



# Switching Head–Tail Funnel UNITER for Dual Referring Expression Comprehension with Fetch-and-Carry Tasks

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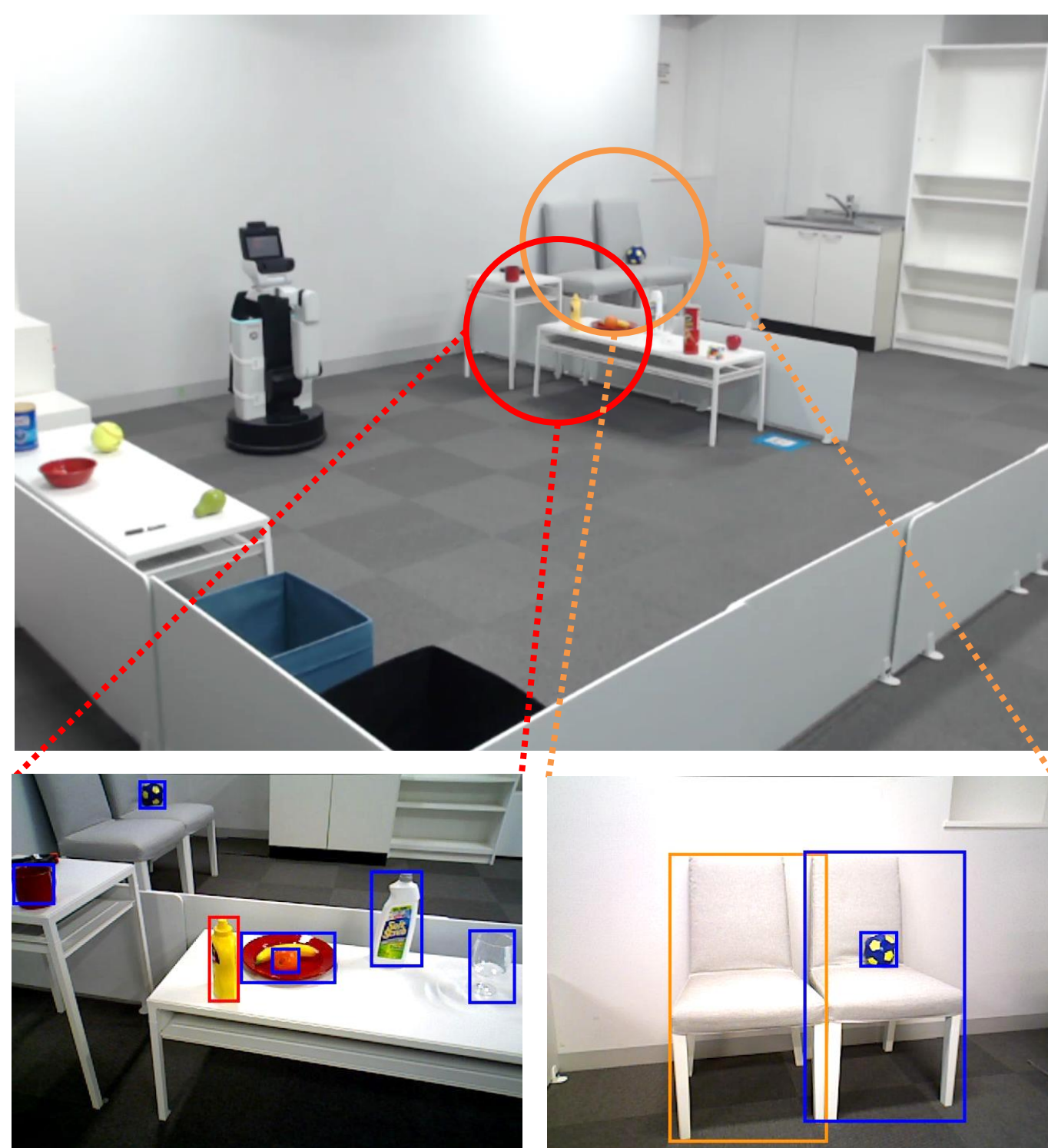
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## Abstract

<b>Target task</b>	Multimodal language understanding method that comprehends object fetching and carrying instructions
<b>Novelty</b>	Introduce a <b>Switching Head–Tail</b> mechanism so that both target objects and destinations can be predicted individually using a single model
<b>Results</b>	Outperformed the baseline method in terms of language comprehension accuracy on the newly-built dataset and physical experiments

“Move the bottle on the left side of the plate to the empty chair.”



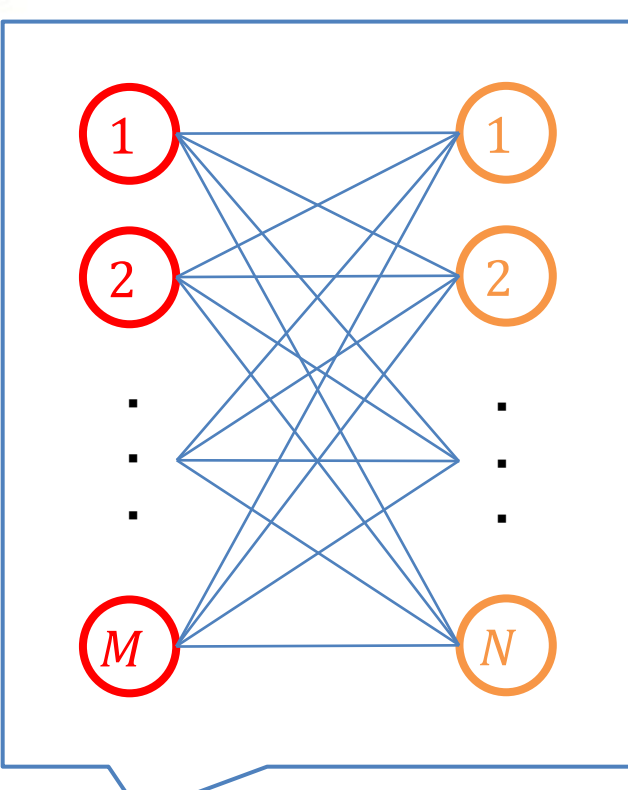
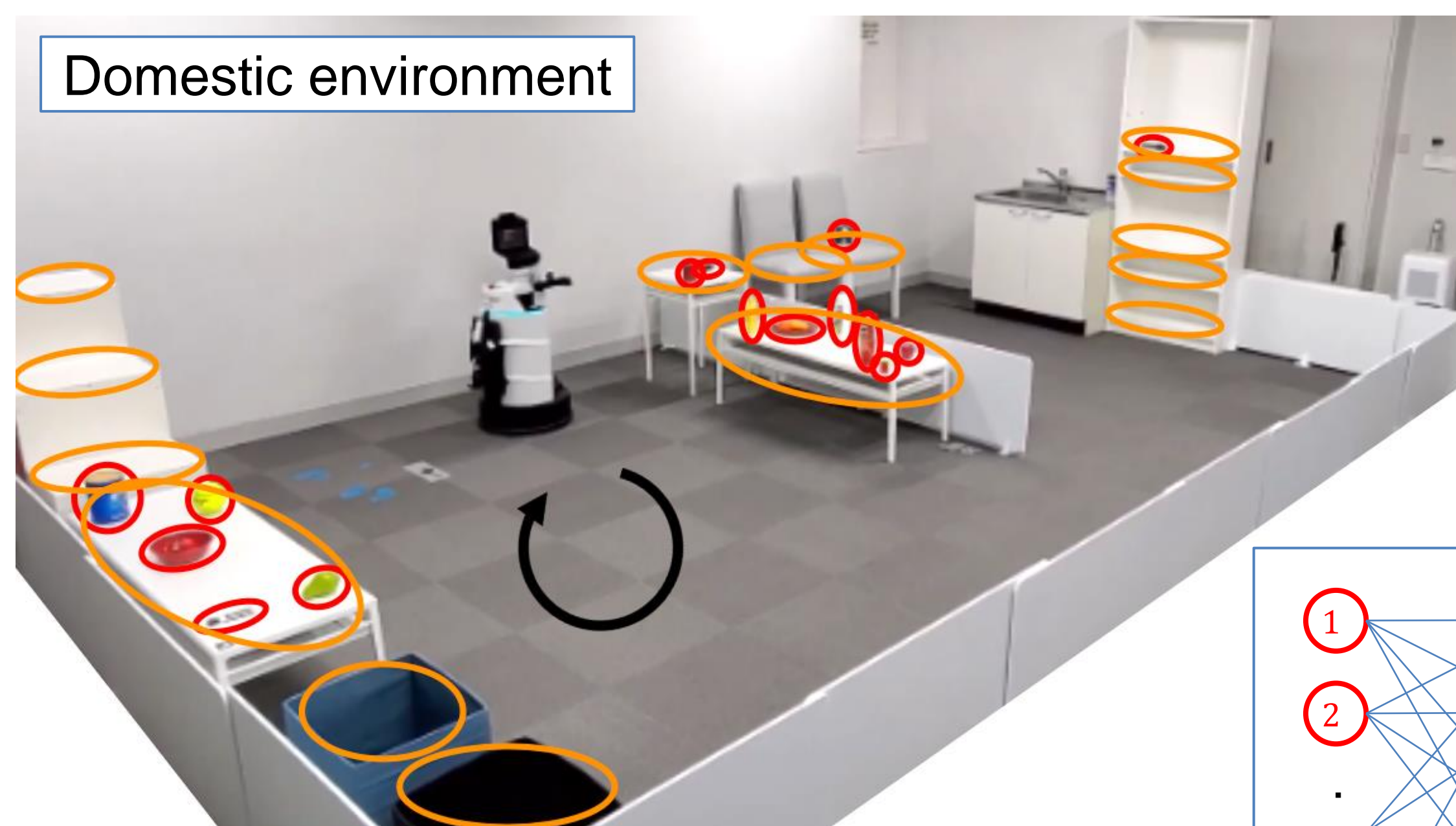
Domestic service robot (DSR)

## Related Work: Large Computational Cost

MTCM [Magassouba+, RA-L19]	Identifies target object from instruction and whole image
Target-dependent UNITER (TDU) [Ishikawa+, RA-L21]	Introduced the transformer attention mechanism based on UNITER [Chen+, ECCV20]

■ Goal: Finding the maximum likelihood pair

Domestic environment



$M$ : Number of candidate target objects

$N$ : Number of candidate destinations

⊗ Time complexity for inference:  $O(M \times N)$

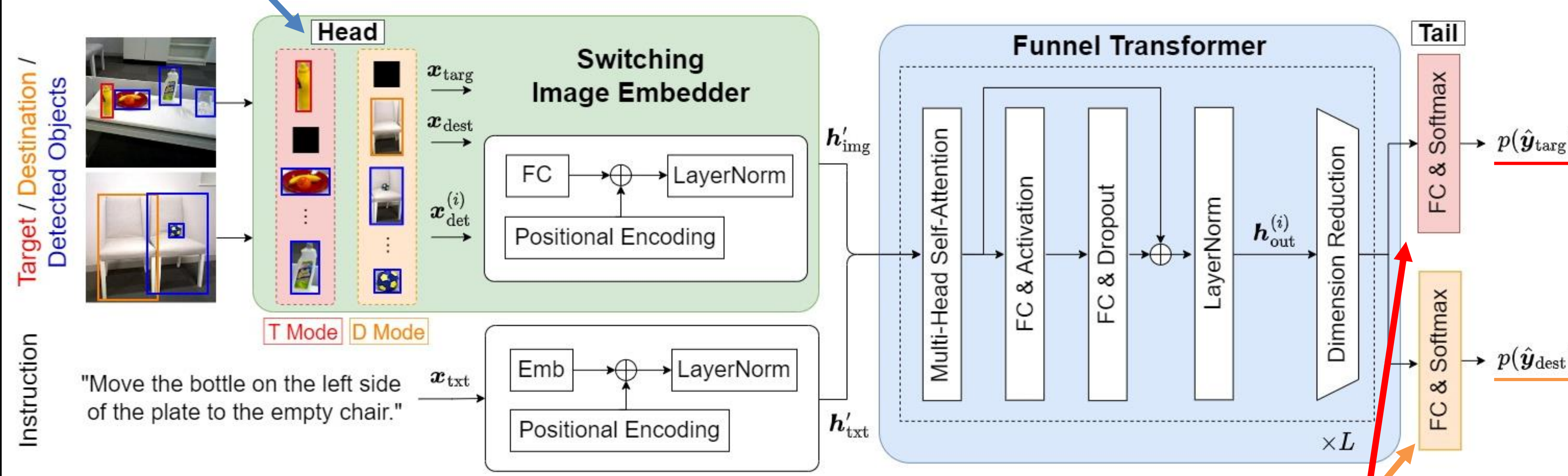
## Method: Switching Head–Tail Funnel UNITER (SHeFU)

■ Both target objects and destinations can be predicted individually using a single model, which reduces the computational cost (= 😊 Time complexity for inference:  $O(M + N)$ )

Step 1: ① ② ... ① ... ① Step 2: ① ② ... ① ... ①

**Switching Head mechanism:** ✓ Conditions the model by partially zero-filling the input

$$(x_{\text{targ}}, x_{\text{dest}}) = \begin{cases} (x_{\text{targ}}, \mathbf{0}) & \text{if target mode} \\ (\mathbf{0}, x_{\text{dest}}) & \text{if destination mode} \end{cases}$$



**Switching Tail mechanism:**

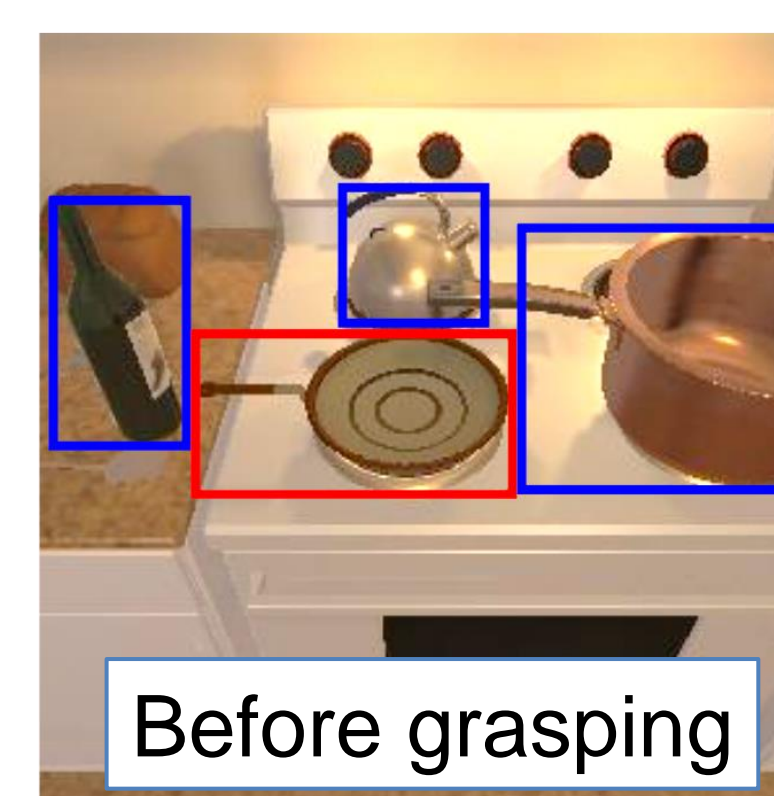
✓ Outputs the predicted probability according to the mode

✓ Multi-task learning:  $\mathcal{L} = \lambda_{\text{targ}} \mathcal{L}_{\text{CE}}(y_{\text{targ}}, p(\hat{y}_{\text{targ}})) + \lambda_{\text{dest}} \mathcal{L}_{\text{CE}}(y_{\text{dest}}, p(\hat{y}_{\text{dest}}))$

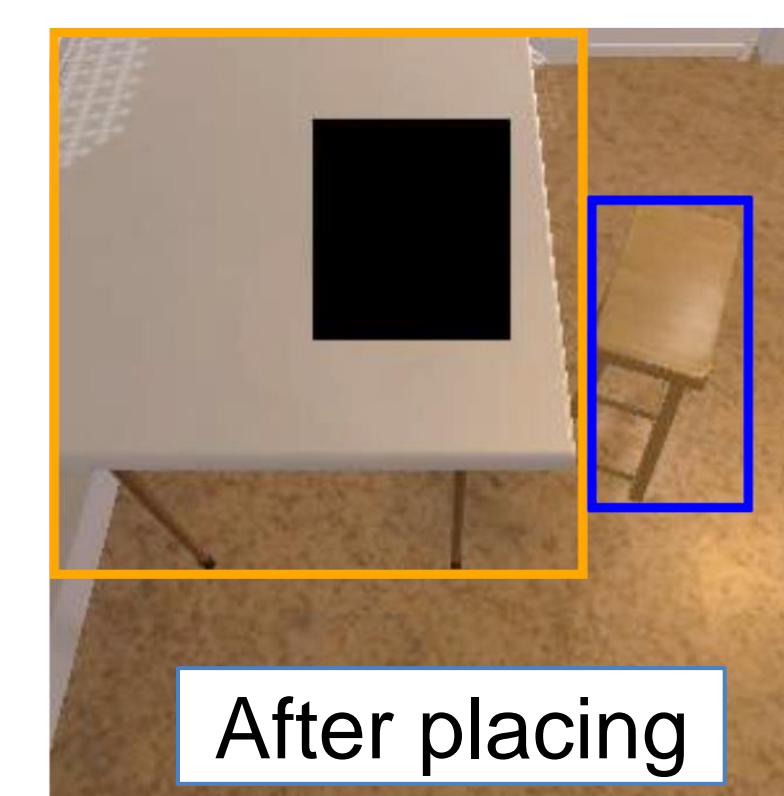
## Settings: Simulation and Physical Experiments

1. ALFRED-fc: Based on ALFRED [Shridhar+, CVPR20] (= Standard Vision-and-Language Navigation benchmark)

Dataset size (train : valid : test)	5748 (4420 : 642 : 686)
# Images	1099
# Instructions	3452
# Unique words	646
# Average words	8.4

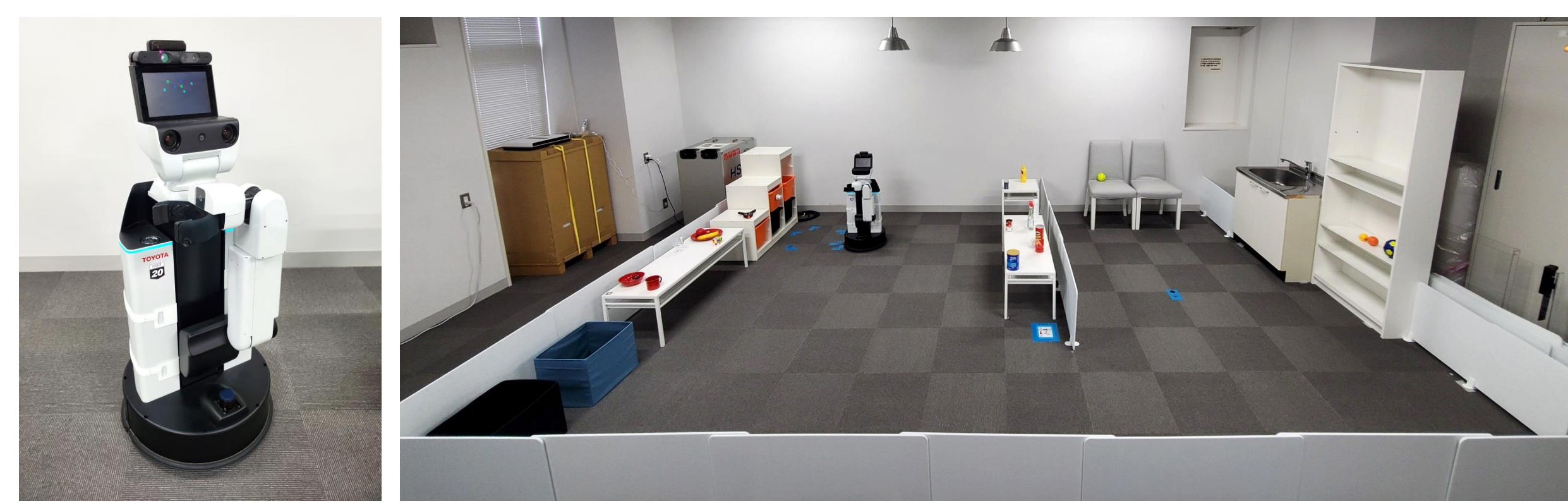


Before grasping

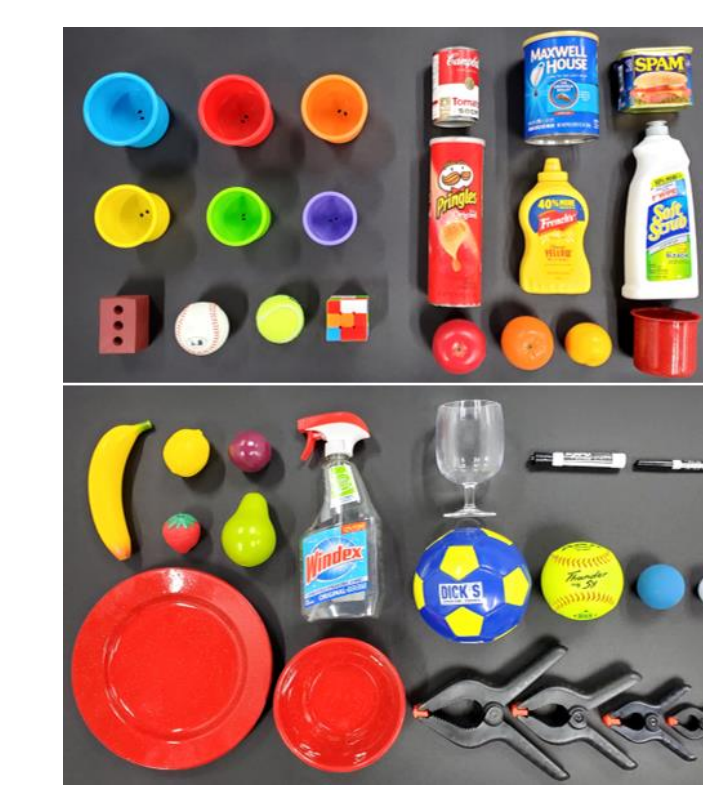


After placing

2. Language comprehension and Grasping/Placing actions (= Heuristic methods)



Robot and environment: WRS [Okada+, AR19]



Objects: YCB [Calli+, RAM15]

## Quantitative Results

■ Metric: Language comprehension accuracy [%]

Method	ALFRED-fc	Real
extended TDU [Ishikawa+, RA-L21]	79.4 ± 2.76	52.0
Ours (W/o Switching Head)	78.4 ± 2.05	-
Ours (W/o Switching Tail)	76.9 ± 2.91	-
Ours (SHeFU)	83.1 ± 2.00	55.9

+3.7 +3.9

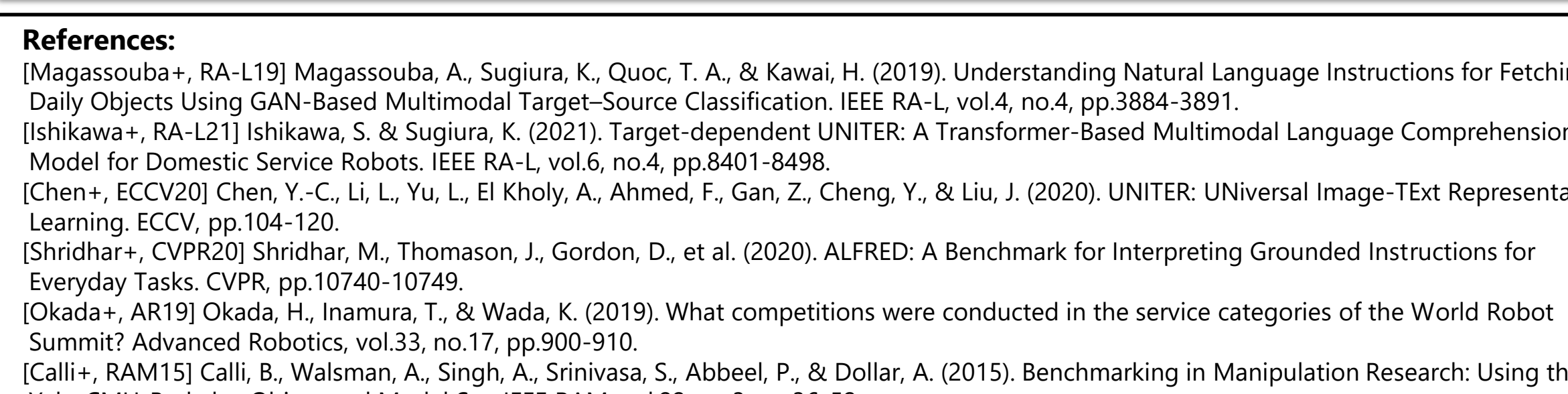
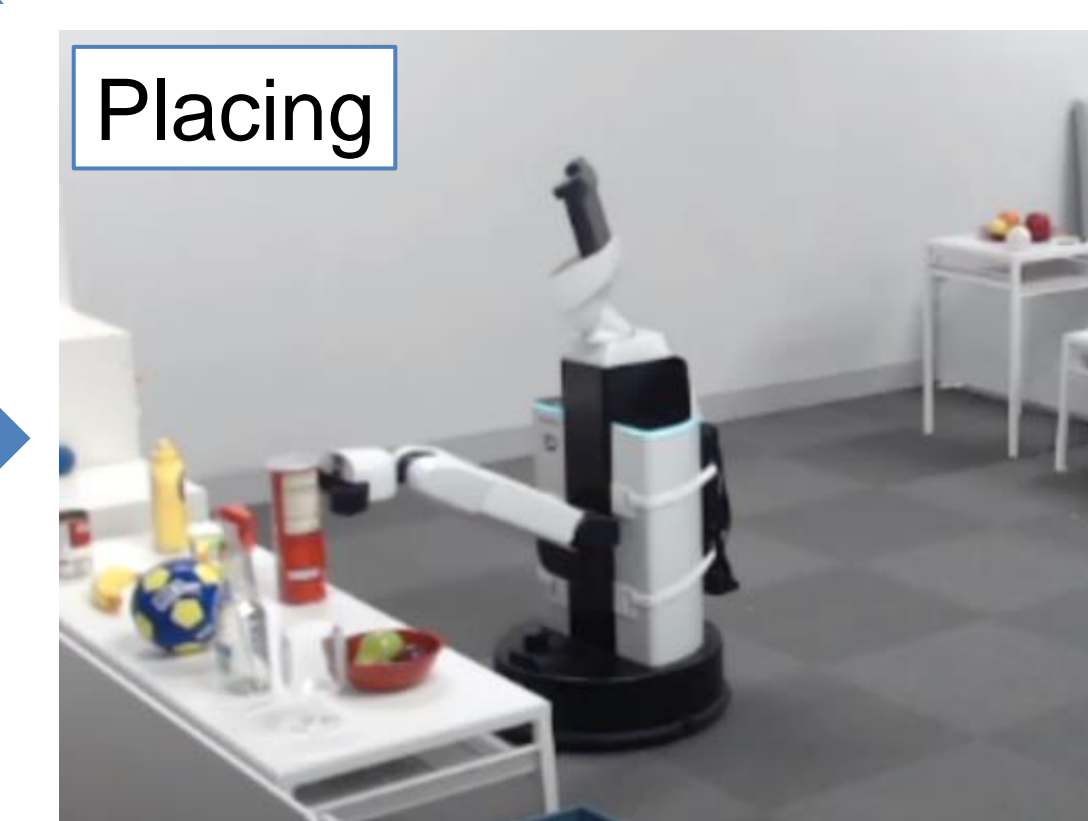
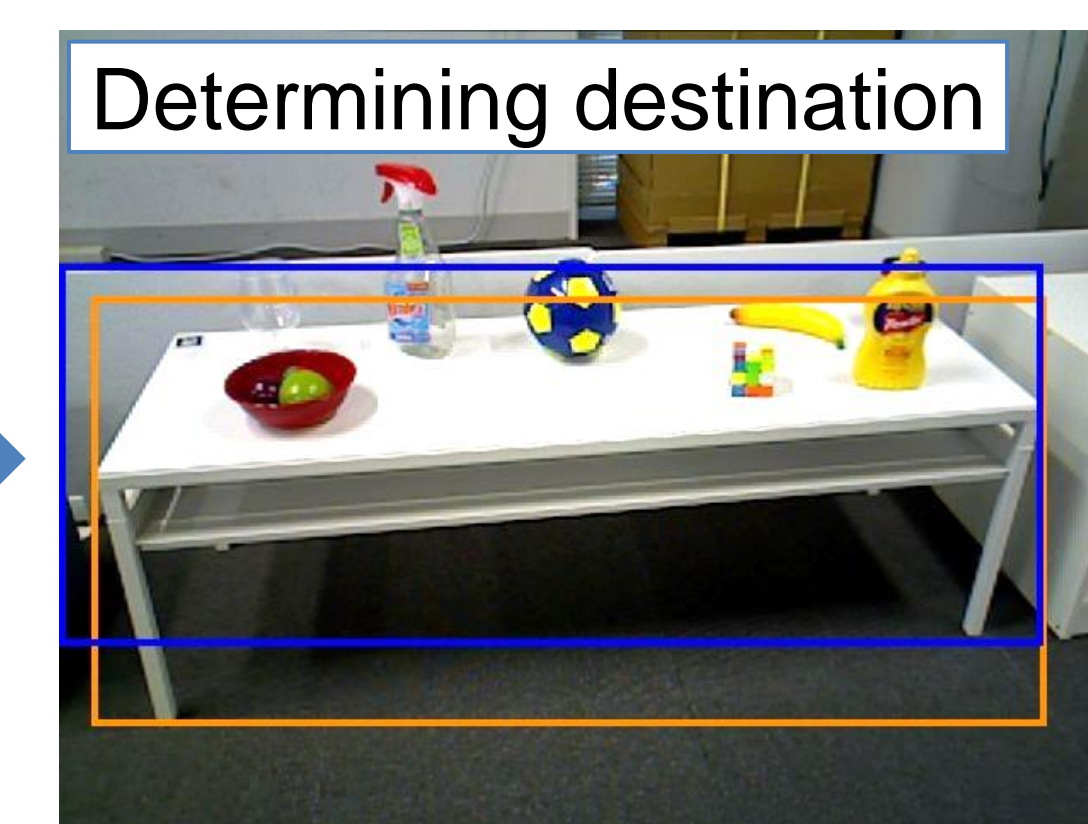
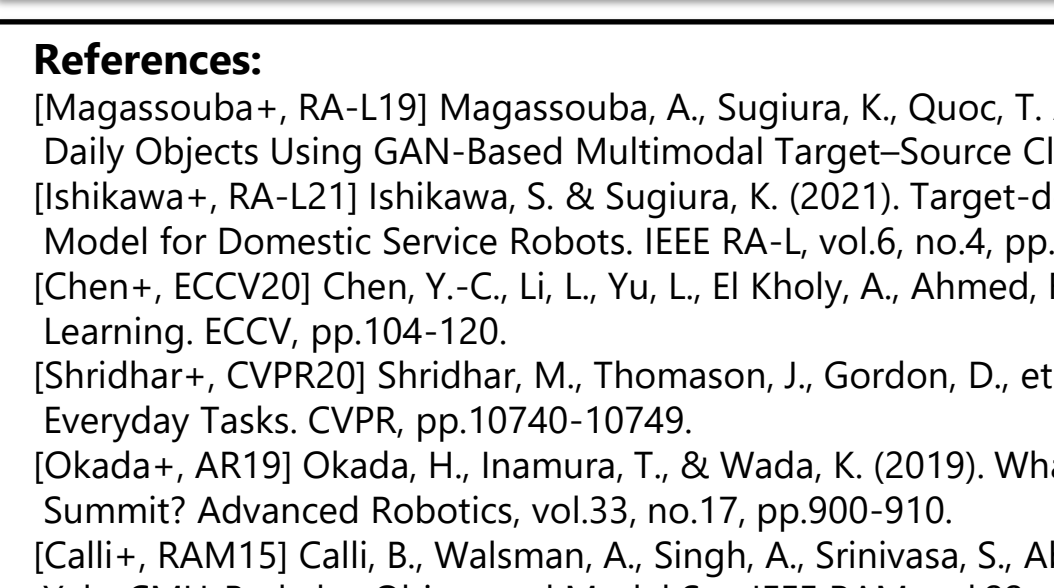
■ Metric: Task success rate (SR) [%]

Task	SR↑	Executed only when language comprehension succeeded
Grasping	95 (60/63)	
Placing	93 (56/60)	

## Qualitative Results

■ Successful case in the physical experiments

“Put the red chips can on the white table with the soccer ball on it.”



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