

AAAI 2021 Workshop on Explainable Agency in Artificial Intelligence

Asking the Right Questions: Active Action-Model Learning

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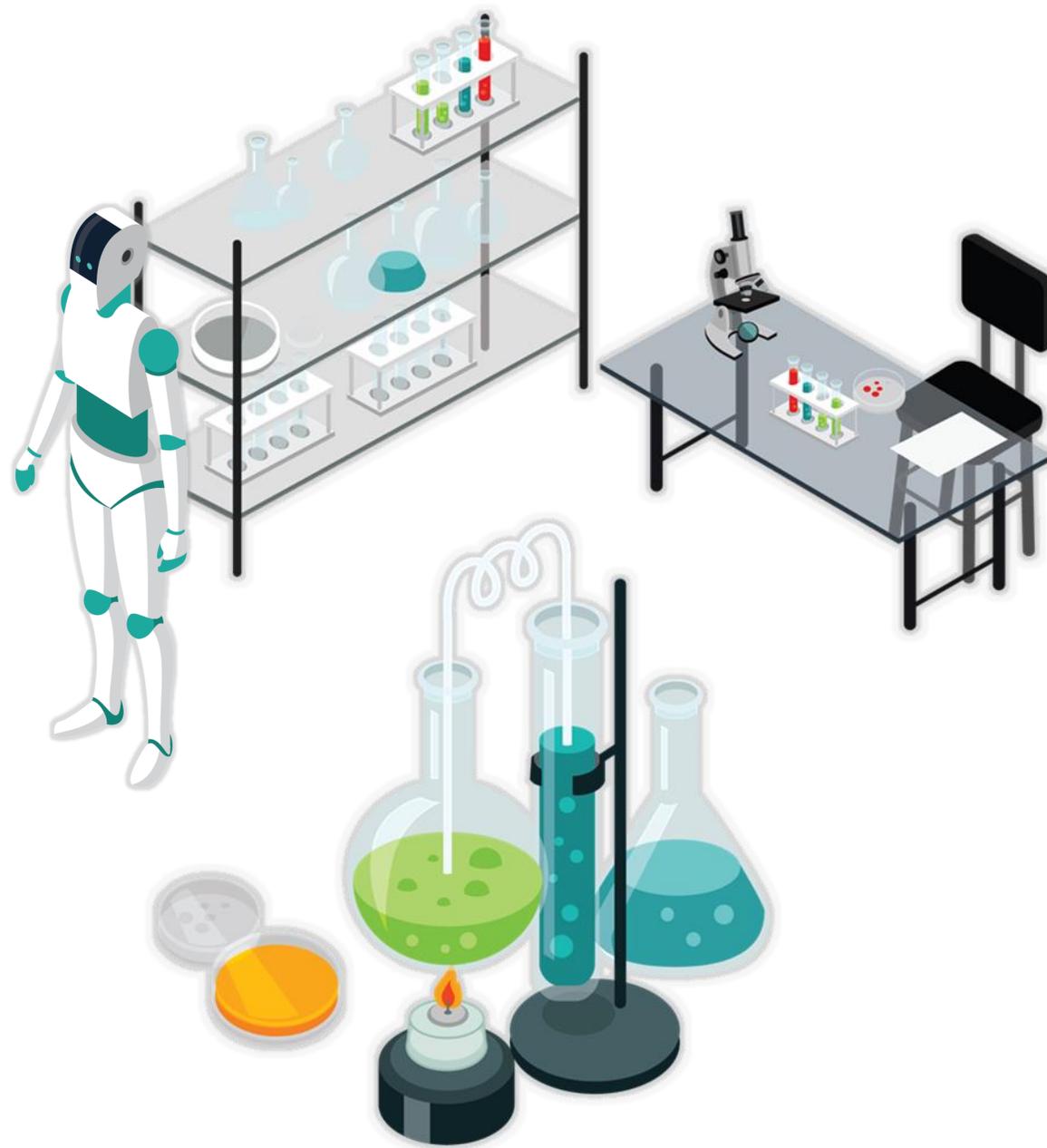


How Would End Users Assess Their AI Systems?

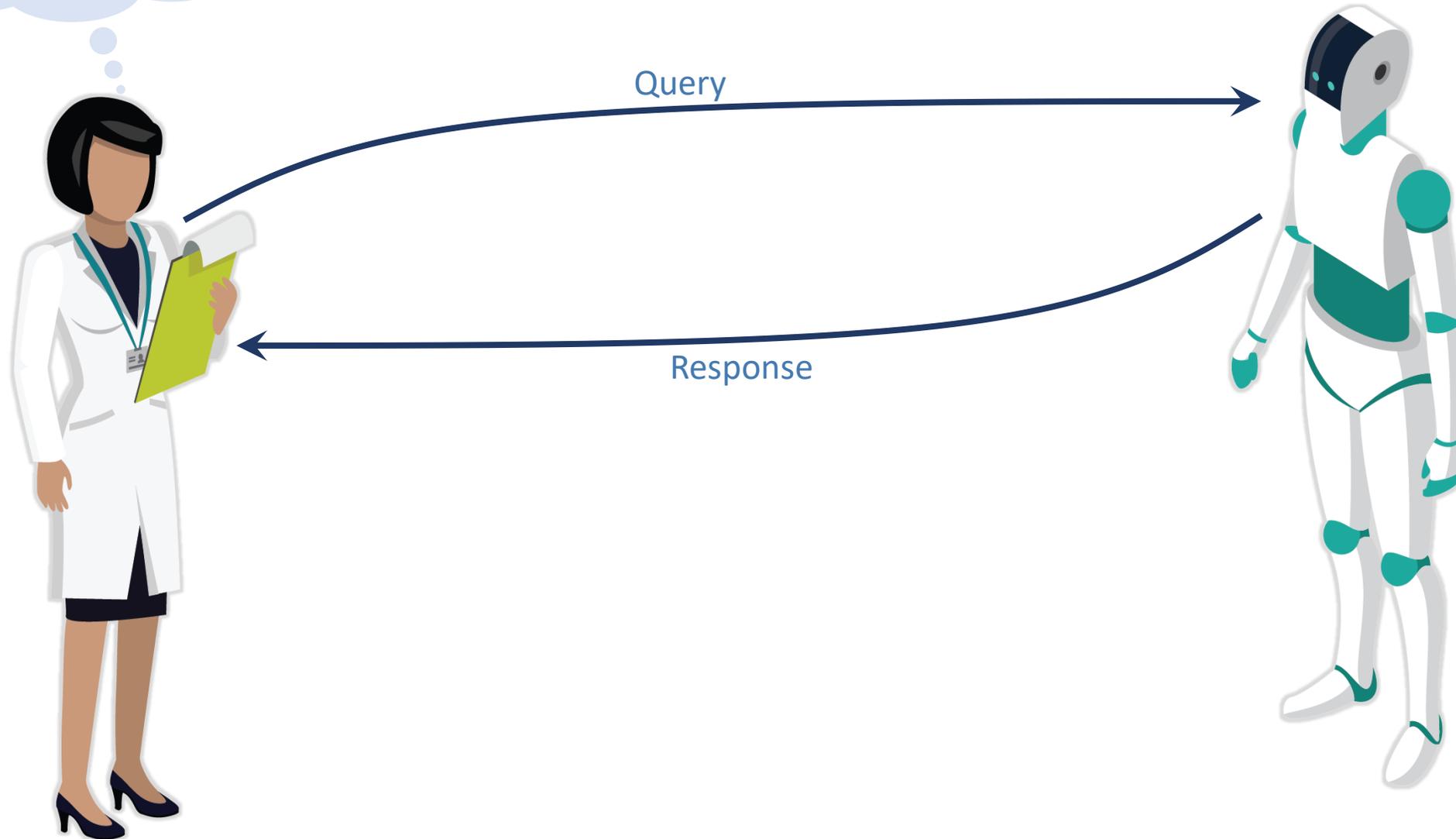
- How would a lay user determine whether an AI agent will be safe/reliable for a certain task?
- More challenging in settings where agent's internal code is not available (black-box).
- Can we get insights from how we assess humans in such situations?

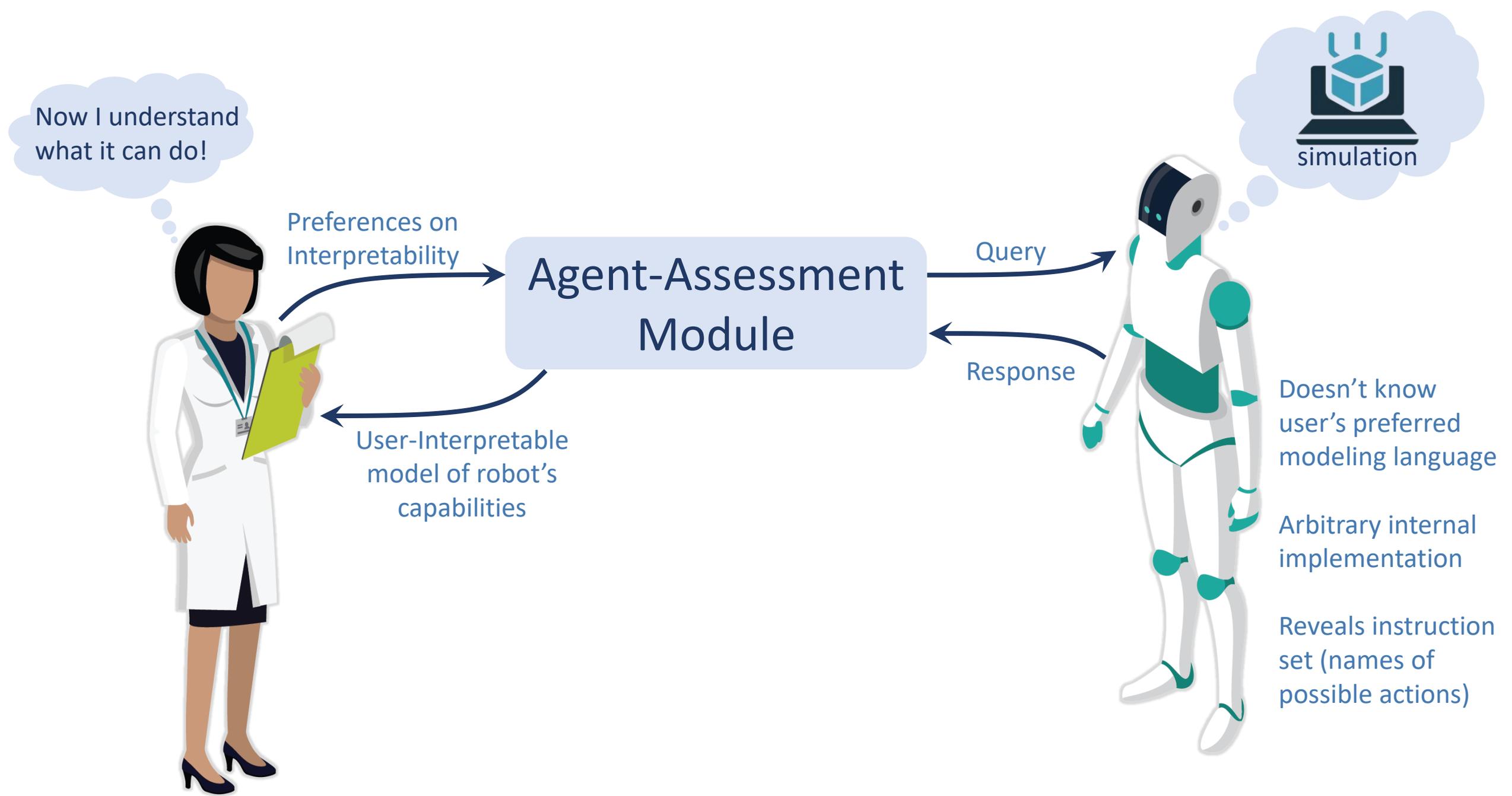


Will it be able to safely rearrange my lab for the next round of experiments?

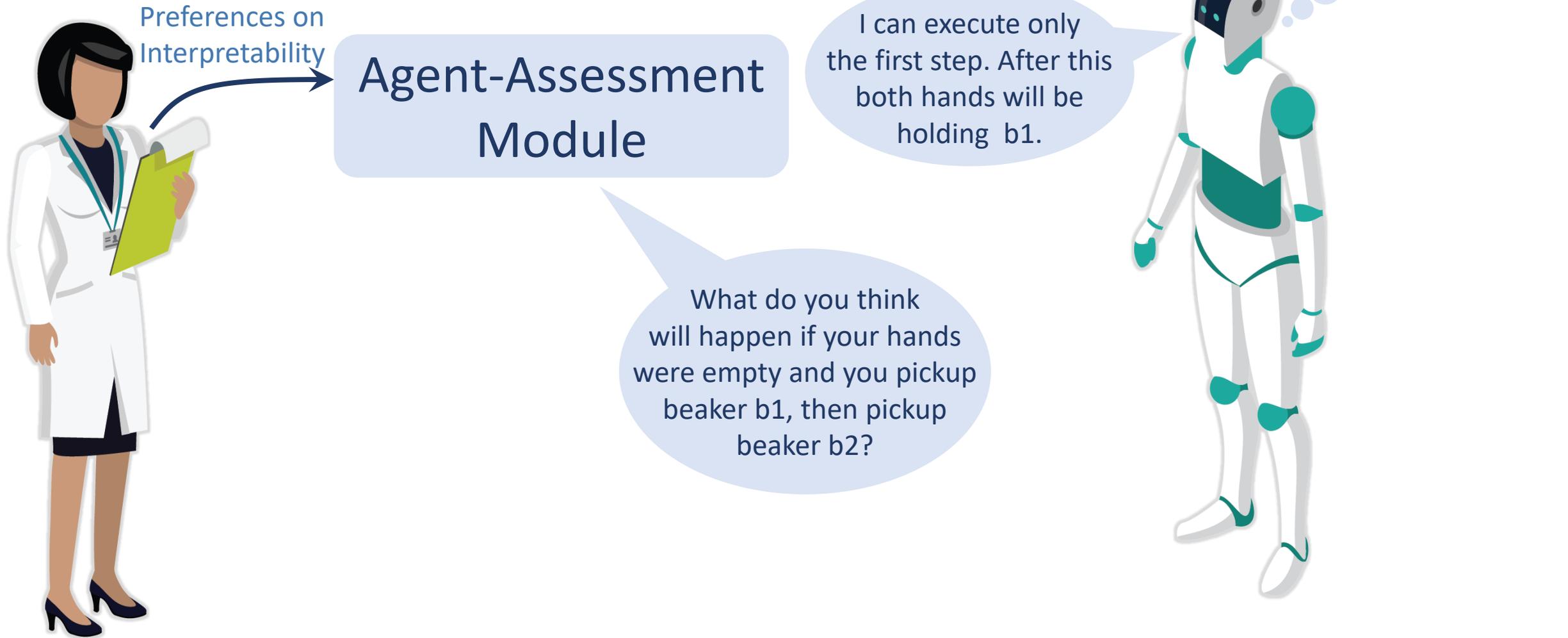


Which Questions to ask?
How to extrapolate?



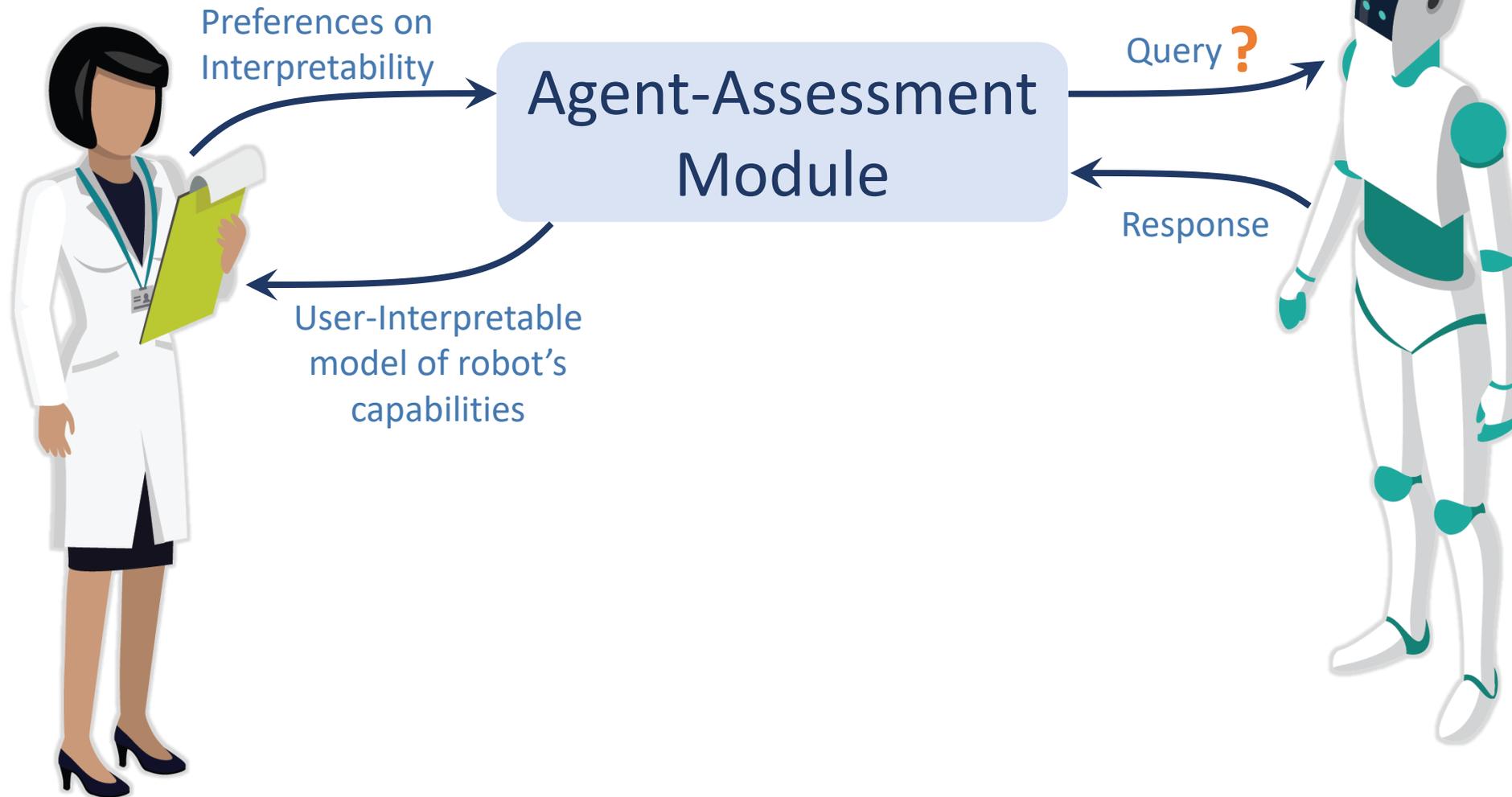


Example of an Interaction



Key Challenges

- Which queries to ask?
- In which order to ask them?



Our Approach: Autonomous, User-Specific Agent Assessment

- Generate an interrogation policy.
- Use agent's answers to queries to estimate a user-interpretable relational model.
- In this work: user-interpretable means STRIPS-like model.

Why STRIPS-like Modeling Language?

Advantages

- Support counterfactuals, assessment of causality
- Easy to convert into natural language text

Disadvantages

- Too many possible models ($9^{|\mathbb{P}| \times |\mathbb{A}|}$)
- \mathbb{P} : variable-instantiated predicates
- \mathbb{A} : parameterized actions

```
(:action pickup
:parameters (?ob)
:precondition (and (handempty)
                  (onrack ?ob))
:effect (and (not (handempty))
            (not (onrack ?ob))
            (holding ?ob)))
```

[Deterministic, Fully Observable]

What is a Query?

- Every query can be viewed as a function from models to responses.

Plan Outcome Queries:

Query: $\langle s_I, \pi \rangle$

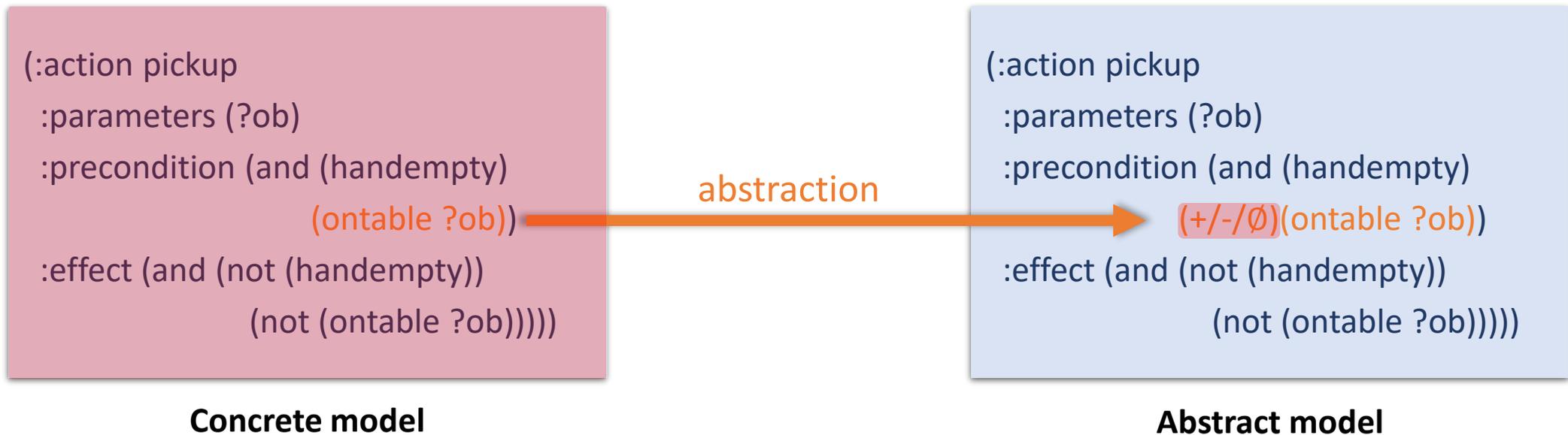
Initial State and Plan

Agent's Response: $\langle \ell, s_F \rangle$

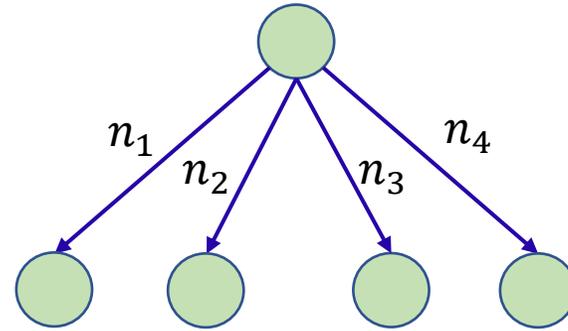
Length of plan that can be executed successfully and the final state.

How do we generate these queries?
How do we use them?

Example of Model Abstraction



Algorithm for Hierarchical Query Synthesis



(:action pickup

:parameters (?ob)

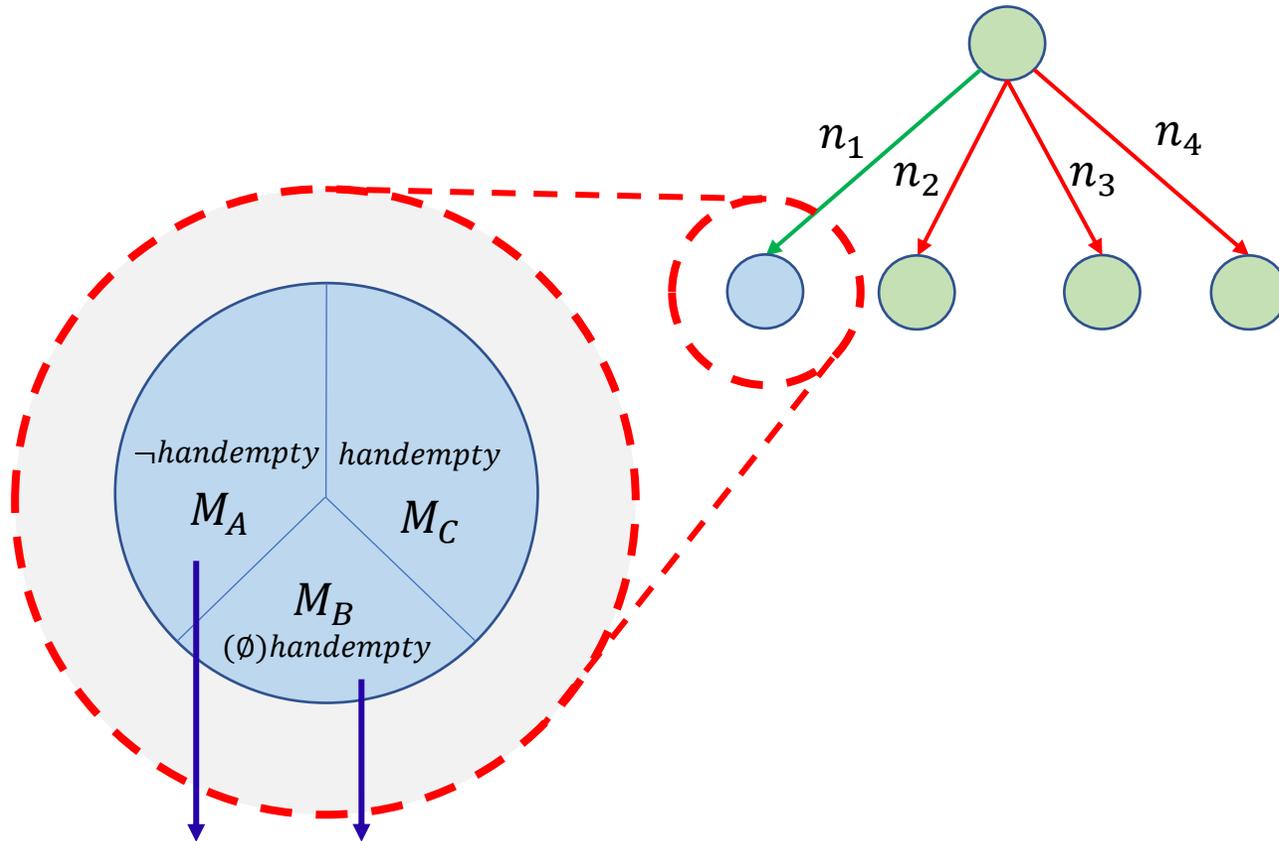
:precondition (and (+/-/∅) (handempty) n_1

(+/-/∅) (ontable ?ob)) n_2

:effect (and (+/-/∅) (handempty) n_3

(+/-/∅) (ontable ?ob))) n_4

Algorithm for Hierarchical Query Synthesis



(:action pickup

:parameters (?ob)

:precondition (and (+/-/∅) (handempty) ←
 (+/-/∅) (ontable ?ob))

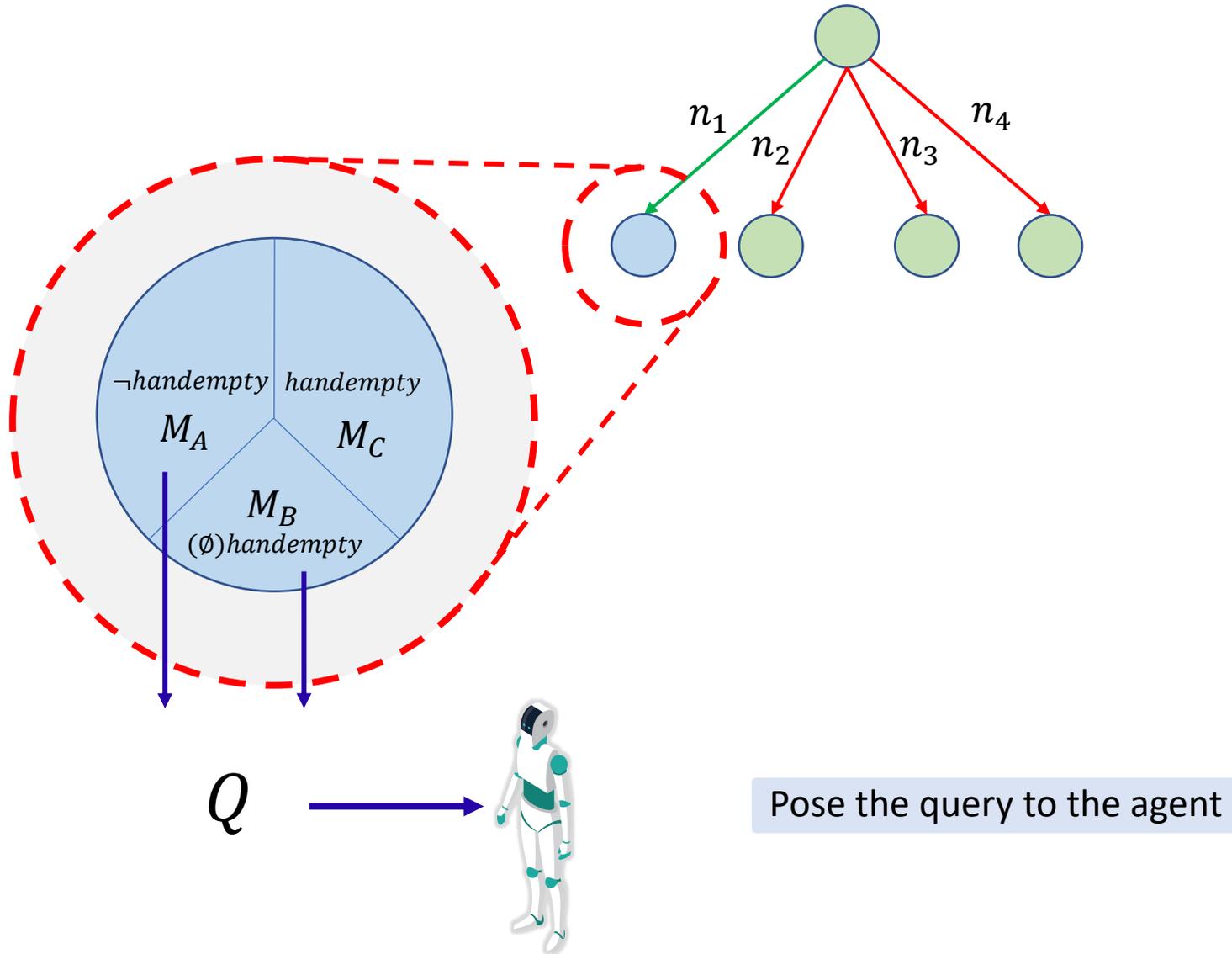
:effect (and (+/-/∅) (handempty)

(+/-/∅) (ontable ?ob)))

Generate a
distinguishing query:
 Q such that $Q(M_A) \neq Q(M_B)$

Query-plan generated automatically
 by reduction to planning

Algorithm for Hierarchical Query Synthesis



(:action pickup

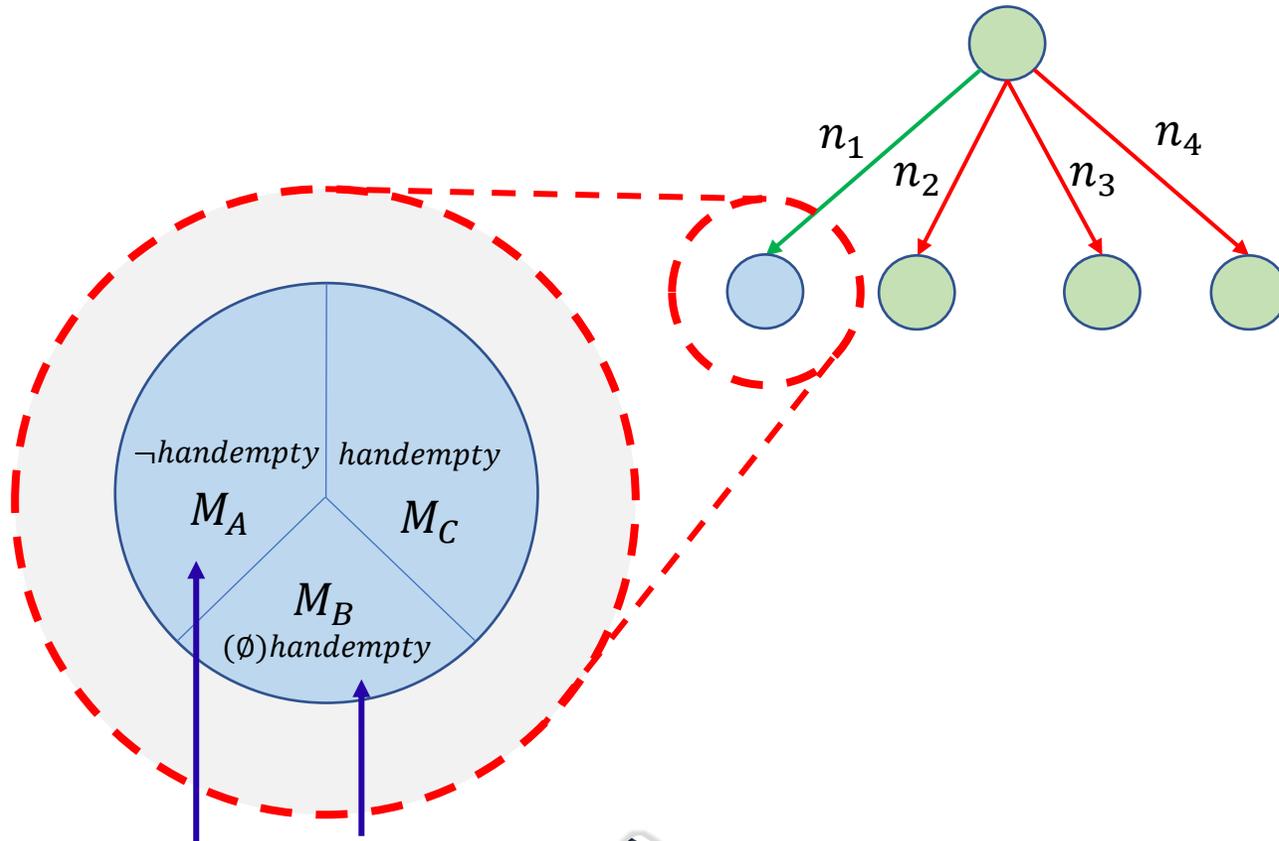
:parameters (?ob)

:precondition (and (+/-/ \emptyset) ($handempty$) ←
 (+/-/ \emptyset) ($ontable ?ob$))

:effect (and (+/-/ \emptyset) ($handempty$)
 (+/-/ \emptyset) ($ontable ?ob$)))

Pose the query to the agent

Algorithm for Hierarchical Query Synthesis



$$\theta = Q(\text{Agent})$$

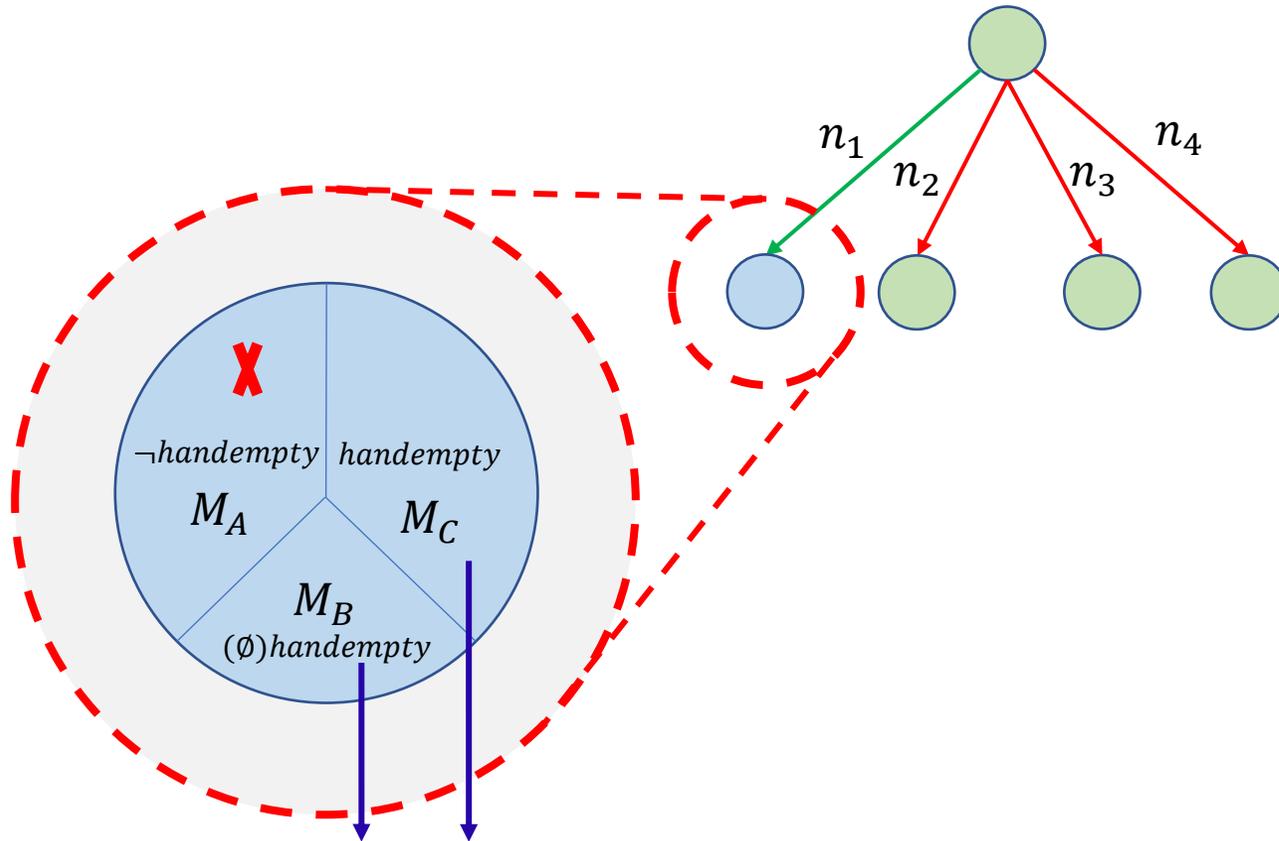
$$Q(M_A) \neq Q(M_B)$$



Check the consistency of refinements with the agent response

- (:action pickup
- :parameters (?ob)
- :precondition (and (+/-/∅) (handempty) ←
- (+/-/∅) (ontable ?ob))
- :effect (and (+/-/∅) (handempty)
- (+/-/∅) (ontable ?ob)))

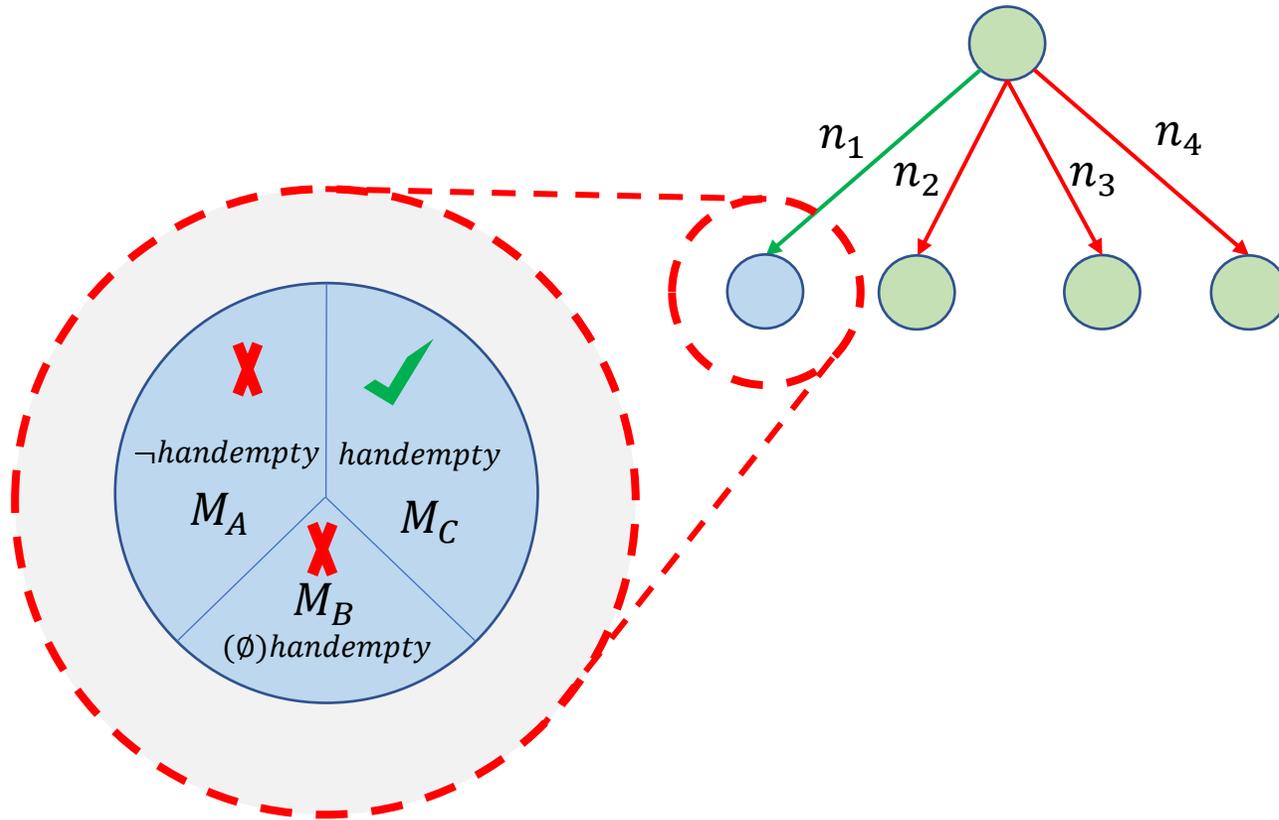
Algorithm for Hierarchical Query Synthesis



Generate a distinguishing query
for these two refinements

(:action pickup
 :parameters (?ob)
 :precondition (and (+/-/∅) (handempty) ←
 (+/-/∅) (ontable ?ob))
 :effect (and (+/-/∅) (handempty)
 (+/-/∅) (ontable ?ob)))

Algorithm for Hierarchical Query Synthesis



(:action pickup

:parameters (?ob)

:precondition (and (handempty)

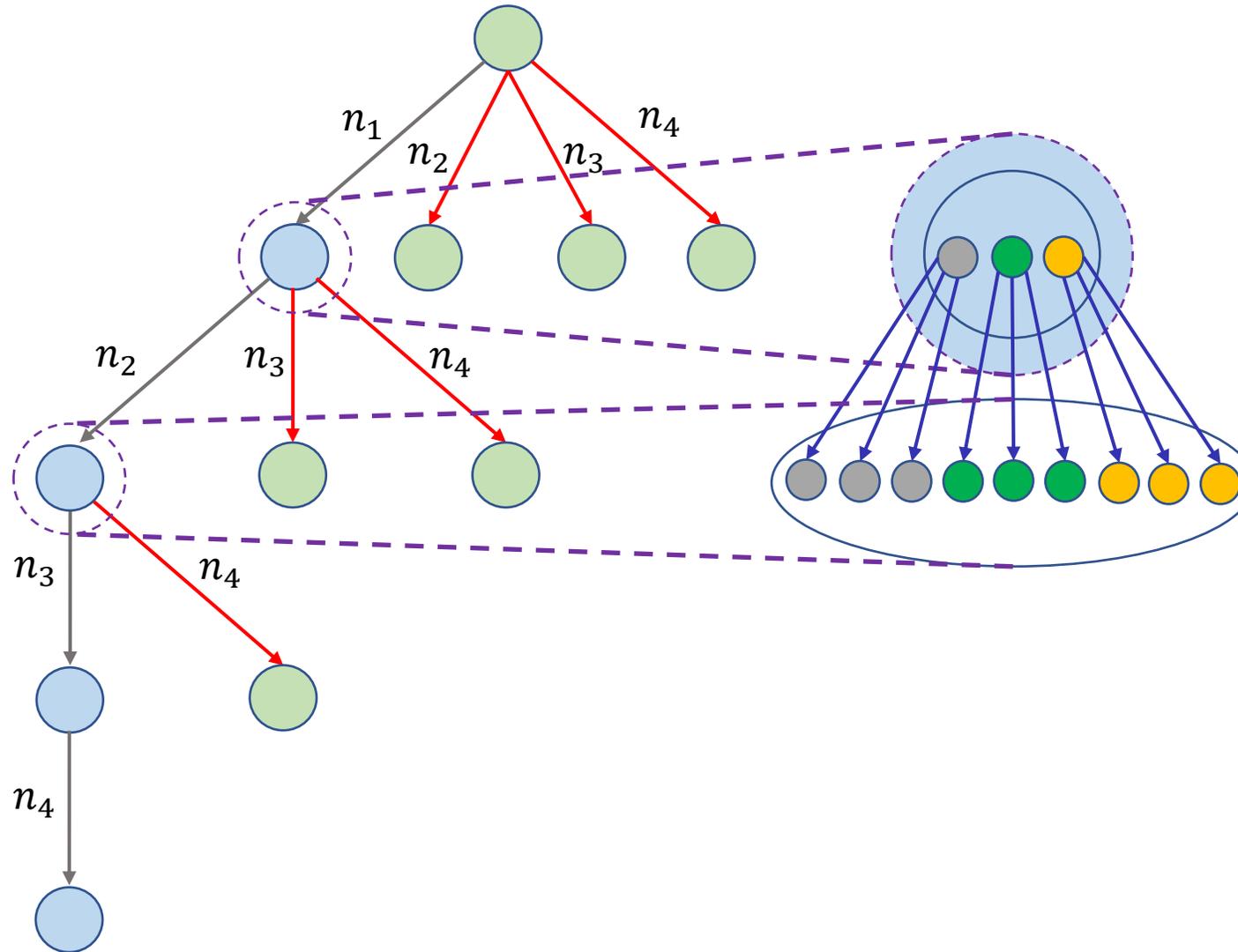
(+/-/∅) (ontable ?ob))

:effect (and (+/-/∅) (handempty)

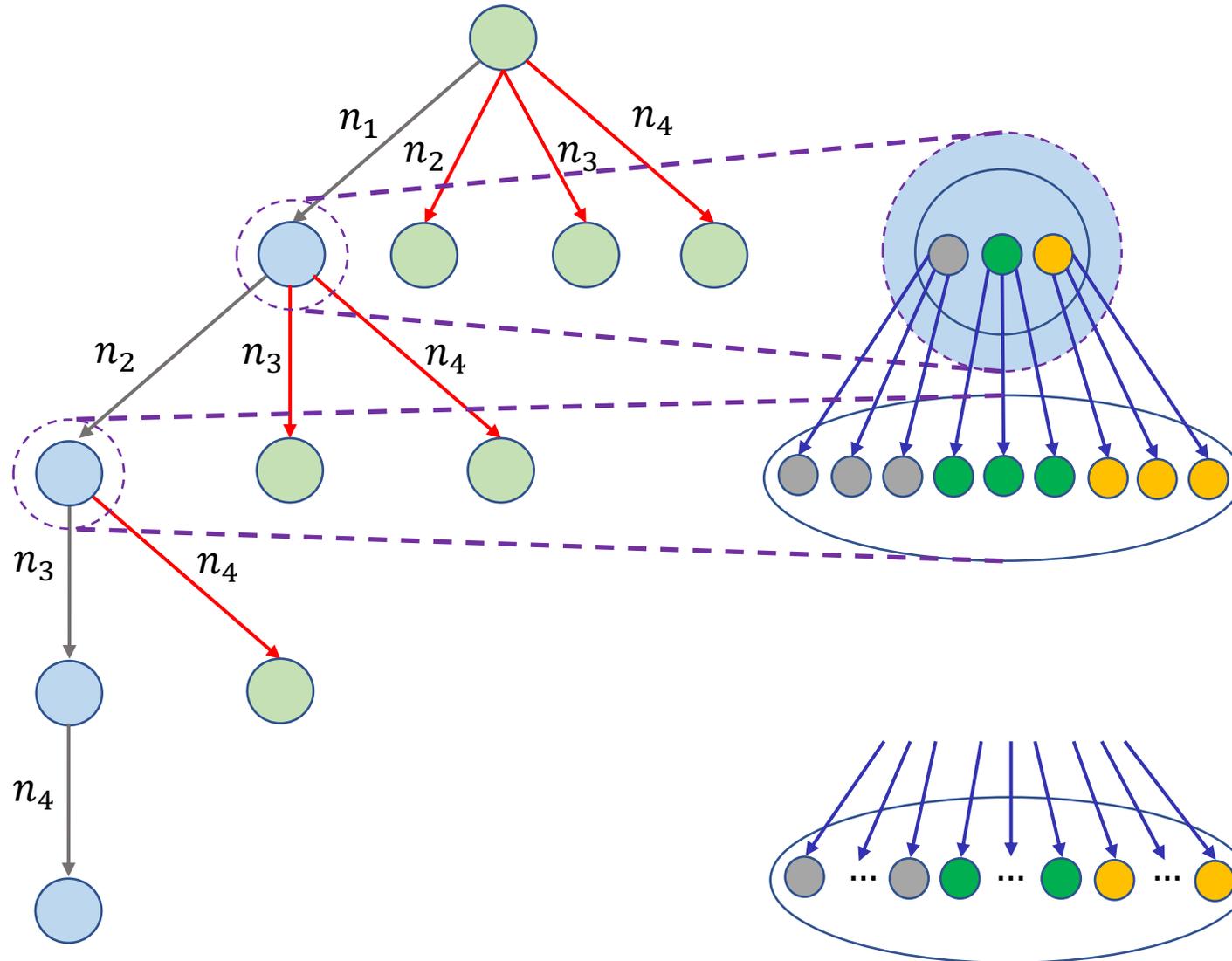
(+/-/∅) (ontable ?ob)))



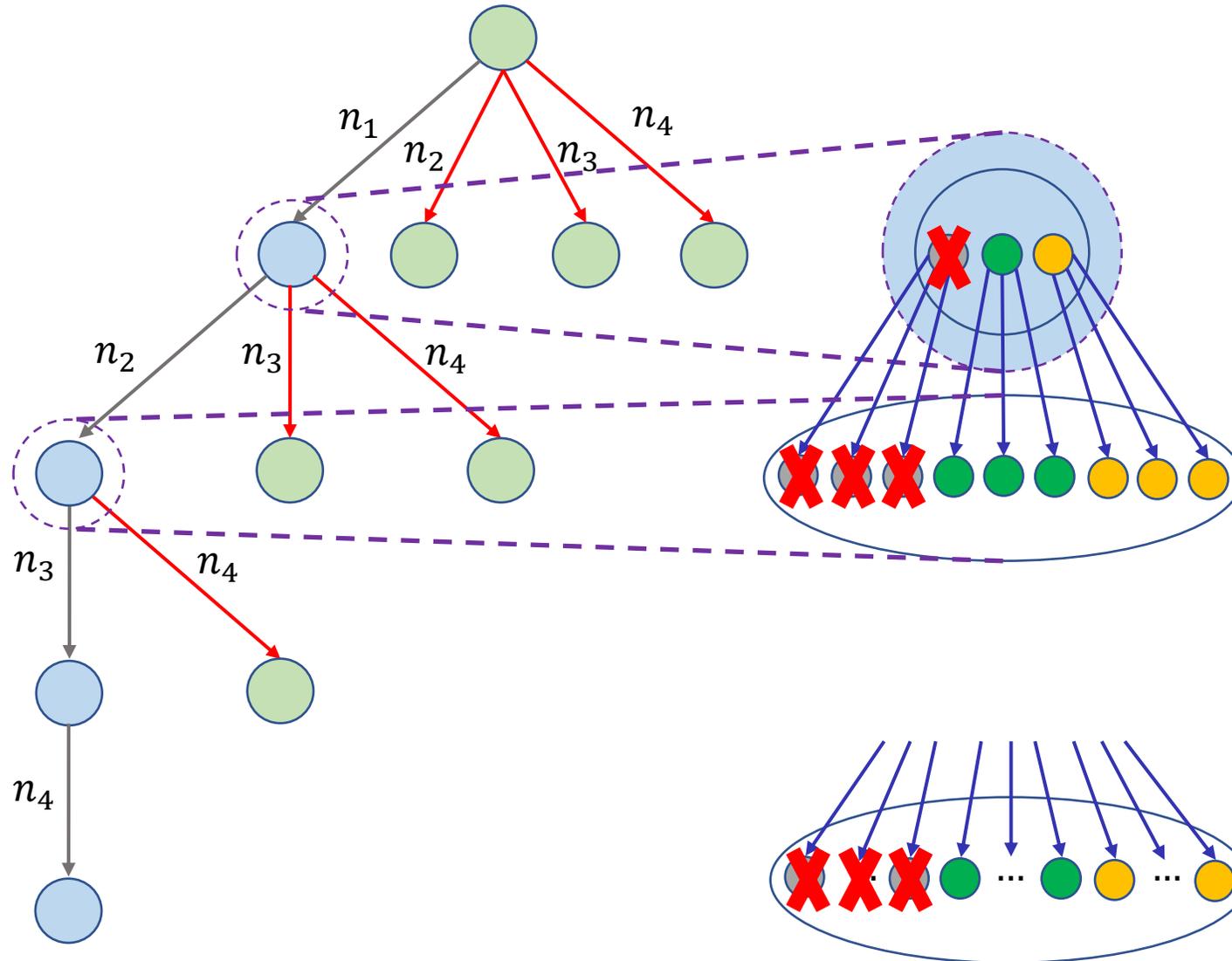
Algorithm for Hierarchical Query Synthesis



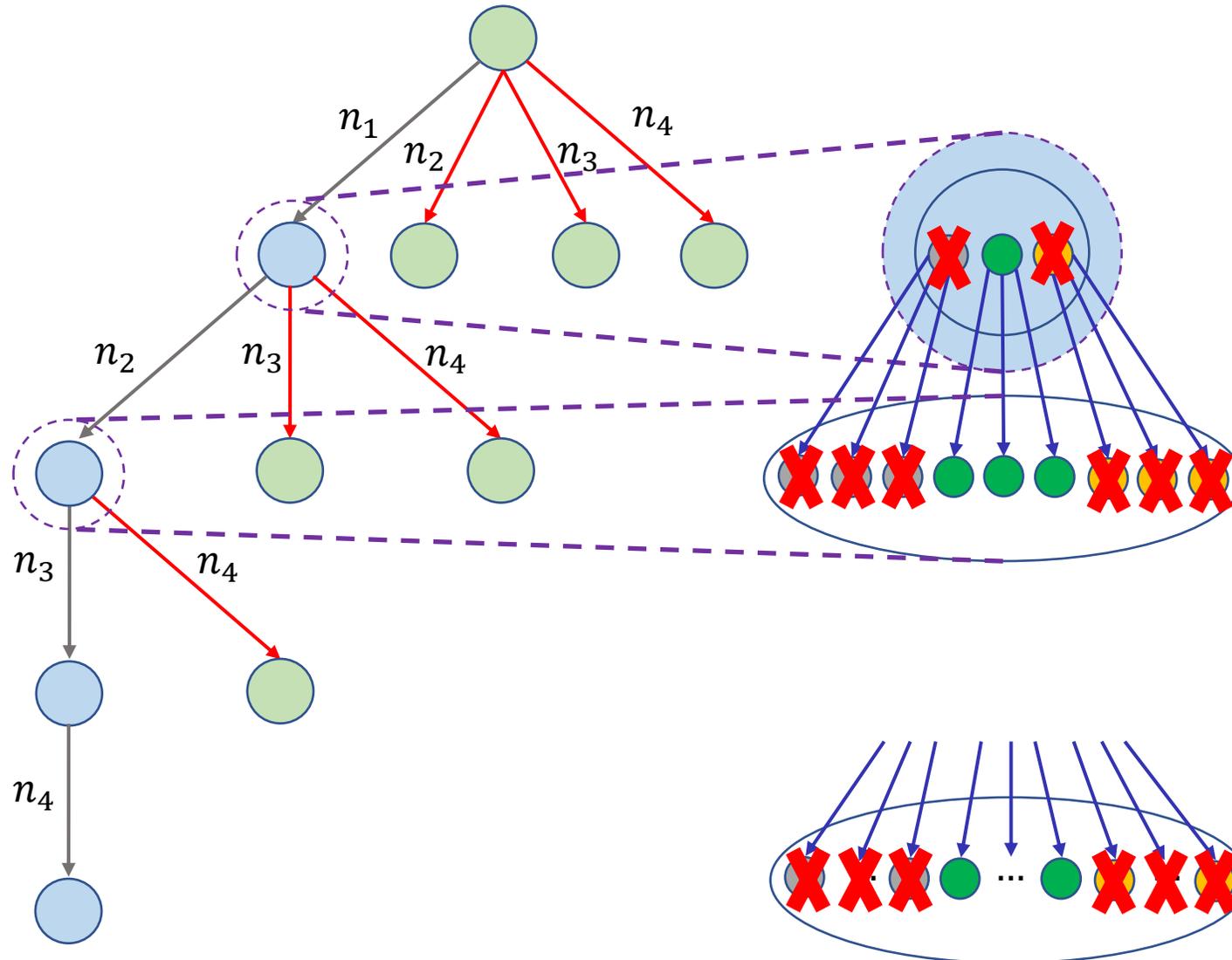
Algorithm for Hierarchical Query Synthesis



Algorithm for Hierarchical Query Synthesis



Algorithm for Hierarchical Query Synthesis



Key feature of the algorithm

Whenever we prune an abstract model, we prune a large number of concrete models.

Related Approaches

Several approaches have been developed for inferring interpretable models:

- Based on passively observed agent behavior.
 - E.g., ARMS – Yang et al. (AIJ 2007), LOCM - Cresswell et al. (ICAPS 2009), LOUGA - Kučera and Barták (KMAIS 2018), FAMA - Aineto et al. (AIJ 2019) ←
 - These approaches are susceptible to unsafe model inference.
- Based on explicit specification of the entire transition graph.
 - E.g., Bonet and Geffner (ECAI 2020)
 - This work requires no symbolic information but is more suited for smaller problems.

Experimental Setup

- 2 types of agents:
 - Symbolic sims: Agents that use symbolic, analytical models as simulators.
 - Black-box sims: Agents that use black-box models as simulators.
- Used FAMA[†] as baseline.

[†]Aineto, D.; Celorrio, S. J.; and Onaindia, E. 2019. *Learning Action Models With Minimal Observability*. *Artificial Intelligence* 275: 104–137.

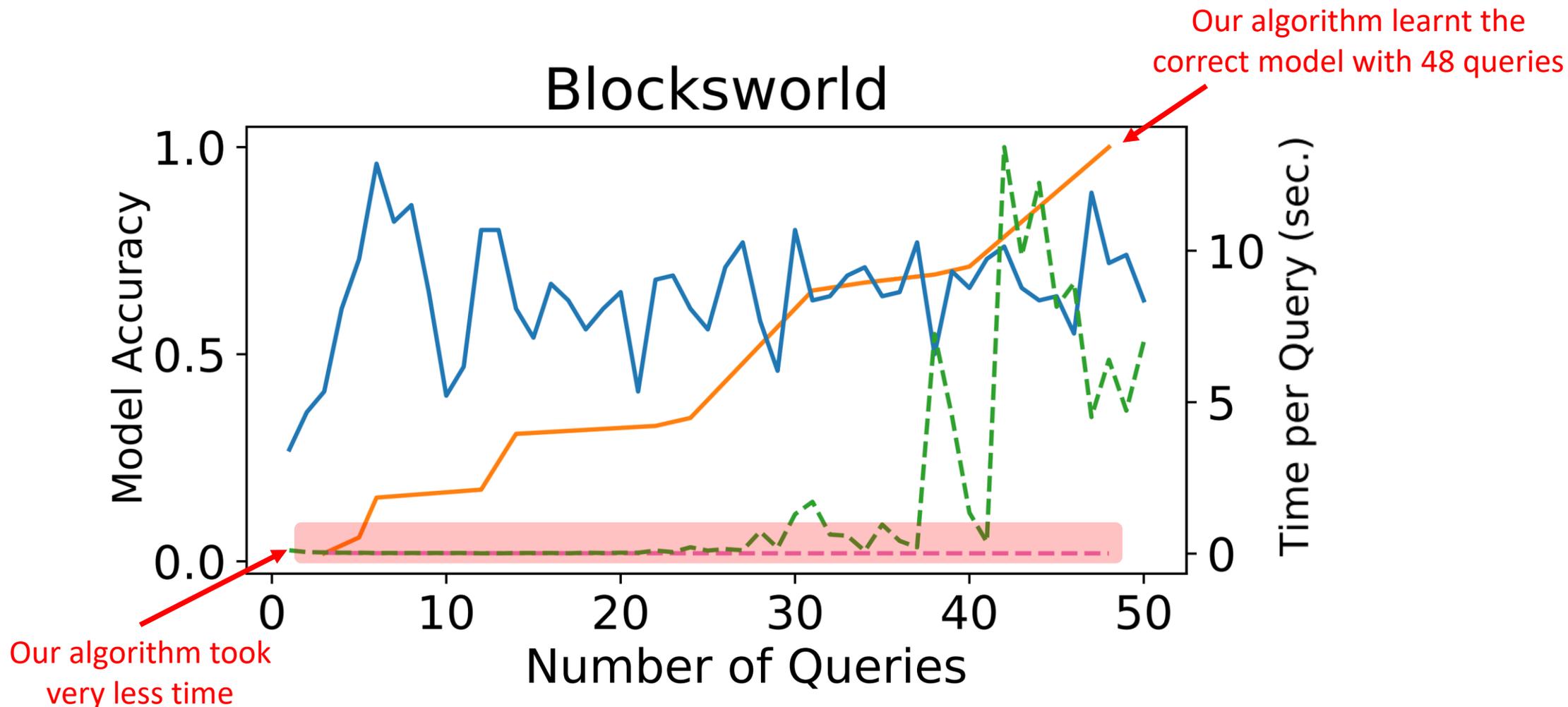
How we Evaluate Symbolic Sims?

- Randomly generate an agent and environment from IPC benchmark suite.
- Agent assessment module doesn't get this information.
- Agent reports results as logic-based states (lists of grounded predicates that are true).
- Evaluate performance of agent assessment module and compare it with FAMA.

Results: Symbolic Sims

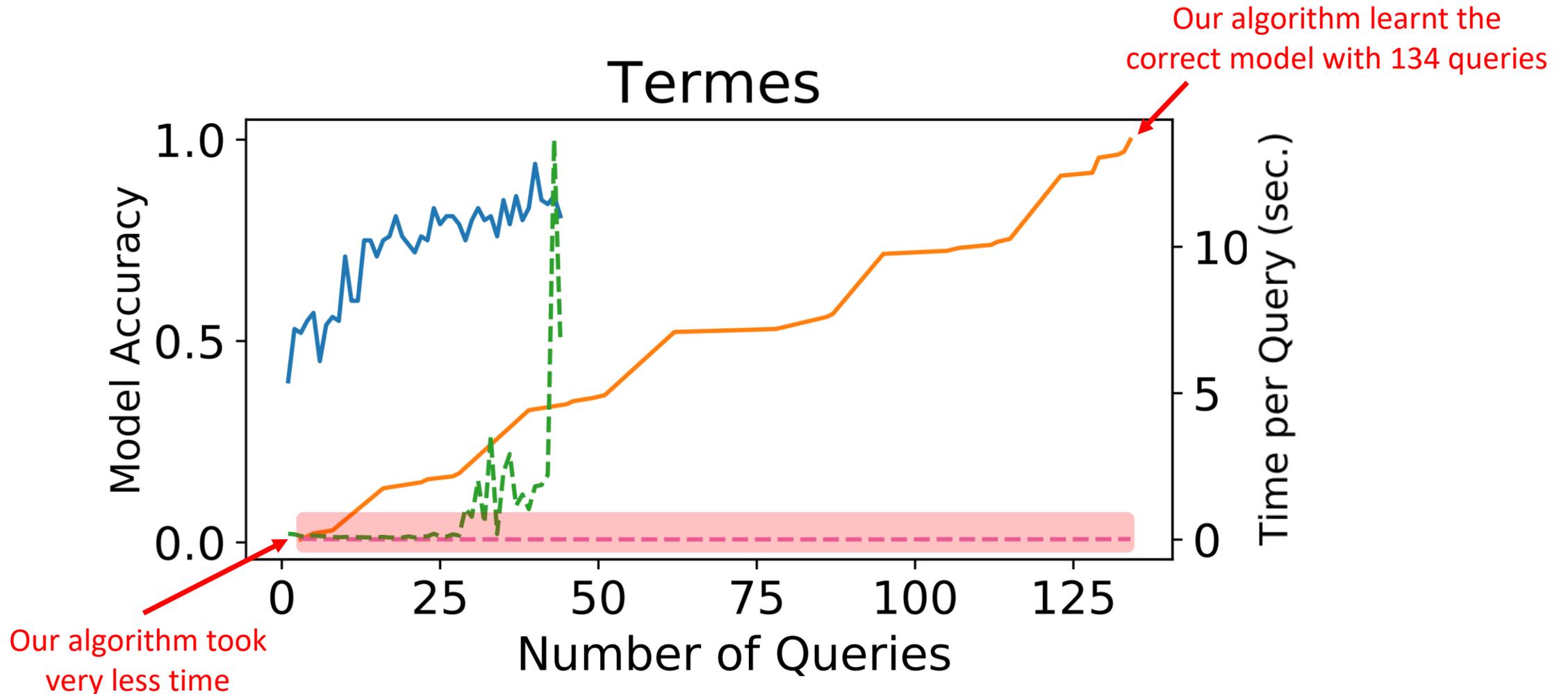
Accuracy: — AIA — FAMA
Time: - - - AIA - - - FAMA

Blocksworld



Results: Symbolic Sims

Accuracy: — AIA — FAMA
Time: - - - AIA - - - FAMA



Results: Symbolic Sims

Domain	$ \mathbb{P} $	$ \mathbb{A} $	$ \hat{Q} $	t_μ (ms)	t_σ (μ s)
Gripper	5	3	17	18.0	0.2
Blocksworld	9	4	48	8.4	36
Miconic	10	4	39	9.2	1.4
Parking	18	4	63	16.5	806
Logistics	18	6	68	24.4	1.73
Satellite	17	5	41	11.6	0.87
Termes	22	7	134	17.0	110.2
Rovers	82	9	370	5.1	60.3
Barman	83	17	357	18.5	1605
Freecell	100	10	535	2242	3340

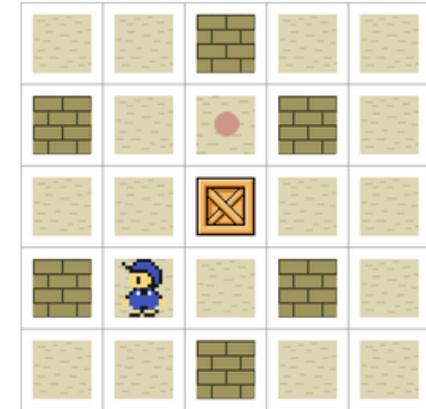
Results with FD planner:

- $|\mathbb{P}|$: Number of instantiated predicates in the domain
- $|\mathbb{A}|$: Number of actions in the domain
- $|\hat{Q}|$: Number of queries posed by the assessment module
- $|t_\mu|$: Average time per query
- $|t_\sigma|$: Variance in average time per query

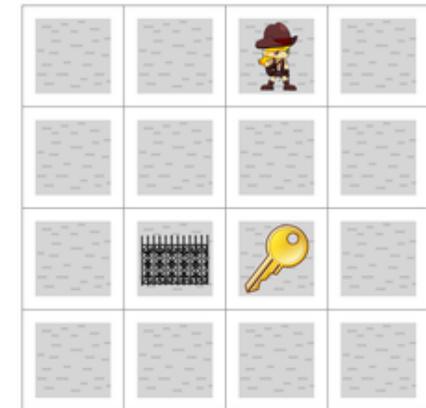
Average and variance are calculated for 10 runs of the algorithm, each on a separate problem.

How we Evaluate Black-Box Sims?

- Agent uses PDDL[†]Gym to simulate the query plan.
- Reports results as images from the sim.
- Uses image classifiers for each predicate.
- Correctly inferred the model with:
 - 217 queries for Sokoban, and
 - 188 queries for Doors.



Sokoban



Doors

[†]Silver, T.; and Chitnis, R. 2020. *PDDL[†]Gym: Gym Environments from PDDL Problems*. In ICAPS 2020 PRL Workshop.

Conclusions

The proposed approach:

- Efficiently learns internal model of an agent in a STRIPS-like form.
- Needs no prior knowledge of the agent model.
- Only requires an agent to have rudimentary query answering capabilities.
- Learns the model accurately with a small number of queries.
- Can be extended :
 - to handle noisy image classifiers; or
 - to replace communication interface with natural language.

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bit.ly/3a0cmDI

Paper



bit.ly/3p4cVRu

AAAI Version[†]

[†]Verma, P.; Marpally S. R.; and Srivastava, S. *Asking the Right Questions: Learning Interpretable Action Models through Query Answering*. In AAAI 2021.