A Contributions

A.1 By Type

- **Designed and built distributed robot learning infrastructure:** Michael Ahn, Anthony Brohan, Noah Brown, Yevgen Chebotar, Byron David, Keerthana Gopalakrishnan, Karol Hausman, Alex Herzog, Daniel Ho, Jasmine Hsu, Julian Ibarz, Alex Irpan, Eric Jang, Nikhil J Joshi, Ryan Julian, Dmitry Kalashnikov, Yuheng Kuang, Yao Lu, Peter Pastor, Kanishka Rao, Nicolas Sievers, Fei Xia, Ted Xiao, Peng Xu, Sichun Xu, and Mengyuan Yan.
- **Designed, implemented, or trained the underlying manipulation policies:** Yevgen Chebotar, Keerthana Gopalakrishnan, Karol Hausman, Julian Ibarz, Alex Irpan, Eric Jang, Nikhil Joshi, Ryan Julian, Kuang-Huei Lee, Yao Lu, Kanishka Rao, and Ted Xiao.
- **Designed or implemented the data generation and curation or collected data:** Noah Brown, Omar Cortes, Jasmine Hsu, Alex Irpan, Eric Jang, Rosario Jauregui Ruano, Kyle Jeffrey, Linda Luu, Jornell Quiambao, Kanishka Rao, Jarek Rettinghouse, Diego Reyes, Pierre Sermanet, Clayton Tan, and Sichun Xu.
- **Designed or implemented SayCan:** Karol Hausman, Brian Ichter, Sergey Levine, Alexander Toshev, and Fei Xia.
- **Managed or advised on the project:** Chelsea Finn, Karol Hausman, Eric Jang, Sally Jesmonth, Sergey Levine, Yao Lu, Carolina Parada, Kanishka Rao, Alexander Toshev, and Vincent Vanhoucke.
- **Ran evaluations or experiments:** Noah Brown, Omar Cortes, Brian Ichter, Rosario Jauregui Ruano, Kyle Jeffrey, Linda Luu, Jornell Quiambao, Jarek Rettinghouse, Diego Reyes, Clayton Tan, and Fei Xia.
- **Scaled simulation infrastructure:** Nikhil J Joshi, Yao Lu, Kanishka Rao, and Ted Xiao.
- **Wrote the paper:** Chelsea Finn, Karol Hausman, Brian Ichter, Alex Irpan, Sergey Levine, Fei Xia, and Ted Xiao.

A.2 By Person

Michael Ahn developed the deployment system that enabled the ability to scale up data collection on real robots.
Anthony Brohan implemented the logging system for the project and designed and implemented the data labeling pipelines.
Noah Brown led and coordinated the real-robot operations including data collection with teleoperators, evaluations and the real-world setup.
Yevgen Chebotar designed and implemented multiple offline RL methods allowing the manipulation policies to process data coming from different sources.
Omar Cortes collected data on the robots and ran and supervised real-world evaluations.
Byron David developed simulation assets and performed system identification.
Chelsea Finn advised on the project, helped set the research direction and wrote parts of the paper.
Keerthana Gopalakrishnan provided multiple infrastructure contributions that allowed for scalable learning of manipulation policies.
Karol Hausman co-led the project as well as developed SayCan, helped set the research direction, trained the underlying manipulation policies, and wrote the paper.
Alex Herzog developed the teleoperation tools and implemented multiple infrastructure tools that allowed for continuous robot operation.
Daniel Ho helped develop sim-to-real pipelines for manipulation policies.
Jasmine Hsu provided logging and monitoring infrastructure tools as well as data labeling pipelines.
Julian Ibarz provided multiple contributions that enabled scaling learning algorithms for manipulation policies, and helped set the research direction.
Brian Ichter initiated and led the SayCan algorithm, combined the manipulation and navigation skills, ran experiments for the paper, and wrote the paper.
Alex Irpan set up and led the autonomous data collection effort as well as verified the data collected by the robots, and wrote parts of the paper.
Eric Jang helped set the research and team direction, managed the data for learning, developed the behavioral cloning manipulation policies, and wrote parts of the paper.

Rosario Jauregui Ruano collected data on the robots and ran and supervised real-world evaluations.
Kyle Jeffrey collected data on the robots and ran and supervised real-world evaluations.
Sally Jesmonth was the program manager for the project.
Nikhil J Joshi developed a number of simulation and infrastructure tools that allowed to scale up simulation training.
Ryan Julian developed multi-modal network architectures and trained manipulation policies.
Dmitry Kalashnikov contributed infrastructure pieces that enabled training from logged data.
Yuheng Kuang implemented the logging system for the project and designed and implemented the data labeling pipelines
Kuang-Huei Lee made improvements to training algorithms for manipulation policies.
Sergey Levine advised on the project, helped set the research direction, developed SayCan, and wrote parts of the paper.
Yao Lu led and designed the robot learning infrastructure for the project providing most of the tools and improving manipulation policies.
Linda Luu ran multiple evaluations, collected data and helped establish real-robot operations.
Carolina Parada advised on the project, managed the team, helped write the paper, and helped set the research direction.
Peter Pastor provided infrastructure tools that allowed for continuous robot operations.
Jornell Quiambao collected data on the robots and ran and supervised real-world evaluations.
Kanishka Rao co-led the project, managed the team, helped set the research direction and contributed to training manipulation policies.
Jarek Rettinghouse collected data on the robots and ran and supervised real-world evaluations.
Diego Reyes collected data on the robots and ran and supervised real-world evaluations.
Pierre Sermanet set up the crowd compute rating pipeline.
Nicolas Sievers provided simulation assets and environments used for simulation training.
Clayton Tan collected data on the robots and ran and supervised real-world evaluations and helped establish real-robot operations.
Alexander Toshev advised on the project, developed SayCan, helped write the paper, and helped set research direction.
Vincent Vanhoucke advised on the project, managed the team, and helped write the paper.
Fei Xia developed, implemented, and led on-robot SayCan, ran the experiments for the paper, created the demos, and wrote the paper.
Ted Xiao led the scaling of manipulation skills, designed and developed learning from simulation for manipulation skills, and developed multi-modal network architectures.
Peng Xu was the engineering lead for integrating manipulation and navigation and developed the underlying infrastructure for SayCan.
Sichun Xu developed remote teleoperation tools that allowed scaling up data collection in simulation.
Mengyuan Yan implemented infrastructure and learning tools that allowed for learning manipulation policies from different data sources.

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B Background

Large Language Models. Language models seek to model the probability $p(W)$ of a text $W = \{w_0, w_1, w_2, ..., w_n\}$, a sequence of strings w. This is generally done through factorizing the probability via the chain rule to be $p(W) = \Pi_{j=0}^{n} p(w_j | w_{<j})$, such that each successive string is predicted from the previous. Recent breakthroughs initiated by neural network-based Attention architectures [82] have enabled efficient scaling of so-called Large Language Models (LLMs). Such models include Transformers [82], BERT [19], T5 [83], GPT-3 [2], Gopher [84], LAMDA [85], FLAN [86], and PaLM [11], each showing increasingly large capacity (billions of parameters and terabytes of text) and subsequent ability to generalize across tasks.

In this work, we utilize the vast semantic knowledge contained in LLMs to determine useful tasks for solving high-level instructions.

Value functions and RL. Our goal is to be able to accurately predict whether a skill (given by a language command) is feasible at a current state. We use temporal-difference-based (TD) reinforcement learning to accomplish this goal. In particular, we define a Markov decision process (MDP) $\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, R, \gamma)$, where $\mathcal{S}$ and $\mathcal{A}$ are state and action spaces, $P : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}_+$ is a state-transition probability function, $R : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ is a reward function and γ is a discount factor. The goal of TD methods is to learn state or state-action value functions (Q-function) $Q^\pi(s, a)$, which represents the discounted sum of rewards when starting from state s and action a, followed by the actions produced by the policy π, i.e. $Q^\pi(s, a) = \mathbb{E}_{a \sim \pi(a|s)} \sum_t R(s_t, a_t)$. The Q-function, $Q^\pi(s, a)$ can be learned via approximate dynamic programming approaches that optimize the following loss: $L_{TD}(\theta) = \mathbb{E}_{(s,a,s') \sim \mathcal{D}} \left[R(s, a) + \gamma \mathbb{E}_{a^* \sim \pi} Q^\pi_\theta(s', a^*) - Q^\pi_\theta(s, a)\right]$, where $\mathcal{D}$ is the dataset of states and actions and θ are the parameters of the Q-function.

In this work, we utilize TD-based methods to learn said value function that is additionally conditioned on the language command and utilize those to determine whether a given command is feasible from the given state. It is worth noting that in the sparse reward case, where the agent receives the reward of 1.0 at the end of the episode if it was successful and 0.0 otherwise, the value function trained via RL corresponds to an affordance function [87] that specifies whether a skill is possible in a given state. We leverage that intuition in our setup and express affordances via value functions of sparse reward tasks.

C RL and BC Policies

C.1 RL and BC Policy Architecture

The RL models use an architecture similar to MT-Opt [6], with slight changes to support natural language inputs (see Fig. 6 for the network diagram). The camera image is first processed by 7 convolutional layers. The language instruction is embedded by the LLM, then concatenated with the robot action and non-image parts of the state, such as the gripper height. To support asynchronous control, inference occurs while the robot is still moving from the previous action. The model is given how much of the previous action is left to execute [88]. The conditioning input goes through FC layers, then tiled spatially and added to the conv. volume, before going through 11 more convolutional layers. The output is gated through a sigmoid, so the Q-value is always in $[0, 1]$.

The BC models use an architecture similar to BC-Z [5] (see Fig. 7 for the network diagram). The language instruction is embedded by a universal sentence encoder [8], then used to FiLM condition a Resnet-18 based architecture. Unlike the RL model, we do not provide the previous action or gripper height, since this was not necessary to learn the policy. Multiple FC layers are applied to the final visual features, to output each action component (arm position, arm orientation, gripper, and the termination action).

C.2 RL and BC Policy Training

RL training. In addition to using demonstrations in the BC setup, we also learn language-conditioned value functions with RL. For this purpose, we complement our real robot fleet with a simulated version of the skills and environment. To reduce the simulation-to-real gap we transform robot images via RetinaGAN [9] to look more realistic while preserving genera object structure. In order to learn a language-conditioned RL policy, we utilize MT-Opt [6] in the Everyday Robots simulator using said simulation-to-real transfer. We bootstrap the performance of simulation policies by utilizing simulation demonstrations to provide initial successes, and then continuously improve the RL performance with online data collection in simulation. Standard image augmentations (random brightness and contrast) as well as random cropping were applied. The 640 x 512 input image was padded by 100 pixels left-right and 40 pixels top-down, then cropped back down to a 640 x 512 image, so as to allow for random spatial shifts without limiting the field of view. We use a network architecture similar to MT-Opt (shown in Fig. 6).

The RL model is trained using 16 TPUv3 chips and for about 100 hours, as well as a pool of 3000 CPU workers to collect episodes and another 3000 CPU workers to compute target Q-values. Computing target Q-values outside the TPU allows the TPU to be used solely for computing gradient updates. Episode rewards are sparse and always 0 or 1, so the Q-function is updated using a log loss. Models were trained using prioritized experience replay [89], where episode priority was tuned to encourage replay buffer training data for each skill to be close to 50% success. Episodes were sampled proportionally to their priority, defined as $1 + 10 \cdot |p - 0.5|$, where p is the average success rate of episodes in the replay buffer.

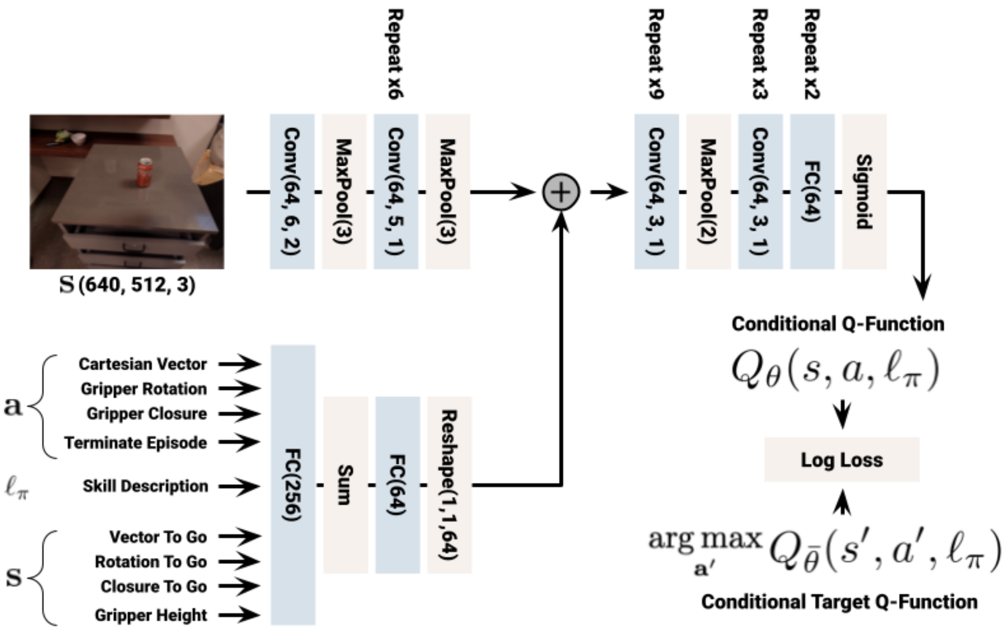


Figure 6: Network architecture in RL policy

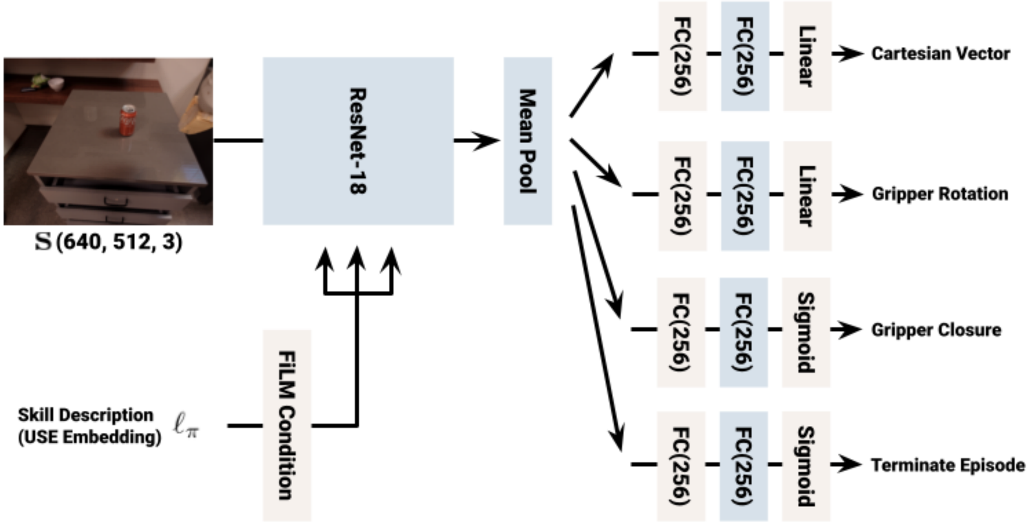


Figure 7: Network architecture in BC policy

BC training. We use 68000 teleoperated demonstrations that were collected over the course of 11 months using a fleet of 10 robots. The operators use VR headset controllers to track the motion of their hand, which is then mapped onto the robot's end-effector pose. The operators can also use a joystick to move the robot's base. We expand the demonstration dataset with 276000 autonomous episodes of learned policies which are later success-filtered and included in BC training, resulting in an additional 12000 successful episodes. To additionally process the data, we also ask the raters to mark the episodes as unsafe (i.e., if the robot collided with the environment), undesirable (i.e., if the robot perturbed objects that were not relevant to the skill) or infeasible (i.e., if the skill cannot be done or is already accomplished). If any of these conditions are met, the episode is excluded from training.

To learn language-conditioned BC policies at scale in the real world, we build on top of BC-Z [5] and use a similar policy-network architecture (shown in Fig. 7). It is trained with an MSE loss for the continuous action components, and a cross-entropy loss for the discrete action components. Each action component was weighted evenly. Standard image augmentations (random brightness and contrast) as well as random cropping were used. The 640 x 512 input image was padded by 100 pixels left-right and 40 pixels top-down, then cropped back down to a 640 x 512 image, so as to allow for random spatial shifts without limiting the field of view. For faster iteration speeds with negligible training performance reduction, image inputs were down sampled to half-size (256 x 320 images). Affordance value functions were trained with full-size images, since half-size images did not work as well when learning $Q(s, a, \ell_\pi)$. The BC model is trained using 16 TPUv3 chips and trained for about 27 hours.

C.3 RL and BC Policy Evaluations

In order to obtain the best possible manipulation capabilities for use in SayCan, we use a separate evaluation protocol for iterating on the RL and BC policies in the Mock Office Kitchen stations. Evaluations are divided by skill (pick up, knock over, place upright, open/close drawers, move object close to another one), and within each skill, 18-48 skills are sampled from a predetermined set of three objects. Object positions are randomized on each episode, with one or two objects serving as a distractor.

The episode ends when 50 actions have been taken or the policy samples a terminate action. A human operator supervises multiple robots performing evaluation and performs scene resets as needed, and records each episode as a success or failure. Models whose per-skill performance outperforms prior models are ”graduated” to the same evaluation protocol in the real kitchen, and then integrated into SayCan. We found that despite the domain shift from Mock Office Kitchen stations to the actual kitchen counter and drawers, higher success rates on mock stations usually corresponded to higher success rates in the real kitchen setting.

Figure 8 shows the development of the manipulation skills over time. It reports the per-skill success rate, the average success rate across all skills, and the number of instructions the policy was trained on. Over the course of the project, we increased the number of skills evaluated, from 1 instruction in April 2021 to hundreds of instructions at time of publication over the course of 366 real-world model evaluations.

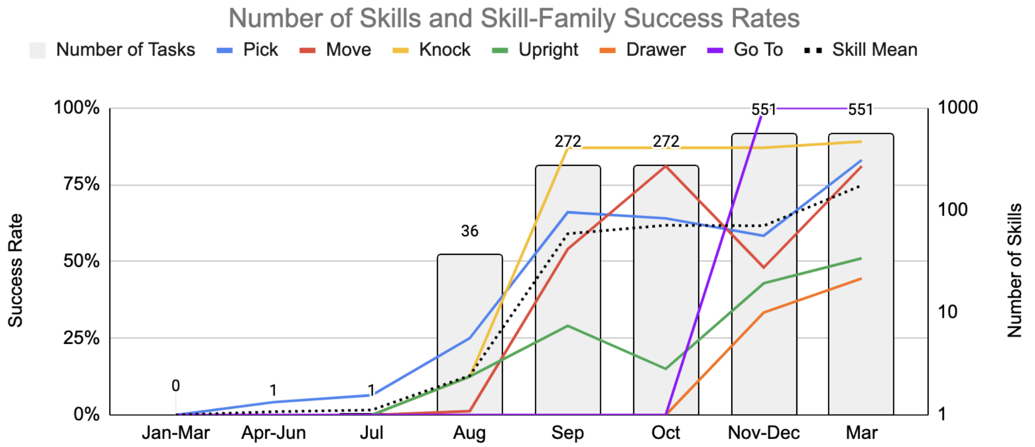
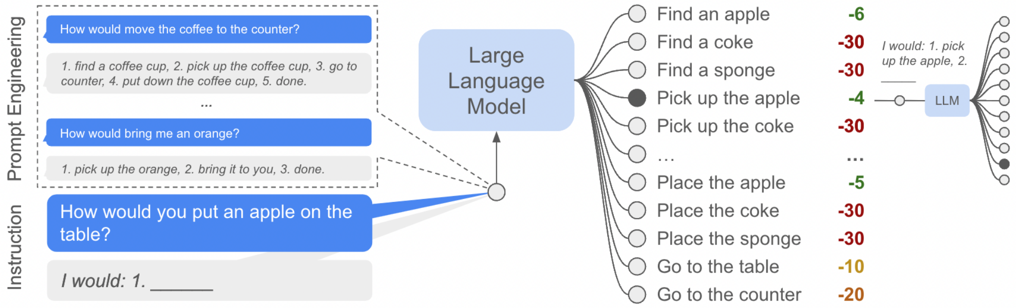


Figure 8: Per-skill evaluation performance of the best policies and number of skills over the duration of the project. The performance as well as the number of skills that the robots are able to handle grow over time due to the continuous data collection efforts as well as improving the policy training algorithms.

D SayCan Details and Parameters

D.1 SayCan Details

Figure 9 shows scoring approach used and prompt engineering for the LLM side of SayCan. Figure 10 shows how robotic affordances are computed with value functions and real value function computations at different states. These two components are combined to form SayCan, as detailed in Algorithm 1 and in Figure 11.



How would move the coffee to the counter?

1. find a coffee cup, 2. pick up the coffee cup, 3. go to counter, 4. put down the coffee cup, 5. done.

...

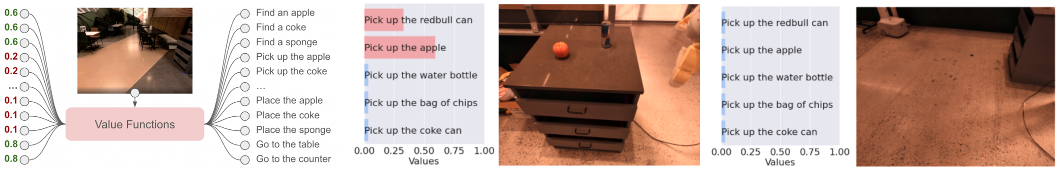
How would bring me an orange?

1. pick up the orange, 2. bring it to you, 3. done.

How would you put an apple on the table?

I would: 1. ______

Figure 9: A scoring language model is queried with a prompt-engineered context of examples and the high-level instruction to execute and outputs the probability of each skill being selected. To iteratively plan the next steps, the selected skill is added to the natural language query and the language model is queried again.



(a) (b) (c)

Figure 10: A value function module (a) is queried to form a value function space of action primitives based on the current observation. Visualizing "pick" value functions, in (b) "Pick up the red bull can" and "Pick up the apple" have high values because both objects are in the scene, while in (c) the robot is navigating an empty space, and thus none of the pick up actions receive high values.

D.2 Skills, Policies, and Affordance Functions

We also note a few practical considerations for setting up our affordance functions and policies. The flexibility of our approach allows us to mix and match policies and affordances from different methods. For the pick manipulation skills we use a single multi-task, language-conditioned policy, for the place manipulation skills we use a scripted policy with an affordance based on the gripper state, and for navigation policies we use a planning-based approach which is aware of the locations where specific objects can be found and a distance measure. In order to avoid a situation where a skill is chosen but has already been performed or will have no effect, we set a cap for the affordances indicating that the skill has been completed and the reward received.

SayCan is capable of incorporating many different policies and affordance functions through its probability interface. Though in principle each type of skill has been trained with the pipeline described in Appendix C, to the success rates seen in Figure 8, we wish to show the generality of SayCan to different policies and affordance functions as well as the robustness of other functions (e.g. distance for navigation). Furthermore, some skills (such as the manipulation skill "move

Algorithm 1 SayCan

```
Given: A high level instruction $i$, state $s_0$, and a set of skills $\Pi$ and their language descriptions $\ell_\Pi$
$n = 0, \pi = \emptyset$
while $\ell_{\pi_{n-1}} \neq$ "done" do
    $\mathcal{C} = \emptyset$
    for $\pi \in \Pi$ and $\ell_\pi \in \ell_\Pi$ do
        $p_\pi^{\text{LLM}} = p(\ell_\pi | i, \ell_{\pi_{n-1}}, ..., \ell_{\pi_0})$        ▷ Evaluate scoring of LLM
        $p_\pi^{\text{affordance}} = p(c_\pi | s_n, \ell_\pi)$        ▷ Evaluate affordance function
        $p_\pi^{\text{combined}} = p_\pi^{\text{affordance}} p_\pi^{\text{LLM}}$
        $\mathcal{C} = \mathcal{C} \cup p_\pi^{\text{combined}}$
    end for
    $\pi_n = \arg\max_{\pi \in \Pi} \mathcal{C}$
    Execute $\pi_n(s_n)$ in the environment, updating state $s_{n+1}$
    $n = n + 1$
end while
```

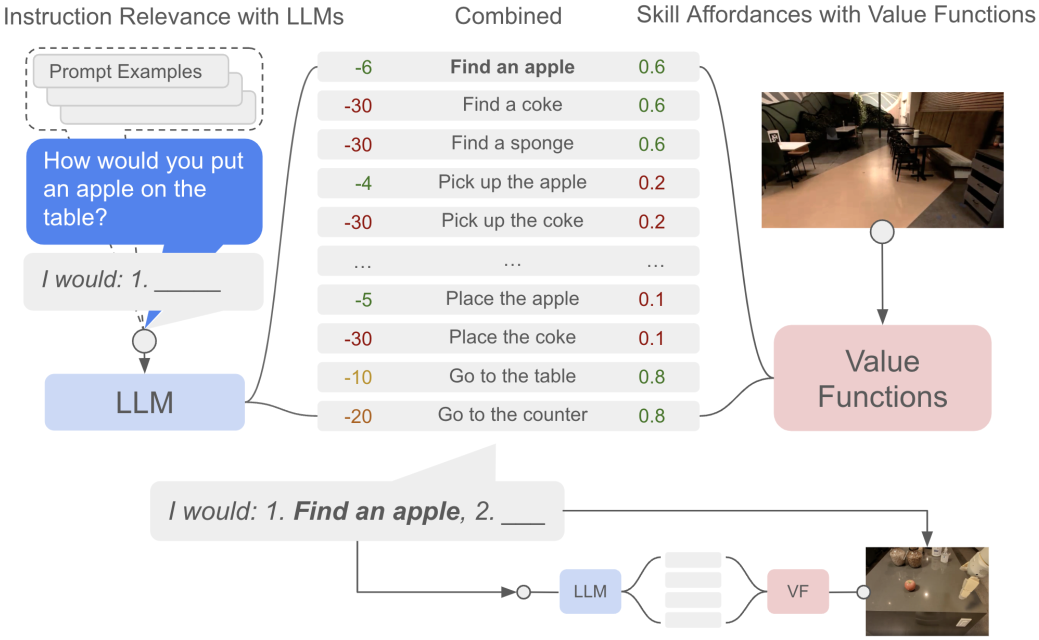


Figure 11: (A copy of Figure 2 here for clarity) Given a high-level instruction, SayCan combines probabilities from a language model (representing the probability that a skill is useful for the instruction) with the probabilities from a value function (representing the probability of successfully executing said skill) to select the skill to perform. This emits a skill that is both possible and useful. The process is repeated by appending the selected skill to the robot response and querying the models again, until the output step is to terminate.

`object` near `object`" and "knock `object` over") are not naturally part of long-horizon tasks and thus we do not utilize them. Other skills, such as drawer opening, were not consistent enough for long-horizon planning and thus unused. However, we note that as skills become performant or as new skills are learned, it is straightforward to incorporate these skills by adding them as options for LLM scoring and as examples in the prompt. We use the following for each skill family:

- **Pick.** For pick we use the learned policies in Appendix C and Section 3 with actions from BC and value functions from RL trained on the same skill. In natural language these are specified as "pick up the `object`".
- **Go to.** Since the focus of this work is mainly on planning, we assume the location of objects are known. Thus any navigation skill maps to the coordinate of the object with a classical planning-based navigation stack. In natural language these are specified as "go to `location`" and "find `object`".
- **Place.** Though our manipulation policies have a "place upright" skill, this skill only applies to objects that have a canonical upright direction, e.g., a water bottle but not a bag of chips. One could also train a universal "place" command, but our current policies are trained in a setup-free environment and thus are not amenable to an initial pick. Thus to have a consistent place policy across all objects we use a classical motion planning policy. We use Cartesian space motion planning to plan a path from pre-grasp pose shown in Figure 3 to a gripper release pose. The robot executes that path until the gripper is in contact with a supporting surface, and then the gripper opens and releases the object. In natural language these are specified as "put down the `object`".

Each skill is thus an explicit text command performed by a low-level policy for that skill. For `object` above, we use the objects shown in Figure 3 placed in random configurations at locations throughout the scene (e.g., coke can, water bottle, jalapeno chips, apple, sponge, etc.). These objects can be placed in random configurations at locations throughout the scene. For `location` above, we consider several named locations with known positions shown in Figure 3 (e.g., table, trash can, etc.). This results in skills such as the following:

- "Pick up the coke", "pick up the 7up", "pick up the apple", "pick up the sponge", etc. Note that each is different for different objects and this distinction is learned through demonstration data.
- "Go to the trash can", "go to the table", etc.
- "Place the coke", "place the 7up", etc.

Recall that we wish to find the affordance function $p(c_\pi|s, \ell_\pi)$, which indicates the probability of c-ompleting the skill with description ℓ_π successfully from state s. Our learned policies produce a Q-function, $Q^\pi(s, a)$. Given $Q^\pi(s, a)$ with action a and state s, value $v(s) = \max_a Q^\pi(s, a)$ is found through optimization via the cross entropy method, similar to MT-Opt. For brevity below we refer to the value functions by their skill-text description ℓ_π as v^{ℓ_π} and the affordance function as $p^{\text{affordance}}_{\ell_\pi}$. Furthermore, SayCan enforces logic that if a skill that has already been completed and the reward received (e.g., navigating to the table the robot is already in front of) then it should not be performed. Due to artifacts of training and each implementation, the value functions require calibration to be directly applied as a probability. The parameters used for calibration are determined empirically. In practice we found this calibration fairly robust and straightforward and that the combination of the LLM and affordance function complement each other to reduce errors. For picking for instance, we see when an object is not present or when the robot is navigating, we find a consistent minimum value, while if the object is present the value rises quickly when the object is able to be picked, and peak consistently when the object is picked. For navigation, we set this value so that it is calibrated to the size of the scene.

- **Pick.** We find the trained value functions generally have a minimum value for when a skill is not possible and a maximum when the skill is successful and thus we normalize the value function to get a affordance function with

  $$p^{\text{affordance}}_{\text{pick}} = \text{clamp}(\frac{v^{\text{pick}} - v^{\text{pick}}_{\text{min}}}{v^{\text{pick}}_{\text{max}} - v^{\text{pick}}_{\text{min}}}, 0, 1), \text{where } v^{\text{pick}}_{\text{max}} = 0.5, v^{\text{pick}}_{\text{min}} = 0.2.$$

- **Go to.** The affordance function of go to skills are based on the distance d (in meters) to the location. We use

  $$p^{\text{affordance}}_{\text{goto}} = \text{clamp}(\frac{d^{\text{goto}}_{\text{max}} - d^{\text{goto}}}{d^{\text{goto}}_{\text{max}} - d^{\text{goto}}_{\text{min}}}, 0, 1), \text{where } d^{\text{goto}}_{\text{max}} = 100, d^{\text{goto}}_{\text{min}} = 0.$$

- **Place.** We assume place is always possible, $p^{\text{affordance}}_{\text{place}} = 1.0$, since we find language is sufficient to understand place is only possible after a pick. In the future work having an affordance function module for place could further improve the performance of SayCan.
- **Terminate.** We give terminate a small affordance value, to make sure the planning process terminates when there is no feasible skills to choose from. $p^{\text{affordance}}_{\text{terminate}} = 0.1$.

D.3 LLM Size

SayCan is able to improve with improved language models. The LLM used herein was PaLM [11], a 540B parameter model. In this section we ablate over 8B, 62B, and 540B parameter models as well as the 137B parameter FLAN model [86] which is finetuned on a "instruction answering" dataset. Table 3 shows each model on the generative problem. Table 4 shows PaLM 540B and FLAN on robot. We find that generally larger models perform better, though the difference between the 62B and 540B model is small. Results in other works, such as Chain of Thought Prompting [20], indicate this difference may be more pronounced on more challenging problems. We also find that PaLM outperforms FLAN. Though FLAN was finetuned on instruction answering, the broader and improved dataset for PaLM may make up for this difference in training.

D.4 LLM Prompt

The LLM uses prompt engineering and a strict response structure to score skills. But, as SayCan as a whole requires affordances from a world embodiment, it is not straightforward to optimize this structure and tune parameters quickly. Thus we built a language-based simulator which, given a query and a solution sequence of skills, outputs affordances consistent with the query and solution. It also generates consistent distractor affordances to ensure robustness. The simulator then verifies that SayCan recovers the correct solution and tests how confident SayCan is in the correct solutions.

Family	**Num**	**PaLM 540B [11]**	**PaLM 62B**	**PaLM 8B**	**FLAN 137B [86]**
NL Single	15	87%	73%	20%	40%
NL Nouns	15	53%	47%	20%	40%
NL Verbs	15	93%	100%	60%	87%
Structured	15	100%	100%	67%	73%
Embodiment	11	36%	27%	27%	0%
Crowd Sourced	15	80%	73%	47%	47%
Long-Horizon	15	60%	73%	20%	0%
Total	101	74%	72%	38%	43%

Table 3: Ablations over the size of the LLM. Compared only with the generative outputs (no value function) with USE embeddings [8].

		PaLM [11]		**FLAN [86]**	
Family	**Num**	Plan	Execute	Plan	Execute
NL Single	15	100%	100%	67%	67%
NL Nouns	15	67%	47%	60%	53%
NL Verbs	15	100%	93%	80%	67%
Structured	15	93%	87%	100%	87%
Embodiment	11	64%	55%	64%	55%
Crowd Sourced	15	87%	87%	73%	67%
Long-Horizon	15	73%	47%	47%	33%
Total	101	84%	74%	70%	61%

Table 4: Success rates of instructions by family. SayCan achieves a planning success rate of 84% and execution success rate of 74% with PaLM and FLAN achieves 70% planning and 61% success. SayCan scales and improves with improved LLMs.

In Table 5 we test the effect of the number of examples in the prompt on the planning success rate in the language-based simulator (over 50 demonstrative instructions). We show a success rate with and without requiring the plan to terminate; without examples we found the LLM was unlikely to issue a "done" phase. With no examples SayCan is able to successfully plan 54% without the done condition, but only 10% with the done condition. Though it makes mistakes, clearly some information is already imbued within the language model. It is able to correctly solve "Can I have a redbull please?" and "Move the chips bag from the table to the counter.". With only one example the LLM quickly improves in both planning rates, though still fails to terminate the plan occasionally. After only four examples the LLM is performant, planning 82% of the queries correctly, though the remaining errors are largely within a single instruction family: Long-Horizon. Finally, the prompt used in this work, Listing 1, involved 17 examples and recovered 88% of the solutions correctly.

We note here briefly a few lessons learned in prompt engineering and structuring the final prompt. Providing explicit numbers between steps (e.g., 1., 2., instead of combining skills with "and then" or other phrases) improved performance, as did breaking each step into a separate line (e.g. adding a "\n" between steps). Examples which overly include objects used in the actual planning tend to bias results to those objects (e.g., if every example is about apples then the apple scoring will be off in planning). Phrasing of the natural language names of skills and objects is important due to the auto-regressive nature of the LLM scoring – skills and objects should be naturally named and errors such as misspellings or mismatches in "a" vs "an" can be problematic. Notably, since user generated instructions are taken as given such fragility is not issues for the input, allowing a robustness to user queries. For our language model, PaLM [11], structuring the interaction as dialog was both more natural and performant. Although dialog is used as prompt, the model generalized to imperative sentences at deployment time.

Num Examples	Require Termination	No Termination Required
0	10%	52%
1	64%	74%
2	68%	76%
4	82%	84%
8	80%	80%
Full Prompt (17)	88%	88%

Table 5: Number of prompt engineering examples versus planning rate (when requiring the plan to know when to terminate, e.g., issue a "done" command, or not).

Listing 1: Prompt in SayCan.

```
Robot: Hi there, I'm a robot operating in an office kitchen.
Robot: You can ask me to do various tasks and I'll tell you the sequence of actions I would do to
     accomplish your task.
Human: How would you hold the snickers?
Robot: 1. pick up the snickers, 2. done.
Human: How would you put the trailmix here?
Robot: 1. put down the trailmix, 2. done.
Human: How would you put a water bottle and an oatmeal next to the microwave?
Robot: 1. find a water bottle, 2. pick up the water bottle, 3. go to microwave, 4. put down the water
     bottle, 5. find an oatmeal, 6. pick up the oatmeal, 7. go to the microwave, 8. put down the oatmeal,
     9. done.
Human: How would you put a grapefruit from the table into the bowl?
Robot: 1. find a grapefruit, 2. pick up the grapefruit, 3. go to the bowl, 4. put down the grapefruit, 5.
     done.
Human: How would you get a sponge from the counter and put it in the sink?
Robot: 1. find a sponge, 2. pick up the sponge, 3. go to the sink, 4. put down the sponge, 5. done.
Human: How would you move the water bottle from the table to the counter?
Robot: 1. find a water bottle, 2. pick up the water bottle, 3. go to the counter, 4. put down the water
     bottle, 5. done.
Human: How would you bring me some snacks?
Robot: 1. find a twix, 2. pick up the twix, 3. bring it to you, 4. put down the twix, 5. find an dried
     fruit, 6. pick up the dried fruit, 7. bring it to you, 8. put down the dried fruit, 9. done.
Human: How would you bring me an orange?
Robot: 1. find an orange, 2. pick up the orange, 3. bring it to you, 4. put down the orange, 5. done.
Human: How would you deliver a can of coke to me?
Robot: 1. find a coke can, 2. pick up the coke can, 3. bring it to you, 4. put down the coke can, 5. done.
Human: I finished my drink, can you throw it away and bring me a mountain dew?
Robot: 1. find a sprite can, 2. pick up the sprite can, 3. go to the trash can, 4. put down the sprite can
     , 5. find a mountain dew can, 6. pick up the mountain dew can, 7. bring it to you, 8. put down the
     mountain dew can, 9. done.
Human: How would you let go of the banana?
Robot: 1. put down the banana, 2. done.
Human: How would you put the grapes in the bowl and then move the cheese to the table?
Robot: 1. find the grapes, 2. pick up the grapes, 3. go to the bowl, 4. put down the grapes, 5. pick up
     the cheese, 6. go to the table, 7. put down the cheese, 8. tell you I'm done.
Human: How would you pick up the peanuts?
Robot: 1. pick up the peanuts, 2. done.
Human: How would you bring me the peanuts?
Robot: 1. pick up the peanuts, 2. bring it to you, 3. put down the peanuts, 4. done.
Human: How would you throw away a coffee cup?
Robot: 1. find a coffee cup, 2. pick up the coffee cup, 3. go to trash can, 4. put down the coffee cup, 5.
      done.
Human: How would you place a knife and a banana to the table?
Robot: 1. find a knife, 2. pick up the knife, 3. go to the table, 4. put down the knife, 5. find a banana,
      6. pick up the banana, 7. go to the table, 8. put down the banana, 9. done.
```

E Experiments

E.1 Tasks

Below we include every instruction run, which environment it was run in, and its planning and execution success rate. Table 5 shows all instructions as broken down by instruction family, listed below and initially defined in Section 4 Table 1.

- **Natural Language (NL) Single Primitive.** Given a natural language command corresponding to performing a single primitive, can SayCan recover that primitive skill and terminate?
- **NL Noun.** Given a natural language query that replaces a noun (typically an object or location) with a synonym, can SayCan execute the appropriate sequence?

- **NL Verbs.** Given a natural language query that replaces a verb (typically an action) with a synonym, can SayCan execute an appropriate sequence?
- **Structured Language.** Given a structure language query that mirrors the NL Verbs and spells out the sequence of commands, how well can SayCan plan compared to NL Verbs? This acts as an ablation to see the performance loss of understanding a natural language query over an explicit solution.
- **Embodiment.** Given a query with different environment and robot states, can SayCan still execute at a high rate? This tests the performance of SayCan's affordance model and the LLM's ability to reason within it.
- **Crowd-Sourced.** These queries were crowd sourced from Mechanical Turk by giving humans a description of what occurred (e.g., an apple was moved in front of you) and asking them what they would ask the robot to do. They were also crowd sourced by asking humans in a real office kitchen to command the robot to perform tasks (given knowledge of the robot's abilities). This tests SayCan's performance with natural requests.
- **Long-Horizon.** These challenging queries require SayCan to reason over temporally extended instructions to investigate how well it scales to such regimes.

E.2 Adding Skills: Drawer Manipulation

In order to support drawer manipulation we added another category of skills in SayCan.

- **Drawer Manipulation.** For drawer manipulation we use the learned policies in Appendix C and Section 3 with actions from BC and value functions from heuristics (If the robot is next to the drawer, all drawer tasks are possible). In natural language these are specified as "open the drawer", "close the drawer" and "put the `object` in the drawer".

A few drawer-specific prompts also need to be added to teach the robot how to chain the drawer skills together. The prompts are shown in Listing 2.

Listing 2: Drawer Prompt in SayCan.

```
Human: open the drawer
Robot: 1. go to the drawers, 2. open the drawer, 3. done.
Human: restock orange juice into the drawer
Robot: 1. go to the drawers, 2. open the drawer, 3. put orange juice in the drawer, 4. close the drawer,
     5. done.
Human: restock two bottles of orange juice into the drawer
Robot: 1. go to the drawers, 2. open the drawer, 3. put orange juice in the drawer, 4. put orange juice in
      the drawer, 5. close the drawer, 6. done.
```

The results of the drawer tasks are shown in Table. 6. SayCan achieved an overall planning success rate of 100% and execution success rate of 33%. The main failure cases are manipulation failures,

Instruction
How would you pick up the coke can
How would you put the coke can in the your gripper
How would you grasp the coke can
How would you hold onto the coke can
How would you lift and hold the coke can up
How would you put the coke can down
How would you place the coke can on the table
How would you let go of the coke can
How would you release the coke can
How would you place the coke can
How would you move to the table
How would you go to the table
How would you park at the table
How would you come to the table
How would you navigate to the table

(a) NL Single Primitive

Instruction
How would you throw away the apple
How would you bring me a sponge?
How would you bring me a coke can
How would you grab me an apple
How would you grab me a 7up from the table
How would you deliver the red bull to the close counter
How would you throw away the jalapeno chips
How would you restock the rice chips on the far counter
How would you recycle the coke can
How would you throw away the water bottle
How would you bring me something hydrating
How would you put the apple back on the far counter
How would you recycle the 7up
How would you throw away jalapeno chips
How would you compost the apple

(b) NL Verb

Instruction
How would you bring me lime drink
How would you bring me something to clean the kitchen with
How would you bring me something to eat
How would you put the grapefruit drink on the close counter
How would you move the sugary drink to the far counter
How would you move something with caffine from the table to the close counter
How would you bring me an energy bar
How would you bring me something to quench my thirst
How would you bring me a fruit
How would you bring me a fruit from the close counter
How would you bring me something that is not a fruit from the close counter
How would you bring me a soda from the table
How would you bring me a soda
How would you bring me a bag of chips from close counter
How would you bring me a snack

(c) NL Nouns

Instruction
How would you pick up the apple and move it to the trash
How would you pick up the sponge and bring it to me
How would you pick up the coke can and bring it to me
How would you pick up the apple and bring it to me
How would you pick up the 7up and bring it to me
How would you pick up the redbull and move it to the close counter
How would you pick up the jalapeno chips and move it to the trash
How would you pick up the rice chips and move it to the far counter
How would you pick up the coke can and move it to the trash
How would you pick up the water bottle and move it to the trash
How would you pick up the grapefruit soda and bring it to me
How would you pick up the apple and move it to the far counter
How would you pick up the 7up and move it to the trash
How would you pick up the jalepeno chips and move it to the trash
How would you pick up the apple and move it to the trash

(d) Structured Language

Instruction
How would you put the coke can down on the far counter(with operator)
How would you put the coke can down on the far counter(at table)
How would you put the coke can down on the far counter(at table with coke can in hand)
How would you put the coke can down on the far counter(at far counter with coke can in hand)
How would you put the sponge on the close counter(with operator)
How would you put the sponge on the close counter(at far counter)
How would you put the sponge on the close counter(at far counter with sponge in hand)
How would you put the sponge on the close counter(at close counter with coke can in hand)
How would you pick up the drink from the far counter
I left something on the table, can you throw it away?
I left something on the table or the counter, can you bring it to me?

(e) Embodiment

Instruction
I opened a pepsi earlier. How would you bring me an open can?
I spilled my coke, can you bring me a replacement?
I spilled my coke, can you bring me something to clean it up?
I accidentally dropped that jalapeno chip bag after eating it. Would you mind throwing it away?
I like fruits, can you bring me something I'd like?
There is a close counter, far counter, and table. How would you visit all the locations?
There is a close counter, trash can, and table. How would you visit all the locations?
Redbull is my favorite drink, can I have one please?
Would you bring me a coke can?
Please, move the pepsi to the close counter
Please, move the ppsi(intentional typo) to the close cuonter
Can you move the coke can to the far counter?
Can you move coke can to far counter?
Would you throw away the bag of chips for me?
Would you throw away the bag of chpis(intentional typo) for me?

(f) Crowd-Sourced

Instruction
How would you put an energy bar and water bottle on the table
How would you bring me a lime soda and a bag of chips
Can you throw away the apple and bring me a coke
How would you bring me a 7up can and a tea?
How would throw away all the items on the table?
How would you move an multigrain chips to the table and an apple to the far counter?
How would you move the lime soda, the sponge, and the water bottle to the table?
How would you bring me two sodas?
How would you move three cokes to the trash can?
How would you throw away two cokes?
How would you bring me two different sodas?
How would you bring me an apple, a coke, and water bottle?
I spilled my coke on the table, how would you throw it away and then bring me something to help clean?
I just worked out, can you bring me a drink and a snack to recover?
How would you bring me a fruit, a soda, and a bag of chips for lunch

(g) Long-Horizon

Table 5: **List of all instructions** We evaluate the algorithm on 101 instructions on 2 scenes. The metrics and success definitions can be found in Sec. 4.

where the robot fails to open the drawer wide enough to put objects in it, or fails to completely close the drawer.

Instruction	Plan rate	Execution rate
restock the coke and pepsi into the drawer	1.0	0.0
hide the 7up in the drawer	1.0	0.83
restock the coke into the drawer	1.0	0.17

Table 6: Drawer tasks

E.3 Chain of Thought Reasoning

One limitation of vanilla SayCan is that it doesn't handle tasks that involves negation. This is inherited from underline language models, and studied in the NLP community [14]. However, we found by using chain-of-thought prompting [20] we can improve SayCan on this front.

For chain-of-thought prompting-based SayCan, we need to modify the prompt to include a part called "Explanation". We also slightly change how we use the language model. Instead of directly using the scoring interface to rank possible options, we first use the generative decoding of LLM to create an explanation, and then use the scoring mode, by including the explanation into the prompt. The full prompt is shown in Listing 3.

Listing 3: Chain-of-thought prompt in SayCan.

```
Robot: Hi there, I'm a robot operating in an office kitchen.
You can ask me to do various tasks and I'll tell you the sequence of actions I would do to accomplish your
      task.
The following objects are in the scene: 7up, apple, tea, multigrain chips, kettle chips, jalapeno chips,
     rice chips, coke, grapefruit soda, pepsi, redbull, energy bar, lime soda, sponge, and water bottle.
The following locations are in the scene: close counter, far counter, table, you, trash, bowl.
Human: Hold the sponge
Explanation: The user has asked for a single skill, I will just pick up the sponge.
Robot: 1. pick up the sponge, 2. done.
Human: Put the kettle chips here
Explanation: The user has asked for a type of chips, I will bring those to them.
Robot: 1. put down the kettle chips, 2. done.
Human: Move the grapefruit drink from the table to the close counter
Explanation: The user has asked me to move the grapefruit drink to the counter.
Robot: 1. find a grapefruit soda, 2. pick up the grapefruit soda, 3. go to the counter, 4. put down the
     grapefruit soda, 5. done.
Human: Bring me some snacks
Explanation: The user has asked for snacks, I will bring jalapeno chips and an apple.
Robot: 1. find a jalapeno chips, 2. pick up the jalapeno chips, 3. bring it to you, 4. put down the
     jalapeno chips, 5. find an apple, 6. pick up the apple, 7. bring it to you, 8. put down the apple, 9.
      done.
Human: Bring me something that isn't a fruit
Explanation: The user has asked for something food that isn't an fruit, I will bring an energy bar.
Robot: 1. find an energy bar, 2. pick up the energy bar, 3. bring it to you, 4. put down the energy bar,
     5. done.
Human: Put the rice chips in the bowl and then move the tea to the table
Explanation: The user has asked me to do two tasks, I will do one and then the other.
Robot: 1. find the rice chips, 2. pick up the rice chips, 3. go to the bowl, 4. put down the rice chips,
     5. pick up the tea, 6. go to the table, 7. put down the tea, 8. done.
Human: Throw away a redbull
Explanation: The user has asked me to throw away the redbull can, I will move it to the trash.
Robot: 1. find a redbull, 2. pick up the redbull, 3. go to trash, 4. put down the redbull, 5. done.
```

A few successful rollouts of the model at evaluation time is shown in Listing 4. As we can see, with chain of thought prompting, the model can handle negations and tasks that require reasoning.

Listing 4: Chain-of-thought planning rollout with SayCan.

```
Human: Can you bring a drink without caffeine but has some fruit flavor?
Explanation: The user has asked for a drink without caffeine but has some fruit flavor, I will bring the
     lime soda.
Robot: 1. find a lime soda, 2. pick up the lime soda, 3. bring it to you, 4. done

Human: Bring me chips that taste spicy
Explanation: The user has asked for chips that taste spicy, I will bring the Jalapeno chips.
Robot: 1. find the jalapeno chips, 2. pick up the jalapeno chips, 3. bring it to you, 4. put down the
     jalapeno chips, 5.done

Human: I do not like pepsi, bring me something similar
Explanation: The user has asked for something similar to coke, I will bring coke
Robot: 1. find a coke, 2. pick up the coke, 3. bring it to you, 4. put down the coke, 5. done

Human: The snack is too small, bring me something more filling
Explanation: The user has asked for a snack that is more filling, I will bring the multigrain chips
Robot: 1. find the multigrain chips, 2. pick up the multigrain chips, 3. bring it to you, 4. put down the
     multigrain chips, 5. done
```

E.4 Multilingual Queries

Since the underlying LM we used [11] has been trained on multilingual corpora, SayCan can handle multilingual queries out of the box. The results of SayCan on multilingual queries are summarized in Table. 7, and there is almost no performance drop on planning success rate when chaning the queries from English to Chinese, French and Spanish.

Instruction	**Plan rate**
bring me a can of coke	1.0
throw away the coke can	1.0
I spilled my coke, can you bring me something to help clean	1.0
拿一罐可乐给我	1.0
扔掉可乐罐	1.0
我的可乐洒了，你能给我拿点东西来帮忙打扫吗	1.0
apporte moi une canette de coca	1.0
jeter la canette de coca	1.0
J'ai renversé mon coca, peux-tu m'apporter quelque chose pour m'aider à nettoyer	0.0
tráeme una lata de coca cola	1.0
tirar la lata de coca cola	1.0
Derramé mi coca cola, ¿puedes traerme algo para ayudar a limpiar	1.0

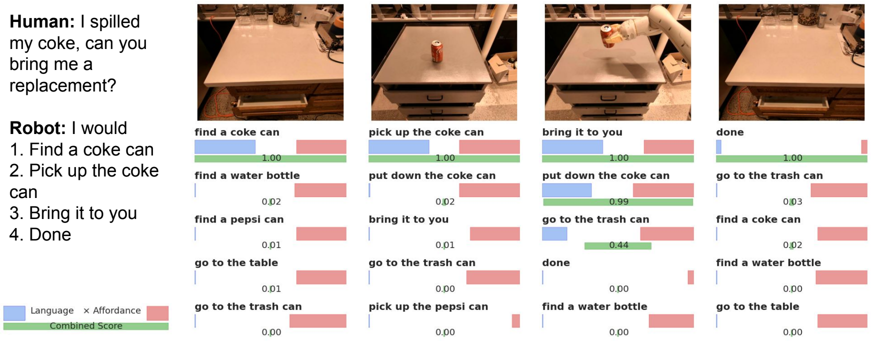
Table 7: Multilingual queries plan success rate. instruction 4-12 are the Chinese, French and Spanish translation of first 3 queries.

E.5 Additional Results

Additional results are shown in Figure 12 and Figure 13 and some failure cases in Figure 14. For videos of the rollouts, please visit the anonymous website `https://saycan-corl.github.io`

F Open Source Environment

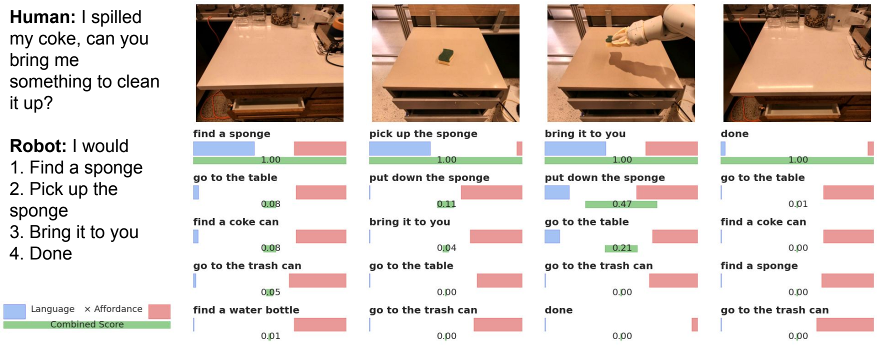
We have open sourced an implementation of SayCan in a Google Colab notebook for a tabletop robot. Code can be found here. The environment is shown in Figure 16 and is a tabletop with a UR5 robot and randomly generated sets of colored blocks and bowls. It is implemented with a ViLD object detector for affordances [90] and GPT-3 as the large language model [2]. Steps are output in the form `robot.pick_and_place(object, location)`, leveraging the ability of LLMs to output code structures. The policy is implemented with CLIPort [48], which is trained to output a pick and place location.



Human: I spilled my coke, can you bring me a replacement?

Robot: I would
1. Find a coke can
2. Pick up the coke can
3. Bring it to you
4. Done

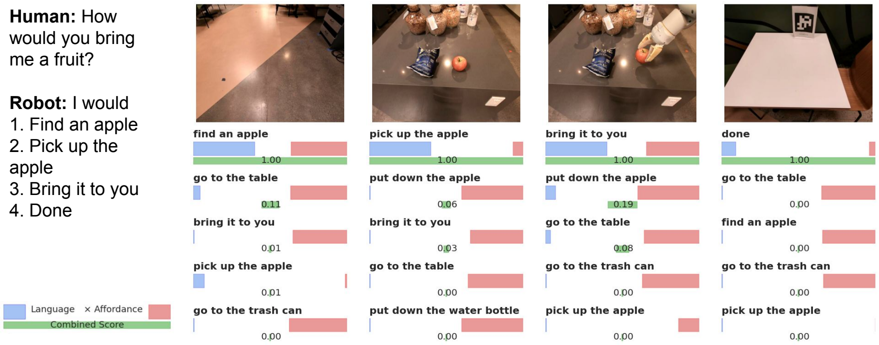
(a)



Human: I spilled my coke, can you bring me something to clean it up?

Robot: I would
1. Find a sponge
2. Pick up the sponge
3. Bring it to you
4. Done

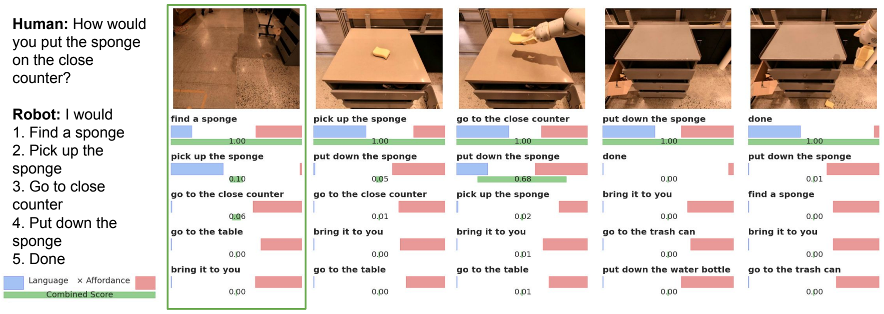
(b)



Human: How would you bring me a fruit?

Robot: I would
1. Find an apple
2. Pick up the apple
3. Bring it to you
4. Done

(c)

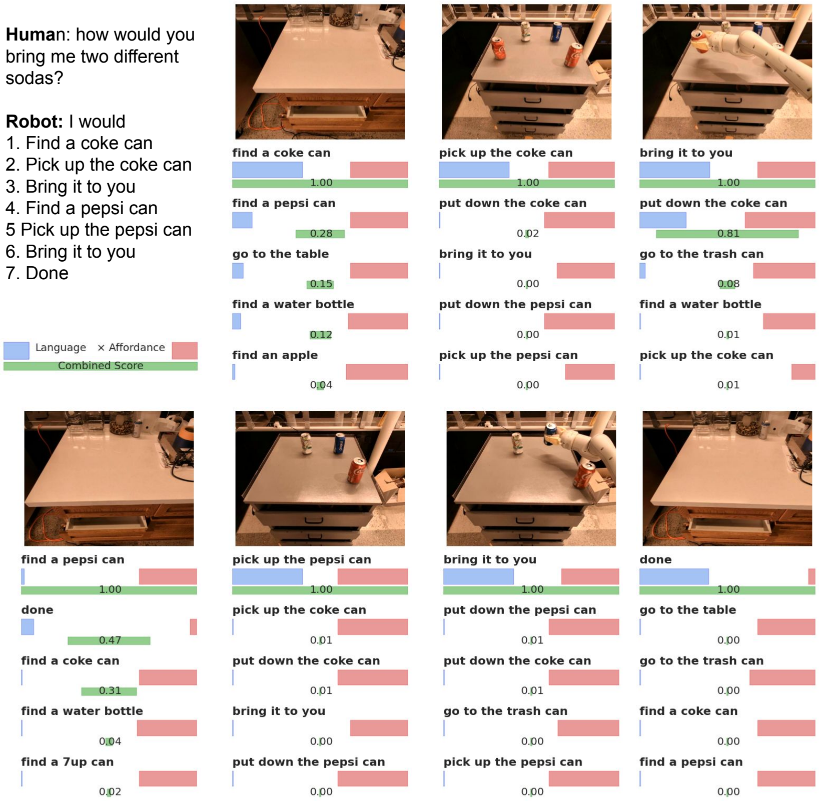


Human: How would you put the sponge on the close counter?

Robot: I would
1. Find a sponge
2. Pick up the sponge
3. Go to close counter
4. Put down the sponge
5. Done

(d)

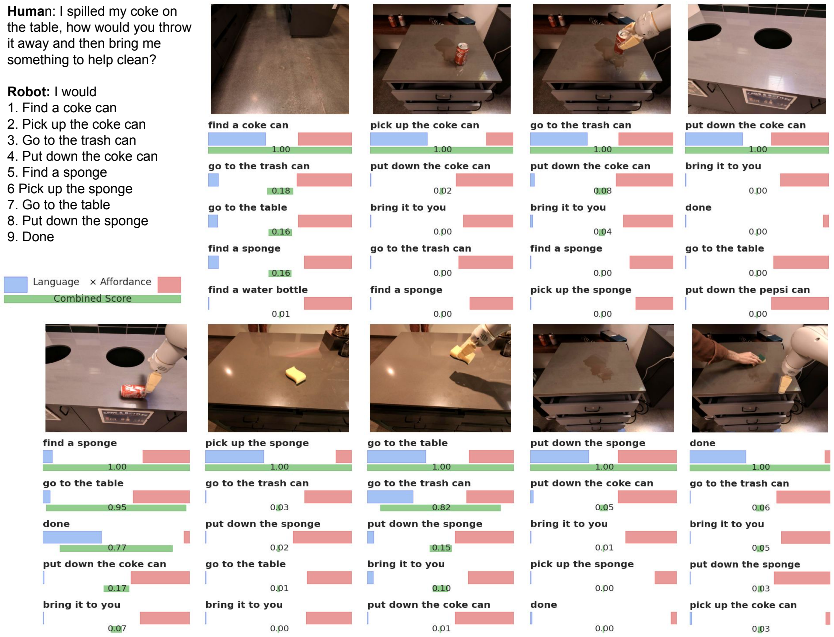
Figure 12: Visualization of the decision making process of SayCan shows its interpretability and successful temporally extended execution, where the top combined score chooses the correct skill.



Human: how would you bring me two different sodas?

Robot: I would
1. Find a coke can
2. Pick up the coke can
3. Bring it to you
4. Find a pepsi can
5 Pick up the pepsi can
6. Bring it to you
7. Done

(a) In this long-horizon task, the language model gives high score to the two sodas. After the coke is delivered, the language model scores pepsi higher. The affordance rating overcomes potential early termination after the first can has been delivered.

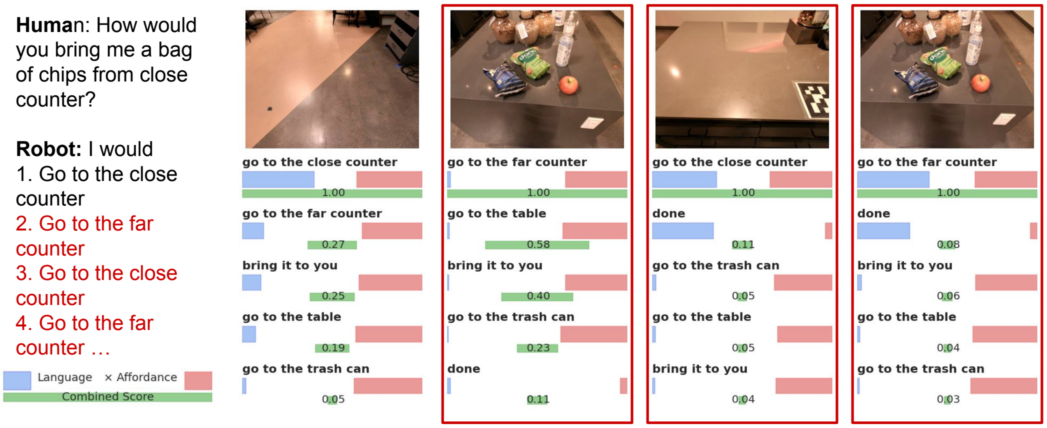


Human: I spilled my coke on the table, how would you throw it away and then bring me something to help clean?

Robot: I would
1. Find a coke can
2. Pick up the coke can
3. Go to the trash can
4. Put down the coke can
5. Find a sponge
6 Pick up the sponge
7. Go to the table
8. Put down the sponge
9. Done

(b) In this task, the model completes a 9-step plan. It narrowly avoids an early termination at step 5.

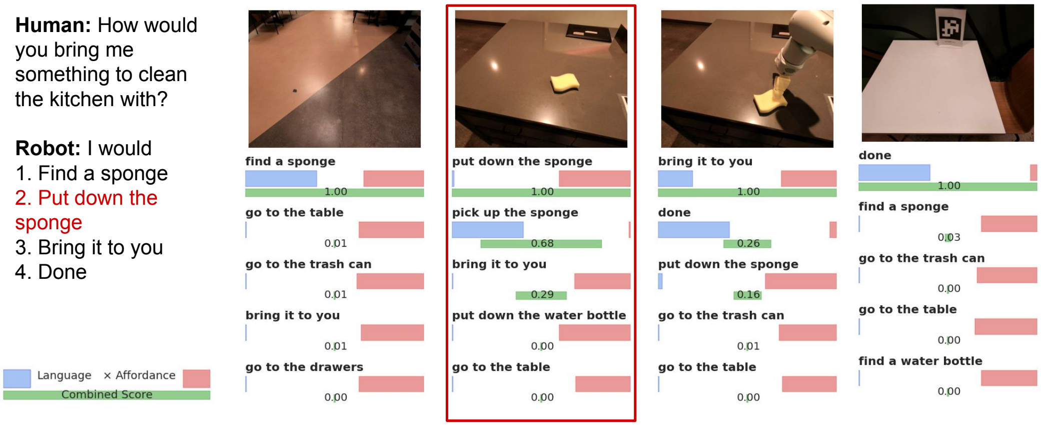
Figure 13: Long horizon sequences, see the video on our website `say-can.github.io` for more.



Human: How would you bring me a bag of chips from close counter?

Robot: I would
1. Go to the close counter
2. Go to the far counter
3. Go to the close counter
4. Go to the far counter …

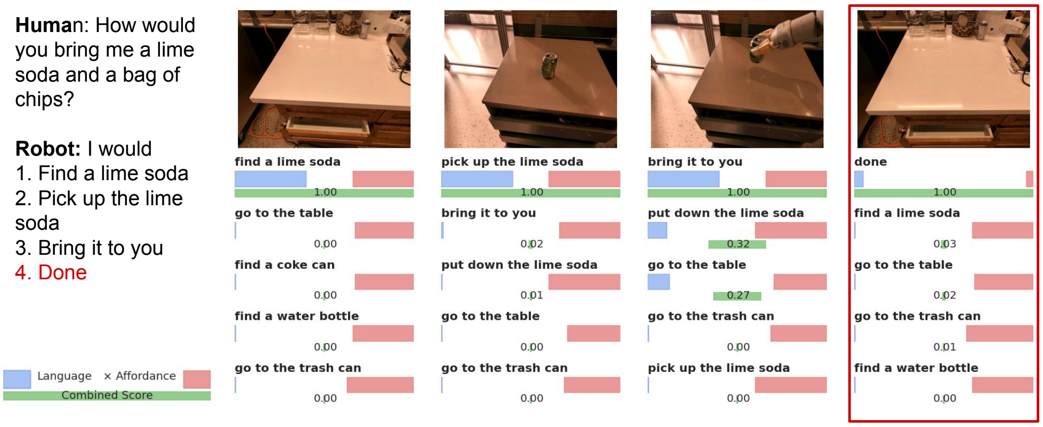
(a) The affordance model fails to identify either bag of chips as pickable, though the language model approaches the counter twice.



Human: How would you bring me something to clean the kitchen with?

Robot: I would
1. Find a sponge
2. Put down the sponge
3. Bring it to you
4. Done

(b) The affordance model fails to identify the sponge as pickable.

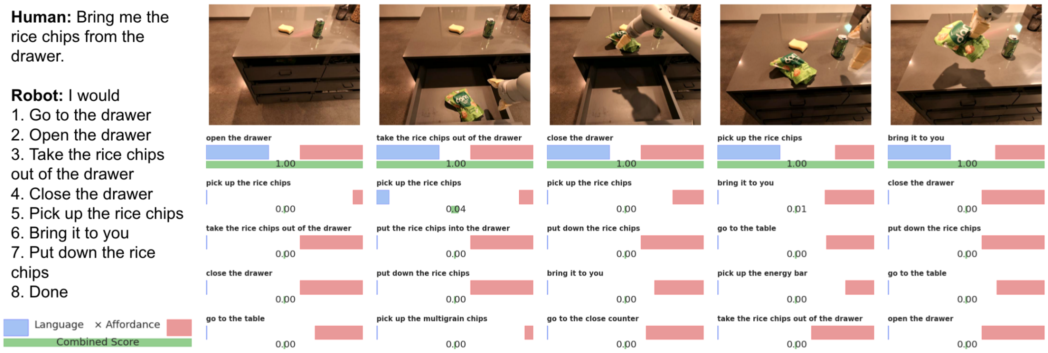


Human: How would you bring me a lime soda and a bag of chips?

Robot: I would
1. Find a lime soda
2. Pick up the lime soda
3. Bring it to you
4. Done

(c) Language model terminates a long-horizon task prematurely.

Figure 14: Failure cases. The planning success rate was 84%. Of the errors, 65% were a result of an LLM error and 35% were affordance errors.



Human: Bring me the rice chips from the drawer.

Robot: I would
1. Go to the drawer
2. Open the drawer
3. Take the rice chips out of the drawer
4. Close the drawer
5. Pick up the rice chips
6. Bring it to you
7. Put down the rice chips
8. Done

Figure 15: A sequence of the robot taking rice chips from the drawers. Note the robot only has one arm, so it needs to plan a long sequence to first take rice chips out of drawer and place on the counter, and then pick it up again after closing the drawer.

```
Task: move all the blocks into
their matching colored bowls.
Step 1.
robot.pick_and_place("blue
block", "blue bowl")
Step 2.
robot.pick_and_place("green
block", "green bowl")
Step 3.
robot.pick_and_place("yellow
block", "yellow bowl")
```

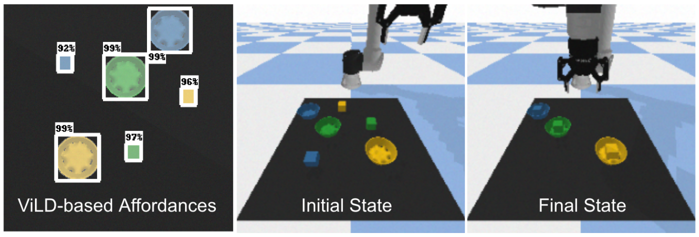


Figure 16: We have open sourced a Colab with a tabletop environment, a UR5 robot, and CLIPort-based policy here: `https://github.com/google-research/google-research/blob/master/saycan/SayCan-Robot-Pick-Place.ipynb`.