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Discovering User-Interpretable Capabilities of Black-Box Planning Agents

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Personalized Assessment of Taskable AI Systems

- Users can give them multiple tasks.
 - How would users know what they can do?
- They should make it easy for its operators to learn how to use them safely.[†]
- Should work with black-box AI systems.



[†]Srivastava S. *Unifying Principles and Metrics for Safe and Assistive AI*. In Proc. AAAI 2021.

Capability v/s Functionality

- Functionality: Set of possible low-level actions of the agent.
- Capability: What agent's planning and learning algorithms can do.



Learned Agent Actions (Keystrokes) Capabilities W (defeat ganon) (go to door) А (go to key) S (go to ganon) (pick key) D (open door)

Knowledge of primitive actions might be insufficient to understand the agent's capabilities

Ε

User-vocabulary may be limited



Agent's State
Representation
pixel_1_1(#42A8B3)
pixel_1_2(#42A8B3)
pixel_n_m(#203A3D)

Interpretable State Representation

> (at ganon 5,3) (at link 6,3) (at key 9,4)

(at door 9,2)



Might be more expressive than what the user understands

Vocabulary Acquisition

- Users share same vocabulary in same workspaces.
 - E.g., factory workers, coworkers, etc.
- Training the users on some predefined vocabulary.
- Using vocabulary acquisition techniques like TCAV[†], etc.



[†]Kim et al. *Interpretability beyond feature attribution: Testing with Concept Activation Vectors*. In Proc. ICML 2018.

Previous Work

Learning high-level symbolic models of AI systems using observations or interventions.

- Konidaris et al. (JAIR'18) : not interpretable, assume access to predefined options
- AIA Verma et al. (AAAI'21): assume precise user-vocabulary
- Zhang et al. (ICML'18): Needs hand-coding of states
- Schema Networks Kansky et al. (ICML'17), Agarwal et al. (NIPS'16): require lot of data
- LOCM Cresswell et al. (ICAPS'09), ARMS Yang et al. (AIJ 2007), LOUGA Kučera and Barták (KMAIS 2018), SAM - Stern and Juba (IJCAI 2017, KR 2021), FAMA - Aineto et al. (AIJ 2019) – based on observations, works for known set of operators

Discovering Capabilities



Parameterizing a Capability



```
at(p0,cell_6_3)
clear(cell_0_0)...
wall(cell_0_1)...
door_at(cell_9_2)
key_at(9_4)
```

[Sample pre and post states of a capability]

```
(:capability c4
:parameters (?player1 ?cell1
  ?monster1 ?cell2)
:precondition
  (and (alive ?monster1)
      (at ?player1 ?cell1)
      (at ?monster1 ?cell2)
      (next_to ?monster1))
:effect
  (and (clear ?cell2)
      (not(alive ?monster1)))
  (not(at ?monster1 ?cell2))
      (not(next_to ?monster1)))))
```

[Learned capability description]

For each capability:

- Extract what predicates were different in the pre and post states of the capability.
- Extract the parameters from those predicates to create a candidate parameter set.
- Complete the parameter set along with capability description as precondition and effect of a capability by active querying.









What will happen if you open the door without the key?



High-level Query Generator

Iterative Capability Model Learning [iCaML]

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 (in terms of capabilities)

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?

(:action pickup

:parameters (?ob)

- :precondition (and $(+/-/\emptyset)$ (handempty) n_1
 - (+/-/ \emptyset) (ontable ?ob)) n_2
- :effect (and (+/-/ \emptyset) (handempty) n_3
 - (+/-/ \emptyset) (ontable ?ob))) n_4



(:action pickup

:parameters (?ob)

:precondition (and $(+/-/\emptyset)$ (handempty) n_1

- $(+/-/\emptyset)$ (ontable ?ob)) n_2
- :effect (and (+/-/ \emptyset) (handempty) n_3
 - (+/-/ \emptyset) (ontable ?ob))) n_4



(:action pickup :parameters (?ob) :precondition (and (+/-/Ø) (handempty) - $(+/-/\emptyset)$ (ontable ?ob)) :effect (and $(+/-/\emptyset)$ (handempty) $(+/-/\emptyset)$ (ontable ?ob)))

by reduction to planning



(:action pickup :parameters (?ob) :precondition (and (+/-/Ø) (handempty) - $(+/-/\emptyset)$ (ontable ?ob)) :effect (and $(+/-/\emptyset)$ (handempty) $(+/-/\emptyset)$ (ontable ?ob)))

Pose the query to the agent



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Reject refinement(s) that are not consistent with the agent



Generate a distinguishing query for these two refinements



Reject the refinement that is not consistent with the agent Lemma

At least one of the refinements will be consistent with the agent.



Key feature of the algorithm

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





What will happen if you open the door without the key?



High-level Query Generator

Iterative Capability Model Learning [iCaML]



State Reachability Query

Query: $\langle s_I, s_G \rangle$ Initial State and Goal State

Agent's Response: (*Yes*, *No*)

Whether it can reach from initial state to goal using its internal mechanism.

How do we generate these queries from plan outcome queries?

Query Refinement



State Reachability Queries



Response Interpretation



Response Interpretation



Formal Results

- The learned descriptions are consistent with the observations and the queries.
- This approach is maximally consistent, i.e., we cannot add any more literals to the preconditions or effects without ruling out some truly possible models.
- Learned capabilities are realizable, i.e., downward refinement is ensured.
- If a high-level model is expressible deterministically using the user vocabulary and local connectivity holds, then in the limit of infinite execution traces, the probability of discovering all capabilities expressible in the user vocabulary is 1.

Experimental Setup

- Randomly generate an environment from one of four GVGAI Games.
- Initialize two kinds of agents
 - Search Agent: Use search algorithms to generate plan and answer queries.
 - Policy Agent: Use black-box policies to answer queries.
- Vary grid size to see variations in number of queries and time taken per query.

Results

Zelda 2^{×10³} 80 60 20 30 42 20 Cook-Me-Pasta ×10³ 8 20 Time per Query (ms) Number of Queries 10 64 20 30 42 Escape ×10³ .50 100 50 0 42 16 20 Snowman $\times 10^{3}$ 8 20 2 20 42 25 30 Grid Size (number of cells)



Results: Example of Learned Capability





Utility of Discovered Capability Models

- Rules of Zelda-like game explained to users.
- 108 participants split into two groups of 54 each.
- Didn't train the users, only descriptions shown in English:
 - Capability Group participants shown learned capability descriptions.
 - Functionality Group participants shown descriptions of keystrokes.

We created a single-player game like *The Legend of Zelda* that looks something like this:



The hero of the game is called *Link. Link* must defeat the evil spider *Ganon* and escape. The **rules of the game** are as follows: 1. *Link* can move around the grid, whereas *Ganon* cannot. 2. *Link* must defeat *Ganon* and get the key (in any order), then enter the door to win.

- 3. *Link* cannot go through the cells containing walls, keys, *Ganon*, or door.
- 4. Game ends in *Link*'s loss if *Link* moves into a cell with *Ganon*.

The empty cells are represented as . All other kinds of cells are impassable.

Utility of Discovered Capability Models

4. Capability C4:

The *player* can execute this capability when:

- The monster is not defeated.
- The player is in cell1.
- The monster is in *cell2*.
- The player is in a cell adjacent to the *monster*.

After the *player* executes this capability:

- Cell2 is empty.
- The monster is defeated.
- The *monster* is not in *cell2*.
- The player is not in a cell adjacent to the *monster*.

Question 4 of 12:

Select the phrase that best summarizes the capability **C4**? We will use your response while referring to this capability **C4** later in the survey.

Ŷ
Go next to Door
Go next to Ganon
Go next to Key
Go next to Wall
Defeat Ganon
Break Key
Pick Key
Open Door

W: Pressing this key does the following:

- If Link is facing up and there is no wall, door, or key in the cell above, then Link moves to the cell above.
- If there is a wall, door, or key in the cell above Link, then Link stays in the same cell.
- If Link is facing Left, Right, or Down before pressing W, then Link faces up but stays in the same cell.

Question 1 of 11:

Select the phrase that best summarizes pressing **W**? We will use your response while referring to this key **W** later in the survey.

	~
Up	
Down	
Left	
Right	
Interact	

[Capability Description Example]

[Functionality Description Example]

Utility of Discovered Capability Models

If Link starts in the state shown below:



 \bigcirc C1 \rightarrow C5 (Go next to Ganon \rightarrow Go next to Key)

[Example of an option for Capability Group]

Which sequence of actions can *Link* take to reach the state shown below?



[Example of an option for Functionality Group]

Results: Behavior Prediction Study



Key Takeaways

The proposed approach:

- Efficiently discovers capabilities of an agent in a STRIPS-like form in fully observable and deterministic settings.
- Needs no prior knowledge of the agent model.
- Only requires an agent to have rudimentary query answering capabilities.
- Learns a maximally consistent capability model accurately with a small number of queries.
- Learns capability descriptions that are interpretable as shown using a user study.



