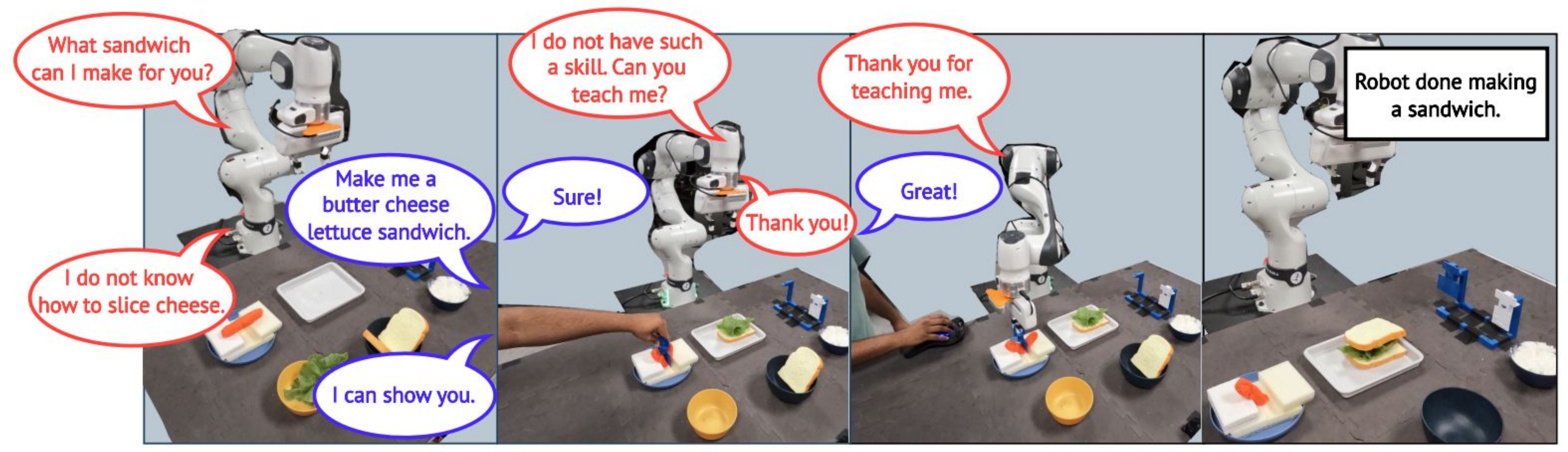
Continual Robot Skill and Task Learning via Dialogue

LOGOS Robotics Lab

Weiwei Gu, Suresh Kondepudi, Anmol Gupta, Lixiao Huang, and Nakul Gopalan

Motivation

The capability of dialog is desirable for robots as it allows robots to ask for help in a way that non-expert users can understand. Furthermore, robots need to leverage the feedback from users and learn to perform the task.



Related Work

- Human-robot dialog. [1]
- Continual skill learning. [2]
- Active Learning. [3]

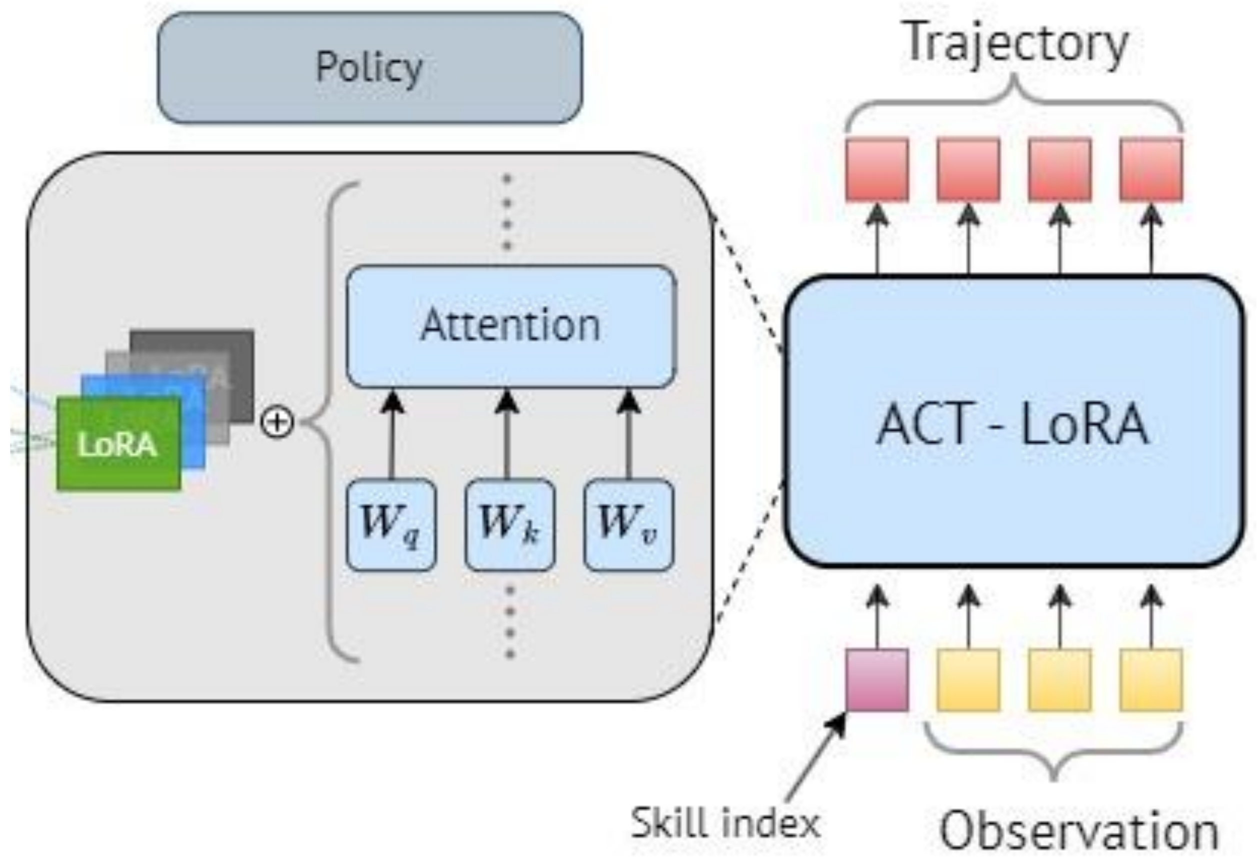
Challenges

- How does the robot know that it does not know the skill to perform a task?
- How to continually learn novel skills without forgetting the existing ones, with only few instances?

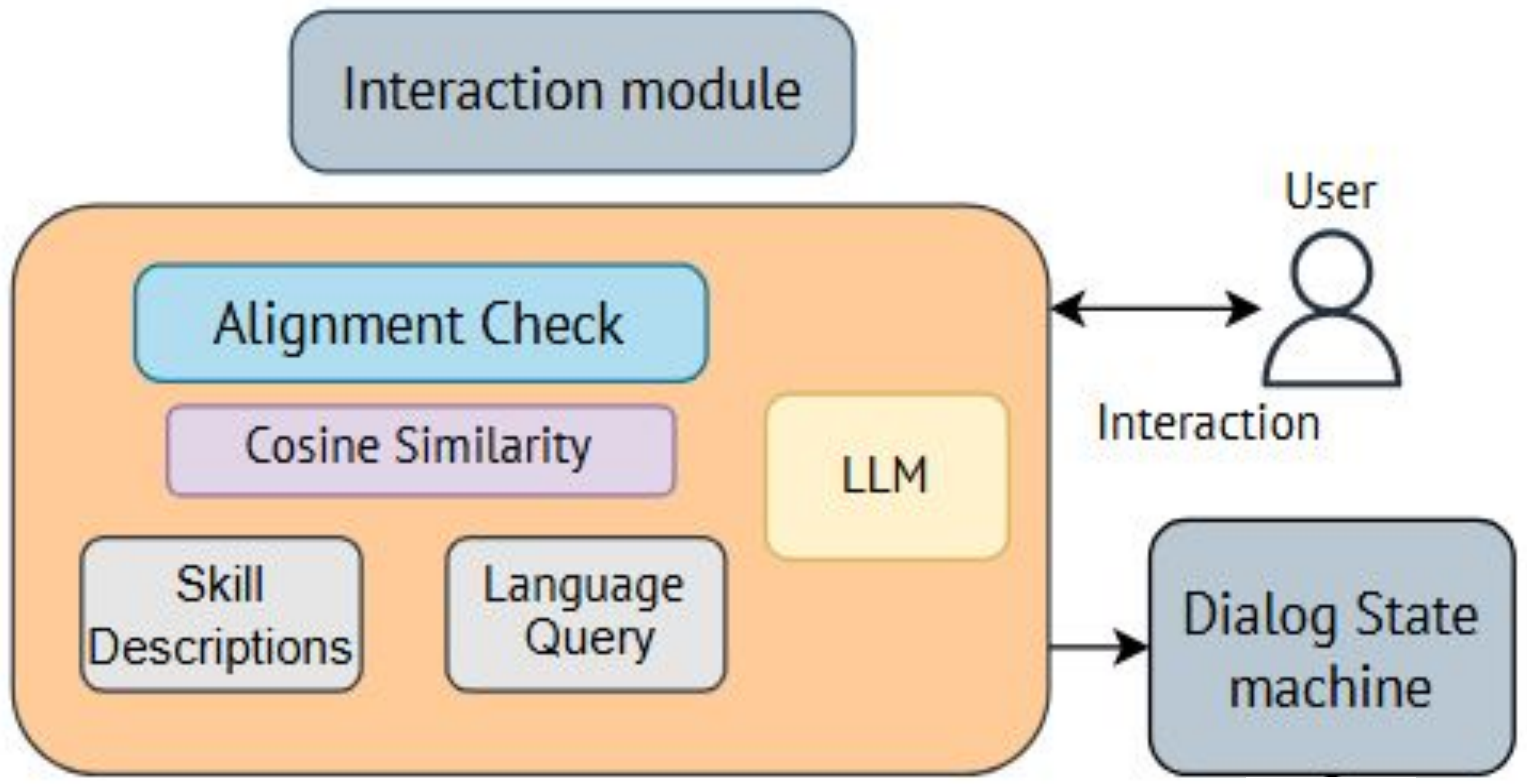
Methods

- Use language embedding spaces to estimate whether the robot possesses the skill or not.
- Introduce LoRA adapters to ACT to continually learn fine-grained control tasks
- Combine a state machine with LLM to request information via dialog

ACT-LoRA



COLADA Agent



Limitations

- Restricted domain for the human subject study.
- Demographic limitation of participants of the human subject study.
- Doesn't handle turn-taking naturally.
- Have issues with heterogeneous demonstrations

Human Subject Study Results

Objective metrics on agent task performance:

Agent	Phase 1		Phase 2		
	Sandwich SR	Pre-train SR	Sandwich SR	Few-shot SR	Pre-train SR
COLADA	93.75%(15/16)	97.92%(47/48)	81.25%(13/16)	100.00%(16/16)	91.67%(44/48)
Inverse Semantics	81.25%(13/16)	93.75%(45/48)	87.50%(14/16)	N/A	91.67%(44/48)
Inarticulate	0.00%(0/16)	93.75%(15/16)	0.00%(0/16)	0.00%(0/16)	87.50%(14/16)

Objective metrics on distraction tasks:

Agent	Interruption Count	Normalized Completed Email Count	Normalized Word Count	Total Time	Task Time
Phase One					
COLADA	2.13 ± 0.13	0.27 ± 0.03	0.24 ± 0.01	2176.67 ± 57.06	1035.21 ± 26.10
Inverse Semantics	1.13 ± 0.09	0.16 ± 0.02	0.20 ± 0.01	943.93 ± 32.41	753.21 ± 25.85
Inarticulate	0.00 ± 0.00	0.07 ± 0.02	0.08 ± 0.01	493.01 ± 58.62	412.98 ± 56.69
Phase Two					
COLADA	0.00 ± 0.00	0.25 ± 0.03	0.23 ± 0.02	1083.42 ± 27.28	1033.70 ± 26.32
Inverse Semantics	1.00 ± 0.00	0.17 ± 0.02	0.17 ± 0.01	870.77 ± 26.26	738.27 ± 24.02
Inarticulate	0.00 ± 0.00	0.08 ± 0.01	0.07 ± 0.01	426.94 ± 51.85	376.78 ± 48.74

Simulation Results

Results on RLBench:

Model	Pre-trained Skills(1000 traj.)	Fine-tune Skills(1000 traj.)	Overall Success Rate(1000 traj.)	Fine-tune Skills(5 traj.)	Overall Success Rate(5 traj.)
ACT-LoRA	$\mathbf{60.75 \pm 2.40}$	$54.00 \pm 9.73^*$	$\mathbf{59.40 \pm 1.52}$	77.67 ± 9.36	$\mathbf{64.13 \pm 1.80}$
GMM-LoRA	26.08 ± 4.02	13.33 ± 4.50	23.53 ± 2.99	16.67 ± 4.92	24.20 ± 3.72
ACT	9.25 ± 2.51	$62.00 \pm 8.84^*$	19.80 ± 1.69	$\mathbf{95.00 \pm 4.22}$	26.40 ± 2.45

Results on LIBERO:

Model	Pre-trained Skills(50 traj.)	Fine-tune Skills(50 traj.)	Overall Success Rate(50 traj.)	Fine-tune Skills(5 traj.)	Overall Success Rate(5 traj.)
LIBERO-Spatial					
ACT-LoRA	$65.38 \pm 4.51^*$	40.50 ± 6.09	$\mathbf{60.40 \pm 4.20}$	35.50 ± 8.27	$59.40 \pm 4.40^*$
GMM-LoRA	$64.75 \pm 2.49^*$	9.00 ± 5.16	53.60 ± 1.70	6.00 ± 2.92	$53.0 \pm 2.21^*$
ACT	0.03 ± 0.02	$\mathbf{68.50 \pm 6.50}$	13.90 ± 1.31	$\mathbf{55.00 \pm 7.66}$	11.20 ± 1.43
LIBERO-Object					
ACT-LoRA	67.00 ± 2.20	$68.00 \pm 8.57^*$	$67.20 \pm 1.50^*$	$48.00 \pm 10.23^*$	$63.20 \pm 1.60^*$
GMM-LoRA	$\mathbf{77.75 \pm 1.90}$	15.00 ± 5.65	$65.20 \pm 2.15^*$	14.00 ± 5.89	$65.00 \pm 1.08^*$
ACT	12.88 ± 2.78	$63.00 \pm 9.33^*$	22.90 ± 2.45	$35.50 \pm 7.92^*$	17.40 ± 3.45
LIBERO-Goal					
ACT-LoRA	$73.63 \pm 2.96^*$	$\mathbf{49.00 \pm 8.54}$	$\mathbf{68.70 \pm 3.70}$	$23.00 \pm 8.57^*$	$63.50 \pm 4.00^*$
GMM-LoRA	$75.38 \pm 1.63^*$	10.50 ± 5.61	62.40 ± 1.39	3.5 ± 2.92	$61.00 \pm 1.72^*$
ACT	0.00 ± 0.00	19.50 ± 3.66	3.90 ± 0.73	$10.50 \pm 4.57^*$	2.10 ± 0.91

References

- [1] Dai et al., 2024. Think, act, and ask: Open-world interactive personalized robot navigation
- [2] Liu et al., 2024. Tail: Task-specific adapters for imitation learning with large pre-trained models
- [3] Maeda et al. Active incremental learning of robot movement primitives