Language-conditioned Learning for Robotic Manipulation: A Survey

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Abstract—Language-conditioned robotic manipulation represents a cutting-edge area of research, enabling seamless communication and cooperation between humans and robotic agents. This field focuses on teaching robotic systems to comprehend and execute instructions conveyed in natural language. To achieve this, the development of robust language understanding models capable of extracting actionable insights from textual input is essential. In this comprehensive survey, we systematically explore recent advancements in language-conditioned approaches within the context of robotic manipulation. We analyze these approaches based on their learning paradigms, which encompass reinforcement learning, imitation learning, and the integration of foundational models, such as large language models and vision-language models. Furthermore, we conduct an in-depth comparative analysis, considering aspects like semantic information extraction, environment & evaluation, auxiliary tasks, and task representation. Finally, we outline potential future research directions in the realm of language-conditioned learning for robotic manipulation, with the topic of generalization capabilities and safety issues.

Index Terms—Language-conditioned learning, robotic manipulation, imitation learning, reinforcement learning

I. Introduction

In the ever-evolving landscape of robotics and artificial intelligence, a profound transformation is underway—one that promises to bridge the gap between machines and humanity, enabling seamless interaction between humans and robots. At the heart of this transformation lies the concept of language-conditioned robot manipulation. This groundbreaking paradigm shift heralds a future where robots are no longer confined to the factory floor or research laboratories but are seamlessly integrated into our daily lives, becoming indispensable companions and collaborators. To achieve this ultimate goal of robotics, integrating robot manipulation and natural language commands has gained more research attention recently. This emerging field represents a convergence of natural language processing, computer vision, and robotics, enabling robots to understand the surrounding environment and interpret human language commands, instructions, and queries, and subsequently translate this linguistic input into precise physical actions based on current scenarios within the real world. Language-conditioned learning achieves remarkable success in robotic arm manipulation [1] [2] [3] [4] [5] [6], game playing [7] [8], navigation tasks [9] [10], humanrobot interaction[11],[12], [13], and autonomous driving [14] [15]. In the near future, advancements in language-conditioned

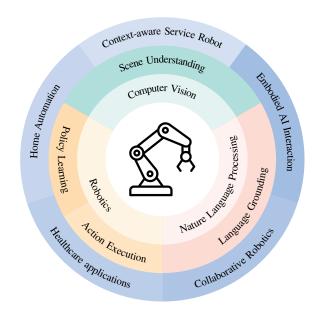


Fig. 1: Language-conditioned robot manipulation sits at the cross-roads of computer vision, natural language processing, and robotics. Common tasks like scene understanding, language grounding, policy learning, and action execution are widely studied in this realm. The potential for language-conditioned robot manipulation is bright, particularly in use cases such as home automation, healthcare, collaborative robots, and service robotics, where significant benefits are anticipated from its development.

robot manipulation will greatly benefit fields like collaborative robotics, healthcare, and home automation. Figure 1 demonstrates a summary of common tasks and use cases for language-conditioned robot manipulations.

However, this field also presents significant challenges:

- 1) How to extract the semantic meaning of natural language?
- 2) How to enable the robot to understand the surrounding environment by utilizing its built-in sensors?
- 3) How to ground natural language to those perceived entities in the environment and precise mechanical actions?

In order to address these three problems, many approaches modularize the robot with three parts, namely the language module, the perception module, and the control module, as illustrated in Figure 2.

To extract the semantic meaning of natural language, some early research works leverage formal specification languages such as temporal logic [16] [17], which support formal

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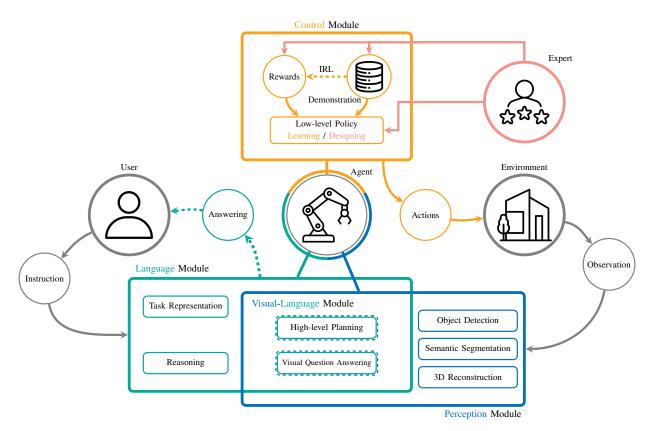


Fig. 2: This architectural framework provides an overview of language-conditioned robot manipulation. The agent comprises three key modules: the language module, the perception module, and the control module. These modules serve the functions of understanding instructions, perceiving the environment's state, and acquiring skills, respectively. The vision-language module establishes a connection between instructions and the surrounding environment to achieve a more profound comprehension of both aspects. This interplay of information from both modalities enables the robot to engage in high-level planning and perform visual question answering tasks, ultimately enhancing its overall performance. The control module has the capability to acquire low-level policies through learning from rewards (reinforcement learning) and demonstrations (imitation learning) which engineered by experts. At times, these low-level policies can also be directly designed or hard-coded, making use of path and motion planning algorithms. There are two key loops to highlight. The interactive loop, located on the left, facilitates human-robot language interaction. The control loop, positioned on the right, signifies the interaction between the agent and its surrounding environment.

verification of provided commands. Nevertheless, specifying instructions in these languages can be challenging, complex, and time-consuming. In recent times, advancements in the field of natural language processing have led to the creation of pretrained language models like BERT [18], RoBERTa [19], and GloVe [20], enabling seamless encoding of natural language into embeddings. More recently, an increasing number of researchers have employed large language models (LLMs) to extract semantic information and perform high-level planning and reasoning tasks because of the robust capacity for extensive generalization exhibited by large language models.

Moreover, the development of computer vision builds a solid foundation for robots to perceive the surrounding environment. Advancements in technology for environmental perception, from Convolutional Neural Networks (CNN) like ResNet [21] to two-stage multi-object detection network such as Faster-RCNN [22] and YOLO [23] for one-stage multi-object detection, along with innovations like transformer-based DETR [24], vision transformers [25], and expansive vision-language models like CLIP [26], signify a maturation in the ability to understand our surroundings. Nevertheless, combining the

observed information with robotic skills still requires further investigation.

In regard to the control module, there are two primary learning paradigms used to map from languages to actions: reinforcement learning (RL) [27] and imitation learning (IL) [28]. RL serves as a powerful framework for tackling challenges in sequential decision-making. Within this paradigm, an agent learns through interaction with its environment, progressively enhancing its proficiency through a process of trial and error. Imitation learning requires a large amount of offline training data demonstrated by experts. This supervised learning approach endeavors to minimize the discrepancy between ground truth, represented by expert demonstrations, and predicted actions. In certain cases, researchers opt to design low-level policies for robots, making use of traditional path and motion planning algorithms without the involvement of neural networks.

The main contributions of our survey involve that

 We investigate the up-to-date language-conditioned robot manipulation approaches in recent years. To the best of our knowledge, this survey represents the first attempt to have a detailed review of the area of language-conditioned robotic manipulation.

- We provide a systematic comparative analysis, covering the topic of semantic information extraction, environment & evaluation, auxiliary tasks, and task representation to compare different techniques leveraged in current approaches.
- Considering the recent ongoing research, we outline potential future research directions in the realm of language-conditioned learning for robotic manipulation, with the scope of generalization capabilities and safety issues.

The rest of this survey is organized as follows: Section 2 presents certain foundational concepts relevant to language-conditioned robotic manipulation. In the next section, current language-conditioned manipulation approaches are introduced, encompassing strategies of reinforcement learning, imitation learning, and approaches empowered by LLMs and VLMs. In Section 4, we conduct a comprehensive comparative analysis of various approaches, with a focus on the perspective of semantic information extraction, environments & evaluation, auxiliary tasks, and task presentations. Finally, we provide some potential future directions in Section 5 and conclusions in Section 6.

II. BACKGROUND

In this section, we present fundamental terms and concepts essential for understanding robotic manipulation. Table I provides an overview of important abbreviations we used in this article.

TABLE I: Abbreviations

Abbreviations	Definition
MDP	Markov decision process
CMDP	Contextual markov Decision Process
IL	Imitation learning
RL	Reinforcement learning
GCRL	Goal-conditioned reinforcement learning
BC	Behavior cloning
IRL	Inverse reinforcement learning
NLMs	Neural language model
PLMs	Pre-trained language models
LLMs	Large language models
VLMs	Vision-language models

A. Markov Decision Process

Markov decision process (MDP) is a discrete-time stochastic control process. It provides a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision-maker. Formally, an MDP is defined by the tuple $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, where:

• S is the state space.

- \mathcal{A} is the action space.
- $\mathcal{P}: S \times A \times S \to \mathbb{R}$ is the transition probability distribution, where $\mathcal{P}(s'|s,a)$ indicates the probability that action a in state s will lead to state s' in the next time step.
- $\mathcal{R}: S \times A \to \mathbb{R}$ is the reward function that $\mathcal{R}(s,a)$ represents the reward that an agent can get by taking action a at state s.
- γ is a discount factor to ensure the convergence of the learning process.

Moreover, Contextual Markov Decision Process (CMDP) [29] is introduced to enable the utilization of contextual information in the decision process. A CMDP is defined as a set of tuple $(\mathcal{C}, \mathcal{S}, \mathcal{A}, \mathcal{F})$, in which the \mathcal{C} is contextual information provided to the agent, and $\mathcal{F}(c) = (\mathcal{R}^c, \mathcal{P}^c)$ is a mapping function between the context $c \in \mathcal{C}$ and MDP parameters. CMDP establishes a theoretical foundation enabling agents to leverage so-called meta-data or side information for inference. A graphic model of CMDP is shown in Figure 3.

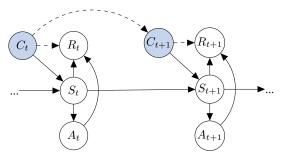


Fig. 3: Graphic model of CMDP [30], [29].

B. Reinforcement Learning

In reinforcement learning, an agent interacts with an MDP to learn an optimal policy that maximizes the cumulative expected reward over time. The agent uses the MDP's components to make decisions and improve its policy through exploration and exploitation.

Reinforcement learning adds the concept of a policy (π) into the MDP framework. A policy is mapping from states to actions that guide the agent's decision-making process. Mathematically, $\pi(s)$ represents the action chosen by the policy in state s.

The goal of reinforcement learning is to find the optimal policy π^* that maximizes the expected cumulative reward over time. This is often expressed using the state-value function $V^{\pi}(s)$ and the action-value function $Q^{\pi}(s,a)$:

• The state-value function $V^{\pi}(s)$ represents the expected cumulative reward that an agent can obtain starting from state s and following policy π . It can be defined as

$$V^{\pi}(s) = \mathbb{E}_{\substack{a_t \sim \pi(\cdot|s_t) \\ s_{i+1} \sim \mathcal{P}(\cdot|s_t, a_t)}} \left[\sum_{t=t}^{\infty} \gamma^t \mathcal{R}(s_t, a_t) \middle| s_0 = s \right], \quad (1)$$

where $R(s_t, a_t)$ is the reward that the agent receive by taking action a_t in the state s_t . The value function estimates the *potential* of being in state s, by evaluating the expected rewards that an agent can get from s following policy π

• The action-value function $Q^{\pi}(s,a)$ represents the expected cumulative reward that an agent can obtain starting from state s, taking action a, and then following policy π . It can be formally defined as

$$Q^{\pi}(s, a) = \mathbb{E}_{s' \sim \mathcal{P}(\cdot | s, a)} [\mathcal{R}(s, a) + \gamma V^{\pi}(s')]. \tag{2}$$

Reinforcement Learning Objective: Reinforcement learning aims to learn an optimal policy π^* with the optimal value function and Q-function:

$$J(\pi) = \mathbb{E}_{\substack{a_t \sim \pi(\cdot \mid s_t) \\ s_{t+1} \sim P(\cdot \mid s_t, a_t)}} \left[\sum_t \gamma^t \mathcal{R}(s_t, a_t) \right]. \tag{3}$$

As deep learning has progressed, the estimation of the value function and Q-function can now be accomplished through neural networks. This approach is termed deep reinforcement learning (DRL).

Expanding on the advancements in Deep Reinforcement Learning (DRL), certain studies have further developed the RL objective to encompass diverse objectives within varying contexts. This extension is known as Goal-Conditional RL (GCRL). Compared to the original RL, GCRL extends the markov decision process in the following aspects:

- G: The goal space which contains the goal representations.
- $\mathcal{R}: \mathcal{S} \times \mathcal{A} \times \mathcal{G} \to \mathbb{R}$. The reward function is extended by taking the goal into consideration.

The agent policy $\pi(\cdot|s,g)$ is dependent not only on state observation s but also on the goal g. Each individual goal $g \sim \mathcal{G}$ can be differentiated by its reward function $\mathcal{R}(s_t,a_t,g)$. The objective of GCRL turns to maximizing the expected return over the distribution of goals:

$$J(\pi) = \mathbb{E}_{\substack{a_t \sim \pi(\cdot|s_t), g \sim \mathcal{G} \\ s_{t+1} \sim P(\cdot|s_t, a_t)}} \left[\sum_t \gamma^t \mathcal{R}(s_t, a_t, g) \right]. \tag{4}$$

C. Imitation Learning

Imitation learning encompasses a process where agents learn tasks without relying on direct task reward feedback, denoted as r. this approach leverages expert demonstrations of the task, with the goal of developing a policy, represented as π , that emulates the behavior exhibited by experts in executing the desired tasks. These demonstrations consist of sequences of states and actions experienced by the experts, typically represented as $\tau = (s_t, a_t)$. The field of imitation learning can be primarily divided into two key categories: 1) Behavioral Cloning (BC) and 2) Inverse Reinforcement Learning (IRL). 1) Behavioral Cloning: Behavior cloning is a category of imitation learning algorithms introduced in [31]. In behavior cloning, the trajectory executed by expert agents is treated as

the reference or ground truth trajectory. Through supervised learning, an imitation policy is acquired by minimizing the disparity between the anticipated actions and the actual actions observed in the ground truth trajectory. Considering a set of trajectories are collected from experts $\tau \in \mathcal{T}$, the optimization problem can be defined as:

$$\hat{\pi}^* = \arg\min_{\pi} \sum_{\tau \in \mathcal{T}} \sum_{x \in \tau} L(\pi(x), \pi^*(x)). \tag{5}$$

where L is the cost function, $\pi^*(x)$ and $\pi(x)$ are the expert's and predicted actions at the state s, respectively.

2) Inverse Reinforcement Learning: An alternative approach to behavioral cloning is to reason about and try to learn a representation of the underlying reward function that the expert was using to generate its actions. By learning the expert's intent behind its behaviors, the agent can potentially outperform the expert or adjust for differences in capabilities. This approach, which reasons about the rewards to drive the expert's behaviors, is called inverse reinforcement learning (IRL). In the context of Inverse Reinforcement Learning approaches, a particular parameterization of the reward function is presumed. In most cases, the reward is parameterized as a linear combination of (nonlinear) features: $r(s, a) = w^T \phi(s, a)$, where $w \in \mathbb{R}^n$ is a weight vector and $\phi(s,a)$ is a feature map which maps a state-action combination to a vector embedding. For a given feature map ϕ , the goal of inverse RL can be simplified to determining the weights w. Integrating reward function $R(s,a) = w^T \phi(s,a)$ in the state-value function, we

$$V^{\pi}(x) = w^{T} \mu(\pi, s),$$

$$\mu(\pi, s) = \mathbb{E}_{\substack{a_{t} \sim \pi(\cdot \mid s_{t}) \\ s_{t+1} \sim \mathcal{P}(\cdot \mid s_{t}, a_{t})}} \left[\sum_{t}^{\infty} \gamma^{t} \phi(s_{t}, a_{t}) | s_{0} = s \right].$$
(6)

where $\mu(\pi, s)$ is defined by an expectation over the trajectories of the system under policy π and is referred to as *feature* expectation. For given demonstrations with N trajectories $\mathcal{D} = \{\tau_0, \tau_1, ..., \tau_N\}$, the feature expectation can be calculated as:

$$\mu(\mathcal{D}, s) = \frac{1}{N} \sum_{\tau \in \mathcal{D}} \sum_{t}^{\infty} \gamma^{t} \phi(s_{t}, a_{t}). \tag{7}$$

Finally, identifying the weight vector w can be done by finding a vector that satisfies the condition $w^T \mu(\pi^*,s) \geq w^T \mu(\pi,s)$, $\forall s \in \mathcal{S}, \forall \pi$, since $V^{\pi^*}(s) \geq V^{\pi}(s)$, $\forall s \in \mathcal{S}, \forall \pi$. Nevertheless, this could give rise to what is commonly referred to as *reward ambiguity*, a prominent obstacle encountered in inverse reinforcement learning [32]. Addressing this concern, there exist two approaches: Apprenticeship Learning [33] and Maximum Entropy IRL [34], both aimed at mitigating this challenge.

D. Large Language Model

Language model is a type of machine learning algorithm designed to understand, generate, and manipulate human language. It learns patterns, structures, and semantics from vast amounts of textual data, enabling it to predict and generate coherent and contextually relevant text. The development of the language model goes through the following three stages.

- Neural Language Models (NLMs): NLMs [35] [36] [37] characterize the probability of word sequences by neural networks, e.g., recurrent neural networks (RNNs). A remarkable contribution is that developing a general neural network approach to build a unified solution for various NLP tasks [38]. Furthermore, an additional innovation in the realm of word representations emerged with word2vec [39] [40]. This pioneering approach introduced a streamlined shallow neural network structure, engineered to grasp distributed word embeddings. These embeddings proved immensely efficacious, showcasing their prowess across a diverse spectrum of Natural Language Processing (NLP) undertakings.
- Pre-trained Language Models (PLMs): PLM is an early attempt to extract semantic meaning from natural language. ELMo [41] aims to capture context-aware word representations by first pre-training a bidirectional LSTM (biLSTM) network and then fine-tuning the biLSTM network according to specific downstream tasks. Moreover, drawing inspiration from the Transformer architecture [42] and incorporating self-attention mechanisms, BERT [18] takes language model pre-training a step further. It accomplishes this by conducting bidirectional pre-training exercises on extensive unlabeled text corpora. These specially crafted pre-training tasks imbue BERT with contextual understanding, resulting in highly potent word representations.
- Large Language Models (LLMs): LLMs become popular recently because researchers find that scaling PLM often leads to an improved performance on downstream tasks. Many researchers attempt to study the performance limit of PLMs by scaling the size and dataset of models, e.g., 1.5Bparameter GPT-2 [43], 175B-parameter GPT-3 [44], 540B parameter PaLM [45]. Despite that these models share a similar structure, the enlarged models display different behaviors and show surprising abilities compared to previous works. A remarkable contribution is the ChatGPT which adapts the LLMs from the GPT family for dialogues, which achieves amazing conversation ability with human beings.
- Vision-Language Models (VLMs): In the rapidly evolving domain of robotics and artificial intelligence, the synergy of computer vision and natural language processing has catalyzed a series of breakthroughs. Specifically, Vision-Language Models (VLMs) emerge as instrumental frameworks, adept at extracting intricate semantic content from large-scale web data. These models, by ingesting both visual and linguistic information, facilitate simultaneous multimodal processing, enabling nuanced inferences about agent-environment interactions. Notably, this paradigm equips the agent with an expansive and empirically anchored understanding of the world. Seminal models in this domain, such as PaLM-E [46], Pali-x [47], CLIP [26], Flamingo [48], RT-1 [49], and RT-2 [50], underscore the potential of VLMs. Integrating these pre-trained VLMs into robotic systems makes it feasible

for robots to undertake a diverse spectrum of tasks in real-world scenarios, heralding a transformative phase in robotic manipulation.

III. APPROACHES

In this section, we will explore the contemporary language-conditioned learning methods used in robot manipulation over the past few years. We delve into these works through a dual lens, exploring both traditional aspects (RL and IL) and the latest methodologies enhanced by foundational models like LLMs and VLMs. The subsections are structured as follows: the first and second subsections introduce methods with RL and IL paradigms, which ground languages to actions. Following this, the discussion transitions to approaches empowered by LLMs and VLMs in the third and fourth subsections. The final subsection provides a summary of the common approach to ground languages to actions from the perspectives of LLMs and VLMs. A comprehensive overview of recent approaches is outlined in the accompanying Figure 4.

A. Language-conditioned Reinforcement Learning

In this part, we aim to discuss the approaches related to the reinforcement learning paradigm. Treating language instructions as goals and transforming language-conditioned problems into goal-conditioned problems is the key idea in language-conditioned reinforcement learning. We start by introducing goal-conditioned reinforcement learning methods, laying a sturdy groundwork for language-conditioned reinforcement learning. Following that, we explore crucial approaches that expand into language-conditioned paradigms. Lastly, we delve into reward-shaping techniques for language-conditioned reinforcement learning.

- 1) Goal-conditioned reinforcement learning: Goalconditioned reinforcement learning allows the trained agent to solve various tasks and it builds a solid foundation for language-conditioned reinforcement learning. In the field of robotic manipulation, goal-conditioned reinforcement learning aims to solve multi-tasks with one trained policy. These task descriptions of the agent can be image goals [51] [52] [53] [54], task id [55]. By adapting goals into language instructions, the agent can learn a policy handling various tasks described by natural languages. The following parts then introduce popular approaches, which extend goal-conditioned reinforcement learning to language-conditioned reinforcement learning.
- 2) Language-conditioned reinforcement learning: In the initial phases, many studies of language-conditioned reinforcement learning concentrate on games [9] [56] [57] [8] [7], since games always have well-defined rules and objectives, and also easy to reproduce experiments and compare the performance. These studies train an agent capable of comprehending natural language instructions given by humans. During the game, human languages are given to control the agent to solve navigation tasks [58] [59] [60] [56] [61], scoring games [8] [7], object manipulations [57]. Recently, more studies [5] [62] [63] [6] [62] [64] [65] have been carried out to solve robotic arm manipulation tasks. These

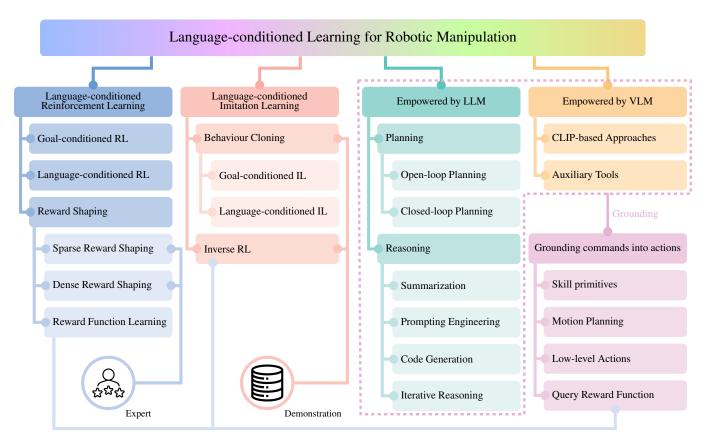


Fig. 4: Overview list of language-conditioned robotic manipulation methods.

studies consider language instructions as goals for modeling RL models. When the agent achieves the goal outlined in the language instruction, it receives rewards and learns from this feedback. These approaches leverage different kinds of reward designs and training strategies to achieve high sample efficiency. For instance, symmetry, which exists in the environment, can accelerate learning [63]. Dividing the training phase into several stages [65] [6] can also be one strategy.

- 3) Reward Shaping: One crucial aspect of reinforcement learning is reward shaping. How to integrate language instruction into reward shaping represents the most important topic. Methods for reward shaping can be categorized as follows:
 - Dense reward shaping: These approaches leverage dense reward design to guide the exploration. Rewards are given not only upon finishing the specified instruction but also while progressing towards its completion. Some approaches [63] [6] leverage the dense reward setting in the Meta-world [66] benchmark. In [63], the authors make use of the concept "symmetry" existing in language and actions to improve learning efficiency. [6] separates the training procedure into two phases, namely, instruction phase and trial phase. In the instruction phase, the language instruction is provided to the agent while the rewards from the environment are ignored. In terms of the trial phase, the agent learns from the rewards defined in specific tasks. In this manner, the agent learns from both language instructions and also rewards defined in the environments to get a better learning performance.
- Sparse reward shaping: These approaches utilize the sparse reward framework for simpler tasks. Usually, the agent receives rewards solely from the environment after successfully completing the instruction. In the work of [5], they utilize the Meta-World benchmark and establish a reward of 10 for achieving the desired goal state while imposing a penalty of -0.01 for each time step taken. Their training encompasses 10 distinct tasks. Instead of relying on task ids represented as one-hot vectors, they make use of a pre-trained language encoder module to transform natural language instructions into embeddings, which serve as the training objectives. Despite the convenience of reward design, such approaches often grapple with the challenge of low sample efficiency, necessitating extended training periods or even failing to converge altogether.
- Reward function learning: These approaches learn a reward function from demonstrations. Some studies map the language instructions to rewards [62] [64] [65]. They initially pre-train a reward mapping model using offline demonstrations provided by experts. These models translate visual observations and language instructions into reward signals. Also some approaches [67] [68] [69] leverage visual language model (VLMs) for reward design. During the reinforcement learning process, this pre-trained model is employed as the reward function. Additional methods utilize IRL or LLMs to acquire rewards, as detailed in subsequent sections. The reward

frameworks established by these approaches are dense and tailored specifically to tasks, enhancing the agent's ability to learn more efficiently.

The first two methods involve manually crafting rewards by experts, drawing from their knowledge. Conversely, the third approach is data-driven rather than knowledge-driven. Here, rewards are learned from gathered demonstration data or the extensive wealth of knowledge embedded in LLMs, extracted from vast repositories of human-generated textual information.

B. Language-conditioned Imitation Learning

Despite reinforcement learning has achieved huge success in the field of language-conditioned robot manipulation, these approaches often confront limitations due to low sample efficiency and the requirement for careful reward development to learn, which poses challenges in obtaining sufficient training data for effective learning. As a result, other researchers have turned to language-conditioned imitation learning approaches, which train agents using demonstration datasets to overcome the limitations associated with reinforcement learning. There are two main approaches in the field of imitation learning, namely, behaviour cloning and inverse reinforcement learning. Hence, we start our discussion on language-conditioned imitation learning from these two points.

1) Behavior Cloning: The core of behavior cloning involves training an agent to replicate actions and decisions demonstrated by experts. The objective is to minimize the difference between expert behavior and predicted behavior under current observations. Similar to reinforcement learning, many language-conditioned imitation learning algorithms are developed from goal-conditioned imitation learning by alternative the goal to the language instruction. The goal-conditioned policy enables the agent to handle multiple language instructions. Initially, we explore various goal-conditioned imitation learning approaches, which serve as a stepping stone to comprehend modern language-conditioned methodologies. Subsequently, we delve into the discourse surrounding language-conditioned imitation learning approaches.

Goal-conditioned imitation learning gives the agent abilities to solve multi-tasks. By introducing goal space, and integrating goals into a policy, the trained agent is capable of handling various tasks when given a specific goal. Many studies [70] [71] [72] first collect demonstrations from experts and label these demonstrations with different task ids, and then apply supervised learning to imitate the behavior of experts under specific goals. These approaches successfully solve multi-task problems with one trained policy. However, the burden of collecting and labeling high-quality demonstrations impedes the agent from learning more complex tasks. The concept of task-agnostic learning is proposed to address this issue. The motivation is that the expert trajectories collected to reach a specific goal g^j are also valid to reach any other state visited within the demonstration. This insight provides a new type of relabeling: if the translation $(s_t^j, a_t^j, s_{t+1}^j, g^j)$ is in a demonstration, the transition $(s_t^j, a_t^j, s_{t+1}^j, g' = s_{t+k}^j)$ can also be considered as a valid translation from expert.

This idea is similar to the idea of HER in reinforcement learning [73] which leverages hindsight goals to increase the sample efficiency of learning from rewards. Utilizing this task-agnostic concept, the authors of [74] introduce goalGAIL as an extension of the earlier GAIL framework [75]. This enhancement significantly expedites policy convergence, enabling the agent to achieve a wide range of goals. In [76], the authors introduce the concept of play data, which leverage the idea of task-agnostic, to reduce the burden of collecting and labeling large amount of demonstration data, and therefore leads to high performance to solve 18 difficult tasks with one trained policy.

Goal-conditioned imitation learning has laid a robust groundwork for the advancement of language-conditioned imitation learning. This is because the former provides the agent abilities to master various tasks based on instructions, aligning well with the requisites of the latter approach. In [3], the authors propose multi-context imitation learning (MCIL), which trains the agent with multiple context goal spaces including task ids, visual images, and natural language instructions. In this manner, with only less than 1% demonstration data labeled with language instructions, the trained agent can successfully solve 18 distinct tasks with a high success rate in the tabletop environment. HULC [4] was developed to enhance the performance of language-conditioned imitation learning by integrating a transformer encoding structure and contrastive representation learning. HULC++ [77] further improved the performance of HULC by integrating the visual affordances model and also supporting the long-horizon, multi-tier tasks in the real world by leveraging large language models (LLMs). SPIL [78], which is implemented based on HULC, makes use of base skill priors to enhance the generalization ability of the agent in unfamiliar environments. There exist other approaches [79] [80] which leverage task-focused visual attention (TFA) to make the vision system pay attention to relevant regions of each frame regarding the current task or command, allowing for more precision in grasping and manipulation. These approaches build connections between visual observations and language instructions to improve the accuracy of manipulating the correct objects.

2) Inverse Reinforcement Learning: Alternative approaches in this field include leveraging inverse reinforcement learning (IRL) which infers the reward from experts' demonstration and use the reward function for potentially getting better performance than experts. The authors of [56] present a system that grounds natural language commands into reward functions through IRL, using demonstrations of different natural language commands being carried out in the environment. In paper [9], the authors propose language-conditioned reward learning (LC-RL) based on MAXEnt IRL [34], which grounds language commands as a reward function represented by a deep neural network, incorperating generic, differentiable function approximators that can handle arbitrary observations, including raw images.

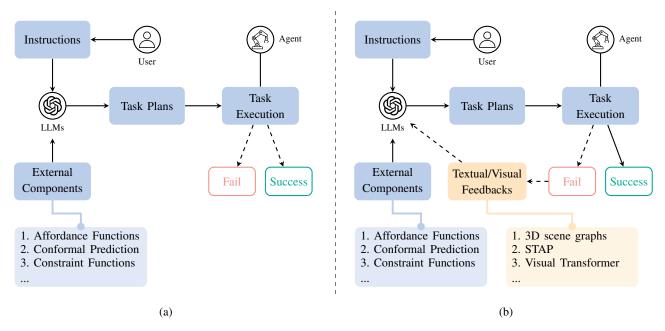


Fig. 5: (a) Open-loop models guide planning with auxiliary information. (b) Closed-loop models update planning with state feedback.

C. Empowered by Large Language Models

Many studies have demonstrated that language instructions can accelerate the agent's learning rate and improve its adaptability to new tasks [6], [62], [64], [78]. However, these prior works have equipped agents with language embeddings using learning-based methods, which require collecting large amounts of training data [65], [80]. Moreover, most of these prior works focus on connecting language instruction with low-level action primitives such as pick-and-place and sequencing the actions to solve long-horizon tasks in simulated domains [3], [78]. This makes them struggle with solving multi-step tasks in real-world environments.

Meanwhile, LLMs pre-trained with web-scale data have significant potential for the generalizability of language-conditioned robots. Many LLMs with billions of parameters, such as ChatGPT from openai, BARD from google, InstructGPT [81], Claude [82], LLaMA-1[83], and LLaMA-2[84], are capable of zero-shot learning capabilities, strong commonsense understanding, and contextual reasoning. Thus, more and more recent studies have focused on LLM for robotic manipulation. For example, Ahn et al. [85] leverage vast commonsense knowledge of ChatGPT as an LLM-based planner to generate several action predictions. Combined with an affordance function, the embodied robot executes the most accessible action. In addition, more recent research aims to leverage LLM to complete a diverse set of tasks in large-scale [86] or openended environments [87]. Specifically, Rana et al. [86] train a mobile manipulator to solve housework tasks on two largescale environments spanning up to 3 floors, 36 rooms, and 140 objects. Wang et al. [87] designed an embodied agent to solve 75 tasks in the Minecraft game world.

As agents equipped with LLMs are applied to solve diverse

and multi-step tasks in unstructured environments, LLMs show some potential and non-negligible issues.

- LLMs are prone to confidently hallucinate predictions [86] and generate a plausible but not feasible plan [85], [88]. For example, LLMs will plan an action involving objects unavailable in the real environment.
- Natural language is highly ambiguous, especially in expressing spatial and geometrical relationships such as "moving faster" or "placing objects slightly left" [89].
- LLMs lack real-world environmental experience and receive no feedback at real-time steps, which may lead to unfeasible or even unsafe action. For example, the robot will put a metal bowl in the microwave when executing a multi-step plan to heat up food [90].

We categorize LLMs according to their functions in robotic manipulation into different sections, including planning, and reasoning. Then, we summarize how recent papers address these potential and non-negligible problems in different functional sections.

1) Planning: Planning refers to a process wherein an agent decomposes a high-level task into subgoals or sequences a set of learned actions to accomplish a specific objective [86]. Recent research has highlighted the remarkable capabilities of LLMs in planning tasks, including semantic classification, common-sense reasoning, and contextual understanding. These capabilities can potentially be harnessed by embodied agents for task planning. Huang et al. [91] posited that LLMs inherently possess the knowledge required to achieve goals without further training. Specifically, pre-trained autoregressive LLMs necessitate only minimal prompts [87], [88], [90], [92] or no prompts at all [85], [91] to generate coherent plans expressed in natural language. In contrast, traditional learning-

based planning methods rely on intricate heuristics [93] and extensive training datasets [94]. Amassing such vast data is often prohibitive, especially for diverse tasks and unpredictable real-world scenarios.

However, pre-trained LLMs encode a large amount of taskagnostic knowledge and lack state feedback from the environment, which leads to task planning with LLMs often struggling with the hallucination issue. LLMs tend to generate plausible but infeasible plans, such as an action involving an unavailable object in the environment [85], [88]. Ding et al. [95] mentioned that grounding domain-independent knowledge into a specific domain with many domain-relevant constraints is challenging for task planning with LLMs. Therefore, we ask: how to ground planning into the environment? i.e., how to enable LLMs to generate more feasible plans and executable actions? Recent works integrate LLM with external components or leverage the code generation capability of LLM to remedy these problems. We discuss from the following two perspectives: Open-loop planning and Close-loop planning. Figure 5 demonstrates the overall process of these two kinds of approaches.

• Open-loop planning: In recent years, many researchers have designed LLM-based planners that integrate LLMs with different external components. These external components can provide LLMs additional input information or embodied feedback from the environment, thus ensuring the output actions adhere to the constraints and achieve the goal. Ahn et al. [85] leverage the affordance function to quantify the success rate of each action in the current state, and LLMs reorder the set of predicted actions and outputs the most accessible action. Ren et al. [90] combine LLMs with conformal prediction to measure and align uncertainty. LLM planning can be formulated as multiple-choice Q&A. It generates a series of candidate actions in the next step. Then, LLMs choose the correct options by a conformal prediction threshold calculated based on a user-specified success rate. If the robot cannot select the only correct option, it will ask humans for help, thus aligning the uncertainty, e.g., "Put a plastic bowl in the microwave" and "Put a metal bowl in the microwave" for the task "Heating up the food". Moreover, Huang et al. [91] let two pre-trained LLMs play different roles in task planning. A pre-trained causal LLM decomposes the high-level task into a sensible midlevel action plan. The other pre-trained masked LLMs leverage semantic similarity to translate these mid-level actions into admissible learned actions, e.g., translating the action "squeeze out a glob of lotion" into "pour lotion into right hand". Wu et al. [96] utilize CLIP and a masked RCNN as an open-vocabulary object detector to collect multiple RGB images and predict a list of objects existing in the scene, solving LLMs to generate multi-step actions involving unavailable objects in the specific environment.

However, these prior approaches still cannot solve the long-horizon tasks successfully, which is caused by two major issues. Firstly, the prior approaches adopt myopic

or open loop execution strategies, trusting LLMs to generate the correct strategies without accounting for the geometric dependence over a skill sequence [97] that is an essential factor in solving the long-horizon task. Open-loop approaches like Saycan [85], [90], [91], [96] have distinct planning and control components, separately. LLMs as offline planners never received embodied feedback to reflect on previous executions. Therefore, most open-loop approaches must assume faultless skill execution in solving long-horizon tasks [85], [91]. This assumption limits their scalability and success rate of solving tasks in a new environment. Additionally, many current approaches output a plan that can be seen as a one-shot plan [87], i.e., the approaches have no replanning function. LLMs lacking state feedback do not replan the generated skill but only focus on reasoning over more accessible skills in the next step. Obviously, it is extremely difficult for these open-loop approaches to generate a flawless one-shot plan that can solve longhorizon tasks directly. On one hand, various complex preconditions and unknown accidents will happen in the real world, which makes the one-shot plan non-executable easily. On the other hand, many challenging long-horizon tasks, such as household tasks or rearrangement tasks, involve multiple objects and a set of subgoals.

- Closed-loop planning: To solve these two major issues, more recent studies [97], [98], [99], [100] integrate LLMs with external components in a closed loop, where these external components can provide embodied state feedback to LLMs, then LLMs can constantly replan more executable skills until the plan succeeds completely. This iterative replanning leverages the strong contextual reasoning of LLMs and continuous feedback through the closed loop to improve the scalability and generalizability [86], [101]. For example, compared to Saycan [85] which only accomplishes tasks in kitchen scenarios, Sayplan [86] operates in a larger-scale environment that covers almost all daily office scenarios. Rana et al. [86] use a hierarchical 3D scene graph to represent the environment in four levels: floor, room, asset, and object, while a scene graph simulator generates textual feedback to LLMs, combining the scene graph's predicates, current states, and affordances. Text2Motion [97] leverages Sequencing Task-Agnostic Policies (STAP) [102] as geometric feasibility approaches. LLMs will plan a new skill if STAP finds the previous plan failing to adhere to geometric dependence. Jin et al. [99] and Huang et.al [103] utilize a pre-trained visual transformer as a scene descriptor that can translate visual observation into real-time textual feedback to LLMs.
- 2) Reasoning: In general, reasoning refers to the ability of a policy to mimic human-like thinking and make inferences using information or embedding observation. In the field of robotic manipulation, planning and, reasoning are two crucial capabilities for embodied agents to solve multi-step and long-horizon tasks. They are distinct but highly interconnected. Feasible reasoning at each step ensures the generation of an



Object: yellow shirt, dark purple shirt, white socks, black shirt Receptacles: drawer, closet



pick and place("yellow shirt", "drawer") pick and place("dark purple shirt", "closet") pick and place("white socks", "drawer") pick and place("black shirt", "closet")



Summery: Put light-colored clothes in the drawer and dark-colored clothes in the closet

Fig. 6: An example of summarization from Tidybot [104]. LLM can summarize a general strategy with few-shot prompting.



Question

Prepare a cup of coffee

Chain-of-Thought

- 1. locate and gather a coffee mug, coffee grounds, a coffee maker and water.
- Ensure the coffee maker is ready.
- 3. Add coffee grounds.
- 4. Start the coffee maker.
- 5. Wait for the coffee to brew.
- Pour the coffee.
- 7. Serve the coffee and clean up



Fig. 7: An example of Chain-of-Thought with few-shot prompting.

executable action plan, i.e., reasoning is a prerequisite for planning. Some prior surveys do not make a clear distinction between planning and reasoning. In our work, we categorize them into two different sections. In section *Planning III-C1*, most of the works are developed for a closed world, assuming that complete knowledge of the world is provided and the agent can enumerate all possible states [95]. LLMbased models utilizing auxiliary information [85], [92], [96] or feedback[87], [97], [99] to solve spatial and geometric dependencies in action sequences. For unseen objects, LLM-based planners are trained to avoid them rather than to generalize them. Meanwhile, many other researchers [95], [105] operate their agents in an open world, leveraging different types of reasoning to improve the generalizability of unseen objects or unseen instructions. They improve the agent's performance by making it robust to unforeseen situations. These works are

categorized as summarization, prompt engineering, and code generation in this section *Reasoning*.

• Summarization: Summarization, also called inductive reasoning, is a cognitive ability to draw logical conclusions or provide a general strategy from limited information. Summarization of LLM shows the significant potential of embodied agents in the household scenario. The rearrangement task of tidying up a room is challenging for classical methods [106], [107]; On the one hand, where objects are placed is highly personal, depending on different people's preferences and habits. On the other hand, it is impractical to enumerate all the objects that exist in the task-specific domain and to specify the goal state for every novel object. Thus, the prior models of rearrangement tasks through specifying target locations manually [108], [109] struggle to execute in a large-scale or real-world environment. To solve this issue, Housekeep [105] utilizes a large-scale dataset of human preferences instead of learning from a small set of tidying samples. Consequently, the housekeep assesses the capability to reason the target location and rearrange unseen objects. Wu et al. [104] argue that such a rearrangement preference is still generic rather than personal. It takes into account the expensive computational cost and the demand of a large-scale dataset, Wu et al. have constructed a mobile manipulator Tidybot, which reasons individual preference by few-shot prompting and summaries a general strategy, e.g., though textual prompts "yellow shirts go in the drawer" and "white socks go in the drawer" Tidybot outputs "lighter-colored clothes go in the drawer", as shown in Figure 6. By executing a corresponding preference strategy, Tidybot can decide where to place the unseen object in the test. While an agent with inductive reasoning can enhance their performance for unseen objects, a significant drawback is that the LLM encodes much task-agnostic knowledge, resulting in the failure to generate an entirely correct summary. For example, a rearrangement category may be too specific and not generalize well to unseen objects [104].



Ouestion

Objects: blue bowl, red block, red bowl, blue block Command: move the red block a bit to the right

Pythonic Code

from utils import get_pos, put_first_on_second

objs = ['blue bowl', 'red block', 'red bowl', 'blue block'] $target_pos = get_pos('red block') + [0.1, 0]$ put_first_on_second('red block', target_pos)



Fig. 8: An example of code generation from [89] with fewshot prompting.

• Eliciting reasoning via prompt engineering: Large language models are sensitive to prompting, so prompt



Fig. 9: LLM could also iteratively replan based on the observations and feedback given from environments.

engineering can elicit better reasoning in large language models. The chain of thought (CoT) [110] is one of the most known promptings. CoT decomposes a problem into a set of subproblems and then solves the subproblems sequentially, where the answer to the next subproblem depends on the previous one. Consequently, CoT encourages LLMs to perform more intermediate reasoning steps before generating the final output. Figure 7 illustrates an example of CoT for better understanding. As a follow-up work, Zhang et al. [111] input LLMs additional communication information from other agents to generate high-level plans involving multi-agent cooperation. In addition, Socratic models [112] use multimodalinformed prompting, i.e., Socratic models use visual language models and audio language models to substitute perceptual information into the textual language input to generate plans [89]. Socratic-model-based systems thus have access to open-ended reasoning such as video Q&A and forecasting, which make these systems more robust to unseen objects.

• Code-generation: LLMs have shown that it is capa-

ble of code generation. Some code-writing LLMs can automatically generate new policy code by sampling a few prompts. An example can be seen in Figure 8. Mialon et al. [113] demonstrated that different versions of the openAI's language models have different inference capabilities. Code-davinci-002 with CoT, optimized for code generation, has a higher reasoning accuracy (63.1%) than text-davinci-002 with CoT (46.9%), optimized for text-based tasks. By the way, the accuracy of vanilla textdavinci-002 is only 19.7%. Wang et al. [114] mentioned that programs can represent temporally extended and compositional actions. Otherwise, Liang et al. [89] also argued that policy code generated by LLM can run on the controller directly, avoiding the requirement of the language-conditioned plan to map every textual instruction into the executable action in the pre-trained skill library. Liang et al. [89] utilize the prompting hierarchical code-gen approach to re-compose the original API calls to define a more complex function flexibly, which can generalize the unseen objects better. Similar works like VOYAGER [114] can code a new skill using skill retrieval and memorize it in the skill library. Then, VOYAGER will refine learned skills to deal with unseen objects. For example, fighting unseen zombies is similar to fighting spiders. However, LLMs for code generation struggle to interpret much longer and more complex commands than the sample, and still may call functions that do not exist in the control primitive APIs. Ha et al. [101] prompt LLMs to output a success function code snippet as a labeler. Through this success function, the LLM can verify unlabelled trajectories and label them with success or failure. Singh et al. [88] design a Pythonic program prompt structure that ensures the generated plan is formulated as code. This Pythonic plan inherits features from the code, such as getting state feedback by assert and error-collection by else. Several works [115], [95] design a PDDL-shaped prompting aiming to translate a natural language goal into an action-centered language goal that is interpretable and is capable of constraint checking and goal verification.

• Iterative reasoning: Like the working principle of iterative replanning, Iterative reasoning is a cycle process where each iteration builds upon the feedback of the previous one (Figure 9). Inner Monologue [103] receives feedback from the success detector and scene descriptor. Huang et al. [103] have demonstrated that Inner Monologue has enhanced high-level instruction completion across different domains. As mentioned above, LLMs for code generation may call nonexistent functions in the control primitive calls. Thus, VOYAGER [114] not only utilizes code generation and prompt engineering but also leverages the advantage of iterative reasoning. VOYAGER incorporates the environment feedback and execution error into GPT-4's prompt for another round of code refinement, which circumvents hallucination effectively. For example, GPT-4, via Error('No item named \${silver_sword}'), realizes that the embodied agent should craft an iron sword instead of a silver sword since there is no silver sword in Minecraft. In the future, models like Voyager that combine different types of reasoning might be a new research direction to improve the inference performance of agents.

D. Empowered by Vision-Language Model

VLMs epitomize the fusion of visual and textual data, having a revolution in the realm of machine perception and understanding. Their proficiency in interpreting both modalities marks a significant milestone in the arena of robotic manipulation. Notably, there has been a burgeoning body of research dedicated to enhancing robot manipulation through the integration of vision-language models, yielding noteworthy achievements.

CLIP [26], a well-known attempt to traverse the boundaries of language and visual data, allowing it to connect images and their textual descriptions seamlessly. It leverages contrastive loss to align the similar features and separate dissimilar features of both modalities in the latent space. CLIP-based approaches are widely used in the field of robot manipulation. CLIPORT [116], a language-conditioned imitation learning agent that combines the broad semantic understanding of CLIP with the spatial precision of Transporter [117], is capable of solving a variety of language-specified tabletop tasks. CLIP-Field is capable of mapping from spatial locations to semantic embedding vectors trained with CLIP-based approaches so that navigation and localization can be conducted by the agent. EmbCLIP [118] which investigate the effectiveness of CLIP visual backbones for Embodied AI tasks. Instruction2Act [119] leverage CLIP model to accurately locate and classify objects in the environments. LATTE [120], LLaVA [96] utilize CLIP encoders for better alignment of visual and textual information.

Furthermore, large-scale approaches [46] [112] combine several extensive pre-trained models, to boost the generalization ability of the agent. PaLM-E integrates 540B PaLM [45], 22B ViT [121] into 562B vision-language-model, capable of solving zero-shot multimodal chain-of-thought (CoT) reasoning, few-shot prompting, OCR-free math reasoning and Embodied reasoning. Zeng et. al. [112] introduce the concept of Socratic Models, a modular framework that allows for the seamless composition of multiple pre-trained models using multimodal-informed prompting. Within this framework, these models interact and exchange information, ultimately culminating in the acquisition of novel multimodal capabilities.

Vision-language Models can serve as auxiliary tools to help agents complete tasks. Patel et. al. [122] utilize VLMs to develop a planner capable of generating plans based on textual task descriptions and video footage of the task execution process. LAMP [67] leverages VLMs as a pretraining reward signal for Reinforcement Learning. Du et al. [68] take VLMs as success detectors for reward design by conducting visual question-answering (VQA) tasks. MOO [123] queries a VLM to produce a bounding box of the object of interest with the prompt "An image of an X". Xiao et. al. [124] utilizes

VLMs for instruction augmentation. They achieve this by finetuning a pre-trained VLM using robot manipulation trajectories alongside crowd-sourced natural language annotations, followed by the labeling of a larger dataset with this VLM for subsequent training.

E. Grounding Language commands into Actions in LLMs

Due to the training of Internet-scale data, foundation models demonstrate significant potential for language-conditioned robotic manipulation. Unlike traditional Natural Language Processing approaches that focus on word semantics and grammar analysis, Large Language Models (LLMs) can bypass these complexities [125]. Their robust generalizability allows LLMs to create new skill primitives through minimal or zero prompting, overcoming the limitations of human effort and scalability in constructing skill libraries. Similarly, foundation models in other modalities, like CLIP [26], which aligns image and language features, provide essential prior knowledge for identifying semantic concepts such as color, category, and shape [116]. As various foundation models increasingly prevalent in robotics, the challenge of effectively grounding instructions into actions for language-conditioned robotic manipulation grows more pressing. As Figure 10 shows, we intend to discuss from the perspective of a) LLMs as higher-level planners, b) LLMs for end-to-end learning, c) LLMs for reward shaping.

- 1) LLMs as high-level planner: Recent studies have employed these foundation models for language-conditioned robot manipulation through various strategies, including sub-task planning [85], [97], data augmentation [101], [126], scene descriptors [103], and Code as policy [89]. However, in these approaches, LLMs function primarily as high-level planners, not as agent policies. They convert language instructions into skill or motion primitives, which are then executed by separate low-level controllers. This hierarchical structure, which separates planning and execution, limits LLMs to the role of invoking low-level controllers and prevents these controllers from leveraging the extensive semantic knowledge embedded in LLMs [116].
- 2) LLMs for end-to-end learning: To address this limitation, more recent studies advocate for end-to-end models that enable LLM policies to directly generate language-conditioned actions. RT-2 [50] employs LLMs for the conceptual generalization of learned skills, representing robotic actions in language form. These actions are encoded and trained alongside an Internet-scale visual-language dataset, with the textual output subsequently converted into robotic actions. Prompt2walk [127] utilizes a specially crafted textual prompt comprising task descriptions, actions, and observations, empowering LLMs to directly determine the 12-dimensional target joint positions of a robotic dog. Several works have utilized the representation capability of the end-to-end approach to obtain instruction embedding and then input them into reinforcement learning [128] or imitation learning [116], [129], [130] to train together with other information. CLIPORT [116], a languageconditioned imitation learning agent, merges CLIP's extensive semantic understanding with the spatial precision of an endto-end Transporter agent. Lynch et al. [130] trained policies

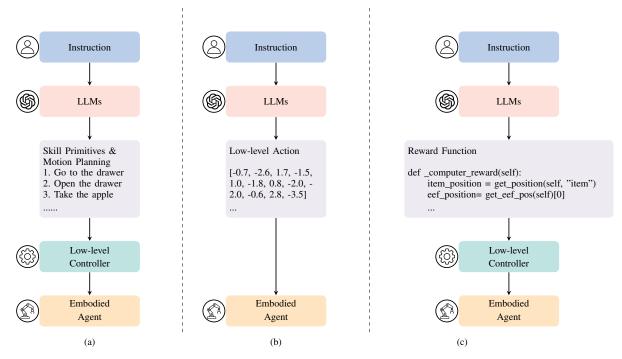


Fig. 10: Grounding language commands into actions for embodied agent. (a) LLM is a high-level planner and is not grounded. (b) LLM is used as an agent policy for low-level actions. (c) LLM is used as a reward function to optimize low-level control.

via behavioral cloning on a dataset of extensive languageannotated trajectories, enabling the execution of comprehensive visual-lingua-motor skills.

3) LLMs for rewards shaping: Furthermore, converting language commands into reward functions through inverse reinforcement learning has emerged as a prominent strategy for grounding instructions. Fu et al. [9] suggest that languageconditioned rewards offer better environmental transferability than language-conditioned policies. Their proposed LC-RL employs convolutional neural networks as a reward function, aligning language with visual cues for rewards. Language2Reward [131] directly uses LLMs as a reward function, generating reward codes for motion controllers to optimize robot motion. Other notable works in this area include instructRL [91] and Kwon et al.'s framework [132]. Additionally, ROBOGEN [133] integrates reinforcement learning, action primitive&motion planning, and gradient optimization, each suited to specific subtasks. Reinforcement learning is particularly effective for tasks involving rich environmental interaction. In summary, while reinforcement learning and gradient optimization translate language commands into rewards, action primitive&motion planning convert language into intermediate primitives.

IV. COMPARATIVE ANALYSIS

In this section, we provide a comparative analysis of language-conditioned learning from four different aspects, namely, semantic information extraction, environments and evaluation, auxiliary tasks, and task representations. The overview structure of the comparative analysis can be found in Figure 11. We aim to offer a detailed comparison of current language-conditioned robot manipulation approaches across these four

aspects that the figure demonstrates, granting the author a deeper comprehension of ongoing methodologies. Also, an overall comparerison of different approaches can be found in Table IV.

A. Semantic Information Extraction

Semantic information extraction emerges as a pivotal paradigm within the domain of robot manipulations, offering the potential to bridge the gap between raw sensory data and high-level understanding. Sensors like RGB cameras and depth cameras provide the agent with observations of the surrounding environment. Extracting high-level information from the observations enhances the agent's decision-making process, depending on the task description. Since we aim to command the robot with natural language, extracting the high-level semantic information from language instruction is also important. Hence, we delve into the techniques of symbolic information extraction from two focal points: observations and natural languages.

1) Observations: Observations are acquired through various sensors embedded within robots, encompassing options such as RGB cameras, depth cameras, and radar systems. Some studies do not leverage sensors for observation, instead, they directly get the location and state of the objects from simulation environments. For instance, in most of experiments conducted in game environments [59] [60] [8], the states of the environments are easily acquired from game engines. Some studies [6] [63] [5] in the field of robotic arm manipulation also directly leverage the states provided by simulators to mitigate the impact of visual observations, allowing a more concentrated emphasis on refining algorithm's learning efficiency.

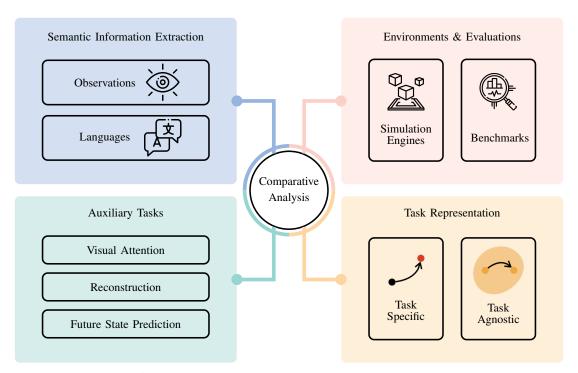


Fig. 11: Overall structure of our comparative analysis section.

Additional investigations incorporate visual observations as a pivotal factor. These methodologies typically involve the utilization of RGB images as inputs and leverage image encoder backbones, such as CNN, CNN + Spatial Softmax [134], [21], Faster R-CNN [22], VGG [135]. For instance, in papers [71] [72] [51] [62] [64] [9], the authors apply CNN module to extract the semantic features from visual inputs. Approaches like [70] [76] [3] [4] leverage additional spatial softmax layers to better extract spatial features. The residual network is applied in [65]; Faster R-CNN is applied in [80]; Abolghasemi et al. [79] makes use of VGG.

To address temporal data, Goyal et al. [62] and Rahmatizadeh et al. [71] employ Long Short-Term Memory (LSTM) networks to encode trajectory embeddings. In a similar vein, Lynch et al. [76] [3] utilize bidirectional LSTM, while Mees et al. [4] opt for a Transformer-based approach.

Vision transformer (ViT) has recently emerged as a competitive alternative to Convolutional Neural Networks (CNNs), gathering increasing research attention recently because of its advantages of computational efficiency and accuracy. Many approaches [136] [46] [137] make attempts to leverage this encoder to extract the information from the environment. OWL-ViT, the multi-modal version of ViT, is used in [123] [138]. Also some other approaches [85] [139] [89] take advantage of ViLD [139], which distills the knowledge from a open-vocabulary image classification model (teacher) into a two-stage detector (student), resulting in impressive performance, even when the student model is compactly sized. CLIP models are also widely used [116] [103] [140] [120] [119] [104] [112] in the field of language-conditioned robot manipulation since its outstanding

capacity to synchronize information from both the visual and textual realms.

2) Natural Languages: How to extract semantic information from natural language is also a topic we intend to discuss. Some studies choose not to use neural networks. Yao et al. [63] leverage syntax tree to parse the semantic meaning of nature language. Squire et al. [56] choose IBM Model 2 (IBM2) [141]. Conversely, a majority of approaches leverage neural language models to extract semantic information from natural language.

Numerous methods in this category learn from scratches and leverage the RNN structure like LSTM and GRU. LSTM structures are applied in articles [8] [9] [10] [59] [61] [62] [79]. Chaplot et al. [58] leverage Gate Recurrent Unit (GRU) for their gated attention mechanism. They opt not to pre-train their language model; rather, they train the language encoders specifically within the domains of their respective tasks. Another interesting study was proposed in [142], where natural-language specifications were first translated to temporal logic [16] via a deep neural network.

Additional strategies embrace pre-trained language models, such as the work BERT by Devlin et al. [18] and the GLoVe model developed by Pennington et al. [20]. These pre-trained language models encompass a substantial quantity of prior knowledge, which proves valuable in constructing distinct task representations, ultimately enhancing the performance of the trained agent. For instance, Shao et al. [65] utilize the pre-trained BERT model to encode instructional features. Similarly, Nair et al. [64] employ a pre-trained distilBERT sentence encoder [143], which is a variant of the BERT model with reduced size. The authors of [5] [7] [6] [80]

employ GLoVe to extract semantic information from language instructions. Lynch et al. [3] choose MUSE [144], which represents a multitask language architecture trained on generic multilingual corpora (e.g., Wikipedia, mined question-answer pair datasets). Mees et al. [4] select paraphrase-MiniLM-L3-v2 [145], which distills a large Transformer based language model and is trained on paraphrase language corpora. They also conduct ablation studies for applying other language models like BERT [18], RoBERTa [19], and MPNet [146] for comparisons.

Building on the conventional methods of extracting symbolic information from natural languages, Large Language Models (LLMs) like GPT-3 and beyond offer a transformative approach. Unlike RNN structures that might require taskspecific training or pre-trained models like BERT and GLoVe which provide a strong starting point, LLMs integrate extensive pre-training across diverse datasets, enabling a more comprehensive understanding of language nuances. For instance, utilizing an LLM such as GPT-4, one could input a complex narrative and have the model generate symbolic representations of the text's meaning, actions, and entities. It could perform tasks like summarizing task descriptions, extracting thematic elements, or converting instructions into executable code [88], [89], [101], [114]. These models can also apply advanced techniques such as few-shot learning, where they generate accurate representations with minimal examples. This adaptability and depth of understanding position LLMs as powerful tools for symbolic extraction in a wide range of natural language processing applications.

B. Environments and Evaluations

In order to assess the efficacy of their novel methodologies, researchers developed diverse task domains and benchmarks. In this section, we delve into the well-used environmental settings and benchmarks that find common use within the realm of language-conditioned robot manipulation.

- 1) Simulators: Simulation plays a pivotal role in accelerating advancements in robot manipulation by enabling rapid prototyping, thorough testing, and the exploration of complex scenarios that might be challenging to replicate in the real world. We introduce several simulators widely used in the field of robot manipulations, as shown in Table II.
- 2) Benchmark: Benchmarks are important in assessing and advancing the capabilities of robotic systems. We will explore the fundamental significance of benchmarks in the domain of robot manipulation based on simulators discussed previously. A detailed comparison can be seen in Table III. Benchmarks in simulation environments are listed as follows:
 - CALVIN: CALVIN [152] (Composing Actions from Language and Vision), an open-source simulated benchmark to learn long horizon language-conditioned tasks constructed on Pybullet. It has four different, yet structurally related environments so that it can be used for general playing as well as evaluating specific tasks. 34 different tasks can be performed under such environments. It has two different evaluation metrics, namely Multi-Task

Language Control (MTLC) and Long-Horizon MTLC (LH-MTLC). MTLC aims to verify how well the learned multi-task language-conditioned policy generalizes to 34 manipulation tasks; LH-MTLC aims to verify how well the learned multi-task language-conditioned policy can accomplish several language instructions in a row. Mees et al. [4] [77] and Zhou et al. [78] evaluate their models on this benchmark.

- Meta-World: Meta-World is a collection of 50 diverse robotic manipulation tasks built on the MuJoCo physics simulator. It contains two widely-used benchmarks, namely, ML10 and ML45. The ML10 contains a subset of the ML45 training tasks, which are split into 10 training tasks and 5 test tasks, and the ML45 consists of 45 training tasks and 5 test tasks. It used to be a platform to evaluate the performance of meta-reinforcement learning. Researchers [6] [5] [62] [64] use Meta-world to test their language-conditioned models' performance.
- LEMMA: In LEMMA [140], the authors introduce a benchmark to evaluate their model under multi-robot settings. This benchmark allows robots with different physical configurations to collaborate on manipulation tasks. Two types of robots are provided in LEMMA, namely UR10 and UR5. They also evaluate their work multi-agent Cliport (M-Cliport) module, based on Cliport [116], in the LEMMA benchmark.
- RLbench: This benchmark [153] includes 100 completely unique, hand-designed tasks ranging in difficulty, which share a common Franka Emika Panda robot arm, featuring a range of sensor modalities, including joint angles, velocities, and forces, an eye-in-hand camera and an over-the-shoulder stereo camera setup. RLBench is built around a CoppeliaSim/V-REP, allowing for drag-and-drop style scene building, and a whole host of robotic tools, such as inverse/forward kinematics, motion planning, and visualizations. Shridhar et al. [136] use RLbenchmark to evaluate their models' performance on 18 tasks.
- VIMAbench: VIMAbench [137] is a new simulation benchmark designed to evaluate multimodal robot learning agents. It builds on the Ravens robot simulator [117] and provides a suite of 17 representative tabletop manipulation tasks that can be specified via multimodal prompts combining text and images. The tasks cover a diverse range of skills including goal-reaching, imitation learning, novel concept grounding, constraint satisfaction, and reasoning. Each task is procedurally generated into thousands of instances by varying combinations of objects, textures, and initial configurations. VIMAbench generates training demonstrations using scripted oracle agents with access to the full simulator state. The dataset contains nearly 650,000 successful expert trajectories for imitation learning. A key feature of VIMAbench is the multilevel evaluation protocol to systematically test an agent's generalization capabilities. It defines 4 levels of difficulty: 1) randomized object placement with seen prompts, 2)

TABLE II: Comparison of Simulation Engines

Simulator	Description	Use Cases			
Pybullet[147]	With its origins rooted in the Bullet physics engine, PyBullet transcends the boundaries of conventional simulation platforms, offering a wealth of tools and resources for tasks ranging from robot manipulation and locomotion to computer-aided design analysis.	Shao et al. [65], mees et al. [77] [4] leverage pybullet to build a table-top environment to conduct object manipulations tasks.			
MuJoCo[148]	MuJoCo, short for "Multi-Joint dynamics with Contact", originates from the vision of creating a physics engine tailored for simulating articulated and deformable bodies. It has evolved into an essential tool for exploring diverse domains, from robot locomotion and manipulation to human movement and control.	Lynch et al. [3] [76] build a table-top environment based on MuJoCo. The famous benchmark Meta-world also builds on this simulator.			
CoppeliaSim[149]	CoppeliaSim is formerly known as V-REP (Virtual Robot Experimentation Platform). It offers a comprehensive environment for simulating and prototyping robotic systems, enabling users to create, analyze, and optimize a wide spectrum of robotic applications. Its origins as an educational tool have evolved into a full-fledged simulation framework, revered for its versatility and user-friendly interface.	Some approaches like [80] leverage CoppeliaSim to construct an environment where the agent can manipulate cups and bowls with different sizes and colors.			
NVIDIA Omniverse	NVIDIA Omniverse offers real-time physics simulation and lifelike rendering, creating a virtual environment for comprehensive testing and fine-tuning of robotic manipulation algorithms and control strategies, all prior to their actual deployment in the physical realm.	Recently, more and more simulation environments are constructed based on NVIDIA Omniverse because of its physically accurate rendering techniques. For example, LEMMA benchmark [140] builds a multi-robot environment based on NVIDIA Omniverse.			
Unity	Unity is a cross-platform game engine developed by Unity Technologies. Renowned for its user-friendly interface and powerful capabilities, Unity has become a cornerstone in the worlds of video games, augmented reality (AR), virtual reality (VR), and also simulations.	Some benchmarks such as Alfred [150] which is based on Ai2-thor [151] hausehold environment, using Unity game engine.			

novel combinations of seen objects, 3) introduction of new objects not seen during training, and 4) completely new tasks and prompts. The benchmark aims to support the development of generalist robot learning agents that can handle a wide variety of tasks specified via intuitive multimodal interfaces. VIMAbench facilitates targeted probing of model capabilities on diverse skills beyond its training distribution.

- LoHoRavens: LoHoRavens [154] is built based on the Ravens robot simulator [117] and contains ten long-horizon language-conditioned tasks in total. The tasks are split into seen tasks and unseen tasks to evaluate the robot's generalization performance. We define tasks in which the robot needs to execute at least five pick-and-place steps to complete the high-level instruction as a long-horizon task.
- Other benchmarks: Some approaches use their own benchmark to evaluate their models' performance. Stepputtis et al. [80] leverage CoppeliaSim to build a table-top environment with several bowls and cups with different colors and shapes. The trained agent is supposed to manipulate these objects under given commands. Shao et al. [65] use 20BN-something-something dataset [155] to train a reward classifier, so that they define 78 different

tasks based on such dataset and use PyBullet to simulate each environment associated with one of the 78 tasks. Fu et al. [9] leverage SUNCG Environment [156] to conduct 716 picking tasks and 697 navigation tasks in a household environment. Recently, an emerging number of studies, leveraging foundation models conduct their experiments with their own benchmarks [46] [120] [123] [138] [104] [112] and et cetera.

C. Auxiliary Tasks

In the dynamic landscape of robot manipulation, achieving precise and adaptive control is a constant challenge. This is where the concept of auxiliary tasks emerges as a strategic and innovative approach to elevate the capabilities of robotic systems. In the realm of robotics, auxiliary tasks refer to secondary objectives incorporated alongside the primary manipulation task, aimed at enriching the robot's learning process and enhancing its overall performance. These auxiliary tasks can be visual attention, reconstruction, and predicting future states. These additional learning objectives have two main advantages: 1) Ensuring important information flow in the neural networks, which is critical for the decision-making. 2) Guiding the direction of gradient descent during training, which can potentially lead the neural network to a more optimal location in the weight space. These methods are widely used in robot

TABLE III: Comparison of existing language-conditioned robotic manipulation benchmarks

Benchmark	Simulation Engine	Manipulator	Observations			Tool used	Multi-agents	Long-horizon	
Demonman	Simulation Engine		RGB	Depth	Masks	1001 4504	man agento		
CALVIN [157]	Pybullet	Franka Panda	/	1	Х	Х	Х	✓	
Meta-world [66]	MuJoCo	Sawyer	1	X	X	X	X	X	
LEMMA [140]	NVIDIA Omniverse	UR10 & UR5	1	✓	X	✓	✓	✓	
RLbench [153]	CoppeliaSim	Franka Panda	1	✓	✓	X	X	✓	
VIMAbench [137]	Pybullet	UR5	1	X	X	X	X	✓	
LoHoRavens [154]	Pybullet	UR5	✓	✓	X	X	X	✓	

TABLE IV: Comparison of language-condition robot manipulation approaches

Models	Years Benchmark Simulation Engine Language Perception Module Module		•	Real world experiments	LLM	Reinforcement Learning	Imitation Learning		
DREAMCELL [158]	2019	#	-	LSTM	*	Х	Х	Х	✓
PixL2R [62]	2020	Meta-World	MuJoCo	LSTM	LSTM CNN		Х	1	Х
Concept2Robot [65]	2020	#	PyBullet	BERT [18]	ResNet-18	X	Х	X	✓
LanguagePolicy[80]	2020	#	CoppeliaSim	GLoVe [20]	Faster RCNN [22]	X	X	X	✓
LOReL [64]	2021	Meta-World	MuJoCo	distillBERT [143] CNN		✓	Х	✓	Х
CARE [30]	2021	Meta-World	MuJoCo	RoBERTa	*	X	1	✓	X
MCIL [3]	2021	#	MuJoCo	MUSE [144]	CNN	X	X	X	✓
BC-Z [129]	2021	#	-	MUSE	ResNet18	✓	X	X	✓
CLIPort [116]	2021	#	Pybullet	CLIP	CLIP/ResNet	✓	X	X	✓
LanCon-Learn [5]	2022	Meta-World	MuJoCo	GLoVe	*	Х	Х	√	✓
MILLION [6]	2022	Meta-World	MuJoCo	GLoVe	*	✓	Х	✓	X
PaLM-SayCan [85]	2022	#	-	PaLM	ViLD	✓	1	✓	✓
ATLA [159]	2022	#	Pybullet	BERT-Tiny [160]	CNN	X	1	✓	Х
HULC [4]	2022	CALVIN	PyBullet	MiniLM-L3-v2 [145]	CNN	X	Х	X	/
PerAct [136]	2022	RLbench	CoppelaSim	CLIP	ViT	✓	Х	X	✓
RT-1 [49]	2022	#	-	USE [161]			1	X	Х
DIAL [124]	2022	#	-	CLIP CLIP		✓	1	X	/
R3M [162]	2022	#	-	distillBERT	ResNet18,34,50	✓	Х	X	✓
Inner Monologue [103]	2022	#	-	CLIP	CLIP	✓	1	X	X
PROGPROMPT [88]	2023	Virtualhome[163]	Unity3D	GPT-3	*	1	/	Х	Х
Language2Reward [131]	2023	#	MuJoCo MPC	GPT-4	*	✓	1	✓	Х
LfS [63]	2023	Meta-World	MuJoCo	Cons. Parser [164]	*	✓	Х	✓	X
HULC++ [77]	2023	CALVIN	PyBullet	MiniLM-L3-v2 CNN		✓	Х	X	✓
LEMMA [140]	2023	LEMMA	NVIDIA Omniverse	CLIP CLIP		X	Х	X	✓
SPIL [78]	2023	CALVIN	PyBullet	MiniLM-L3-v2 CNN		✓	X	X	/
PaLM-E [46]	2023	#	PyBullet	PaLM	PaLM ViT		1	X	✓
LATTE [120]	2023	#	CoppeliaSim	distillBERT, CLIP CLIP		✓	Х	X	X
LAMP [67]	2023	RLbench	CoppelaSim	ChatGPT R3M		X	1	✓	X
MOO [123]	2023	#		OWL-ViT OWL-ViT		✓	X	X	✓
Instruction2Act [119]	2023	VIMAbench	Pybullet	ChatGPT	CLIP	X	1	X	X
VoxPoser [138]	2023	#	SAPIEN [165]	CPT-4 OWL-ViT		✓	1	X	X
SuccessVQA [68]	2023	#	IA Playroom [166]	Flamingo[48]	Flamingo	✓	1	X	X
VIMA [137]	2023	VIMAbench	PyBullet	T5 model	ViT	✓	1	X	✓
TidyBot [104]	2023	#	· -	GPT-3	CLIP	✓	1	X	X
Text2Motion [97]	2023	#	-	GPT-3, Codex[167]	*	✓	1	✓	X
LLM-GROP [92]	2023	#	Gazebo	GPT-3	*	/	/	X	X
Scaling Up [101]	2023	#	MuJoCo	CLIP, GPT-3	ResNet-18	/	1	X	√
Socratic Models [112]	2023	#	-	RoBERTa, GPT-3	CLIP	1	1	X	Х
SayPlan [86]	2023	#	-	GPT-4	*	/	/	X	X
RT-2 [50]	2023	#	_	PaLI-X, PaLM-E PaLI-X, PaL		/	/	X	X
KNOWNO [90]	2023	#	PyBullet	PaLM-2L	*	/	/	X	X
NLMap [139]	2023	#	- /	CLIP	ViLD	/	/	X	/
Code as Policies [89]	2023	#	_	GPT3, Codex	ViLD	/	/	X	Х

^{*} directly get environment states; # their own benchmark;

manipulation tasks. We aim to introduce these techniques within the language-conditioned domain and explore their utilization within language-conditioned approaches.

- Visual attention: To ensure proper manipulation of the intended objects, certain methodologies suggest incorporating a visual attention module into their neural networks. This module's purpose is to deduce the relevant regions of objects described by the task. Stepputtis et al. [80] leverage the F-RCNN backbone to identify the specific object region to manipulate, guided by linguistic instructions. Abolghasemi et al. [79] utilize a GAN-based approach designed to create visual attention masks for objects intended to be manipulated. Mees et al. [77] employ visual affordance model VAPO [168] to learn a language-conditioned affordance and combine it with a 7-DoF low-level policy of agent to improve the success rate of manipulating right objects.
- Reconstruction: (Visual) reconstruction serves as a frequently employed strategy to ensure the essential information is extracted from observations. Popular models for reconstruction tasks encompass VAEs and GANs, which find extensive application as auxiliary tools in robotic manipulations. Shridhar et al. [136] leverage VAEs for encoding and decoding voxel information, aiming to optimize the extraction of semantic details from observations. CC-VAE proposed by [54] to encode the observations into latent space. In contrast to original VAEs, CC-VAEs additionally incorporate the initial state of a trajectory as input. Rahmatizadeh et al. [71] and Abolghasemi et al. [79] use GAN autoencoder to reconstruct input images. Ebert et al. [52] reconstruct masks of the current frame and flow field between the current frame and the next frame in their architecture.
- Predicting future states: Some approaches predict future states in order to help the agent better understand the dynamic of environments. Paxton et al. [158] train the agent by not only predicting the next actions based on present observations but also the next world states (including RGB, depth, and pose) as well as the next subgoals expressed in natural language. These auxiliary tasks aid the agent in comprehending its environment and breaking down tasks into multiple sequential steps. Ebert et al. [52] also forecast the image observations for the subsequent frame. It achieves this by predicting the motion of pixels from the current image observation to the next one.

Also, there exist some other kinds of auxiliary tasks, like predicting the depth information of the current frame [77]. Zhou et al. [78] learn extra base skill composition (such as translation \rightarrow rotation \rightarrow grasping \rightarrow translation) for each task to improve the generalization ability under an unfamiliar environment. Some commonly used auxiliary tasks (pseudo rewards) in reinforcement learning like *Pixel change*, *Network feature* [169] can also be applied [70].

D. Task representations

Enabling agents to perform a diverse range of tasks efficiently and seamlessly remains a challenge in the field of robot manipulation. In this field, a crucial question emerges: How can we effectively acquire an understanding of similarities among diverse tasks, such as grasping tasks, while concurrently discerning finer differences, such as variations in colors and shapes? In other words, how to represent different tasks? In this part, we introduce two main concepts in this field, namely task-specific learning, and task-agnostic learning. Task-specific learning involves the agent focusing solely on learning from particular tasks, typically language-based instructions in the training data. Conversely, task-agnostic learning aims to train an agent capable of reaching any attainable state within the space of possible states. Given the disjointed nature of language instructions, task-agnostic learning often relies on visual data, treating visual states as goals (tasks).

1) Task specific learning: Task-specific learning represents the most intuitive way to learn language-conditioned policy. The agent only learns to complete those predefined tasks described by language instructions and undergoes training on such a given task set, potentially acquiring the capability to generalize to additional language commands due to the inherent generalization capacity of the language encoding module. For instance, "grasp the red block" and "lift the red block" should have a similar task representation in the latent space after language encoding. Sodhani et. al. [30] introduce the CMDP [29] into the RL framework to enable the utilization of language-based side information as the task indicator. PerAct [136] encodes language goals and RGB-D voxel level observation with Transformer structure, and directly output action sequences. CLIPort [116] combines the broad semantic understanding of CLIP with the spatial precision of Transporter to map observation and languages to action sequences.

Moreover, certain methods harness the robust generalization proficiency exhibited by LLMs, enabling the trained agent to extend its competence to a range of unfamiliar tasks and environments. Ren et. al. [159] introduce the feature representation of tools used in manipulation tasks, leveraging a pre-trained LLM. It enables the agent to adapt to new tools based on text descriptions during the meta-learning phase. A similar approach is also introduced by Tang et al. [170] in task-oriented grasping, wherein the agent leverages a pretrained LLM to extract features of objects to be grasped and demonstrates generalization capabilities when confronted with new objects in real-world grasping tasks. Tidybot [104] leverages LLMs to separate complex tasks into simple subtasks, enabling the robot to clean up the room based on language commands. Also, Palo et al. [171] uses FLAN-T5 [172], an LLM finetuned on datasets of language instructions, to translate text instruction to a set of sub-goals for the robot to address. Some approaches also learn in an interactive way [173] [174] and some approaches are strengthened by VLMs [175].

2) Task agnostic learning: Contrary to task-specific learning, task-agnostic learning refers to the ability to reach any

reachable goal state from any state within the environment [176]. The concept of a "task" transforms from discrete to continuous, delineated by the pair of (initial state, goal state). Task-agnostic learning approaches aim to discover solutions that seamlessly traverse state-to-state transitions within the given boundaries of the environment. Considering that tasks described by language instructions can not cover the whole continuous task space, these approaches usually combine the language instructions and goal images to build a continuous tasks space, since goal images can describe any state in the environment. Some approaches like [76] [3] [4] [77] [78] leverage play-data, which refers to trajectories collected by teleoperation of human beings, driven by their curiosity or some other intrinsic motivation. The task agnostic data can be collected by taking random two observations in the middle of trajectories as (initial state, goal state) pairs. Visionlanguage-based multi-modal representation learning is frequently employed in such scenarios. Specifically, the CLIPbased approaches, which align the languages and images with contrastive loss in the latent space, are widely used in taskagnostic representation. Recent works use image frames [96], [177] or video datasets [112], [178] combined with natural language alignment to train a multi-modal based representation, which enables efficient downstream action pattern learning, planning and navigation in various robotic tasks. Typical frameworks based on this idea include [46], [96], [177], [162], [179], [180].

V. FUTURE DIRECTIONS

Language-conditioned robot manipulation provides us with a novel perspective to interact with intelligent robots. There is no doubt that the development of computer vision and natural language processing provides a solid foundation for language-conditioned robotic manipulation. Many approaches achieve outstanding performance in both simulation and real-world environments. This field is promising while also challenging. Here, we would like to discuss two vital challenges, namely, generalization ability and safety issues.

The generalization ability of language-conditioned robot manipulation systems is a critical aspect that needs to be addressed in future research. It is widely understood that the trained agent will not be helpful in our daily work if it only works well in specific domains or ad hoc settings. There is a need for these systems to generalize their knowledge and skills to handle a broader range of scenarios. How can the agent understand and perform unseen language instructions? How to stabilize the performance of the trained agent in unfamiliar environments? How to make sure the learned or designed skills can be transferred to a new domain with few-shot or even zero-shot setting? These three questions correspond to the generalization ability of language, visual, and control modules. We notice that the current trend to acquire better generalization ability is to leverage larger models and more data. "The more we see, the better we know" is the motivation behind that. Large language models, vision-language models, and foundation models contain a large amount of knowledge in our daily lives which is definitely helpful for robot manipulation

tasks. Many studies [104] [46] [112] demonstrate the strong generalization ability, leveraging large models. How to combine these foundation models with the control module becomes a new research hotspot. We anticipate the development of a substantial Vision-Language-Control Model (VLCM) that is trained end-to-end to reliably address language-conditioned manipulation tasks encountered in everyday life. Such a model would address the limitations of current foundational models, which lack the ability to interact with the real-world environment. It's akin to repeatedly studying a food recipe and finally venturing into cooking a sunny-side-up egg, or extensively reading martial arts manuals and eventually engaging in the first combat.

Rather than relying on foundation models to offer essential knowledge, it could be intriguing to utilize knowledge graphs to create a more human-readable knowledge structure. There are two concerns of large foundation models we need to take into consideration:

- There is still no definitive theoretical evidence suggesting that even larger models can elevate AI intelligence to the next level
- 2) Training larger models requires a significant investment of time and resources.

Knowledge graph, which contains numerous graph-formed knowledge, could be another option to increase the generalization ability of a robot.

In terms of safety issues, it is related to safety during interaction with human beings. There exist two main concerns:

- Ambiguity in language: One of the primary safety concerns is the inherent ambiguity in human language. Natural language instructions often leave room for interpretation. For instance, given the instruction "Remove the chemicals from the table.", the user may intend for the robot to carefully relocate the containers of chemicals from the table to a designated storage area, ensuring safety by avoiding spills or accidents. However, this instruction might be interpreted as physically removing the chemicals by tipping over or mishandling the containers, which could result in a hazardous situation with chemical spills and potential harm.
- Handling corner cases: Corner cases, which represent unusual, unexpected, or challenging scenarios, pose a significant challenge in language-conditioned robot manipulation. These cases seldom occur in real-world scenarios but can be extremely significant, demanding considerable attention. Handling these cases poses a significant challenge. When we attempt to retrain the network with these gathered corner cases, it introduces a critical concern: model forgetfulness: altering the frequency of corner cases may result in unforeseen model behavior for other cases. It is akin to the concept of "robbing Peter to pay Paul". This challenge in managing corner cases also stands as the foremost issue in the realm of autonomous driving.

We have reasons to believe that above mentioned two safety issues - *ambiguity in language* and *corner cases handling* represent two potential research directions in the field of language-conditioned robotic manipulations.

VI. CONCLUSION

In summary, this survey presents an overview of the current approaches to integrating language instructions into robot manipulations. Our analysis focuses on various approaches with reinforcement learning or imitation learning paradigms and also emphasizes state-of-the-art LLMs or VLMs-empowered models. We have conducted a comprehensive comparative analysis, evaluating these approaches based on factors such as semantic information extraction, environments & evaluations, auxiliary tasks, and task representations.

Furthermore, our discussion delves into the challenges present in this field and suggests potential research directions, aiming to inspire more researchers to engage in this area. We aspire for this paper to stimulate interest within the research community, encouraging further meaningful investigations that advance the synergy between language and robotic manipulation.

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