

A Survey on Vision-Language-Action Models for Embodied AI

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Abstract—Deep learning has demonstrated remarkable success across many domains, including computer vision, natural language processing, and reinforcement learning. Representative artificial neural networks in these fields span convolutional neural networks, Transformers, and deep Q-networks. Built upon unimodal neural networks, numerous multi-modal models have been introduced to address a range of tasks such as visual question answering, image captioning, and speech recognition. The rise of instruction-following robotic policies in embodied AI has spurred the development of a novel category of multi-modal models known as vision-language-action models (VLAs). Their multi-modality capability has become a foundational element in robot learning. Various methods have been proposed to enhance traits such as versatility, dexterity, and generalizability. Some models focus on refining specific components. Others aim to develop control policies adept at predicting low-level actions. Certain VLAs serve as high-level task planners capable of decomposing long-horizon tasks into executable subtasks. Over the past few years, a myriad of VLAs have emerged, reflecting the rapid advancement of embodied AI. Therefore, it is imperative to capture the evolving landscape through a comprehensive survey.

Index Terms—Embodied AI, Robotics, Multi-modality, Computer Vision, Natural Language Processing, Large Language Model

I. INTRODUCTION

Vision-language-action models (VLAs) are a class of multi-modal models within the field of embodied AI, designed to process information from vision, language, and action modalities. Unlike conversational AI such as ChatGPT [1], embodied AI requires controlling physical embodiments that interact with the environment. Consequently, robotics is the most prominent domain of embodied AI. In language-conditioned robotic tasks, the policy must possess the capability to understand language instructions, visually perceive the environment, and generate appropriate actions, necessitating the multi-modal capabilities of VLAs. The term was recently coined by RT-2 [2]. Compared to earlier deep reinforcement learning approaches, VLAs offer superior versatility, dexterity, and generalizability in complex environments. As a result, they are well-suited not only for controlled settings like factories but also for everyday tasks in household environments [3].

Early developments in deep learning primarily consist of unimodal models. In computer vision (CV), models like

AlexNet [4] showcased the potential of artificial neural networks (ANNs) [5]. Recurrent neural networks (RNNs) [6] laid the groundwork for numerous natural language processing (NLP) models but have seen a transition in recent years, with Transformers [7] taking precedence. The Deep Q-network demonstrated that ANNs can successfully tackle reinforcement learning problems. Leveraging advancements of unimodal models across diverse machine learning fields, multi-modal models have evolved to be powerful enough to tackle a variety of tasks [8], such as visual question answering, image captioning, speech recognition, etc.

Conventional robot policies based on reinforcement learning mostly concentrate on a restricted set of tasks, typically within controlled environments like factories and laboratories. For instance, [9] trains a policy specifically for grasping items. However, there is a growing need for more versatile multi-task policies, akin to recent developments in large language models (LLMs) [1], [10] and vision-language models (VLMs) [11]. Developing a multi-task policy is more challenging as it requires learning a broader set of skills and adapting to dynamic and uncertain environments. Additionally, task specification adds another layer of complexity. Some approaches use a one-hot vector to select tasks [12], but they are limited by the number of tasks in the training set.

Built upon the success of pretrained vision foundation models, LLMs, and VLMs, Vision-Language-Action models have demonstrated their competency in addressing these challenges. Pretrained visual representations from state-of-the-art vision encoders assist VLAs in perceiving complex environments [13]–[15], providing more precise estimations such as object class, object pose, and object geometry. With the increasing power of language models [2], [10], task specification based on language instructions becomes a viable option. Numerous ways of integrating vision models and language models have been explored by foundation VLMs, including BLIP-2 [16], Flamingo [11], etc. These innovations from different fields empower VLAs to address the challenges of embodied AI.

Different VLAs exhibit distinct emphases, as depicted by the taxonomy in Figure 1. Some works strive to enhance specific constituents of VLAs, such as pretrained visual representations, dynamics learning, and world models. Meanwhile, a substantial body of work is dedicated to robotic control policy. In this category, language instructions are input into the control policy, which generates primitive actions based on the environment. In contrast, another category of VLAs functions as high-level task planners that abstract away low-level controls. Instead, these models focus on decomposing long-horizon robotic tasks into subtasks. These subtasks can

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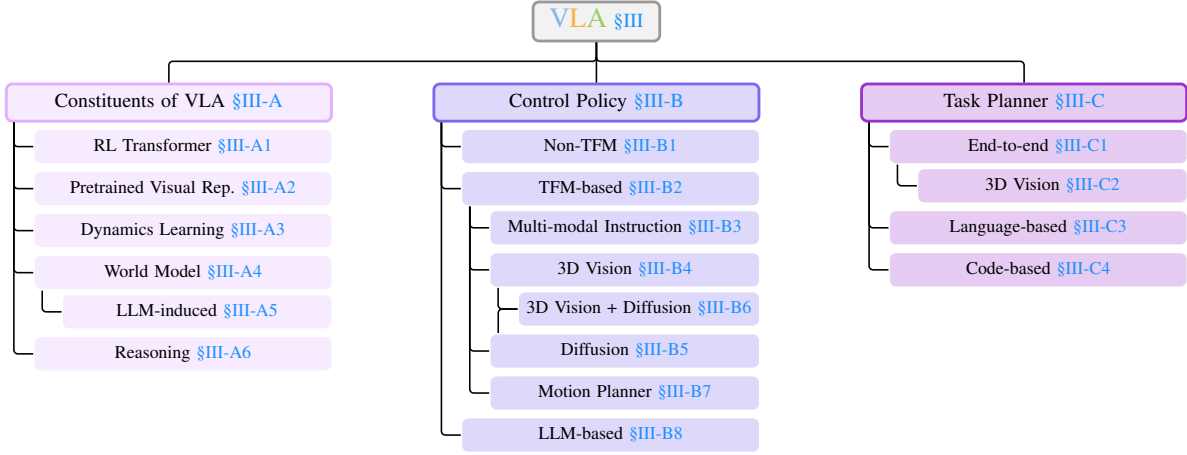


Figure 1: The taxonomy of Vision-Language-Action models.

then be completed by control policies one by one, eventually fulfilling the overall task.

Related Work. Although surveys for VLAs are currently lacking, existing surveys in related domains provide valuable insights for VLA research. In the field of computer vision, surveys cover a wide range of visual models, ranging from convolutional neural networks [17] to Transformers [18]. Natural language processing models are comprehensively summarized in surveys [19], [20]. In-depth reviews of reinforcement learning can be found in surveys [21]–[23]. Surveys on graph neural networks are also available [24]. Furthermore, existing surveys comparing vision-language models offer inspiration for VLAs [8], [25]–[27]. Additionally, a survey on earlier works of embodied AI exists [28].

Contributions. This survey stands as the first thorough review of the emerging vision-language-action model in the field of embodied AI.

- **Comprehensive Review.** We present a thorough review of emerging VLA models in embodied AI, covering various aspects including architectures, training objectives, and robotic tasks.
- **Taxonomy.** We introduce a taxonomy of the hierarchical structure in current robot systems, comprising three main components: pretraining, control policy, and task planner. Pretraining techniques aim to enhance specific aspects of VLAs, such as the vision encoder or dynamics model. Low-level control policies execute low-level actions based on specified language commands and the perceived environment. High-level task planner decomposes long-horizon tasks into subtasks executable by control policies.
- **Abundant Resources.** We provide an overview of necessary resources for training and evaluating VLA models. We investigate recently introduced datasets and simulators by comparing their key characteristics. Additionally, we include widely-adopted benchmarks for tasks such as robot control and embodied reasoning.
- **Future Directions.** We outline current challenges and promising future opportunities in the field, such as addressing data scarcity, enhancing robot dexterity, achiev-

ing generalization across different tasks, environments, and embodiments, as well as improving robot safety.

Paper Organization. §II-A provides an overview of representative developments and milestones in unimodal models. Because vision-language models are closely related to vision-language-action models, recent advancements in vision-language models are compared in §II-B. §III explores various types of vision-language-action models. §IV summarizes recent datasets and benchmarks for embodied AI. Challenges and future directions are included in §V.

II. BACKGROUND

A. Unimodal Models

Vision-language-action models integrate three modalities, often relying on existing unimodal models. The transition from convolutional neural networks (e.g., ResNet [29]) to visual Transformers (e.g., ViT [30], SAM [31]) in computer vision has facilitated the development of more general vision models. In natural language processing, the evolution from recurrent neural networks (e.g., LSTM [6], GRU [32]) to Transformers [7] initially led to the pretrain-finetune paradigm (e.g., BERT [33], ChatGPT [1]), followed by the recent success of prompt tuning driven by large language models. Reinforcement learning (e.g., DQN [34], AlphaGo [35], PPO [36], Dactyl [37]) has also witnessed a shift towards employing Transformers (§III-A1) to model the Markov Decision Process as autoregressive sequential data.

B. Vision-Language Models

Vision-language tasks, encompassing image captioning [38], visual question answer [39], visual grounding [40], require the fusion of computer vision and natural language processing models. Early attempts like Show and Tell [41] capitalized on the success of early CNNs and RNNs. The introduction of high-capacity language models such as BERT [33] and GPT [42] ushered in a new era of Transformer-based VLMs, which have evolved in three major directions: self-supervised pretraining, contrastive pretraining, and multi-modal LLMs. One of the pioneering self-supervised pretraining methods

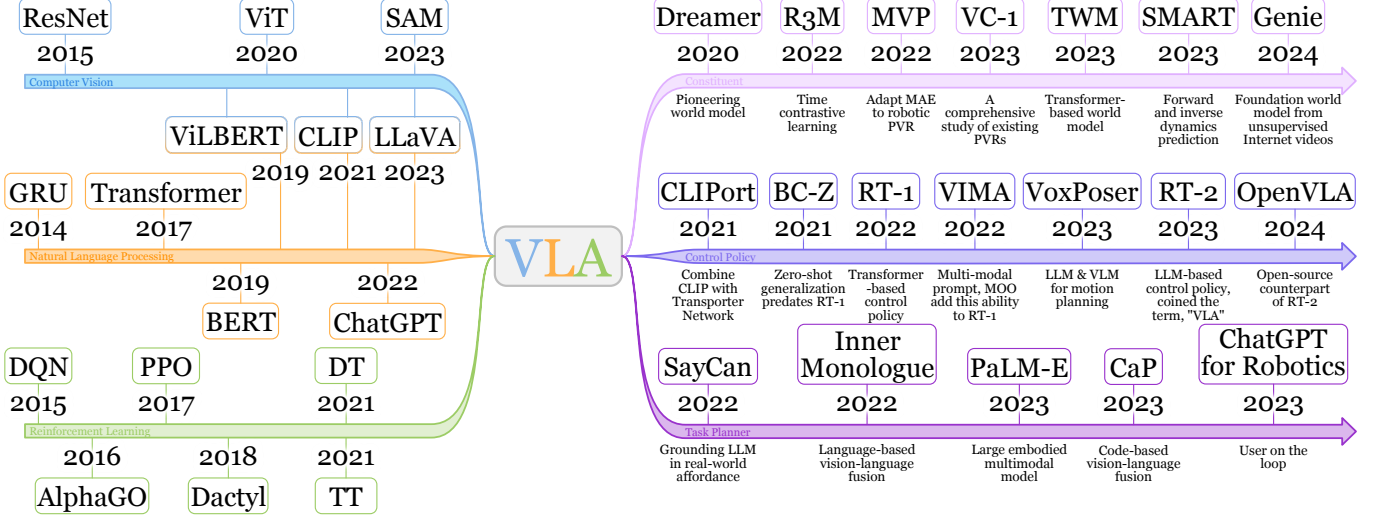


Figure 2: A brief timeline traces the evolution from unimodal models to multimodal models, laying the groundwork for the introduction of VLA models.

is ViLBERT [43], while CLIP [44] popularized contrastive pretraining approaches for multi-modal alignment. The recent emergence of large language models has driven the development of multi-modal LLMs (MLLMs) or large multi-modal models (LMMs), which achieve state-of-the-art performance on multi-modal instruction-following tasks. Representative MLLMs include Flamingo [11], BLIP-2 [16], LLaVA [45]. VLMs share a close relationship with VLAs, as the multi-modal architectures of VLMs can be readily adopted for VLAs. For example, attaching an action decoder to VLMs can transform them into VLAs for low-level control [46]. VLMs can also serve as high-level task planners if they possess sufficient reasoning abilities.

C. Embodied AI & Robot Learning

Embodied AI is a unique form of artificial intelligence that actively interacts with the physical environment. This sets it apart from other AI models, such as conversational AI, which primarily handles textual conversations (ChatGPT [1]), or generative AI models that focus on tasks like text-to-video generation (Sora [47]). Embodied AI encompasses a broad spectrum of embodiments, including smart appliances, smart glasses, autonomous vehicles, and more. Among them all, robots stand out as one of the most prominent embodiments.

Robot learning is also usually framed as reinforcement learning problems, represented as a Markov Decision Process (MDP) consisting of states (s), actions (a), and rewards (r). A MDP trajectory is denoted as $\tau = (s_{t=1}, a_{t=1}, r_{t=1}, \dots, s_{t=T}, a_{t=T}, r_{t=T})$. In certain scenarios, robotic tasks may also be viewed as partially-observable Markov Decision Processes (POMDPs) due to incomplete observations. The primary objective of reinforcement learning is to train a policy capable of generating optimal actions for the current state $\pi_{\theta}(a_t|p, s_{\leq t}, a_{< t})$. Various methods such as TD learning, policy gradients, etc., can be employed to achieve this. However, in cases where defining the reward function

proves challenging, imitation learning is utilized to directly model the action distribution within trajectories devoid of rewards $\tau = (s_{t=1}, a_{t=1}, \dots, s_{t=T}, a_{t=T})$. Furthermore, many multi-task robot models employ language as instructions to determine which task or skill to execute, thereby engaging in language-conditioned reinforcement learning.

III. VISION-LANGUAGE-ACTION MODELS

Vision-language-action models (VLAs) are the models that handle multi-modal inputs of vision and language and output robot actions to complete embodied tasks. They serve as the cornerstone for instruction following robotic policies in the field of embodied AI. These models rely on robust vision encoders, language encoders, and action decoders. Consequently, some works focus on improving the constituent components of VLA models (Sec III-A). Others concentrate on refining low-level control policies, adept at handling simple instructions and executing primitive actions (Sec III-B). Additionally, certain VLAs abstract away from low-level control and primarily aim to solve task decomposition (Sec III-C). Thus, the combination of low-level control policy and high-level task planner can be treated as a hierarchical policy, as illustrated in Figure 3.

A. Constituents of VLA

A variety of technologies serve as integral components of VLA models. Pioneering works such as Decision Transformer and Trajectory Transformer have paved the way for using Transformers in reinforcement learning (§III-A1), facilitating the development of scalable and high-capacity policies. The vision encoder is also crucial, as it must effectively encode the state and provide sufficient information about the environment to VLAs. Several works aim to pretrain vision encoders to obtain improved pretrained visual representations (PVRs) (§III-A2). Other research emphasizes learning the dynamics of the environment (§III-A3), enabling VLAs to understand the consequences of their actions and make more informed



Figure 3: Illustration of a hierarchical robot policy comprising a high-level task planner and a low-level control policy. The high-level task planner generates a plan based on the user instruction, which is then executed step by step by the low-level control policy.

decisions. An extension of dynamics learning involves developing a world model (§III-A4) that can provide additional information, such as reward signals. This approach allows the model to sample imagined rollouts, reducing the need for interaction with the actual environment and improving data efficiency. Additionally, by leveraging internet-scale common-sense knowledge from large language models, LLM-induced world models (§III-A5) have been gaining popularity.

1) *Reinforcement Learning Transformer*: Reinforcement learning (RL) trajectories, characterized by state-action-reward sequences, naturally align with the structure of sequence modeling problems, rendering them conducive to Transformer models. Pioneering efforts in this direction include Decision Transformer [48] and Trajectory Transformer [49]. Decision Transformer focuses on learning a policy, i.e., modeling the actions. Trajectory Transformer shares commonalities with Decision Transformer but distinguishes itself by extending its modeling objectives to include both states and returns within the trajectory. These innovative approaches showcase the applicability of Transformer architectures to the intricacies of RL sequence modeling. Gato [50] further extends this paradigm to a multi-modal, multi-task, multi-embodiment setting.

2) *Pretrained Visual Representations*: The effectiveness of the vision encoder directly influences the performance of the policy, as it supplies crucial information regarding object categories, positions, and environmental affordance. Consequently, numerous methods are devoted to pretraining the vision encoder to improve the quality of PVRs. Their technical details are compared in Table I.

Although Contrastive Language-Image Pre-training (CLIP) [44] was not initially designed for robotics tasks, it has gained widespread adoption as a vision encoder in robotic models, such as CLIPort [13], EmbCLIP [51], and CoW [52]. The training objective of CLIP is to identify the correct text-image pair among all possible combinations in a given batch. By training to enhance alignment between the vision encoder and the language encoder, CLIP proves particularly effective in tasks where text instructions are provided as input. CLIP undergoes training on the WebImageText dataset (WIT), comprising 400 million image-text pairs. This large-scale

training allows CLIP to develop a rich understanding of the relationship between visual and textual information. Notably, CLIP conducts a comprehensive comparison of various vision encoders, exploring different configurations of ResNet [29] and ViT [30]. This analysis provides valuable insights into the trade-off between accuracy and efficiency.

Reusable Representations for Robotic Manipulation (R3M) [53] proposes two main pretraining objectives: time contrastive learning and video-language alignment. The objective of time contrastive learning is to minimize the distance between video frames that are temporally close while simultaneously increasing the separation between frames that are temporally distant. This objective aims to create PVRs that capture the temporal relationships within the video sequence. On the other hand, video-language alignment is to learn whether a video corresponds to a language instruction. This objective enriches the semantic relevance embedded in the PVRs.

Masked Visual Pre-training (MVP) [14] adopts the methodology of Masked Autoencoder (MAE) from computer vision. The MAE involves masking out a portion of input patches to a ViT model and training it to reconstruct the corrupted patches. This approach closely resembles the masked language modeling technique used in BERT [33] and falls within the purview of self-supervised training. MVP extends this MAE objective across diverse robotic datasets, demonstrating that the pre-trained vision encoder significantly enhances performance in downstream manipulation tasks.

Value-Implicit Pre-training (VIP) [54] capitalizes on the temporal sequences present in videos, distinguishing itself from R3M [53] by attracting both the initial and target frames while simultaneously repelling successive frames. This objective aims to capture long-range temporal relationships and uphold local smoothness. While their own experiments demonstrate superior performance compared to R3M in specific tasks, subsequent research presents conflicting findings through more comprehensive evaluations [15].

Visual Cortex (VC-1) [15] conducts an in-depth examination of prior PVRs and introduces an enhanced PVR model by systematically exploring optimal ViT configurations across diverse datasets. Additionally, they perform a comprehensive comparative analysis of their model against previous methods on various manipulation and navigation datasets, shedding light on the critical factors that contribute to the improvement of PVR. Another study [55] also compares previous PVRs obtained under supervised learning or self-supervised learning.

Voltron [56] introduces a novel pretraining objective by incorporating language conditioning and language generation into the masked autoencoding (MAE) objective. Employing an encoder-decoder Transformer structure [7], the pretraining alternates between language-conditioned masked image reconstruction and language generation from masked images. This enhances the alignment between language and vision modalities, consequently resulting in a significantly improved success rate on language-conditioned imitation tasks.

RPT [57] undergoes pretraining with a focus not only on reconstructing visual inputs and robotic actions but also on proprioceptive states. In evaluating three distinct masking schemes, it was noted that token masking, in particular, yielded

Table I: Pretrained visual representations. V: Vision. L: Language. Net: Backbone network. CL: contrastive learning. MAE: masked auto-encoding. TFM: Transformer. **Sim/Real**: simulated/real-world. **Mani/Navi**: manipulation/navigation. [SC]: self-collect data. For simplicity, we only show the main part of the objective equation, omitting elements such as temperature, auxiliary loss, etc. $\mathcal{S}(\cdot)$ is the similarity measurement. (Ego-Data): Ego4D [60], Epic Kitchens [61], Something-Something-v2 [62], 100DOH [63].

Model	V-Encoder	Net	Objective	Formula	Notation	Dataset	Robotic Tasks
CLIP [44]	ViT-B [30]	-	VL-CL	$\sum_{i=1}^N -\log \frac{\exp(\mathcal{S}(x_i, y_i))}{\sum_{j=1}^N \exp(\mathcal{S}(x_i, y_j))}$	(x_i, y_i) : image-text pair	WIT [SC]	(EmbCLIP [51])
R3M [53]	ResNet-50 [29]	-	Time-CL	$\sum_{i=1}^T -\log \frac{\exp(\mathcal{S}(x_i, x_j))}{\exp(\mathcal{S}(x_i, x_j)) + \exp(\mathcal{S}(x_i, x_k))}$	x_i : i -th video frame, $i < j < k$	Ego4D	Sim-Mani : Meta-World, Franka Kitchen, Adroit
MVP [14]	ViT-B ViT-L	-	MAE [64]	$\sum_{i=1}^N -\log P(x_i x_{\neq i})$	x_i : image patch	(Ego-Data)	Real-Mani (xArm7): pick, reach block, push cube, close fridge
VIP [54]	ResNet-50	-	Time-CL	$\sum_{i=1}^T -\log \frac{\exp(\mathcal{S}(x_0, x_j))}{\exp(\mathcal{S}(x_0, x_j)) + \exp(\mathcal{S}(x_i, x_j))}$	x_i : i -th video frame, $0 < i < j$	Ego4D	Real-Mani (Franka): pick and place, close drawer, push bottle, fold towel
VC-1 [15]	ViT-L	-	MAE, CL	(A study of previous works, CLIP, R3M, MVP, VIP, including most previous datasets: (Ego-Data), Real Estate 10K [65], OpenHouse24 [SC])			Sim-Mani : Meta-World, Adroit, DMC, TriFinger, Habitat 2.0; Sim-Navi : Habitat
Volttron [56]	TFM [7]	MAP [66]	MAE, Lang-Gen	$\sum_{i=1}^N -\log P(x_i x_{\neq i}, y);$ $\sum_{i=1}^{N'} -\log P(y_i x, y_{< i})$	x_i : image patch; y : language instruction	Something-Something-v2	Sim-Mani : Franka Kitchen; Real-Mani (Franka): custom study desk
RPT [57]	ViT [14], [30]	TFM	MAE	$\sum_{i=1}^N -\log P(x_i x_{\neq i}, y, z, \dots)$	x_i : token from any modality; y, z : other modalities	[SC]	Real-Mani (Franka): stack, pick, pick from bin
GR-1 [58]	ViT-MAE	TFM	MAE	$\sum_{i=1}^N -\log P(x_i x_{\neq i}, y)$	x_i : image patch; y : language instruction	Ego4D	Sim-Mani : CALVIN

the most significant improvement in the model’s performance.

GR-1 [58] introduces a novel pretraining task of video prediction tailored for a GPT-style model. This video prediction objective is also subsequently employed during the finetuning phase, specifically utilizing robot data. The rationale behind this approach is that the ability to anticipate future frames contributes to more accurate action prediction. The experimental results, in the domain of robot manipulation, provide empirical support for their assertion.

SpawnNet [59] utilizes a two-stream architecture incorporating adapter layers to fuse features from both a pretrained vision encoder and features learned from scratch. This innovative approach eliminates the necessity of training the pre-trained vision encoders while surpassing the performance of parameter-efficient finetuning (PEFT) methods, as evidenced by experimental results in robot manipulation tasks.

Holo-Dex [67] proposes learning low-dimensional representations for visual policies using self-supervised learning (SSL). In Dobb-E [68], SSL is also explored for 3D visual inputs, through a method termed “Home Pretrained Representations,” using data collected from 22 homes in NYC. The authors extend SSL-pretrained representations beyond visual inputs. AuRL [69] introduces learning dynamic behaviors from audio, an often-overlooked yet important information source. Additionally, visual inputs were found to be insufficient for multi-fingered robotic hands, leading to T-Dex [70], a tactile-based dexterous policy.

3) *Dynamics Learning*: Dynamics learning encompasses objectives aimed at imbuing the model with an understanding of forward or inverse dynamics. Forward dynamics involves predicting the subsequent state resulting from a given action, whereas inverse dynamics entails determining the action required to transition from a previous state to a known subsequent state. Some research approaches also frame these objectives as reordering problems for shuffled state sequences. While forward dynamics models closely relate to world mod-

els, this subsection focuses specifically on works that leverage dynamics learning as an auxiliary task to enhance the performance of the primary robot task. We compare them in Table II.

Vi-PRoM [71] presents three distinct pretraining objectives. The first involves a contrastive self-supervised learning objective designed to distinguish between different videos. The remaining two objectives are centered around supervised learning tasks: temporal dynamics learning, aimed at recovering shuffled video frames, and image classification employing pseudo labels. Through a comprehensive comparison with preceding pretraining methods, Vi-PRoM demonstrates its effectiveness for behavior cloning and PPO.

MIDAS [73] introduces an inverse dynamics prediction task as part of its pretraining. The objective is to train the model to predict actions from observations, formulated as a motion-following task. This approach enhances the model’s understanding of the transition dynamics of the environment.

SMART [75] presents a pretraining scheme encompassing three distinct objectives: forward dynamics prediction, inverse dynamics prediction, and randomly masked hindsight control. The forward dynamics prediction task involves predicting the next latent state, while the inverse dynamics prediction task entails predicting the last action. In the case of hindsight control, the entire control sequence is provided as input, with some actions masked, and the model is trained to recover these masked actions. The incorporation of the first two dynamics prediction tasks facilitates capturing local and short-term dynamics, while the third task is designed to capture global and long-term temporal dependencies.

MaskDP [72] features the masked decision prediction task, wherein both state and action tokens are masked for reconstruction. This masked modeling task is specifically crafted to equip the model with an understanding of both forward and inverse dynamics. Notably, in contrast to preceding masked modeling approaches like BERT or MAE, MaskDP is applied directly to downstream tasks

Table II: Dynamics learning methods for VLAs. $f(\cdot)$ is the dynamic model. Fwd: forward. Inv: Inverse.

Model	V-Encoder	Objective	Formula	Notation	Robotic Tasks
Vi-PRoM [71]	ResNet [29]	Temporal dynamics	$\sum_{i=1}^T \text{CE}(i, f(x_i x'))$	$f(\cdot)$ predicts the frame index in original seq. x , given a shuffled seq. x'	Sim-Mani : Meta-World, Franka Kitchen; Real-Mani : open and close drawer/door
MaskDP [72]	ViT-MAE [64]	MAE (implicit fwd & inv dynamics)	$\sum_{i=1}^T -\log P(x_i x_{\neq i}, y)$	x_i : state or action token; y : the other modality	Sim : DeepMind Control Suite
MIDAS [73]	ViT, Mask R-CNN [74]	Inverse dynamics	$\sum_{i=1}^T \text{MSE}(a_t, f_{\text{inv}}(s_t, s_{t+1}))$	s_t, a_t : state, action	Sim-Mani : VIMA-Bench
SMART [75]	CNN	Forward & inverse dynamics	$\sum_{i=1}^T (\text{MSE}(s_{t+1}, f_{\text{fwd}}(s_t, a_t)) + \text{MSE}(a_t, f_{\text{inv}}(s_t, s_{t+1})))$	s_t, a_t : state, action	Sim : DeepMind Control Suite
PACT [76]	ResNet-18, PointNet [77]	Forward dynamics	$\sum_{i=1}^T \text{MSE}(s_{t+1}, f_{\text{fwd}}(s_t, a_t))$	s_t, a_t : state, action	Sim-Navi : Habitat; Real-Navi (MuSHR vehicle)
VPT [78]	ResNet	Inverse dynamics	$\sum_{i=1}^T \text{MSE}(a_t, f_{\text{inv}}(s_t, s_{t+1}))$	s_t, a_t : state, action	Sim : Minecraft

Perception-Action Causal Transformer (PACT) [76] introduces a pretraining objective aimed at modeling state-action transitions. PACT receives sequences of states and actions as input, and predicts each state and action token in an autoregressive manner. This pretrained model serves as a dynamics model, which can then be finetuned for various downstream tasks such as localization, mapping, and navigation.

Video Pretraining (VPT) [78] proposes a method that harnesses unlabeled internet data to pretrain a foundational model for the game of Minecraft. The approach begins by training an inverse dynamics model using a limited amount of labeled data, which is then utilized to label internet videos. Subsequently, this newly auto-labeled data is employed to train the VPT foundation model through behavior cloning. This methodology follows semi-supervised imitation learning. As a result of this process, the model demonstrates human-level performance across a multitude of tasks.

4) *Classical World Model*: Dreamer [79] employs three primary modules to construct a latent dynamics model: the representation model, responsible for encoding images into latent states; the transition model, which captures transitions between latent states; and the reward model, predicting the reward associated with a given state. Under the actor-critic framework, Dreamer utilizes an action model and a value model to learn behavior through imagination by propagating analytic gradients through the learned dynamics. Building upon this foundation, DreamerV2 [80] introduces a discrete latent state space along with an improved objective. DreamerV3 [81] extends its focus to a broader range of domains with fixed hyperparameters. DayDreamer [82] applies this method to physical robots performing real-world tasks.

Masked World Model (MWM) [83] innovates by modifying the vision encoder of DreamerV2 to a hybrid composition of Convolutional Neural Network and Vision Transformer. In training this novel Convolutional-ViT vision encoder, MWM draws inspiration from the approach proposed in MAE [64]. Through the incorporation of an auxiliary reward prediction loss, the resulting learned latent dynamics model exhibits a notable performance improvement across various visual robotic tasks.

Iso-Dream [84] introduces two key enhancements to the Dreamer framework. The first enhancement focuses on optimizing inverse dynamics by decoupling controllable and noncontrollable dynamics. The second enhancement involves

optimizing agent behavior based on the decoupled latent imaginations. This approach is particularly advantageous, as the noncontrollable state transition branch can be rolled out independently of actions, yielding benefits for long-horizon decision-making processes.

Transformer-based World Model (TWM) [85] shares the same motivation as Dreamer but adopts a different approach by constructing a world model based on the Transformer-XL architecture [86]. This Transformer-based world model trains a model-free agent in latent imagination by generating new trajectories. Additionally, TWM suggests a modification to the balanced KL divergence loss from DreamerV2 and introduces a novel thresholded entropy loss tailored for the advantage actor-critic framework.

IRIS [87] employs a GPT-like autoregressive Transformer as the foundation of its world model, with a VQ-VAE serving as the vision encoder. Subsequently, a policy is trained using imagined trajectories, which are unrolled from a real observation by the world model, akin to TWM’s approach.

SWIM [88] advocates for the use of human videos in training a world model due to the availability of large-scale human-centric data. However, acknowledging the substantial gap between human and robot data, SWIM addresses this disparity by grounding actions in visual affordance maps. This approach involves inferring target poses based on the affordance maps, facilitating an effective transfer of knowledge from human data to enhance robot control.

Genie [89] introduces a new class of generative models, termed Generative Interactive Environments. It consists of three main components: a spatiotemporal video tokenizer, an autoregressive dynamics model, and a latent action model. After being trained on unlabeled videos in an unsupervised manner, Genie allows users to interact with the generative environment on a frame-by-frame basis. Consequently, Genie establishes a foundation world model.

5) *LLM-induced World Model*: DECKARD [90] prompts LLM to generate abstract world models (AWMs) represented as directed acyclic graphs, specifically tailored for the task of item crafting in Minecraft. DECKARD iterates between two phases: in the Dream phase, it samples a subgoal guided by the AWM; in the Wake phase, DECKARD executes the subgoal and updates the AWM through interactions with the game. This guided approach, centered around AWMs, enables DECKARD to achieve markedly faster item crafting compared

to baselines lacking such guidance.

LLM-DM [91] uses an LLM to construct world models in planning domain definition language (PDDL)—a capability that LLM+P [92] did not achieve, as its PDDL world model was hand-crafted. The LLM also acts as an interface, mediating between the generated PDDL model and corrective feedback from syntactic validators and human experts. Finally, the PDDL world model serves as a symbolic simulator, assisting the LLM planner in generating plans.

RAP [93] repurposes an LLM to act as both a policy that predicts actions and a world model that provides the state transition distribution. Unlike previous chain-of-thought prompting methods, RAP incorporates Monte Carlo Tree Search (MCTS) to enable principled planning, allowing the LLM to build a reasoning tree incrementally. This reasoning strategy helps RAP find a high-reward path that balances exploration and exploitation. Tree-Planner [94] improves efficiency by prompting the LLM only once to generate diverse paths within an action tree.

LLM-MCTS [95] builds upon RAP but extends the problem setting to Partially Observable Markov Decision Processes (POMDPs). It proposes using the LLM as both a world model and a heuristic policy within an MCTS planning algorithm. As a world model, the LLM generates the initial belief of the current state; as a policy, it serves as a heuristic to guide action selection. By leveraging its commonsense knowledge, the LLM reduces the search space of MCTS, thereby improving search efficiency.

E2WM [96] is an LLM training paradigm that focuses on collecting embodied experiences from world models using MCTS. Unlike prior works, E2WM treats simulators as world models, as they emulate real-world physical interactions, and MCTS is used solely for data collection. By fine-tuning LLMs with this embodied knowledge, the models gain enhanced embodied abilities, such as plan generation, activity recognition, and tracking.

3D-VLA [97] proposes a 3D world model capable of goal generation. It processes visual inputs, such as images, depth map, and point clouds, and then generates a goal state—either as an image or a point cloud—using diffusion models in response to the user’s query. The generated goal state can subsequently be used to guide robot control.

6) *Reasoning*: Reasoning has become an important capability in LLMs, as pioneered by chain-of-thought (CoT) methods [98], [99]. Recent OpenAI o1 models [100] further demonstrate its potential in building more powerful AI systems. A similar trend has also emerged in the field of embodied AI. EmbodiedGPT [101] uses CoT to enhance embodied planning, and ThinkBot [102] applies it to recover missing action descriptions. RAT [103] combines retrieval-augmented generation and CoT to elicit context-aware reasoning, improving long-horizon generation. ReAct [104] interleaves verbal reasoning traces and actions to address diverse decision-making tasks. Tree-Planner [94] employs a Tree-of-Thoughts approach. Text2Motion [105] uses symbolic and geometric reasoning to verify the feasibility of an LLM-generated task plan. Reflexion [106] proposes a novel verbal reinforcement

learning framework, replacing weight updates in RL models with linguistic feedback.

Pros and Cons. Pretrained visual representations underscore the importance of the vision encoder, as visual observation plays a crucial role in perceiving the current state of the environment. Consequently, it sets an upper bound on the performance of the overall model. In VLAs, general vision models are pretrained using robot or human data to enhance their capabilities in tasks such as object detection, affordance map extraction, and even vision-language alignment, which are essential for robotic tasks. In contrast, dynamics learning focuses on understanding the transition between states. This involves not only mapping visual observations to good state representations but also comprehending how different actions lead to different states, and vice versa. Existing dynamics learning methods typically aim to capture the relationship between states and actions using simple masked modeling or reordering objectives. On the other hand, a world model aims to completely model the dynamics of the world, enabling the robot models to roll out states multiple steps into the future based on the current state, facilitating better prediction of optimal actions. Therefore, while a world model is more desired, it is also more challenging to achieve.

B. Low-level Control Policy

Through the integration of an action decoder with perception modules, such as vision encoders and language encoders, a control policy network is formed to execute language instructions in both simulated and real-world environments. The diversity among control policy networks arises from the selection of individual modules and the integration strategy. This section explores various approaches to designing a low-level control policy. Based on the backbone of their action decoder, control policies can be broadly categorized into three types: non-Transformer (§III-B1), Transformer-based (§III-B2), and LLM-based (§III-B8). Other approaches focus on specific aspects of control policies, such as multi-modal instructions (§III-B3), 3D Vision (§III-B4), diffusion-based action generation (§III-B5), and motion planning (§III-B7). In Table III, we compare the architectural details of these control policies.

1) *Early Non-Transformer Control Policies*: CLIPort [13] integrates the vision and language encoders of CLIP [44] with the Transporter network [108], creating a two-stream architecture. In one stream, CLIP’s vision encoder extracts “semantic” information from the RGB image, while in the other stream, the Transporter network extracts “spatial” information from the RGB-D image. The CLIP sentence encoder encodes the language instruction and guides the output action, which is a pair of end-effector poses: the picking and placing poses. CLIPort demonstrates the ability to pick and place objects as specified by the language instruction.

BC-Z [130] processes two types of task instructions: a language instruction or a human demonstration video. A language instruction undergoes encoding using the USE language encoder [172], while the video is encoded with ResNet18 [29]. The environment is presented to the model in the form

Table III: Low-level control policies. We also include some non-VLA models as they are closely related, marked in gray text. BC: behavior cloning (action type, cont/disc: continuous/discrete). TFM: Transformer. Xattn: cross-attention. Concat: concatenation. *p/s*: prompt/state vision encoder. (SC): self-collect data. LMP: Latent Motor Plans [107]. MPC: model predictive control.

Model	V-Encoder	L-Encoder	VL-Fusion	Action-Decoder	Objective	Training Dataset	Robotic Tasks
CLIPort [13]	CLIP-ResNet50, Transporter-ResNet [108]	CLIP-GPT	Hadamard	LingUNet [109]	BC (SE(2))	(SC)	Sim : Ravens [108]
MCIL [110]	Custom-CNN	USE	LMP RNN	LMP RNN	MCIL	Play-LMP + (SC)	Sim : 3D Playroom environment
HULC [111], HULC++ [112]	MCIL CNN	Sentence-BERT [113]	LMP TFM	LMP RNN	MCIL	CALVIN data	Sim : CALVIN
Language costs [114]	CLIP-ViT, UNet [115]	CLIP-GPT	Concat	STORM [116]	Max Likelihood Est. (cost map)	(SC)	Sim & Real (Franka): pick, place
Interactive Language [117]	ResNet [29]	CLIP-GPT	Xattn	TFM	BC (cont)	Language-Table (SC)	Sim & Real (xArm6): rearrangement
Hiveformer [118]	UNet	CLIP-GPT	Concat	TFM, UNet	BC (cont)	RLBench data [119]	Sim : RLBench
PerAct [120]	3D CNN	CLIP-GPT	Concat	PerceiverIO [121]	3D affordance	RLBench data [119]	Sim : RLBench; Real (Franka): put marker, place food, etc.
Act3D	CLIP-ResNet50	CLIP-GPT	Xattn	TFM	3D affordance (voxel)	RLBench, (BC)	Sim : RLBench; Real (Franka): reach target, wipe, stack, etc.
RVT, RVT-2 [122], [123]	CLIP-ResNet50	CLIP-GPT	Concat	TFM	2D affordance (project to 3D)	RLBench data [119], (SC)	Sim : RLBench; Real (Franka): stack, press, place
RoboPoint [124]	ViT-L/14	Vicuna-V1.5 13B [125]	Concat	-	2D affordance (project to 3D)	(SC)	Real (Franka): pick, place
Gato [50]	ViT	Sent.Piece [126]	Concat	TFM	BC (cont & disc)	(SC)	Sim & Real (Sawyer): RGB-stacking
RoboCat [127]	VQ-GAN (<i>p, s</i>) [128]	-	-	TFM	BC, Observation prediction	Self-improve	Sim & Real (Sawyer, Franka, KUKA): stacking, building, lifting, insertion, removal
VIMA [129]	ViT, Mask R-CNN [74]	T5 [10]	Xattn	TFM	BC (SE(2))	VIMA-Data (SC)	Sim (Ravens): VIMA-Bench
BC-Z [130]	ResNet18 (<i>p, s</i>) [29]	USE	FiLM [131]	MLP	BC (cont)	(SC)	Real (Everyday Robots): pick-place, pick-wipe, pick-drag, grasp, push
RT-1 [3]	EfficientNet [132]	USE	FiLM	TFM	BC (disc)	Kitchen (SC)	Real (Everyday Robots): pick-place, move, knock
MOO [129]	OWL-ViT (<i>p</i>) [133], EfficientNet (<i>s</i>)	USE	FiLM	TFM	BC (disc)	(SC)	Real (Everyday Robots): pick, move near, knock, place upright, place into
Q-Transformer [134]	EfficientNet	USE	FiLM	TFM	TD error	Auto-collect + RT-1 data	Sim : pick; Real (Everyday Robots): pick, place, open/close drawer, move near
RT-Trajectory [135]	EfficientNet	-	-	TFM	BC (disc)	(SC)	Real (Everyday Robots): pick, place, fold towel, swivel chair, etc.
ACT [136]	ResNet18	-	-	CVAE-TFM	BC (cont, action chunking)	(SC) with ALOHA	Sim : transfer cube, bimanual insertion; Real (ViperX, WidowX): slot battery, open cup, etc
MT-ACT [137]	CNN	N/A	FiLM	CVAE-TFM	BC (cont, action chunking)	RoboSet	Real (Franka): pick, place, open/close drawers, pour, push, drag, etc.
RT-2 [2]	ViT-22B [138], ViT-4B [139]	PaLI-X [140], PaLM-E	Concat	Symbol-tuning [141]	BC (disc), Co-fine-tuning	VQA + Kitchen	Real : RT-1 evaluation tasks, Language-Table
RT-H [142]	ViT-22B [138]	PaLI-X 55B [140]	Concat	Symbol-tuning	BC (disc)	Diverse + Kitchen	Real : Kitchen, Diverse
RT-X [143]	(Models from RT-1 and RT-2)				BC (disc)	OXE (SC)	Real : Kitchen Mani., NYU Door Open, BridgeV2, etc.
OpenVLA [144]	DINOv2 [145], SigLIP [146]	LLaMA 2 [147] (Prismatic-7B VLM [148])	Concat	Symbol-tuning	BC (disc)	OXE, DROID [149]	Real : BridgeV2, RT-1 evaluation tasks
RoboFlamingo [46]	CLIP-ViT-L/14	LLaMA [150], GPT-NeoX [151], MPT [152]	Xattn	LSTM, TFM, MLP	BC (cont)	CALVIN data	Sim : CALVIN
RoboUniView [153]	UVFormer	(Model design follows RoboFlamingo)			BC (cont)	CALVIN data	Sim : CALVIN
VoxPoser [154]	ViLD [155], MDETR [156], OWL-ViT [133], SAM [31]	GPT-4 [157]	Code	MPC	-	-	Sim : Sapien; Real (Franka): move & avoid, set up table, close drawer, open bottle, sweep Trash
UniPi [158]	Imagen video [159]	T5-XXL [10]	Xattn	CNN	Inverse dynamics	PF (SC), Ravens, BridgeV1	Sim : Painting Factory (PF) [160], Ravens
Diffusion Policy [161]	ResNet18 [29]	-	-	UNet, TFM	DDPM [162]	(SC)	Sim : Robomimic, Franka Kitchen, etc; Real (UR5, Franka): push-T, flip mug, pour sauce
DP3 [163]	DP3 Encoder	(Model design follows Diffusion Policy)			DDIM	(SC)	Sim : (72 tasks); Real (Franka, Allegro hand): roll-up, dumpling, drill, pour
SUDD [164]	ResNet18 [29]	CLIP-GPT	Concat	UNet, TFM	DDPM	Lang-Guided Data Gen	Sim : MuJoCo; Real (UR5e): pick, place
Octo [165]	CNN	T5-base [10]	Concat	TFM	DDPM	OXE	Real : BridgeV2, Stanford Coffee, Berkeley Peg Insert, etc.
3D Diffuser Actor [166]	(Model design follows Act3D)				DDPM	RLBench, CALVIN, (SC)	Sim : RLBench, CALVIN; Real (Franka): put, open, close, stack, etc.
MDT [167]	CLIP-ViT-B/16 (<i>p</i>), Voltron / ResNet18 (<i>s</i>)	CLIP-GPT	Concat	DiT [168]	DDIM [169]	CALVIN, LIBERO, Kitchen (SC)	Sim : CALVIN, LIBERO [170]; Real (Franka): pick, push, open, close, etc.
RDT-1B [171]	SigLIP	T5-XXL	Xattn	DiT	DDPM	(Aggregated Datasets)	Real (ALOHA dual-arm): wash, pour, fold, etc.

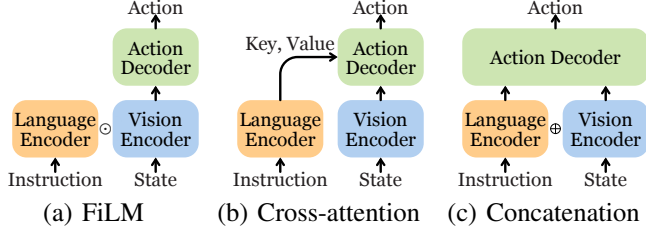


Figure 4: Three common architectures of Transformer-based control policies are characterized by their vision-language fusion methods. FiLM layers (Hadamard product \odot) are employed to fuse language and vision in RT-1 models. Some action decoders utilize cross-attention to condition on the instruction. Concatenation (\oplus) is the prevailing method of vision-language fusion for action decoders.

of an RGB image, also encoded using ResNet18. Then the instruction embedding and the image embedding are combined through the FiLM layer [131], culminating in the generation of actions. This conditional policy is asserted to exhibit zero-shot task generalization to unseen tasks.

MCIL [110] represents a pioneering robot policy that integrates free-form natural language conditioning. This is in contrast to earlier approaches that typically rely on conditions in the form of task id or goal image. MCIL introduces the capability to leverage unlabeled and unstructured demonstration data. This is achieved by training the policy to follow either image or language goals, with a small fraction of the training dataset consisting of paired image and language goals.

HULC [111] introduces several techniques aimed at enhancing robot learning architectures. These include a hierarchical decomposition of robot learning, a multimodal transformer, and discrete latent plans. The Transformer learns high-level behaviors, hierarchically dividing low-level local policies and the global plan. Additionally, HULC incorporates a visuo-lingual semantic alignment loss based on contrastive learning to align VL modalities. HULC++ [112] further integrates a self-supervised affordance model. This model guides HULC to the actionable region specified by a language instruction, enabling it to fulfill tasks within this designated area.

Universal Policy (UniPi) [158] treats the decision-making problem as a text-conditioned video generation problem. To predict actions, UniPi generates a video based on a given text instruction, and actions are extracted from the frames of the video through inverse dynamics. This innovative policy-as-video formulation offers several advantages, including enhanced generalization across diverse robot tasks and the potential for knowledge transfer from internet videos to real robots.

2) *Transformer-based Control Policies*: Interactive Language [117] presents a robotic system wherein the low-level control policy can be guided in real-time by human instructions conveyed through language, enabling the completion of long-horizon rearrangement tasks. The efficacy of such language-based guidance is primarily attributed to the utilization of a meticulously collected dataset containing diverse language instructions, which surpasses previous datasets by an

order of magnitude in scale.

Hiveformer [118] places significant emphasis on leveraging multi-view scene observations and maintaining the full observation history for a language-conditioned policy. This approach represents an advancement over previous systems such as CLIPort and BC-Z that only use the current observation. Notably, Hiveformer stands out as one of the early adopters of Transformer architecture as its policy backbone.

BeT [173], an imitation learning variant of the Trajectory Transformer, addresses the noisy and multi-modal nature of non-expert human demonstration data by using k-means-based action discretization coupled with continuous action correction. C-BeT [174] extends BeT by adding a target frame or demonstration as the goal specification. VQ-BeT [175] further improves BeT by incorporating vector quantization instead of k-means, enabling better modeling of long-range actions.

Gato [50] proposes a model that can play Atari games, caption images, and stack blocks, all with a single set of model parameters. This achievement is facilitated by a unified tokenization scheme, harmonizing the input and output across diverse tasks and domains. Consequently, Gato enables the simultaneous training of different tasks. Representing a significant milestone, Gato exemplifies the potential of constructing a “multi-modal, multi-task, multi-embodiment generalist agent”.

RoboCat [127] proposes a self-improvement process designed to enable an agent to rapidly adapt to new tasks with as few as 100 demonstrations. This self-improvement process iteratively finetunes the model and self-generates new data with the finetuned model. Built upon the Gato model [50], RoboCat incorporates the VQ-GAN image encoder [128]. During training, RoboCat predicts not only the next action but also future observations. The effectiveness of the self-improvement process is demonstrated through comprehensive experiments conducted in both simulated and real-world environments under multi-task, multi-embodiment settings.

RT-1 [3], developed by the same team as BC-Z [130], shares similarities with BC-Z but introduces some key distinctions. Notably, RT-1 employs a vision encoder based on the more efficient EfficientNet [132], departing from BC-Z’s use of ResNet18. The language instruction is also encoded using USE [172] and is integrated with image embeddings through FiLM layers [131]. However, RT-1 does not use video as a task instruction, unlike BC-Z. Additionally, RT-1 replaces the MLP action decoder in BC-Z with a Transformer decoder, producing discretized actions. This modification enables RT-1 to attend to past images, enhancing its performance compared to BC-Z.

Q-Transformer [134] extends RT-1 [3] by introducing autoregressive Q-functions. In contrast to RT-1, which learns expert trajectories through imitation learning, Q-Transformer adopts Q-learning methods. Alongside the TD error objective of Q-learning, a conservative regularizer is incorporated to ensure that the maximum value action remains in-distribution. This approach allows Q-Transformer to leverage not only successful demonstrations but also failed trajectories for learning.

RT-Trajectory [135] adopts trajectory sketches as policy conditions instead of relying on language conditions or goal conditions. These trajectory sketches consist of curves that delineate the intended trajectory for the robot end-effector to

follow. They can be manually specified through a graphical user interface, extracted from human demonstration videos, or generated by foundation models. RT-Trajectory’s policy is built upon the backbone of RT-1 and trained to control the robot arm to accurately follow the trajectory sketches. This approach facilitates generalization to novel objects, tasks, and skills, as trajectories from various tasks are transferable.

ACT [136] builds a conditional VAE policy with action chunking, requiring the policy to predict a sequence of actions rather than a single one. During inference, the action sequence is averaged using a method called temporal ensembling. RoboAgent [137] extends this approach with its MT-ACT model, demonstrating that action chunking improves temporal consistency. Additionally, RoboAgent introduces a semantic augmentation method that leverages inpainting to augment existing demonstrations.

3) *Multi-modal-instruction Control Policies*: VIMA [176] places a significant emphasis on multi-modal prompts and the generalization capabilities of models. By incorporating multi-modal prompts, more specific and intricate tasks can be formulated compared to traditional pure text prompts. VIMA introduces four main types of tasks: object manipulation, visual goal reaching, novel concept grounding, one-shot video imitation, visual constraint satisfaction, visual reasoning. These tasks are often challenging or even infeasible to express using only language prompts. VIMA-Bench has been developed to evaluate across four generalizability levels: placement, combinatorial, novel object, novel task.

MOO [129] extends RT-1 to handle multi-modal prompts. Leveraging the backbone of RT-1, MOO incorporates OWL-ViT [129] to encode images within the prompt. By expanding the RT-1 dataset with new objects and additional prompt images, MOO enhances the generalization capabilities of RT-1. This extension also facilitates new methods of specifying target objects, such as pointing with a finger, and clicking on graphical user interfaces.

4) *Control Policies with 3D Vision*: We live in a 3D world, and it is intuitive that using 3D representations as visual inputs should provide richer information than 2D images. Point clouds are a popular choice for representing 3D inputs due to their straightforward derivation from RGBD inputs, as demonstrated by both DP3 and 3D Diffuser Actor. However, voxels have also been explored in various works. RoboUniView [153] shows improved performance by injecting 3D information into RoboFlamingo through a novel UVFormer module as its vision encoder, which provides 3D occupancy information from multi-perspective images. VER [177] also proposes voxelizing multi-view images into 3D cells in a coarse-to-fine manner, enhancing performance in vision-language navigation tasks.

Perceiver-Actor (PerAct) [120] represents an advancement in both the observation and action spaces by leveraging 3D voxel representations. This approach offers a robust structural prior for action learning, enabling natural processing of multi-view observations and facilitating data augmentation in 6-DoF. In this framework, the input to the model comprises voxel maps reconstructed from RGBD images, while the output corresponds to the best voxel for guiding the gripper’s movement. By adopting this formulation, PerAct facilitates

efficient task learning even with a few demonstrations. On the other hand, Act3D [178] introduces a continuous resolution 3D feature field, with adaptive resolutions based on current task, addressing the computational cost of voxelization. RVT, RVT-2 [122], [123] propose re-rendering images from virtual views and using these images as inputs, rather than directly relying on 3D inputs. RoboPoint [124] leverages VLM to predict affordance points directly on 2D images, which are then projected into 3D space using depth maps.

SceneScript [179] introduces a set of structured language commands that can define an entire scene, specifying the layout and objects. This language-based scene representation distinguishes itself from previous methods—such as meshes, voxel grids, point clouds, or radiance fields—by generating scenes in an autoregressive, token-based fashion. It achieves competitive results against state-of-the-art methods in layout estimation and object detection.

5) *Diffusion-based Action Generation*: Diffusion-based action generation leverages the success of diffusion models in the field of computer vision [162]. Diffusion policy [161] formulates a robot policy as Denoising Diffusion Probabilistic Models (DDPMs) [162]. This approach incorporates a variety of innovative techniques, including receding horizon control, visual conditioning, and the time-series diffusion transformer. The effectiveness of this diffusion-based visuomotor policy is underscored by its proficiency in multimodal action distributions, high-dimensional action spaces, and training stability.

Scaling Up and Distilling Down (SUDD) [164] presents a framework where LLM guides data generation and subsequently the filtered dataset is distilled into a visuo-linguo-motor policy. This framework achieves language-guided data generation by composing LLM with a suite of primitive robot utilities, such as grasp samplers, motion planners. Then it extends Diffusion Policy [161] through the incorporation of language-based conditioning for multi-task learning. This diffusion-based policy learns from successful trajectories, facilitating the distillation of the filtered dataset.

Octo [165] introduces a transformer-based diffusion policy characterized by a modular open-framework design, allowing for flexible connections from different task definition encoders, observation encoders, and action decoders to the Octo Transformer. Being among the first to utilize the Open X-Embodiment dataset [143], Octo demonstrates positive transfer and generalizability across diverse robots and tasks.

MDT [167] adapts the newly introduced DiT model [168] from computer vision to the action prediction head. DiT, originally proposed as a transformer-based diffusion model, replaces the classical U-Net architecture for video generation. Coupled with two auxiliary objectives—masked generative foresight and contrastive latent alignment—MDT demonstrates better performance than the U-Net-based diffusion model, SUDD.

RDT-1B [171] is a diffusion-based foundation model for bimanual manipulation, also built on DiT. It addresses data scarcity by introducing a unified action format across various robots, enabling pre-training on heterogeneous multi-robot datasets with over 6K trajectories. As a result, RDT scales up to 1.2B parameters and demonstrates zero-shot generalization.

6) *Diffusion-based Control Policy with 3D Vision*: Several works have proposed combining 3D Vision with diffusion-based policies. DP3 [163] introduces 3D inputs to a diffusion policy, resulting in improved performance. Similarly, 3D Diffuser Actor [166] shares the core idea of DP3 but differs in model architecture by combining Act3D with Diffusion Policy.

7) *Motion Planner*: Language costs [114] presents a novel approach to robot correction using natural language for human-in-the-loop robot control systems. This method leverages predicted cost maps generated from human instructions, which are then utilized by the motion planner to compute the optimal action. This framework enables users to correct goals, specify preferences, or recover from errors through intuitive language commands.

VoxPoser [154] employs LLM and VLM to create two 3D voxel maps that represent affordance and constraint. It leverages the programming capability of LLM [157], and the perception capability of VLM models: ViLD [155], MDETR [156], OWL-ViT [133], SAM [31]. LLM translates language instructions into executable code, invoking VLM to obtain object coordinates. Based on the composed affordance and constraint maps, VoxPoser employs model predictive control to generate a feasible trajectory for the robot arm’s end-effector. Notably, VoxPoser does not require any trainings, as it directly connects LLM and VLM for motion planning.

RoboTAP [180] breaks down demonstrations into stages marked by the opening and closing of the gripper. In each stage, RoboTAP uses the TAPIR algorithm to detect active points that track the relevant object from the source pose to the target pose. The path can then be used by classical visual servoing to control the robot. A motion plan is created by stringing together these stages, enabling few-shot visual imitation.

8) *LLM-based Control Policies*: RT-2 [2] endeavors to harness the capabilities of large multi-modal models in robotics tasks, drawing inspiration from models like PaLI-X [140] and PaLM-E [181]. The approach introduces co-fine-tuning, aiming to fit the model to both Internet-scale visual question answering (VQA) data and robot data. This training scheme enhances the model’s generalizability and brings about emergent capabilities. RT-2 represents an effort to integrate low-level control policy [3] with high-level task planners in pursuit of a more comprehensive robotic system.

RT-X [143] builds upon the previous RT-1 and RT-2 models. These models are re-trained using the newly introduced open-source large dataset, named Open X-Embodiment (OXE), which is orders of magnitude larger than previous datasets. OXE comprises 160,266 tasks from 527 skills with 22 embodiments. The resulting models, RT-1-X and RT-2-X, both outperform their original versions, owing to the more diverse and larger OXE dataset. OpenVLA [144] was later developed as an open-source counterpart to RT-X.

RT-H [142] introduces an action hierarchy that includes an intermediate prediction layer of language motions, situated between language instructions and low-level actions (translation and rotation). This additional layer facilitates improved data sharing across different tasks. For example, both the language instructions “pick” and “pour” may involve the language

motion “move the arm up”. Moreover, this action hierarchy enables users to specify corrections to recover from failures, which the model can then learn from.

RoboFlamingo [46] adapts the existing VLM, Flamingo [11], [182], to a robot policy by attaching an LSTM-based policy head to the VLM. This demonstrates that pretrained VLMs can be effectively transferred to language-conditioned robotic manipulation tasks.

Pros and Cons.

a) *Architectures*: Various VLA architectures explore different methods of fusing vision and language inputs, including cross-attention, FiLM, and concatenation, as illustrated in Figure 4. FiLM is used in RT-1 and thus its follow-up works inherit this mechanism. While cross-attention may offer superior performance with smaller model sizes, concatenation is simpler to implement and can achieve comparable results with larger models [176].

b) *Action types and their training objectives*: Most low-level control policies predict actions for the end-effector pose while abstracting away the motion planning module that controls the motion of individual joints with inverse kinematics. While this abstraction facilitates better generalization to different embodiments, it also imposes limitations on dexterity.

The behavior cloning (BC) objective is used in imitation-learning, with different variants for different action types. The BC objective for continuous action [46] can be written as:

$$\mathcal{L}_{\text{Cont}} = \sum_t \text{MSE}(\mathbf{a}_t, \hat{\mathbf{a}}_t), \quad (1)$$

where $\text{MSE}(\cdot)$ stands for mean squared error. $\hat{\mathbf{a}}_t = \text{argmax}_{a_t} \pi_{\theta}(a_t | p, s_{\leq t}, a_{< t})$ is predicted action while \mathbf{a}_t is the action from expert demonstrations.

Discrete action is achieved by dividing the action value range into a number of bins [3]. Its BC objective is:

$$\mathcal{L}_{\text{Disc}} = \sum_t \text{CE}(\mathbf{a}_t, \hat{\mathbf{a}}_t), \quad (2)$$

where $\text{CE}(\cdot)$ stands for cross-entropy loss.

CLIPort [13] and VIMA [176] use $\text{SE}(2)$ action and its BC objective can be expressed as follows:

$$\mathcal{L}_{\text{SE}(2)} = \text{CE}(\mathbf{a}_{\text{pick}}, \hat{\mathbf{a}}_{\text{pick}}) + \text{CE}(\mathbf{a}_{\text{place}}, \hat{\mathbf{a}}_{\text{place}}) \quad (3)$$

The DDPM objective in diffusion-based control policies [161] is represented as:

$$\mathcal{L}_{\text{DDPM}} = \text{MSE}(\varepsilon^k, \varepsilon_{\theta}(\mathbf{x}^0 + \varepsilon^k, k)) \quad (4)$$

where \mathbf{x}^0 is the raw example from the dataset and ε^k is a random noise for iteration k ; ε_{θ} is the noise prediction network, i.e., the VLA model.

While discrete action has demonstrated superior performance in RT-1 [3], Octo [165] argues that it leads to early grasping issues. $\text{SE}(2)$ action only necessitates the model to predict the two end-effector poses, e.g., pick pose and place pose. While this action type can be predicted in at most two forward passes, it also imposes limitations on action dexterity and generalizability.

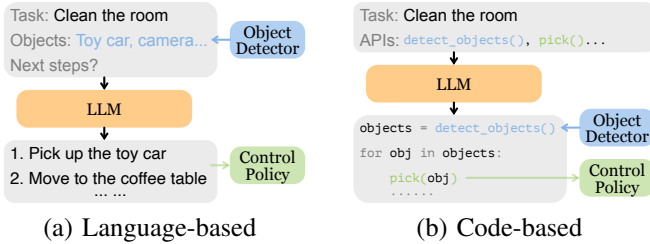


Figure 5: Different approaches to connect LLM to multi-modal modules in high-level task planner.

c) *LLM vs non-LLM*: While LLM-based control policies can greatly enhance instruction-following abilities because LLM can better parse user intentions, concerns arise regarding their training cost and deployment speed. Slow inference speed, in particular, can significantly impact performance in dynamic environments, as changes in the environment may occur during LLM inference.

d) *RT series*: RT-1 [3] inspired a series of “Robotic Transformer” models. Preceding RT-1 was BC-Z [130], which solely utilized MLP layers for action prediction. Subsequent to RT-1, several works emerged, each introducing new capabilities. MOO [129] adapted RT-1 to accommodate multi-modal prompts. RT-Trajectory [135] enabled RT-1 to process trajectory sketches as prompts. Q-Transformer [134] utilized Q-learning to train RT-1. RT-2 [2], based on ViT and LLM, introduced a completely different architecture from RT-1. RT-X [143] retrained RT-1 and RT-2 with a significantly larger dataset, resulting in improved performance. The Transformer backbone surpasses previous RNN backbones [110]–[112] by harnessing the higher capacity of Transformers to absorb larger robot datasets. Based on RT-2, RT-H [142] introduces action hierarchies for better data sharing.

C. High-level Task Planner

A high-level task planner aims to divide a complex task into a series of executable sub-tasks. This approach is often referred to as task decomposition, and is also related to the classical Task and Motion Planning (TAMP) setting. Many high-level task planners are constructed on top of LLMs. While integrating multi-modal modules into LLMs in an end-to-end fashion (§III-C1) is a common approach, training with multi-modal data can be expensive. Consequently, some task planners explore to utilize language (§III-C3) or code (§III-C4) as the medium for exchanging multi-modal information instead, as they can be natively processed by LLMs.

1) *End-to-end*: While control policies are effective in understanding and executing simple language instructions, they tend to struggle in long-horizon tasks that involve multiple sub-tasks. Large language models have been identified as powerful tools to interpret such complex long-horizon tasks. Consequently, several approaches are dedicated to integrating LLMs as high-level task planners. Their goal is to decompose long-horizon tasks into simpler sub-tasks, enabling low-level control policies to execute them sequentially, contributing to

the development of a hierarchical robotic system. Table IV outlines important details about these high-level task planners.

SayCan [183] is a framework designed to integrate high-level LLM planners with low-level control policies. In this framework, the LLM planner accepts users’ high-level instruction and “says” what the most probable next low-level skill is, a concept referred to as *task-grounding*. The low-level policy provides the value function as the affordance function, determining the possibility that the policy “can” complete the skill, known as *world-grounding*. By considering both LLM’s plan and affordance, the framework selects the optimal skill for the current state.

LID [184] introduces a novel data collection procedure termed Active Data Gathering (ADG). A key aspect of ADG is hindsight relabeling, which reassigns labels to unsuccessful trajectories, effectively maximizing the utilization of data irrespective of their success. By converting all environmental inputs into textual descriptions, their language-model-based policy demonstrates enhanced combinatorial generalization.

Translated ⟨LM⟩ [188] employs a two-step process to translate high-level instructions into executable actions. Initially, a pretrained causal LLM is utilized for *plan generation*, breaking down the high-level instruction into the next action expressed in free-form language phrases. Then, as these phrases may not directly map to VirtualHome actions, a pretrained masked LLM is then employed for *action translation*. This step involves calculating the similarity between the generated action phrases and VirtualHome action. The translated action is appended to the plan, and the updated plan is read by the LLM to generate the next action phrase. The two-step process is repeated until a complete plan is formed. A “Re-prompting” strategy [222] is further proposed to generate corrective actions when the agent encounters precondition errors.

Semi-Supervised Skill Learning with Latent Language ((SL)³) [191] is a learning algorithm that alternates between three steps: segmentation, labeling, and parameter update. In the segmentation step, high-level subtasks are aligned with low-level actions, subtask descriptions are then inferred in the labeling step, and finally, the network parameters are updated. This approach enables a hierarchical policy to discover reusable skills with sparse natural language annotations.

EmbodiedGPT [101] introduces the embodied-former, which outputs task-relevant instance-level features. This is achieved by incorporating information from vision encoder embeddings and embodied planning information provided by LLM. The instance feature serves to inform the low-level policy about the immediate next action to take.

PaLM-E [181] integrates ViT [30] and PaLM [185] to create a large embodied multi-modal language model capable of performing high-level embodied reasoning tasks. Based on perceived images and high-level language instructions, PaLM-E generates a text plan that serves as instructions for low-level robotic policies. In a mobile manipulation environment, they map the generated plan to executable low-level instructions with SayCan [183]. As the low-level policy executes actions, PaLM-E can also replan based on changes in the environment. With PaLM as its backbone, PaLM-E can handle both normal

Table IV: High-level task planners. VL: vision-language fusion. **Sim/Real**: simulated/real-world. **Mani/Navi**: manipulation/navigation.

Model	V-Encoder	Lang Model	VL	Control Policy	Train	Robotic Tasks
SayCan [183]	CNN	PaLM [185] FLAN [186]	Concat	BC-Z [130] MT-Opt [12]	Yes	Real-Navi&Mani (Everyday Robots): kitchen
LID [184]	CNN	GPT-2 [187]	Concat	-	Yes	Sim : VirtualHome
Translated (LM) [188]	-	GPT-3 [189] Codex [190]	-	-	No	Sim : VirtualHome
(SL) ³ [191]	ResNet18 [29]	T5-small [10]	Xattn	HLSM [192]	Yes	Sim-Navi : ALFRED
EmbodiedGPT [101]	EVA ViT-G/14 [193]	LLaMA-7B [150]	Embodied-former	MLP	Yes	Sim-Mani : Franka Kitchen, Meta-World
PaLM-E [181]	ViT [30], OSRT [194]	PaLM [185]	Concat	Interactive Language policy [117], RT-1 [3]	Yes	Sim : TAMP; Sim&Real-Mani : Lang.-Table; Real : SayCan setup
LEO [195]	ConvNeXt [196], PointNet++ [197]	Vicuna-7B [125]	Concat	MLP	Yes	Sim-Mani : CLIPort task subset; Sim-Navi : Habitat-web
3D-LLM [198]	CLIP, 3D-CLR [199], ConceptFusion [200]	Flamingo [11], BLIP-2 [16]	Concat	DD-PPO [201]	Yes	Sim-Navi : Habitat
StructFormer [202], StructDiffusion [203]	PCT [204]	-	Concat	[205], RRT-connect [206]	Yes	Sim-Mani : PyBullet; Real-Mani (Franka): rearrange
ShapeLLM [207]	ReCon++	LLaMA	Concat	-	Yes	3D MM-Vet Benchmark
Inner Monologue [208]	MDETR [156], CLIP	InstructGPT [209] PaLM [185]	Language	CLIPort, MDETR, SayCan policies	No	Sim&Real-Mani : Tabletop Rearrangement; Real-Navi&Mani : Kitchen Mobile Mani.
LLM-Planner [210]	HLSM object detector [192]	GPT-3 [189]	Language	HLSM [192]	Yes	Sim-Navi : ALFRED
SMs [211]	CLIP, ViLD [155]	GPT-3 [189], RoBERTa [212]	Language & Code	CLIPort [13]	No	Sim-Mani : pick, place
ProgPrompt [213]	ViLD [155]	GPT-3 [189]	Code	API [214], [215]	No	Sim : VirtualHome
ChatGPT for Robotics [216]	YOLOv8 [217]	ChatGPT [1]	Code	API	No	Real-Navi : drone flight; Sim-Navi : AirSim, Habitat
CaP [218]	ViLD [155], MDETR [156]	GPT-3 [189] Codex [190]	Code	API	No	Sim-Mani & Sim-Navi : pick, place, etc.
DEPS [219]	CLIP	ChatGPT [220]	Code	MC-Controller, Steve-1	No	Sim : Minecraft
ConceptGraphs [221]	SAM [31], CLIP, LLaVA [45]	GPT-4	Code (JSON)	API	No	Sim : AI2-THOR; Real (Spot Arm): pick, place

visual question answering (VQA) tasks, along with the additional embodied VQA tasks.

2) *3D Vision*: 3D information is vital in embodied tasks, and thus it is also explored for task planners. Because the majority of current VLMs deal with images as visual inputs, it requires architectural change to VLMs to incorporate 3D visual inputs and therefore they are usually end-to-end models.

LEO [195] identifies the conventional use of image inputs to be a limiting factor for multi-modal generalist agents in interacting with the 3D world. This novel approach involves training an LLM-based architecture using a new dataset with two stages. The first stage focuses on 3D vision-language alignment, followed by the second stage, which involves 3D vision-language-action instruction tuning. LEO demonstrates proficiency not only in 3D captioning and question-answering tasks but also in embodied tasks, including embodied reasoning, embodied navigation, and robotic manipulation.

3D-LLM [198] injects 3D information into LLMs and empowers them to perform 3D tasks, such as 3D-assisted dialog, and navigation. The 3D features can come in diverse forms, including point cloud, gradSLAM, and neural voxel field. MultiPLY [223] is an object-centric embodied LLM that incorporates even more modalities, including audio, tactile, and thermal.

StructFormer [202] addresses the task of arranging objects into complex structures. Previous methods rely on pairwise semantic relations and sequential manipulation, while StructFormer explicitly reasons about the relationships among all ob-

jects and predicts their target positions. StructDiffusion [203] extends this by incorporating a diffusion-based generation approach.

ShapeLLM [207] is built on the novel 3D vision encoder ReCon++, which distills knowledge from multi-view image and text teachers, along with a point cloud MAE. By integrating ReCon++ with LLaMA, ShapeLLM improves embodied interaction performance on their newly proposed 3D benchmark, 3D MM-Vet.

3) *Language-based*: Inner Monologue [208] sits between high-level command and low-level policy to enable closed-loop control planning. It employs LLM to generate language instructions for low-level control policies and dynamically updates these instructions based on feedback received from the control policies. The feedback encompasses various sources: success feedback, object and scene feedback, and human feedback. As the feedback is communicated to the LLM in textual format, no additional training is required for the LLM. A similar approach is also proposed in ReAct [104], which supports more flexible reasoning traces, allowing for more diverse types of reasoning for various tasks.

LLM-Planner [210] introduces a novel approach to constructing a hierarchical policy comprising a high-level planner and a low-level planner. The high-level planner harnesses the capabilities of LLM to generate natural language plans, while the low-level planner translates each subgoal within the plan into primitive actions. While sharing similarities with previous methods in its overall architecture, LLM-Planner distinguishes

Table V: Recent datasets for robot learning. Following the definition in RT-X, skills correspond to verbs, and tasks are different combinations of verbs and objects. * Dataset collected in simulators rather than in the real world. Some datasets are continuously updated; this table is based on the information from their original papers. This table is partially based on [149], [224].

Name	Collection	Visual	Instruction	Embodiment	Skills	Tasks	Scenes	Objects	Episodes
MIME [225]	Human Teleop	RGB, D	Demo	Baxter	12	20	1	-	8.3K
RoboTurk [226] *	Human Teleop	RGB	-	Sawyer	2	-	1	-	2.1K
RoboNet [227]	Scripted	RGB	Goal image	(7 robots)	-	-	10	-	162K
MT-Opt [12]	Scripted	RGB	Lang	(7 robots)	2	12	1	-	800K
BC-Z [130]	Human Teleop	RGB	Lang, Demo	Everyday	3	100	1	-	25.9K
RT-1 [3]	Human Teleop	RGB	Lang	Everyday	12	700+	2	16	130K
MOO [129]	Human Teleop	RGB	Multi-modal	Everyday	5	-	-	106	59.1K
VIMA [176] *	Scripted	RGB	Multi-modal	UR5	17	-	1	29	650K
RoboSet [228]	Human, Scripted	RGB, D	Lang	Franka Panda	12	38	11	-	98.5K
BridgeData V2 [229]	Human, Scripted	RGB, D	Lang	WidowX 250	13	-	24	100+	60.1K
RH20T [224]	Human Teleop	RGB, D	Lang	(4 robots)	42	147	7	-	110K+
DROID [149]	Human Teleop	RGB, D	Lang	Franka Panda	86	-	564	-	76K
OXE [143]	Aggregated Datasets	RGB, D	Lang	(22 robots)	527	160,266	311	-	1M+

itself by incorporating a re-planning mechanism, aiding the robot to “get unstuck”.

Socratic Models (SMs) [211] presents a unique framework wherein diverse pretrained models are effectively composed without the need for finetuning. The framework is based on the key component, named multimodal-informed prompting, facilitating information exchange among models with varied multimodal capabilities. The idea is to utilize multimodal models to convert non-language inputs into language descriptions, effectively unifying different modalities within the language space. Beyond excelling in conventional multimodal tasks, SMs showcases its versatility in robot perception and planning. In addition to natural language plans, task plans can also be represented in the form of pseudocode.

4) *Code-based*: ProgPrompt [213] introduces a novel task-planning approach by prompting LLMs with program-like specifications detailing available actions and objects. This enables LLMs to generate high-level plans for household tasks in a few-shot manner. Environmental feedback can be incorporated through assertions within the program. This prompting scheme leverages the world knowledge and programming skills of LLMs.

ChatGPT for Robotics [216] take advantage of the programming ability of ChatGPT to facilitate “user on the loop” control, a departure from the conventional “engineer in the loop” methodology. The procedure includes several steps: firstly, a list of APIs is defined, such as an object-detection API, a grasp API, a move API; secondly, a prompt is then constructed for ChatGPT, specifying the environment, API functionality, task goal, etc.; thirdly, iteratively prompting ChatGPT to write code with the defined APIs that can execute the task, provided the access to simulation and user feedback for evaluating the code quality and safety; finally, executing the ChatGPT generated code. In this procedure, ChatGPT serves as a high-level task planner, similar to PaLM-E [181], and actions are generated through function calls to corresponding low-level APIs.

Code as policies (CaP) [218] also leverages the code-writing capability of LLMs. It employs GPT-3 [189] or Codex [190] to generate policy code, which, in turn, invokes perception modules and control APIs. CaP exhibits proficiency on spatial-

geometric reasoning, generalization to new instructions, and parameterization for low-level control primitives. By leveraging the multimodal capabilities of GPT-4V, COME-robot [230] eliminates the need for perception APIs in CaP. This also opens up possibilities for open-ended reasoning and adaptive planning within a closed-loop framework, enabling capabilities such as failure recovery and free-form instruction following.

DEPS [219] stands for “Describe, Explain, Plan and Select”. This approach employs an LLM to generate plans and explain failures based on feedback descriptions collected from the environment—a process referred to as “self-explanation”, aiding in re-planning. Additionally, DEPS introduces a trainable goal selector to choose among parallel candidate sub-goals based on how easily they can be achieved, a crucial aspect often overlooked by other high-level task planners.

ConceptGraphs [221] introduces a method to convert observation sequences into open-vocabulary 3D scene graphs. Objects are extracted from RGB images using 2D segmentation models, and VLMs are employed to caption objects and establish inter-object relations, resulting in the formation of the 3D scene graph. This graph can then be translated into a text description (JSON), offering rich semantic and spatial relationships between entities to LLMs for task planning.

Pros and Cons. While end-to-end task planners like SayCan [183] share a similar architecture to low-level control policies and can be optimized for specific tasks, their training costs can be prohibitive due to the large model size of the combined LLM and visual transformer. Language-based task planners offer the advantage of seamless integration with existing language-conditioned control policies. However, they often require finetuning or alignment methods to map the generated plan to executable language instructions for low-level control policies. On the other hand, code-based task planners leverage the programming capability of LLMs to connect perception and action modules. This approach does not require additional training, but its performance may be constrained by the capabilities of existing models.

IV. DATASETS AND BENCHMARKS

The collection of real-world robot data presents significant challenges due to various factors. Firstly, the collection process

Table VI: Simulators for benchmarking VLA models. D: Depth. Seg: segmentation. A: Audio. N: Normals. Force: simulated contact force between the end-effector and the item. PD: Pre-defined. **Vers**: versions. This table is partially based on [231], [232].

Name	Scenes /Rooms	Objects /Cat	UI	Engine	Task	Observation	Action	Agent	Description	Related
Gibson [233]	572/-	-	-	Pybullet	Navi	RGB, D, N, Seg	-	-	Navi only	-
iGibson [232], [234], [235]	15/108	152/5	Mouse, VR	Pybullet	Navi, Mani	RGB, D, Seg, N, Flow, LiDAR	Force	Husky, TurtleBot v2, LoCoBot, etc.	VR, Continuous Extended States. Vers : iGibson 0.5, 1.0, 2.0	Benchmarks: BEHAVIOR-100 [231], BEHAVIOR-1K [236]
SAPIEN [237]	-	2346/-	Code	PhysX	Navi, Mani	RGB, D, Seg	Force	Franka	Articulation, Ray Tracing	VoxPoser
AI2-THOR [238]	-/120	118/118	Mouse	Unity	Navi, Mani	RGB, D, Seg, A	Force, PD	ManipulaTHOR, LoCoBot, etc.	Object States, Task Planning. Vers : [239], [240]	Benchmarks: ALFRED, RoPOR [241]
VirtualHome [242]	7/-	-/509	Lang	Unity	Navi, Mani	RGB, D, Seg, F	Force, PD	Human	Object States, Task Planning	LID, Translated(LM), ProgPrompt
TDW [243]	15/120	112/50	VR	Unity, Flex	Navi, Mani	RGB, D, Seg, A	Force	Fetch, Sawyer, Baxter	Audio, Fluids	-
RLBench [119]	1/-	28/28	Code	Bullet	Mani	RGB, D, Seg	Force	Franka	Tiered Task Difficulty	Hiveformer, PerAct
Meta-World [244]	1/-	80/7	Code	MuJoCo	Mani	Pose	Force	Sawyer	Meta-RL	R3M, VC-1, Vi-PRoM, EmbodiedGPT
CALVIN [245]	4/-	7/5	-	Pybullet	Mani	RGB, D	Force	Franka	Long-horizon Lang-cond tasks	GR-1, HULC, RoboFlamingo
Franka Kitchen [246]	1/-	10/6	VR	MuJoCo	Mani	Pose	Force	Franka	Extended by R3M with RGB	R3M, Voltron, Vi-PRoM, Diffusion Policy, EmbodiedGPT
Habitat [247], [248]	Matterport + Gibson		Mouse	Bullet	Navi	RGB, D, Seg, A	Force	Fetch, Franka, AlienGO	Fast, Navi only. Vers : Rearrangement [249], Habitat 2.0	VC-1, PACT, OVMM [250]
ALFRED [251]	-/120	84/84	-	Unity	Navi, Mani	RGB, D, Seg	PD	Human	Diverse long-horizon tasks	(SL) ³ , LLM-Planner
DMC [252]	1/-	4/4	Code	MuJoCo	Control	RGB, D	Force	-	Continuous RL	VC-1, SMART
OpenAI Gym [253]	1/-	4/4	Code	MuJoCo	Control	RGB	Force	-	Single agent RL environments	-

is hindered by the substantial costs associated with procuring robot equipment, setting up environments, and dedicating extensive human resources. Secondly, the gathering of expert demonstration data requires considerable time investments. Thirdly, the diverse types and configurations of robots introduce inconsistency in sensory data, control modes, gripper types, etc. Lastly, achieving precision in capturing object 6D poses and exactly replicating or resetting setups remains elusive. As a result of these difficulties, public real-world robot datasets are relatively scarce. Furthermore, evaluating a robot system’s performance in real-world conditions introduces another layer of complexity, as it is challenging to precisely reproduce a setup and often requires human supervision. We summarize the robot datasets from recent VLAs in Table V.

Consequently, many researchers resort to simulated environments as a means to mitigate these obstacles and accelerate the data collection process. We compare the most relevant simulators in Table VI. Nevertheless, this strategy presents its own challenges, chief among them being the sim-to-real gap. This discrepancy arises when models trained on simulated data exhibit poor performance in real-world deployment. The causes of this gap are multifaceted, encompassing differences in rendering quality, inaccuracies in physics simulations, and domain shifts characterized by unrealistic object properties and robot motion planners. For instance, simulating non-rigid objects like liquids or towels presents significant difficulties. Moreover, incorporating new objects into simulators requires considerable effort, often involving techniques such as 3D scanning and mesh editing. Despite these hurdles, simulated environments provide automated evaluation metrics that aid researchers in consistently evaluating robotic models. Many benchmarks are based on simulators because only simulated

environments can reproduce the experimental setup exactly, while real-world evaluation varies between different models, making it infeasible to compare them reliably. The HomeRobot OVMM Benchmark [250] proposes a sim-to-real benchmark, yet its consistency remains to be observed.

Several approaches advocate for automated data collection. RoboGen [254] employs a generative simulation paradigm that proposes interesting skills, simulates corresponding environments, and selects optimal learning approaches to train policies for acquiring those skills. AutoRT [255] functions as a robot orchestrator driven by LLMs, generating tasks, filtering them by affordance, and utilizing either autonomous policies or human teleoperators to collect and evaluate data. DIAL [256] focuses on augmenting language instructions in existing datasets using VLMs. RoboPoint [124] generates scenes procedurally with randomized 3D layouts, objects, and camera viewpoints.

An alternative strategy to address the data scarcity issue in real-world settings is to leverage human data. Human behavior offers plentiful guidance for robot policies due to its dexterity and diversity. However, this strategy also comes with inherent drawbacks. Capturing and transferring human hand/body motions to robot embodiments is inherently difficult. Moreover, the inconsistency in human data poses a hurdle, as some data may be egocentric while others are captured from third-person perspectives. Additionally, filtering human data to extract useful information can be labor-intensive. These obstacles underscore the complexities involved in incorporating human data into robot learning processes. Due to limited space, we refer interested readers to a comprehensive comparison of existing datasets in [257].

Furthermore, some datasets and benchmarks may not be

Table VII: Embodied question answering benchmarks. Acc: accuracy. PPL: perplexity.

	# QA	# Videos	Video source	Answer type	Active	Data collection	Metrics
EQA [258]	5K	750 envs	House3D simulator	Answer set 172	Yes	Template	Acc
IQUAD [259]	75K	30 rooms	AI2-THOR	Multiple-choice	Yes	Template	Acc
MT-EQA [260]	19.3K	588 envs	House3D simulator	Binary answer	Yes	Template	Acc
MP3D-EQA [261]	1,136	83 envs	MatterPort3D	Answer set 53	Yes	Template	Acc
EgoVQA [262]	600	16	IU Multi-view	Multiple-choice (1 out of 5)	No	Human annotators	Acc
EgoTaskQA [263]	40K	2K	LEMMA	Answer set (open-answer and binary verifications)	No	Human annotators for relationship triples, then template	Acc
EgoPlan [264]	3,355	2,432 + 923	Epic-Kitchen + Ego4D	Multiple-choice (1 out of 4)	No	GPT-4 filtering, question template, human verification	Acc
OpenEQA [265]	557 + 1079	180 envs	HM3D + ScanNet	Open-answer (LLM scorer)	No	Human annotators	Score
EgoCOT [101]	5,246 plans	129	Ego4D	Caption and planning (not QA)	No	ChatGPT	PPL
EQA-MX [266]	8.2M	750K images	CAESAR simulator	Answer set	No	Question templates, answer set (simulator ground truth)	Acc
LoTa-Bench [267]	17K instruction-plan pairs		AI2-THOR, VirtualHome	Goal condition	-	ALFRED + WAH-NL	Success

directly dedicated to robot manipulation and navigation, but they are aimed at other relevant abilities for embodied AI, such as spatial reasoning, physics understanding, as well as world knowledge. One of the most prominent embodied tasks is embodied question answering (EQA), as summarized in Table VII. EQA is akin to previous visual question answering and video question answering tasks but differs in that the agent can actively explore the environment before providing an answer. EmbodiedQA [258] and IQUAD [259] were among the first works to introduce this task. MT-EQA [260] focuses on questions involving multiple targets, increasing the complexity of understanding and answering the questions. MP3D-EQA [261] converts previous RGB input to point clouds, testing the 3D perception capability. However, active exploration requires access to a simulator, limiting the types of data that can be used, such as real-world videos. Therefore, some EQA benchmarks do not involve active exploration. EgoVQA [262] shifts the focus of VQA to egocentric videos. EgoTaskQA [263] emphasizes spatial, temporal, and causal relationship reasoning. EQA-MX [266] focuses on multimodal expressions (MX), including regular verbal utterances and nonverbal gestures like eye gaze and pointing. OpenEQA [265] evaluates seven main categories, including functional reasoning and world knowledge, which were not covered in previous benchmarks. EgoPlan-Bench [264] and EgoCOT [101] measure the model’s ability to generate task plans, using metrics like accuracy and perplexity. PlanBench [268], [269] comprehensively assesses various aspects of task planning ability, such as cost optimality, plan verification, and replanning, etc. LoTa-Bench [267] directly evaluates task planning by executing the generated plans in simulators and calculating the success rate.

V. CHALLENGES AND FUTURE DIRECTIONS

Vision-language-action (VLA) models face several persistent challenges in the domain of Robotics, necessitating focused attention and concerted research efforts:

Scarcity of Robotic Data. Obtaining sufficient real-world robotic data remains a significant obstacle. Collecting such data is time-consuming and resource-intensive, while relying solely on simulation data exacerbates the sim-to-real gap problem. Diverse real-world robotic datasets require close and extensive collaboration among different institutions. Simulated data depends on the development of more realistic and efficient simulators.

Motion Planning. Current motion planning modules often lack the necessary dexterity to address the complexities in various environments. This limitation hampers robots’ abilities to interact effectively with tools, navigate complex environments, and execute high-precision operations, etc. Overcoming these challenges necessitates the development of more robust motion planning algorithms.

Real-Time Responsiveness. Many robotic applications require real-time decision-making and action execution to meet operational requirements. VLA models should be designed to operate responsively, with minimal latency. Furthermore, the entire stack of a robot system necessitates global optimization, from the high-level task planner down to the motion planner.

Integration of Multiple Modalities. VLAs must process and integrate information from multiple modalities, including vision, language, and action. While significant progress has been made in this regard, achieving optimal integration of these modalities remains an ongoing challenge. Addressing this challenge requires advancements in multi-modal representation learning, fusion techniques, and task-specific adaptation. Expanding beyond mere visual and linguistic capacities, robots can greatly benefit from incorporating modalities like audio or speech. Embracing a broader range of perceptual and communicative abilities empowers robots to engage in more effective collaboration with users.

Generalization to Unseen Scenarios. A truly versatile robotics system should be capable of comprehending and executing natural language instructions across diverse and unseen scenarios. Achieving this level of generalization, akin to the capabilities demonstrated by ChatGPT in natural language processing, requires robustness to variations in instructions, environments, objects, and embodiments. This necessitates the development of adaptable and scalable VLA architectures.

Long-Horizon Task Execution. Single instructions can often translate into long-horizon tasks for robots, such as the instruction “clean the room” which involves object rearrangement, floor sweeping, table wiping, and more. Successfully executing such tasks requires the robot to plan and execute a sequence of low-level actions over extended time horizons. While current high-level task planners have achieved initial success, they still fall short in many scenarios because most LLMs are not tuned to embodied tasks. Addressing this challenge entails devising efficient planners that possess powerful perception abilities and a wide range of common sense.

Foundation Model. The exploration of foundation models for VLAs in robot tasks remains uncharted territory, primarily due to the diverse embodiments, environments, and tasks encountered in robotics. Isolated datasets and evaluation setups further compound this challenge. To establish a robust foundation VLA model for robotics, it is imperative to leverage internet-scale embodied datasets and state-of-the-art multi-modal models.

Multi-agent Systems. The large-scale deployment of robots is highly desirable in many scenarios, but it introduces the challenge of multi-agent cooperation. Effective communication, task distribution among multiple robots can be difficult [270]. Fleet heterogeneity may further complicate these issues. While multi-agent systems offer benefits like distributed perception, collaborative fault recovery, and autonomous fleet maintenance, realizing the full potential of these advantages remains elusive.

Benchmarks. Although numerous benchmarks exist for evaluating low-level control policy VLAs, they often vary significantly in terms of the skills they assess. Additionally, the objects and scenes included in these benchmarks are typically limited by what the simulator can provide. To more comprehensively evaluate VLA models, there is a need for benchmarks that cover a diverse set of skills based on realistic simulators. For high-level task planner VLAs, many benchmarks claim to measure planning capability, often in the form of question-answering tasks. However, it is more desirable to evaluate the high-level task planner together with the low-level control policy to execute long-horizon tasks and measure success rate, rather than relying on isolated measures of the planner alone. This approach provides a more holistic assessment of the VLA system’s capabilities.

Safety Considerations. Safety is paramount in robotics, as robots interact directly with the real world. Ensuring the safety of robotic systems requires the integration of real-world commonsense and complex reasoning into their development and deployment processes. This involves the incorporation of robust safety mechanisms, risk assessment frameworks, and human-robot interaction protocols. Interpretability and expandability of VLA decision-making processes are also crucial for enhancing robot safety through error diagnosis and troubleshooting.

Ethical and Societal Implications. The deployment of robots has always raised various ethical, legal, and societal concerns. These include risks related to privacy, safety, job displacement, bias in decision-making, and the impact on social norms and human relationships. Effective regulation plays a crucial role in promoting the ethical use of robots.

VI. CONCLUSION

VLA policy holds immense promise for enabling embodied AI to interact effectively with the world around them. Recent advances have demonstrated the capabilities of these models in completing complex tasks under diverse conditions. However, significant challenges remain in terms of generalization, efficiency, and safety. Further research is needed to address these challenges and pave the way for the widespread adoption of VLA-powered robots in real-world applications.

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APPENDIX

A. Milestone Unimodal Models.

Vision-language-action models involve three modalities, and consequently, many VLAs depend on existing unimodal models for processing inputs from different modalities. Therefore, it is crucial to summarize representative developments in unimodal models, as they often serve as integral components in VLAs. Specifically, for the vision modality, we collect models designed for image classification, object detection, and image segmentation, as these tasks are particularly relevant for robotic learning. Natural language processing models play a crucial role in enabling VLAs to understand language instructions or generate language responses. Reinforcement learning is a foundational component for obtaining optimal policies, facilitating the generation of appropriate actions in a given environment and condition. A brief time of the development of unimodal models is depicted in Figure 6. Additionally, Figure 7 highlights the progressive increase in model size within these fields.

1) *Computer Vision*: Computer vision witnessed the inception of modern neural networks. In robotics, object classification models can be used to inform a policy about which objects are of interest, and models for object detection or image segmentation can help precisely locate objects. Therefore, we mainly summarize approaches for these tasks, but numerous excellent surveys on visual models, ranging from convolutional neural networks (CNNs) [17] to Transformers [18], offer more detailed insights. Interested readers are directed to these surveys for a more comprehensive introduction. Here, we will briefly touch upon some of the key developments in the field of computer vision.

a) *Convolutional neural network*.: Early developments in computer vision (CV) were primarily focused on the image classification task. LeNet [271] was among the first convolutional neural networks, designed for identifying handwritten digits in zip codes. In 2012, AlexNet [4] emerged as a breakthrough by winning the ImageNet challenge, showcasing the potential of neural networks. VGG [272] demonstrated the benefits of increasing the depth of CNNs. GoogLeNet [273], also known as Inception-V1, introduced the concept of blocks. ResNet [29] introduced skip connections or residual connections. Inception-ResNet [274], as the name suggests, combines residual connects and inception blocks. ResNeXt [275] explored the concept of split, transform, and merge. SENet [276] introduces the squeeze-and-excitation blocks, utilizing a type of attention mechanism. EfficientNet [132] studied the width, depth, and resolution of CNN models with “compound scaling”, highlighting the trade-off between efficiency and performance.

Alongside image classification, object detection became an integral component in many applications. Building upon the success of image classification backbone networks, a series of works optimized region-based methods: R-CNN [277], Fast R-CNN [278], Faster R-CNN [279], and Mask R-CNN [74]. Grid-based methods like YOLO [217] are also widely adopted. Bottom-up, top-down is also a popular strategy, employed by FPN [280], RetinaNet [281], BUTD [282], etc. In scenarios

requiring more detailed and precise object detection, image segmentation aims to determine the exact outline of objects. Many popular models adopt an “encoder-decoder” architecture, where the encoder understands both the global and local context of the image, and the decoder produces a segmentation map based on this context information. Representative works following this idea include FCN [283], SegNet [284], Mask R-CNN [74], and U-Net [115].

b) *Vision Transformer*.: Convolutional neural networks (CNNs) have historically been the foundation of computer vision models. However, the landscape shifted with the introduction of the Transformer architecture in the seminal work by [7]. This paradigm shift was initiated by ViT [30]. It revolutionizes image processing by breaking down images into 16-by-16 pixel patches, treating each as a token akin to those in NLP; leveraging a BERT-like model, ViT encodes these patches and has exhibited superior performance over many traditional CNN models in image classification tasks.

The transformative power of the Transformer extends beyond classification. DETR [285] employs an encoder-decoder Transformer architecture to tackle object detection. The encoder processes the input image, and its output embeddings are fed into the decoder through cross-attention. Notably, DETR introduces learnable object queries to the decoder, facilitating the extraction of crucial object-wise information from the encoder’s output. Venturing into image segmentation, Segmenter [286] was the first to utilize Transformer on this task. The Segment Anything model (SAM) [31] achieves remarkable milestones in promptable segmentation, zero-shot performance, and versatile architecture, further underlining the transformative impact of Vision Transformer models in various computer vision domains.

c) *Vision in 3D*.: Aside from the most common RGB data, other types of visual inputs are widely used [287], [288]. In robotics, depth maps are useful since they provide essential 3D information that is not explicitly stored in RGB images. Depth maps can be captured with Microsoft Kinect ¹ or Intel RealSense ² or recovered from pure RGB images. Point clouds [289] are also popular visual input types due to the widespread adoption of LiDARs and 3D scanners; depth maps can be easily converted to point clouds. Volumetric data [290], such as voxels or octrees, is usually more information-rich than depth maps and is suitable for representing rigid objects. Despite the widespread use of 3D meshes as the default data format in computer graphics, their irregular nature poses challenges for neural networks [291].

2) *Natural Language Processing*: Natural Language Processing (NLP) plays a pivotal role in VLA, serving as a vital component for understanding user instructions, or even generating appropriate textual responses. The recent surge in NLP owes much to the success of Transformer models [7]. In the landscape of contemporary NLP, there is a noticeable shift towards implicit learning of language syntax and semantics, a departure from the previous paradigms. To provide context, this subsection will commence with a concise overview of

¹<https://azure.microsoft.com/en-us/products/kinect-dk/>

²<https://www.intelrealsense.com>

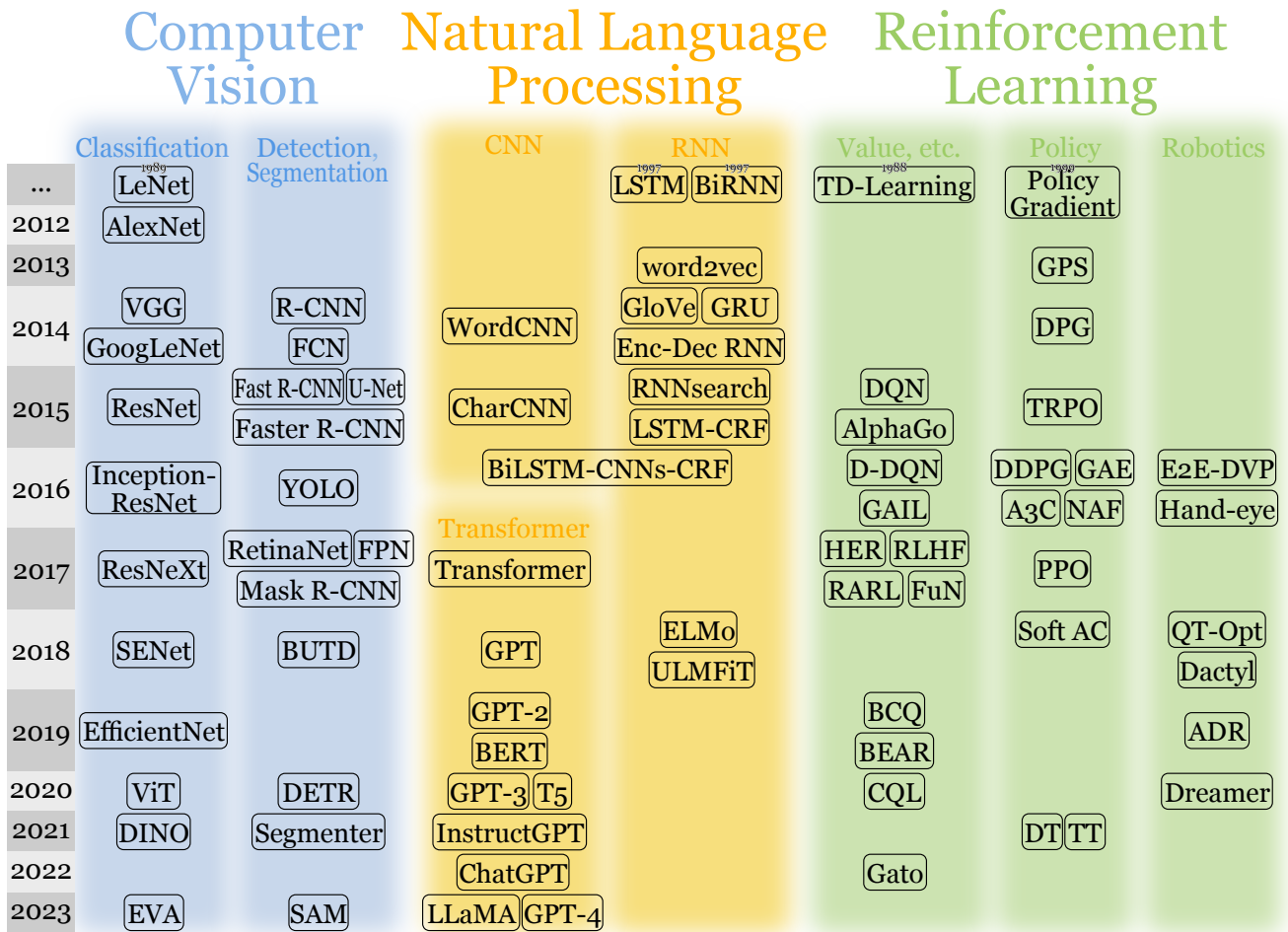


Figure 6: A brief timeline of pivotal unimodal models leading to the development of vision-language-action models, organized by their publication years. Details can be found in Appendix:A.

fundamental yet enduring concepts before delving into the noteworthy advancements in contemporary NLP. For an in-depth exploration of the progress in the NLP domain, readers are directed to comprehensive surveys by [19] and [20], which meticulously reviews the trajectory of advancements in NLP.

a) Early developments.: The field of NLP, which was more frequently referred to as Computational Linguistics (CL) in the early days, tries to solve various tasks regarding to natural language. In CL, natural languages used to be processed in a hierarchical way: word, syntax, and semantics. Firstly, on the word level, many aspects need to be accounted for, including morphology, lexicology, phonology, etc. This leads to problems like tokenization, lemmatization, stemming, semantic relations, word sense disambiguation, and Zipf’s Law problem. Then in terms of syntax, natural language, in contrast to formal language, has much less restricted grammar and thus is more challenging to parse: in the Chomsky hierarchy, natural language is generally considered to follow context-sensitive grammar while programming languages are covered under context-free grammar. Syntactic parsing includes tasks such as part-of-speech tagging, constituency parsing, dependency parsing, and named entity recognition. Finally, to understand the semantics of a sentence in written language or an utterance

in spoken language, the following tasks were studied: semantic role labeling, frame semantic parsing, abstract meaning representation, logical form parsing, etc.

b) Recurrent neural network & convolutional neural network.: In the initial stages of NLP, rudimentary models relied on simple feed-forward neural networks to tackle various tasks [292]. After the introduction of word embeddings like word2vec [293], [294] and GloVe [295], NLP techniques embraced recurrent neural networks (RNNs) [296], such as LSTM [6], GRU [32], RNNsearch [297], LSTM-CRF [298], etc. Examples of representative RNNs in NLP include ELMo [299] and ULMFiT [300]. While RNNs played a significant role, alternative models utilizing convolutional neural networks also emerged. WordCNN [301] employed CNNs at the word level, with word2vec features serving as input to the CNNs. Another approach, CharCNN [302], focused on modeling language at the character level with CNN. Subsequent research [303] highlighted that character-level CNNs excel at capturing word morphology, and their combination with a word-level LSTM backbone can significantly enhance performance.

c) Transformer & large language model.: The groundbreaking Transformer model, introduced by [7], revolutionized natural language processing through the introduction of the

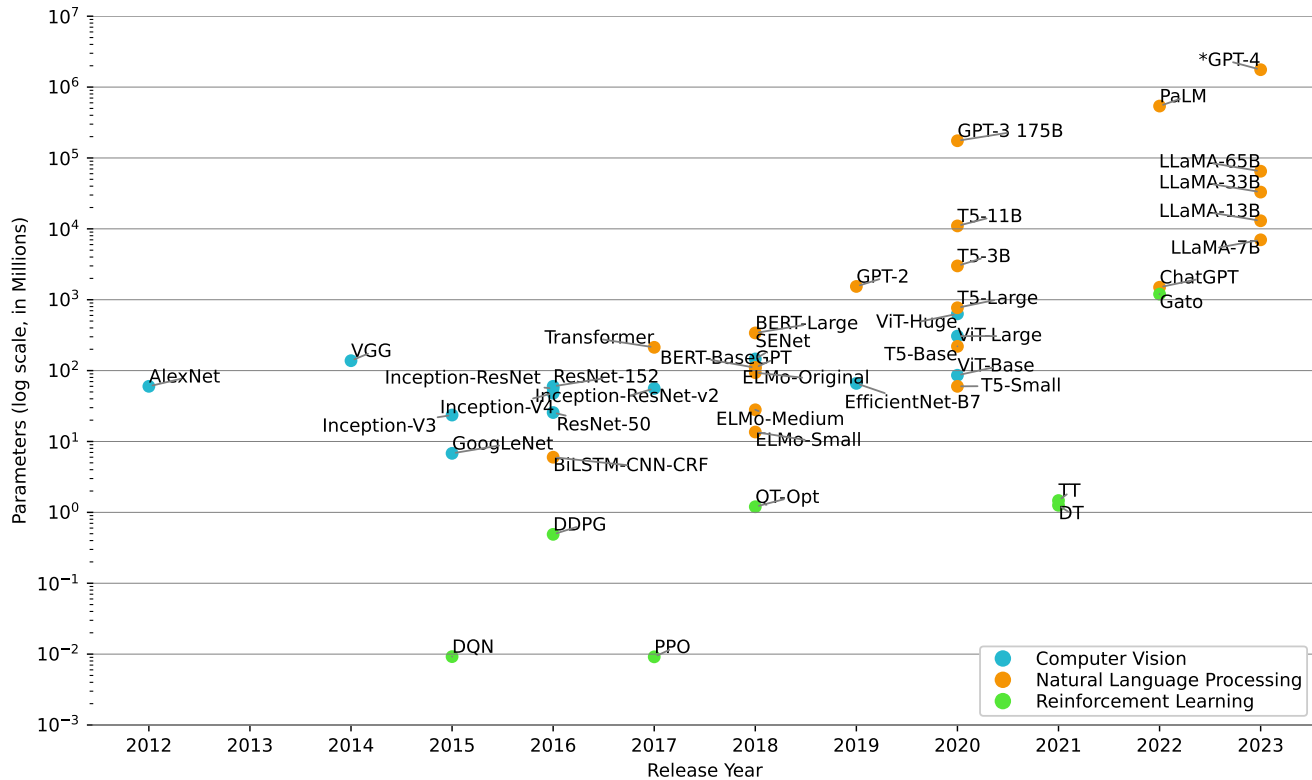


Figure 7: The growing scale of unimodal models over the years. *GPT-4’s model size is estimated since it has not been officially disclosed.

self-attention mechanism, inspiring a cascade of subsequent works. BERT [33] leverages the Transformer encoder stack, excelling in natural language understanding. On the other hand, the GPT family [42], [157], [187], [189] is built upon Transformer decoder blocks, showcasing prowess in natural language generation tasks. A line of work strives to refine the original BERT, including RoBERTa [212], ALBERT [304], ELECTRA [305]. Simultaneously, a parallel line of research following the GPT paradigm has given rise to models like XLNet [306], OPT [307]. BART [308], an encoder-decoder Transformer, distinguishes itself through pretraining using the denoising sequence-to-sequence task. Meanwhile, T5 [10] introduces modifications to the original Transformer, maintaining the encoder-decoder architecture. T5 unifies various NLP tasks through a shared text-to-text format, exhibiting enhanced performance in transfer learning. These diverse models collectively showcase the versatility and ongoing evolution within the NLP landscape.

Over the past few years, there has been a remarkable expansion in the size of language models, driven by the scalability of the Transformer architecture. This trend has given rise to a series of large language models (LLMs) that have demonstrated breakthrough performance and capabilities not achievable with smaller models. A landmark model in this evolution is ChatGPT [1], which has sparked considerable interest and inspired a series of works in this domain, such as GPT-4 [157], PaLM [185], PaLM-2 [309], LLaMA

[150], LLaMA 2 [147], ERNIE 3.5 [310]. Notably, LLaMA stands out as one of the few open-source LLMs, fostering interesting developments. The introduction of “instruction-tuning” has allowed efficient fine-tuning of a pretrained LLM to become an instruction-following model. This technique is popularized by InstructGPT [220] and FLAN [186], [311]. Recent advancements in instruction-following models include Alpaca [312], employing self-instruction, and Vicuna [125], leveraging conversations from ShareGPT. As LLMs grow in scale and power, there is a shift away from the need for fine-tuning on downstream tasks. With appropriate prompts, LLMs can produce accurate outputs without task-specific training, a paradigm known as *prompt engineering*. This approach differs from the traditional *pretrain-finetune* paradigm.

3) *Reinforcement Learning*: Reinforcement learning (RL) seeks to acquire a policy capable of taking optimal actions based on observations of the environment. Numerous vision-language-action models are constructed based on paradigms such as imitation learning or Temporal Difference (TD) learning within RL. Many challenges faced in the development of robotic policies can be effectively addressed through insights gained from the field of RL. Consequently, delving into RL methods presents a valuable avenue for enhancing robotic learning. For a deeper exploration of RL methods, readers can refer to more comprehensive reviews provided by [21], [22], and [23].

a) *Deep reinforcement learning*.: The advent of deep reinforcement learning can be attributed to the success of pioneering models, Deep Q-Network [34] and AlphaGo [35]. Deep learning, with its ability to provide low-dimensional representations, proved instrumental in overcoming traditional computational and memory complexity challenges in reinforcement learning. In recent years, a multitude of value-function based approaches has surfaced. Double DQN (D-DQN) [313] addresses the action value overestimation issue of DQN. Hindsight experience replay (HER) [314] focuses on the sparse reward issue. Batch-Constrained deep Q-learning (BCQ) [315] presents an approach aimed at enhancing off-policy learning by constraining the action space. BEAR [316] endeavors to alleviate instability arising from bootstrapping errors in off-policy RL. [317] introduces conservative Q-learning (CQL) to address the overestimation of values by standard off-policy RL methods.

Another paradigm within reinforcement learning is policy search, encompassing methods such as policy gradient and actor-critic techniques. These approaches aim to combat persistent challenges, including instability, slow convergence, and data inefficiency. Guided policy search (GPS) [318] learns a policy with importance sampling guided by another controller toward a local optimum. Deterministic policy gradient (DPG) [319], deep deterministic policy gradient (DDPG) [320], asynchronous advantage actor-critic (A3C) [321] improve efficiency without compromising stability. Normalized advantage functions (NAF) [322] is a continuous variant of Q-learning, allowing for Q-learning with experience replay. Soft actor-critic (Soft AC) [323] take advantage of maximum entropy RL framework to lower sample complexity and improve convergence properties. Trust region policy optimization (TRPO) [324] and proximal policy optimization (PPO) [36] utilize trust region methods to stabilize policy gradients, with PPO additionally incorporating a truncated generalized advantage estimation (GAE) [325].

Beyond these, various other RL methodologies exist, such as imitation learning and hierarchical reinforcement learning. Generative adversarial imitation learning (GAIL) [326] is an imitation learning method that uses a generative adversarial framework to discriminate expert trajectories against generated trajectories. Robust adversarial reinforcement learning (RARL) [327] incorporates adversarial agents to enhance generalization. RLHF [328] utilizes human preferences without access to the reward function. FeUdal Networks (FuN) [329] introduce a hierarchical reinforcement learning architecture featuring a Manager module and a Worker module.

b) *Robotics*.: In the field of RL, robotics stands out as one of the most prevalent and impactful applications. A noteworthy contribution to this field is E2E-DVP [330]. This pioneering model represents one of the first end-to-end solutions for robotic control. Its neural network is designed to take raw images as input and generate motor torques as output. [9] curated a substantial real-world dataset and developed a CNN that predicts grasps based on monocular input images. Building upon these foundations, QT-Opt [331] further expands the dataset and model scale, introducing closed-loop control capabilities to enhance robotic control systems.

Then Dreamer [79] addresses long-horizon tasks. OpenAI also developed a dexterous robot hand that can solve the Rubik's cube [37], [332].

4) *Graph*: Graph is ubiquitous in many scenarios, such as social network, molecule structure, 3D object meshes, etc. Even images and text can be modeled as 2D grid and linear graph (path graph), respectively. To process graph-structured data, recurrent graph neural networks [333] were first introduced, which were later optimized by convolutional graph neural networks. The review of graph neural networks (GNN) [24] can be referred to for more in-depth details.

Convolutional graph neural networks can be generally divided into two categories: spectral-based and spatial-based. Spectral-based convolutional GNNs draw inspiration from graph signal processing, which provides theoretical support for the design of the networks. However, spatial-based convolutional GNNs have advantage in terms of their efficiency and flexibility. Spectral CNN [334] is one of the first convolutional GNNs but it is not robust to changes in graph structure and has high computational cost. ChebNet [335] and GCN [336] significantly reduced the cost: ChebNet used approximation based on Chebyshev polynomials and GCN is its first-order approximation. Neural Network for Graphs (NN4G) [337] is the first spatial network. MPNN [338] introduced a general framework of spatial-based networks under which most existing GNNs can be covered. But the drawback of MPNN is that it does not embed graph structure information, which is later solved by GIN [339]. GraphSage [340] improves efficiency by sampling a fixed number of neighbors. Graph Attention Network (GAT) [341] incorporates the attention mechanism.

Besides recurrent and convolutional graph neural networks, there are graph autoencoders [342], [343] and spatial-temporal graph neural networks [344]. Equivariant message passing networks are recently introduced to handle 3D graphs, including E(n)- and SE(3)- Equivariant GNN [345], [346]. Graph Transformer models make use of the power of transformers to processing graph data. There are already over 20 such graph Transformer models, such as GROVER [347] and SE(3)-Transformers [348].

a) *Graph and vision*: Graph structures also exist in some computer vision tasks. Scene graph [349] can be used to express object relationships in most visual inputs. In addition to detecting objects in an image, scene graph generation necessitates the understanding of the relationships between detected objects. For example, a model needs to detect a person and a cup, and then understand that the person is holding the cup, which is the relationship between the two objects. Knowledge graphs often contain visual illustrations, such as WikiData. Those graph can be helpful in downstream computer vision tasks.

b) *Graph and language*: Graph structures are ubiquitous in language data [350]. Word-level graphs include dependency graph, constituency graph, AMR graph, etc. Word-level means each node of those graphs corresponds to a word in the original text. There graphs can be used to explicitly represent the syntax or semantics of the raw sentence. Sentence-level graphs can be useful in dialog tracking [351], fact checking [352], etc. Document-level graphs include knowledge graphs [353],

citation graphs [354], etc. They can be used in document-level tasks, such as document retrieval, document clustering, etc. Different types language graphs are often processed using aforementioned GNNs to facilitate downstream tasks.

B. Vision-Language Models

Comprehensive surveys on VLMs exist, covering early BERT-based VLMs [8], [25] (Section B1), as well as more recent VLMs with contrastive pretraining [26], [27] (Section B2). Given the rapid evolution of this field and the emergence of new VLMs based on large language models, commonly known as large multi-modal models (LMMs), we also compile the latest developments of LMMs (Section B3). To compare the most representative VLMs, we include their specifications in Table VIII.

1) *Self-supervised pretraining*: The evolution of the Transformer architecture to accommodate various modalities has given rise to robust multi-modal Transformer models. Initial VLMs based on BERT can be broadly categorized into two types: single-stream and multi-stream [8]. Single-stream models employ a single stack of Transformer blocks to process both visual and linguistic inputs, whereas multi-stream models utilize a separate Transformer stack for each modality, with Transformer cross-attention layers exchanging multi-modal information. To enhance alignment among modalities, these models incorporate various pretraining tasks aimed at absorbing knowledge from out-of-domain data. ViLBERT [43] stands as the pioneer in this line of work, featuring a multi-stream Transformer architecture. Text input undergoes standard processing in the language Transformer; image input is first processed using Faster R-CNN, and the output embeddings of all objects are then passed into the vision stream. The two Transformer outputs—language embeddings and vision embeddings—are combined using a novel co-attention transformer layer. VL-BERT [357] adopts a single-stream multi-modal Transformer, simply concatenating vision and language tokens into a single input sequence. VideoBERT [395] adapts multi-modal Transformer models to video inputs. UNITER [358] proposes the word-region alignment loss to explicitly align word with image regions. ViLT [359] uses ViT-style [30] image patch projection to embed images, deviating from previous region or grid features.

SimVLM [360] opts for a streamlined approach, relying solely on a single prefix language modeling objective to reduce training costs. VLMo [396] and BEiT-3 [364] both introduce mixture-of-modality-experts Transformers to effectively handle multi-modal inputs.

2) *Contrastive pretraining*: Vision-language pretraining in the initial series of BERT-based VLMs has evolved, with refinements such as curating larger-scale pretraining datasets, leveraging multi-modal contrastive learning, and exploring specialized multi-modal architectures. CLIP [44] is one of the earliest attempts in vision-language contrastive pretraining. By contrastive pretraining on a large-scale image-text pair dataset, CLIP exhibits the capability to be transferred to downstream tasks in a zero-shot fashion. In the same line of work, other few-/zero-shot learners have emerged. FILIP

[365] concentrates on finer-grained multi-modal interactions with a token-wise contrastive objective. ALIGN [366] focuses on learning from noisy datasets collected without filtering and post-processing. “Locked-image Tuning” (LiT) [397] posits that only training the text model while freezing the image model yields the best results on new tasks. In Frozen [398], the pretrained language model is frozen and a vision encoder is trained to produce image embeddings as a part of language model prompts, exemplifying an instance of prompt tuning.

Unlike the two-tower frameworks of CLIP, FILIP, and ALIGN, which solely train unimodal encoders (image encoder and text encoder), ALBEF [368] additionally incorporates training a multimodal encoder on top of the unimodal encoders, with FLAVA [369] sharing a similar idea. In contrast to contrastive pretraining methods, CoCa [399] seeks to amalgamate the strengths of CLIP’s contrastive learning and SimVLM’s generative objective. Florence [363] generalizes representations from coarse, scene-level to fine, object-level, expands from images to videos, and encompasses modalities beyond RGB channels. OFA [400] draws inspiration from T5 [10] and proposes unifying diverse unimodal and multi-modal tasks under a sequence-to-sequence learning framework.

3) *Large multi-modal model*: Large language models (LLMs) encapsulate extensive knowledge, and efforts have been made to transfer this knowledge to multi-modal tasks. Given the resource-intensive nature of fine-tuning entire LLMs on multi-modal tasks due to their large size, various techniques have been explored to effectively connect frozen LLMs with vision encoders, enabling the combined model to acquire multi-modal capabilities. Flamingo [11] connects pretrained vision encoder, NFNet [372], and a large language model, Chinchilla [373], by inserting trainable gated cross-attention layers while keeping the rest of the model frozen. BLIP-2 [16] introduces Q-Former, bootstrapping vision-language representation learning first from a frozen CLIP ViT [44] and then from a frozen LLM, OPT [307] or Flan-T5 [311]. PaLI [139] and PaLI-X [140] investigate the advantages of jointly scaling up the vision and language components using large-scale multilingual image-text data.

Similar to developments in NLP, instruction-following has become a crucial aspect of VLMs, prompting the exploration of various multi-modal instruction-tuning methods. LLaMA-Adapter [376], [377] employs a parameter-efficient finetuning (PEFT) technique, enabling LLaMA [150] to process visual inputs. Kosmos-1 [378] introduces a less restrictive input format that accommodates interleaved image and text. Its Magneto LLM [380] serves as a “general-purpose interface” for docking with perception modules [44]. Kosmos-2 [379] adds additional grounding and referring capabilities. InstructBLIP [381] achieves instruction-following using an instruction-aware Q-Former based on BLIP-2’s Q-Former [16]. Comparable to Kosmos-2, ChatSpot [387] excels at following precise referring instructions, utilizing CLIP ViT [44] and Vicuna [125]. X-LLM [392] converts multi-modality data into LLM inputs using X2L interfaces and treats them as foreign languages, where the X2L interface is inspired by the Q-Former from BLIP-2 [16]. mPLUG-Owl [388], [389] introduces a two-stage training paradigm that establishes a

Table VIII: Vision-language models. In the “Objective” column: “MLM”: masked language modeling, “MVM”: masked vision modeling, reconstructing masked image regions. “VLM”: binary classification of whether vision and language inputs are a match. “LM”: autoregressive language modeling, “VLCL”: vision-language contrastive learning. We only include representative multi-modal datasets due to limited space. “MM” includes multi-modal tasks such as visual question answering, image captioning, and vision-language retrieval. “Vision” represents computer vision tasks, like image classification. “Language” represents natural language processing tasks.

	Vision Encoder			Language Encoder		VL-Fusion	Objectives	Datasets	Tasks
	Model	Name	Params	Name	Params				
Self-supervised	ViLBERT [43]	Faster R-CNN [279], [282]	44M	Dual-stream BERT-base [33]	221M	Dual-stream	MLM, MVM, VLM	COCO, VG	MM
	LXMERT [355]	Faster R-CNN [279], [282]	44M	Dual-stream BERT-base [33]	183M	Dual-stream	MLM, MVM, VLM, VQA	COCO, VG, VQA, GQA, VGQA	MM
	VisualBERT [356]	Faster R-CNN [279], [282]	60M	BERT-base [33]	110M	Single-stream	MLM, VLM	COCO	MM
	VL-BERT [357]	Faster R-CNN [279], [282]	44M	BERT-base [33]	110M	Single-stream	MLM, MVM	CC	MM
	UNITER [358]	Faster R-CNN [279], [282]	44M	BERT-base/ BERT-large [33]	86M/ 303M	Single-stream	MLM, VLM, MVM, WRA	COCO, VG, SBU, CC	MM
	ViLT [359]	Linear projection [30]	2.4M	BERT-base [33]	85M	Single-stream	MLM, VLM	COCO, VG, SBU, CC	MM
	SimVLM [360]	ViT/CoAtNet-huge (shared encoder) [361]	632M	Shared encoder	632M	Single-stream	PrefixLM	ALIGN dataset	MM
	GIT [362]	Florence [363]	637M	Transformer [7]	60M	Single-stream	LM	COCO, VG, SBU, CC, etc.	MM
	BEiT-3 [364]	V-FFN (+Shared Attn)	692M (+317M)	L-FFN (+Shared Attn)	692M (+317M)	Modality experts	MLM, VLM	COCO, VG, SBU, CC	MM, Vision
Contrastive	CLIP [44]	ViT [30]	428M	GPT-2 [187]	63M	Two-tower	VLCL	WTI	Vision
	FILIP [365]	ViT-L/14 [30]	428M	GPT [187]	117M	Two-tower	VLCL	FILIP300M (Self-collect)	MM, Vision
	ALIGN [366]	EfficientNet-L2 [367]	480M	BERT-large [33]	336M	Two-tower	VLCL	ALIGN dataset (Self-collect)	MM, Vision
	ALBEF [368]	ViT-B/16 [30]	87M	BERT-base [33]	85M	Dual-stream	MLM, VLM, VLCL	COCO, VG, CC, SBU	MM
	FLAVA [369]	ViT-B/16 [30]	87M	RoBERTa-base [212]	125M	Dual-stream	MLM, MVM, VLM, VLCL	COCO, VG, CC, SBU, etc. (PMD)	MM, Vision, Language
	Florence [363]	Hierarchical Vision Transformers [370], [371]	637M	RoBERTa [212]	125M	Two-tower	VLCL	FLD-900M (Self-collect)	Vision
Large Multi-modal Model	Flamingo [11]	NFNet-F6 [372]	438M	Chinchilla [373]	70B	Dual-stream	LM	M3W, ALIGN dataset, LTIP, VTP	MM
	BLIP-2 [16]	CLIP ViT-L/14 [44], EVA ViT-G/14 [193] + Q-Former	428M, 1B	OPT [307] Flan-T5 [311]	6.7B 3B/11B	Single-stream	BLIP, LM	COCO, VG, CC, SBU, LAION	MM
	PaLI [139]	ViT-e [139]	4B	mT5-XXL [374]	13B	Single-stream	Mixed	WebLI, etc	MM
	PaLI-X [140]	ViT-22B [138]	22B	UL2 [375]	32B	Single-stream	Mixed	WebLI, etc	MM
	LLaMA-Adapter [376]	CLIP ViT-B/16 [44]	87M	LLaMA [150]	7B	Single-stream	LM	Self-instruct	Instruction-following
	LLaMA-Adapter-V2 [377]	CLIP ViT-L/14 [44]	428M	LLaMA [150]	7B	Single-stream	LM	GPT-4-LLM, COCO, ShareGPT	Instruction-following
	Kosmos-1 [378], Kosmos-2 [379]	CLIP ViT-L/14 [44]	428M	Magneto [380]	1.3B	Single-stream	LM	LAION, COYO, CC; Unnatural Instructions, FLANv2	Instruction-following (Kosmos-2 w/ grounding, referring)
	InstructBLIP [381]	EVA ViT-G/14 [193]	1B	Flan-T5 [311] Vicuna [125]	3B/11B 7B/13B	Single-stream	BLIP, LM	COCO, VQA, LLaVA-Instruct-150K, etc. (26 datasets)	Instruction-following
	LLaVA [45]	CLIP ViT-L/14 [44]	428M	LLaMA [150]	13B	Single-stream	LM	CC, (FT: GPT-assisted Visual Instruction Data Generation)	Instruction-following
	MiniGPT-4 [382]	EVA ViT-G/14 [193] + Q-Former [16]	1B	Vicuna [125] LLaMA2 [147]	7B/13B 7B	Single-stream	LM	CC, SBU, LAION (FT: SC)	Instruction-following
	Video-LLaMA [383]	EVA ViT-G/14 [193] + Q-Former [16]	1B	LLaMA [150]	7B/13B	Single-stream	BLIP, LM	CC595k	Instruction-following
	PandaGPT [209]	ImageBind ViT-H [384]	632M	Vicuna [125]	13B	Single-stream	LM	(FT: LLaVA data, MiniGPT-4 data)	Instruction-following
	VideoChat [385]	EVA ViT-G/14 [193] + Q-Former [16]	1B	StableVicuna [386]	13B	Single-stream	LM	COCO, VG, CC, SBU (FT: SC, MiniGPT-4, LLaVA data)	Instruction-following
	ChatSpot [387]	CLIP ViT-L/14 [44]	428M	Vicuna [125]	7B	Single-stream	LM	MGVLID, RegionChat	Instruction-following, Vision
	mPLUG-Owl [388], mPLUG-Owl2 [389]	CLIP ViT-L/14 [44] + Visual Abstractor	428M	LLaMA [150]	7B	Single-stream	LM	LAION, COYO, CC, COCO (FT: Alpaca, Vicuna, Baize [390] data)	Instruction-following
	Visual ChatGPT [391]	(22 different models)	-	ChatGPT [1]	-	Prompt Manager	-	Add image understanding and generation to ChatGPT	
	X-LLM [392]	ViT-G [393] + Q-Former [16] + Adapter	1.8B	ChatGLM [394]	6B	Single-stream	Three-stage training	MiniGPT-4 data, AISHELL-2, ActivityNet, VSDial-CN (SC)	Instruction-following

connection between a pretrained LLM with visual encoder and visual abstractor, thereby endowing LLMs with multi-modality abilities. Visual ChatGPT [391] proposes a prompt manager that manages the interaction between ChatGPT and 22 visual foundation models, with the goal of equipping ChatGPT with the capability to understand and generate images.

Rather than employing intricate mechanisms to connect components for different modalities, both LLaVA [45] and MiniGPT-4 [382] propose connecting vision encoders with LLMs through a single linear layer. LLaVA adopts a two-stage instruction-tuning approach, pretraining the CLIP ViT vision encoder [44] in the first stage and finetuning the linear layer and the LLaMA LLM [150] in the second stage. In contrast, MiniGPT-4 freezes both the vision encoder (BLIP-2’s ViT + Q-Former [16]) and the Vicuna LLM [125], only training the linear layer. Following MiniGPT-4, Video-LLaMA [383] handles videos by incorporating two branches for video and audio, each comprising a video/audio encoder and a BLIP-2-style Q-Former [16]. PandaGPT [209] leverages ImageBind [384] to encode vision/text/audio/depth/thermal/IMU data, feeding them to the Vicuna model [125] also through a linear layer. PandaGPT diverges from MiniGPT-4 by using LoRA [401] to train Vicuna alongside the linear layer.

C. Self-attention

Transformer [7] is built upon the novel Multi-head Self-Attention mechanism:

$$\begin{aligned}\text{MultiHead}(Q, K, V) &= \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \\ \text{head}_i &= \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \\ \text{Attention}(Q, K, V) &= \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V\end{aligned}$$

where the trainable weights are $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$; d_{model} , d_k , d_v are hyperparameters and h is the number of self-attention heads. Because it is permutation equivariant, positional encodings are injected into the token embeddings.

Two representative lines of Transformers were BERT [33] and GPT [42], [187], [189]. BERT [33] is a deep bidirectional Transformer, which is a stack of Transformer encoder layers:

$$\begin{aligned}X &= \text{MultiHead}(E_{\text{out}}^{l-1}, E_{\text{out}}^{l-1}, E_{\text{out}}^{l-1}) \\ X' &= \text{LayerNorm}(X + E_{\text{out}}^{l-1}) \\ E_{\text{out}}^l &= \text{LayerNorm}(\text{FFN}(X') + X')\end{aligned}$$

where E_{out}^l are the encoder output at the l^{th} layer. In BERT pre-training, *masked language modeling* (MLM) was proposed. It is a self-supervised setting where the model needs to predict the tokens that are masked out (with a probability of 15%) from the remaining tokens.

GPT models [42], [187], [189] are a stack of Transformer decoders:

$$\begin{aligned}X &= \text{MaskedMultiHead}(D_{\text{out}}^{l-1}, D_{\text{out}}^{l-1}, D_{\text{out}}^{l-1}) \\ X' &= \text{LayerNorm}(X + D_{\text{out}}^{l-1}) \\ D_{\text{out}}^l &= \text{LayerNorm}(\text{FFN}(X') + X')\end{aligned}$$

where D_{out}^l are the decoder output at the l^{th} layer.

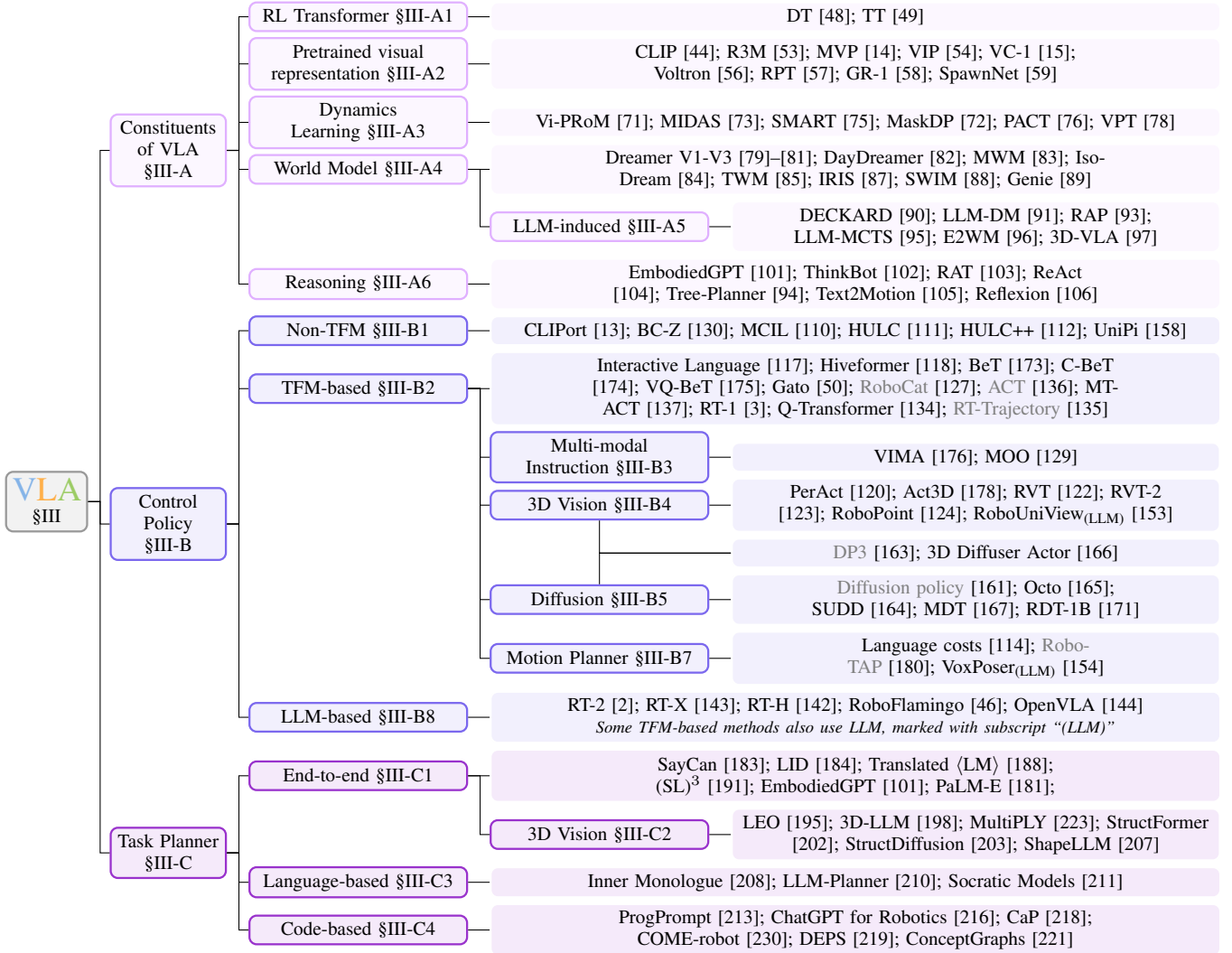


Figure 8: The taxonomy of VLA models. Control policies in gray text are closely related to VLAs but cannot be strictly classified as VLAs, as they do not utilize language instructions.