What Foundation Models can Bring for Robot Learning in Manipulation : A Survey

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Abstract

The realization of universal robots is an ultimate goal of researchers. However, a key hurdle in achieving this goal lies in the robots' ability to manipulate objects in their unstructured environments according to different tasks. The learning-based approach is considered an effective way to address generalization. The impressive performance of foundation models in the fields of computer vision and natural language suggests the potential of embedding foundation models into manipulation tasks as a viable path toward achieving general manipulation capability. However, we believe achieving general manipulation capability requires an overarching framework akin to auto driving. This framework should encompass multiple functional modules, with different foundation models assuming distinct roles in facilitating general manipulation capability. This survey focuses on the contributions of foundation models to robot learning for manipulation. We propose a comprehensive framework and detail how foundation models can address challenges in each module of the framework. What's more, we examine current approaches, outline challenges, suggest future research directions, and identify potential risks associated with integrating foundation models into this domain.

Keywords

Robot learning, manipulation, foundation model, survey, universal robot

1 Introduction

Researchers aim to create universal robots that can seamlessly integrate into human life to boost productivity, much like those depicted in the movie "I, Robot". However, a key hurdle in achieving this lies in the robots' ability to manipulate objects in their unstructured environments according to different tasks. There is abundant literature available for improving the general manipulation capability of robots, which can be roughly categorized into model-based and learning-based approaches (Zarrin et al. (2023)). The real world is too diverse for universal robots and they must adapt to unstructured environments and arbitrary objects to manipulate effectively. Therefore, learning-based methods are crucial for manipulation tasks (Kleeberger et al. (2020)).

The predominant methodologies in learning-based approaches are deep learning, reinforcement learning and imitation learning. Learning-based methods have spanned from acquiring specific manipulation skills through labeled datasets like human demonstration, to acquiring abstract representations of manipulation tasks conducive to highlevel planning, to exploring an object's functionalities through interaction and encompassing various objectives in between (Kroemer et al. (2021)). However, challenges persist, including 1) unnatural interaction with humans; 2) high-cost data collection; 3) limited perceptual capability; 4) non-intelligent hierarchy of skills; 5) inaccurate pre- and post-conditions & post-hoc correction; 6) unreliable skill learning; 7) poor environment transition (Hu et al. (2023b)).

Foundation models are primarily pretrained on vast internet-scale datasets, enabling them to be fine-tuned for diverse tasks. Their significant advancements in vision and language processing contribute to mitigating the aforementioned challenges. Based on the different input modalities and functionalities of the models, we categorize foundation models into the following six types.

- 1. Large Language Models (LLMs) like BERT (Devlin et al. (2018)), GPT-3 (Brown et al. (2020)) demonstrate the capability to generate coherent chains of thought.
- 2. **Vision Foundation Models (VFMs)** like SAM (Kirillov et al. (2023)) demonstrate strong segmentation capability for open-set objects.
- 3. **Visual Content Generation Models (VGMs)** like DALL-E (Ramesh et al. (2021)), Zero-1-to-3 (Liu et al. (2023c)), demonstrate the capability to generate 2D images or 3D meshes through text or images.
- Vision Language Models (VLMs) like GPT-4V (Achiam et al. (2023)), CLIP (Radford et al. (2021)) showcase robust comprehension of both vision and

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language, such as open-set image classification and visual question answering.

- 5. Large Multimodal Models (LMMs) expand their scope beyond vision and language to create novel categories of foundation models incorporating additional modalities, such as ULIP (Xue et al. (2023a)) aligns point cloud representation to the pre-aligned imagetext feature space.
- 6. Robot Foundation Models (RFMs), like RT-X (Padalkar et al. (2023a)). Internet-scale dataset, such as images and text data, are suitable for pretraining visual and language models, but lack task level manipulation data. Therefore, researchers aim to train end-to-end RFMs by collecting task-level manipulation datasets to enable observations-to-action mapping.

In this survey, we investigate how foundation models are utilized in robot learning for manipulation, like Fig. 1:

- LLMs enable the direct generation of policy codes or action sequences and facilitate natural interaction with the environment.
- 2. **VFMs** enhance open-world perception.
- VLMs serve as the cornerstone for alignment between vision and language, facilitating understanding of multimodality.
- 4. **LMMs** expand their modalities to include 3D point cloud and haptic data, among others.
- VGMs generate 2D images or 3D meshes based on prompting, aiding in scene generation within simulation environments.
- 6. **RFMs** serve as an end-to-end policy model, directly outputting actions based on input blue observations.

These findings underscore the potential of embedding foundation models into manipulation tasks as a viable path toward achieving general manipulation capability. However, we do not believe that a single foundation model alone can achieve general manipulation capability. Although RFMs currently represent a single-model endto-end training approach, ensuring safety and stability, particularly in achieving an over 99% success rate in manipulation tasks, remains a challenge. Achieving over a 99% success rate in manipulation tasks is crucial, as human manipulation success rates are around 99%. Without this level of accuracy, robots can't replace humans. Therefore, drawing inspiration from the development of autonomous driving systems (Hu et al. (2023c)), achieving general manipulation capability necessitates an overarching framework that encompasses multiple functional modules, with different foundation models assuming distinct roles in facilitating general manipulation capability.

The ultimate general manipulation framework should be able to interact with human or other agent and to manipulate arbitrary objects in open-world scenarios and achieve diverse manipulation tasks. However, the interaction between robot and human involves not only recognizing intentions but also learning new skills or improving old skills from human experts in the external world. Openworld scenarios may be static or dynamic. Objects can be either rigid or deformable. Task objectives can vary from

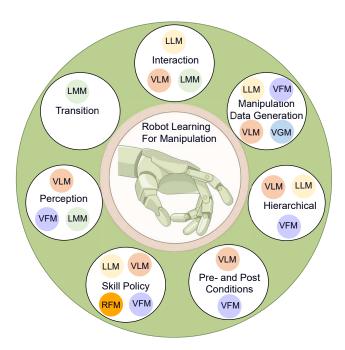


Figure 1. LLMs help address challenges in Interaction, Manipulation Data Generation, Hierarchy of Skills, Skill Policy Learning, and Environment Transition Model. VLMs assist in tackling challenges in Interaction, Manipulation Data Generation, Hierarchy of Skills, Pre- and Post-conditions Detection, Skill Policy Learning, and Perception. LMMs aid in addressing challenges in Interaction and Perception. VGMs tackle the challenge of Manipulation Data Generation. VFMs help address challenges in Manipulation Data Generation, Hierarchy of Skills, Pre- and Post-conditions Detection, Skill Policy Learning, and Perception. RFMs assist in addressing the challenge of Skill Policy Learning.

short-term to long-term. Furthermore, tasks may necessitate different degrees of precision with respect to contact points and applied forces/torques. We designate the restriction of the robot's learning capability to improving old skills and to manipulating rigid objects in static scenes in order to achieve short-horizon task objectives with low precision requirements for contact points and forces/torques as Level 0 (L0). Drawing from Kroemer et al. (2021), we propose a comprehensive framework for general manipulation task at L0. Hence, we aim to use this survey not only to enlighten scholars on the issues that foundation models can address in robot learning for manipulation but also to stimulate their exploration of the general manipulation framework and the role various foundation models can play in the general manipulation framework.

Di Palo et al. (2023) and Firoozi et al. (2023) provide detailed descriptions of the application of foundation models in navigation and manipulation, but these lack thoughtful consideration of the relationship between foundation models across different applications. The survey most closely related to this paper is Xiao et al. (2023). Compared to this survey, our survey focuses on the contributions of foundation models to robot learning for manipulation, proposing a comprehensive framework and detailing how foundation models can address challenges in each module of the framework.

This paper is structured as follows: In Sec. 2, we present a comprehensive framework of robot learning for

general manipulation, based on the developmental history of robot learning for manipulation and general manipulation definition. We elaborate on the impact of foundation models on each module in the framework in the following sections. Sec. 3 is Human/Agnet Interaction module, Sec. 4 is Preand Post-conditions Detection module, Sec. 5 is Hierarchy of Skills module, Sec. 6 is State Perception module, Sec. 7 is Policy module, Sec. 8 is Manipulation Data Generation module. In Sec. 9, we discuss several issues of particular concern to us. In Sec. 10, we summarize the contributions of this survey and identify the limitations of the current framework as well as the challenges in each module.

2 Framework of Robot Learning for General Manipulation

Over the past decade, there has been a significant expansion in research concerning robot manipulation, with a focus on leveraging the growing accessibility of cost-effective robot arms and grippers to enable robots to interact directly with the environment in pursuit of their objectives. As the real world encompasses extensive variation, a robot cannot expect to possess an accurate model of its unstructured environment, the objects within it, or the skills necessary for manipulation in advance (Kroemer et al. (2021)).

Early stage, robot manipulation is defined as learning a policy Π through deep learning, reinforcement learning, or imitation learning, etc. This policy controls the robot's joint movements and executes tasks based on observations of the environment and the robot's state S, mapping to actions α . such as Rlafford (Geng et al. (2023)) and Graspnet (Fang et al. (2020)) take point cloud as input and output the target pose. This process is represented by the Skill Execution module, as shown in Fig. 2.

In the mid-term, many tasks in robotics require a series of correct actions, which are often long-horizon tasks. For example, making a cup of tea with a robot involves multiple sequential steps such as boiling water, adding a tea bag, pouring hot water, etc. Learning to plan for longhorizon tasks is a central challenge in episodic learning problems (Wang et al. (2020)). Decomposing tasks has several advantages. It makes learning individual skills more efficient by breaking them into shorter-horizon, thus aiding exploration. Reusing skills in multiple settings can speed up learning by avoiding the need to relearn elements from scratch each time. Researchers train a hierarchy model to decompose the task into a sequence of subgoals (Ahn et al. (2022)), and observe pre- and post-conditions to ensure that the prerequisites and outcomes of each subgoals are met (Cui et al. (2022)). These three processes are represented as the Hierarchy of Skills module H, the Pre-conditions Detection module P, and the Post-conditions Detection module Pin Fig. 2. However, detecting only task success with postconditions detection is insufficient. It should also identify the reasons for task failure to help the robot self-correct and improve success rates. Therefore, we add a Post-hoc Correction module, as shown in Fig. 2.

Recently, researchers have realized that training policies require real-world interaction between the robot and environments, which inevitably increases the probability of unforeseen hazardous situations. Therefore, researchers aim to train the environment's transition model T. Once the model is fitted, robot can generate samples based on it, significantly reducing the frequency of direct interaction between the robot and environments (Liu et al. (2024)). This process is represented as the Transition module T in Fig. 2.

The modules described above are summarized from the development of robot learning for manipulation. However, they are still insufficient for a comprehensive framework for general manipulation. The ultimate general manipulation framework should be able to interact with human or other agent and control whole-body to manipulate arbitrary objects in open-world scenarios, achieving diverse manipulation tasks. When interacting with human or other agent to understand task objectives, the transmitted instruction may sometimes be unclear, such as when there are two cups in the environment, it needs to determine which cup to pour water. Therefore, we add the Interaction module *I* in Fig. 2 to understand the precise task objective.

The aforementioned modules all require datasets for learning. The data collection process for the Hierarchy of skills H and Pre- and Post-conditions detection modules P is similar to that in the fields of CV and NLP. Compared to data collection in CV and NLP domains, gathering datasets for manipulation tasks requires the robot's trajectory to train the policy. Therefore, we include the Manipulation Data Generation module in Fig. 2.

We organize the framework of robot learning for general manipulation according to its development history and definition, as shown in Fig. 2. In the caption of Fig. 2, we outline the flow of the entire framework. To better illustrate the role of each module, we list the inputs and outputs of each module below, along with their specific functions.

- 1. Pre-conditions Detection. This module takes raw information observed by the robot as input. It outputs perception information about objects in the environment and affordances of those object. Perception information helps ensures that requirements are met and helps select the execution method based on object affordances. For instance, when placing a tea bag in a teacup, perception information can help determine whether there are tea bags and teacups and chooses between pick-place or pushing based on their affordances, such as, a tea bag is spherical, and it has the affordance of rolling when pushed.
- 2. **Human/Agent Interaction.** The input to the Human/Agent Interaction module *I* consists of an instruction or answer from the collaborating agent or human, and perception information from the Preconditions Detection module *P*. The output includes a question if the instruction or answer has ambiguities and provides a precise instruction to the Hierarchy of Skills module *H*. The main function of this module is to understand the exact task objectives.
- 3. Hierarchy of skills. This module takes as input the perception information about objects in the environment and their affordances for the task from the Pre-conditions Detection module P, as well as the precise instruction from the Interaction module I. It then produces a sequence of subgoals as output. The concept of 'Hierarchy of skills' often involves

creating a sequence of subgoals (Song et al. (2023)). Each subgoal necessitates a skill, which may consist of one or multiple primitive actions (Zhang et al. (2023c)). For instance, tasks like filling the kettle with water, heating the water, and getting the tea leaves are examples of subgoals that robot needs to achieve in a specific order to fulfill the final goal as instructed.

- 4. **State.** The input to the State module is the current environment, objects and robot states. States require the use of multiple sensors for perception. The output is the features of states. The states consists of robot proprioception S_{robot} , environment state S_e , and objects states S_o . The difference between S_e and S_o is analogous to the foreground and background of an image. S_{robot} generally relates to the mechanical structure of the robot. Currently, there are limited studies focusing on the improvement of robot mechanical structure using foundation models, with Stella et al. (2023) being one of them. However, researches in this direction are scarce and still in their initial stages.
- 5. **Policy.** The Policy module takes as input features from the State module S and subgoals generated by the Hierarchy of Skills module H. The policy outputs action to accomplish task goals based on the input states. We categorize action into three types: Code, Target Pose, and Delta Pose. Code refers to the direct control code of the robot. Target Pose refers to the desired pose of the end-effector, which is input to motion planning to generate the trajectory. Delta Pose refers to the next waypoint the end-effector moves to, with continuously outputted delta pose forming the trajectory. At present, the methods for generating actions using foundation models include LLMs directly generating code for robot execution, VLMs directly generating or VLMs combined with LLMs generating corresponding target poses, RFMs directly outputting target pose or delta pose through end-to-end training, and foundation models assisting reinforcement learning in generating various actions.
- 6. **Post-conditions Detection.** This module takes as input the environment, objects and robot states observed after the robot performs a task, along with the subgoals generated by the Hierarchy of Skills module H. It outputs whether the current subgoal is successful. If not, it provides the reason for failure to Post-hoc Correction module. The Post-hoc Correction module generates a sequence of actions for self-correction based on the failure reason. For example, if a teacup is knocked over during pick-and-place, inform post-hoc correction and use pick-and-place to upright the cup and reinsert the tea bag.
- 7. **Transition.** The Transition module T takes an action generated by the Policy module P as input. It outputs the next state after executing this action, thus helping to reduce the interaction between the robot and the real environment. Zhang and Soh (2023) uses LLM as a human model, predicting the changes in human state after robot actions, and selecting the most suitable robot actions for interaction with humans. In various algorithms, the transition environment model is not a

- mandatory module. Therefore, in Fig. 2, we enclose this module with a dashed box.
- Manipulation Data Generation. This module functions as a database. It takes in existing manipulation data and correction data generated from robot tasks. The output is to provide task-level manipulation datasets for offline training.

Current research on foundation models for manipulation primarily focuses on several key modules: the Interaction module in Sec. 3, the Pre- and Post-conditions Detection module in Sec. 4, the Hierarchy of Skills module in Sec. 5, the State module in Sec. 6, the Policy module in Sec. 7, and the Manipulation Data Generation module in Sec. 8. The following section will provide an overview of these modules.

3 Human/Agent Interaction

There are two ways for human or other agent to interact with robot: 1) Providing task instruction to the robot to help it understand the task objective and complete the task independently (Khan et al. (2023)). 2) Collaborating with the human or other agent to complete tasks, sharing workspace information, and conveying corrective instruction when useful or error-correcting information is identified to optimize the robot's current action (Lynch et al. (2023)).

When conveying task instruction to the robot, there may contain language ambiguity in the task goal, such as having both red and green cups in the scene, and the task instruction is 'grasp the cup.' This ambiguity may confuse the robot regarding which color cup to grasp. To address this issue, the robot needs to inquire about and confirm the final task objective from the human or other agent, thus requiring enhancement of their capability in text generation and comprehension. When conveying corrective instruction to a robot, it needs to comprehend the meaning of the corrective instruction and translate corrective instruction into appropriate actions. If needed, the robot should be able to convey its current state to human or agent. For instance, if a robot is picking up a book from a shelf filled with books, lifting too quickly may cause other books to fall. Human or collaborating agent need to alert the robot that the current lifting action is dangerous and advise it to lift slowly. If necessary, the robot should also report its current execution state, such as its grasping speed, and inquire whether this speed is considered high. However, corrective instruction are diverse; thus, understanding them is essential.

In addressing instruction ambiguity and text generation and comprehension challenges, SeeAsk (Mo et al. (2023)) utilizes CLIP's perceptual module to identify objects in the scene and employs a fixed questioning template to organize language to ask about which object will be manipulated. Although the use of CLIP enhances the generalization ability for object recognition, it can't generate text for asking questions and to comprehend answers from the outside world and SeeAsk (Mo et al. (2023)) focuses solely on addressing ambiguities concerning object color and spatial relationship due to a fixed questioning template. KNOWNO (Ren et al. (2023a)) utilizes LLM to score the next action to be taken. If the score difference between the top two actions is less than a threshold, it's considered ambiguity, prompting a confirmation for the final action. This approach

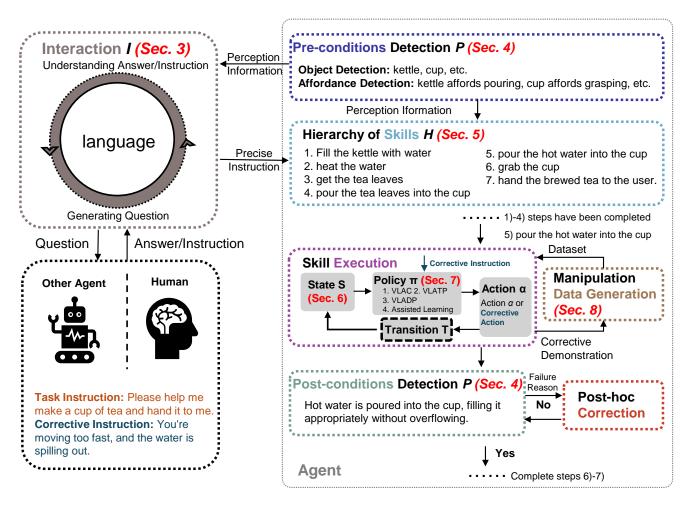


Figure 2. Framework of Robot Learning for General Manipulation. The Pre-conditions Detection module P perceives the environment to identify objects and the affordances objects support. The Interaction module I receives instruction from a human or other agent. It uses perception information from the Pre-conditions Detection module P to check for ambiguities in the instruction. If there are any ambiguities, it generates a question to clarify the instruction by asking the human or other agent. The Hierarchy of Skills module I generates subgoals by using precise instruction from the Interaction module I and perception information from the Pre-conditions Detection module P. Each subgoal is then passed to the Skill Execution module. In the Skill Execution module, Policy module I generates Action I0 based on the State I1. To obtain the next state after executing the current action, State I2 can either perceive it from the environment or use the Transition module I2. To train the Skill Execution module, including the State module I3, the Policy module I3 and the Transition module I4. The Manipulation Data Generation module is required. This module provides a task-level manipulation dataset. When issues arise during execution, corrective instruction is sent to the Policy module I3 for manual adjustment. Policy module I4 modifies the current action to corrective action and saves corrective demonstration to the dataset for self-improvement of Policy module I5. After skill execution, Post-conditions Detection module I6 determines the success of execution. If successful, proceed to the next subgoal; if not, the failure reason is conveyed to Post-hoc Correction module for self-correction.

improves efficiency and autonomy. Matcha (Zhao et al. (2023b)) not only employs vision but also utilizes haptic and sound senses to perceive object properties, such as material. When encountering ambiguity in object attribute recognition, it leverages LLM to generate inquiry content. CoELA (Zhang et al. (2023b)) utilizes LLM as both a communication module and a planning module to enhance interaction text generation and comprehension, as well as task scheduling, with collaborative agent. LLM-GROP (Ding et al. (2023)) utilizes LLM to extract latent commonsense knowledge embedded within task instruction. For example, a task instruction might be "set dinner table with plate and fork," while the latent commonsense knowledge could be "fork is on the left of a bread plate."

As for corrective instruction, LILAC (Cui et al. (2023)) utilizes GPT-3 to distinguish between task instruction and corrective instruction. It then employs Distil-RoBERTa to

extract text features and input them into the network to modify the robot's original trajectory. LATTE (Bucker et al. (2023)), on the other hand, employs BERT and CLIP to extract features from corrective instruction and observation images and input them into the network to modify the robot's original trajectory.

Following Fig. 3, LLMs using chain of thought efficiently identifies ambiguity, surpassing the limitations of enumerating ambiguity. LLMs' comprehension of text effectively understands corrective instruction and transforms the original trajectory into a corrective trajectory.

4 Pre- and Post-conditions Detection

In pre- and post-conditions detection, it is necessary to identify the initial and termination conditions. In preconditions detection, recognize objects and observe the

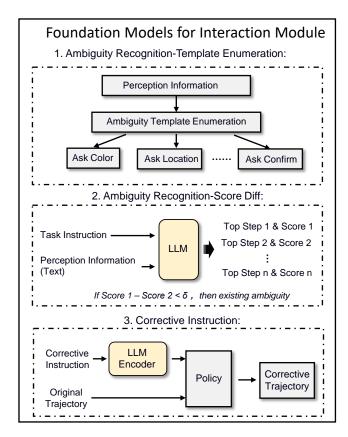


Figure 3. Foundation Models for Interaction Module. Interaction mainly involves the exchange between task instruction and corrective instruction. Ambiguity often arises in task instruction interaction, hence robot needs to detect ambiguities. 1) One approach is to perceive objects in a multi-modal environment and enumerate possible ambiguities based on perception information (Mo et al. (2023)). 2) Another approach involves using LLM to be the next step prediction module, which predicts and scores the next step; if the scores of the top 2 steps are less than δ , it is considered that the task goal is ambiguous (Ren et al. (2023a)). 3) Strong comprehension skills are required during the transmission of corrective instruction, and the current mainstream approach involves using the encoder of LLM to extract tokens and input them into the policy to modify the original trajectory (Bucker et al. (2023)).

affordances of objects. Object recognition will be addressed in the section 6. In post-conditions detection, identify whether a task has been successfully executed and provide reasons for task failure after skill execution. Currently, there are few papers focusing on identifying termination conditions. Cui et al. (2022) utilizes CLIP to compare the target's text or image with the termination environment to determine the success of task execution. Few articles are found in this study that address the output of task failure reasons after skill execution. RobotGPT (Jin et al. (2024)) analysis task failure utilizes the positions of manipulated objects after execution, but task failure should be determined during execution. Therefore, this section focuses on literature discussing foundation models in object affordance.

4.1 Affordance

The affordances associated with an object represent the range of manipulations that the object affords the robot (Gibson (2014)). Early approaches addressed the issue by

treating it as a supervised task (Kokic et al. (2017)). However, the process of annotating datasets is laborious and time-consuming, making it impractical to exhaustively cover all geometric information present in real-world environments. Consequently, researchers are exploring the application of reinforcement learning, enabling robots to collect data and train affordance perception modules through continuous exploration (Wu et al. (2021)). Nevertheless, current reinforcement learning methods are trained in simulated environments, leading to a significant sim-to-real gap. To address these challenges, researchers propose training the affordance perception module using videos of human interactions in real-world scenarios (Ye et al. (2023b); Bahl et al. (2023)).

For supervised learning methods, GraspGPT (Tang et al. (2023)) utilizes LLM outputs for object class descriptions and task descriptions. Object class descriptions detail the geometric shapes of each part of an object, while task descriptions outline the desired affordances for task execution, such as the types of manipulation actions to be taken. Integrating both components into the task-oriented grasp evaluator enhances the quality of the generated grasp pose. 3DAP (Nguyen et al. (2023)) utilizes the text encoder of LLM for feature extraction. The extracted features from desired affordances text are inputted into both the affordance detection module and pose generation module. This enhances the quality of the predicted affordance map and the generated pose.

In reinforcement learning, ATLA (Ren et al. (2023b)) utilizes GPT-3 to generate language descriptions of tools. These descriptions are then inputted into a pre-trained BERT model to obtain representations. The extracted features are finally fed into the SAC network module. Meta-learning techniques are employed to enhance the learning efficiency for the use of new tools. Xu et al. (2023a) employ CLIP's text and image encoders to extract features from language instruction and scene image, improving the quality of grasp pose generation in the SAC module.

The methods mentioned above utilize foundation models to assist other learning methods in improving affordance maps or grasp poses. There are also direct approaches using foundation models to generate affordance maps and grasp poses. PartSLIP (Liu et al. (2023b)) converts 3D point clouds into 2D rendering images and inputs multi-view 2D images and textual descriptions of object parts into GLIP for object parts detection, ultimately fusing 2D bounding boxes into 3D segmentation to generate affordance maps. LAN-grasp (Mirjalili et al. (2023)) inputs human instruction into LLM, utilizing its prior knowledge to output the shape of part to be grasped. These shapes, along with the object's 2D image, are then inputted into VLM to detect the bounding box for the grasping part. Finally, the bounding box and the point cloud from object 3D reconstruction are inputted into the grasp planner to generate grasp poses.

Following Fig. 4, current research explores LLMs' zero/few-shot capability in providing object part-level prior knowledge via text, aiding in generating affordance maps or grasp poses. Direct use of foundation models for affordance is possible but still shows instability, with unclear performance boundaries.

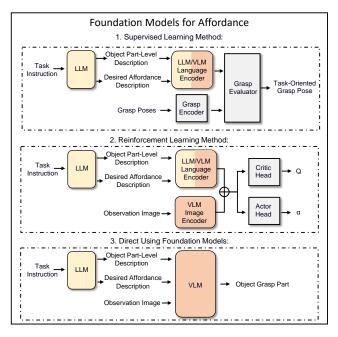


Figure 4. Foundation Models for Affordance. The main approaches of task-oriented grasp are supervised learning and reinforcement learning. Both methods utilize LLM to generate object part-level description and desired affordance description in task instruction, then fuse tokens and features into the original network through language encoder and image encoder to output task-oriented grasp pose (Tang et al. (2023); Ren et al. (2023b)). In reinforcement learning, it is possible to choose between a LLM language encoder with a custom-designed image encoder, or a VLM language encoder with a VLM image encoder. When selecting the LLM language encoder with a custom image encoder, the LLM language encoder should be frozen, and the custom image encoder should be trained. When using the VLM language encoder with the VLM image encoder, both encoders are typically frozen. Direct using foundation method utilizes LLM to generate object part-level description and desired affordance description according to task instruction. VLM marks out the part of the object to grasp in the image based on the description (Liu et al. (2023b))

5 Hierarchy of skills

In the last two decades, research on skill hierarchy has led to powerful domain-independent planners and various realworld applications (Silver et al. (2022)). Models for skill hierarchy can be trained using text or videos, similar to how humans learn assembly procedures from instructional manuals or tutorial videos, such as VLaMP (Patel et al. (2023)), which trains models to understand human video operations. Currently, the text-based approach dominates the skill hierarchy domain. PDDL, a Lisp-like language (Silver et al. (2022)), is commonly used to address skill hierarchy issues. However, as LLMs excel in natural language tasks and PDDL is not a natural language, researchers are exploring how LLMs can be employed by robot for skill hierarchy tasks (Vemprala et al. (2023); Jansen (2020); Driess et al. (2023)). Additionally, various benchmarks such as PlanBench (Valmeekam et al. (2023)) and CALVIN (Mees et al. (2022)) can assess the planning and reasoning capability of LLMs.

LLMs possess a notable limitation: they lack practical experience, hindering their utility for decision-making within

a specific context, so the output of LLMs often cannot be translated into executable actions for the robot. Huang et al. (2022) first use pre-trained causal LLM to break down highlevel tasks into logical mid-level action plans. Then, a pretrained masked LLM is employed to convert mid-level action plans into admissible actions. The pre-trained causal LLM and pre-trained masked LLM can be the same LLM model, which plays different roles depending on various prompts. However, prompts usually require the context of the robot's capability, its current state, and the environment. LLMs are considered "forgetful" and don't treat information in the system prompt as absolute. Despite efforts to reinforce task constraints in the objective prompt and extract numerical task contexts from the system prompt, storing them in data structures, errors caused by LLM forgetfulness remain unresolved (Chen and Huang (2023)).

SayCan (Ahn et al. (2022)) scores pre-trained tasks based on prompting and observation images, generating the task sequence with the highest score. Saycan provides a paradigm for generating action sequences using LLM, but there are still some drawbacks: 1) The generated action sequences do not incorporate user preferences. 2) Safety regulations are not adequately addressed. 3) The limitation of the skill library. 4) LLM focuses solely on reasoning when generating action sequences, neglecting feedback on action execution. 5) The limitation of scene grounding. GD (Huang et al. (2023d)) proposes a paradigm to address the aforementioned issues by not only scoring the generated action sequence using LLM but also introducing a grounded function model for scoring the generated action sequence. The grounded function model encompasses token-conditioned robotic functions, such as affordance functions that capture the abilities of a robot based on its embodiment, safety functions, and more. This approach tackles drawbacks by designing grounded functions, avoiding fine-tuning in LLM.

Regarding user preferences, TidyBot (Wu et al. (2023b)) trains LLM by collecting users' preference data, enabling the trained LLM to choose behaviors that better align with user preferences. As for safety regulations, Yang et al. (2023d) incorporate ISO 61508, a global standard for safely deploying robots in industrial factory settings, into the constraints of the action sequence generation. As for the skill library, BOSS (Zhang et al. (2023c)) suggests using LLMs' rich knowledge to guide skills chaining in the skill library, aiming to create new skills through combinations. RoboGen (Wang et al. (2023b)) employs generative models to create new skill task scenarios, then utilizes either reinforcement learning or gradient optimization methods to automatically learn new skills based on the reward function generated by the LLM. As for action execution feedback, REACT (Yao et al. (2022b)), COWP (Ding et al. (2022)), LLM-Planner (Song et al. (2023)), CoPAL (Joublin et al. (2023)) provide feedback on robot action execution to LLMs. This allows LLMs to adjust action sequences based on execution status, creating a closed-loop process for generating action sequences.

As for the limitation of scene grounding, LLMs need to inquire about the scene representation to determine the availability, relationship and location of objects. NLMap (Chen et al. (2023a)) proposes an open-vocabulary, queryable semantic representation map built on ViLD and

CLIP. This map outputs the pose of related objects based on task instruction, which are then handed over to the LLM for planning. Text2Motion (Lin et al. (2023)) incorporates a geometric value function on top of the value function, enabling the robot to select actions that adhere to geometric constraints based on scene descriptions. Xu et al. (2023b) explore the possibility of teaching robots to creatively utilize tools within scenarios, which involve implicit physical limitations and require long-term planning. VILA (Hu et al. (2023a)) seamlessly incorporates perceptual data into ChatGPT-4V for its reasoning and planning processes, facilitating a deep comprehension of common sense knowledge within the visual domain, encompassing spatial arrangements and object characteristics. PHYSOBJECTS (Gao et al. (2023)) fine-tunes a VLM to enhance its understanding of physical object attributes, such as material. This integration of a physically informed VLM into an interactive framework with a LLM enhances task planning performance in tasks incorporating instruction related to physical object attributes.

The hierarchy of skills possessed by LLMs or VLMs can be applied not only to single agent but also to multiple agents. SMART-LLM (Kannan et al. (2023)) utilizes LLM for the hierarchy of skills and allocates each task to every agent through the task assignment module.

When utilizing LLMs for skill hierarchy, it provides generalization. Regardless of whether the prompting input to LLMs is in natural language or PDDL format (Silver et al. (2022)), the hierarchy of skills possessed by LLMs or VLMs still exhibits instability. Hence, researchers are exploring approaches that integrate LLMs with classical PDDL-based planning methods for the hierarchy of skills. LLM+P (Liu et al. (2023a)) utilize LLMs to translate natural language into PDDL and input into a classical planner for the hierarchy of skills. Xie et al. (2023b) indicate that LLMs exhibit greater efficacy in translation tasks as opposed to planning.

Following Fig. 5, we focus on the application of video in hierarchy of skills. Video data, being internet-based and possessing large-scale attributes, enables robust generalization when learning high-level task operation descriptions mapped from videos. This approach not only aids in hierarchy of skills but also supports one-shot and few-shot learning from human video. By watching a person perform a task, the video is broken down into steps. Each step is then executed using the skill library. Utilizing LLMs for hierarchy of skills, we emphasize the GD (Huang et al. (2023d)) framework, which circumvents the high cost of LLM fine-tuning. LLMs exhibit powerful translation abilities, thus offering significant utility in assisting classical planner.

6 State Perception

Compared to passive perception, active perception adjusts the perspective to the areas of interest (Kroemer et al. (2021)). Then, modeling manipulation tasks and generalizing manipulation skills necessitate representations of both the robot's environment and the manipulated objects. These representations form the foundation for skill hierarchies, preand post-condition detection, skill learning, and transition model learning. The Vision Transformers (ViTs) and similar

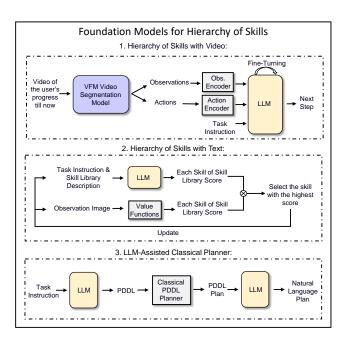


Figure 5. Foundation Models for Hierarchy of Skills. 1) Utilize human video operation to learn the skill sequence for task execution, decompose the video of the user's progress so far into observations and human actions through segmentation, and input them along with task instruction into a pre-trained language model to predict the next step (Patel et al. (2023)). 2) LLM scores the skills in the skill library based on task instruction and the skills already executed, and the value function also scores the skills in the skill library based on observation images. The highest-scoring skill, obtained by multiplying the two scores, is selected as the next step (Ahn et al. (2022)). The value function can consider multiple factors such as affordance, safety, user preference, and more (Huang et al. (2023d)), and these considerations can also be fine-tuning LLM (Wu et al. (2023b)). 3) LLM assists the classical planner by translating task instruction into PDDL descriptions, sending them to the classical planner to generate a PDDL plan, and then translating the PDDL plan into a natural language plan using LLM (Liu et al. (2023a)).

attention-based neural networks have recently achieved state-of-the-art performance on numerous computer vision benchmarks (Han et al. (2022); Khan et al. (2022); Zhai et al. (2022)) and the scaling of ViTs has driven breakthrough capability for vision models (Dehghani et al. (2023)).

As for pre-trained visual representations, the algorithms mentioned have various training objectives: for instance, contrastive methods like Vi-PRoM (Caron et al. (2021)), R3M (Nair et al. (2022)), VIP (Ma et al. (2022)), CLIP (Radford et al. (2021)), LIV (Ma et al. (2023a)); distillation-based methods such as DINO (Caron et al. (2021)); or masked autoencoder methods like MAP (Radosavovic et al. (2023)), MAE (He et al. (2022)). The primary datasets utilized comprise the CLIP dataset (Radford et al. (2021)), consisting of 400 million (image, text) pairs sourced from the internet, along with ImageNet (Deng et al. (2009)), Ego4D (Grauman et al. (2022)), and EgoNet (Jing et al. (2023)).

Pre-trained visual representations have high transfer ability to policy learning (Xiao et al. (2022b); Yang et al. (2023c)), but visual representation involves not just recognizing spatial features but also understanding semantic features. Masked autoencoding methods prioritize low-level spatial aspects, sacrificing high-level semantics,

whereas contrastive learning methods focus on the inverse (Karamcheti et al. (2023)). The fusion of masked autoencoder and contrastive learning is employed in both Voltron (Karamcheti et al. (2023)) and iBOT (Zhou et al. (2021)). The loss function achieves a balanced trade-off between these two aspects. To compare different pretrained visual representations, benchmarks are established by CORTEXBENCH (Majumdar et al. (2023)) and EmbCLIP (Khandelwal et al. (2022)) to assess which model could provide a better "artificial visual cortex" for manipulation tasks. However, the models included in these benchmarks are still not comprehensive enough. At the same time, it is important to consider the potential of the diffusion model (Ze et al. (2023)). The aforementioned pre-trained visual representations mainly involve the extraction of features from 2D images. The experience of learning representations on 2D images can also be extended to other modalities. For the object point cloud modality, ULIP (Xue et al. (2023a)) and ULIP2 (Xue et al. (2023b)) employ contrastive learning to align features between point clouds and text-images. Point-BERT (Yu et al. (2022)) uses the masked autoencoding method to learn point cloud features by reconstructing point clouds. In the haptic modality, MOSAIC (Tatiya et al. (2023)) utilizes contrastive learning to train the haptic encoder.

As for segmentation, SAM (Kirillov et al. (2023)) develops a transformer-based architecture and creates the largest segmentation dataset, with over 1 billion masks from 11 million images. The model is adaptable and enables zeroshot transfer to new tasks and image distributions. Fast-SAM (Zhao et al. (2023a)) and Faster-SAM (Zhang et al. (2023a)) aim to improve the training and inference speed of the network by enhancing its network structure. TAM (Yang et al. (2023a)) merges SAM (Yang et al. (2023a)) and XMem (Cheng and Schwing (2022)) for high-performance interactive tracking and segmentation in videos.

As for detection, traditional detection models are usually confined to a narrow range of semantic categories because of the cost and time involved in gathering localized training data within extensive or open-label domains. However, advancements in language encoders and contrastive imagetext training enable open-set detection. Researchers integrate language into a closed-set detector to generalize open-set concepts, detecting various classes through language generalization despite being trained solely on existing bounding box annotations, such as OWL-ViT (Minderer et al. (2022)), Grounding-DINO (Liu et al. (2023d)), OVD (Zareian et al. (2021)), ViLD (Gu et al. (2021)), DetCLIP (Yao et al. (2022a)).

Deploying such models in open-set detection presents a significant challenge, primarily because even slight alterations in prompting can greatly impact performance. Fine-tuning can enhance a foundation model's understanding of prompting. However, foundation models are often over-parameterized, leading to slow training processes. COOP (Zhou et al. (2022)) maps prompting to a set of learnable vectors, which can be optimized through network training. In CLIP-Adapter (Gao et al. (2024)), two extra linear layers are appended after the final layer of either the vision or language backbone to enable efficient few-shot transfer learning through fine-tuning.

The method for open-set detection on 2D images can be extended to the research direction of open-set detection on 3D point clouds. PointCLIP (Zhang et al. (2022)) utilizes pre-trained CLIP to extract multi-view depth image features of point cloud, then compares the extracted features with language features to identify the point cloud category.

As for scene reconstruction, due to the foundation model's robust open-set detection capability for objects, DFF (Shen et al. (2023)), CLIP-Fields (Shafiullah et al. (2022)) and LERF (Kerr et al. (2023)) employ CLIP to extract features from multi-view 2D images for NeRF (Mildenhall et al. (2021)) reconstruction. These features are then integrated as part of the output of the NeRF network, enriching the semantic information of the reconstructed 3D scenes. 3D-LLM (Hong et al. (2023)) extracts 2D features from multiview rendered images using the CLIP image encoder. These features are then fused into 3D features through Direct Reconstruct, gradSLAM (Jatavallabhula et al. (2023)), or Neural Field methods (Hong et al. (2023)), endowing 3D features with semantic information. CLIP-NeRF (Wang et al. (2022a)) integrates semantic features extracted by CLIP into NeRF reconstruction to change object textures during rendering.

Following Fig. 6, representation learning facilitates the learning of the multimodal encoder, aligning features from various modalities to the text domain, aiding the model's cognition, akin to how humans learn and think through words. The learning of the encoder promotes openset perception tasks, such as open-set detection, openset segmentation, and open-set scene reconstruction. When applied to specific scenarios, models often require fine-tuning. CLIP-Adapter (Gao et al. (2024)) offers a fine-tuning method. However, fine-tuning involves different techniques for different model architectures.

7 Policy

In the realm of manipulation, policies can generate signals for robots' execution based on input. The types of outputs from policies encompass code, delta pose, and target pose. Policies generate code for robot execution directly, aiding detailed observation by humans for debugging. Generating delta poses directly through policies allows for conversion into trajectory through time sequences, offering a more end-to-end approach compared to target pose, which often requires subsequent motion planning.

The policy model for outputting delta pose resembles more closely the paradigm of human task execution, as it does not require camera and spatial calibration or robot body configuration. Instead, it takes observation images as input and directly outputs the direction and magnitude of the next movement. While this approach is more end-to-end, it still necessitates extensive data training to embed the parameters of robot execution in the policy model's hidden layers. RT-2 (Brohan et al. (2023)) refers to this approach as Vision-Language-Action (VLA). Following this naming convention, we divide the policy into Vision-Language-Action-Code (VLAC), Vision-Language-Action-Target-Pose (VLATP), and Vision-Language-Action-Delta-Pose (VLADP) based on different output action.

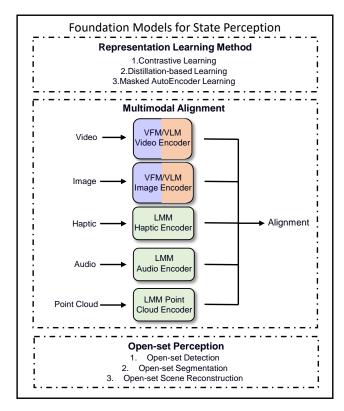


Figure 6. Foundation Models for State Perception. The representation learning methods in state perception mainly include contrastive learning (Radford et al. (2021)), distillationbased learning (Caron et al. (2021)), and masked autoencoder learning (Radosavovic et al. (2023)). Masked autoencoding methods prioritize low-level spatial aspects, sacrificing highlevel semantics, whereas contrastive learning methods focus on the inverse, the fusion of masked autoencoder and contrastive learning is employed in both Voltron (Karamcheti et al. (2023)) and iBOT (Zhou et al. (2021)). Multimodal representation learning focuses primarily on multimodal alignment (Xue et al. (2023b); Tatiya et al. (2023)). Training the encoder with large-scale data and parameters has facilitated open-set perception, including tasks such as open-set detection, open-set segmentation, and open-set scene reconstruction. For instance, SAM (Kirillov et al. (2023)) utilizes the MAE (He et al. (2022)), ViLD (Gu et al. (2021)) employs the CLIP (Radford et al. (2021)), and LERF (Kerr et al. (2023)) utilizes the CLIP (Radford et al. (2021)).

7.1 VLAC

Code generation and program synthesis have been demonstrated to be capable of developing generalizable, interpretable policy (Trivedi et al. (2021). However, a robot capable of generating code for multiple tasks, rich knowledge across various domains is essential (Ellis et al. (2023)). Therefore, scholars aim to apply the prior knowledge of LLM to code generation task (Chen et al. (2021); Austin et al. (2021)). Code-As-Policy (Liang et al. (2023)) demonstrates the possibility of using LLMs to directly generate code for robot execution based on prompts. The study shows that 1) code-writing LLMs enable novel reasoning capability, such as encoding spatial relationships by leveraging familiarity with third-party libraries and 2) hierarchical code-writing inspired by recursive summarization improves code generation. In PROGPROMPT (Singh et al. (2023)), assertions are added to the generated code. When executing assertions, environment state feedback is obtained to check if the environment satisfies the pre- and post-conditions of the task.

7.2 VLATP

The utilization of foundation models to generate target pose can be categorized into three approaches: 1) Directly using existing foundation models to output target pose. 2) Training RFMs to output target pose through reinforcement learning. 3) Training RFMs to generate target pose through imitation learning.

Utilizing foundation models trained on existing large-scale internet datasets enables the direct perception of observation images and outputting target poses. Instruct2Act (Huang et al. (2023b)) utilizes CLIP and SAM to identify manipulated objects within observation images and outputs the 3D position of these manipulated objects from 2D image. DALL-E-Bot (Kapelyukh et al. (2023)) employs DALL-E to generate target images for tasks and generates target poses for manipulation by combining the target image with the observation image.

Training via the collection of a large manipulation dataset primarily involves utilizing off-line reinforcement learning. PI-QT-Opt (Lee et al. (2023)) leverages a large-scale, multi-task dataset and employs a model-free off-policy reinforcement learning approach for training. RL@Scale (Herzog et al. (2023a)) provides extensive empirical validation through training on real-world data collected over 24 months from experimentation across a fleet of 23 robots in three office buildings in the waste sorting application. Q-Transformer (Chebotar et al. (2023a)) facilitates training high-capacity sequential architectures on mixed-quality data by applying transformer models to RL.

As for imitation learning methods, CLIPort (Shridhar et al. (2021)) and BC-Z (Jang et al. (2022)) demonstrate the capability of imitation learning in language-conditioned general manipulation. LEO (Huang et al. (2023a)) expands upon language foundation models by incorporating modalities like images and 3D point clouds. It fine-tunes manipulation datasets using the LoRA method. This showcases the ability to transfer the original foundation model to more modalities and manipulation tasks. VIMA (Jiang et al. (2023)) and MIDAS (Li et al. (2023b)) observe that many robot manipulation tasks can be represented as multimodal prompts intertwining language and image/video frames. They construct multimodal prompts manipulation datasets and utilize pretrained language foundation models for fine-tuning to control robot outputs. Xu et al. (2024) considers the task goal, the object's physical properties, and the end-effector's design and creates a ManiFoundation model to generate the target pose. However, the target pose output by the ManiFoundation model is not 6D pose. Instead, it provides the positions of multiple contact points and the force to be applied at each contact point.

7.3 VLADP

RoboNet (Dasari et al. (2019)) establishes an initial pool of 15 million video frames from 7 different robot platforms, aiming to learn a generalizable model for vision-based robotic manipulation through an end-to-end approach. This learning method closely mimics human learning, eliminating

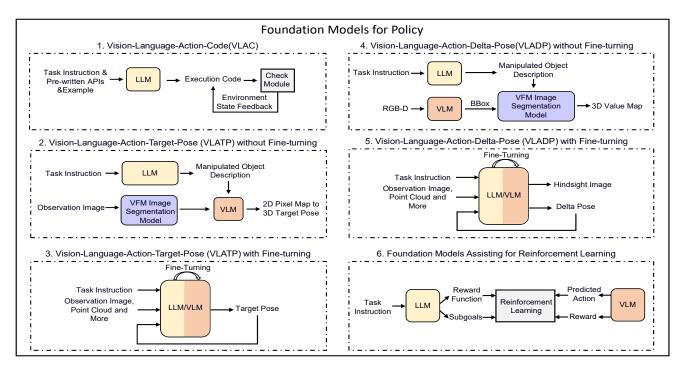


Figure 7. Foundation Models for Policy, VLAC integrates task instruction, pre-written APIs, and example inputs into LLM. It generates corresponding execution code. When the code is executed, feedback from the environment is obtained. This feedback checks if the environment meets the task's pre- and post-conditions (Singh et al. (2023)). 2) VLATP without foundation models fine-turning inputs task instruction into LLM, which specifies the manipulated object. The observation image is fed into VFM for object segmentation, and both the manipulated object and object segmentation images are input into VLM, outputting the pixel mapping of the object to be manipulated into cartesian 3D target pose (Huang et al. (2023b)). 3) VLATP with foundation models fine-tuning inputs task instruction and multimodal perception into a pre-trained model such as LLM or VLM after fine-tuning to output target pose (Huang et al. (2023a)). 4) VLADP without fine-turning. LLM outputs the description of the object to be manipulated based on task instruction. VLM then outputs the BBox of the corresponding object in RGB. Next, segmentation is performed using VFM. 3D Value Map is updated based on depth information, generating delta pose (Huang et al. (2023c)). 5) VLADP outputs delta pose and the predicted observation image after action execution by inputting task instruction and multimodal perception into a pre-trained model after finetuning. The difference between VLADP and VLATP with fine-tuning lies in generating delta poses directly through policies, allowing for conversion into trajectory through time sequences, offering a more end-to-end approach compared to target pose. Target pose often requires subsequent motion planning. Outputting delta pose resembles more closely the paradigm of human task execution, as it does not require camera and spatial calibration or robot body configuration. However, it still necessitates extensive data training to embed the parameters of robot execution in the policy model's hidden layer. As for imagining the image after the next movement, predicting both the next action and the hindsight image can improve the performance (Bousmalis et al. (2023)). 6) Foundation Models assisting for Reinforment Learning. LLM generates subgoals based on task instruction to transform long-horizon tasks into shorthorizon ones (Di Palo et al. (2023)), facilitating RL learning. LLM also creates a reward function for RL according to task instruction (Ma et al. (2023b)), while VLM can utilize prior knowledge to provide predicted action and sparse/dense reward, enhancing the effective exploration in reinforcement learning. (Ye et al. (2023a)).

the need for calibration and 2D-to-3D mapping to understand spatial 3D coordinates. Due to imagination, RoboNet generates predicted 2D images of the next movement and estimates which pixel the robot should move to in the next step, ultimately converting it into the action the robot should take. This concept of imagination is applied in both 3D-VLA (Zhen et al. (2024)) and SuSIE (Black et al. (2023)). However, RobotNet can only achieve one-model corresponding to one-task.

Effective robotic multi-task learning necessitates a high-capacity model, hence Gato (Reed et al. (2022)) and RT-1 (Brohan et al. (2022)) devise transformer-based architectures. Nonetheless, RT-1 and Gato differ; RT-1's input lacks proprioception from the robot body, while Gato incorporates proprioception. Though there's no evidence indicating the superiority of either input method, intuitively, solely observing through images may compromise stability by omitting proprioception. Building upon Gato, RoboCat (Bousmalis et al. (2023)) demonstrates that a large sequence

model can learn unseen tasks through few-shot learning. It proposes a simple but effective self-improvement process. Additionally, it shows that predicting both the next action and the hindsight image after executing that action can enhance performance. Building upon RT-1, RoboAgent (Bharadhwaj et al. (2023)) enhances model generalization and stability through data augmentation and action-chunking. MOO (Stone et al. (2023)) leverages Owl-ViT to extract object locations from observation images, enhancing RT-1's openset detection capability.

Utilizing pre-trained VLMs (Zhang et al. (2024a)) for fine-tuning to construct RFMs is considered efficient. GR-1 (Wu et al. (2023a)) is initially pre-trained on a large-scale video dataset for video prediction, and then seamlessly fine-tuned with manipulation data. RT-2 (Brohan et al. (2023)) collects manipulation trajectory data and fine-tunes manipulation datasets using VLM models like PaLI-X (Chen et al. (2023b)) and PaLM-E (Driess et al. (2023)) after treating delta pose as tokens. However, this approach necessitates

sample data for the hidden layers to learn parameters related to the robot body, objects, and environment. Open X-Embodiment (Padalkar et al. (2023b)) assembles a dataset from 22 different robots, demonstrating 527 skills (160266 tasks). Therefore, RT-H (Belkhale et al. (2024)) employs VLMs in a two-step operation, initially outputting abstract delta-pose representations like "move left," which are then converted into delta poses. Human intervention is added, enabling robots to adjust their trajectories promptly based on human input. However, democratizing such an expensive framework for all robotics practitioners proves challenging as it relies on private models and necessitates extensive co-fine-tuning on vision-language data to fully exhibit effectiveness. Consequently, there is an urgent need within robot communities for a low-cost alternative solution, hence RoboFlamingo (Li et al. (2023c)) emerges, effectively enabling a robot manipulation policy with VLMs.

Utilizing pre-trained foundation models without fine-tuning reduces the data collection and training steps. Vox-poser (Huang et al. (2023c)) utilizes RGB-D observations of the environment and language instruction as input, then LLMs generate code that interacts with VLMs to produce a sequence of 3D affordance maps and constraint maps, collectively referred to as value maps, grounded in the robot's observation space. These composed value maps serve as objective functions for motion planners to synthesize trajectories for robot manipulation.

7.4 Foundation Models assisting for Reinforcement Learning

Reinforcement learning has garnered widespread attention from researchers due to its ability to explore the environment by not requiring extensive annotated data. However, it also faces numerous challenges, such as dealing with longhorizon sequences, effectively exploring, reusing experience data, and designing reward functions (Kober et al. (2013)). Foundation models have demonstrated the emergence of common sense reasoning, the ability to propose and sequence sub-goals, and visual understanding. Due to the strong capability of foundation models, many studies aim to leverage the unprecedented capability of foundation models to address the challenges faced by reinforcement learning. RobotGPT (Jin et al. (2024)) aims to distill the knowledge of the brain ChatGPT into the mind of a small brain trained with reinforcement learning. At the same time, a plethora of literature investigates the use of foundation models to hierarchically solve challenges like long-horizon problems, effectively exploring and reward function design.

Norman (Di Palo et al. (2023)) employs LLMs to decompose tasks into subgoals and utilizes CLIP to identify the completion of each subgoal, serving as a signal generator for sparse rewards. Eureka (Ma et al. (2023b)) utilizes LLM to craft a reward function for five-fingered hand pen spinning. Subsequently, it engages in a cyclic process encompassing reward sampling, GPU-accelerated reward evaluation, and reward reflection to progressively refine its reward outputs. In contrast to Eureka's self-iteration and sparse reward function design, TEXT2REWARD (Xie et al. (2023a)) incorporates human feedback into the iterative updating of the reward function, yielding a dense reward

function. FAC (Ye et al. (2023a)) proposes using knowledge from foundation models as policy prior knowledge to improve sampling efficiency, as value prior knowledge to measure the values of states and as success-reward prior knowledge to provide final feedback on task success.

Following Fig. 7 and Table. 1, pre-trained foundation models can engage with Policy modules in various forms. However, no benchmark indicates which approach is the most effective at present. Regarding end-to-end RFMs, there are still many architectural considerations to make models more interpretable and reliably stable.

8 Manipulation Data Generation

To propel robots into the era of general manipulation, the acquisition of vast amounts of data is indispensable (Padalkar et al. (2023b)). Collecting real-world data requires a lot of human labor and expensive remote teleoperation equipment. There are currently two methods for data collection: the bottom-up approach and the top-down step-by-step approach. The bottom-up approach focuses on having the robot perform trajectories first. Then, it uses methods like crowd-sourcing to label the data. The top-down step-bystep approach involves decision-makers setting task labels. The robot then performs tasks according to these labels. RoboVQA (Sermanet et al. (2023)) shows that the bottom-up approach is more efficient in data collection compared to the top-down step-by-step approach. It uses the collected data to train VideoCoCa, which helps in handling long-horizon tasks with a hierarchical method. DIAL (Xiao et al. (2022a)) uses a fine-tuned CLIP to replace humans in labeling robot trajectories during bottom-up data collection. This transforms the robot manipulation dataset on the internet into the robot-language manipulation dataset. PAFF (Ge et al. (2023)) points out that incorrect robot trajectories can be linked to new tasks and uses fine-tuned CLIP to label the incorrect robot trajectories with appropriate task labels.

Generating lots of data in simulation is a cheaper solution. However, it still requires human effort to create both scene generation and task execution code for specific tasks (Wang et al. (2023a)). Moreover, the notorious sim-to-real gap issue remains a challenge in transferring policies trained in simulation to real-world applications. But there are many methods to address the sim-to-real challenge. Matas et al. (2018) trains the policy fully in simulation through domain randomization and then successfully deployed in the real world, even though it has never encountered real deformable objects. Therefore, simulation plays an important role in manipulation and this section will analyze existing simulators, scene generation, demonstration generation and sim-to-real gap challenge. Regardless of whether it's in a real or simulated environment, improving the efficiency of the existing dataset is essential. The mainstream approach is dataset augmentation.

8.1 Simulator

The current mainstream simulators (Zhou et al. (2023)) include PyBullet (Coumans and Bai (2016)), MuJoCo (Todorov et al. (2012)), CoppeliaSim (Rohmer et al. (2013)), NVIDIA Omniverse and Unity. Pybullet is easy to use and integrate, but its graphics are quite basic. It

Table 1. Robot Foundation Models. This table organizes information about robot foundation models, specifically focusing on robotic manipulation tasks. In the 'dataset' section, only manipulation datasets are considered. Four collection methods are defined in 'Collection Method': Teleoperation (Human control a robot to perform tasks from a distance, such as the use of VR headsets with controllers), videos (Tasks performed by other robots or humans are recorded for the robot to mimic.), simulation (Tasks are collected in a simulation environment), and skill libraries (Pre-trained models are used to execute in new scene to enhance the dataset with the check module to recognize the task success). 'Size' refers to the parameters of the model. 'Input Modality' refers to the modality in which data is inputted into the model. 'Architecture' refers to the structure of the model. 'Hardware' refers to the devices used during the model training stage. 'Output modality' shares the same definition in Section 7. 'Frequency' refers to the rate at which the model inference and control. 'Benchmark' refers to standard tests, focusing solely on manipulation, used to measure the performance.

Paper	Robotics Dataset	Collection Method	Size	Input Modality	Architecture	Hardware	Output Modality	Frequency	Benchmark
BC-Z (Jang et al. (2022))	BC-Z dataset (Jang et al. (2022))	Human Demonstrations ¹ Human Videos Robot Videos		Image Language or Video	ResNet18 encoder + FiLM layers + a two-layer MLP	18 NVIDIA V100 GPUs	Target Pose	10HZ	Own benchmark (100 tasks in total)
MOO (Stone et al. (2023))	RT-1 dataset (Brohan et al. (2022)) + Self Collection	Human Demonstrations	111M	Image Language	RT-1 + OWL-ViT	-	Delta Pose		Own benchmark (1472 real world valuations)
RT-1 (Brohan et al. (2022))	RT-1 dataset (Brohan et al. (2022))	Teleoperation	35M	Image Language	Conditioned EfficientNet + TokenLearnr + Decoder-only transformer	-	Delta Pose	3HZ	Own benchmark (over 700 instructions)
RT-2 ((Brohan et al. (2023)))	RT-1 dataset (Brohan et al. (2022))	Teleoperation	3/5/12/55B	Image Language	PaLI-X (Chen et al. (2022)), PaLM-E (Driess et al. (2023))	Multi-TPU Cloud Service	Delta Pose	1-3HZ	Language Table Lynch et al. (2023) Own benchmark
RT-X (Padalkar et al. (2023a))	60 individual datasets across 22 embodiments	Human Demonstrations	-	Image Language	PaLI-X (Chen et al. (2022)), PaLM-E (Driess et al. (2023))	Multi-TPU Cloud Service	Delta Pose	3-10Hz	Own benchmark (3600 evaluation trails)
RT-H (Belkhale et al. (2024))	Diverse+Kitchen (Belkhale et al. (2024))	Human Demonstrations	-	Image Language	PaLI-X (Chen et al. (2022))		Delta Pose	-	Own benchmark (Kitchen tasks)
LEO (Huang et al. (2023a))	CLIPort (Shridhar et al. (2021))	Human Demonstrations	1.3/7/13B	Image 3D Point Cloud Language	Decoder-only transformer	4 NVIDIA A100 GPUs	Target Pose	1Hz	Own benchmark (3 tasks for manipulation)
RoboFlamingo (Li et al. (2023c))	CALVIN Bench (Mees et al. (2022))	Teleoperation	3/4/9B	Image Language	OpenFlamingo (Awadalla et al. (2023))	8 NVIDIA Tesla A100 GPUs	Delta Pose	-	CALVIN Bench (Mees et al. (2022))
Robocat (Bousmalis et al. (2023))	Meta-World (Yu et al. (2020)) DeepMind Control Suite (Tassa et al. (2018)) +Self Collection	Simulation Skill Library	364M/1.18B	Image Language Proprioception	Decoder-only transformer		Delta Pose Hindsight Image	10-20HZ	RGB-Stacking Benchmark (Lee et al. (2021))
Roboagent (Bharadhwaj et al. (2023))	RoboSet(MT-ACT) (Bahl et al. (2023))	Teleoperation Skill Library	-	Image Language Proprioception	Transformer	One 2080Ti GPU	Delta Pose	5Hz	RL BENCH (James et al. (2020))
VIMA (Jiang et al. (2023))	VIMA dataset (Jiang et al. (2023))	Simulation	200M	Image Language	Decoder-only transformer	8 NVIDIA V100 GPUs	Target pose	-	VIMA-BENCH (Jiang et al. (2023))
MIDAS (Li et al. (2023b))	VIMA dataset (Jiang et al. (2023))	Simulation	92M	Image Language	Decoder-only transformer	8 NVIDIA A100 GPUs	Target pose	-	VIMA-BENCH (Jiang et al. (2023))
PaLM-E (Driess et al. (2023))	PaLM-E dataset (Driess et al. (2023))	Skill Library	12/22/562B	Image Neural 3D Representations States of robot or objects	Decoder-only transformer	Multi-TPU Cloud Service	Delta Pose Text	1-5Hz	Language Table (Lynch et al. (2023)) Saycan (Ahn et al. (2022))
Gato (Reed et al. (2022))	Meta-World (Yu et al. (2020)) and other 15 datasets	Simulation	1.2B	Image Language Proprioception	Decoder-only transformer	TPU v3	Delta Pose	20HZ	Meta-World (Yu et al. (2020))
GR-1 (Wu et al. (2023a))	Ego4D dataset (Grauman et al. (2022)) CALVIN Bench (Mees et al. (2022)) +Self Collection	Human Videos Teleoperation	195M	Image Language Proprioception	Decoder-only transformer	-	Delta Pose Image		CALVIN Bench (Mees et al. (2022))
QT-Opt (Kalashnikov et al. (2018))	QT-Opt dataset (Kalashnikov et al. (2018))	Simulation		Image Gripper Status Height	Reinforcement Learning	10 NVIDIA P100 GPUs	Target Pose		Own benchmark (28 test objects)
RLS (Herzog et al. (2023b))	RLS dataset (Herzog et al. (2023b))	Skill Library (Simulation + Real World)		Image Proprioception	CNN	TPUv3	Target Pose		Own benchmark (9 scenarios)
Q-Transformer (Chebotar et al. (2023b))	Q-Transformer dataset (Chebotar et al. (2023b))	Human Demonstrations Skill Library	-	Îmage Language	Q-Transformer network	-	Target Pose	3HZ	RT-1 (Brohan et al. (2022))

¹ The articles mention the use of human demonstration but do not provide detailed descriptions of the specific methods employed.

is not suitable for applications that require complex visual effects. Therefore, Pybullet is often used together with Blender (Shi et al. (2024)). Mujoco offers a high-precision physics engine. It is suitable for simulating articulated and deformable object manipulation. However, it has a high entry barrier for beginners. CoppeliaSim offers a wide range of ready-made environments, objects, and prototyping robotic systems for users. However, when dealing with many robots or complex scenes, CoppeliaSim may encounter performance issues. NVIDIA Omniverse provides realtime physics simulation and realistic rendering. However, it requires significant computational resources. NVIDIA Omniverse offers many interfaces. Users can use these to develop various applications. For example, Issac Gym is a platform for robot reinforcement learning, developed using Omniverse. Unity offers rich visual effects and a user-friendly interface. It allows for the creation of highly interactive applications. However, its physics engine is still not precise enough. The basic components of a simulator are the physics engine and the renderer. Improvements in these components can enhance the capability of sensors in simulations, such as optical tactile sensors (Chen et al. (2023d)). We also hope the simulators can add sound engine and other features. This would make the simulated world feel more real. Learning-based simulators also show great potential. For example, Sora (Brooks et al. (2024)) and

UniSim (Yang et al. (2023b)) use vast amounts of data from the internet to simulate the visual effects of many different actions.

8.2 Scene and Demonstration Generation

To create simulation scenes for manipulation tasks, two methods can be used. Real-to-Sim method converts real scenes to simulation. Task-specific automation method generates task-specific simulation scenes automatically. Real-to-Sim method can accurately mimic the real world, but it limits the diversity of scenes. The task-specific automation method can create more diverse scenarios. This approach increases the variety of collected demonstrations.

The Real-to-Sim method needs to reconstruct the real scene (in Sec. 6) and to determine the positions of objects. 3D meshes of objects can be made from point cloud data or from RGB images using a generative model (Chen et al. (2024b)). But this Real-to-Sim method for generating object 3D meshes still fails to capture the object's material and physical properties accurately such as liquid object.

The task-specific automation method requires specific assets tailored to the task. These assets must be imported and sized appropriately, with the scene also being configured to suit the task. RoboGen (Wang et al. (2023b)) utilizes LLM to generate relevant assets, asset sizes, asset configuration, scene configuration based on the task proposals and use

^{* &}quot;-" donates no data is reported.

text-to-image-to-3D generation to create the corresponding assets. These assets are imported into the simulator to generate the appropriate scene. Finally, using VLM for task-specific scene verification. GenSim (Wang et al. (2023a)) uses LLMs to generate new task and task scenario codes based on the pre-cached scene codes in a task library.

To collect demonstrations in simulations, different approaches can be used based on task complexity. For simple tasks, like a two-finger gripper picking up a cube, a hard-coding method (Wang et al. (2022b)) can be used. However, for more complex tasks, remote teleoperation (Chen et al. (2024a)) or skill library (Ha et al. (2023)) should be employed. Building skill library can be done using reinforcement learning or gradient optimization methods. RoboGen (Wang et al. (2023b)) shows that gradient-based trajectory optimization is better for fine-grained manipulation tasks with soft bodies, like shaping dough into a specific form. On the other hand, reinforcement learning and evolutionary strategies are more effective for contactrich tasks and continuous interactions with other components in the scene.

8.3 Sim-to-Real Gap Solutions

The sim-to-real problem is a widespread issue across machine learning, not limited to manipulation (Zhao et al. (2020)). The goal is to successfully transfer the policy from the simulation (source domain) to the real world (target domain). The gap in the manipulation tasks between the simulation and the real-world includes two main types: visual gap and dynamic gap. Visual gap refers to the difference between the vision information produced by the renderer and the vision information in the real world. The dynamic gap consists of several factors. First, there is a difference between the physics engine used in simulations and real-world physics. Second, the properties of objects, including robots, contribute to the object dynamic gap. Lastly, there is a control gap in robots, such as variations in static errors caused by different PID parameters. Currently, there are three main approaches to address sim-to-real gap: system identification, domain randomization, and transfer learning (Zhao et al. (2020)).

System identification (Kristinsson and Dumont (1992)) aims to create an accurate mathematical model for a physical system to make the simulator more realistic. However, it is impossible to accurately build models of complex environments in simulators.

Domain randomization (Ramos et al. (2019)) involves adding random disturbances to the parameters in simulation. This can include various elements, generally divided into visual and dynamic randomization. Visual randomization covers visual parameters like lighting, object textures, and camera positions. Dynamic randomization covers dynamic parameters like object sizes, surface friction coefficients, object masses, and actuator force gains. By experiencing diverse simulated environments, the policy can adapt to a broad range of real-world conditions. For the policy, the real world is essentially just another disturbed environment. However, parameter randomization requires human expertise. Ma et al. (2024) demonstrates that LLM excels in selecting randomized parameters and

determining the randomization distribution. This makes domain randomization more automated.

Transfer learning (Yu and Wang (2022); Tan et al. (2018)) involves using limited real-world data to adapt a policy trained on a abundant simulation data to the real world. Treat policies in the real-world and in the simulation as different tasks. We can use task transfer methods for transfer learning. For example, Rusu et al. (2017) uses the progressive network to apply knowledge from a policy trained in simulation to a new policy trained with limited real-world data, without losing the previous knowledge. Treat the policies in the real-world and in the simulation as the same task, even though the data distributions differ. We can use domain adaptation methods to address this issue. Three common methods for domain adaptation are discrepancybased (Lyu et al. (2024)), adversarial-based (Eysenbach et al. (2020)), and reconstruction-based methods (Bousmalis et al. (2016)). Discrepancy-based methods measure the feature distance between the source and target domains using predefined statistical metrics. This helps to align their feature spaces. Adversarial-based methods use a domain classifier to determine whether features come from the source or target domain. Once trained, the extractor can produce features that are invariant across both domains. Reconstruction-based methods also aim to find shared features between domains through setting up an auxiliary reconstruction task and using the shared features to recover the original input.

The methods discussed above assume that the target domain remains unchanged. However, many physical parameters of the same robot can change significantly. Factors like temperature, humidity, positioning, and wear and tear over time can all affect these parameters. This makes it harder to bridge the sim-to-real gap. To address this issue, DORA (Zhang et al. (2024b)) uses an information bottleneck principle. It aims to maximize the mutual information between the dynamics encoding and environmental data. At the same time, it minimizes the mutual information between the dynamics encoding and the behavior policy actions. Transic (Jiang et al. (2024)) proposes a data-driven approach that enables successful sim-to-real transfer using a human-in-the-loop framework.

8.4 Dataset Augmentation

Current dataset augmentation methods primarily operate at the object level. The main idea is to use semantic segmentation to extract masks for each object, and then employ generative rendering methods to alter the object's visual or pose (Mandlekar et al. (2023); Mandi et al. (2022)). GenAug (Chen et al. (2023c)) leverages language prompts with a generative model to modify object textures and shapes, adding new distractors and background scenes. ROSIE (Yu et al. (2023)) localizes the augmentation region with an open vocabulary segmentation model and then runs image editor to perform text-guided image editing.

Following Fig. 8, LLMs can generate credible descriptions or code for task scenes. VGMs produce 3D object meshes and render textures. Nonetheless, the validity of the generated task scenes must be ultimately assessed by VLMs.

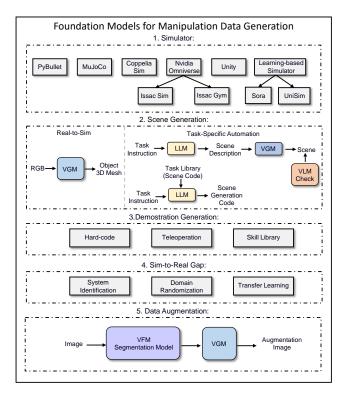


Figure 8. Foundation Models for Manipulation Data Generation. Current mainstream simulators include Pybullet, MuJoCo, CoppeliaSim, NVIDIA Omniverse, and Unity. Meanwhile, learning-based generative models used as simulators have shown potential. Simulation environment generation can be classified into Real-to-Sim and Task-specific automation methods. In the Real-to-Sim method, assuming the object's position is known, the main challenge lies in constructing the object's 3D mesh. This can be achieved through scanning technique or by using VGM to generate the 3D mesh directly from RGB image (Chen et al. (2024b)). In the Task-specific automation method, LLM can output scene descriptions or scene code based on task instruction. When the output is a scene description, VGM generates the objects and arranges them according to the description. Meanwhile, the generated scene need to be evaluated by VLM. (Wang et al. (2023b)). When the output is scene code, it directly generates the corresponding scene (Wang et al. (2023a)). However, this requires substantial prior knowledge of scene code within the task library. There are three methods for generating demonstrations in a scene: Hard-code, Teleoperation, and Skill Library. When building skill library, gradient optimization is effective in training skill for deformable tasks and reinforcement learning works better for contact-rich tasks (Wang et al. (2023b)). Solutions for the Sim-to-Real gap include System Identification, Domain Randomization. and Transfer Learning. For data augmentation, VFM is used to segment images first, and then VGM renders the object's texture on the masked image.

9 Discussion

In this survey, we aim to outline the opportunities brought by foundation models for general manipulation. We believe the potential of embedding foundation models into manipulation tasks as a viable path towards achieving general manipulation. However, the primary applications of LLMs, VFMs, VLMs, LMMs and VGMs focus only on certain aspects of general manipulation capability, such as reasoning, perception, multimodal understanding, and data generation. The current framework for RFMs

resembles human learning, requiring no calibration or robotic parameters, directly learning the mapping between observations and action. However, this demands extensive data for learning, posing a crucial issue of constructing a data close-loop, and ensuring over a 99% success rate remains an unresolved concern. Therefore, this paper proposes a framework of robot learning for manipulation towards achieving general manipulation capability and detailing how foundation models can address challenges in each module of the framework. However, there are still many open questions in this survey. In this section, we delve into several open questions that we are particularly concerned about.

9.1 What is the framework for general manipulation?

9.1.1 Definition of general manipulation. The ultimate general manipulation framework should be able to interact with human or other agent and to manipulate arbitrary objects in open-world scenarios and achieve diverse manipulation tasks. However, the interaction between robot and human involves not only recognizing intentions but also learning new skills or improving old skills from human experts in the external world. Open-world scenarios may be static or dynamic. Objects can be either rigid or deformable. Task objectives can vary from short-term to long-term. Furthermore, tasks may necessitate different degrees of precision with respect to contact points and applied forces/torques. We designate the restriction of the robot's learning capability to improving old skills and to manipulating rigid objects in static scenes in order to achieve short-horizon task objectives with low precision requirements for contact points and forces/torques as Level 0 (L0), the current research has a high probability of achieving L0. However, safety and accuracy remain paramount concerns.

9.1.2 The design logic of the framework in this survey. Based on the definition and considerations of safety and accuracy at the L0 level, this paper proposes a framework for a general manipulation capability. Given that the scenarios are static, the framework is designed in a modular, sequential manner. To facilitate module migration, it is preferable for each module to be plug-and-play. Given the current reliance on human-in-the-loop mechanisms in autonomous driving and medical robotics to ensure safety, this framework aims for human-robot interaction through corrective instruction to ensure the safety of manipulation actions. The corrective action can be collected into the dataset and then improve old skills through offline training.

9.1.3 Product implementation strategy. During robot execution, continuous human supervision is not always feasible. Hence, integrating real-time monitoring through parallel surveillance videos during robot execution could enhance safety. The framework in this paper does not explicitly denote this parallel safety monitoring module, as it resembles the post-conditions detection module. The post-conditions detection module analyzes the robot's execution video to identify reasons for task failure, facilitating post-hoc correction to ensure task success. If the algorithm's task execution safety is 80%, and the monitoring module predicts

safety at 80% as well, the probability of risky movements reduces to 4%. Of course, for household robots, ensuring an over 99% safety rate is imperative. Initially, cloud-based monitoring of multiple robots by a single operator, with human intervention to correct erroneous behaviors, appears to be the best approach. This strategy not only reduces labor requirements but also ensures safety. Later, by gathering extensive data to improve model accuracy. This framework still has shortcomings, such as the sequential execution order leads to inefficient characteristics.

9.2 How to design post-conditions detection and post-hoc correction?

The current data collection only focuses on gathering successful task execution data, ignoring the collection of data related to failed task executions. However, if data on failed task executions are collected and annotated with corresponding error reasons, it would be possible to train a model to both determine task execution success and analyze the reasons for task execution failure. For instance, RoboVQA (Sermanet et al. (2023)) utilizes crowdsourced data collection and trains videoCoCo (Yan et al. (2022)), employing a video-language model to analyze task execution description. Similarly, a post-conditions detection model could utilize a video-language model for training, taking manipulation videos as input to output whether tasks are successfully executed and to analyze the reasons for task execution failure. Post-hoc correction could then generate corrective action sequences based on the reasons for task execution failure and the task objectives, which would be handed over to a policy to generate corresponding corrective actions.

9.3 What kind of learning capability should a general manipulation framework possess?

9.3.1 The importance of learning ability. As an intelligent robot for general manipulation, it is inevitable that one cannot learn all the skills of an open-world during offline development, hence possessing a certain learning capability is necessary. Within the framework of this paper, a module of corrective instruction is introduced, enabling the robot to rectify its actions. These corrective demonstrations are incorporated into the manipulation dataset and used to improve the policy offline through fine-tuning. However, this approach still focuses on learning old task skills and cannot acquire new ones.

9.3.2 Definition of learning ability. The model of Policy should possess the capability of interactive, few-shot, continue, online learning to acquire a new skill and reinforce the policy's mastery of the newly learned skill through corrective instruction offline. Interactive refers to the ability to learn through human demonstration or by observing instructional videos. Learning through demonstration often requires physical control or teleoperation, which is less natural. Learning through observation of instructional videos aligns better with human learning patterns. However, when humans learn from teachers, they often do not predict the teacher's trajectory but rather understand the highlevel description of the actions, akin to VLaMP (Patel

et al. (2023)). Few-shot continue learning enables the robot to learn new skills with minimal demonstrations without forgetting previously learned skills. Online learning entails processing observed data instantly and enabling the model to learn as quickly as possible.

9.4 The strengths and weaknesses of current RFMs

This paper categorizes foundation models trained using manipulation datasets as RFMs. RFMs significantly enhance the policy's generalization. For instance, LEO (Huang et al. (2023a)) directly outputs target pose, while RoboFlamingo (Li et al. (2023c)) directly outputs delta pose. Directly outputting target pose is easier to train compared to delta pose, although delta pose better aligns with human behavior. Currently, RFMs are fine-tuned using pre-trained models, but this deprives them of self-exploratory learning. Designing an architecture for RFMs is crucial. Utilizing foundation models to aid reinforcement learning still holds many unexplored areas, such as using foundation models to assist robots in reinforcement learning within real-world environments.

Training RFMs simultaneously requires a large amount of training data. Current data collection methods include gathering data in simulation, using skill library to generate data, teleoperation, and imitation learning from human videos. While collecting data in simulation is cost-effective, it suffers from the sim-to-real gap. In order to generate data using skill library, it is necessary to construct an initial skill library. Teleoperation can address the sim-to-real gap but comes with high hardware costs and the issue of unnatural third-person demonstration data. Imitation learning from human videos involves mapping human trajectories from videos to robot space, leading to issues with trajectory accuracy. This paper argues that the optimal data collection method involves individuals wearing exoskeleton device equipped with various sensors. This device accurately capture human actions and map the actions to robot space, enabling first-person data collection and addressing the simto-real gap.

9.5 How to enable general manipulation with dexterous capability?

Currently, foundation models for manipulation focus mainly on simple tasks like "Pushing, Pulling, Grasping, and Placing." Complex tasks like "Reorientation & Relocation, Screwing, and In-hand Manipulation" have not been widely studied. The primary difference between these complex tasks and simple tasks is that these complex tasks involve dynamic contact points, high real-time requirements, and contactrich. The primary challenge lies in the data quality and the complexity of the training process. To address this issue, it is necessary to enhance the Skill Execution module of the framework presented in this paper, with a particular focus on the Policy. However, data and training methods for dexterous manipulation are closely tied to the challenges faced in dexterous manipulation. Therefore, this section explores how to enable general manipulation with dexterous capability. It discusses the basic principles and the challenges faced of the dexterous manipulation, and also suggests improvements needed in current foundation models for manipulation to enable general manipulation to achieve dexterity.

Bicchi (2000) offers a thorough and widely accepted definition: dexterous manipulation is the capability of changing the position and orientation of the manipulated object from a given reference configuration to a different one, arbitrarily chosen within the hand workspace. Based on this definition, the dexterous manipulation can be described as: based on the designed end-effector, determining a sequence of contact points and the forces/torques to be exerted on the object, and control the whole-body to accomplish a specific task.

Based on this definition, the challenges of dexterous manipulation lie in the design of the end-effector, determining a sequence of contact points and forces/torques, and whole-body control. The process of determining a sequence of contact points and forces/torques can be divided into model-based approach and the learning-based approach. The model-based approach is interpretable, explicitly showing the factors to consider in dexterous manipulation. Therefore, this section explains both model-based approach and learning-based approach.

9.5.1 End-effector Design. Currently, there are two primary approaches to designing end-effector. The first approach customizes the end-effector for specific tasks. The second approach makes the multi-fingered end-effector resemble a human hand. The end-effector designed with the first approach is usually easier to control because it has fewer degrees of freedom compared to the endeffector designed with the second approach. In Billard and Kragic (2019), dexterity is divided into two types: extrinsic dexterity and intrinsic dexterity. Extrinsic dexterity involves using external support, such as friction, gravity, and contact surfaces, to compensate for the lack of degrees of freedom. Intrinsic dexterity refers to the hand's ability to manipulate objects using its own degrees of freedom. Therefore, the first approach still has certain limitations for general manipulation. The design of the end-effector is related to robot proprioception S_{robot} and this survey includes this topic in the State module.

The first approach requires manual design, extensive testing, and continual adjustments. In Stella et al. (2023), LLMs are used for designing end-effector. However, this area is still in its early exploration stages. Using LLMs for end-effector design generates text descriptions, which still need to be manually translated into designs. This process is not fully automated. If we could develop modules for rotational and translational joints, and use something like protein structure prediction networks (Jumper et al. (2021)), training a foundation model to output graph including these joints could help reduce the challenges of manual design. As for the second approach, the human hand has many sensors and actuators. This makes it nearly impossible to design a robotic hand that closely resembles the human hand. Therefore, it's essential to design the sensors and actuators carefully.

9.5.2 Model-Based Generation of a Sequence of Contact Points and Forces/Torques When solving simple tasks, contact points can remain fixed. However, for complex tasks, contact points need to change. Thus, a sequence

of contact points and forces/torques is required, achieved through regrasping or finger gaiting. The sequence of contact points and forces/torques are positively correlated with the trajectory of the motion and wrench of the manipulated object. When the wrench and motion of the manipulated object at a given moment are determined, they can be mapped to the corresponding contact points and forces/torques between the end-effector and the manipulated object. Therefore, we will explain the pipeline of this mapping relationship for a specific moment.

Assuming the motion trajectory of the object is already obtained, the target wrench can be calculated based on the object's mass and inertia. Contact points can be optimized based on object geometry, object material, and end-effector geometry etc, using appropriate metrics (Ferrari et al. (1992)). Alternatively, they can be generated using a knowledge-based approach (Stansfield (1991)). Subsequently, a coordinate system is established at the centroid of the object. Based on the location of the contact points, the target wrench is converted into fingertip force. Finally, the fingertip force is converted into the forces/torques required by the actuators through inverse kinematics (Okamura et al. (2000)). The pipeline contact points and forces/torques mentioned above are derived sequentially. In practical applications, both can be optimized simultaneously (Xu et al. (2024)).

Rolling and sliding at the contact points can hinder task execution. Tasks like pushing and pulling don't need strong stability between the end-effector and the object. However, for tasks like grasping, stability is crucial and the system must keep stable contact even when disturbed. Form-closure and force-closure are common approaches. Form-closure depends on the end-effector's design. Force-closure involves using force control to counteract external forces, like gravity. Current grasping methods mainly increase grip force to boost friction and achieve force-closure. However, to achieve precise wrench control, it is essential to understand the coefficient of friction represented by the object's material. Tactile-based slip prediction can also enhance stability (Veiga et al. (2015)), but it requires high real-time performance.

From the above analysis, it is evident that choosing appropriate contact points and forces/torques requires considering the object's geometry, mass, inertia, material, and friction parameters, as well as the end-effector's geometry, material, and actuator capability. Tactile-based slip prediction is also needed to ensure the stability of the contact points. The end-effector's properties are known in advance, but the object is unseen. Therefore, estimating the object's properties should mimic human perception, using vision, sound, and touch to estimate the object's properties. Repeated interactions can then refine the accuracy of these estimations.

9.5.3 Learning-Based Generation of a Sequence of Contact Points and Forces/Torques One major challenge in data collection for dexterous manipulation lies in gathering data from multi-fingered end-effectors. Teleoperation requires a real-robot system, which is not portable and cannot achieve in-the-wild data collection. Therefore, current mainstream research focuses on directly tracking human

hand motions during manipulation without controlling the robot.

Hand motion capture can be categorized into camerabased, IMU-based, and electromagnet-based methods. Using camera-based methods, human motion is estimated through pose estimation and retargeted to a multi-fingered endeffector. However, the accuracy of pose estimation needs improvement and occlusions can cause information loss. IMU-based methods are typically used to estimate wrist pose but miss fine-grained finger motion. Additionally, IMU used for pose estimation are prone to drifting over time. Electromagnet-based methods primarily use electromagnetic field gloves to estimate finger motion, but they lack information about wrist pose. At the same time, IMU-based methods and electromagnet-based methods both lack the vision data needed for policy training. DEXCAP (Wang et al. (2024)) designs a portable hand motion capture system. It uses Rokoko gloves to capture finger motion. A Realsense T265 camera is added to the wrist of the gloves to monitor wrist pose. Additionally, a Realsense L515 LiDAR camera is mounted on the chest to sense the environment. However, the glove's design lacks tactile feedback. Therefore, to collect data for a multi-fingered end-effector, hardware improvements are necessary.

Two main learning-based methods for dexterous manipulation are imitation learning (Ze et al. (2024)) and reinforcement learning (Ma et al. (2023b)). Imitation learning can use a visual encoder (in Sec. 6) for visuo-motor control. Diffusion policy (Chi et al. (2023)) adapts the concept of diffusion to visuo-motor control. It addresses challenges in visuo-motor control such as action multimodality, sequential correlation to accommodate high-dimensional action sequences. However, it remains uncertain whether diffusion policy is suitable for one-model to multiple tasks approach. It can also use an existing VLM for fine-tuning (in Sec. 7). Fine-tuning with a VLM allows a skill to work in an open world. This often performs better on unseen objects compared to visuo-motor control (Brohan et al. (2023)). Reinforcement learning offers exploration capability, which address suboptimal issues. This advantage distinguishes it from imitation learning. However, reinforcement learning is primarily trained in simulation. It still has limitations in addressing the sim-to-real challenge of complex tasks, such as pen-spinning. In Sec. 7, the use of foundation models to assist reinforcement learning is introduced. FAC (Ye et al. (2023a)) offers potential for training reinforcement learning in real-world environment, but it still lacks consideration of environment resets (Gupta et al. (2021)) and safety. Therefore, using foundation models to assist reinforcement learning in real-world training requires further exploration.

Current learning methods each have their strengths and weaknesses. Therefore, learning approaches for dexterous manipulation should integrate different methods. For example, diffusion policy can assist reinforcement learning in addressing high-dimensional action spaces issue, while reinforcement learning can help diffusion policy overcome issues with suboptimal and negative data. Additionally, the learning models should consider both inputs and outputs. The factors necessary for achieving dexterous manipulation are summarized in the "Model-Based Generation of a Sequence of Contact Points and Forces/Torques".

ManiFoundation(Xu et al. (2024)) generates contact point and force heatmaps based on task goals, object material, object geometry and end-effector geometry. However, ManiFoundation lacks sensors such as tactile for real-time servoing of the manipulated object's motion.

9.5.4 Whole-body Control The above discussion primarily focuses on the contact between the end-effector and the object. However, whole-body control is still needed in dexterous manipulation. For example, in a polishing robot, force-position hybrid control of the robotic arm is often required to manage the trajectory of contact points and forces/torques. Mobile manipulation is essential for dexterous manipulation reachability. This idea is inspired by how humans handle objects. For example, when playing badminton, people use their waists, shoulders, elbows, and wrists together to hit the shuttlecock further. This aspect is often overlooked by current foundational models for manipulation. Although LEO (Huang et al. (2023a)) can provide poses for both navigation and manipulation, it still does not address the synchronization issue between the two.

For whole-body control, the focus is on low-level control issues. A straightforward idea is to expand the action space of the policy module's robot foundation models to include all joints of the robot. However, as the output dimensions increase, end-to-end training methods are more likely to diverge. Therefore, most current models output cartesian space poses and force/torques. These outputs are then optimized and converted into position or torque for each joint through a post-processing module (Haviland and Corke (2021)). To address end-to-end whole-body control issues, principal research is needed to facilitate network training and deployment.

9.6 How to establish a benchmark?

Current research on foundation models for manipulation focuses on various tasks, including interaction, hierarchical tasks, perception, detecting pre- and post-conditions, policy, and manipulation data generation. Therefore, a benchmark for foundation models for manipulation should include a comprehensive framework with diverse tasks. This framework should test individual tasks and tasks that involve connecting different modules. Building a benchmark should include existing datasets. However, since different simulators have unique physics engines and renderers, the benchmark should include various simulators and separately test all existing datasets in different simulators.

Table. 1 lists the benchmarks used in current RFMs, highlighting a lack of standardization. This inconsistency hinders the development of RFMs for three main reasons. Firstly, current RFMs are tied to the specific parameters of each robot, such as the choice of sensors, camera pose, and the robot's degrees of freedom. These factors prevent RFMs from being easily transferred across different robots. Secondly, testing the generalization and success rate of general manipulation capability requires a wide range of scenes and tasks. Thirdly, there is no standardized metric for assessing general manipulation capability.

As for the RFMs are not transferable between different robots. The issue arises from focusing solely on testing RFM algorithms without considering hardware, which is an ineffective approach. General manipulation requires whole-body control. Thus, evaluating the generalization and success rate of RFMs should involve both algorithms and hardware, unlike in computer vision where only algorithms are considered. To address this, the simulation benchmark should include an easy interface for importing various robot hardware configurations.

As for the requirment of a wide range of scenes and tasks. Although iGibson (Li et al. (2021)) and BEHAVIOR-1K (Li et al. (2023a)) support simulating a variety of household tasks with high realism, they are still manually constructed. In Section 8, we discuss how foundation models can automate the generation of scenes and tasks. Using foundation models to create numerous scenes, combined with VLMs for accuracy checking and minimal human intervention, could be a valuable approach to explore.

As for the metric for assessing general manipulation. The current evaluation standards mainly focus on success rates. However, in real-world applications, user preferences should also be considered. For instance, the system's real-time performance is important. Most algorithms focus on building the generalization of skills. They often overlook the amount of data and speed required for RFMs to learn a new skill. Therefore, evaluation metric should also include the learning ability of RFMs.

Overall, to assess the ability for general manipulation, methods used for testing medical robots can be referenced. Start with extensive testing in simulation environments, followed by limited tests in real-world settings. Continue evaluating the general manipulation capability during the product's application phase.

10 Conclusion

The impressive performance of foundation models in the fields of computer vision and natural language suggests the potential of embedding foundation models into manipulation tasks as a viable path toward achieving general manipulation capability. However, current research lacks consideration of a general manipulation framework. Thus, this paper proposes a general manipulation framework based on the development of robot learning for manipulation and the definition of general manipulation. It also describes the opportunities that foundation models bring to each module of the framework.

We designate the restriction of the robot's learning capability to improving old skills and to manipulating rigid objects in static scenes in order to achieve short-horizon task objectives with low precision requirements for contact points and forces/torques as Level 0 (L0), the current research has a high probability of achieving L0.

Then, we discuss the following points: (1) the logic and implementation strategies of the designed framework, (2) how to design the modules of post-conditions detection and post-hoc correction, due to limited research on foundation models for these areas, (3) the learning capability required for general manipulation, (4) the strengths and weaknesses of current RFMs, (5) how to make the general manipulation with the dexterous capability, and (6) how to establish a foundation models for manipulation benchmark.

Additionally, the proposed framework has certain limitations: (1) The framework is designed with a sequential

structure, which contrasts with the parallel execution in human operation. (2) Both the proposed framework and the surveyed literature are based on learning-based approaches. While model-based methods may not generalize as well, they tend to significantly outperform learning-based methods in terms of success rates and safety for specific tasks. Therefore, investigating the integration of learning-based and model-based approaches remains an important research. (3) The framework is limited to static environments, rigid objects, short-horizon tasks, improving old skills, and low precision requirements for contact points and forces/torques. Further research is needed to advance from L0 to L5.

Finally, foundation models present opportunities for each module of the framework, but many challenges still remain:

- Interaction Human interaction involves not only language but also gestures and actions. Incorporating multimodal inputs into interaction modules can enhance recognition capability.
- Hierarchical of skills The hierarchy of skills still has many unconsidered factors, such as achieving tasks in the shortest time with the highest efficiency, and how to generate strategies for dynamic scenes.
- Pre- and post-conditions detection Current research
 on post-condition detection primarily focuses on
 detection after robot execution. However, this delay is
 unacceptable. Therefore, it is necessary to implement
 failure detection and analysis of failure reasons during
 the robot execution.
- 4. State The representation of state requires integration of multiple modalities, such as touch and hearing. Additionally, it's important to consider the opportunities that foundation models can bring to active perception.
- 5. Policy Current research on RFMs primarily involves fine-tuning VLMs. This approach deprives RFMs of the ability to self-explore. The extensive parameters of RFMs require significant computational resources for training and real-time reference, and model training also needs abundant data. Additionally, there is a lack of a unified benchmark for evaluating different RFMs.
- Environment Transition Module The foundation models inherently contain abundant physical priors. Applying foundation models to build a highly realistic physical model assist reinforcement learning training is a direction worth exploring.
- Data Generation The accuracy of data generated by LLMs and VGMs remains insufficient, necessitating appropriate check module and data cleaning algorithms.

References

Achiam J, Adler S, Agarwal S, Ahmad L, Akkaya I, Aleman FL, Almeida D, Altenschmidt J, Altman S, Anadkat S et al. (2023) Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Ahn M, Brohan A, Brown N, Chebotar Y, Cortes O, David B, Finn C, Fu C, Gopalakrishnan K, Hausman K et al. (2022) Do as i can, not as i say: Grounding language in robotic affordances. *arXiv preprint arXiv:2204.01691*.

Austin J, Odena A, Nye M, Bosma M, Michalewski H, Dohan D, Jiang E, Cai C, Terry M, Le Q et al. (2021) Program synthesis

with large language models. arXiv preprint arXiv:2108.07732

- Awadalla A, Gao I, Gardner J, Hessel J, Hanafy Y, Zhu W, Marathe K, Bitton Y, Gadre S, Sagawa S et al. (2023) Openflamingo: An open-source framework for training large autoregressive vision-language models. arXiv preprint arXiv:2308.01390.
- Bahl S, Mendonca R, Chen L, Jain U and Pathak D (2023) Affordances from human videos as a versatile representation for robotics. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 13778–13790.
- Belkhale S, Ding T, Xiao T, Sermanet P, Vuong Q, Tompson J, Chebotar Y, Dwibedi D and Sadigh D (2024) Rt-h: Action hierarchies using language. arXiv preprint arXiv:2403.01823.
- Bharadhwaj H, Vakil J, Sharma M, Gupta A, Tulsiani S and Kumar V (2023) Roboagent: Generalization and efficiency in robot manipulation via semantic augmentations and action chunking. arXiv preprint arXiv:2309.01918.
- Bicchi A (2000) Hands for dexterous manipulation and robust grasping: A difficult road toward simplicity. IEEE Transactions on robotics and automation 16(6): 652-662.
- Billard A and Kragic D (2019) Trends and challenges in robot manipulation. Science 364(6446): eaat8414.
- Black K, Nakamoto M, Atreya P, Walke H, Finn C, Kumar A and Levine S (2023) Zero-shot robotic manipulation with pretrained image-editing diffusion models. arXiv preprint arXiv:2310.10639.
- Bousmalis K, Trigeorgis G, Silberman N, Krishnan D and Erhan D (2016) Domain separation networks. Advances in neural information processing systems 29.
- Bousmalis K, Vezzani G, Rao D, Devin C, Lee AX, Bauza M, Davchev T, Zhou Y, Gupta A, Raju A et al. (2023) Robocat: A self-improving foundation agent for robotic manipulation. arXiv preprint arXiv:2306.11706.
- Brohan A, Brown N, Carbajal J, Chebotar Y, Chen X, Choromanski K, Ding T, Driess D, Dubey A, Finn C et al. (2023) Rt-2: Vision-language-action models transfer web knowledge to robotic control. arXiv preprint arXiv:2307.15818.
- Brohan A, Brown N, Carbajal J, Chebotar Y, Dabis J, Finn C, Gopalakrishnan K, Hausman K, Herzog A, Hsu J et al. (2022) Rt-1: Robotics transformer for real-world control at scale. arXiv preprint arXiv:2212.06817.
- Brooks T, Peebles B, Holmes C, DePue W, Guo Y, Jing L, Schnurr D, Taylor J, Luhman T, Luhman E, Ng C, Wang R and Ramesh A (2024) Video generation models as world simulators URL https://openai.com/research/ video-generation-models-as-world-simulators. Chi C, Feng S, Du Y, Xu Z, Cousineau E, Burchfiel B and Song S
- Brown T, Mann B, Ryder N, Subbiah M, Kaplan JD, Dhariwal P, Neelakantan A, Shyam P, Sastry G, Askell A et al. (2020) Language models are few-shot learners. Advances in neural information processing systems 33: 1877–1901.
- Bucker A, Figueredo L, Haddadin S, Kapoor A, Ma S, Vemprala S and Bonatti R (2023) Latte: Language trajectory transformer. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 7287–7294.
- Caron M, Touvron H, Misra I, Jégou H, Mairal J, Bojanowski P and Joulin A (2021) Emerging properties in self-supervised vision transformers. In: Proceedings of the IEEE/CVF international conference on computer vision. pp. 9650-9660.
- Chebotar Y, Vuong Q, Hausman K, Xia F, Lu Y, Irpan A, Kumar A, Yu T, Herzog A, Pertsch K et al. (2023a) Q-transformer:

- Scalable offline reinforcement learning via autoregressive qfunctions. In: Conference on Robot Learning. PMLR, pp. 3909-3928.
- Chebotar Y, Vuong Q, Irpan A, Hausman K, Xia F, Lu Y, Kumar A et al. (2023b) Q-transformer: Scalable offline reinforcement learning via autoregressive q-functions.
- Chen B, Chen Z, Chen X, Mao S, Pan F, Li L, Liu W, Min H, Ding X, Fang B et al. (2024a) Teleoperation of an anthropomorphic robot hand with a metamorphic palm and tunable-stiffness soft fingers. Soft Robotics.
- Chen B, Xia F, Ichter B, Rao K, Gopalakrishnan K, Ryoo MS, Stone A and Kappler D (2023a) Open-vocabulary queryable scene representations for real world planning. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 11509-11522.
- Chen JT and Huang CM (2023) Forgetful large language models: Lessons learned from using llms in robot programming. arXiv preprint arXiv:2310.06646.
- Chen M, Tworek J, Jun H, Yuan Q, Pinto HPdO, Kaplan J, Edwards H, Burda Y, Joseph N, Brockman G et al. (2021) Evaluating large language models trained on code. arXiv preprint arXiv:2107.03374.
- Chen X, Djolonga J, Padlewski P, Mustafa B, Changpinyo S, Wu J, Ruiz CR, Goodman S, Wang X, Tay Y et al. (2023b) Pali-x: On scaling up a multilingual vision and language model. arXiv preprint arXiv:2305.18565.
- Chen X, Wang X, Changpinyo S, Piergiovanni A, Padlewski P, Salz D, Goodman S, Grycner A, Mustafa B, Beyer L et al. (2022) Pali: A jointly-scaled multilingual language-image model. arXiv preprint arXiv:2209.06794.
- Chen Z, Kiami S, Gupta A and Kumar V (2023c) Genaug: Retargeting behaviors to unseen situations via generative augmentation. arXiv preprint arXiv:2302.06671.
- Chen Z, Walsman A, Memmel M, Mo K, Fang A, Vemuri K, Wu A, Fox D and Gupta A (2024b) Urdformer: A pipeline for constructing articulated simulation environments from realworld images. arXiv preprint arXiv:2405.11656.
- Chen Z, Zhang S, Luo S, Sun F and Fang B (2023d) Tacchi: A pluggable and low computational cost elastomer deformation simulator for optical tactile sensors. IEEE Robotics and Automation Letters 8(3): 1239–1246.
- Cheng HK and Schwing AG (2022) Xmem: Long-term video object segmentation with an atkinson-shiffrin memory model. In: European Conference on Computer Vision. Springer, pp. 640-
- (2023) Diffusion policy: Visuomotor policy learning via action diffusion. arXiv preprint arXiv:2303.04137.
- Coumans E and Bai Y (2016) Pybullet, a python module for physics simulation for games, robotics and machine learning.
- Cui Y, Karamcheti S, Palleti R, Shivakumar N, Liang P and Sadigh D (2023) No, to the right: Online language corrections for robotic manipulation via shared autonomy. In: Proceedings of the 2023 ACM/IEEE International Conference on Human-Robot Interaction. pp. 93-101.
- Cui Y, Niekum S, Gupta A, Kumar V and Rajeswaran A (2022) Can foundation models perform zero-shot task specification for robot manipulation? In: Learning for Dynamics and Control Conference. PMLR, pp. 893-905.

- Dasari S, Ebert F, Tian S, Nair S, Bucher B, Schmeckpeper K, Singh S, Levine S and Finn C (2019) Robonet: Large-scale multirobot learning. *arXiv preprint arXiv:1910.11215*.
- Dehghani M, Djolonga J, Mustafa B, Padlewski P, Heek J, Gilmer J, Steiner AP, Caron M, Geirhos R, Alabdulmohsin I et al. (2023) Scaling vision transformers to 22 billion parameters. In: *International Conference on Machine Learning*. PMLR, pp. 7480–7512.
- Deng J, Dong W, Socher R, Li LJ, Li K and Fei-Fei L (2009) Imagenet: A large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. Ieee, pp. 248–255.
- Devlin J, Chang MW, Lee K and Toutanova K (2018) Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv* preprint arXiv:1810.04805.
- Di Palo N, Byravan A, Hasenclever L, Wulfmeier M, Heess N and Riedmiller M (2023) Towards a unified agent with foundation models. *arXiv preprint arXiv:2307.09668*.
- Ding Y, Zhang X, Amiri S, Cao N, Yang H, Esselink C and Zhang S (2022) Robot task planning and situation handling in open worlds. arXiv preprint arXiv:2210.01287.
- Ding Y, Zhang X, Paxton C and Zhang S (2023) Task and motion planning with large language models for object rearrangement. arXiv preprint arXiv:2303.06247.
- Driess D, Xia F, Sajjadi MS, Lynch C, Chowdhery A, Ichter B, Wahid A, Tompson J, Vuong Q, Yu T et al. (2023) Palme: An embodied multimodal language model. *arXiv preprint* arXiv:2303.03378.
- Ellis K, Wong L, Nye M, Sable-Meyer M, Cary L, Anaya Pozo L, Hewitt L, Solar-Lezama A and Tenenbaum JB (2023) Dreamcoder: growing generalizable, interpretable knowledge with wake–sleep bayesian program learning. *Philosophical Transactions of the Royal Society A* 381(2251): 20220050.
- Eysenbach B, Asawa S, Chaudhari S, Levine S and Salakhutdinov R (2020) Off-dynamics reinforcement learning: Training for transfer with domain classifiers. *arXiv preprint arXiv:2006.13916*.
- Fang HS, Wang C, Gou M and Lu C (2020) Graspnet-1billion: A large-scale benchmark for general object grasping. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. pp. 11444–11453.
- Ferrari C, Canny JF et al. (1992) Planning optimal grasps. In: ICRA, volume 3. p. 6.
- Firoozi R, Tucker J, Tian S, Majumdar A, Sun J, Liu W, Zhu Y, Song S, Kapoor A, Hausman K et al. (2023) Foundation models in robotics: Applications, challenges, and the future. *arXiv* preprint arXiv:2312.07843.
- Gao J, Sarkar B, Xia F, Xiao T, Wu J, Ichter B, Majumdar A and Sadigh D (2023) Physically grounded vision-language models for robotic manipulation.
- Gao P, Geng S, Zhang R, Ma T, Fang R, Zhang Y, Li H and Qiao Y (2024) Clip-adapter: Better vision-language models with feature adapters. *International Journal of Computer Vision* 132(2): 581–595.
- Ge Y, Macaluso A, Li LE, Luo P and Wang X (2023) Policy adaptation from foundation model feedback. In: *Proceedings* of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 19059–19069.
- Geng Y, An B, Geng H, Chen Y, Yang Y and Dong H (2023) Rlafford: End-to-end affordance learning for robotic

- manipulation. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 5880–5886.
- Gibson JJ (2014) The ecological approach to visual perception: classic edition. Psychology press.
- Grauman K, Westbury A, Byrne E, Chavis Z, Furnari A, Girdhar R, Hamburger J, Jiang H, Liu M, Liu X et al. (2022) Ego4d: Around the world in 3,000 hours of egocentric video. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. pp. 18995–19012.
- Gu X, Lin TY, Kuo W and Cui Y (2021) Open-vocabulary object detection via vision and language knowledge distillation. *arXiv* preprint arXiv:2104.13921.
- Gupta A, Yu J, Zhao TZ, Kumar V, Rovinsky A, Xu K, Devlin T and Levine S (2021) Reset-free reinforcement learning via multitask learning: Learning dexterous manipulation behaviors without human intervention. In: 2021 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 6664–6671.
- Ha H, Florence P and Song S (2023) Scaling up and distilling down: Language-guided robot skill acquisition. In: *Conference on Robot Learning*. PMLR, pp. 3766–3777.
- Han K, Wang Y, Chen H, Chen X, Guo J, Liu Z, Tang Y, Xiao A, Xu C, Xu Y et al. (2022) A survey on vision transformer. *IEEE transactions on pattern analysis and machine intelligence* 45(1): 87–110.
- Haviland J and Corke P (2021) Neo: A novel expeditious optimisation algorithm for reactive motion control of manipulators. *IEEE Robotics and Automation Letters* 6(2): 1043–1050.
- He K, Chen X, Xie S, Li Y, Dollár P and Girshick R (2022) Masked autoencoders are scalable vision learners. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. pp. 16000–16009.
- Herzog A, Rao K, Hausman K, Lu Y, Wohlhart P, Yan M, Lin J, Arenas MG, Xiao T, Kappler D et al. (2023a) Deep rl at scale: Sorting waste in office buildings with a fleet of mobile manipulators. *arXiv preprint arXiv:2305.03270*.
- Herzog A, Rao K, Hausman K, Lu Y, Wohlhart P, Yan M, Lin J, Arenas MG, Xiao T et al. (2023b) Deep rl at scale: Sorting waste in office buildings with a fleet of mobile manipulators.
- Hong Y, Zhen H, Chen P, Zheng S, Du Y, Chen Z and Gan C (2023) 3d-llm: Injecting the 3d world into large language models. Advances in Neural Information Processing Systems 36: 20482–20494.
- Hu Y, Lin F, Zhang T, Yi L and Gao Y (2023a) Look before you leap: Unveiling the power of gpt-4v in robotic vision-language planning. *arXiv preprint arXiv:2311.17842*.
- Hu Y, Xie Q, Jain V, Francis J, Patrikar J, Keetha N, Kim S, Xie Y, Zhang T, Zhao Z et al. (2023b) Toward general-purpose robots via foundation models: A survey and meta-analysis. *arXiv* preprint arXiv:2312.08782.
- Hu Y, Yang J, Chen L, Li K, Sima C, Zhu X, Chai S, Du S, Lin T,
 Wang W et al. (2023c) Planning-oriented autonomous driving.
 In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 17853–17862.
- Huang J, Yong S, Ma X, Linghu X, Li P, Wang Y, Li Q, Zhu SC, Jia B and Huang S (2023a) An embodied generalist agent in 3d world. *arXiv preprint arXiv:2311.12871*.
- Huang S, Jiang Z, Dong H, Qiao Y, Gao P and Li H (2023b) Instruct2act: Mapping multi-modality instructions to

robotic actions with large language model. arXiv preprint arXiv:2305.11176.

- Huang W, Abbeel P, Pathak D and Mordatch I (2022) Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. In: *International Conference on Machine Learning*. PMLR, pp. 9118–9147.
- Huang W, Wang C, Zhang R, Li Y, Wu J and Fei-Fei L (2023c) Voxposer: Composable 3d value maps for robotic manipulation with language models. *arXiv preprint arXiv:2307.05973*.
- Huang W, Xia F, Shah D, Driess D, Zeng A, Lu Y, Florence P, Mordatch I, Levine S, Hausman K et al. (2023d) Grounded decoding: Guiding text generation with grounded models for robot control. arXiv preprint arXiv:2303.00855.
- James S, Ma Z, Arrojo DR and Davison AJ (2020) Rlbench: The robot learning benchmark & learning environment. *IEEE Robotics and Automation Letters* 5(2): 3019–3026.
- Jang E, Irpan A, Khansari M, Kappler D, Ebert F, Lynch C, Levine S and Finn C (2022) Bc-z: Zero-shot task generalization with robotic imitation learning. In: *Conference on Robot Learning*. PMLR, pp. 991–1002.
- Jansen PA (2020) Visually-grounded planning without vision: Language models infer detailed plans from high-level instructions. arXiv preprint arXiv:2009.14259.
- Jatavallabhula KM, Kuwajerwala A, Gu Q, Omama M, Chen T, Maalouf A, Li S, Iyer G, Saryazdi S, Keetha N et al. (2023) Conceptfusion: Open-set multimodal 3d mapping. arXiv preprint arXiv:2302.07241.
- Jiang Y, Gupta A, Zhang Z, Wang G, Dou Y, Chen Y, Fei-Fei L, Anandkumar A, Zhu Y and Fan L (2023) Vima: Robot manipulation with multimodal prompts .
- Jiang Y, Wang C, Zhang R, Wu J and Fei-Fei L (2024) Transic: Sim-to-real policy transfer by learning from online correction. arXiv preprint arXiv:2405.10315.
- Jin Y, Li D, Yong A, Shi J, Hao P, Sun F, Zhang J and Fang B (2024) Robotgpt: Robot manipulation learning from chatgpt. *IEEE Robotics and Automation Letters*.
- Jing Y, Zhu X, Liu X, Sima Q, Yang T, Feng Y and Kong T (2023) Exploring visual pre-training for robot manipulation: Datasets, models and methods. *arXiv* preprint *arXiv*:2308.03620.
- Joublin F, Ceravola A, Smirnov P, Ocker F, Deigmoeller J, Belardinelli A, Wang C, Hasler S, Tanneberg D and Gienger M (2023) Copal: Corrective planning of robot actions with large language models. arXiv preprint arXiv:2310.07263.
- Jumper J, Evans R, Pritzel A, Green T, Figurnov M, Ronneberger O, Tunyasuvunakool K, Bates R, Žídek A, Potapenko A et al. (2021) Highly accurate protein structure prediction with alphafold. *nature* 596(7873): 583–589.
- Kalashnikov D, Irpan A, Pastor P, Ibarz J, Herzog A, Jang E, Quillen D, Holly E, Kalakrishnan M, Vanhoucke V et al. (2018) Scalable deep reinforcement learning for vision-based robotic manipulation. In: *Conference on robot learning*. PMLR, pp. 651–673
- Kannan SS, Venkatesh VL and Min BC (2023) Smart-Ilm: Smart multi-agent robot task planning using large language models. arXiv preprint arXiv:2309.10062.
- Kapelyukh I, Vosylius V and Johns E (2023) Dall-e-bot: Introducing web-scale diffusion models to robotics. *IEEE Robotics and Automation Letters* 8(7): 3956–3963. DOI: 10.1109/lra.2023.3272516. URL http://dx.doi.org/10.1109/lra.2023.3272516.

Karamcheti S, Nair S, Chen AS, Kollar T, Finn C, Sadigh D and Liang P (2023) Language-driven representation learning for robotics. *arXiv preprint arXiv:2302.12766*.

- Kerr J, Kim CM, Goldberg K, Kanazawa A and Tancik M (2023) Lerf: Language embedded radiance fields. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. pp. 19729–19739.
- Khan MA, Kenney M, Painter J, Kamale D, Batista-Navarro R and Ghalamzan-E A (2023) Natural language robot programming: Nlp integrated with autonomous robotic grasping. *arXiv* preprint arXiv:2304.02993.
- Khan S, Naseer M, Hayat M, Zamir SW, Khan FS and Shah M (2022) Transformers in vision: A survey. *ACM computing surveys* (CSUR) 54(10s): 1–41.
- Khandelwal A, Weihs L, Mottaghi R and Kembhavi A (2022) Simple but effective: Clip embeddings for embodied ai. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. pp. 14829–14838.
- Kirillov A, Mintun E, Ravi N, Mao H, Rolland C, Gustafson L, Xiao T, Whitehead S, Berg AC, Lo WY et al. (2023) Segment anything. *arXiv* preprint arXiv:2304.02643.
- Kleeberger K, Bormann R, Kraus W and Huber MF (2020) A survey on learning-based robotic grasping. *Current Robotics Reports* 1: 239–249.
- Kober J, Bagnell JA and Peters J (2013) Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research* 32(11): 1238–1274.
- Kokic M, Stork JA, Haustein JA and Kragic D (2017) Affordance detection for task-specific grasping using deep learning. In: 2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids). IEEE, pp. 91–98.
- Kristinsson K and Dumont GA (1992) System identification and control using genetic algorithms. *IEEE Transactions on Systems, Man, and Cybernetics* 22(5): 1033–1046.
- Kroemer O, Niekum S and Konidaris G (2021) A review of robot learning for manipulation: Challenges, representations, and algorithms. *The Journal of Machine Learning Research* 22(1): 1395–1476.
- Lee AX, Devin C, Zhou Y, Lampe T, Bousmalis K, Springenberg JT, Byravan A, Abdolmaleki A, Gileadi N, Khosid D, Fantacci C, Chen JE, Raju A, Jeong R, Neunert M, Laurens A, Saliceti S, Casarini F, Riedmiller M, Hadsell R and Nori F (2021) Beyond pick-and-place: Tackling robotic stacking of diverse shapes. In: Conference on Robot Learning (CoRL). URL https://openreview.net/forum?id=U0Q8CrtBJxJ.
- Lee KH, Xiao T, Li A, Wohlhart P, Fischer I and Lu Y (2023) Pi-qt-opt: Predictive information improves multi-task robotic reinforcement learning at scale. In: *Conference on Robot Learning*. PMLR, pp. 1696–1707.
- Li C, Xia F, Martín-Martín R, Lingelbach M, Srivastava S, Shen B, Vainio K, Gokmen C, Dharan G, Jain T et al. (2021) igibson 2.0: Object-centric simulation for robot learning of everyday household tasks. *arXiv preprint arXiv:2108.03272*.
- Li C, Zhang R, Wong J, Gokmen C, Srivastava S, Martín-Martín R, Wang C, Levine G, Lingelbach M, Sun J et al. (2023a) Behavior-1k: A benchmark for embodied ai with 1,000 everyday activities and realistic simulation. In: *Conference on Robot Learning*. PMLR, pp. 80–93.
- Li J, Gao Q, Johnston M, Gao X, He X, Shakiah S, Shi H, Ghanadan R and Wang WY (2023b) Mastering robot manipulation with

- multimodal prompts through pretraining and multi-task finetuning. arXiv preprint arXiv:2310.09676.
- Li X, Liu M, Zhang H, Yu C, Xu J, Wu H, Cheang C, Jing Y, Zhang W, Liu H et al. (2023c) Vision-language foundation models as effective robot imitators. *arXiv preprint arXiv:2311.01378*.
- Liang J, Huang W, Xia F, Xu P, Hausman K, Ichter B, Florence P and Zeng A (2023) Code as policies: Language model programs for embodied control. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 9493–9500.
- Lin K, Agia C, Migimatsu T, Pavone M and Bohg J (2023) Text2motion: From natural language instructions to feasible plans. *arXiv preprint arXiv:2303.12153*.
- Liu B, Jiang Y, Zhang X, Liu Q, Zhang S, Biswas J and Stone P (2023a) Llm+ p: Empowering large language models with optimal planning proficiency. arXiv preprint arXiv:2304.11477
- Liu M, Zhu Y, Cai H, Han S, Ling Z, Porikli F and Su H (2023b) Partslip: Low-shot part segmentation for 3d point clouds via pretrained image-language models. In: *Proceedings* of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 21736–21746.
- Liu R, Wu R, Van Hoorick B, Tokmakov P, Zakharov S and Vondrick C (2023c) Zero-1-to-3: Zero-shot one image to 3d object. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 9298–9309.
- Liu S, Zeng Z, Ren T, Li F, Zhang H, Yang J, Li C, Yang J, Su H, Zhu J et al. (2023d) Grounding dino: Marrying dino with grounded pre-training for open-set object detection. *arXiv* preprint arXiv:2303.05499.
- Liu Y, Huang B, Zhu Z, Tian H, Gong M, Yu Y and Zhang K (2024) Learning world models with identifiable factorization. *Advances in Neural Information Processing Systems* 36.
- Lynch C, Wahid A, Tompson J, Ding T, Betker J, Baruch R, Armstrong T and Florence P (2023) Interactive language: Talking to robots in real time. *IEEE Robotics and Automation Letters*.
- Lyu J, Bai C, Yang J, Lu Z and Li X (2024) Cross-domain policy adaptation by capturing representation mismatch. *arXiv* preprint arXiv:2405.15369.
- Ma YJ, Kumar V, Zhang A, Bastani O and Jayaraman D (2023a) Liv: Language-image representations and rewards for robotic control. In: *International Conference on Machine Learning*. PMLR, pp. 23301–23320.
- Ma YJ, Liang W, Wang G, Huang DA, Bastani O, Jayaraman D, Zhu Y, Fan L and Anandkumar A (2023b) Eureka: Humanlevel reward design via coding large language models. arXiv preprint arXiv:2310.12931.
- Ma YJ, Liang W, Wang HJ, Wang S, Zhu Y, Fan L, Bastani O and Jayaraman D (2024) Dreureka: Language model guided simto-real transfer. *arXiv preprint arXiv:2406.01967*.
- Ma YJ, Sodhani S, Jayaraman D, Bastani O, Kumar V and Zhang A (2022) Vip: Towards universal visual reward and representation via value-implicit pre-training. arXiv preprint arXiv:2210.00030.
- Majumdar A, Yadav K, Arnaud S, Ma YJ, Chen C, Silwal S, Jain A, Berges VP, Abbeel P, Malik J et al. (2023) Where are we in the search for an artificial visual cortex for embodied intelligence? arXiv preprint arXiv:2303.18240.

- Mandi Z, Bharadhwaj H, Moens V, Song S, Rajeswaran A and Kumar V (2022) Cacti: A framework for scalable multitask multi-scene visual imitation learning. *arXiv preprint* arXiv:2212.05711.
- Mandlekar A, Nasiriany S, Wen B, Akinola I, Narang Y, Fan L, Zhu Y and Fox D (2023) Mimicgen: A data generation system for scalable robot learning using human demonstrations. *arXiv* preprint arXiv:2310.17596.
- Matas J, James S and Davison AJ (2018) Sim-to-real reinforcement learning for deformable object manipulation. In: *Conference on Robot Learning*. PMLR, pp. 734–743.
- Mees O, Hermann L, Rosete-Beas E and Burgard W (2022) Calvin: A benchmark for language-conditioned policy learning for long-horizon robot manipulation tasks. *IEEE Robotics and Automation Letters* 7(3): 7327–7334.
- Mildenhall B, Srinivasan PP, Tancik M, Barron JT, Ramamoorthi R and Ng R (2021) Nerf: Representing scenes as neural radiance fields for view synthesis. *Communications of the ACM* 65(1): 99–106.
- Minderer M, Gritsenko A, Stone A, Neumann M, Weissenborn D, Dosovitskiy A, Mahendran A, Arnab A, Dehghani M, Shen Z et al. (2022) Simple open-vocabulary object detection. In: European Conference on Computer Vision. Springer, pp. 728– 755.
- Mirjalili R, Krawez M, Silenzi S, Blei Y and Burgard W (2023) Lan-grasp: Using large language models for semantic object grasping. arXiv preprint arXiv:2310.05239.
- Mo Y, Zhang H and Kong T (2023) Towards open-world interactive disambiguation for robotic grasping. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 8061–8067.
- Nair S, Rajeswaran A, Kumar V, Finn C and Gupta A (2022) R3m: A universal visual representation for robot manipulation. *arXiv* preprint arXiv:2203.12601.
- Nguyen T, Vu MN, Huang B, Van Vo T, Truong V, Le N, Vo T, Le B and Nguyen A (2023) Language-conditioned affordance-pose detection in 3d point clouds. *arXiv preprint arXiv:2309.10911*
- Okamura AM, Smaby N and Cutkosky MR (2000) An overview of dexterous manipulation. In: *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065)*, volume 1. IEEE, pp. 255–262.
- Padalkar A, Pooley A, Jain A, Bewley A, Herzog A, Irpan A, Khazatsky A, Rai A, Singh A, Brohan A et al. (2023a) Open x-embodiment: Robotic learning datasets and rt-x models. *arXiv* preprint arXiv:2310.08864.
- Padalkar A, Pooley A, Jain A, Bewley A, Herzog A, Irpan A, Khazatsky A, Rai A, Singh A, Brohan A et al. (2023b) Open xembodiment: Robotic learning datasets and rt-x models. arXiv preprint arXiv:2310.08864.
- Patel D, Eghbalzadeh H, Kamra N, Iuzzolino ML, Jain U and Desai R (2023) Pretrained language models as visual planners for human assistance. *arXiv preprint arXiv:2304.09179*.
- Radford A, Kim JW, Hallacy C, Ramesh A, Goh G, Agarwal S, Sastry G, Askell A, Mishkin P, Clark J et al. (2021) Learning transferable visual models from natural language supervision. In: *International conference on machine learning*. PMLR, pp. 8748–8763.

Radosavovic I, Xiao T, James S, Abbeel P, Malik J and Darrell T (2023) Real-world robot learning with masked visual pretraining. In: Conference on Robot Learning. PMLR, pp. 416– 426

- Ramesh A, Pavlov M, Goh G, Gray S, Voss C, Radford A, Chen M and Sutskever I (2021) Zero-shot text-to-image generation. In: *International Conference on Machine Learning*. PMLR, pp. 8821–8831.
- Ramos F, Possas RC and Fox D (2019) Bayessim: adaptive domain randomization via probabilistic inference for robotics simulators. *arXiv* preprint arXiv:1906.01728.
- Reed S, Zolna K, Parisotto E, Colmenarejo SG, Novikov A, Barth-Maron G, Gimenez M, Sulsky Y, Kay J, Springenberg JT et al. (2022) A generalist agent. arXiv preprint arXiv:2205.06175.
- Ren AZ, Dixit A, Bodrova A, Singh S, Tu S, Brown N, Xu P, Takayama L, Xia F, Varley J et al. (2023a) Robots that ask for help: Uncertainty alignment for large language model planners. arXiv preprint arXiv:2307.01928.
- Ren AZ, Govil B, Yang TY, Narasimhan KR and Majumdar A (2023b) Leveraging language for accelerated learning of tool manipulation. In: *Conference on Robot Learning*. PMLR, pp. 1531–1541.
- Rohmer E, Singh SP and Freese M (2013) V-rep: A versatile and scalable robot simulation framework. In: 2013 IEEE/RSJ international conference on intelligent robots and systems. IEEE, pp. 1321–1326.
- Rusu AA, Večerík M, Rothörl T, Heess N, Pascanu R and Hadsell R (2017) Sim-to-real robot learning from pixels with progressive nets. In: *Conference on robot learning*. PMLR, pp. 262–270.
- Sermanet P, Ding T, Zhao J, Xia F, Dwibedi D, Gopalakrishnan K, Chan C, Dulac-Arnold G, Maddineni S, Joshi NJ et al. (2023) Robovqa: Multimodal long-horizon reasoning for robotics. arXiv preprint arXiv:2311.00899.
- Shafiullah NMM, Paxton C, Pinto L, Chintala S and Szlam A (2022) Clip-fields: Weakly supervised semantic fields for robotic memory. *arXiv preprint arXiv:2210.05663*.
- Shen W, Yang G, Yu A, Wong J, Kaelbling LP and Isola P (2023) Distilled feature fields enable few-shot language-guided manipulation. *arXiv preprint arXiv:2308.07931*.
- Shi J, Jin Y, Li D, Niu H, Jin Z, Wang H et al. (2024) Asgrasp: Generalizable transparent object reconstruction and grasping from rgb-d active stereo camera. *arXiv preprint* arXiv:2405.05648.
- Shridhar M, Manuelli L and Fox D (2021) Cliport: What and where pathways for robotic manipulation.
- Silver T, Hariprasad V, Shuttleworth RS, Kumar N, Lozano-Pérez T and Kaelbling LP (2022) Pddl planning with pretrained large language models. In: NeurIPS 2022 foundation models for decision making workshop.
- Singh I, Blukis V, Mousavian A, Goyal A, Xu D, Tremblay J, Fox D, Thomason J and Garg A (2023) Progprompt: Generating situated robot task plans using large language models. In: 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 11523–11530.
- Song CH, Wu J, Washington C, Sadler BM, Chao WL and Su Y (2023) Llm-planner: Few-shot grounded planning for embodied agents with large language models. In: *Proceedings* of the IEEE/CVF International Conference on Computer Vision. pp. 2998–3009.

Stansfield SA (1991) Robotic grasping of unknown objects: A knowledge-based approach. *The International journal of robotics research* 10(4): 314–326.

- Stella F, Della Santina C and Hughes J (2023) How can llms transform the robotic design process? *Nature Machine Intelligence*: 1–4.
- Stone A, Xiao T, Lu Y, Gopalakrishnan K, Lee KH, Vuong Q, Wohlhart P, Kirmani S, Zitkovich B, Xia F et al. (2023) Openworld object manipulation using pre-trained vision-language models. arXiv preprint arXiv:2303.00905.
- Tan C, Sun F, Kong T, Zhang W, Yang C and Liu C (2018) A survey on deep transfer learning. In: Artificial Neural Networks and Machine Learning—ICANN 2018: 27th International Conference on Artificial Neural Networks, Rhodes, Greece, October 4-7, 2018, Proceedings, Part III 27. Springer, pp. 270– 279.
- Tang C, Huang D, Ge W, Liu W and Zhang H (2023) Graspgpt: Leveraging semantic knowledge from a large language model for task-oriented grasping. *IEEE Robotics and Automation Letters*.
- Tassa Y, Doron Y, Muldal A, Erez T, Li Y, de Las Casas D, Budden D, Abdolmaleki A, Merel J, Lefrancq A, Lillicrap T and Riedmiller M (2018) Deepmind control suite.
- Tatiya G, Francis J, Wu HH, Bisk Y and Sinapov J (2023) Mosaic: Learning unified multi-sensory object property representations for robot perception. *arXiv* preprint *arXiv*:2309.08508.
- Todorov E, Erez T and Tassa Y (2012) Mujoco: A physics engine for model-based control. In: 2012 IEEE/RSJ international conference on intelligent robots and systems. IEEE, pp. 5026–5033.
- Trivedi D, Zhang J, Sun SH and Lim JJ (2021) Learning to synthesize programs as interpretable and generalizable policies. *Advances in neural information processing systems* 34: 25146–25163.
- Valmeekam K, Marquez M, Olmo A, Sreedharan S and Kambhampati S (2023) Planbench: An extensible benchmark for evaluating large language models on planning and reasoning about change. In: *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.
- Veiga F, Van Hoof H, Peters J and Hermans T (2015) Stabilizing novel objects by learning to predict tactile slip. In: 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, pp. 5065–5072.
- Vemprala S, Bonatti R, Bucker A and Kapoor A (2023) Chatgpt for robotics: Design principles and model abilities. *Microsoft Auton. Syst. Robot. Res* 2: 20.
- Wang C, Chai M, He M, Chen D and Liao J (2022a) Clip-nerf: Textand-image driven manipulation of neural radiance fields. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 3835–3844.
- Wang C, Shi H, Wang W, Zhang R, Fei-Fei L and Liu CK (2024) Dexcap: Scalable and portable mocap data collection system for dexterous manipulation. arXiv preprint arXiv:2403.07788.
- Wang D, Kohler C, Zhu X, Jia M and Platt R (2022b) Bulletarm: An open-source robotic manipulation benchmark and learning framework. In: *The International Symposium of Robotics Research*. Springer, pp. 335–350.
- Wang L, Ling Y, Yuan Z, Shridhar M, Bao C, Qin Y, Wang B, Xu H and Wang X (2023a) Gensim: Generating robotic

- simulation tasks via large language models. arXiv preprint arXiv:2310.01361.
- Wang R, Du SS, Yang L and Kakade S (2020) Is long horizon rl more difficult than short horizon rl? Advances in Neural Information Processing Systems 33: 9075–9085.
- Wang Y, Xian Z, Chen F, Wang TH, Wang Y, Fragkiadaki K, Erickson Z, Held D and Gan C (2023b) Robogen: Towards unleashing infinite data for automated robot learning via generative simulation. arXiv preprint arXiv:2311.01455.
- Wu H, Jing Y, Cheang C, Chen G, Xu J, Li X, Liu M, Li H and Kong T (2023a) Unleashing large-scale video generative pre-training for visual robot manipulation. arXiv preprint arXiv:2312.13139.
- Wu J, Antonova R, Kan A, Lepert M, Zeng A, Song S, Bohg J, Rusinkiewicz S and Funkhouser T (2023b) Tidybot: Personalized robot assistance with large language models. arXiv preprint arXiv:2305.05658.
- Wu R, Zhao Y, Mo K, Guo Z, Wang Y, Wu T, Fan Q, Chen X, Guibas L and Dong H (2021) Vat-mart: Learning visual action trajectory proposals for manipulating 3d articulated objects. arXiv preprint arXiv:2106.14440.
- Xiao T, Chan H, Sermanet P, Wahid A, Brohan A, Hausman K, Levine S and Tompson J (2022a) Robotic skill acquisition via instruction augmentation with vision-language models. arXiv preprint arXiv:2211.11736.
- Xiao T, Radosavovic I, Darrell T and Malik J (2022b) Masked visual pre-training for motor control. *arXiv preprint* arXiv:2203.06173.
- Xiao X, Liu J, Wang Z, Zhou Y, Qi Y, Cheng Q, He B and Jiang S (2023) Robot learning in the era of foundation models: A survey. *arXiv preprint arXiv:2311.14379*.
- Xie T, Zhao S, Wu CH, Liu Y, Luo Q, Zhong V, Yang Y and Yu T (2023a) Text2reward: Automated dense reward function generation for reinforcement learning. *arXiv preprint arXiv:2309.11489*.
- Xie Y, Yu C, Zhu T, Bai J, Gong Z and Soh H (2023b) Translating natural language to planning goals with large-language models. arXiv preprint arXiv:2302.05128.
- Xu K, Zhao S, Zhou Z, Li Z, Pi H, Zhu Y, Wang Y and Xiong R (2023a) A joint modeling of vision-language-action for targetoriented grasping in clutter. arXiv preprint arXiv:2302.12610
- Xu M, Huang P, Yu W, Liu S, Zhang X, Niu Y, Zhang T, Xia F, Tan J and Zhao D (2023b) Creative robot tool use with large language models. *arXiv preprint arXiv:2310.13065*.
- Xu Z, Gao C, Liu Z, Yang G, Tie C, Zheng H, Zhou H, Peng W, Wang D, Chen T et al. (2024) Manifoundation model for general-purpose robotic manipulation of contact synthesis with arbitrary objects and robots. arXiv preprint arXiv:2405.06964
- Xue L, Gao M, Xing C, Martín-Martín R, Wu J, Xiong C, Xu R, Niebles JC and Savarese S (2023a) Ulip: Learning a unified representation of language, images, and point clouds for 3d understanding. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 1179–1189.
- Xue L, Yu N, Zhang S, Li J, Martín-Martín R, Wu J, Xiong C, Xu R, Niebles JC and Savarese S (2023b) Ulip-2: Towards scalable multimodal pre-training for 3d understanding. arXiv preprint arXiv:2305.08275.

- Yan S, Zhu T, Wang Z, Cao Y, Zhang M, Ghosh S, Wu Y and Yu J (2022) Videococa: Video-text modeling with zero-shot transfer from contrastive captioners. *arXiv preprint arXiv:2212.04979*
- Yang J, Gao M, Li Z, Gao S, Wang F and Zheng F (2023a) Track anything: Segment anything meets videos. *arXiv preprint* arXiv:2304.11968.
- Yang M, Du Y, Ghasemipour K, Tompson J, Schuurmans D and Abbeel P (2023b) Learning interactive real-world simulators. arXiv preprint arXiv:2310.06114.
- Yang T, Jing Y, Wu H, Xu J, Sima K, Chen G, Sima Q and Kong T (2023c) Moma-force: Visual-force imitation for realworld mobile manipulation. In: 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, pp. 6847–6852.
- Yang Z, Raman SS, Shah A and Tellex S (2023d) Plug in the safety chip: Enforcing constraints for llm-driven robot agents. *arXiv* preprint arXiv:2309.09919.
- Yao L, Han J, Wen Y, Liang X, Xu D, Zhang W, Li Z, Xu C and Xu H (2022a) Detclip: Dictionary-enriched visual-concept paralleled pre-training for open-world detection. *Advances in Neural Information Processing Systems* 35: 9125–9138.
- Yao S, Zhao J, Yu D, Du N, Shafran I, Narasimhan K and Cao Y (2022b) React: Synergizing reasoning and acting in language models. *arXiv preprint arXiv:2210.03629*.
- Ye W, Zhang Y, Wang M, Wang S, Gu X, Abbeel P and Gao Y (2023a) Foundation reinforcement learning: towards embodied generalist agents with foundation prior assistance. *arXiv* preprint arXiv:2310.02635.
- Ye Y, Li X, Gupta A, De Mello S, Birchfield S, Song J, Tulsiani S and Liu S (2023b) Affordance diffusion: Synthesizing hand-object interactions. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 22479–22489.
- Yu C and Wang P (2022) Dexterous manipulation for multi-fingered robotic hands with reinforcement learning: A review. *Frontiers in Neurorobotics* 16: 861825.
- Yu T, Quillen D, He Z, Julian R, Hausman K, Finn C and Levine S (2020) Meta-world: A benchmark and evaluation for multitask and meta reinforcement learning. In: *Conference on robot learning*. PMLR, pp. 1094–1100.
- Yu T, Xiao T, Stone A, Tompson J, Brohan A, Wang S, Singh J, Tan C, Peralta J, Ichter B et al. (2023) Scaling robot learning with semantically imagined experience. *arXiv preprint* arXiv:2302.11550.
- Yu X, Tang L, Rao Y, Huang T, Zhou J and Lu J (2022) Point-bert: Pre-training 3d point cloud transformers with masked point modeling. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 19313–19322.
- Zareian A, Rosa KD, Hu DH and Chang SF (2021) Openvocabulary object detection using captions. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 14393–14402.
- Zarrin RS, Jitosho R and Yamane K (2023) Hybrid learning-and model-based planning and control of in-hand manipulation. In: 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, pp. 8720–8726.
- Ze Y, Liu Y, Shi R, Qin J, Yuan Z, Wang J and Xu H (2024) H-index: Visual reinforcement learning with hand-informed representations for dexterous manipulation. *Advances in*

- Neural Information Processing Systems 36.
- Ze Y, Yan G, Wu YH, Macaluso A, Ge Y, Ye J, Hansen N, Li LE and Wang X (2023) Gnfactor: Multi-task real robot learning with generalizable neural feature fields. In: *Conference on Robot Learning*. PMLR, pp. 284–301.
- Zhai X, Kolesnikov A, Houlsby N and Beyer L (2022) Scaling vision transformers. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12104–12113.
- Zhang B and Soh H (2023) Large language models as zero-shot human models for human-robot interaction. *arXiv preprint* arXiv:2303.03548.
- Zhang C, Han D, Qiao Y, Kim JU, Bae SH, Lee S and Hong CS (2023a) Faster segment anything: Towards lightweight sam for mobile applications. *arXiv preprint arXiv:2306.14289*.
- Zhang H, Du W, Shan J, Zhou Q, Du Y, Tenenbaum JB, Shu T and Gan C (2023b) Building cooperative embodied agents modularly with large language models. *arXiv preprint* arXiv:2307.02485.
- Zhang J, Huang J, Jin S and Lu S (2024a) Vision-language models for vision tasks: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- Zhang J, Zhang J, Pertsch K, Liu Z, Ren X, Chang M, Sun SH and Lim JJ (2023c) Bootstrap your own skills: Learning to solve new tasks with large language model guidance. *arXiv preprint arXiv:2310.10021*.
- Zhang R, Guo Z, Zhang W, Li K, Miao X, Cui B, Qiao Y, Gao P and Li H (2022) Pointclip: Point cloud understanding by clip. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 8552–8562.
- Zhang X, Qiu W, Li YC, Yuan L, Jia C, Zhang Z and Yu Y (2024b) Debiased offline representation learning for fast online adaptation in non-stationary dynamics. *arXiv preprint* arXiv:2402.11317.
- Zhao W, Queralta JP and Westerlund T (2020) Sim-to-real transfer in deep reinforcement learning for robotics: a survey. In: 2020 IEEE symposium series on computational intelligence (SSCI). IEEE, pp. 737–744.
- Zhao X, Ding W, An Y, Du Y, Yu T, Li M, Tang M and Wang J (2023a) Fast segment anything. *arXiv preprint* arXiv:2306.12156.
- Zhao X, Li M, Weber C, Hafez MB and Wermter S (2023b) Chat with the environment: Interactive multimodal perception using large language models. *arXiv* preprint arXiv:2303.08268.
- Zhen H, Qiu X, Chen P, Yang J, Yan X, Du Y, Hong Y and Gan C (2024) 3d-vla: A 3d vision-language-action generative world model. *arXiv preprint arXiv:2403.09631*.
- Zhou H, Yao X, Meng Y, Sun S, BIng Z, Huang K and Knoll A (2023) Language-conditioned learning for robotic manipulation: A survey. *arXiv preprint arXiv:2312.10807*.
- Zhou J, Wei C, Wang H, Shen W, Xie C, Yuille A and Kong T (2021) ibot: Image bert pre-training with online tokenizer. arXiv preprint arXiv:2111.07832.
- Zhou K, Yang J, Loy CC and Liu Z (2022) Learning to prompt for vision-language models. *International Journal of Computer Vision* 130(9): 2337–2348.