Compositional Instruction Following with Language Models and Reinforcement Learning

Vanya Cohen*, **Geraud Nangue Tasse***, Nakul Gopalan, Steven James, Matthew Gombolay, Ray Mooney, Benjamin Rosman













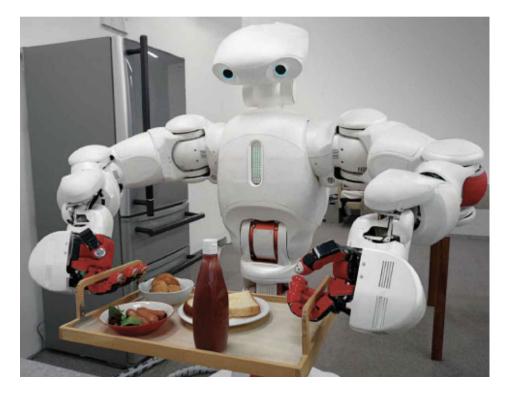
Language and RL Tasks Share Compositional Structure

 "Serve breakfast with plain toast and ketchup..."



Language and RL Tasks Share Compositional Structure

- "Serve breakfast with plain toast and ketchup..."
- Neural networks struggle to generalize compositionally¹.



1. Lake, B. M., & Baroni, M. (2018). Generalization without systematicity: On the compositional skills of sequence-to-sequence recurrent networks. Proceedings of the 35th International Conference on Machine Learning.

Language and RL Tasks Share Compositional Structure

- "Serve breakfast with plain toast and ketchup..."
- Neural networks struggle to generalize compositionally¹.
- Compose existing policies to perform tasks with minimal training.



World Value Functions (Tasse et al. 2020, 2022)

$$Q_{\pi}(s, a) = \mathbb{E}_{s}^{\pi} \left[\sum_{t=0}^{\infty} \overline{r}(s_{t}, a_{t}) \right]$$

Nangue Tasse, G., James, S., & Rosman, B. (2020). A Boolean task algebra for reinforcement learning. Advances in Neural Information Processing Systems, 33, 17279–17290.
 Nangue Tasse, G., James, S., & Rosman, B. (2022, June). World value functions: Knowledge representation for multitask reinforcement learning. Paper presented at the 5th Multi-disciplinary Conference on Reinforcement Learning and Decision Making (RLDM).

World Value Functions (Tasse et al. 2020, 2022)

- Add a goal g to the Q function.
- WVF represents how to achieve all goals and their value
- Learn one WVF for each task in the environment we wish to compose.

$$Q_{\pi}(s, \boldsymbol{g}, a) = \mathbb{E}_{s}^{\pi} \left[\sum_{t=0}^{\infty} \overline{r}(s_{t}, \boldsymbol{g}, a_{t}) \right]$$

Nangue Tasse, G., James, S., & Rosman, B. (2020). A Boolean task algebra for reinforcement learning. Advances in Neural Information Processing Systems, 33, 17279–17290.
 Nangue Tasse, G., James, S., & Rosman, B. (2022, June). World value functions: Knowledge representation for multitask reinforcement learning. Paper presented at the 5th Multi-disciplinary Conference on Reinforcement Learning and Decision Making (RLDM).

World Value Functions (Tasse et al. 2020, 2022)

- Add a goal *g* to the Q function.
- WVF represents how to achieve all goals and their value
- Learn one WVF for each task in the environment we wish to compose.
- Train by penalizing the agent for entering a terminal state for another goal.

$$Q_{\pi}(s, \boldsymbol{g}, a) = \mathbb{E}_{s}^{\pi} \left[\sum_{t=0}^{\infty} \overline{r}(s_{t}, \boldsymbol{g}, a_{t}) \right]$$

$$\overline{r}(s, g, a) = \begin{cases} \overline{r}_{MIN} & \text{if } g \neq s \in G \\ r(s, a) & \text{otherwise} \end{cases}$$

Nangue Tasse, G., James, S., & Rosman, B. (2020). A Boolean task algebra for reinforcement learning. Advances in Neural Information Processing Systems, 33, 17279–17290.
 Nangue Tasse, G., James, S., & Rosman, B. (2022, June). World value functions: Knowledge representation for multitask reinforcement learning. Paper presented at the 5th Multi-disciplinary Conference on Reinforcement Learning and Decision Making (RLDM).

World Value Functions (WVF) (Tasse et al. 2020, 2022)

- Compose these WVFs.
 - Arbitrary expressions of AND, OR, and NOT.
 - Can now solve a combinatorial number of goal reaching tasks

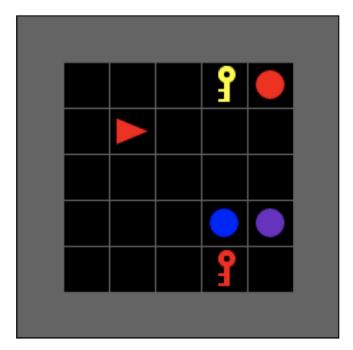
For AND (conjunction) the composed WVF is given by:

$$ar{Q}_1^* \wedge ar{Q}_2^* : \ \mathcal{S} \times \mathcal{G} \times \mathcal{A} \to \mathbb{R}$$

$$(s,g,a) \mapsto \min\{\bar{Q}_1^*(s,g,a), \bar{Q}_2^*(s,g,a)\}$$

BabyAl (Chevalier-Boisvert et al. 2019)

 Gridworld domain consisting of navigation tasks.

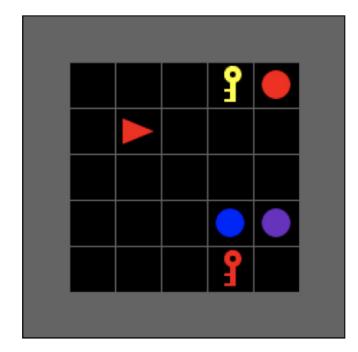


BabyAl (Chevalier-Boisvert et al. 2019)

 Gridworld domain consisting of navigation tasks.

"Pick up a red object" ∧ "Pick up a key"

¬"Pick up a blue object" V "Pick up the ball"



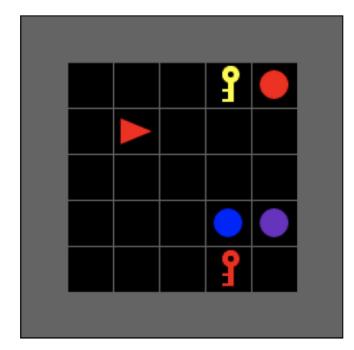
BabyAl (Chevalier-Boisvert et al. 2019)

 Gridworld domain consisting of navigation tasks.

"Pick up a red object" ∧ "Pick up a key"

¬"Pick up a blue object" V "Pick up the ball"

 Modified task set to include 162 goal reaching tasks that can be solved through AND, OR, and NOT expressions over object attributes.



 How can we use compositionality of language + value functions to generalize better?

- How can we use compositionality of language + value functions to generalise better?
- Must learn mapping from natural language to WVF composition

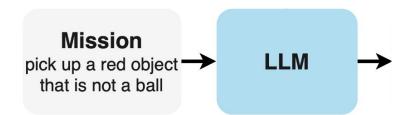
- How can we use compositionality of language + value functions to generalise better?
- Must learn mapping from natural language to WVF composition.
- Idea: <u>Use language models to translate instruction into formal language / boolean symbols (e.g. semantic parsing).</u>

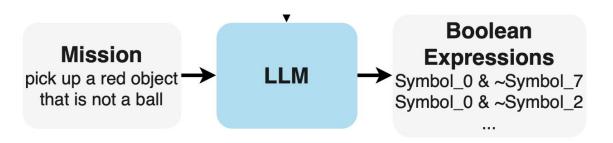
- How can we use compositionality of language + value functions to generalise better?
- Must learn mapping from natural language to WVF composition.
- Idea: <u>Use language models to translate instruction into formal language / boolean symbols (e.g. semantic parsing).</u>
- But these symbols are arbitrary (just an index over WVFs) how do we know translation is correct?

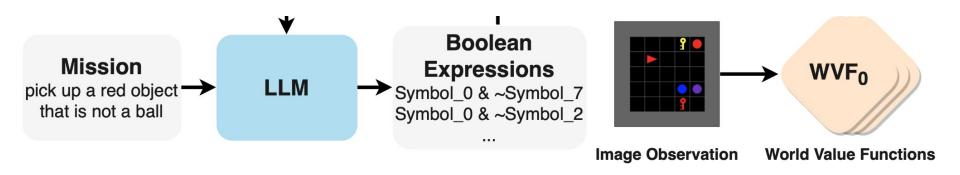
- How can we use compositionality of language + value functions to generalise better?
- Must learn mapping from natural language to WVF composition
- Idea: <u>Use language models to translate instruction into formal language / boolean symbols (e.g. semantic parsing).</u>
- But these symbols are arbitrary (just an index over WVFs) how do we know translation is correct?
- Idea: <u>Use environment feedback to learn the translation!</u>

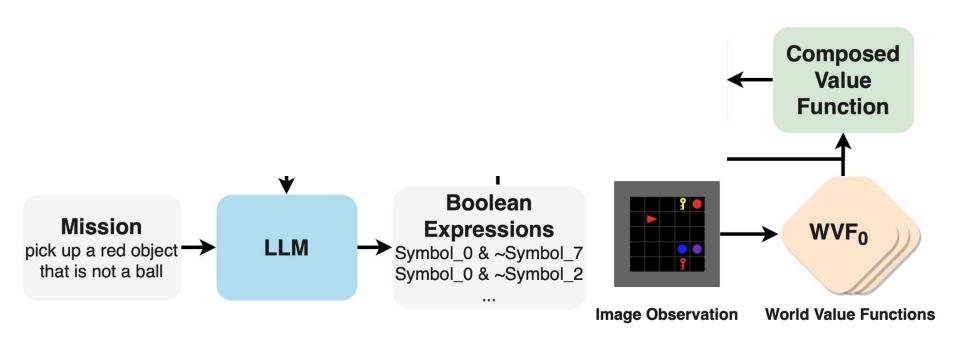
- How can we use compositionality of language + value functions to generalise better?
- Must learn mapping from natural language to WVF composition
- Idea: <u>Use language models to translate instruction into formal language / boolean symbols (e.g. semantic parsing).</u>
- But these symbols are arbitrary (just an index over WVFs) how do we know translation is correct?
- Idea: <u>Use environment feedback to learn the translation!</u>

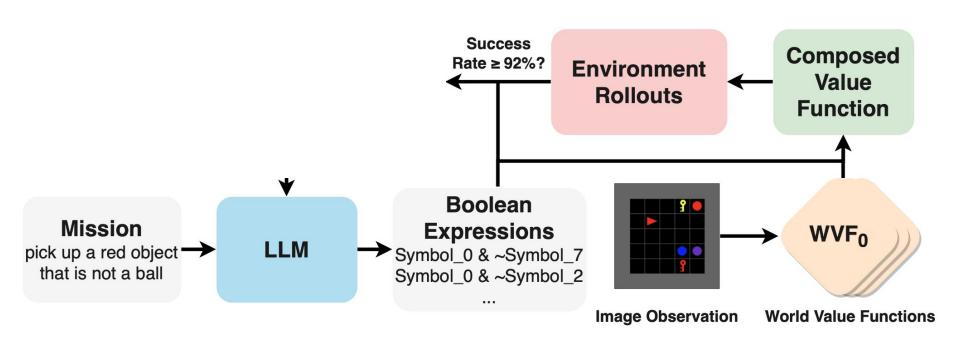
<u>Core challenge:</u> CERLLA learns to parse input commands to **arbitrary symbols** representing WVFs with **unknown semantics**, using **environment rollouts**, a much noisier form of supervision than is typical for weakly supervised parsing methods.

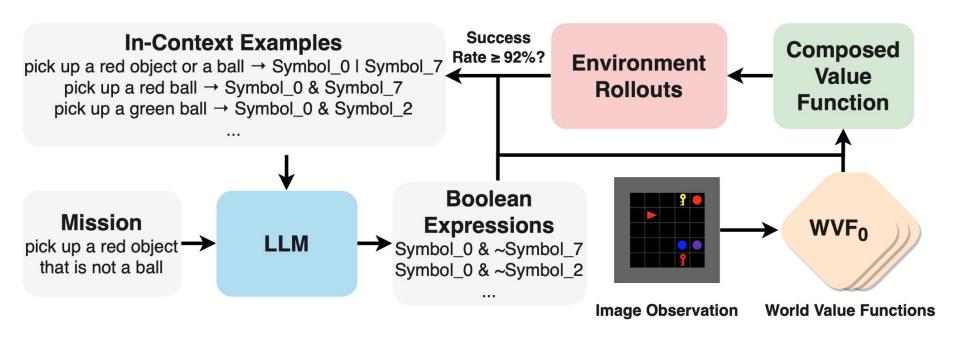












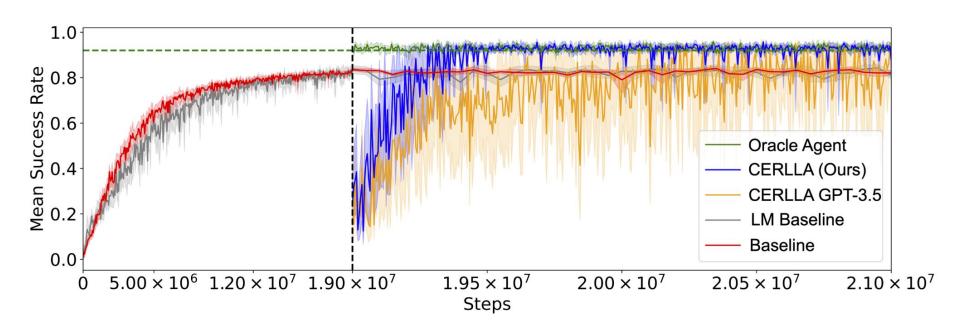
Experiments

• 162 tasks, learned simultaneously from vision and language.

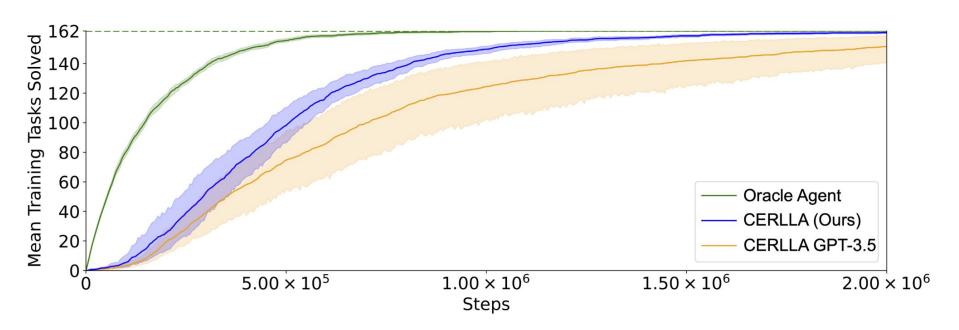
Experiments

- 162 tasks, learned simultaneously from vision and language.
- Evaluate sample efficiency, and generalization, comparing:
 - CERLLA (Ours): using OpenAl's GPT-4 LM
 - CERLLA GPT-3.5
 - Two non-compositional baseline DQNs
 - Baseline: RNN + CNN
 - LM Baseline: pretrained sentence embedding language model + CNN
 - Oracle Agent with access to the ground-truth compositional expressions for each task.

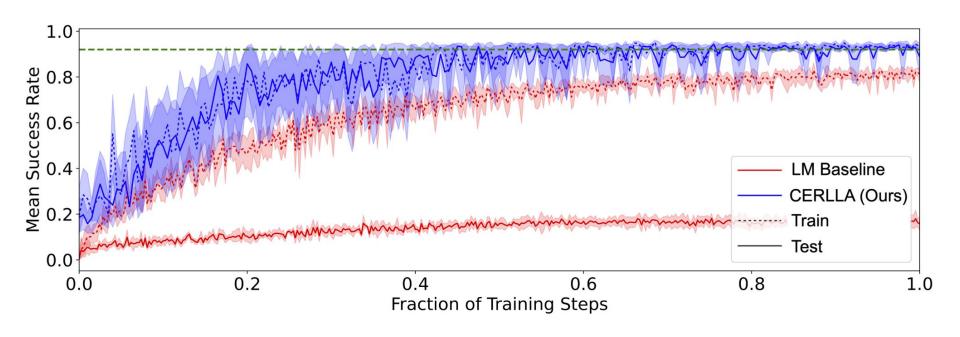
Sample Efficiency



Convergence



Generalization



Conclusion

- Introduces CERLLA, a novel semantic parsing method based on **in-context learning** and that learns from environment feedback.
- Simultaneously learns and solves a large collection of 162 compositional vision-language-RL tasks.
- Outperforms non-compositional baselines with respect to sample efficiency and generalization to held-out tasks.



