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Achieving Explainable AI Through Semantic Technologies: Challenges and Future Directions in Digital Health

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today's agenda

1. Explainable AI (XAI)
- what does "Explainable" mean ?
- history

2. XAI in Digital Health
- motivations
- the problem of trust

3. The Role of Semantic Technologies
- how semantic technologies can support XAI
- food recognition
- recommendations

4. Final Remarks
- open challenges
- take-home messages
- wrap-up

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the main question

**Is Explainable AI the enabler for
adopting artificial intelligence within many domains
for supporting our daily lives?**

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explainable AI
an overview

XAI

What is an ***explainable system****, which are its* ***requirements*** *and how the research community is working on them?*

explainable AI
a very brief history

Newell et al., 1957

Inference tracing

First explanations

Shortliffe and Buchanan, 1975
Swartout et al., 1991
Johnson, 1994
Lacave and Diez, 2002

Core et al., 2006

“Modern” explainability

Domain integration

Pearl, 2009
Gershman et al., 2015

Lipton, 2016
Kieseberg et al., 2016
Doran et al., 2017
Montavon et al., 2017
Miller et al., 2017

State of the art techniques

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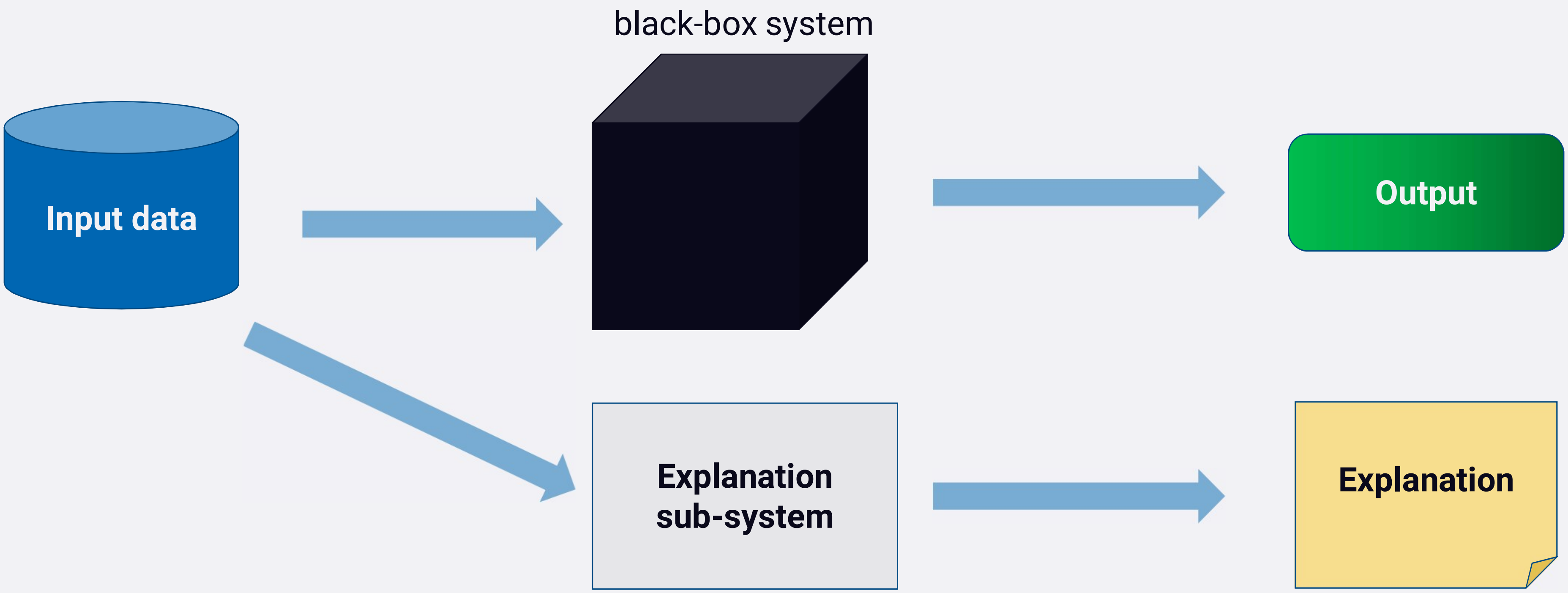
explainable AI
a general view

- No formal, technical, agreed upon definition.
- Comprehensive philosophical overview out of scope of this seminar (Miller, 2017)
- Not limited to machine learning!

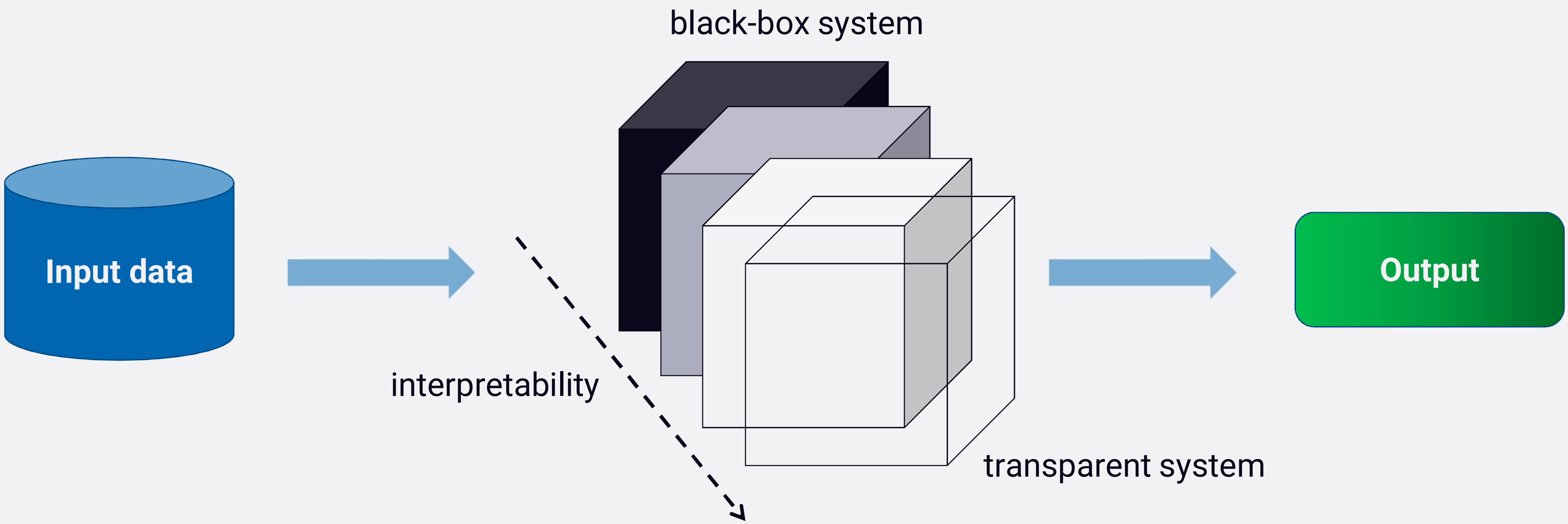
- Two main perspectives:
  1. **Post-hoc explanation**: it explains why a black-box model behaved in that way.
  2. **Transparent design**: it reveals how a model works (also know as ante-hoc explanation).

explainable AI
post-hoc explanation



- Post-hoc explanations can be unreliable.
- Low **Understandability** and Low **Transparency**.

explainable AI
transparent design



- Three levels of transparency:
  1. Simultability
  2. Decomposability
  3. Algorithmic Transparency

- High **Understandability** and High **Interpretability**.

explainable AI
considerations

With thousands features
DNNs perform better:
is post-hoc explanation
the only way?

Design white-box, interpretable
models straight away!

Desirable properties of XAI:
Informativeness
Low cognitive load
Usability
Fidelity
Robustness
Non-misleading
Interactivity/Conversational

explainable AI
from theory to practice

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healthcare

*Why are the **challenges of XAI** amplified within **real-world domains** and in particular within the **Digital Health** one?*

XAI in Digital Health
when do we need explanations?

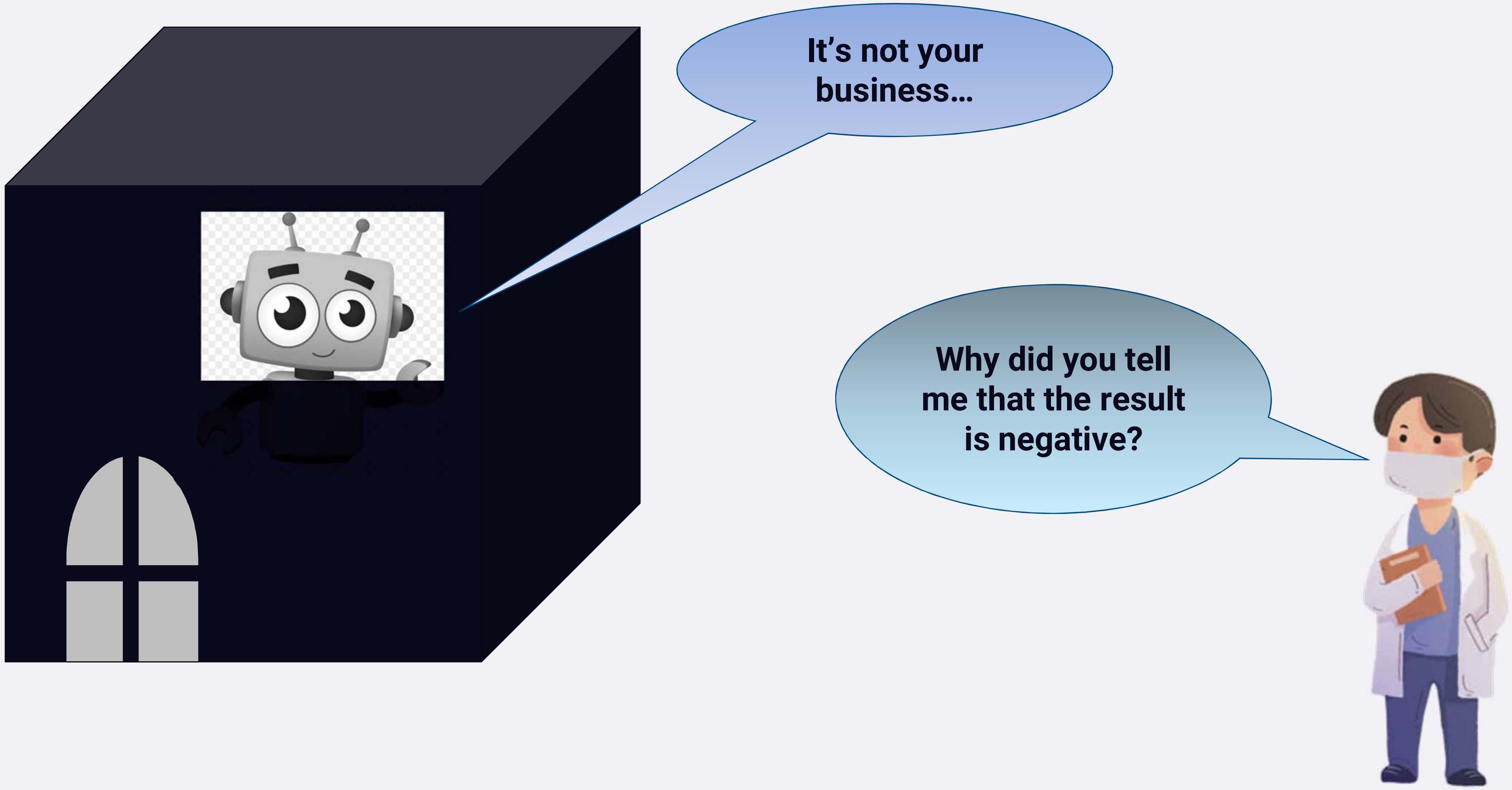
- **When fairness is critical**: any context where humans are required to provide explanations so that people cannot hide behind machine learning models.

- **When consequences are far-reaching**: predictions can have far reaching consequences; e.g., recommend an operation, recommend sending a patient to hospice etc.

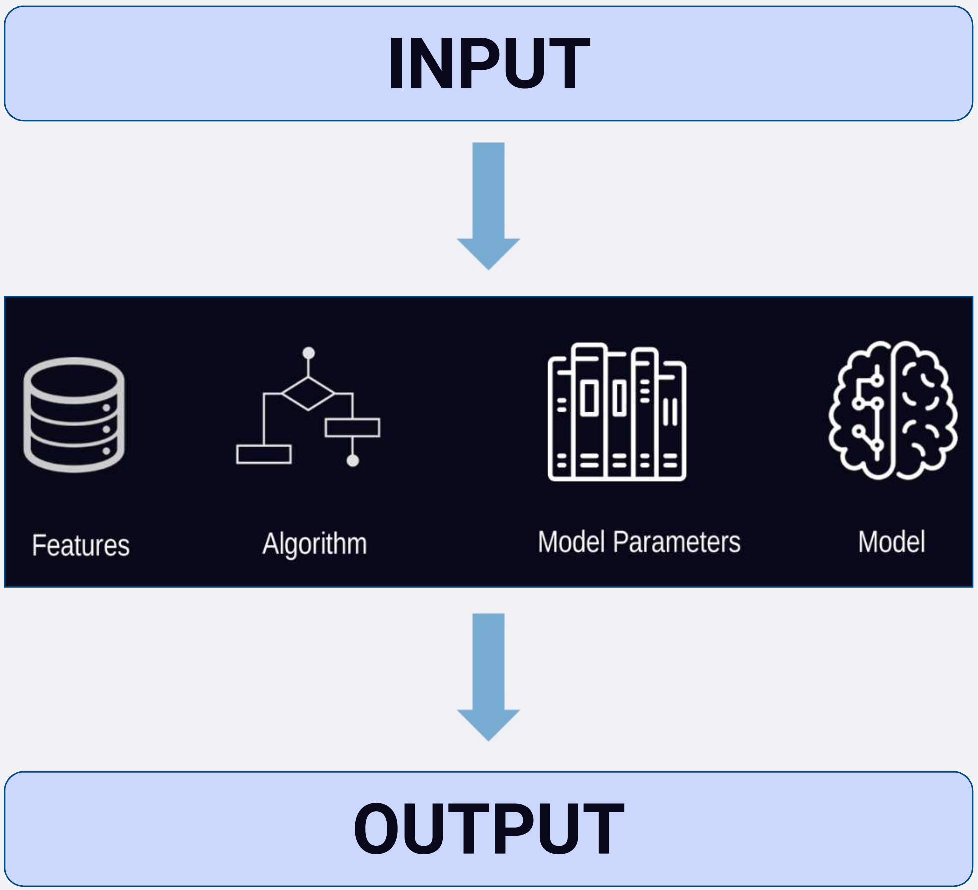
- **When the cost of a mistake is high**: e.g., misclassification of a malignant tumor can be costly and dangerous

- **When a new/unknown hypothesis is drawn**: e.g. “Pneumonia patients with asthma had lower risk of dying”

XAI in Digital Health
a problem with trust



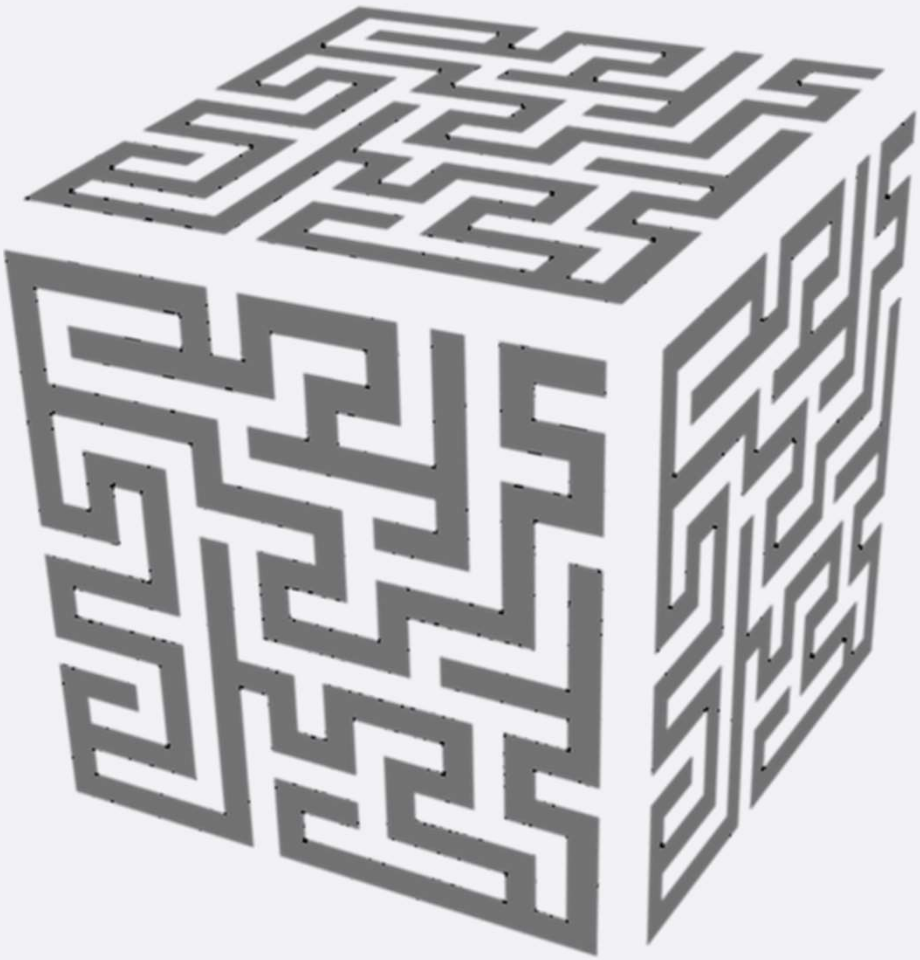
XAI in Digital Health
a problem with trust



Examples of physicians' desiderata:

- To have the certainty that specific input data provide a specific output.
- To have the possibility of changing dynamically the cautiousness of the model.
- To understand how each single feature is treated by the model.

XAI in Digital Health
does more transparency mean more trust?



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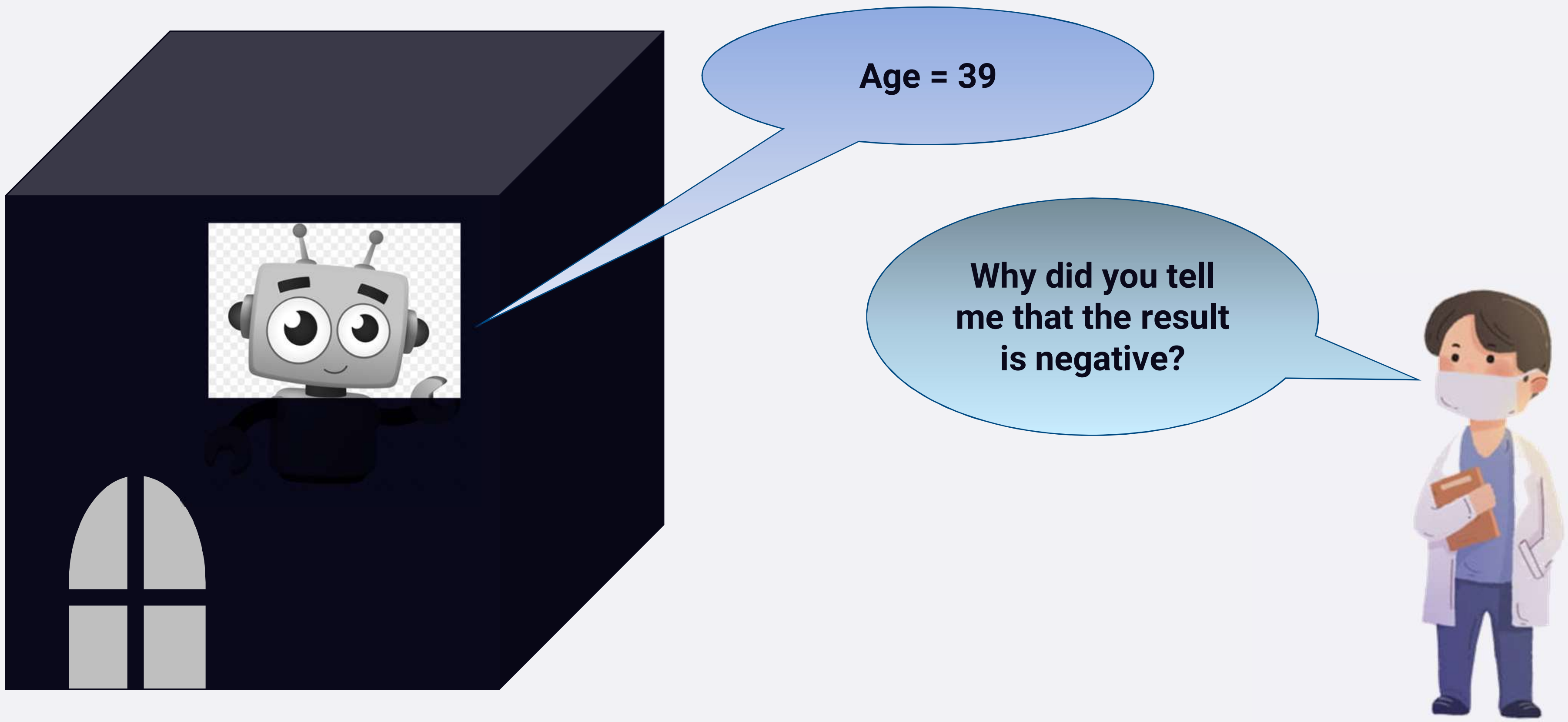
XAI in Digital Health
explanations are role based

- Explanations have to be meaningful.



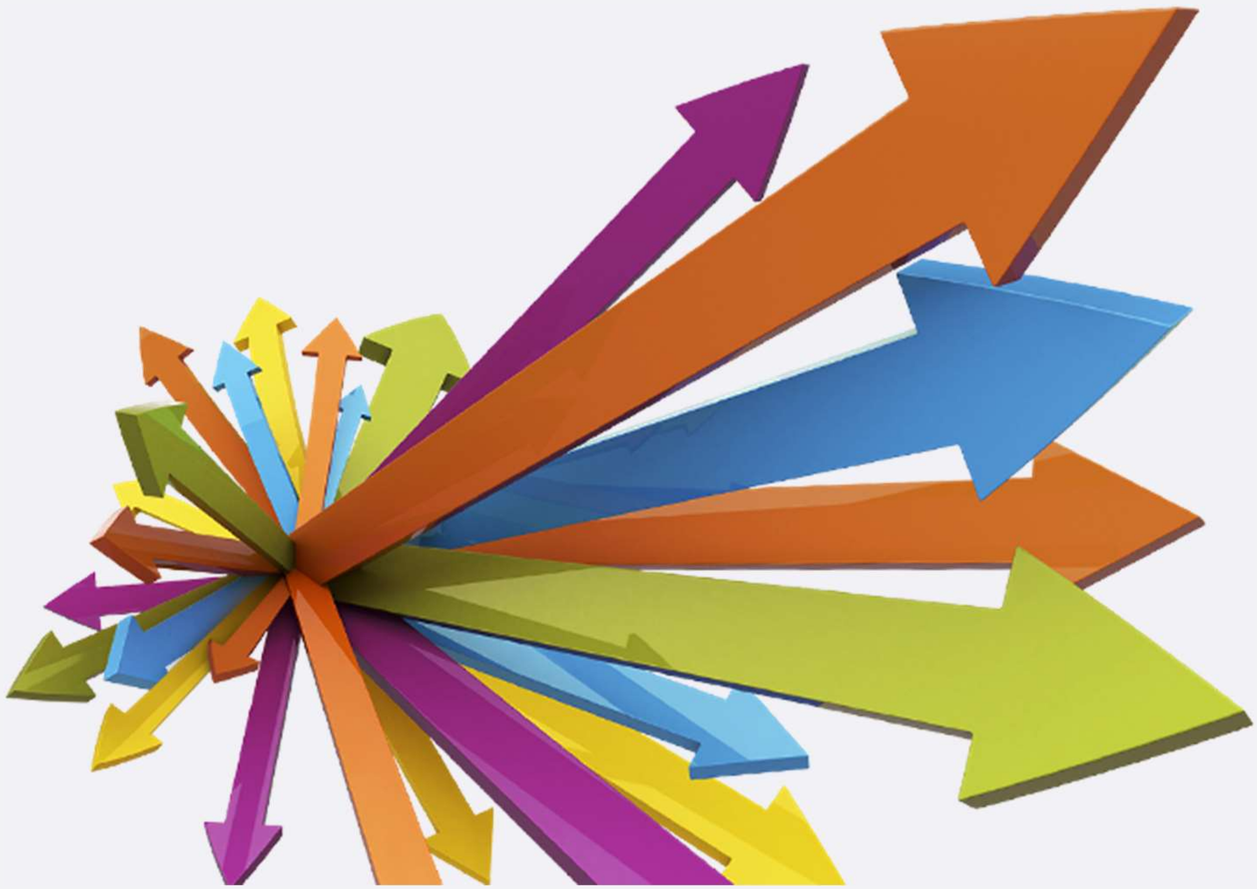
XAI in Digital Health
explanations are role based

- Explanations have to be meaningful.

- A physician requires different explanations as compared to a staffing planner or to a user.

- Explanations need to be provided with the proper language and also within the proper context

XAI in Digital Health
how to solve these challenges?



the role of semantic technologies

knowledge

*How **semantic technologies** can improve the **explainability** and **interpretability** of AI-based system in order to make them more **acceptable** from users?*

to integrate semantic technologies
for enabling the generation of
meaningful explanations

01

the role of semantic technologies
explanation with background knowledge

- We tend to give explanation in terms of our current knowledge.
- When we see any image of dog our thinking automatically try to capture those objects.
- We always want to conform with our previously acquired knowledge (Background Knowledge).

Will not it be better if we can explain in terms of our knowledge?

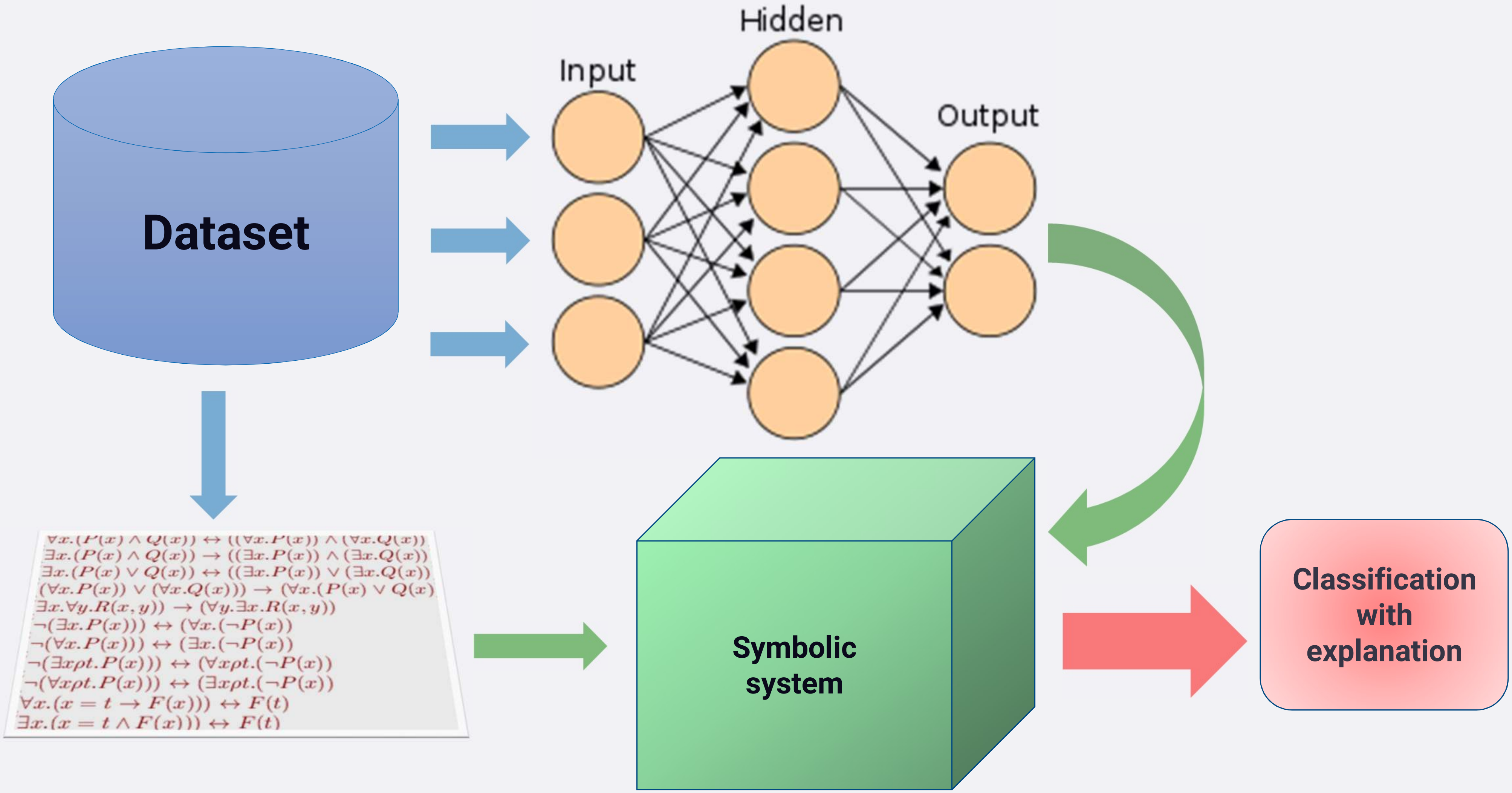
the role of semantic technologies
how to use background knowledge?

- Hard to make connection between our knowledge and a model which is trained by reducing loss.

- Idea found in current literature is similar to inductive programming:

  1. Use background knowledge in the form of linked data and ontologies to help explain.
  2. Link inputs and outputs to background knowledge.
  3. Use a symbolic learning system to generate an explanatory theory.

the role of semantic technologies
how to use background knowledge?



the role of semantic technologies
input needed for these kind of systems

- Background information, ontology, and knowledge graphs
  - Common sense knowledge resources (e.g. Cyc, Wordnet, Suggested Merged Upper Ontology (SUMO), Dbpedia, Freebase)
  - Domain specific resources (e.g. HeLiS)

- Positive and/or negative examples containing concept-related contextual information.

- Mapping between model dataset and the ontology
  - mapping each instance as an individual and put it in exact hierarchy.

the role of semantic technologies
pasta image classification example

- Images come with annotations of objects in the picture.
- Objects in image annotations became individuals (constants), which can be typed with the ontology.

```
contains Pasta
contains Melanzane
contains Pomodori
contains Ricotta
```

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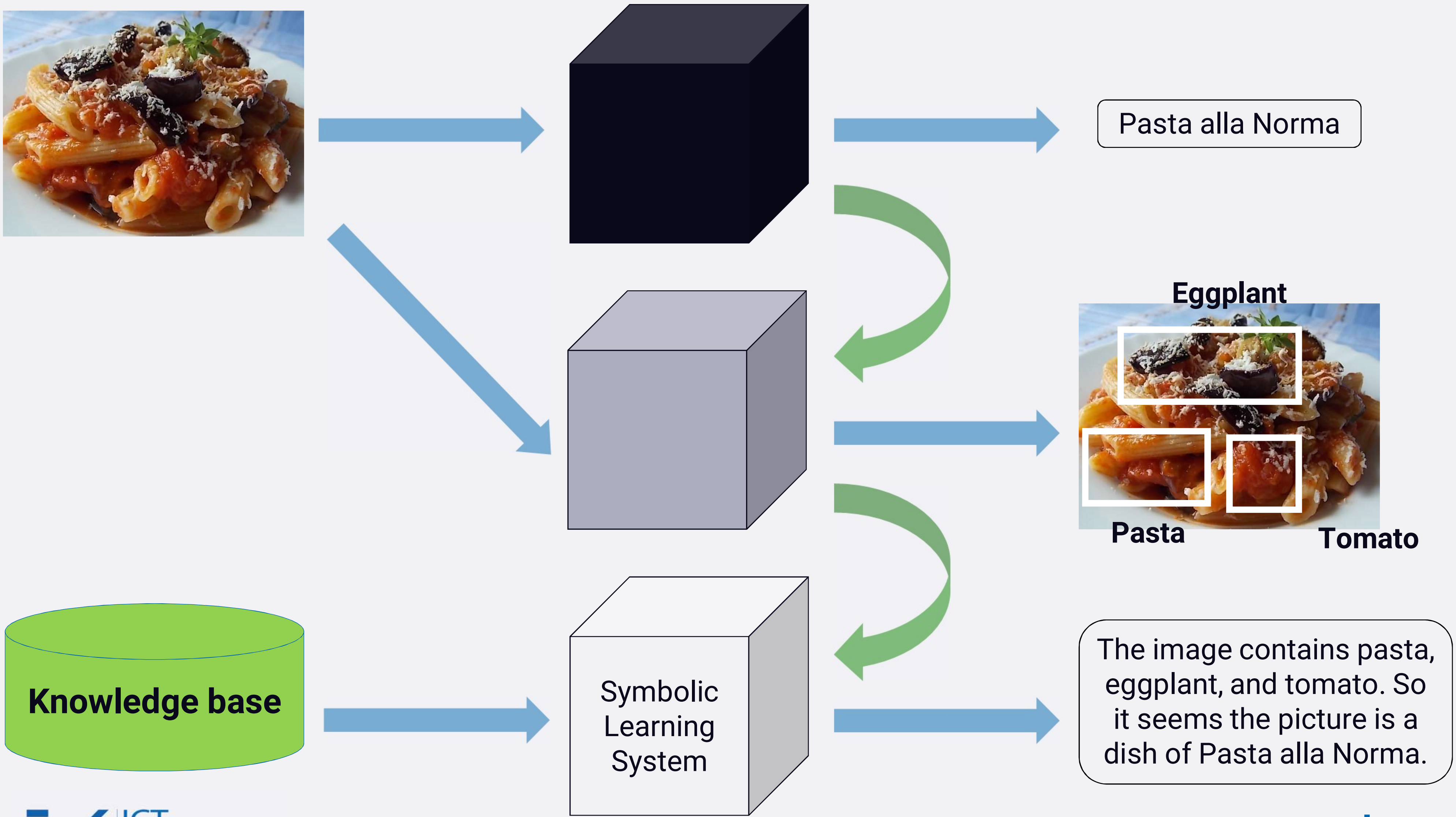
the role of semantic technologies
pasta image classification example



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idea of the diagram extracted from: "On Explainable AI: From Theory to Motivation, Applications and Limitations" tutorial @ AAAI 2019 (xaitutorial2019.github.io)

the role of semantic technologies
open questions

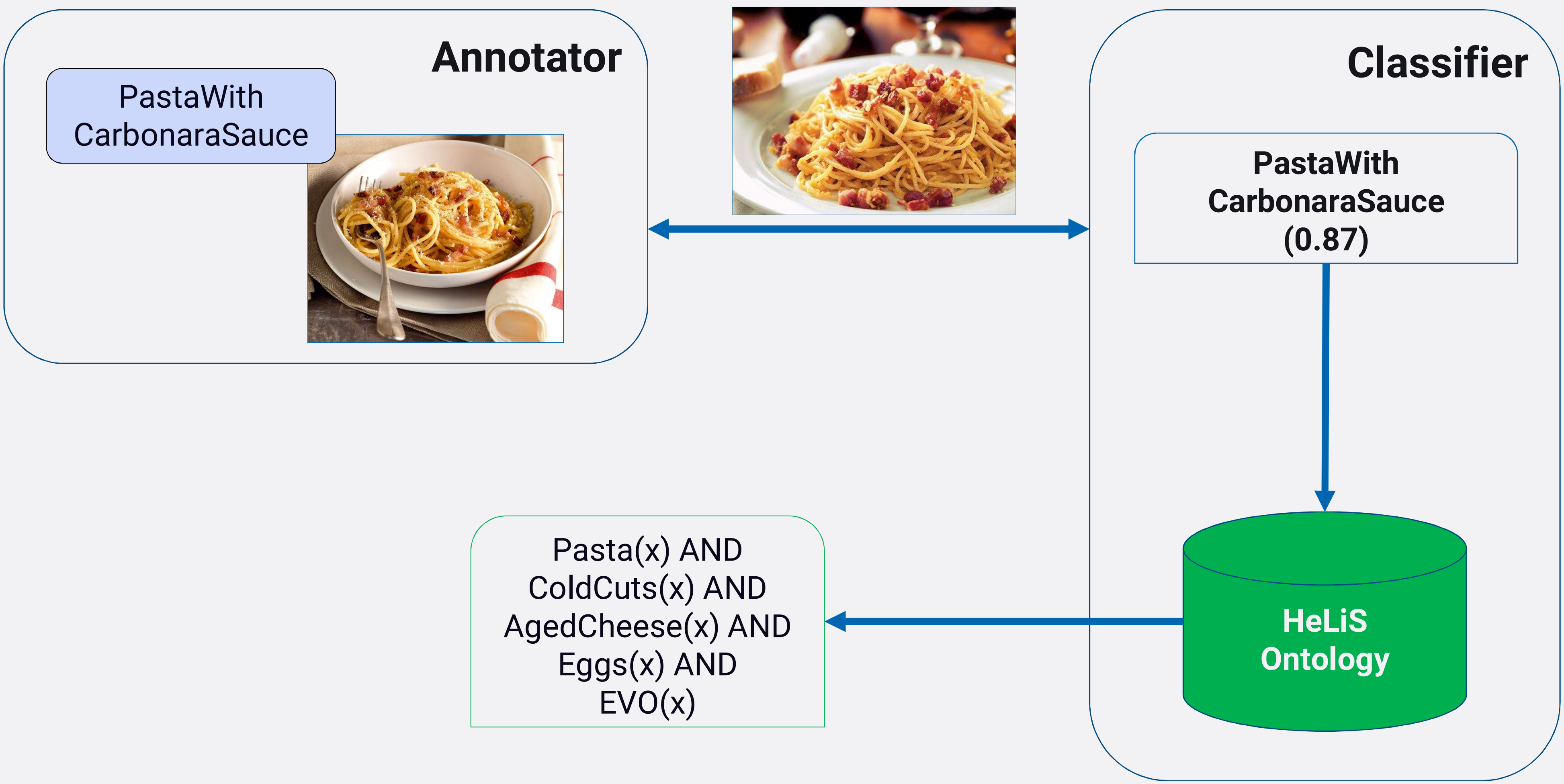
- This is just beginning of using background information to enhance explanation.

- There are some interesting open questions like:
  - Where we can get effective background information?
  - How to relate already available background information with models?
  - Are those explanations enough to satisfy users' quests?

to classify recipe images through the recognition of ingredients

02

food category recognition
single-label annotation and classification



food category recognition
multi-label annotation and classification

Annotator

PastaWith CarbonaraSauce

HeLiS Ontology

Pasta(x) AND
ColdCuts(x) AND
AgedCheese(x) AND
Eggs(x) AND
EVO(x)

Classifier

Pasta - (0.86)
ColdCuts - (0.96)
AgedCheese - (0.88)
Eggs - (0.72)
Tomato - (0.53)

HeLiS Ontology

PastaWith CarbonaraSauce

evaluation
effectiveness of classification models

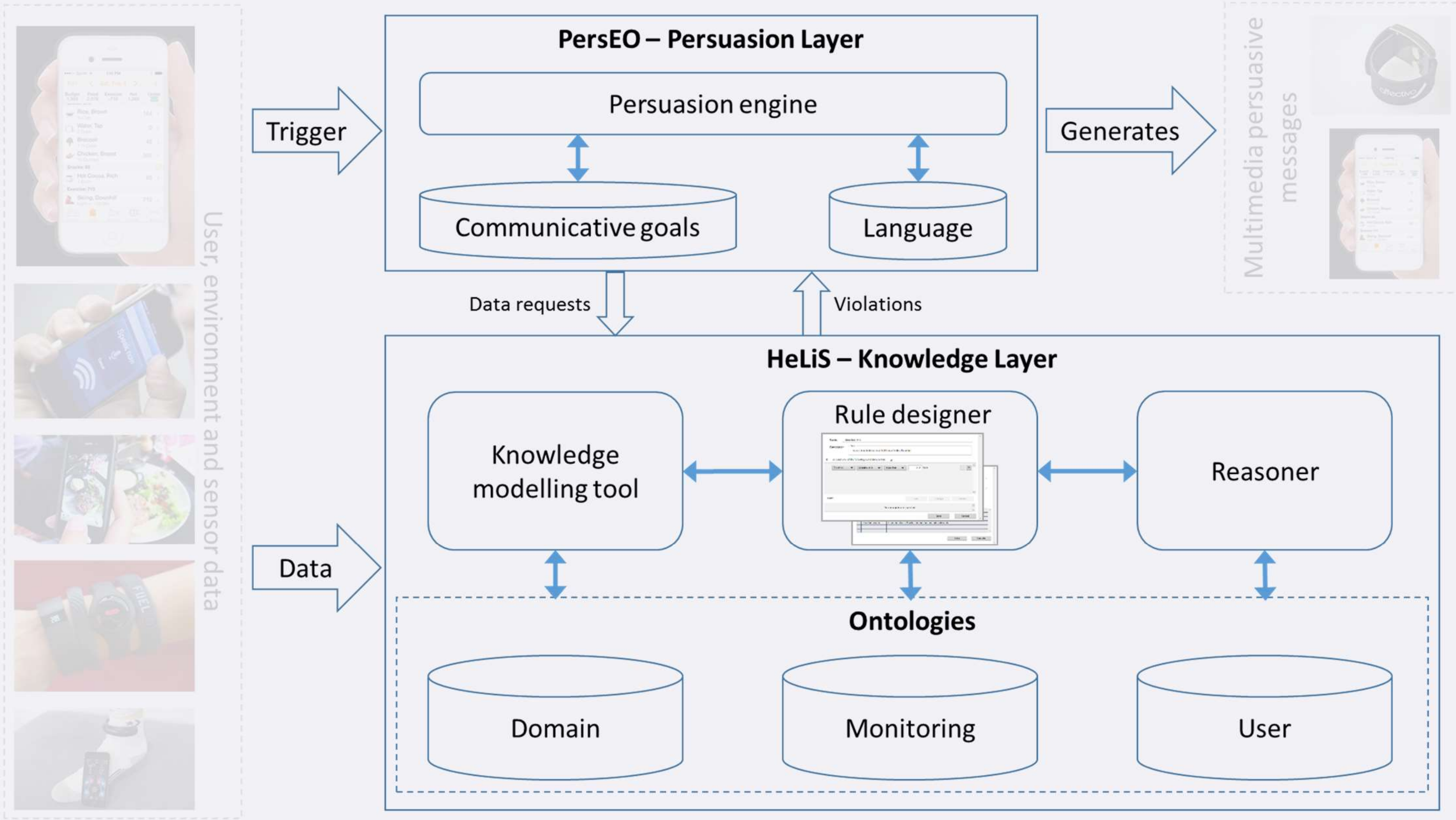
- Besides enabling explanations, we discovered that it can improve the effectiveness of classification models.

Method	Micro-AP (%)	Macro-AP(%)
Multi-label	**76.24**	**50.12**
Single-class (without uncertainty)	50.53	31.79
Single-class (with uncertainty)	60.21	42.51

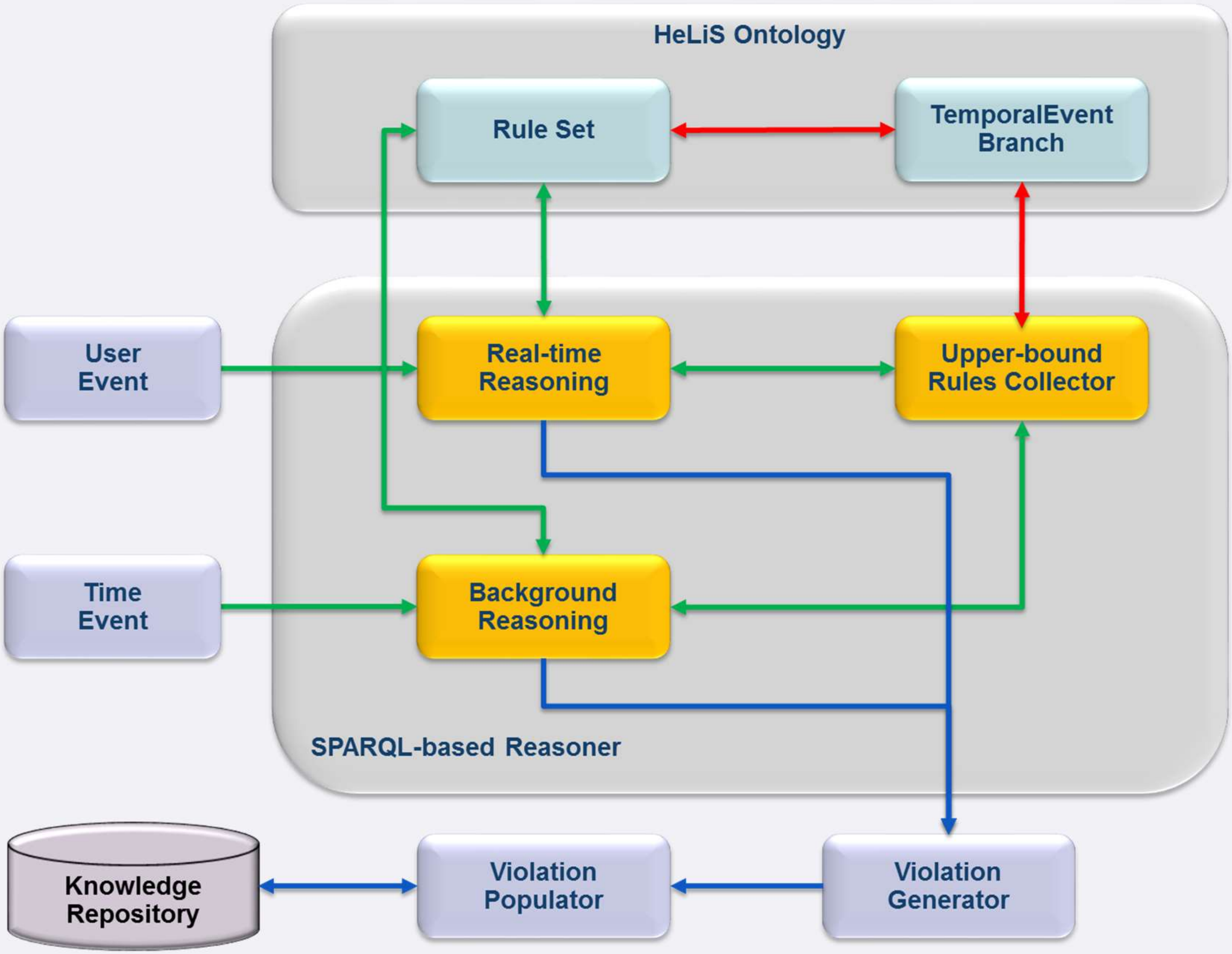
03

to provide recommendations to users by means of knowledge graphs

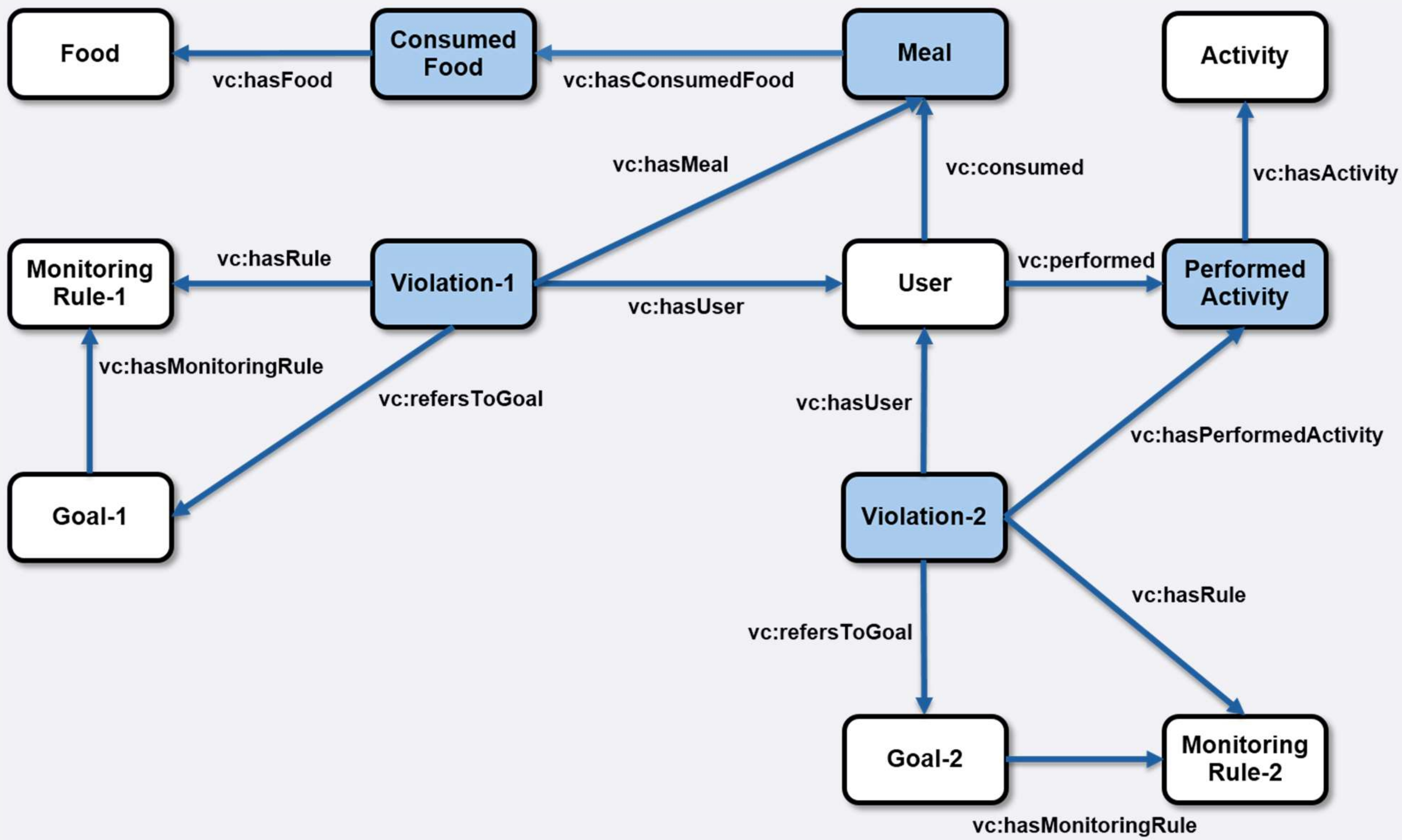
the HORUS.AI platform



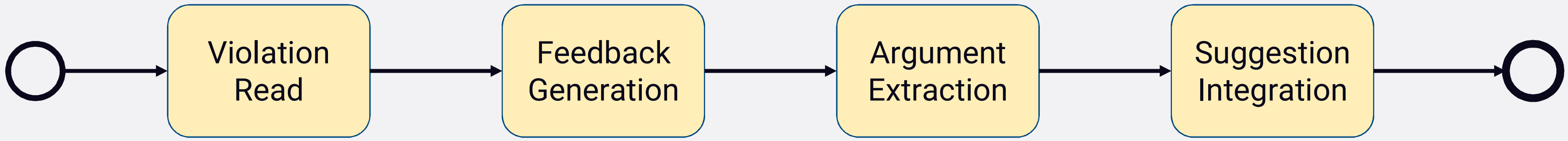
the knowledge layer
the reasoning process

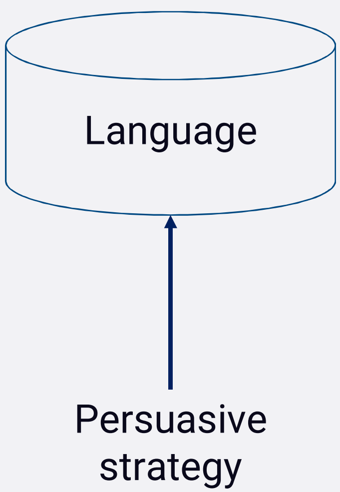


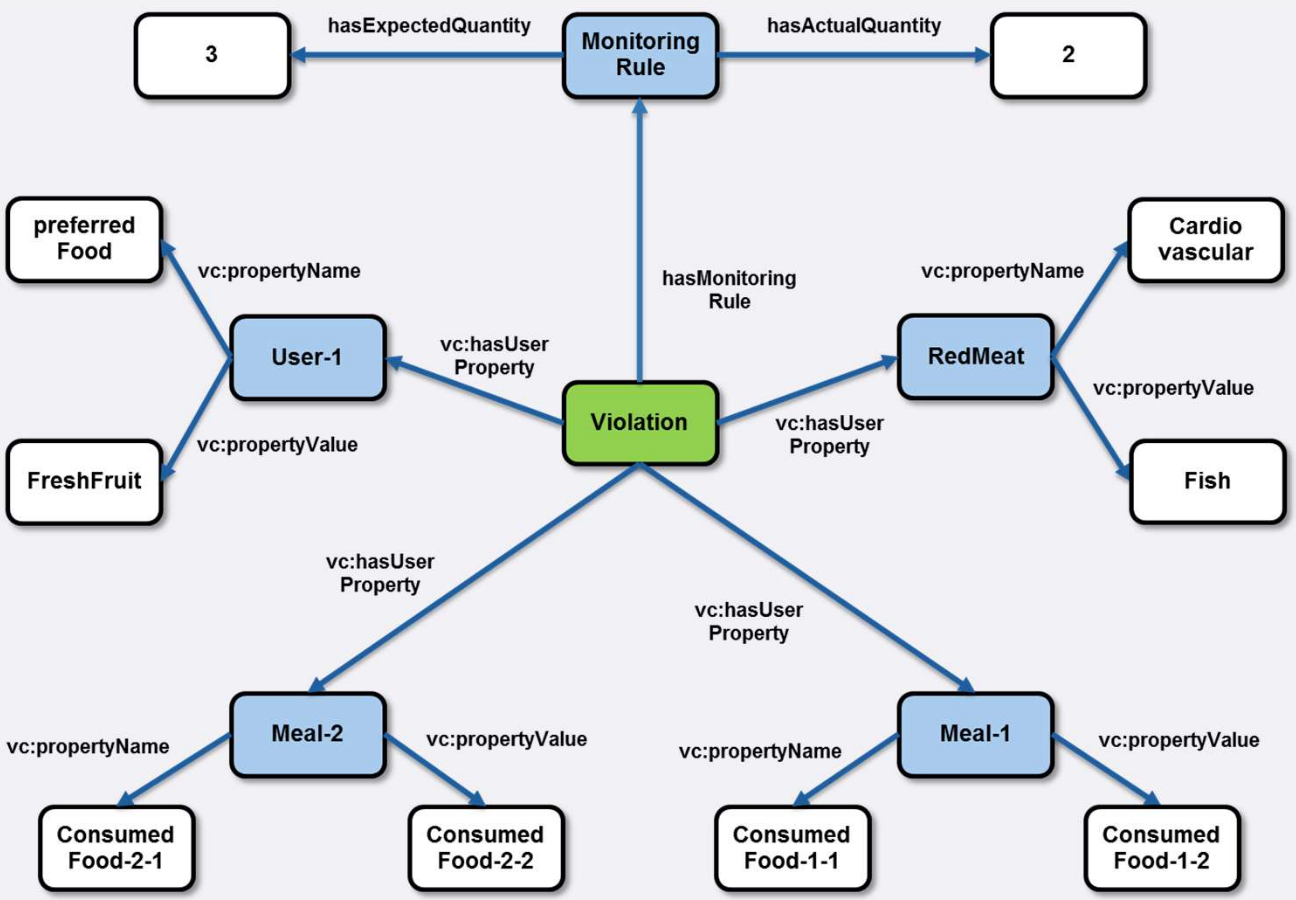
the knowledge layer
population of the knowledge base with undesired behaviors



the persuasive layer
message generator process





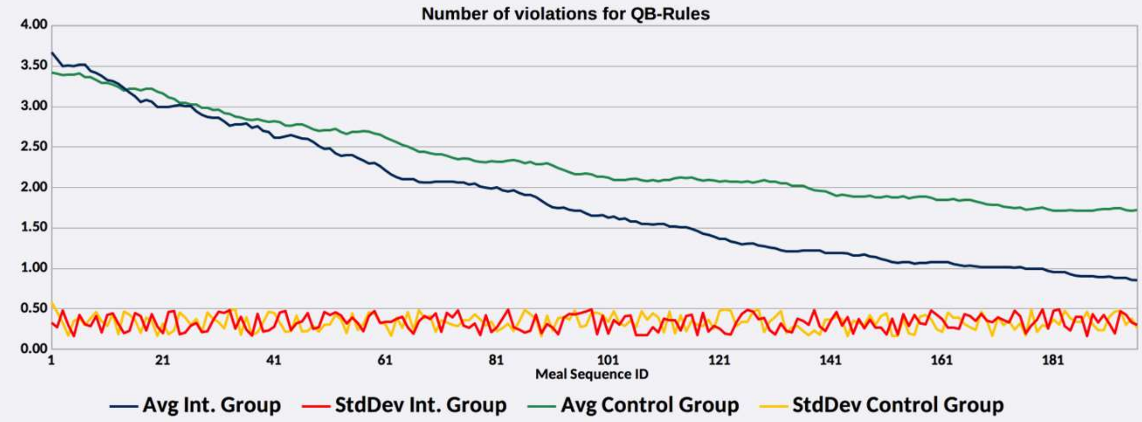


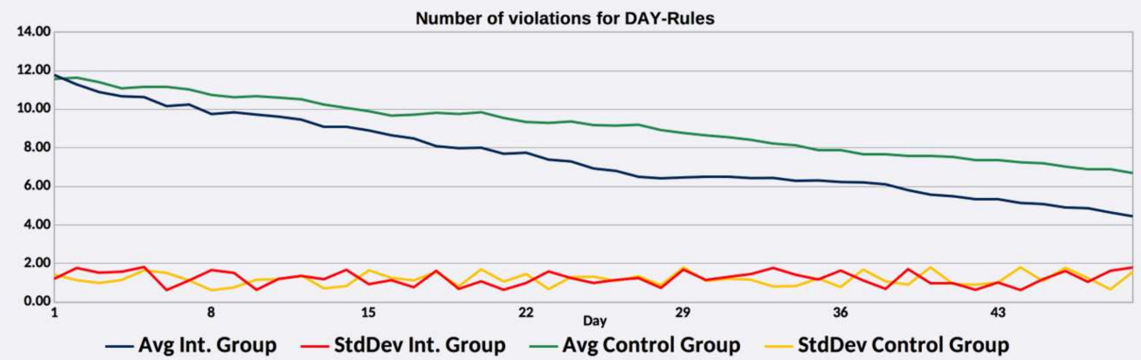
evaluation
living lab

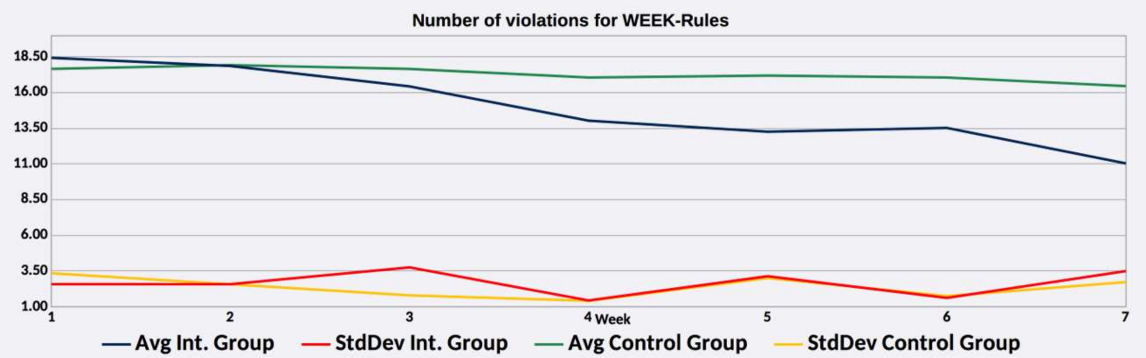
- The evaluation of explanations is an ongoing research activity.

- 120 users have been monitored for 7 weeks.
  - 92 users in the intervention group;
  - 28 users in the control group.

- We observed and reported the effectiveness of generated explanations.







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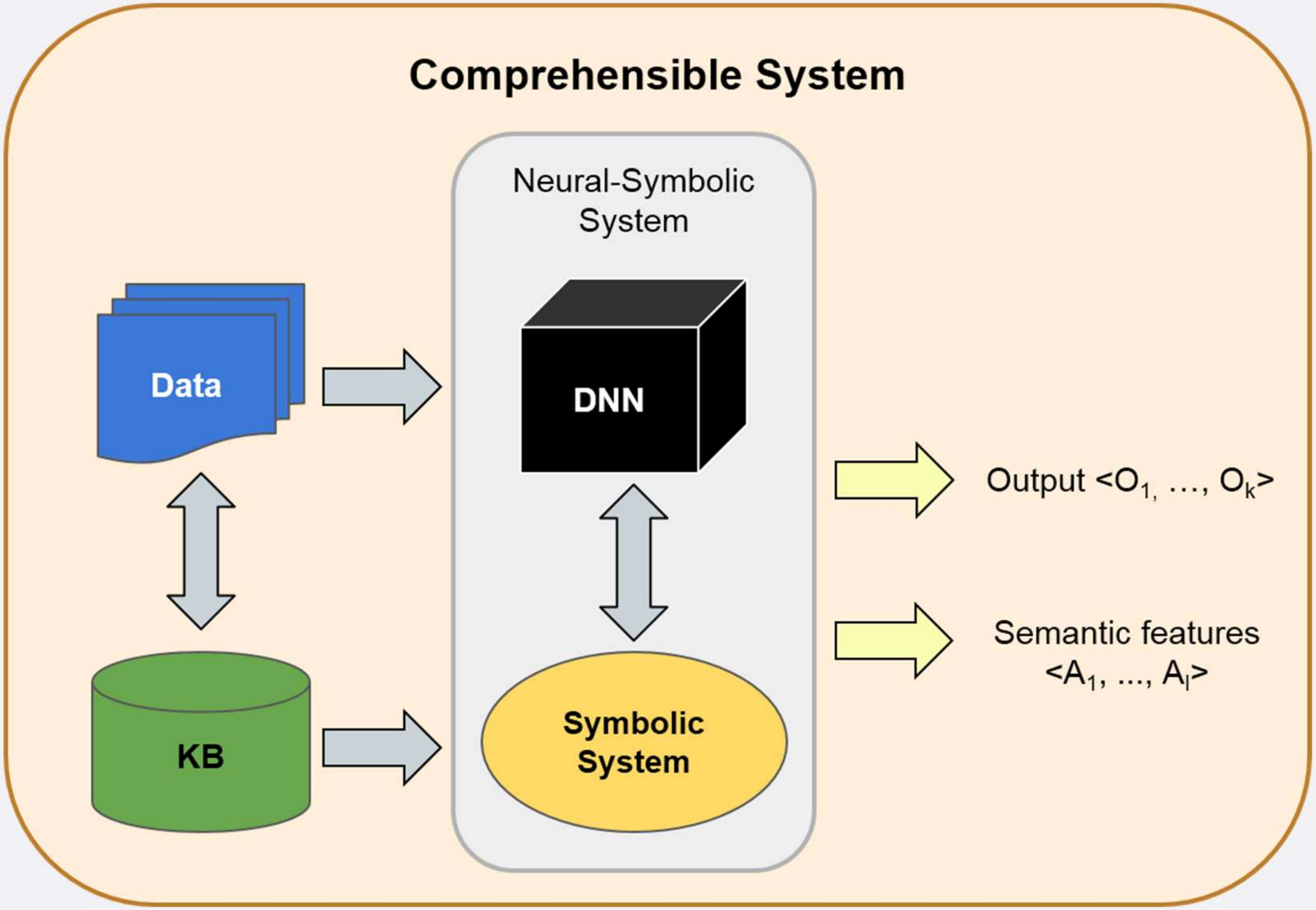
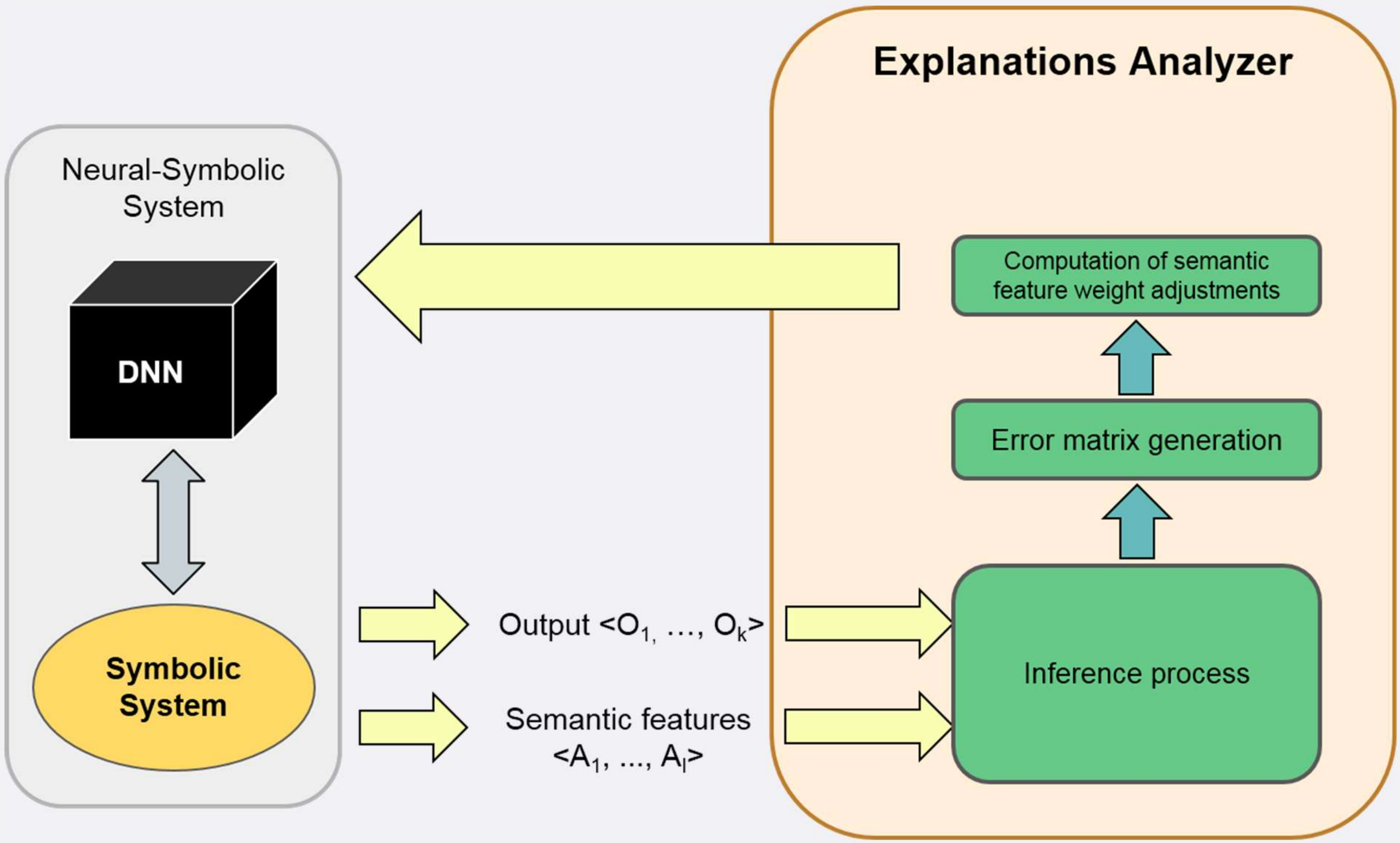
exploit XAI

*Is there a way for **exploiting** the generated **explanations** in an efficient way for **improving the effectiveness** of our AI systems?*

anatomy of a comprehensive system

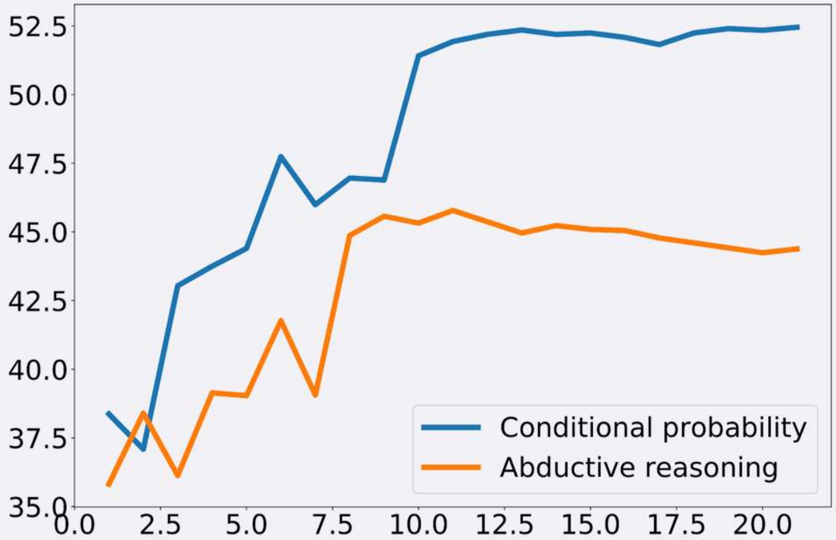


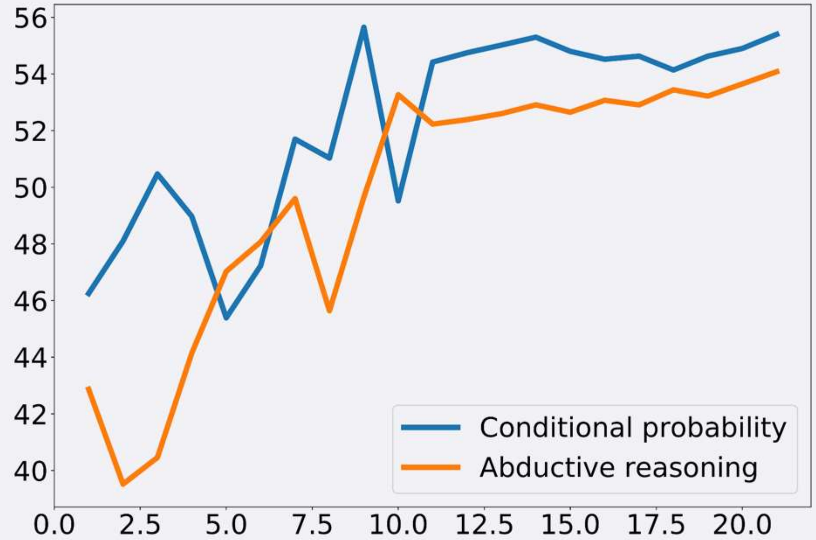
a way for exploiting explanations



does this exploitation strategy work?

Heuristic	Starting values (%)		Refined values (%)	
	Micro-AP	Macro-AP	Micro-AP	Macro-AP
Abductive reasoning	42.87	35.82	**52.23** (+21.83%)	**45.78** (+27.81%)
Conditional probability	46.25	38.37	**54.42** (+17.66%)	**51.93** (+35.34%)





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final remarks

so, in the end?

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final remarks
take-home messages

- Explainable AI is motivated by real-world application of AI.
- Multi-disciplinary: multiple AI fields, HCI, social sciences (multiple definitions).
- Transparent design or post-hoc explanation?
- Background knowledge matters!
- Evaluation:
  - need of benchmark;
  - rigorous, agreed upon, human-based evaluation protocols.

thank you.

contacts

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