



Talk @ IIT Tirupati – Department of CSE

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Learning Interpretable Models for Autonomous Assessment of Taskable AI Systems

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Taskable AI Systems: Systems that can Learn and Plan



User gives a task and robots have to complete it

- Sequential Decision-Making Systems.
- Systems designed to be able to help user.
- User has a task in mind and expects the AI system to help in that task.

Personalized Assessment of AI Systems that can Learn and Plan

- Users would like to give AI systems multiple tasks.
 - How would users know what the AI systems can do?
- AI systems should support third-party assessment.
- The assessment should work with:
 - **Adaptive** AI systems.
 - **Black-Box** AI systems.



```
at(p0,cell_6_3)
clear(cell_0_0)
door_at(cell_9_2)
next_to(m0)
alive(m0)
key_at(9_4)
```

[Input]
Concepts that the
user understands



Personalized
AI-Assessment
Module (AAM)



Arbitrary internal
implementation

Doesn't know
user's vocabulary

Black-Box AI

```
at(p0,cell_6_3)
clear(cell_0_0)
door_at(cell_9_2)
next_to(m0)
alive(m0)
key_at(9_4)
```

[Input]
Concepts that the
user understands



Personalized
AI-Assessment
Module (AAM)

Query

Response



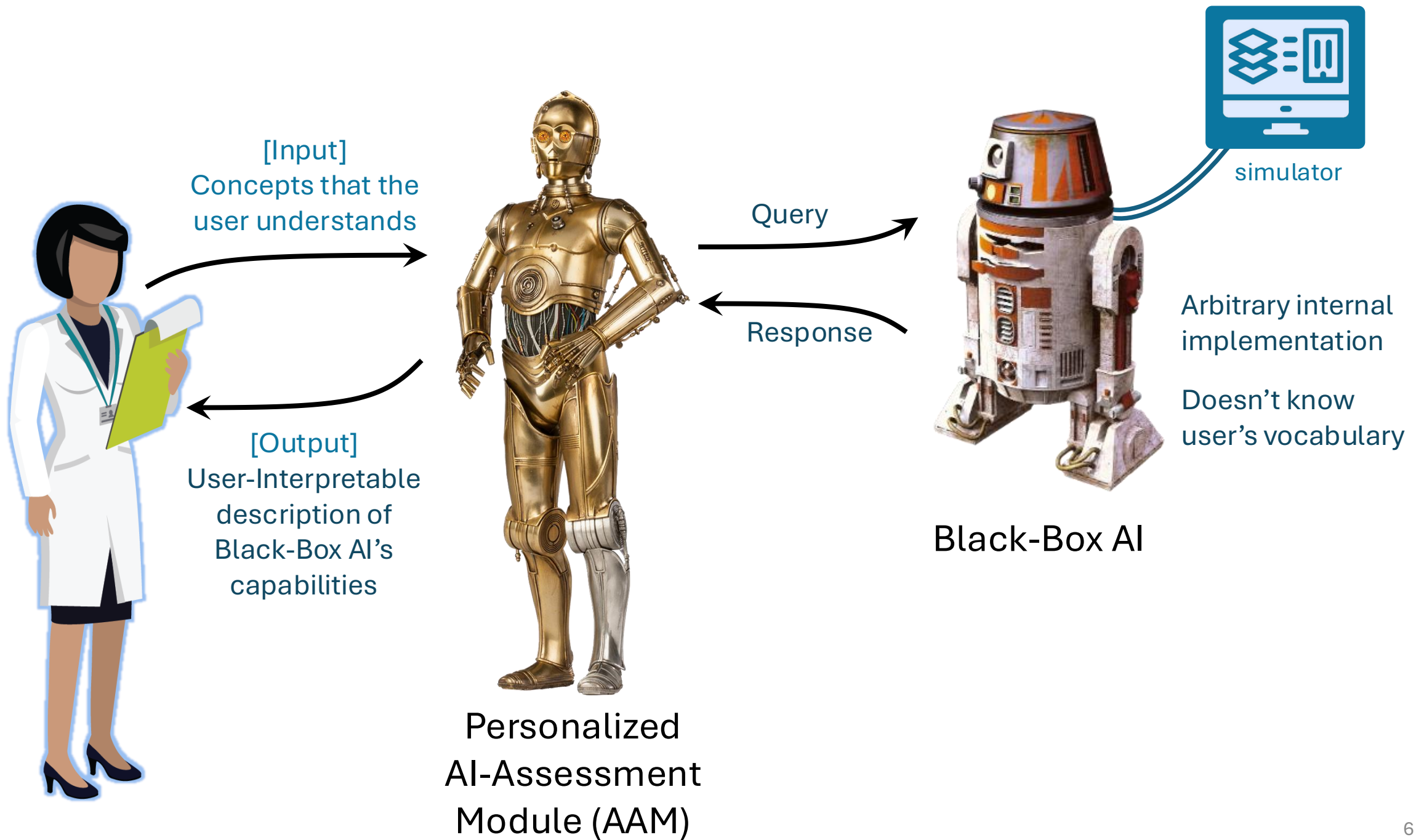
Black-Box AI



simulator

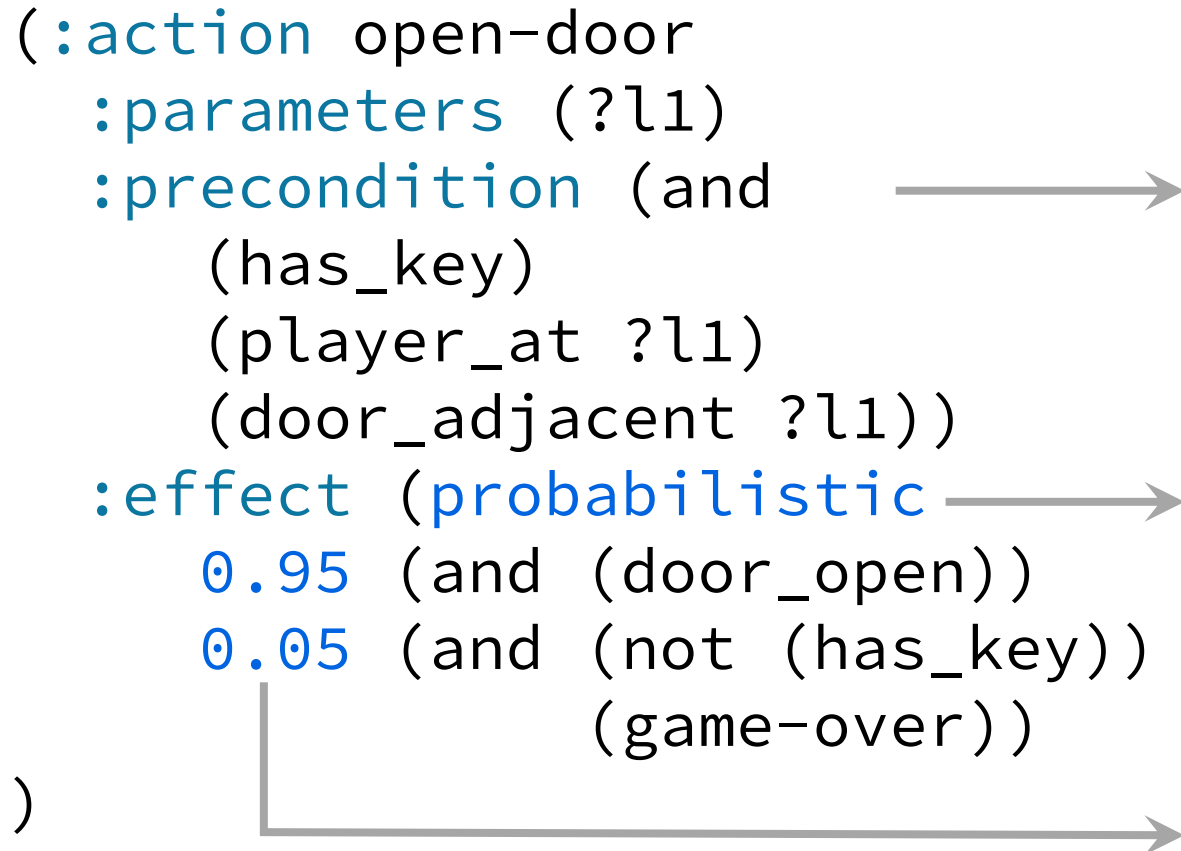
Arbitrary internal
implementation

Doesn't know
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Probabilistic Planning Domain Definition Language

```
(:action open-door
  :parameters (?l1)
  :precondition (and
    (has_key)
    (player_at ?l1)
    (door_adjacent ?l1))
  :effect (probabilistic
    0.95 (and (door_open))
    0.05 (and (not (has_key))
              (game-over))
  )
```



Precondition: This condition must be true for this action to execute

Effect: This is a set of conditions, one of which becomes true when this action is executed

Probabilities: Each set of effect has an associated probability with which that effect set is executed

Interpretable: Easily Convertible to Natural Language

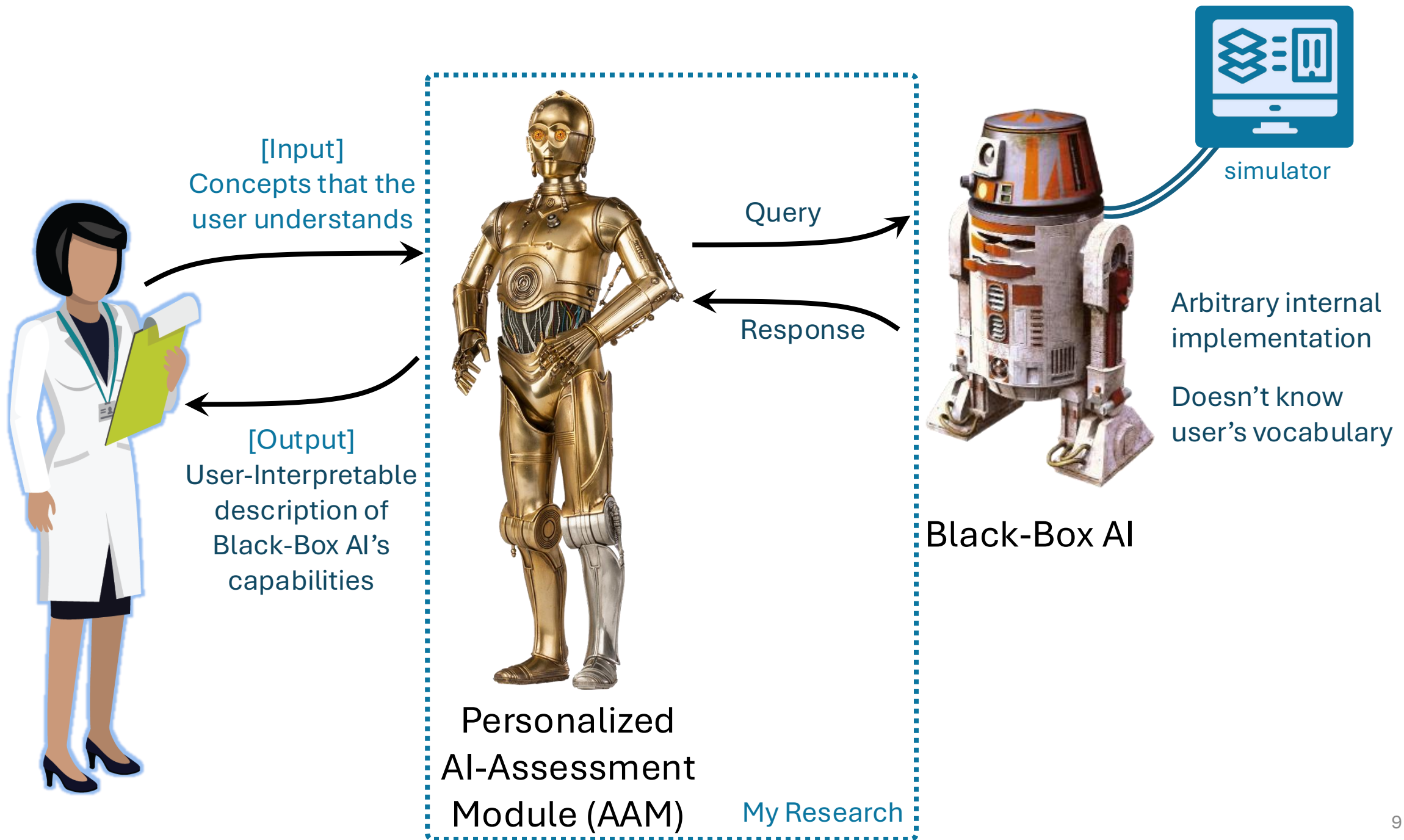
```
(:action open-door
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  :precondition (and
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    (player_at ?l1)
    (door_adjacent ?l1))
  :effect (probabilistic
    0.95 (and (door_open))
    0.05 (and (not(has_key))
              (game-over))
  )
```

The player can open the door when in location ?l1 if:

- It has the key
- The player is at location ?l1
- The door is adjacent to location ?l1

After executing that capability:

- With 95% probability, the door will open
- With 5% probability, the player will not have the key and the game will be over



Deterministic and Stationary Setting

Input

- Predicates (User vocabulary)
 - With their evaluation functions
- List of capabilities.



Output

- PDDL-like description of each capability.

Assumptions

- User's vocabulary matches simulator's vocabulary.
- Black-Box AI provides a list of capabilities.
- Stationary agent model.
- Deterministic environment.
- Fully observable setting.



Siddharth
Srivastava



Shashank
R Marpally

Asking the Right Questions: Learning Interpretable
Action Models Through Query Answering

Pulkit Verma, Shashank Rao Marpally, Siddharth Srivastava

In Proceedings of the Thirty-Fifth AAAI Conference on
Artificial Intelligence, 2021 (CORE Ranking: A*)

Exponential Search for Learning Correct Description

- Consider the following 4 predicates/concepts:
 - (has_key)
 - (door_open)
 - (door_adjacent ?x)
 - (player_at ?x)
- Consider just one capability:
(open-door ?x)
- $9^{|C| \times |P|} = 9^{1 \times 4} = 6561$ possible models
(Assuming deterministic models/
descriptions, i.e., no probabilities).

```
(:action open-door
  :parameters (?l1)
  :precondition (and
    (+/-/∅) (has_key)
    (+/-/∅) (door_open)
    (+/-/∅) (door_adjacent ?l1)
    (+/-/∅) (player_at ?l1))
  :effect (and
    (+/-/∅) (has_key)
    (+/-/∅) (door_open)
    (+/-/∅) (door_adjacent ?l1)
    (+/-/∅) (player_at ?l1)))
```

Stochastic and Stationary Setting

Input

- Predicates (User vocabulary)
 - With their evaluation functions
- List of capabilities.

Output

- PPDDL-like description of each capability.

Assumptions

- User's vocabulary matches simulator's vocabulary.
- Black-Box AI provides a list of capabilities.
- Stationary agent model.
- ~~Deterministic~~ ^{Stochastic} environment.
- Fully observable setting.

Discovering Capabilities

Input

- Predicates (User vocabulary)
 - With their evaluation functions
- Samplers: high-level state to low-level state.
- Low-level state transitions.



Output

- List of capabilities.
- PDDL-like description of each capability.

[Verma, Marpally, Srivastava; KR '22]

Assumptions

- ~~User's vocabulary matches simulator's vocabulary.~~
- Black-Box AI provides a list of ~~capabilities.~~ **transitions.**
- Stationary agent model.
- Deterministic environment.
- Fully observable setting.

Differential Assessment

Input

- Initial model of the AI system.
 - Predicates (User vocabulary)
 - With their evaluation functions
 - List of capabilities.
- Observations of AI system working in the environment.

Output

- Updated PDDL-like description of each capability.

Assumptions

- User's vocabulary matches simulator's vocabulary.
- Black-Box AI provides a list of capabilities.
- ~~Stationary~~ ^{Adaptive} agent model.
- Deterministic environment.
- Fully observable setting.

Capability Discovery and Assessment

Input

- Initial model of the AI system.
 - Predicates (User vocabulary)
 - With their evaluation functions

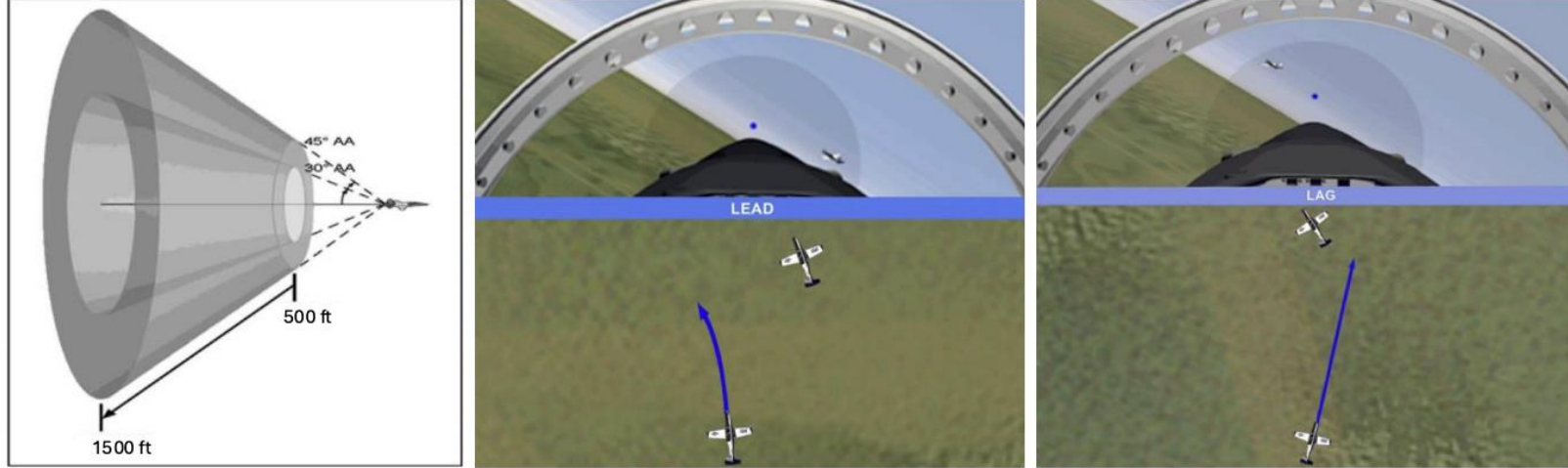
Output

- List of capabilities
- PDDL-like description of each capability.

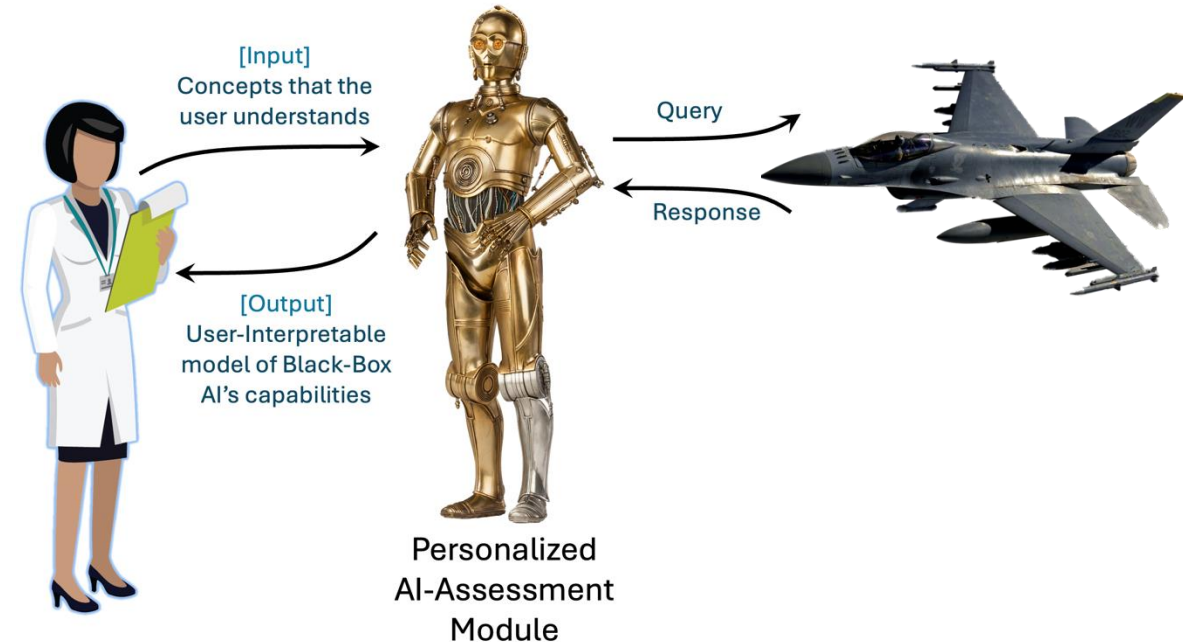
Assumptions

- ~~User's vocabulary matches simulator's vocabulary.~~
- Black-Box AI provides a list of ~~capabilities.~~ *transitions.*
- Stationary agent model.
- *Stochastic* ~~Deterministic~~ environment.
- Fully observable setting.

Real World Setting



- Flying Extended Trail
- Human must collaborate with the AI-powered aircraft.
- How can we explain the aircraft's policy to the human in an interpretable way?



Human Understanding of Deep Neural Policies

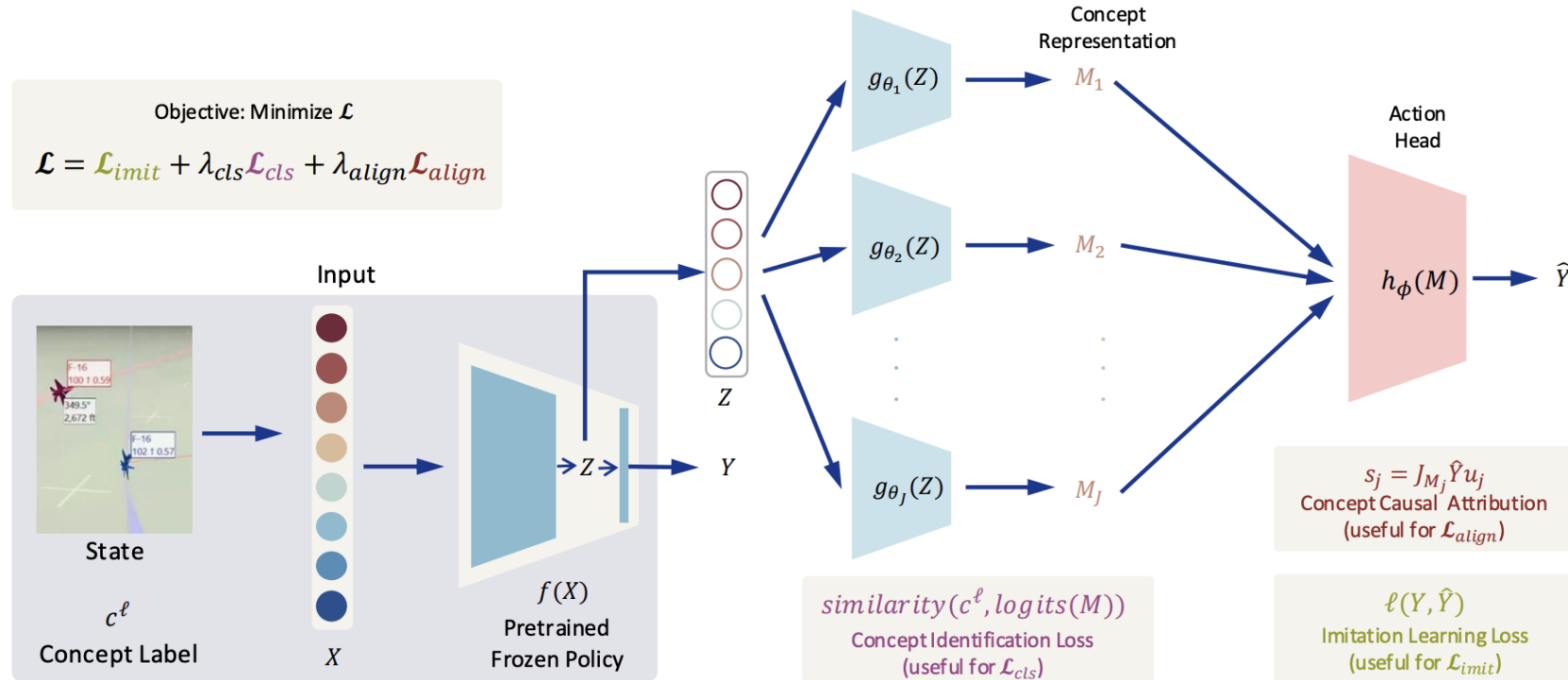
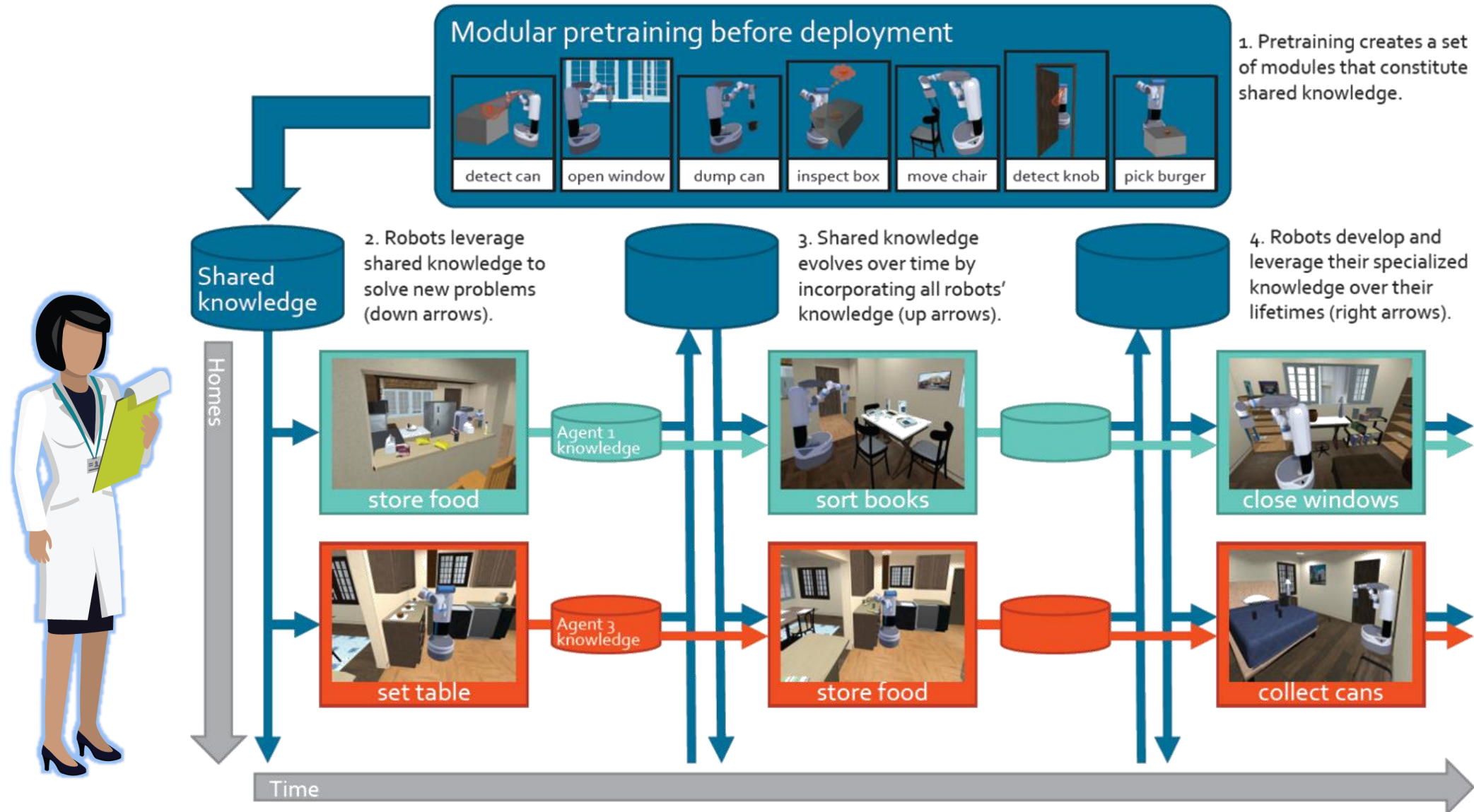
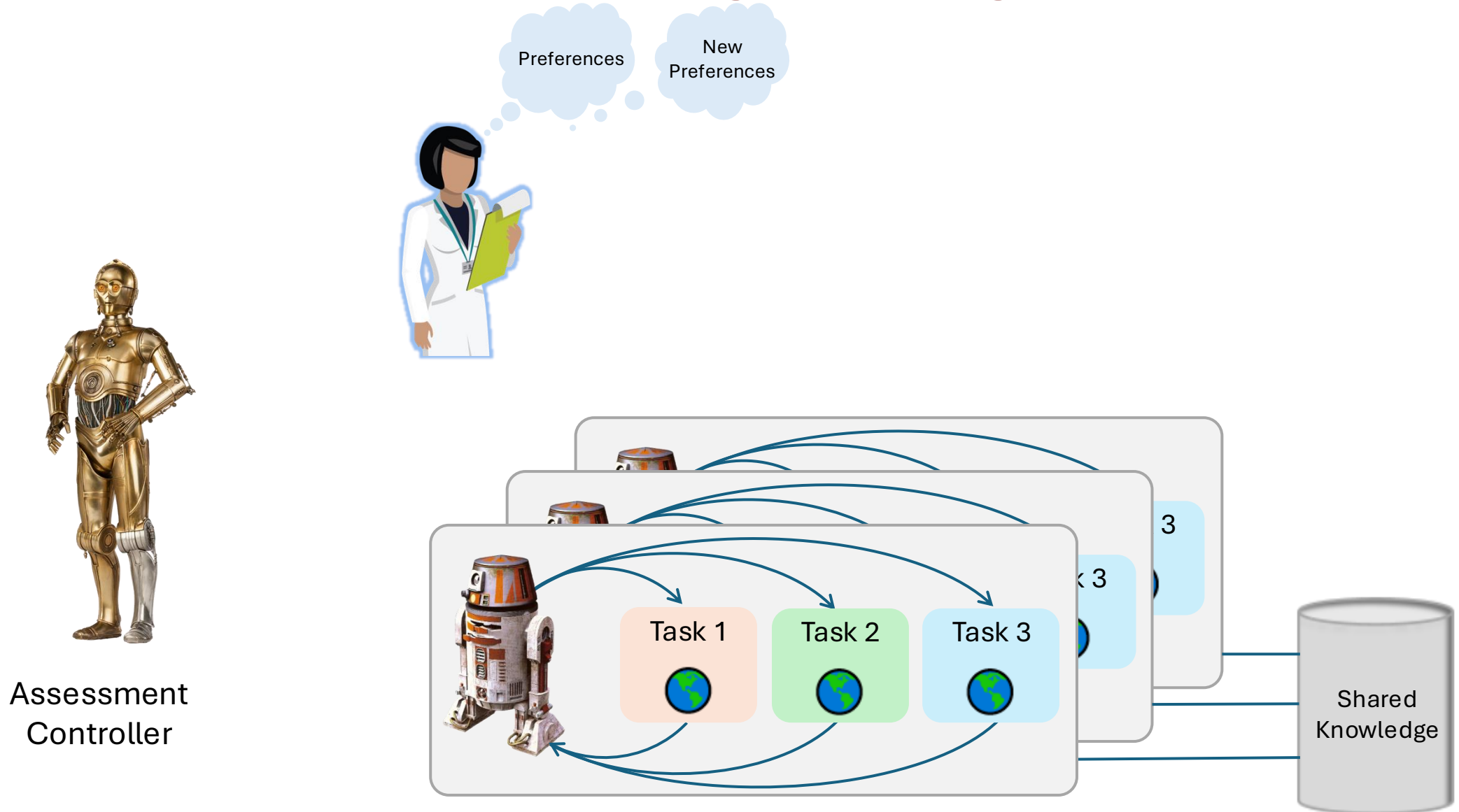


Figure 1: **CCW-Net Architecture.** CCW-Net wraps a frozen backbone f with a concept encoder g_θ that transforms latents Z into human-interpretable vector concepts M , and a differentiable head h_ϕ that maps concepts to wrapper actions $\hat{Y}$. CCW-Net estimates per-concept causal targets IE_j from expert trajectories, computes local concept-to-action sensitivities $s_j = J_{M_j} \hat{Y} u_j$, and aligns them with a masked cosine loss. Vector concepts encode both the strengths and context-dependent expression of each concept, enabling faithful, human-interpretable explanations while preserving task performance.

Lifelong Learning with Human-in-the Loop



Human-in-the Loop Lifelong Learning (HITL3)

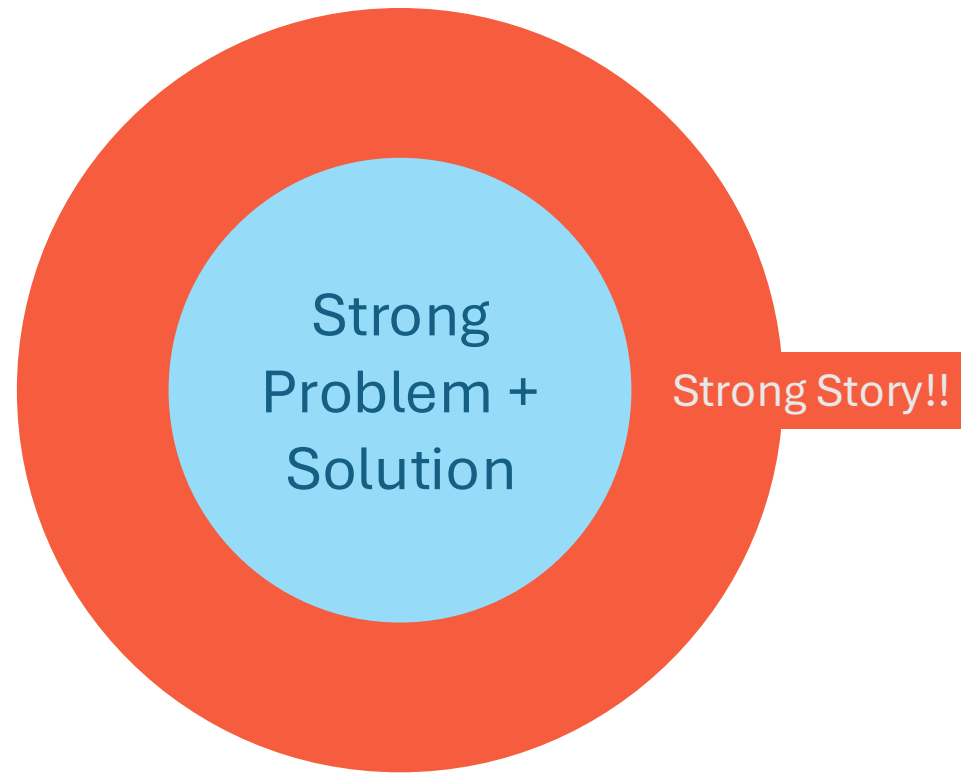


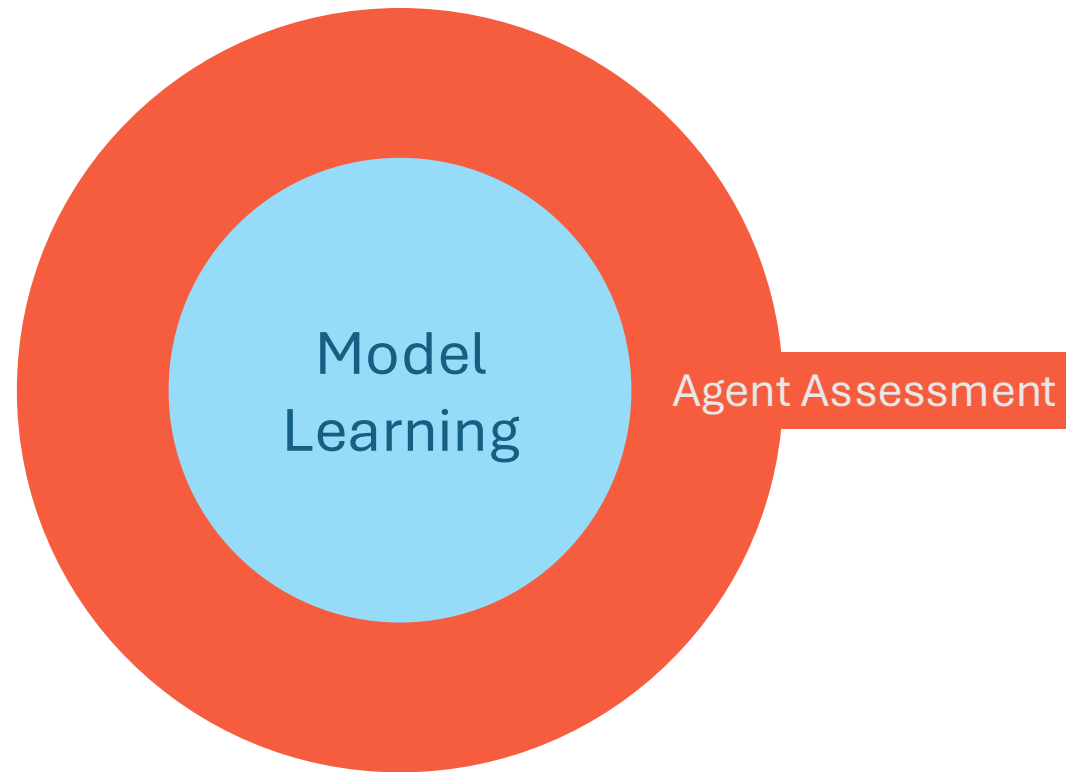
Some Advice for my future colleagues!!

No hook, no fish
(aka No claims, No readers)*

*Subbarao Kambhampati. “Wittgenstein’s papers & Faraday’s Talks: Maxims for a milk-fed researcher”. IJCAI 2013 DC

The Story Matters!!





Don't go after the papers!!

Quality over Quantity

Take the reviews with a grain of salt!!



Rebuttal Matters!!

How to write rebuttals?

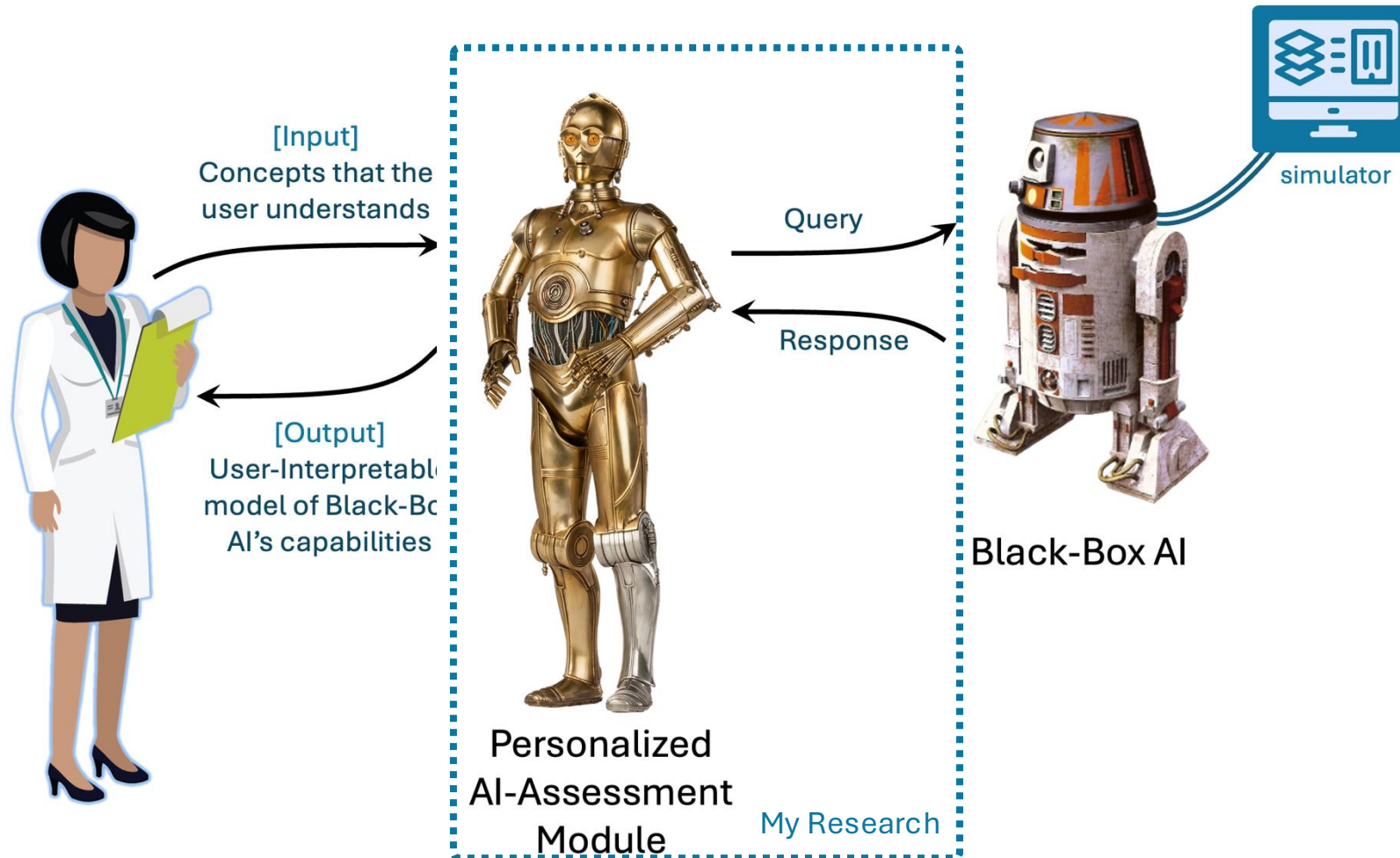
- Give your best
- Expect nothing



<https://deviparikh.medium.com/how-we-write-rebuttals-dc84742fece1>

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Questions?