

Neuro-Symbolic Agents: Reason, Act, and Learn Faithfully in the Complex World



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AI / ML Lab
TU Darmstadt



@SIG-FPAI, 133

August 26, 2025

Neuro-Symbolic AI Summer School



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The image features a purple and white design. On the left is the Centaur Artificial Intelligence Institute logo, which is circular with a centaur holding a torch and a book, surrounded by the text "CENTAUR ARTIFICIAL INTELLIGENCE INSTITUTE". To the right of the logo, the text "Neuro-Symbolic AI Summer School 2025" is displayed in large white letters. Below this, the date "8月 14日木曜日" and time "15:00 - 8月15日 23:00 GMT+2" are shown. A small icon of a person with a speech bubble is followed by the text "オンライン". At the bottom is a small circular icon with a green and red gradient.

The YouTube channel page for "Centaur AI Institute" has a black background. It features the same circular logo as the promotional image. The channel name "Centaur AI Institute" is at the top, followed by the handle "@CentaurAIInstitute" and a subscriber count of "441人". Below this, a short description states "This channel is reserved for live events, please subscribe to Centaur AI Institute" and provides a link "centaurinstitute.org". A "登録済み" button with a bell icon is at the bottom.

Two video thumbnails are shown side-by-side. Both have a purple header with the text "Neuro-Symbolic AI Summer School 2025" and the "CENTAUR ARTIFICIAL INTELLIGENCE INSTITUTE" logo. The left thumbnail shows two men speaking, with a timestamp of "9:21:16". The right thumbnail shows a man speaking, with a timestamp of "6:59:33". Below each thumbnail is a caption: "Neuro-Symbolic AI Summer School 2025 - Day 2 | Centa..." and "Neuro-Symbolic AI Summer School 2025 - Day 1 | Centa...". At the bottom, there are views counts: "1137 回視聴・10日前に配信済み" and "2074 回視聴・11日前に配信済み".

Outline

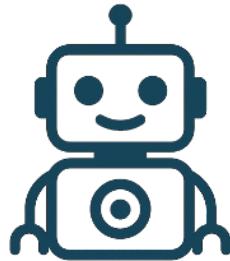


My research goal:

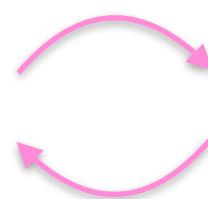
An intelligent agent that can:

- *perform faithful reasoning on noisy observations*
- *act effectively interacting with complex environments*
- *learn efficiently from less data*

Reasoning Agent



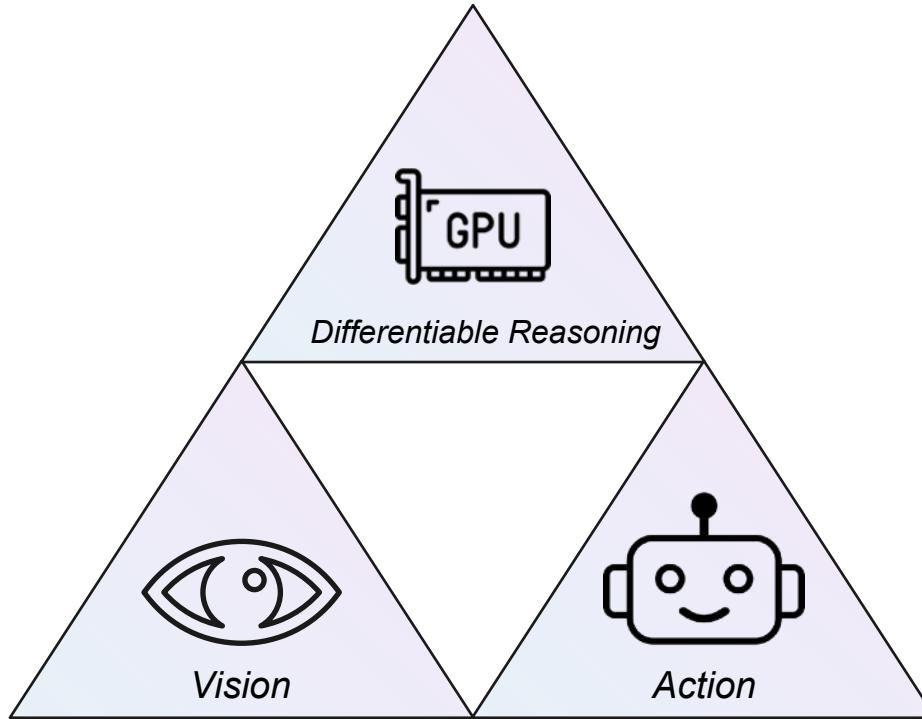
Complex World



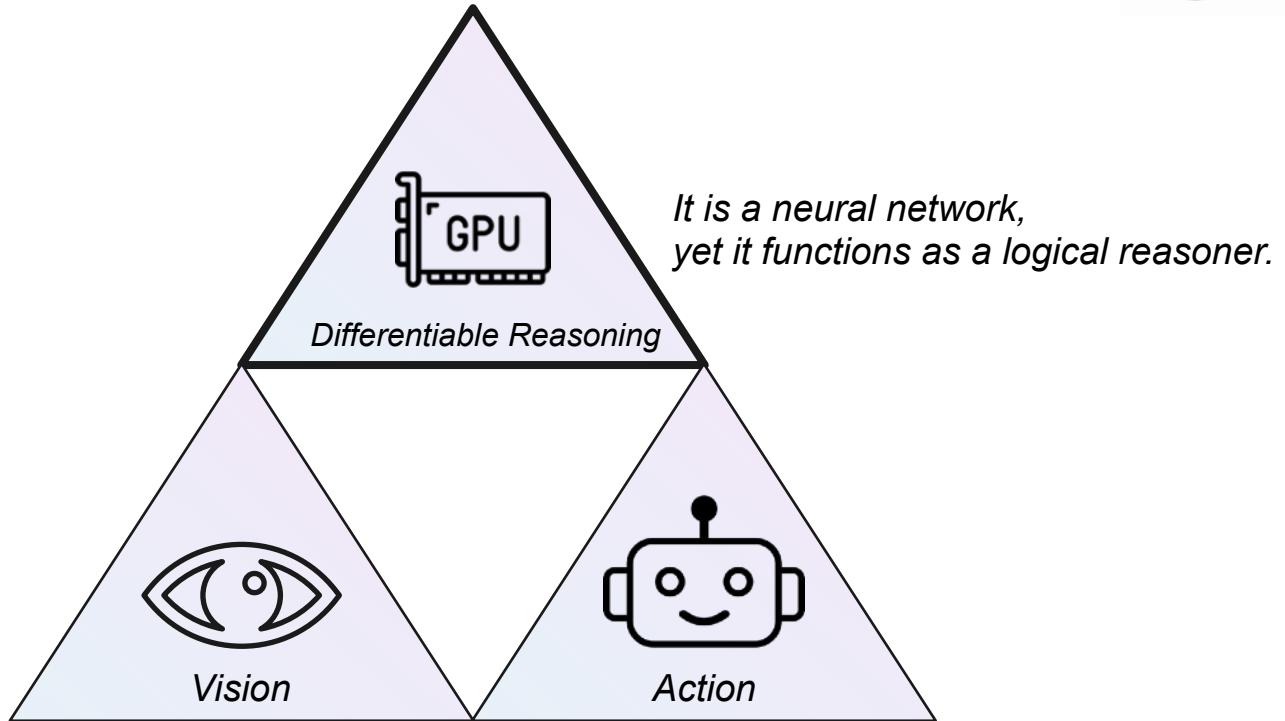
Research Overview



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Research Overview

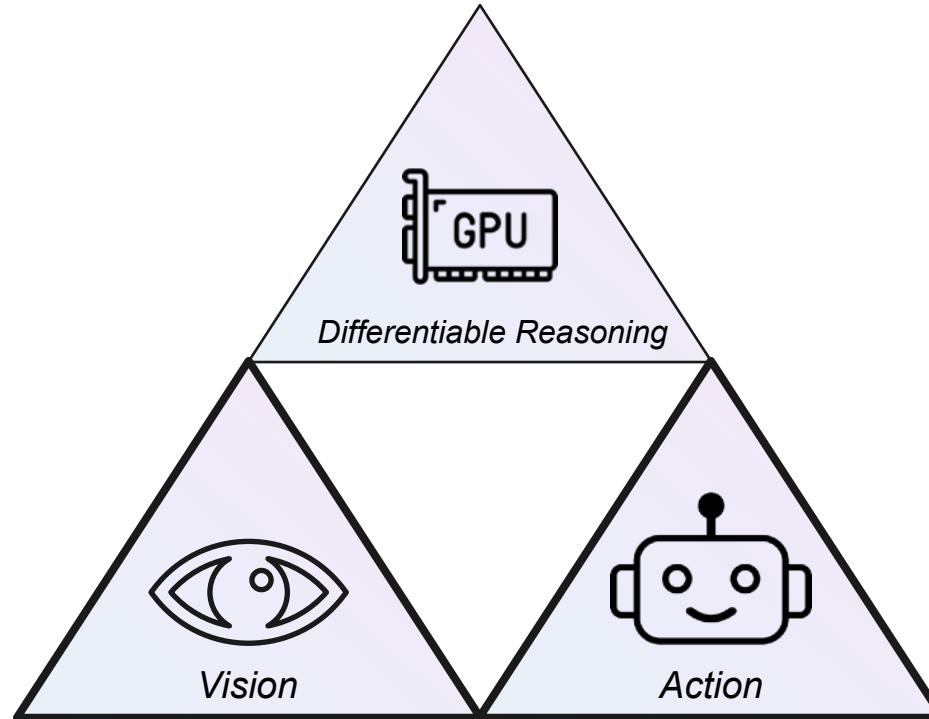


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Segment objects with complex prompts



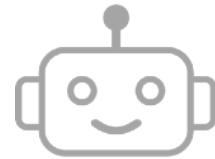
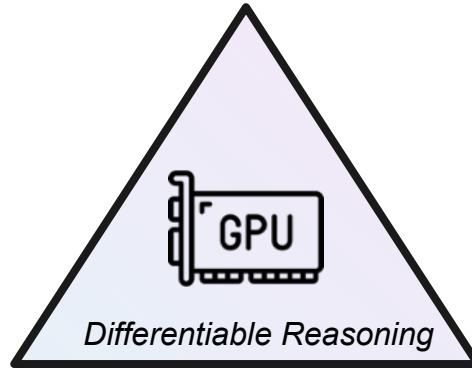
*Reasoning to act,
Learning from experiences*



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Logical Reasoning... Differentiably?

$$\forall x \text{ (human}(x) \rightarrow \text{mortal}(x))$$

Input:

human(socrates).



Logical Reasoning... Differentiably?

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human(socrates).



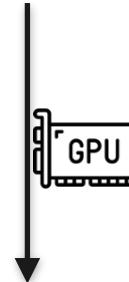
Output:

mortal(socrates).

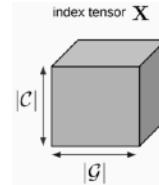
Logical Reasoning... Differentiably?

$$\forall x \text{ (human}(x) \rightarrow \text{mortal}(x))$$
Input:`human(socrates).`

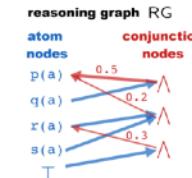
- gradient-based learning
- scalable GPU inference



Tensor Encoding [1,2]



GNN Encoding [3]

**Output:**`mortal(socrates).`[1] Evans, Grefenstette: Learning Explanatory Rules from Noisy Data. *JAI/R* 2018[2] Shindo, Pfanschilling, Dhami, Kersting: oILP: Thinking Visual Scenes as Differentiable Logic Programs. *Mach. Learn.* 2023[3] Shindo, Pfanschilling, Dhami, Kersting: Learning Differentiable Logic Programs for Abstract Visual Reasoning. *Mach. Learn.* 2024

Perception + Differentiable Reasoning

Raw Input



Image



Text

[1] Evans, Grefenstette: Learning Explanatory Rules from Noisy Data. *JAI/R* 2018

[2] Shindo, Pfanschilling, Dhami, Kersting: oILP: Thinking Visual Scenes as Differentiable Logic Programs. *Mach. Learn.* 2023

[3] Shindo, Pfanschilling, Dhami, Kersting: Learning Differentiable Logic Programs for Abstract Visual Reasoning. *Mach. Learn.* 2024

Perception + Differentiable Reasoning

Raw Input



perception

Input



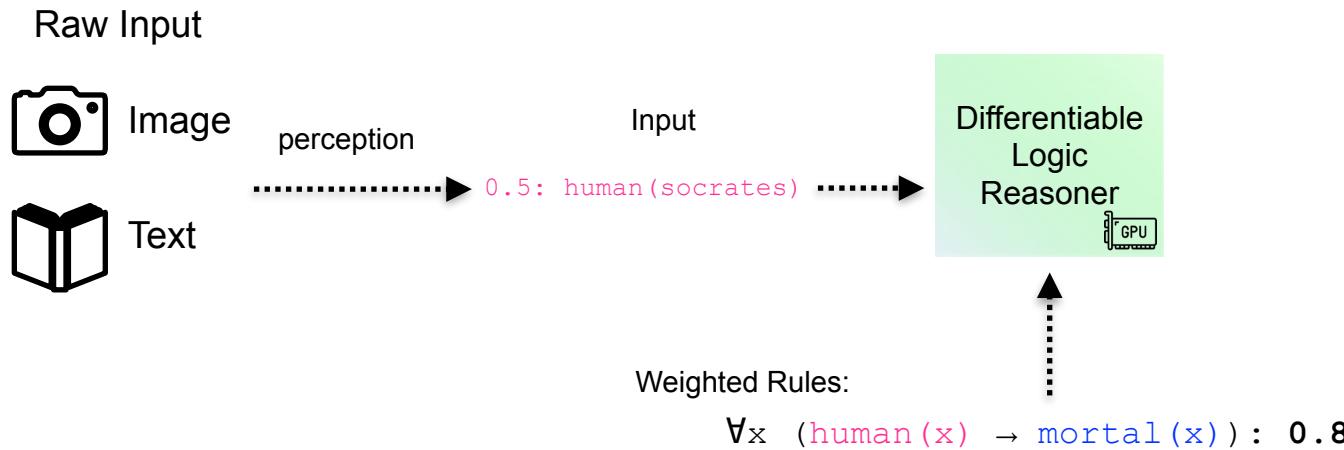
0.5: human(socrates)

[1] Evans, Grefenstette: Learning Explanatory Rules from Noisy Data. *JAI/R* 2018

[2] Shindo, Pfanschilling, Dhami, Kersting: oILP: Thinking Visual Scenes as Differentiable Logic Programs. *Mach. Learn.* 2023

[3] Shindo, Pfanschilling, Dhami, Kersting: Learning Differentiable Logic Programs for Abstract Visual Reasoning. *Mach. Learn.* 2024

Perception + Differentiable Reasoning

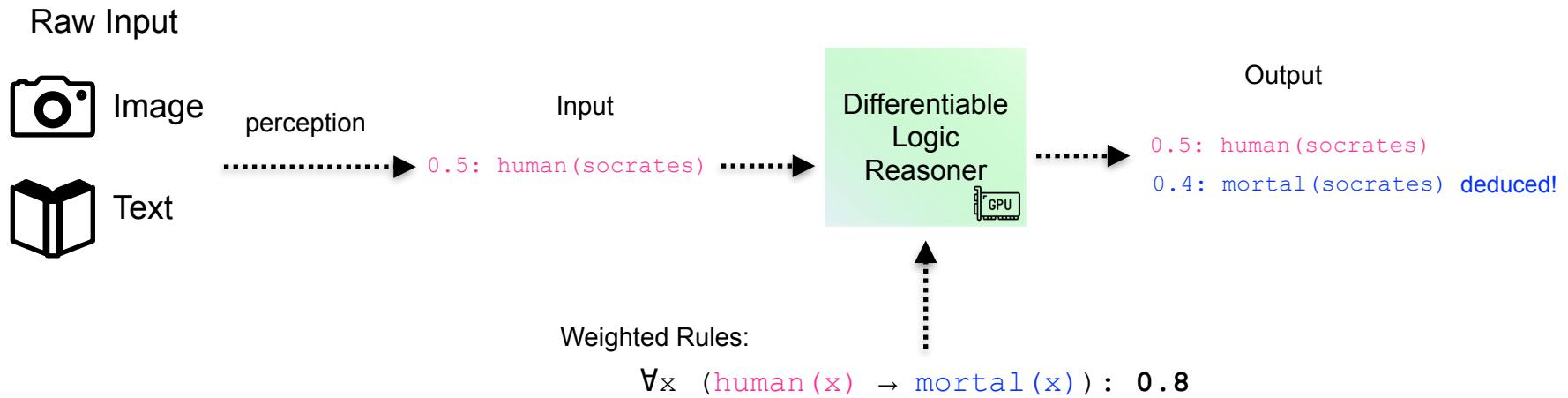


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Perception + Differentiable Reasoning

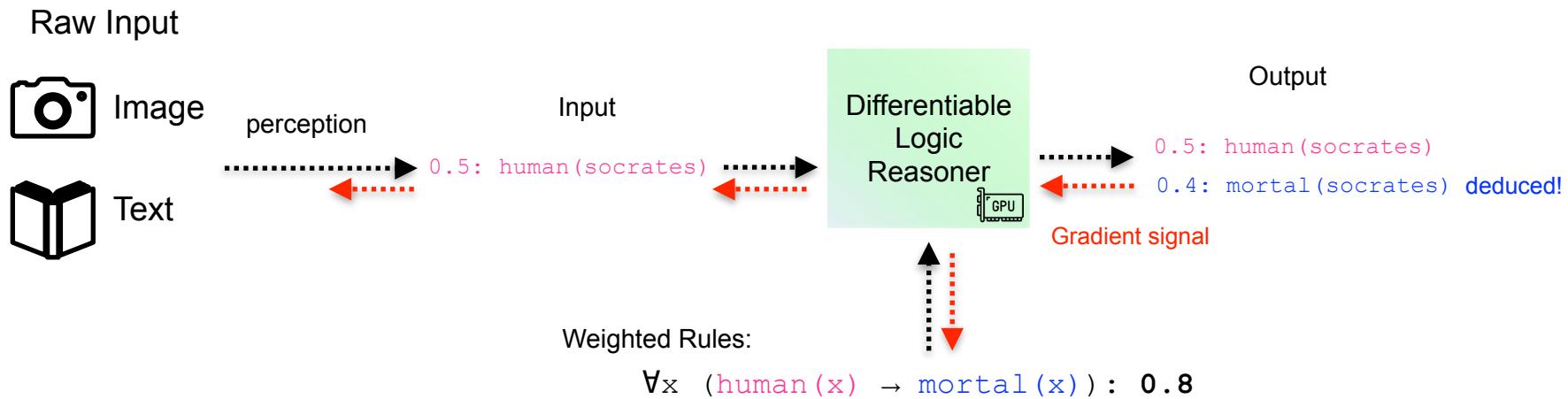


[1] Evans, Grefenstette: Learning Explanatory Rules from Noisy Data. *JAI/R* 2018

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Perception + Differentiable Reasoning



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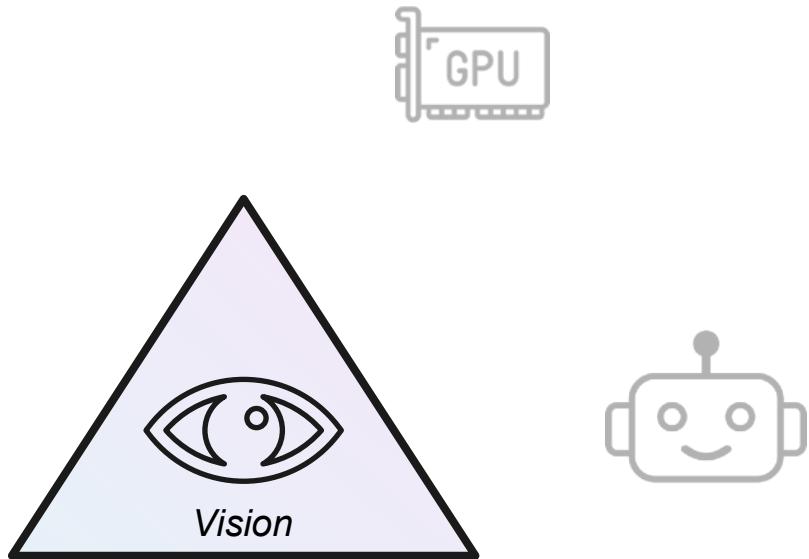


Image Segmentation with Complex Textual Prompts

Visual Input



Deictic Prompt

*“An object that is on the boat,
and that is holding an umbrella.”*

Image Segmentation with Complex Textual Prompts

Visual Input



Segmentation Output



Deictic Prompt

*“An object that is on the boat,
and that is holding an umbrella.”*

Image Segmentation with Complex Textual Prompts

Visual Input



Segmentation Output



Deictic Prompt

*“An object that is on the **boat**,
and that is holding an umbrella.”*



Image Segmentation with Complex Textual Prompts

Visual Input



Segmentation Output



Our approach

Large
Language
Models

Deictic Prompt

*"An object that is on the boat,
and that is holding an umbrella."*

Image Segmentation with Complex Textual Prompts



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Visual Input



Our approach

Large
Language
Models

Differentiable
Logic
Reasoner

Segmentation Output



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Image Segmentation with Complex Textual Prompts

Visual Input



Our approach

Large
Language
Models

Differentiable
Logic
Reasoner

Large
Segmentation
Models

Segmentation Output



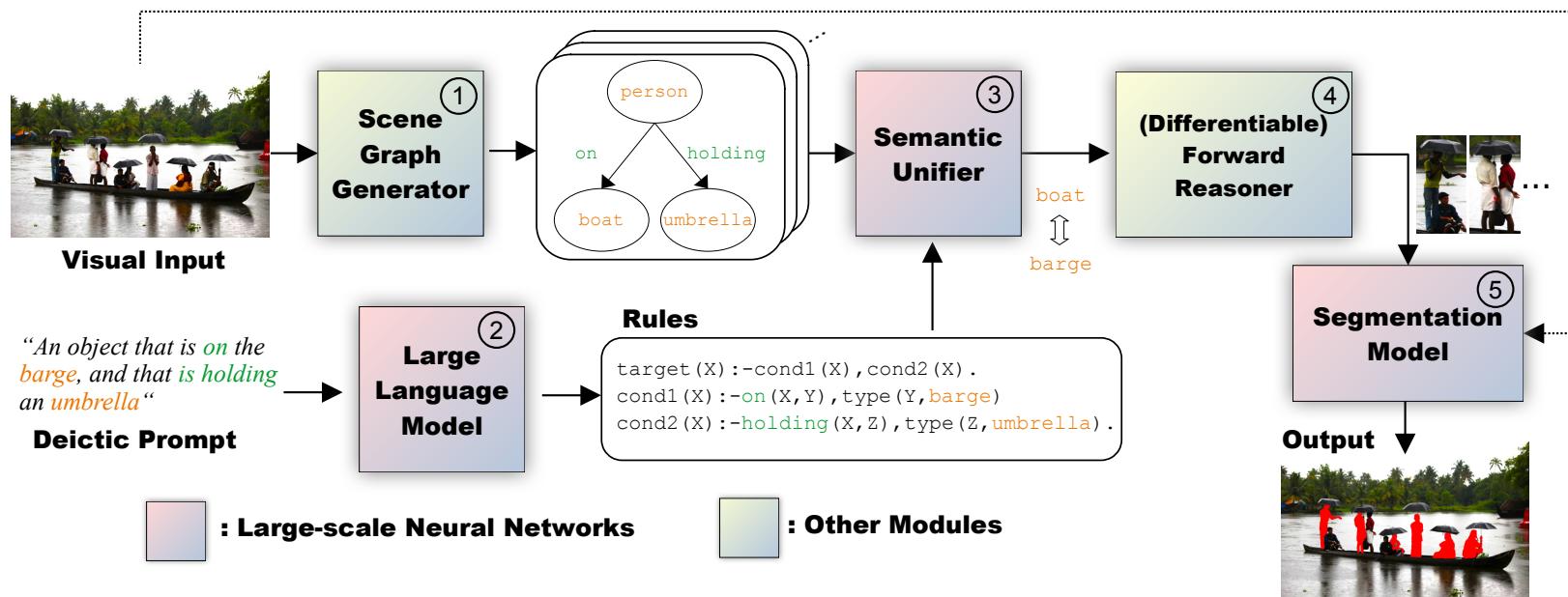
Deictic Prompt

*"An object that is on the boat,
and that is holding an umbrella."*

DeiSAM: Large-scale NNs + Differentiable Reasoners

Deictic Segment Anything Model

Key Idea: **Large-scale Neural Networks + Differentiable Reasoners**

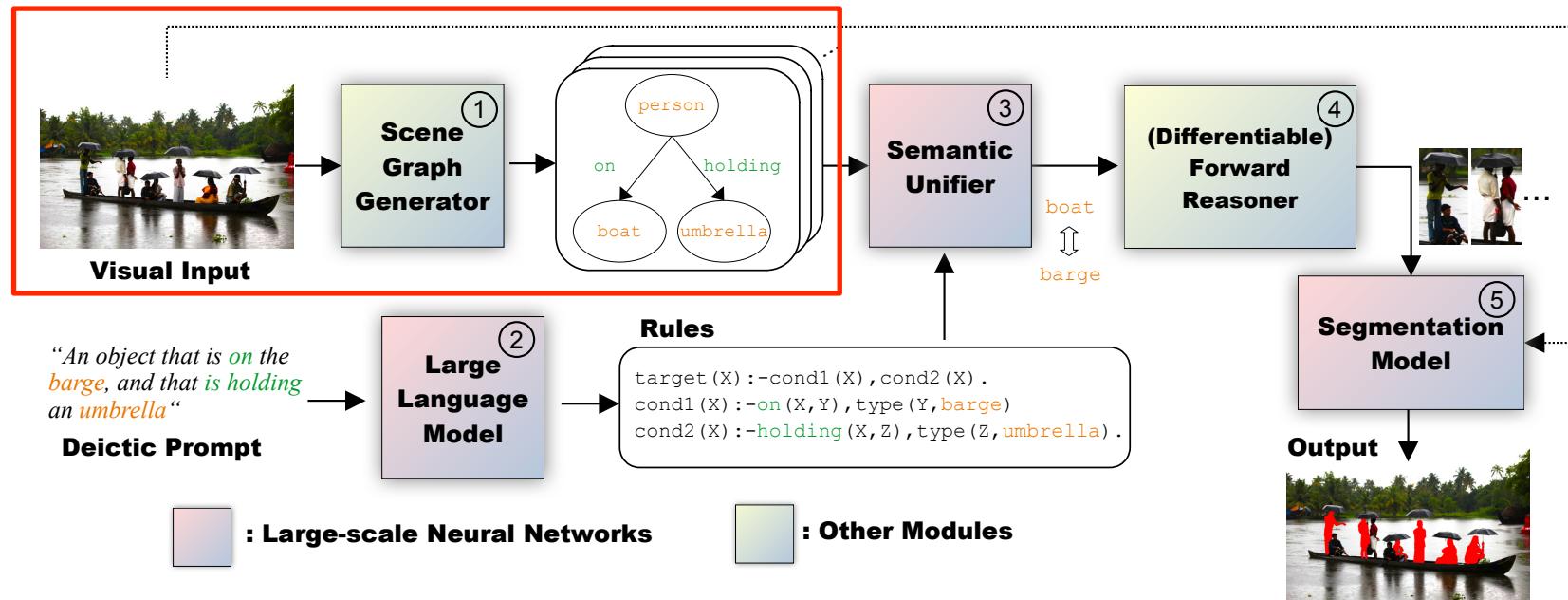


DeiSAM: Large-scale NNs + Differentiable Reasoners



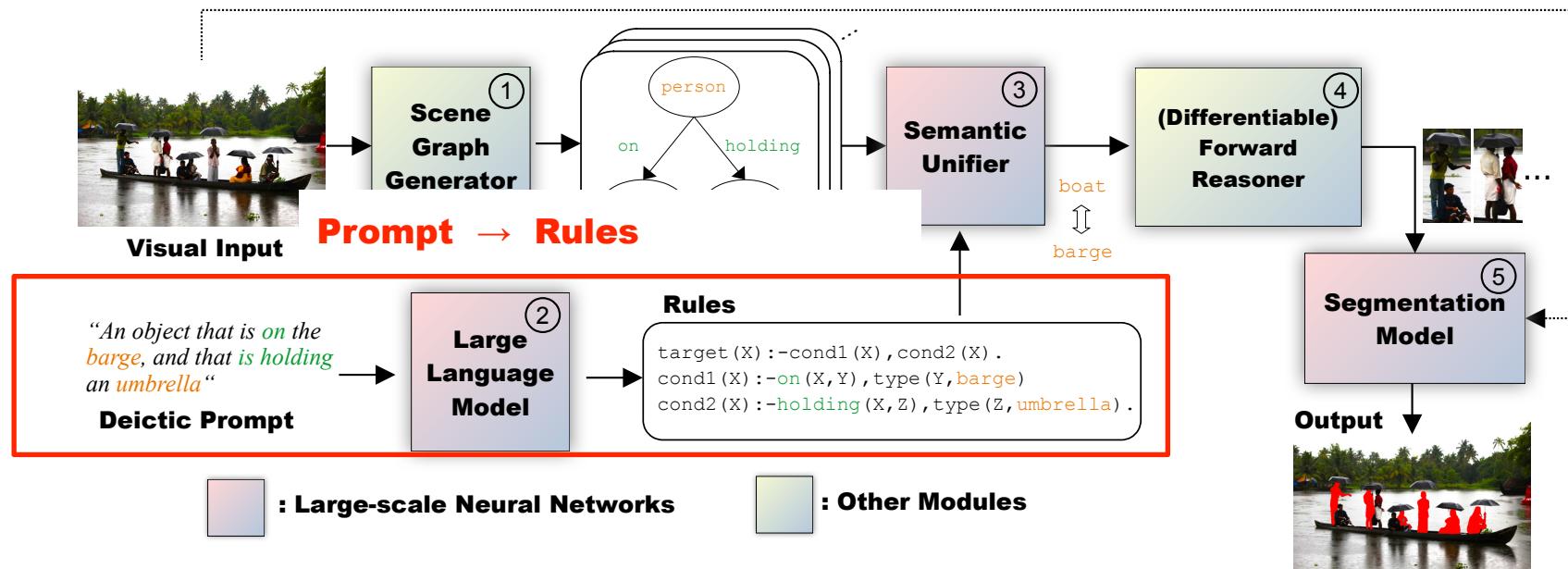
Generate scene graphs from visual input

Image → Scene Graphs



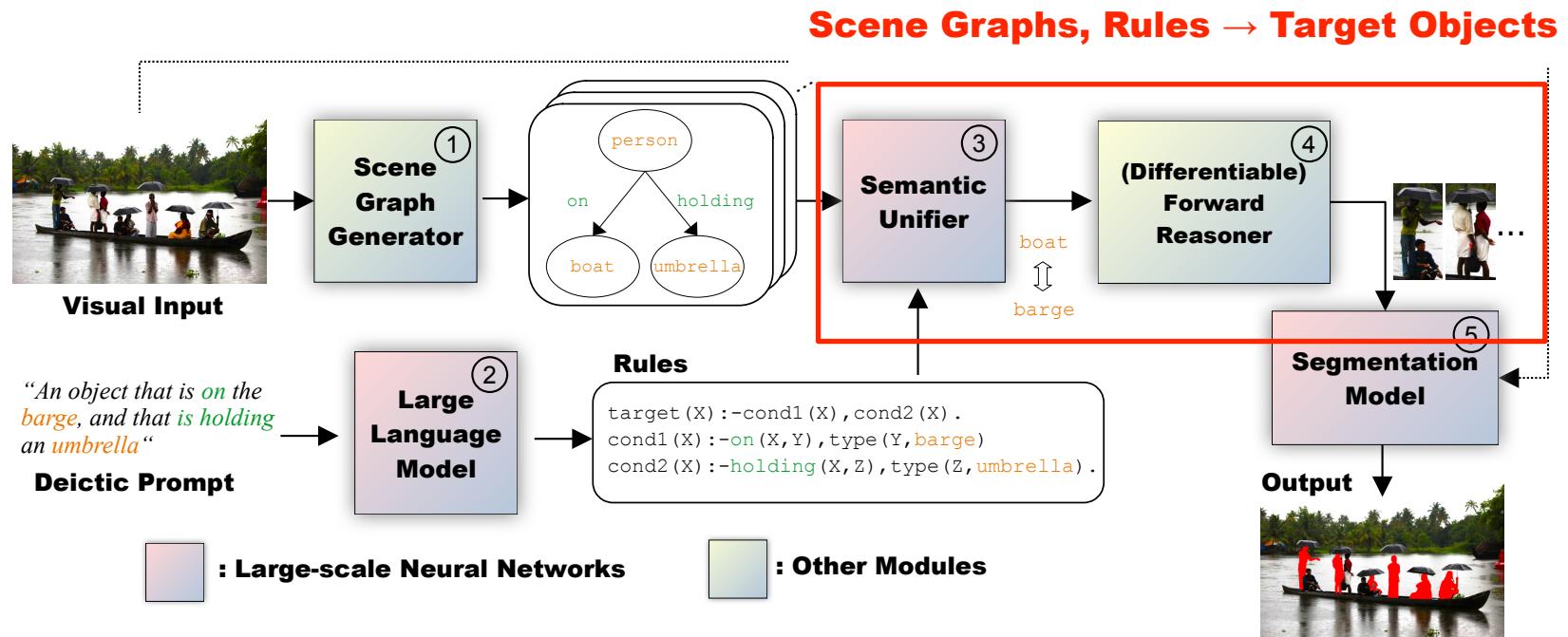
DeiSAM: Large-scale NNs + Differentiable Reasoners

Generate rules from deictic prompt



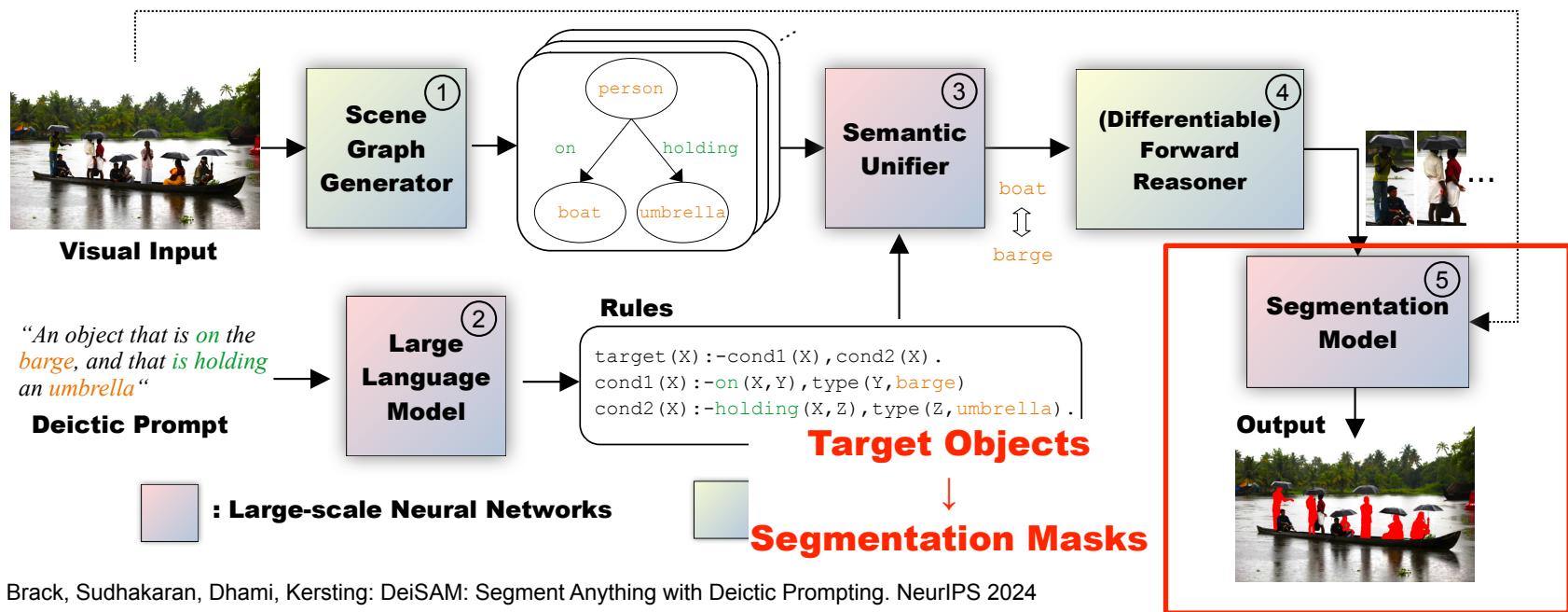
DeiSAM: Large-scale NNs + Differentiable Reasoners

Identify objects by (differentiable) forward reasoning
 - compute logical entailment given scene graphs and rules



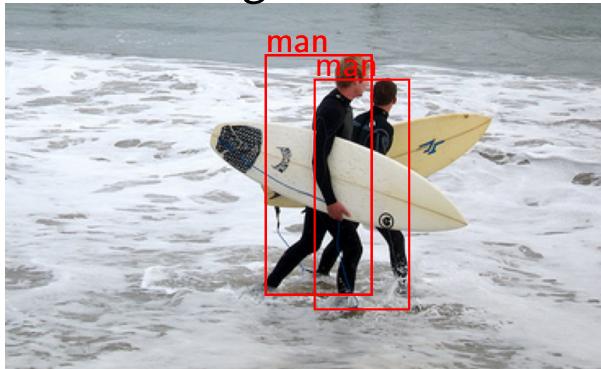
DeiSAM: Large-scale NNs + Differentiable Reasoners

Segment objects by Segment Anything Model (SAM)



DeiVG Dataset

'An object that is wearing a wet suit'



Complexity 1 (DeiVG₁)

'An object that has a handle and that is on a bench'



Complexity 2 (DeiVG₂)

- 10k pairs of visual scene and deictic prompt
- Generated from Visual Genome dataset

Results

An object that is on the table and that is behind a mug.

DeiSAM
(Ours)



GroundedDino
SAM



SEEM



OFA-SAM



GLIP-SAM



An object that is on the boat and that is holding an umbrella.



An object that is on the car and that has ears.



Results



Method	Mean Average Precision (%) ↑		
	val	testA	testB
LISA	67.55	74.86	63.03
GroundedSAM	55.09	66.21	44.21
DeiSAM	71.72	77.29	64.98

Comparison on RefCOCO+

“**kid** wearing navy shirt”

Results



Method	Mean Average Precision (%) ↑		
	val	testA	testB
LISA	67.55	74.86	63.03
GroundedSAM	55.09	66.21	44.21
DeiSAM	71.72	77.29	64.98

Method	Mean Average Precision (%) ↑		
	val	testA	testB
LISA	44.92	47.60	43.23
GroundedSAM	30.06	31.75	28.12
DeiSAM	71.56	79.51	66.43

Comparison on RefCOCO+

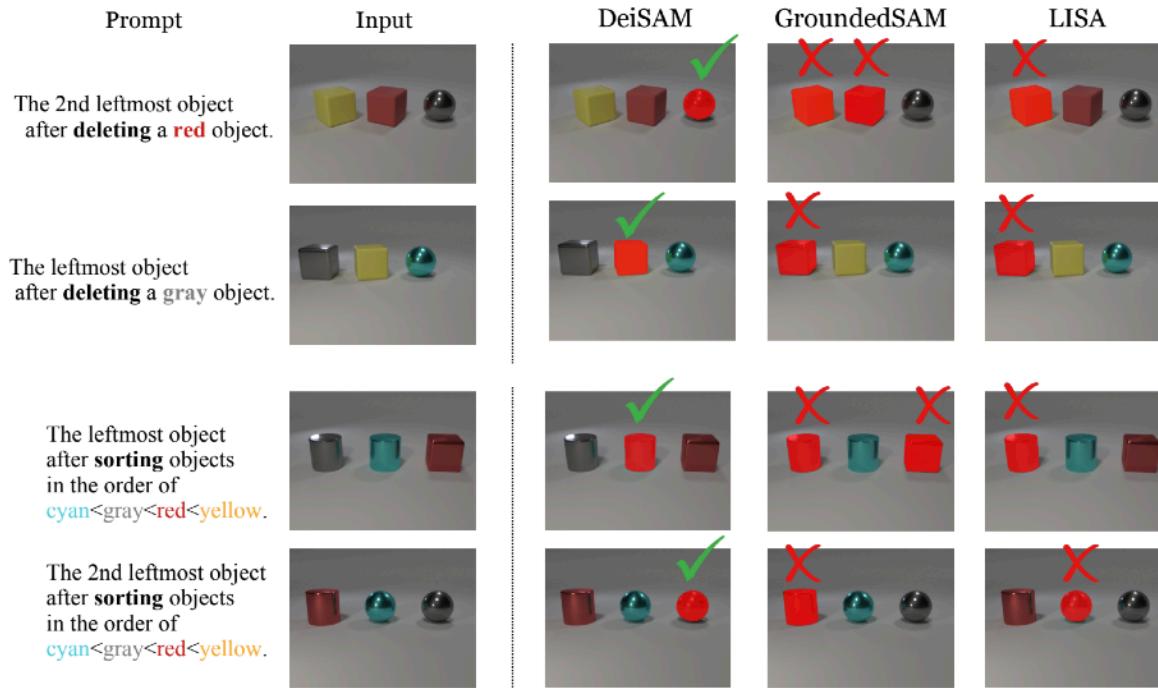
“kid wearing navy shirt”

Comparison on DeiRefCOCO+

“an object that is wearing navy shirt”.

Large neural models fail on the abstract prompts!

Results



Results

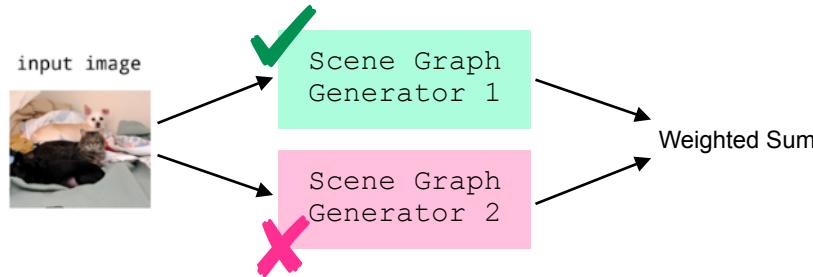


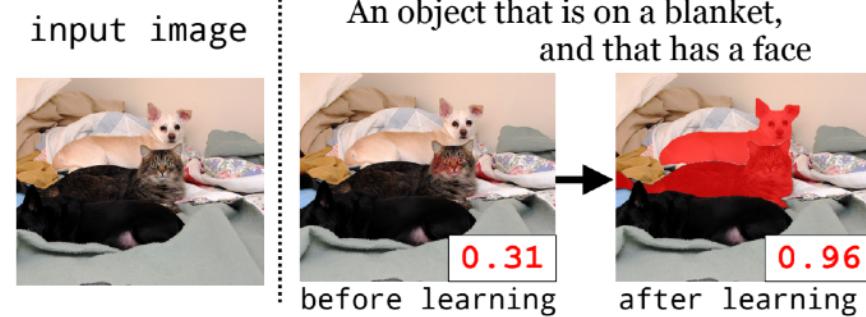
Table 5: End-to-end training improves DeiSAM.
 Mean Average Precision on the test split of the task of learning SGGs. DeiSAM-VETO uses a trained VETO model (Sudhakaran et al., 2023), DeiSAM-Mixture (naive) uses a mixture of a trained VETO model and VG scene graphs with randomly initialized rule weights, DeiSAM-Mixture* uses the resulted mixture model after the weight learning.

Method	mAP (%) ↑	
	DeiVG ₁	DeiVG ₂
DeiSAM-VETO	6.64	15.92
DeiSAM-Mixture (naive)	37.61	59.81
DeiSAM-Mixture*	64.44	86.57

```

% Program 2
targetSgg(X, SG):-cond1(X, SG), cond2(X, SG).
cond1(X, SG):-hasSgg(X, Y, SG), typeSgg(Y, hair, SG).
cond2(X, SG):-onSgg(X, Y, SG), onSgg(Y, surfboard, SG).
% Compose weighted mixtures.
w_1: target(X):-targetSgg(X, sgg1).
w_2: target(X):-targetSgg(X, sgg2).
  
```

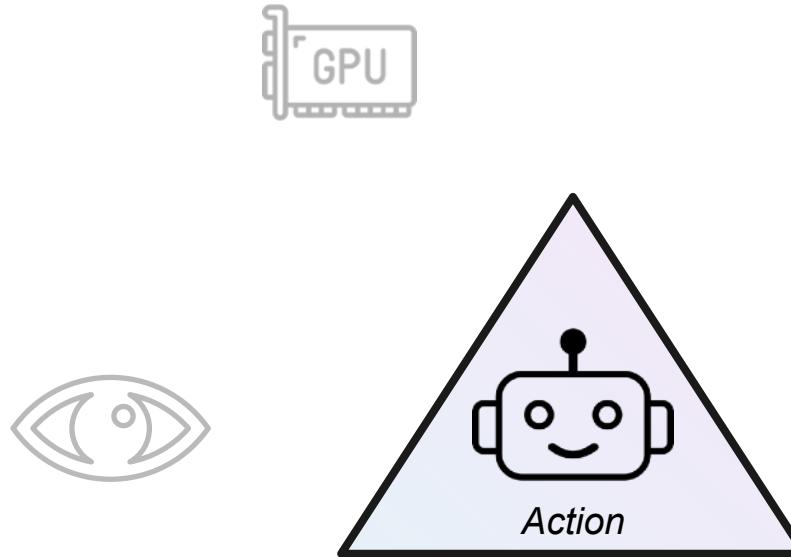
Listing 2: A program for SGG learning.



Research Overview

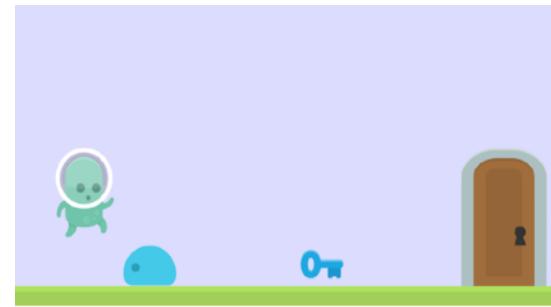
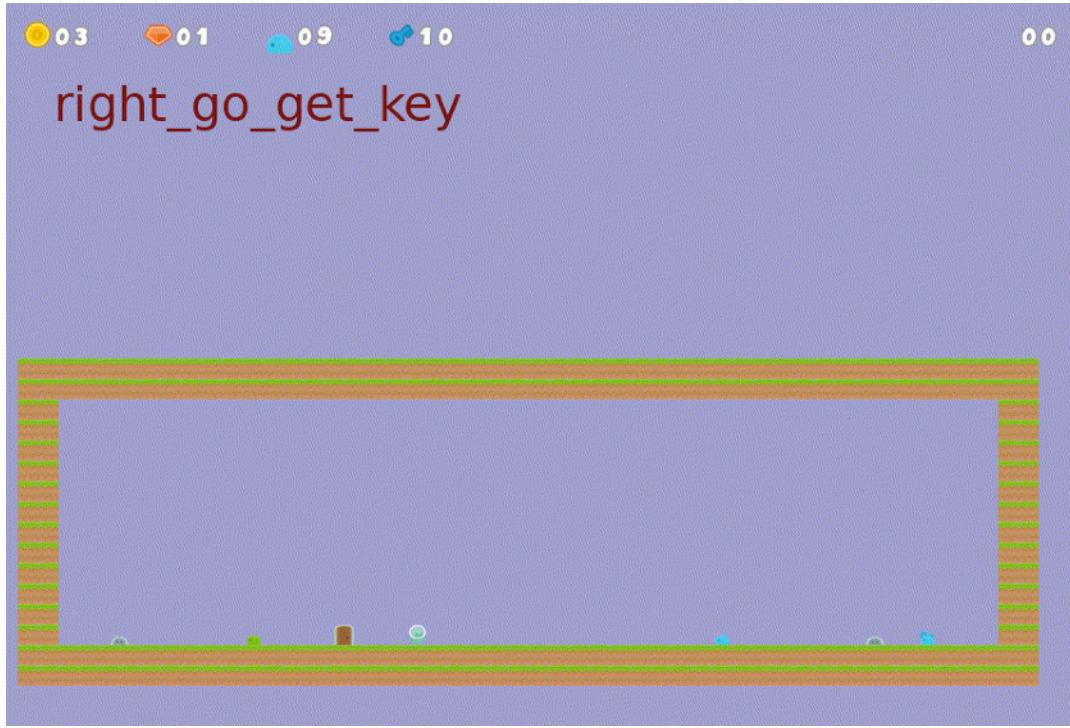


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Fully (Differentiable) Logic Agent

NUDGE: Neurally gUided Differentiable loGic policiEs



0.8: `jump:- closeby(agent, enemy).`

Logic Policy



Neural Critic

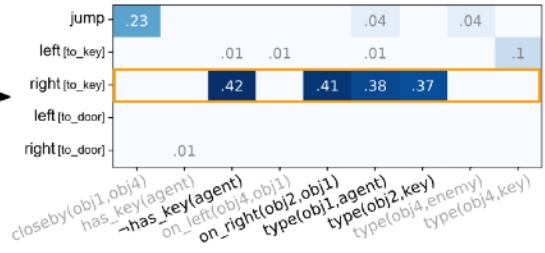
NUDGE is Interpretable and Explainable

Learned Policy

```
0.57:jump:-closeby(agent,enemy).  
0.32:left[to_key]:- ~has_key(agent),on_right(agent,key)  
0.30:left[to_door]:- has_key(agent),on_left(door,agent).  
0.29:right[to_key]:-~has_key(agent),on_left(agent,key).  
0.56:right[to_door]:-has_key(agent),on_left(agent,door)
```

Explanation for action

Why **right**?



"Because the agent does not have the key and the key is on its right."

Are „Neural“ or „Logical“ Policies Enough?

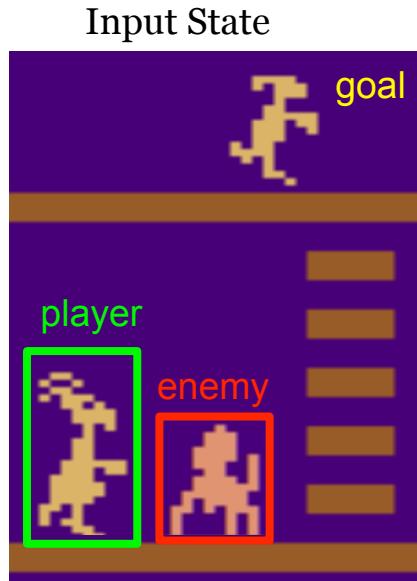


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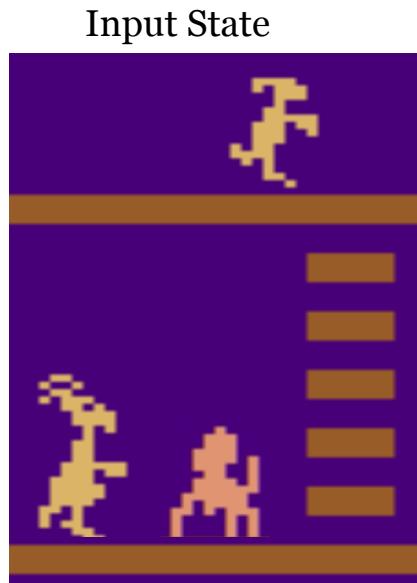


Generated by ChatGPT4o

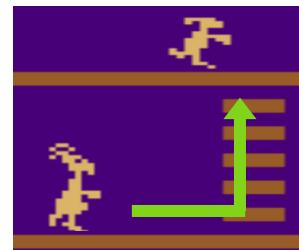
Hybrid Neuro-Symbolic Policies?



Hybrid Neuro-Symbolic Policies?



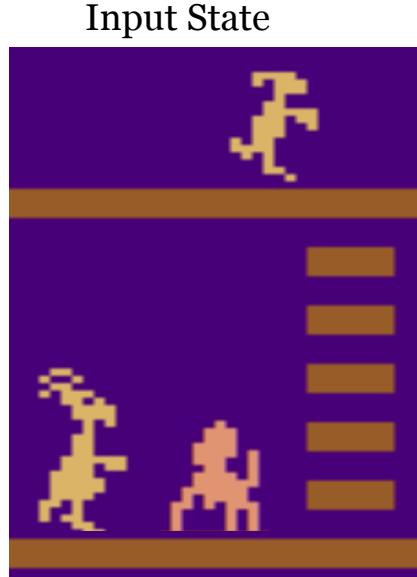
High-level Reasoning



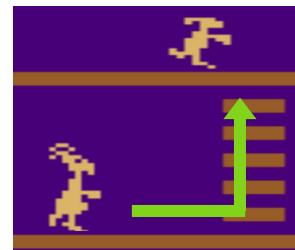
Reach to the goal

- Object-centric state
- Reasoning and Planning

Hybrid Neuro-Symbolic Policies?



High-level Reasoning



Reach to the goal

- Object-centric state
 - Reasoning and Planning
-

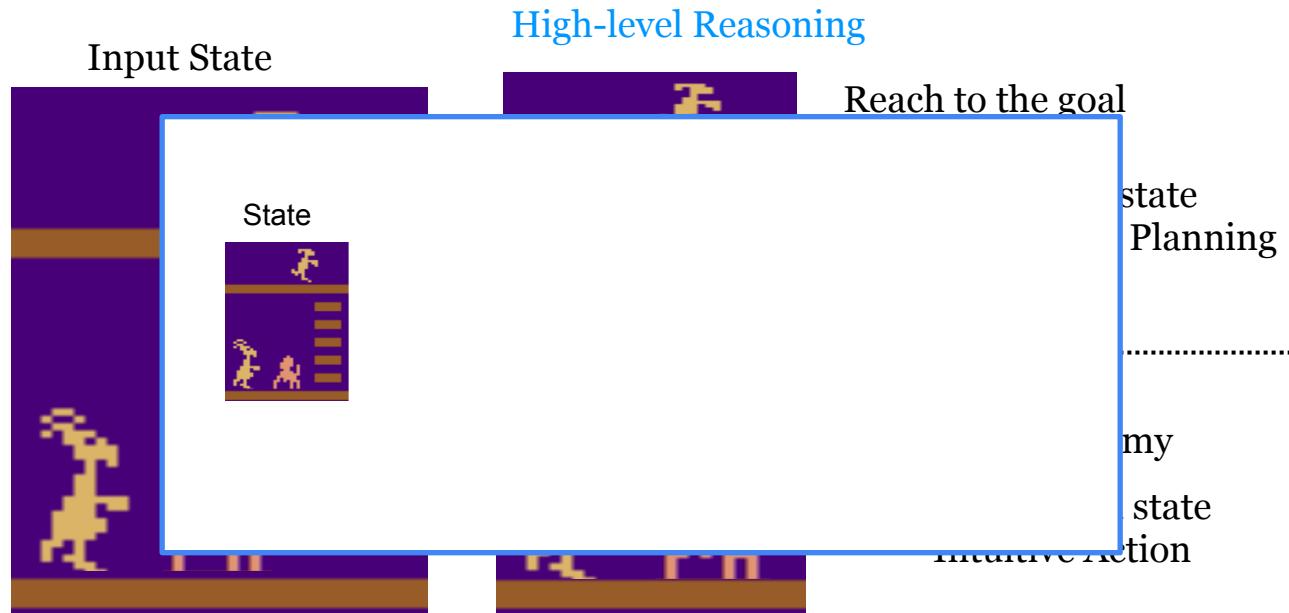
Low-level Reaction



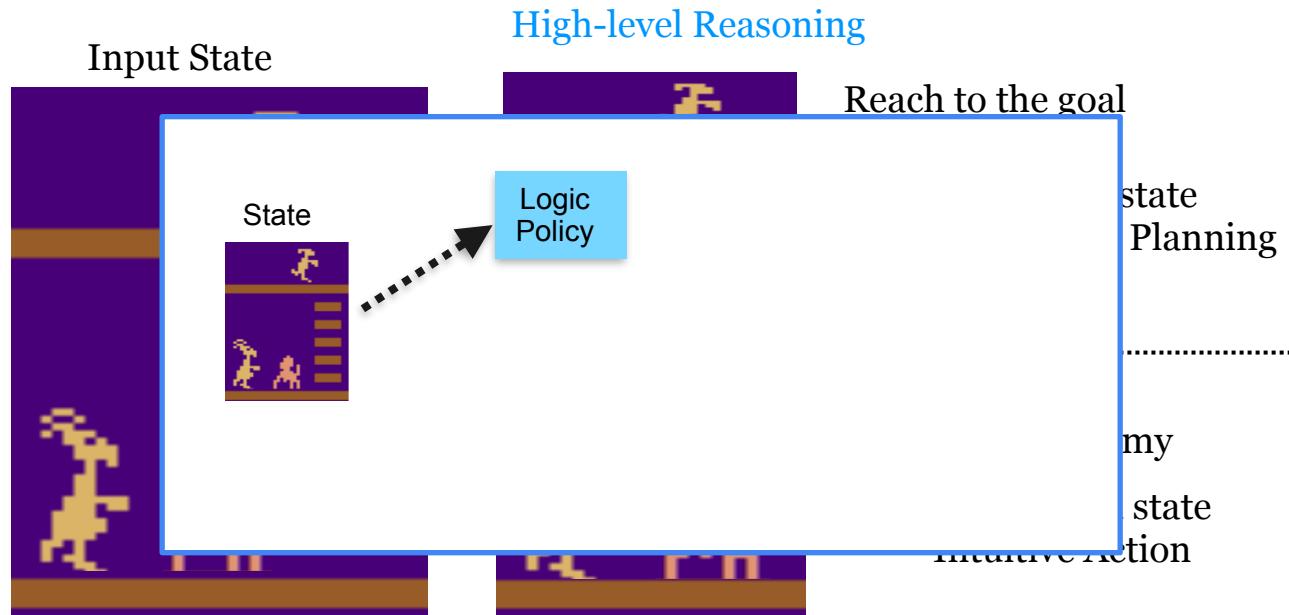
Punch the enemy

- Pixel-based state
- Intuitive Action

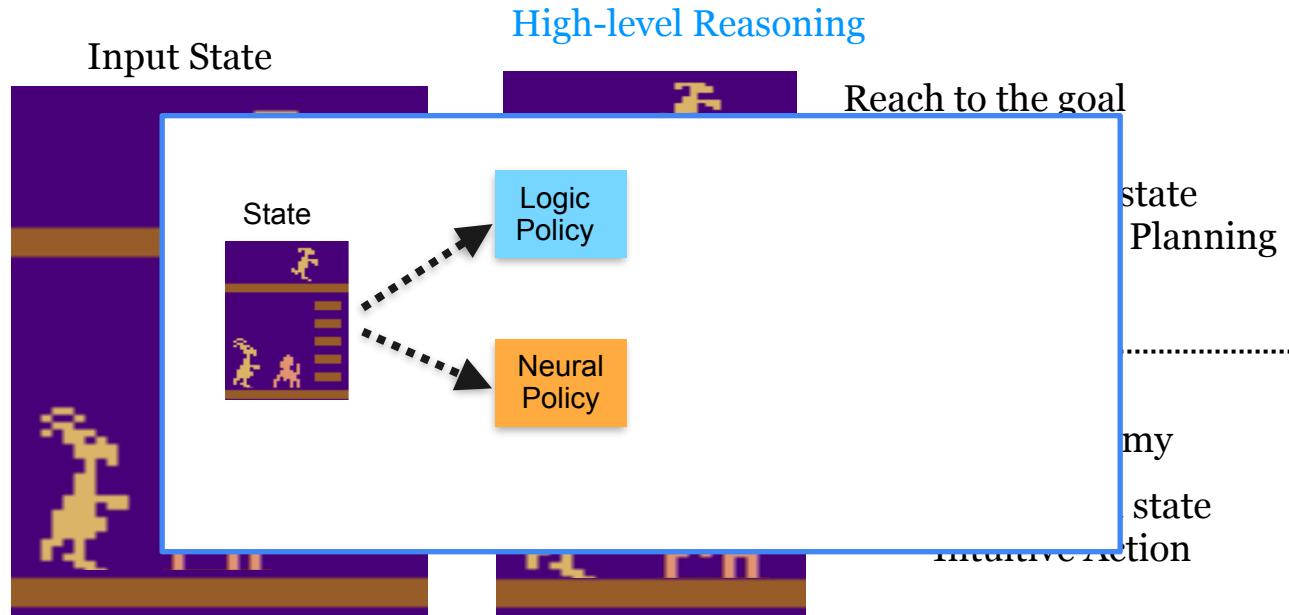
Hybrid Neuro-Symbolic Policies?



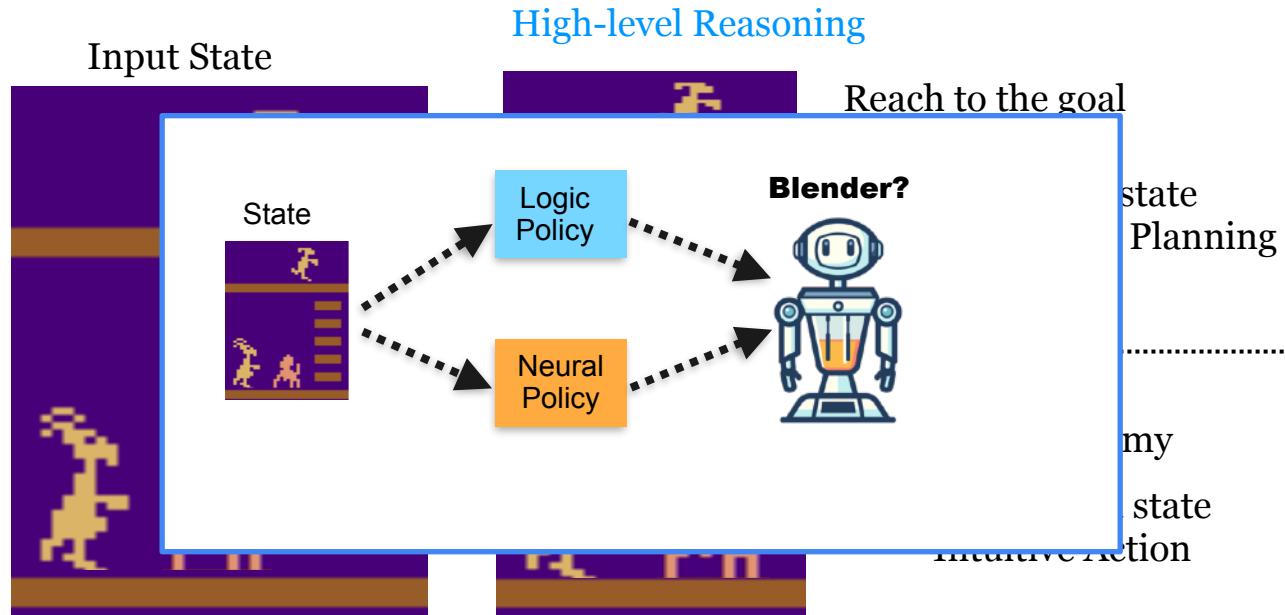
Hybrid Neuro-Symbolic Policies?



Hybrid Neuro-Symbolic Policies?



Hybrid Neuro-Symbolic Policies?

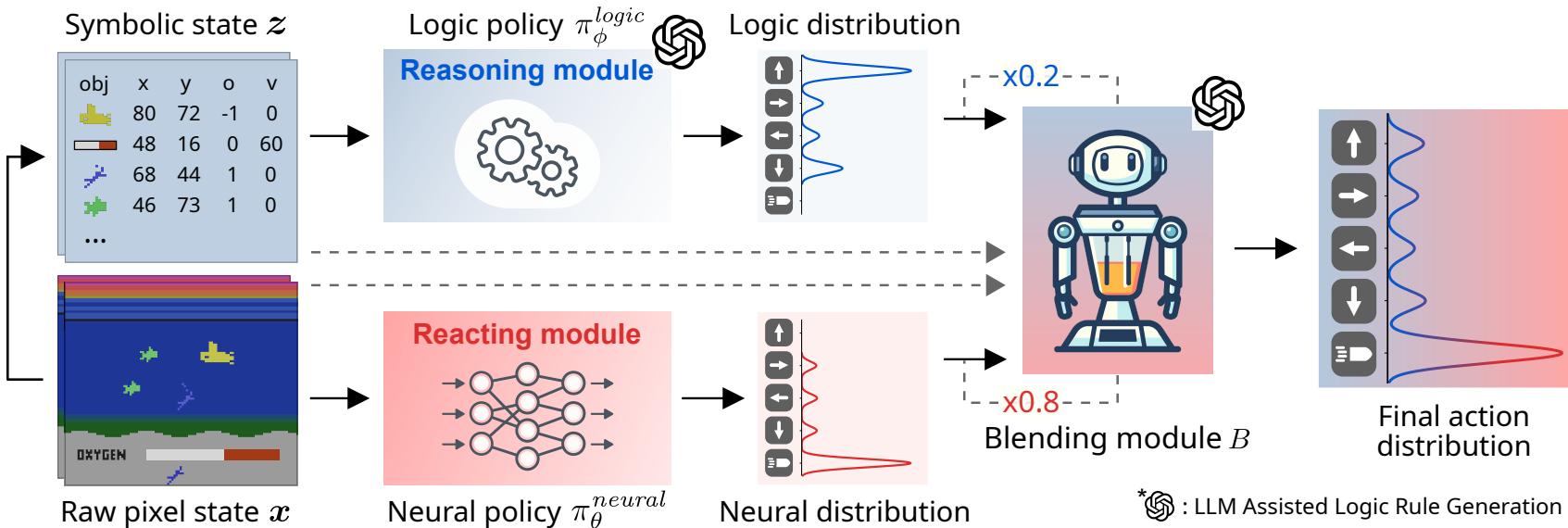


BlendRL: A Framework for Merging Symbolic and Neural Policy Learning

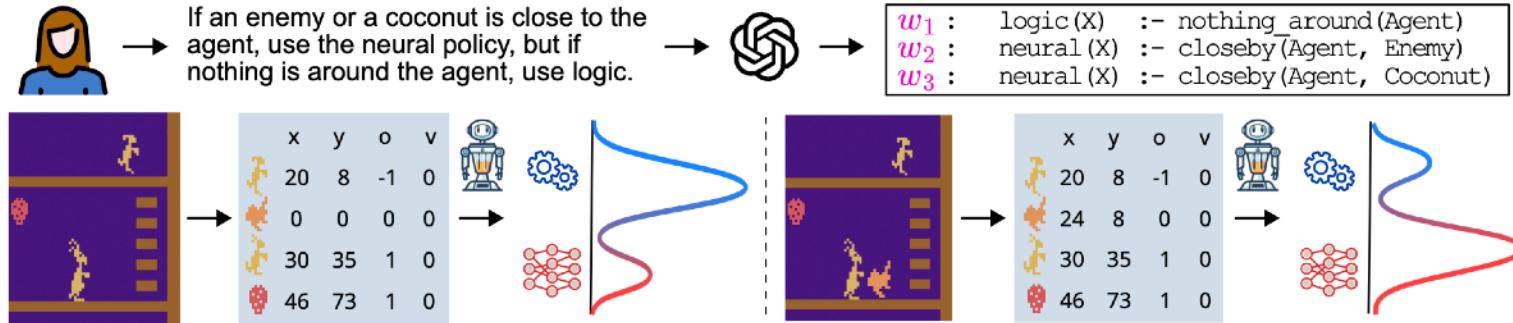


```
[R1] 0.73: up(X):-is_empty(Oxygen).  
[R2] 0.42: up(X):-above(Diver,Agent).  
[R3] 0.31: left(X):-left_of(Diver,Agent).
```

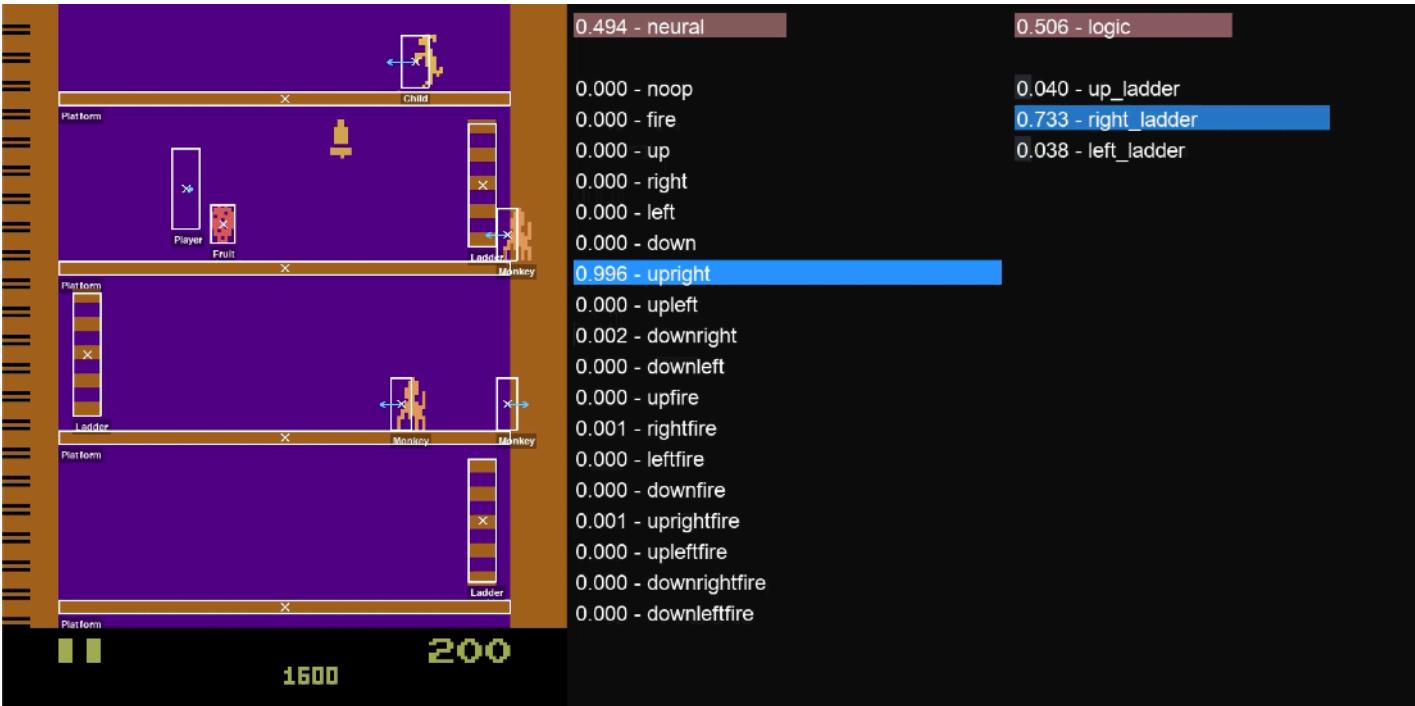
Listing 1: Exemplary action rules for *Seaquest*.



BlendRL: A Framework for Merging Symbolic and Neural Policy Learning



BlendRL: A Framework for Merging Symbolic and Neural Policy Learning



Neural PPO



suboptimal policy!

BlendRL: A Framework for Merging Symbolic and Neural Policy Learning



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Neural PPO



suboptimal policy!



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Thank you for your attention. Happy to answer any questions!

Many thanks to my amazing collaborators!

Quentin
Delfosse



Viktor
Pfanschilling



Manuel
Brack



Gopika
Sudhakaran



Devendra
Singh
Dhami



Patrick
Schramowski



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