PROGPROMPT: Generating Situated Robot Task Plans using Large Language Models

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Abstract

Task planning can require defining myriad domain knowledge about the world in which a robot needs to act. To ameliorate that effort, large language models (LLMs) can be used to score potential next actions during task planning, and even generate action sequences directly, given an instruction in natural language with no additional domain information. However, such methods either require enumerating all possible next steps for scoring, or generate free-form text that may contain actions not possible on a given robot in its current context. We present a programmatic LLM prompt structure that enables plan generation functional across situated environments, robot capabilities, and tasks. Our key insight is to prompt the LLM with program-like specifications of the available actions and objects in an environment, as well as with *executable* example `programs`. We make concrete recommendations about prompt structure and generation constraints through ablation experiments, demonstrate state of the art success rates in VirtualHome household tasks, and deploy our method on a physical robot arm for tabletop tasks.

1 Introduction

Everyday household tasks require *both* commonsense understanding of the world and situated knowledge about the current environment. To create a task plan for "Make dinner," an agent needs common sense: *object affordances*, such as that the stove and microwave can be used for heating; *logical sequences of actions*, such as an oven must be preheated before food is added; and *task relevance of objects and actions*, such as heating and food are actions related to "dinner" in the first place. However, this reasoning is infeasible without *state feedback*. The agent needs to know what food is available *in the current environment*, such as whether the freezer contains fish or the fridge contains chicken.

Autoregressive large language models (LLMs) trained on large corpora to *generate* text sequences conditioned on input *prompts* have remarkable multi-task generalization. This ability has recently been leveraged to generate plausible action plans in context of robotic task planning Huang et al. [2022b,a], Zeng et al. [2022], Ahn et al. [2022] by either scoring next steps or generating new steps directly. In scoring mode, the LLM evaluates an enumeration of actions and their arguments from the space of what's possible. For instance, given a goal to "Make dinner" with first action being "open the fridge", the LLM could score a list of possible actions: "pick up the chicken", "pick up the soda", "close the fridge", . . . , "turn on the lightswitch." In text-generation mode, the LLM can produce the next few words, which then need to be mapped to actions and world objects available to the agent.

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For example, if the LLM produced "reach in and pick up the jar of pickles," that string would have to neatly map to an executable action like "pick up jar." A key component missing in LLM-based task planning is state feedback from the environment. The fridge in the house might not contain chicken, soda, or pickles, but a high-level instruction "Make dinner" doesn't give us that world state information. **Our work introduces situated-awareness in LLM-based robot task planning.**

We introduce PROGPROMPT, a prompting scheme that goes beyond conditioning LLMs in natural language. PROGPROMPT utilizes *programming language* structures, leveraging the fact that LLMs are trained on vast web corpora that includes many programming tutorials and code documentation. PROGPROMPT provides an LLM a Pythonic program header that `imports` available actions and their expected parameters, shows a `list` of environment objects, and then `def`ines functions like `make_dinner` whose bodies are sequences of actions operating on objects. We incorporate situated state feedback from the environment by `assert`ing preconditions of our plan, such as being close to the fridge before attempting to open it, and responding to failed assertions with recovery actions. What's more, we show that including natural language *comments* in PROGPROMPT programs to explain the goal of the upcoming action improves task success of generated plan programs.

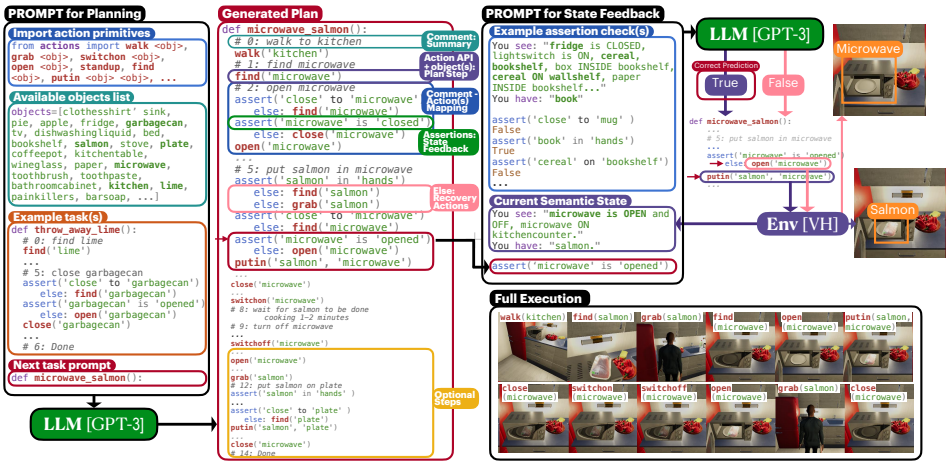

Figure 1: Our PROGPROMPTs include `import` statement, object list, and example tasks (*PROMPT for Planning*). The *Generated Plan* is for `microwave salmon`. We highlight prompt comments, actions as imported function calls with objects as arguments, and `assert`ions with recovery steps. *PROMPT for State Feedback* represents example assertion checks. We further show execution of the program. We illustrate a scenario where an assertion succeeds or fails, and how the generated plan corrects the error before executing the next step. *Full Execution* of the program is shown in bottom-right.

2 Our Method: PROGPROMPT

We represent robot plans as *pythonic* programs. Following the paradigm of LLM prompting, we create a prompt structured as pythonic code and use an LLM to complete the code (Fig. 1). We use features available in Python to construct prompts that elicit an LLM to generate situated robot task plans, conditioned on a natural language instruction.

Representing Robot Plans as Pythonic Functions Plan functions consist of API calls to action primitives, comments to summarize actions, and assertions for tracking execution (Fig. 2). Primitive actions use objects as arguments. For example, the "*put salmon in the microwave*" task includes API calls like `find`(*salmon*).

```
def put_salmon_in_microwave():
    # 1: grab salmon
    assert('close' to 'salmon')
        else: find('salmon')
    grab('salmon')
    # 2: put salmon in microwave
    assert('salmon' in 'hands' )
        else: find('salmon')
        else: grab('salmon')
    assert('close' to 'microwave' )
        else: find('microwave')
    assert('microwave' is 'opened')
        else: open('microwave')
    putin('salmon', 'microwave')
```

Figure 2: Pythonic PROGPROMPT plan for "*put salmon in the microwave.*"

We utilize comments in the code to provide natural language summaries for subsequent sequences of actions. Comments help break down the high-level task into logical sub-tasks (Fig. 2). This partitioning could help the LLM to express its knowledge about tasks and sub-tasks in natural language and aid planning. Comments also inform the LLM about immediate goals, reducing the possibility of incoherent, divergent, or repetitive outputs. Prior work Wei et al. [2022] has also shown the efficacy of similar intermediate summaries called 'chain of thought' for improving performance of LLMs on a range of arithmetic, commonsense, and symbolic

reasoning tasks. We empirically verify the utility of comments (Tab. 1; column COMMENTS). Assertions provide an environment feedback mechanism to make sure that the preconditions hold, and enable error recovery when they do not. For example, in Fig. 2, before the `grab`(*salmon*) action, the plan asserts the agent is `close` to *salmon*. If not, the agent first executes `find`(*salmon*). In Tab. 1, we show that such assert statements (column FEEDBACK) benefit plan generation.

Constructing Programming Language Prompts We provide information about the environment and primitive actions to the LLM through prompt construction. As done in few-shot LLM prompting, we also provide the LLM with examples of sample tasks and plans. Fig. 1 illustrates our prompt function f_{prompt} (appendix Sec. 5.1) which takes in all the information (observations, action primitives, examples) and produces a Pythonic prompt for the LLM to complete. The LLM then predicts the `<next_task>`(.) as an executable function (`microwave_salmon` in Fig. 1).

In the task `microwave_salmon`, a reasonable first step that an LLM could generate is `take_out`(*salmon*, *grocery bag*). However, the agent responsible for the executing the plan might not have a primitive action to `take_out`. To inform the LLM about the agent's action primitives, we provide them as Pythonic `import` statements. These encourage the LLM to restrict its output to only functions that are available in the current context. To change agents, PROGPROMPT just needs a new list of imported functions representing agent actions. A *grocery bag* object might also not exist in the environment. We provide the available objects in the environment as a list of strings. Since our prompting scheme explicitly lists out the set of actions and objects available to the model, the generated plans typically contain actions an agent can take and objects available in the environment.

PROGPROMPT also includes a few example tasks—fully executable program plans. Each example task demonstrates how to complete a given task using available actions and objects in the given environment. These examples demonstrate the relationship between task name, given as the function handle, and actions to take, as well as the restrictions on actions and objects to involve.

Task Plan Generation and Execution The given task is fully inferred by the LLM based on the PROGPROMPT prompt. Generated plans are executed on a virtual agent or a physical robot system using an interpreter that executes each action command against the environment. Assertion checking is done in a closed-loop manner during execution, providing current environment state feedback.

Table 1: Evaluation of generated programs on Virtual Home. PROGPROMPT uses 3 fixed example programs, except the DAVINCI backbone which can fit only 2 in the available API. Huang et al. [2022a] use 1 dynamically selected example, as described in their paper. LANGPROMPT uses 3 natural language text examples. Best performing model with a GPT3 backbone is shown in blue (used for our ablation studies); best performing model overall shown in **bold**. PROGPROMPT significantly outperforms the baseline Huang et al. [2022a] and LANGPROMPT. We also showcase how each PROGPROMPT feature adds to the performance of the method.

#	— Prompt Format and Parameters —						
	Format	COMMENTS	FEEDBACK	**LLM Backbone**	*SR*	*Exec*	*GCR*
1	PROGPROMPT	✓	✓	CODEX	**0.40**±0.11	**0.90**±0.05	**0.72**±0.09
2	PROGPROMPT	✓	✓	DAVINCI	0.22±0.04	0.60±0.04	0.46±0.04
3	PROGPROMPT	✓	✓	GPT3	0.34±0.08	0.84±0.01	0.65±0.05
4	PROGPROMPT	✓	✗	GPT3	0.28±0.04	0.82±0.01	0.56±0.02
5	PROGPROMPT	✗	✓	GPT3	0.30±0.00	0.65±0.01	0.58±0.02
6	PROGPROMPT	✗	✗	GPT3	0.18±0.04	0.68±0.01	0.42±0.02
7	LANGPROMPT	-	-	GPT3	0.00±0.00	0.36±0.00	0.42±0.02
8	Baseline from HUANG ET AL. Huang et al. [2022a]			GPT3	0.00±0.00	0.45±0.03	0.21±0.03

3 Results

3.1 Virtual Experiment Results

Tab. 1 summarizes the performance of our task plan generation and execution system in the *seen* environment of VirtualHome. We utilize a GPT3 as a language model backbone to receive PROGPROMPT prompts and generate plans. Each result is averaged over 5 runs in a single VH environment across 10 tasks. We report plan executability (*Exec*), goal conditions success rate (*GCR*), and overall task success rate (*SR*). See experiment and evaluation metrics details in appendix Sec. 5.2.

We can draw several conclusions from Tab. 1. First, PROGPROMPT (rows 3-6) outperforms prior work Huang et al. [2022a] (row 8) by a substantial margin on all metrics using the same large language

model backbone. Second, we observe that the CODEX Chen et al. [2021] and DAVINCI models Brown et al. [2020]—themselves GPT3 variants—show mixed success at the task. In particular, DAVINCI does not match base GPT3 performance (row 2 versus row 3), possibly because its prompt length constraints limit it to 2 task examples versus the 3 available to other rows. Additionally, CODEX *exceeds* GPT3 performance on every metric (row 1 versus row 3), likely because CODEX is explicitly trained on programming language data. However, CODEX has limited access in terms of number of queries per minute, so we continue to use GPT3 as our main LLM backbone in the following ablation experiments. Our recommendation to the community is to utilize a program-like prompt for LLM-based task planning and execution, for which base GPT3 works well, and we note that an LLM fine-tuned further on programming language data, such as CODEX, can do even better.

We explore several ablations of PROGPROMPT. First, we find that FEEDBACK mechanisms in the example programs, namely the `assert`ions and recovery actions, improve performance (rows 3 versus 4 and 5 versus 6) across metrics, the sole exception being that *Exec* improves a bit without FEEDBACK when there are no COMMENTS in the prompt example code. Second, we observe that removing COMMENTS from the prompt code substantially reduces performance on all metrics (rows 3 versus 5 and 4 versus 6), highlighting the usefulness of the natural language guidance within the programming language structure.

We also evaluate LANGPROMPT, an alternative to PROGPROMPT that builds prompts from natural language text description of objects available and example task plans (row 7). LANGPROMPT is similar to the prompts built by Huang et al. [2022a]. The outputs of LANGPROMPT are generated action sequences, rather than our proposed, program-like structures. Thus, we finetune GPT2 to learn a policy $P(\mathbf{a}_t|\mathbf{s}_t, \text{GPT3 step}, \mathbf{a}_{1:t-1})$ to map those generated sequences to executable actions in the simulation environment. We find that while this method achieves reasonable partial success through *GCR*, it does not match Huang et al. [2022a] for program executability *Exec* and does not generate any fully successful task executions. See additional analysis in appendix Sec. 5.3 and 5.4.

3.2 Physical Robot Results

The physical robot results are shown in Tab. 2. We evaluate on 4 tasks of increasing difficulty listed in Tab. 2. For each task, we perform two experiments: one in a scene that only contains the necessary objects, and with one to three distractor objects added. See Fig. 3, and 4 in appendix for visual setup and rollout example.

Table 2: Results on the physical robot by task type.

Task Description	Distractors	*SR*	Plan *SR*	*GCR*
put the banana in the bowl	0	1	1	1/1
	4	1	1	1/1
put the pear on the plate	0	1	1	1/1
	4	1	1	1/1
put the banana on the plate and the pear in the bowl	0	1	1	2/2
	3	1	1	2/2
sort the fruits on the plate and the bottles in the box	0	0	1	2/3
	1	1	1	3/3
	2	0	0	2/3

All results shown use PROGPROMPT with comments, but not feedback. Our physical robot setup did not allow reliably tracking system state and checking `assert`ions, and is prone to random failures due to things like grasps slipping. The real world introduces randomness that complicates a quantitative comparison between systems. Therefore, we intend the physical results to serve as a qualitative demonstration of the ease with which our prompting approach allows constraining and grounding LLM-generated plans to a physical robot system. We report an additional metric *Plan SR*, which refers to whether the plan would have *likely succeeded*, provided successful pick-and-place execution without gripper failures.

Across tasks, with and without distractor objects, the system almost always succeeds, failing only on the *sort* task. The run without distractors failed due to a random gripper failure. The run with 2 distractors failed because the model mistakenly considered a *soup can* to be a *bottle*. The executability for the generated plans was always *Exec*=1.

4 Conclusions

We present an LLM prompting scheme for robot task planning that brings together the two strengths of LLMs: commonsense reasoning and code understanding. We construct prompts that include situated understanding of the world and robot capabilities, enabling LLMs to directly generate executable plans as programs. Our experiments show that PROGPROMPT programming language features improve task performance across a range of metrics. Our method is intuitive and flexible, and generalizes widely to new scenes, agents and tasks, including a real-robot deployment.

References

Michael Ahn, Anthony Brohan, Noah Brown, Yevgen Chebotar, Omar Cortes, Byron David, Chelsea Finn, Keerthana Gopalakrishnan, Karol Hausman, Alex Herzog, Daniel Ho, Jasmine Hsu, Julian Ibarz, Brian Ichter, Alex Irpan, Eric Jang, Rosario Jauregui Ruano, Kyle Jeffrey, Sally Jesmonth, Nikhil J Joshi, Ryan Julian, Dmitry Kalashnikov, Yuheng Kuang, Kuang-Huei Lee, Sergey Levine, Yao Lu, Linda Luu, Carolina Parada, Peter Pastor, Jornell Quiambao, Kanishka Rao, Jarek Rettinghouse, Diego Reyes, Pierre Sermanet, Nicolas Sievers, Clayton Tan, Alexander Toshev, Vincent Vanhoucke, Fei Xia, Ted Xiao, Peng Xu, Sichun Xu, and Mengyuan Yan. Do as i can, not as i say: Grounding language in robotic affordances, 2022.

Ahmed Akakzia, Cédric Colas, Pierre-Yves Oudeyer, Mohamed CHETOUANI, and Olivier Sigaud. Grounding language to autonomously-acquired skills via goal generation. In *International Conference on Learning Representations*, 2021.

Jorge A. Baier, Fahiem Bacchus, and Sheila A. McIlraith. A heuristic search approach to planning with temporally extended preferences. In *Proceedings of the 20th International Joint Conference on Artifical Intelligence*, IJCAI'07, page 1808–1815, San Francisco, CA, USA, 2007. Morgan Kaufmann Publishers Inc.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners, 2020.

Daniel Bryce and Subbarao Kambhampati. A tutorial on planning graph based reachability heuristics. *AI Magazine*, 28(1):47, Mar. 2007.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating large language models trained on code, 2021.

Michael Danielczuk, Arsalan Mousavian, Clemens Eppner, and Dieter Fox. Object rearrangement using learned implicit collision functions. *IEEE International Conference on Robotics and Automation (ICRA)*, 2021.

Ben Eysenbach, Russ R Salakhutdinov, and Sergey Levine. Search on the replay buffer: Bridging planning and reinforcement learning. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Richard E. Fikes and Nils J. Nilsson. Strips: A new approach to the application of theorem proving to problem solving. In *Proceedings of the 2nd International Joint Conference on Artificial Intelligence*, IJCAI'71, page 608–620, San Francisco, CA, USA, 1971. Morgan Kaufmann Publishers Inc.

Caelan Reed Garrett, Tomás Lozano-Pérez, and Leslie Pack Kaelbling. Pddlstream: Integrating symbolic planners and blackbox samplers via optimistic adaptive planning. *Proceedings of the International Conference on Automated Planning and Scheduling*, 30(1):440–448, Jun. 2020.

Xiuye Gu, Tsung-Yi Lin, Weicheng Kuo, and Yin Cui. Open-vocabulary object detection via vision and language knowledge distillation. In *International Conference on Learning Representations*, 2022.

Malte Helmert. The fast downward planning system. *J. Artif. Int. Res.*, 26(1):191–246, jul 2006. ISSN 1076-9757.

Joerg Hoffmann. Ff: The fast-forward planning system. *AI Magazine*, 22(3):57, Sep. 2001.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. In *International Conference on Learning Representations*, 2020.

Wenlong Huang, Pieter Abbeel, Deepak Pathak, and Igor Mordatch. Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. *arXiv preprint arXiv:2201.07207*, 2022a.

Wenlong Huang, Fei Xia, Ted Xiao, Harris Chan, Jacky Liang, Pete Florence, Andy Zeng, Jonathan Tompson, Igor Mordatch, Yevgen Chebotar, Pierre Sermanet, Noah Brown, Tomas Jackson, Linda Luu, Sergey Levine, Karol Hausman, and Brian Ichter. Inner monologue: Embodied reasoning through planning with language models. In *arXiv preprint arXiv:2207.05608*, 2022b.

Peter Jansen. Visually-grounded planning without vision: Language models infer detailed plans from high-level instructions. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4412–4417, Online, November 2020. Association for Computational Linguistics.

YiDing Jiang, Shixiang (Shane) Gu, Kevin P Murphy, and Chelsea Finn. Language as an abstraction for hierarchical deep reinforcement learning. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Yuqian Jiang, Shiqi Zhang, Piyush Khandelwal, and Peter Stone. Task planning in robotics: an empirical comparison of pddl-based and asp-based systems, 2018.

Thanard Kurutach, Aviv Tamar, Ge Yang, Stuart J Russell, and Pieter Abbeel. Learning plannable representations with causal infogan. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018.

Shuang Li, Xavier Puig, Chris Paxton, Yilun Du, Clinton Wang, Linxi Fan, Tao Chen, De-An Huang, Ekin Akyürek, Anima Anandkumar, Jacob Andreas, Igor Mordatch, Antonio Torralba, and Yuke Zhu. Pre-trained language models for interactive decision-making, 2022.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing, 2021.

Thang Luong, Hieu Pham, and Christopher D. Manning. Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421, Lisbon, Portugal, September 2015. Association for Computational Linguistics.

Suvir Mirchandani, Siddharth Karamcheti, and Dorsa Sadigh. Ella: Exploration through learned language abstraction. In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan, editors, *Advances in Neural Information Processing Systems*, volume 34, pages 29529–29540. Curran Associates, Inc., 2021.

Suraj Nair and Chelsea Finn. Hierarchical foresight: Self-supervised learning of long-horizon tasks via visual subgoal generation. In *International Conference on Learning Representations*, 2020.

Roma Patel and Ellie Pavlick. Mapping language models to grounded conceptual spaces. In *International Conference on Learning Representations*, 2022.

Xavier Puig, Kevin Ra, Marko Boben, Jiaman Li, Tingwu Wang, Sanja Fidler, and Antonio Torralba. Virtualhome: Simulating household activities via programs. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8494–8502, 2018.

Dhruv Shah, Alexander T Toshev, Sergey Levine, and brian ichter. Value function spaces: Skill-centric state abstractions for long-horizon reasoning. In *International Conference on Learning Representations*, 2022.

Pratyusha Sharma, Antonio Torralba, and Jacob Andreas. Skill induction and planning with latent language. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1713–1726, Dublin, Ireland, May 2022. Association for Computational Linguistics.

Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Roozbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. ALFRED: A Benchmark for Interpreting Grounded Instructions for Everyday Tasks. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020.

Tom Silver, Rohan Chitnis, Nishanth Kumar, Willie McClinton, Tomas Lozano-Perez, Leslie Pack Kaelbling, and Joshua Tenenbaum. Inventing relational state and action abstractions for effective and efficient bilevel planning. In *The Multi-disciplinary Conference on Reinforcement Learning and Decision Making (RLDM)*, 2022.

Aravind Srinivas, Allan Jabri, Pieter Abbeel, Sergey Levine, and Chelsea Finn. Universal planning networks: Learning generalizable representations for visuomotor control. In Jennifer Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning*, volume 80 of *Proceedings of Machine Learning Research*, pages 4732–4741. PMLR, 10–15 Jul 2018.

Martin Sundermeyer, Arsalan Mousavian, Rudolph Triebel, and Dieter Fox. Contact-graspnet: Efficient 6-dof grasp generation in cluttered scenes. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 13438–13444, 2021.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models, 2022.

Sam Wiseman, Stuart Shieber, and Alexander Rush. Challenges in data-to-document generation. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2253–2263, Copenhagen, Denmark, September 2017. Association for Computational Linguistics.

Danfei Xu, Suraj Nair, Yuke Zhu, Julian Gao, Animesh Garg, Li Fei-Fei, and Silvio Savarese. Neural task programming: Learning to generalize across hierarchical tasks. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3795–3802, 2018.

Danfei Xu, Roberto Martín-Martín, De-An Huang, Yuke Zhu, Silvio Savarese, and Li F Fei-Fei. Regression planning networks. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Andy Zeng, Maria Attarian, Brian Ichter, Krzysztof Choromanski, Adrian Wong, Stefan Welker, Federico Tombari, Aveek Purohit, Michael Ryoo, Vikas Sindhwani, Johnny Lee, Vincent Vanhoucke, and Pete Florence. Socratic models: Composing zero-shot multimodal reasoning with language. *arXiv*, 2022.

Yifeng Zhu, Jonathan Tremblay, Stan Birchfield, and Yuke Zhu. Hierarchical planning for long-horizon manipulation with geometric and symbolic scene graphs, 2020.

5 Appendix

5.1 Background and Related Work

Task Planning. For high-level planning, most works in robotics use search in a pre-defined domain Fikes and Nilsson [1971], Garrett et al. [2020], Jiang et al. [2018]. Unconditional search can be hard to scale in environments with many feasible actions and objects Puig et al. [2018], Shridhar et al. [2020] due to large branching factors. Heuristics are often used to guide the search Baier et al. [2007], Hoffmann [2001], Helmert [2006], Bryce and Kambhampati [2007]. Recent works have explored learning-based task & motion planning, using methods such as representation learning, hierarchical learning, language as planning space, learning compositional skills and more Eysenbach et al. [2019], Xu et al. [2018, 2019], Silver et al. [2022], Shah et al. [2022], Srinivas et al. [2018], Kurutach et al.

[2018], Akakzia et al. [2021], Nair and Finn [2020], Jiang et al. [2019], Mirchandani et al. [2021], Sharma et al. [2022], Zhu et al. [2020]. Our method *sidesteps* search to directly generate a plan that includes conditional reasoning and error-correction.

We formulate task planning as the tuple $\langle \mathcal{O}, \mathcal{P}, \mathcal{A}, \mathcal{T}, \mathcal{I}, \mathcal{G}, \mathbf{t} \rangle$. $\mathcal{O}$ is a set of all the objects available in the environment, $\mathcal{P}$ is a set of properties of the objects which also informs object affordances, $\mathcal{A}$ is a set of executable actions that changes depending on the current environment state defined as $\mathbf{s} \in \mathcal{S}$. A state $\mathbf{s}$ is a specific assignment of all object properties, and $\mathcal{S}$ is a set of all possible assignments. $\mathcal{T}$ represents the transition model $\mathcal{T} : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$, $\mathcal{I}$ and $\mathcal{G}$ are the initial and goal states. The agent does not have access to the goal state $\mathbf{g} \in \mathcal{G}$, but only a high-level task description $\mathbf{t}$.

Consider the task $\mathbf{t}$ = "*microwave salmon*". Task relevant objects *microwave*, *salmon* $\in \mathcal{O}$ will have properties modified during action execution. For example, action $\mathbf{a} = \texttt{open}(\textit{microwave})$ will change the state from $\texttt{closed}(\textit{microwave}) \in \mathbf{s}$ to $\neg\texttt{closed}(\textit{microwave}) \in \mathbf{s}'$ if $\mathbf{a}$ is admissible, i.e., $\exists(\mathbf{a}, \mathbf{s}, \mathbf{s}')\ s.t.\ \mathbf{a} \in \mathcal{A} \wedge \mathbf{s}, \mathbf{s}' \in \mathcal{S} \wedge \mathcal{T}(\mathbf{s}, \mathbf{a}) = \mathbf{s}'$. In this example a goal state $\mathbf{g} \in \mathcal{G}$ could contain the conditions $\texttt{heated}(\textit{salmon}) \in \mathbf{g}$, $\neg\texttt{closed}(\textit{microwave}) \in \mathbf{g}$ and $\neg\texttt{switchedOn}(\textit{microwave}) \in \mathbf{g}$.

Planning with LLMs. A Large Language Model (LLM) is a neural network with many parameters—currently hundreds of billions Brown et al. [2020], Chen et al. [2021]—trained on unsupervised learning objectives such as next-token prediction or masked-language modelling. An autoregressive LLM is trained with a maximum likelihood loss to model the probability of a sequence of tokens $\mathbf{y}$ conditioned on an input sequence $\mathbf{x}$, i.e. $\theta = \arg\max_\theta P(\mathbf{y}|\mathbf{x};\theta)$, where θ are model parameters. The trained LLM is then used for prediction $\hat{\mathbf{y}} = \arg\max_{\mathbf{y}\in\mathbb{S}} P(\mathbf{y}|\mathbf{x};\theta)$, where $\mathbb{S}$ is the set of all text sequences. Since search space $\mathbb{S}$ is huge, approximate decoding strategies are used for tractability Luong et al. [2015], Wiseman et al. [2017], Holtzman et al. [2020].

LLMs are trained on large text corpora, and exhibit multi-task generalization when provided with a relevant prompt input $\mathbf{x}$. Prompting LLMs to generate text useful for robot task planning is a nascent topic Jansen [2020], Li et al. [2022], Patel and Pavlick [2022], Huang et al. [2022a], Ahn et al. [2022], Huang et al. [2022b]. Prompt design is challenging given the lack of paired natural language instruction text with executable plans or robot action sequences Liu et al. [2021]. Devising a prompt for task plan prediction can be broken down into a *prompting function* and an *answer search* strategy Liu et al. [2021]. A *prompting function*, $f_{\text{prompt}}(.)$ transforms the input state observation $\mathbf{s}$ into a textual prompt. *Answer search* is the generation step, in which the LLM outputs from the entire LLM vocabulary or scores a predefined set of options.

Closest to our work, Huang et al. [2022a] generates open-domain plans using LLMs. In that work, planning proceeds by: 1) selecting a similar task in the prompt example (f_{prompt}); 2) open-ended task plan generation (answer search); and 3) 1:1 prediction to action matching. The entire plan is generated *open-loop without any environment interaction*, and later tested for executability of matched actions. However, action matching based on generated text doesn't ensure the action is admissible in the current situation. INNERMONOLOGUE Huang et al. [2022b] introduces environment feedback and state monitoring, but still found that LLM planners proposed actions involving objects not present in the scene. Our work shows that a *programming language-inspired prompt generator* can inform the LLM of both situated environment state and available robot actions, ensuring output compatibility to robot actions.

The related SAYCAN Ahn et al. [2022] uses natural language prompting with LLMs to generate a set of feasible planning steps, re-scoring matched admissible actions using a learned value function. SayCan constructs a set of all admissible actions expressed in natural language and scores them using an LLM. This is challenging to do in environments with combinatorial action spaces. Concurrent with our work are Socratic models Zeng et al. [2022], which also use code-completion to generate robot plans. We go beyond Zeng et al. [2022] by leveraging additional, familiar features of programming languages in our prompts. We define an f_{prompt} that includes import statements to model robot capabilities, natural language comments to elicit common sense reasoning, and assertions to track execution state. Our answer search is performed by allowing the LLM to generate an entire, executable plan program directly.

5.2 Experiment Details

We evaluate our method with experiments in a virtual household environment and on a physical robot manipulator.

5.2.1 Simulation Experiments

We evaluate our method in the Virtual Home (VH) Environment Puig et al. [2018], a deterministic simulation platform for typical household activities. A VH state $\mathbf{s}$ is a set of objects $\mathcal{O}$ and properties $\mathcal{P}$. $\mathcal{P}$ encodes information like `in`(*salmon*, *microwave*) and `agent_close_to`(*salmon*). The action space is $\mathcal{A}$ = {`grab`, `putin`, `putback`, `walk`, `find`, `open`, `close`, `switchon`, `switchoff`, `sit`, `standup`}.

We experiment with 3 VH environments. Each environment contains 115 unique object instances (Fig. 1), including class-level duplicates. Each object has properties corresponding to its action affordances. Some objects also have a semantic state like `heated`, `washed`, or `used`. For example, an object in the *Food* category can become `heated` whenever `in`(*object*, *microwave*) $\wedge$ `switched_on`(*microwave*).

We create a dataset of 70 household tasks. Tasks are posed with high-level instructions like "*microwave salmon*". We collect a ground-truth sequence of actions that completes the task from an initial state, and record the final state $\mathbf{g}$ that defines a set of symbolic goal conditions, $\mathbf{g} \in \mathcal{P}$.

When executing generated programs, we incorporate environment state feedback in response to `asserts`. VH provides observations in the form of state graph with object properties and relations. To check assertions in this environment, we extract information about the relevant object from the state graph and prompt the LLM to return whether the assertion holds or not given the state graph and assertion as a text prompt (Fig. 1 *Prompt for State Feedback*).

We include 3 Pythonic task plan examples per prompt after evaluating performance on VH for between 1 prompt and 7 prompts and finding that 2 or more prompts result in roughly equal performance for GPT3. The plan examples are fixed to be: "*put the wine glass in the kitchen cabinet*", "*throw away the lime*", and "*wash mug*". For fintuning GPT2, we use the 35 tasks in the training set, and annotate the text steps and the corresponding action sequence to get 400 data points for training and validation of this policy.

5.2.2 Real-Robot Experiments

We use a Franka-Emika Panda robot with a parallel-jaw gripper. We assume access to a pick-and-place policy. The policy takes as input two pointclouds of a target object and a target container, and performs a pick-and-place operation to place the object on or inside the container. We use the system of Danielczuk et al. [2021] to implement the policy, and use MPPI for motion generation, SceneCollisionNet Danielczuk et al. [2021] to avoid collisions, and generate grasp poses with Contact-GraspNet Sundermeyer et al. [2021].

We specify a single `import` statement for the action `grab_and_putin(obj1, obj2)` for PROGPROMPT. We use ViLD Gu et al. [2022], an open-vocabulary object detection model, to identify and segment objects in the scene and construct the available object list for the prompt. Unlike in the virtual environment, where object list was a global variable in common for all tasks, here the object list is a local variable for each plan function, which allows greater flexibility to adapt to new objects. The LLM outputs a plan containing function calls of form `grab_and_putin(obj1, obj2)`. Here, objects `obj1` and `obj2` are text strings that we map to pointclouds using ViLD segmentation masks and the depth image. Due to real world uncertainty, we do not implement `assert`-based closed loop options on the tabletop plans.

5.2.3 Evaluation Metrics

We use three metrics to evaluate system performance: success rate (*SR*), goal conditions recall (*GCR*), and executability (*Exec*). The task-relevant goal-conditions are the set of goal-conditions that changed between the initial and final state in the demonstration. *SR* is the fraction of executions that achieved all task-relevant goal-conditions. *Exec* is the fraction of actions in the plan that are executable in the environment, even if they are not relevant for the task. *GCR* is measured using the set difference

between ground truth final state conditions $\mathbf{g}$ and the final state achieved $\mathbf{g}'$ with the generated plan, divided by the number of task-specific goal-conditions; *SR*$= 1$ only if *GCR*$= 1$.

5.3 Additional experiments

Table 3: PROGPROMPT performance on the VH test-time tasks and their ground truth actions sequence lengths $|A|$.

Task Desc	$\|A\|$	*SR*	*Exec*	*GCR*
watch tv	3	0.20±0.40	0.42±0.13	0.63±0.28
turn off light	3	0.40±0.49	1.00±0.00	0.65±0.30
brush teeth	8	0.80±0.40	0.74±0.09	0.87±0.26
throw away apple	8	1.00±0.00	1.00±0.00	1.00±0.00
make toast	8	0.00±0.00	1.00±0.00	0.54±0.33
eat chips on the sofa	5	0.00±0.00	0.40±0.00	0.53±0.09
put salmon in the fridge	8	1.00±0.00	1.00±0.00	1.00±0.00
wash the plate	18	0.00±0.00	0.97±0.04	0.48±0.11
bring coffeepot and cupcake to the coffee table	8	0.00±0.00	1.00±0.00	0.52±0.14
microwave salmon	11	0.00±0.00	0.76±0.13	0.24±0.09
Avg: $0 \leq \|A\| \leq 5$		0.20±0.40	0.61±0.29	0.60±0.25
Avg: $6 \leq \|A\| \leq 10$		0.60±0.50	0.95±0.11	0.79±0.29
Avg: $11 \leq \|A\| \leq 18$		0.00±0.00	0.87±0.14	0.36±0.16

Task-by-Task Performance PROGPROMPT performance for each task in the test set is shown in Table 3. We observe that tasks that are similar to prompt examples, such as *throw away apple* versus *wash the plate* have higher *GCR* since the ground truth prompt examples hint about good stopping points. Even with high *Exec*, some task *GCR* are low, because some tasks have multiple appropriate goal states, but we only evaluate against a single "true" goal. For example, after microwaving and plating salmon, the agent may put the salmon on a table or a countertop.

Table 4: PROGPROMPT results on Virtual Home in additional scenes. We evaluate on 10 tasks each in two additional VH scenes beyond scene ENV-0 where other reported results take place.

VH Scene	*SR*	*Exec*	*GCR*
ENV-0	0.34±0.08	0.84±0.01	0.65±0.05
ENV-1	0.56±0.08	0.85±0.02	0.81±0.07
ENV-2	0.56±0.05	0.85±0.03	0.72±0.09
Average	0.48±0.13	0.85±0.02	0.73±0.10

Other Environments We evaluate PROGPROMPT in two additional VH environments (Tab. 4). For each, we append a new object list representing the new environment after the example tasks in the prompt, followed by the task to be completed in the new scene. The action primitives and other PROGPROMPT settings remain unchanged. We evaluate on 10 tasks with 5 runs each. For new tasks like *wash the cutlery in dishwasher*, PROGPROMPT is able to infer that *cutlery* refers to *spoons* and *forks* in the new scenes, despite that *cutlery* always refers to *knives* in example prompts.

5.4 Qualitative Analysis and Limitations

We manually inspect generated programs and their execution traces from PROGPROMPT and characterize common failure modes. Many failures stem from the decision to make PROGPROMPT *agnostic* to the deployed environment and its peculiarities, which may be resolved through explicitly communicating, for example, object affordances of the target environment as part of the PROGPROMPT prompt.

- *Environment artifacts*: the VH agent cannot find or interact with objects nearby when `sitting`, and some common sense actions for objects, such as `open`ing a *tvstand*'s cabinets, are not available in VH.
- *Environment complexities*: when an object is not accessible, the generated assertions might not be enough. For example, if the agent finds an object in a *cabinet*, it may not plan to `open` the *cabinet* to `grab` the object.
- *Action success feedback* is not provided to the agent, which may lead to failure of the subsequent actions. Assertion recovery modules in the plan can help, but aren't generated to cover all possibilities.
- *Incomplete generation:* Some plans are cut short by LLM API caps. One possibility is to query the LLM again with the prompt and partially generated plan.

In addition to these failure modes, our strict final state checking means if the agent completes the task *and some*, we may infer failure, because the environment goal state will not match our precomputed ground truth final goal state. For example, after making *coffee*, the agent may take the *coffeepot* to another *table*. Similarly, some task descriptions are ambiguous and have multiple plausible correct programs. For example, "*make dinner*" can have multiple possible solutions. PROGPROMPT generates plans that cooks *salmon* using the *fryingpan* and *stove*, and sometimes the agent adds *bellpepper* or *lime*, or sometimes with a side of *fruit*, or served in a *plate* with *cutlery*. When run in a different VH environment, the agent cooks *chicken* instead. PROGPROMPT is able to generate plans for such complex tasks as well while using the objects available in the scene and not explicitly mentioned in the task. However, automated evaluation of such tasks requires enumerating all valid and invalid possibilities or introducing human verification.

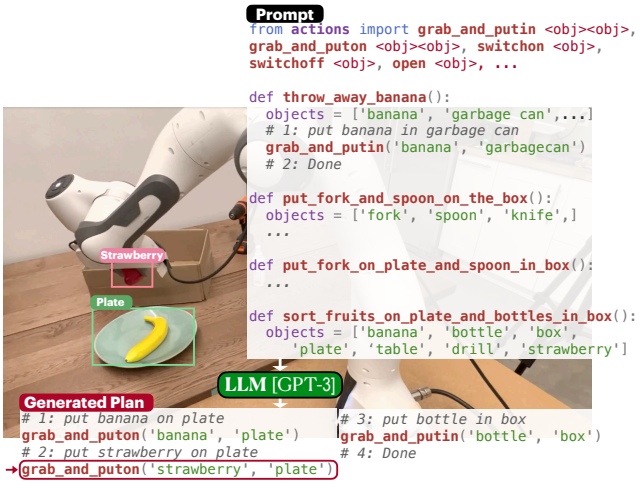

Figure 3: PROGPROMPT leverages LLMs' strengths in both world knowledge and programming language understanding to generate situated task plans that can be directly executed.

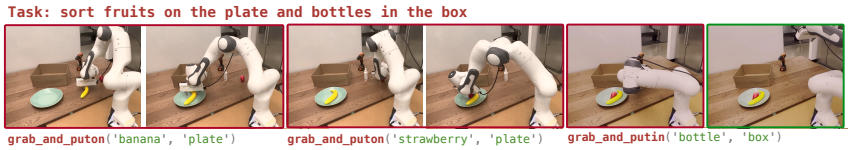

Figure 4: Robot plan execution rollout example on the sorting task showing relevant objects *banana*, *strawberry*, *bottle*, *plate* and *box*, and a distractor object *drill*. The LLM recognizes that *banana* and *strawberry* are *fruits*, and generates plan steps to place them on the *plate*, while placing the *bottle* in the *box*. The LLM ignores the distractor object *drill*. See Figure 3 for the prompt structure used.

5.5 Future Work

As a community, we are only scratching the surface of task planning as robot plan generation and completion. We hope to study broader use of programming language features, including real-valued

numbers to represent measurements, nested dictionaries to represent scene graphs, and more complex control flow. Several works from the NLP community show that LLMs can do arithmetic and understand numbers, yet their capabilities for complex robot behavior generation are still relatively under-explored.