Generation of Robot Manipulation Plans Using Generative Large Language Models

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Outline

Robots in Open World Situations

Goal

Enable cognitive robots to perform household tasks in varying situations

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Households are *open worlds* $\Rightarrow$ unknown environments containing unknown objects and necessitating unknown actions

Solutions [Din+23]

1. Acquiring knowledge via human-robot interaction
2. Dynamically building a knowledge base to assist a task planner
3. **Use generative Large Language Models (LLMs) as a task planner**

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- Open questions:
  - How do LLMs perform on cognitive architectures?
  - How does the example in the prompt influence performance?

Cognitive Robot Abstract Machine (CRAM) [BMT10]

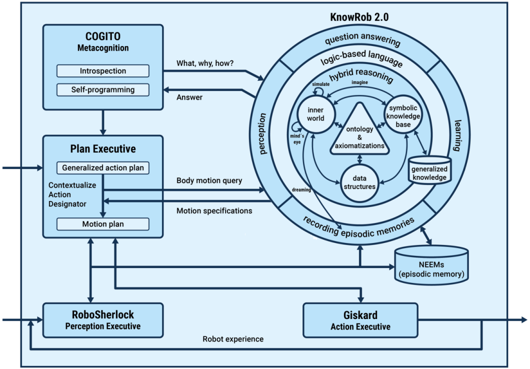

Figure: CRAM Architecture from [Ver+22]

- Hybrid cognitive architecture for autonomous robots

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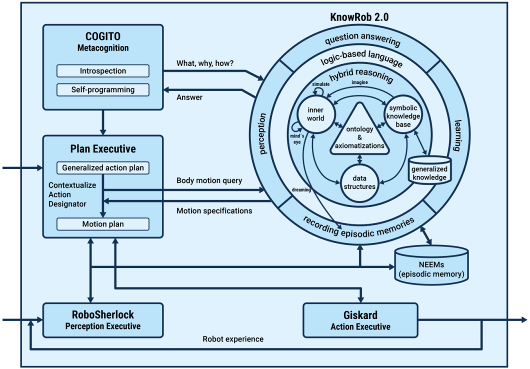

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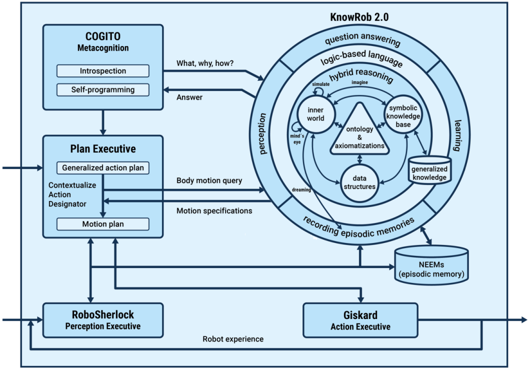

Figure: CRAM Architecture from [Ver+22]

- Hybrid cognitive architecture for autonomous robots
- Tasks are vaguely described as high-level goals from which specific low-level motions are derived
- Plans are written in Common LISP and are called *designators*

Experiment Setup

- 9 designators written by experts for 9 different actions (*Close, Halve, Hold, Open, Pick Up, Place Down, Pour, Slice & Wipe*)

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- Use 3 different models / model versions:
  - `gpt-3.5-turbo-0301`
  - `gpt-3.5-turbo-0613`
  - `gpt-4-0613`

Prompt

The following LISP source code describes a CRAM designator for the action of "*[reference action]*", where the executing robot would be *[reference action description]*:
[reference designator]
Can you please take this example and create a new designator for the action "*[target action]*", where the robot should be *[target action description]*. Your answer should only include the designator and no additional text.

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Example Descriptions

Close → Closing an arbitrary container
Pour → Pouring the content of one container into another
Wipe → Cleaning a surface using some kind of towel

Code Generation Metrics

- Machine Translation Metrics:
  - BLEU [Pap+01]
  - ROUGE-1 (R-1), ROUGE-2 (R-2) & ROUGE-L (R-L) [Lin04]
  - chrF [Pop15]

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Action Similarity Metrics

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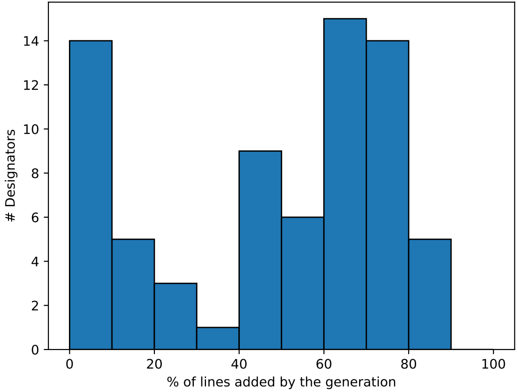
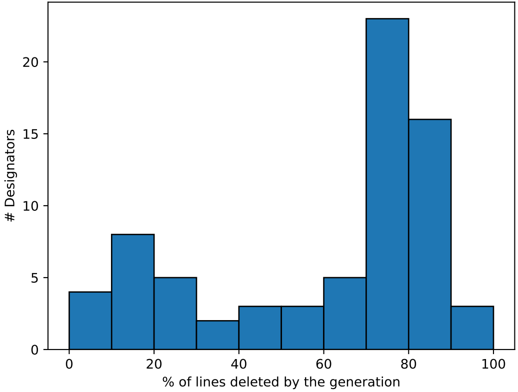
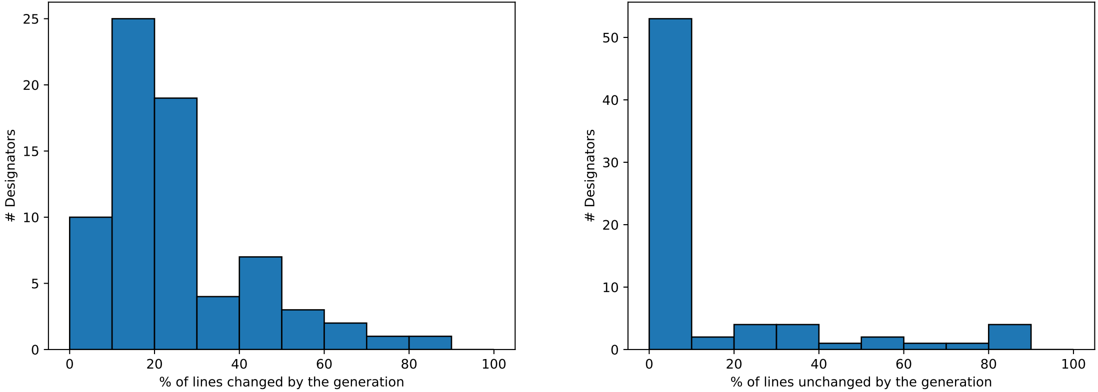
Manual Analysis - Added & Deleted Lines





Manual Analysis - (Un-)Changed Lines



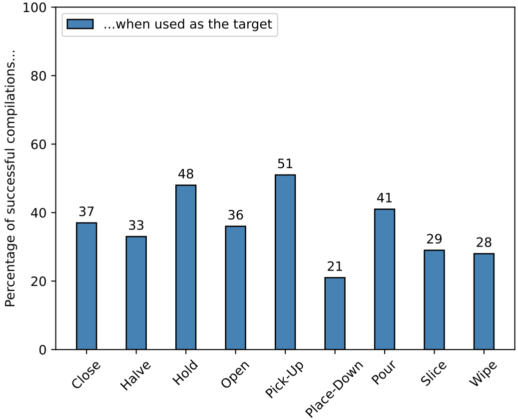
Metrics

Model	BLEU	R-1	R-2	R-L	chrF	CBS
`gpt-3.5-turbo-0301`	.595	.630	.527	.621	**.674**	.942
`gpt-3.5-turbo-0613`	.579	.614	.511	.612	.639	.940
`gpt-4-0613`	**.605**	**.631**	**.532**	**.623**	**.674**	**.945**

Compilation Success

Model	Compiles	¬Compiles
`gpt-3.5-turbo-0301`	147 / 40,83%	213 / 59,17%
`gpt-3.5-turbo-0613`	101 / 28,06%	259 / 71,94%
`gpt-4-0613`	139 / 38,61%	221 / 61,39%
Σ	387 / 35,83%	693 / 64,17%

Compilation Success per Action



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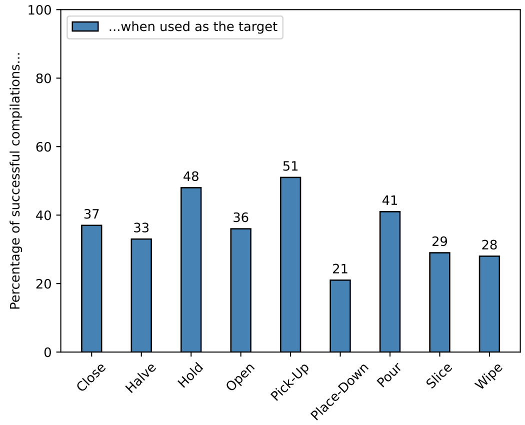

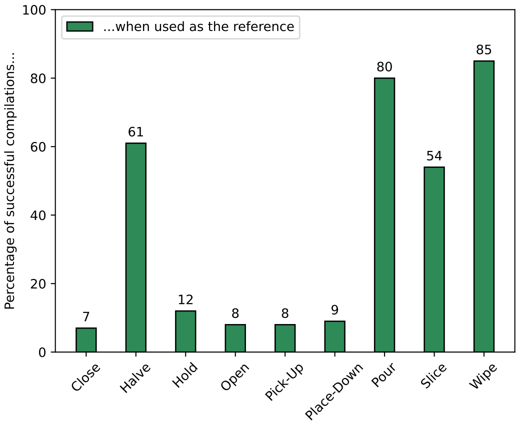

Action Similarity and Generation Correlation

Hypothesis

The **higher** the similarity between the reference and the target action, the **better** the generated designator

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Testing

Calculate the Spearman Rank Correlation ρ between the code generation metrics and the action similarity metrics
Expectation: positive, significant ($p \leq 0.05$) correlations

Action Similarity and Generation Quality Correlation

Metric	WuP [WP94] ρ	WuP [WP94] p	GloVe [PSM14] ρ	GloVe [PSM14] p	SMD [WC22] ρ	SMD [WC22] p
BLEU [Pap+01]	**-.248**	**.000**	**-.282**	**.000**	**-.200**	**.000**
ROUGE-1 [Lin04]	-.086	.104	**-.270**	**.000**	**-.355**	**.000**
ROUGE-2 [Lin04]	**-.141**	**.008**	**-.264**	**.000**	**-.395**	**.000**
ROUGE-L [Lin04]	-.082	.122	**-.264**	**.000**	**-.358**	**.000**
chrF [Pop15]	**-.188**	**.000**	**-.296**	**.000**	**-.241**	**.000**
CBS [Zho+23]	-.101	.056	**-.215**	**.000**	**-.279**	**000**
Lines of Code	**-.287**	**.000**	**-.336**	**.000**	**-.204**	**.000**
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`gpt-3.5-turbo-0301`

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`gpt-3.5-turbo-0613`

$\Rightarrow$ All significant correlations (except for compilation success) are positive ($n = 360$)

Action Similarity and Generation Quality Correlation

	WuP [WP94]		GloVe [PSM14]		SMD [WC22]	
Metric	ρ	p	ρ	p	ρ	p
BLEU [Pap+01]	-.061	.250	**-.133**	**.011**	**-.104**	**.050**
ROUGE-1 [Lin04]	.039	.464	**-.126**	**.017**	**-.240**	**.000**
ROUGE-2 [Lin04]	.013	.803	**-.115**	**.029**	**-.256**	**.000**
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chrF [Pop15]	-.012	.822	**-.136**	**.010**	**-.142**	**.007**
CBS [Zho+23]	-.001	.992	**-.127**	**.016**	**-.203**	**.000**
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gpt-4-0613

$\Rightarrow$ All significant correlations are negative ($n = 360$)

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Results

- Action similarity negatively correlates with generation quality in the old ChatGPT and the GPT-4 model
- Action similarity positively correlates with generation quality in the new ChatGPT model
- significant correlations with the compilation success are always negative

$\Rightarrow$ Using a similar action as a reference **decreases** the chance of compiling successfully

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- Sensorimotor Distance is susceptible to semantic inaccuracy
- No fine-tuning of the models due to limited sample size ($n = 9$)

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- Action similarity negatively influences code generation quality for GPT-4 & Old ChatGPT
- Action similarity positively influences code generation quality for new ChatGPT

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- Simulate the successfully compiled designators

Thank you for your attention!

Questions?

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Zero-Shot Prompting

```
(defaction slice-food (food-object)
    :precondition (and (is-sliceable food-object)
        (not (is-sliced food-object)))
    :effect (and (is-sliced food-object)
        (small-slice (make-slice food-object))
        (big-slice (make-slice food-object)))
    :body (progn (cut-food-object food-object)))
```

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Task

- Refine a generated designator through interacting with ChatGPT (`gpt-3.5-turbo-0613`)
- In each step, tell ChatGPT one mistake and prompt it to fix it without just telling "add this line"
- Chosen example: *Pick-Up* based on *Close*
    - 1 added line (needs to be removed)
    - 8 missing lines (need to be added)
    - 14 changed lines (not all need changing)

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Summary

⇒ ChatGPT could successfully refine the designator

⇒ ChatGPT is not reliable since it introduces unforeseen changes

⇒ This demonstration worked well because the final result was known beforehand