Very **intuitive** modeling approach (no acrobatics like common in optimization theory)
  *The **interpreter** allows one to easily model problems of interest*

- **Rich modeling capabilities:**
  ***Simulation**: E.g., POMDPs for brake control*
  ***Catalogues**: E.g., Sensors, vehicles, computers, algorithms, ...*
  ***Analytical**: E.g., LQG closed-form solutions, discomfort models, ...*

- **Compositionality** and **modularity** allow **interdisciplinarity**
  *We did all of this, but technically this could have been possible with different **teams***

- Co-design comes with a **formal language** and an **optimizer**
  *After easily modeling the problem, you can directly solve **queries** of your choice*

- Co-design produces **actionable information** for designers to **reason** about their problems
  *We have shown actionable information for **designers***

Outlook and references

- Showcase **compositionality** by including the co-design of specific **robot tasks** in the co-design of the entire **system**
- In the future:
  - Include the co-design of the **AV** in the co-design of the entire **mobility system**
  - Exploit the framework to synthesize **energy** and **computation-aware** design solutions

- **References:**

G. Zardini, D. Milojevic, A. Censi, E. Frazzoli, "**Co-design of embodied intelligence: a structured approach** “, *in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS),* 2021.

G. Zardini, A. Censi, and E. Frazzoli, “**Co-design of autonomous systems: From hardware selection to control synthesis**”, in *2021 20th European Control Conference (ECC), 2021*.

G. Zardini, N. Lanzetti, A. Censi, E. Frazzoli, M. Pavone, "**Co-design to enable user-friendly tools to assess the impact of future mobility solutions**", *arXiv preprint arXiv:2008.08975*, 2021.

This is a **new** topic, we are making an effort in **evangelization:**

We are writing a **book,** teaching **classes**, both at ETH and internationally, and organizing **workshops**

https://applied-compositional-thinking.engineering *https://idsc.ethz.ch/research-frazzoli/workshops/compositional-robotics*

http://gioele.science