From Specific-MLLMs to Omni-MLLMs: A Survey on MLLMs Aligned with Multi-modalities

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Abstract

To tackle complex tasks in real-world scenarios, more researchers are focusing on Omni-MLLMs, which aim to achieve omni-modal understanding and generation. Beyond the constraints of any specific non-linguistic modality, Omni-MLLMs map various non-linguistic modalities into the embedding space of LLMs and enable the interaction and understanding of arbitrary combinations of modalities within a single model. In this paper, we systematically investigate relevant research and provide a comprehensive survey of Omni-MLLMs. Specifically, we first explain the four core components of Omni-MLLMs for unified multi-modal modeling with a meticulous taxonomy that offers novel perspectives. Then, we introduce the effective integration achieved through two-stage training and discuss the corresponding datasets as well as evaluation. Furthermore, we summarize the main challenges of current Omni-MLLMs and outline future directions. We hope this paper serves as an introduction for beginners and promotes the advancement of related research. Resources will be made public.

1 Introduction

The remarkable performance of continuously evolving Multi-modal Large Language Models (MLLMs) has pointed to a possible direction for achieving general artificial intelligence (Bubeck et al., 2023; OpenAI, 2023b). MLLMs extend Large Language Models (LLMs) by integrating them with pre-trained models tailored to specific modalities, such as Vision-MLLMs (Liu et al., 2023c; Wang et al., 2024b; Sun et al., 2024c), Audio-MLLMs (Zhang et al., 2023a; Chu et al., 2023), and 3D-MLLMs (Xu et al., 2024b). However, these modality-specific MLLMs (Specific-MLLMs) are insufficient to tackle complex tasks in real-world scenarios that simultaneously involve multiple modalities. Therefore, efforts are being made to expand the range of modalities for understanding and generation, giving rise to the omni-modality MLLMs (Omni-MLLMs).

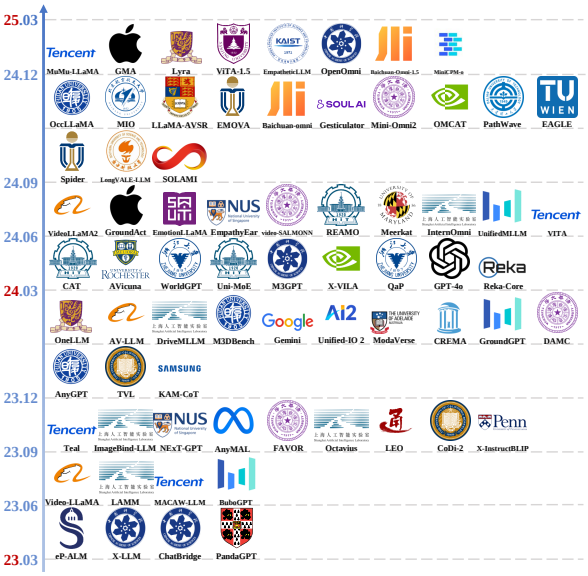

Figure 1: The timeline of representative Omni-MLLMs.

By integrating multiple pre-trained models of more non-linguistic modalities (Radford et al., 2021, 2023; Xue et al., 2024b; Rombach et al., 2022; Liu et al., 2023b), Omni-MLLMs expand the modalities for understanding and even generation based on Specific-MLLMs. Omni-MLLMs leverage the emergent capabilities of LLMs to treat various non-linguistic modalities as different *foreign languages*, enabling the interaction and understanding of information across different modalities within a unified space (Chen et al., 2023a; Panagopoulou et al., 2024). Compared to Specific-MLLMs, Omni-MLLMs can perform multiple uni-modal[1] understanding and generation tasks, as well as cross-modal tasks across two or more non-linguistic modalities, allowing a single model to

[1]"Uni" and "Cross" refer to the number of non-linguistic modalities involved in the interaction, in contrast to "multi-modal reasoning," traditionally reserved for vision-language tasks (Panagopoulou et al., 2024).

handle arbitrary combinations of modalities.

A review of the development of Omni-MLLMs reveals that it has been continuously expanding in three directions. On the one hand, the types of modalities processed by Omni-MLLM have been continuously increasing, from X-LLMs that handle vision and audio to X-InstructBLIP (Panagopoulou et al., 2024) which adds 3D modality capabilities, PandaGPT (Su et al., 2023) that incorporates IMU modality, and finally One-LLM (Han et al., 2024a), which processes eight different modalities simultaneously. On the other hand, the ability to interact across modalities of Omni-MLLMs has also expanded, from the joint 3D-Image and Audio-Image cross-modal reasoning capability in ImageBind-LLM (Han et al., 2023) to the cross-modal generation capability of CoDi-2 that leverages interleaved audio and image contexts to generate both audio and images (Tang et al., 2024b). The Omni-MLLM is thus trending towards an "Any-to-Any" model. Besides, the application scenarios of Omni-MLLMs have been broadened, encompassing real-time multimodal speech interaction like Mini-Omni2 and Lyra (Xie and Wu, 2024; Zhong et al., 2024), world simulation like WordGPT (Ge et al., 2024b), multi-sensor autonomous driving like DriveMLM (Wang et al., 2023b), etc. In addition to the open-source models, there are also some closed-source Omni-MLLMs such as GPT-4o (OpenAI), Gemini (Reid et al., 2024), and Reka (Ormazabal et al., 2024). The timeline of Omni-MLLMs is shown in Figure 1. Despite the emergence of numerous Omni-MLLMs, there is still a lack of systematic evaluation and analysis.

To fill the gap, we propose this work to conduct a comprehensive and detailed analysis of Omni-MLLMs. We first review the architecture of Omni-MLLMs in four parts (§2). Next, we summarize how Omni-MLLMs expand across multiple modalities through the two-stage training process (§3); then present the training data construction and performance evaluation (§4). Furthermore, we highlight some key challenges and future directions (§5). Finally, we provide a brief summary (§6) and discuss related surveys in the Appendix A.

Our contributions can be summarized as follows: (1) ***Comprehensive Survey***: This is the first comprehensive survey dedicated for Omni-MLLMs; (2) ***Meticulous taxonomy***: We introduce a meticulous taxonomy (shown in Figure 2); (3) ***Challenges and Future***: We outline the challenges of Omni-MLLMs and shed light on future research.

2 Omni-MLLM Architecture

As the extension of Specific-MLLMs, Omni-MLLMs inherit the architecture of *encoding, alignment, interaction, and generation* and broaden the types of non-linguistic modalities involved. This section introduces the implementation methods and functions of the four components in Omni-MLLM: Multi-modalities Encoding (§2.1), Multi-modalities Alignment (§2.2), Multi-modalities Interaction (§2.3), and Multi-modalities Generation (§2.4). More details about the architecture of Omni-MLLMs are shown in Appendix B.

2.1 Multi-modalities Encoding

Based on the encoding feature spaces of multiple modalities, we categorize the Omni-MLLM encoding methods into three types: 1) continuous encoding, 2) discrete encoding, and 3) hybrid encoding.

2.1.1 Continuous Encoding

Continuous encoding refers to encoding the modality into the continuous feature space. Omni-MLLMs that adopt continuous encoding, such as X-LLM (Chen et al., 2023a) and ChatBridge (Zhao et al., 2023b), often integrate multiple pre-trained uni-modality encoders. These modality-specific encoders encode different modalities $\boldsymbol{X}$ into distinct feature spaces $\mathbb{R}_x$ as $\mathbf{F}_x$, formulated as:

$$\mathbf{F}_x = \text{SpecificEncoder}\left(\boldsymbol{X}\right), \quad \mathbf{F}_x \in \mathbb{R}_x \tag{1}$$

where SpecificEncoder refers to different modality-specific encoders used in Omni-MLLMs, such as InternVit (Chen et al., 2023g) for encoding visual modality, Whisper (Radford et al., 2023) for encoding auditory modality, ULIP-2 (Xue et al., 2024b) for encoding 3D modality, IMU2CLIP (Moon et al., 2022) for encoding IMU modality, etc.

Besides using heterogeneous encoders for continuous encoding, some Omni-MLLMs (Han et al., 2024a, 2023; Su et al., 2023; Fu et al., 2024c) employ pre-aligned encoders for multiple modalities, encoding different modalities $\boldsymbol{X}$ into the same feature space $\mathbb{R}_{uni}$, as shown in Equation 2.

$$\mathbf{F}_x = \text{PreAlignEncoder}\left(\boldsymbol{X}\right), \quad \mathbf{F}_x \in \mathbb{R}_{uni} \tag{2}$$

where PreAlignEncoder refer to encoders that uniformly encode multiple modalities, such as LanguageBind (Zhu et al., 2024a) which uses text as a bridge to align different modalities, and ImageBind (Girdhar et al., 2023) which uses images as a bridge to align different modalities.

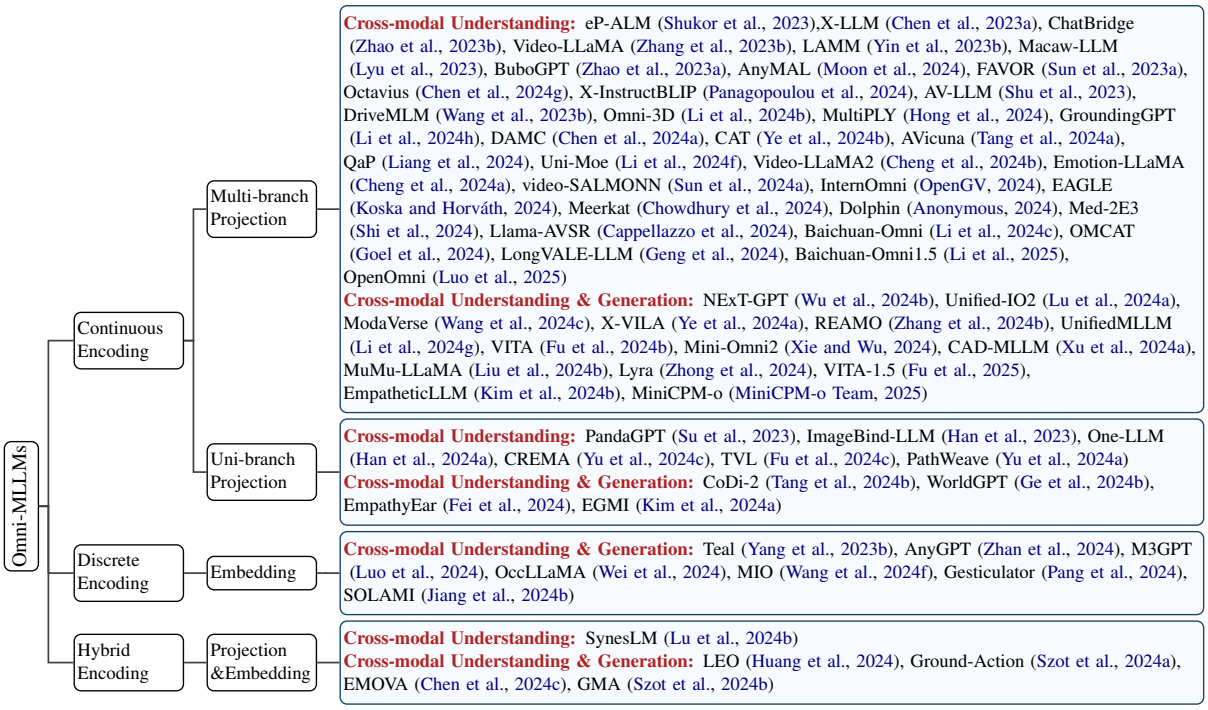

Figure 2: Taxonomy for Omni-MLLMs based on their encoding and alignment methods.

2.1.2 Discrete Encoding

To better facilitate the seamless integration and generation of new non-linguistic modalities, some Omni-MLLMs, such as AnyGPT (Zhan et al., 2024) and Teal (Yang et al., 2023b), adopt a discrete encoding approach. This method encodes different raw modalities $\boldsymbol{X}$ into the same discrete token space $\mathbb{V}_{uni}$ as $\mathbf{T}_x$, formulated as follows:

$$\mathbf{T}_x = \text{SpecificTokenizer}\left(\boldsymbol{X}\right), \quad \mathbf{T}_x \in \mathbb{V}_{uni} \quad (3)$$

where SpecificTokenizer refers to different modality-specific tokenizers used in Omni-MLLMs, including the SEED tokenizer (Ge et al., 2024a) based on Vector Quantized Tokenization (VQ), the SpeechTokenizer (Zhang et al., 2023c) based on Residual Vector Quantized Tokenization (RVQ), the AudioTokenizer of Teal (Yang et al., 2023b) based on k-means clustering, and so on.

2.1.3 Hybrid Encoding

Although discrete encoding facilitates the unified processing of different non-linguistic modalities and text compared to continuous encoding, discrete modality tokens often struggle to capture the detailed information inherent in raw continuous modalities (Chen et al., 2024c; Xie and Wu, 2024). Therefore, some Omni-MLLMs combine both encoding approaches instead of a fully discretized manner, choosing different encoding methods for different modalities. For instance, EMOVA (Chen et al., 2024c) uses the discrete S2U tokenizer to encode auditory modalities while employing the continuous encoder InternVit for visual modalities to retain more vision semantic information. Similarly, GroundAction (Szot et al., 2024a) encodes visual modalities using the CLIP Vit and action modalities with its trained action tokenizer.

2.2 Multi-modalities Alignment

Omni-MLLMs align the encoded features of various non-linguistic modalities with the embedding space of LLMs. The multi-modality alignment can be categorized into two approaches: 1) projection alignment and 2) embedding alignment.

2.2.1 Projection Alignment

The continuous encoding Omni-MLLMs insert adapters, referred to as *projectors*, between the encoders and the LLMs. These projectors map the continuously encoded modality features $\mathbf{F}_x$ into the text embedding space as $\mathbf{F}_p$. As discussed in Section 2.1.1, $\mathbf{F}_x$ may either reside in distinct feature spaces $\mathbb{R}_x$ or share the same feature space $\mathbb{R}_{uni}$. For the former, multiple projectors are typically employed to align the $\mathbf{F}_x$ of each modality into $\mathbb{R}_t$ as $\mathbf{F}_p$ independently, addressing dimensional mismatch and feature misalignment across modalities (Ye et al., 2024a; Lyu et al., 2023; Moon et al.,

2024), formulated as follows:

$$\mathbf{F}_p = \text{SpecificProjector}(\mathbf{F}_x),\ \mathbf{F}_p \in \mathbb{R}_t \quad (4)$$

where SpecificProjector refers to the modality-specific projector corresponding to different modalities, called *multi-branch projection*.

For the latter case, besides the multi-branch approach, Omni-MLLMs like PandaGPT (Su et al., 2023) and WorldGPT (Ge et al., 2024b) adopt a shared projector to achieve unified alignment across modalities to reduce the parameters of multiple projectors, as shown in Equation 5.

$$\mathbf{F}_p = \text{UnifiedProjector}(\mathbf{F}_x),\ \mathbf{F}_p \in \mathbb{R}_t \quad (5)$$

where UnifiedProjector refers to the unified projector used to align multiple modalities, a design known as the *uni-branch projection*. A comparison of the two approaches is illustrated in Figure 3.

In terms of the ***specific implementation*** of the projector, the most straightforward approach is to use a multi-layer perceptron (MLP) or a single linear layer (Wu et al., 2024b; Cheng et al., 2024b; OpenGV, 2024). Alternatively, attention mechanisms can be employed to compress the encoded information of non-linguistic modalities. This includes cross-attention-based methods like Q-Former (Panagopoulou et al., 2024; Chen et al., 2023a) and Perceiver (Zhao et al., 2023b; Liang et al., 2024), as well as self-attention-based methods such as UPM in OneLLM (Han et al., 2024a). Additionally, BaiChuan-Omni (Li et al., 2024c) and EMOVA (Chen et al., 2024c) incorporate CNNs to compress the projected features, thereby achieving locality preservation (Cha et al., 2024).

It is also worth noting that in multi-branch Omni-MLLMs, different branches may utilize distinct implementations to better accommodate the unique characteristics of each modality (Li et al., 2024h). For example, Uni-MoE (Li et al., 2024f) uses a linear projection for the visual modality and a Q-Former for the auditory modality. Meanwhile, uni-branch Omni-MLLMs, when using an attention-based projector, typically design multiple modality-specific learnable vectors to extract key information from various non-linguistic modalities (Yu et al., 2024a; Han et al., 2024a; Yu et al., 2024c).

2.2.2 Embedding Alignment

As for discrete encoding Omni-MLLMs, the features of non-linguistic modalities are represented as quantized codes, which reside in the same discrete space $\mathbb{V}_{uni}$ as text tokens. Therefore, new

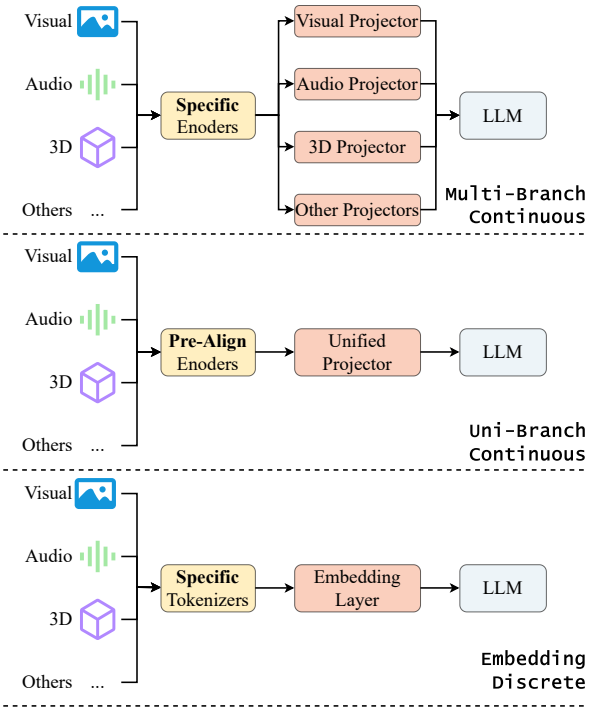

Figure 3: The three combinations of encoding and alignment in Omni-MLLM are based on different encoding spaces and alignment structures.

modality-specific discrete tokens $\mathbf{T}_x$ are embedded into the continuous feature space $\mathbb{R}_t$ by modifying the vocabulary of LLMs and the corresponding embeddings layer, as shown in Equation 6.

$$\mathbf{F}_p = \text{Embedding}(\mathbf{T}_x),\ \mathbf{F}_p \in \mathbb{R}_t \quad (6)$$

where Embedding refers to the unified embedding layer corresponding to different modalities, which is typically achieved by adding discrete codebooks from various modalities to the vocabulary and expanding the embedding layer of LLMs (Zhan et al., 2024; Yang et al., 2023b; Wei et al., 2024). For instance, AnyGPT extends the vocabulary of the LLaMA-2 by incorporating 17,408 codes across three modalities—image, speech, and music (Zhan et al., 2024). Besides, some works like Ground-Action (Szot et al., 2024a) and LEO (Huang et al., 2024) overwrite infrequently used tokens in the original vocabulary for alignment, as they extend a smaller set of modality-specific discrete tokens.

Additionally, for hybrid encoding models, alignment is achieved by simultaneously employing both the projection method and the embedding method (Chen et al., 2024c; Szot et al., 2024b).

2.3 Multi-modalities Interaction

Omni-MLLMs utilize transformer-based LLMs to facilitate information interaction between different

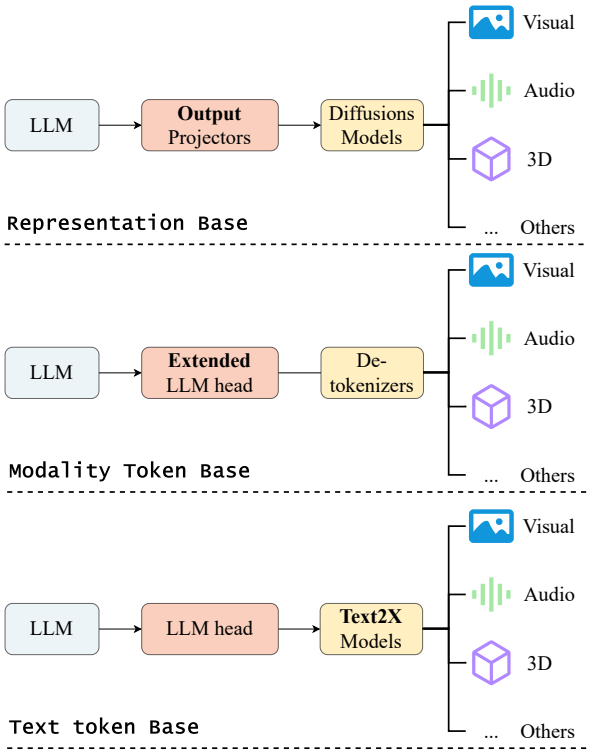

Figure 4: Three generation methods in Omni-MLLMs are implemented based on different output spaces of LLM and the corresponding generative models.

modalities within a unified feature space $\mathbb{R}_t$. Commonly used LLMs include the LLaMA series (Touvron et al., 2023), the Qwen series (Bai et al., 2023), and others (Cai et al., 2024; Zeng et al., 2024).

For interaction, most Omni-MLLMs (Chen et al., 2023a; Ye et al., 2024a; OpenGV, 2024; Li et al., 2025) concatenate aligned non-linguistic modality features $\mathbf{F}_p$ with textual features $\mathbf{F}_t$ at the input level, enabling interaction in a progressive and layer-by-layer manner. Meanwhile, some works, such as ImageBind-LLM (Han et al., 2023) and TVL-LLaMA (Fu et al., 2024c), insert $\mathbf{F}_p$ into specific layers or all layers of the LLMs to mitigate the loss of modality information (Shukor et al., 2023).

In terms of the number of modalities involved in interactions, compared to Specific-MLLMs that are limited to dual-modal interactions between a single non-linguistic modality and text (Liu et al., 2023c; Xu et al., 2024b), Omni-MLLMs not only support multiple dual-modal interactions but also enable omni-multimodal interactions involving more than two non-linguistic modalities (Zhao et al., 2023b; Wang et al., 2024f). For example, X-InstructBLIP (Panagopoulou et al., 2024) enables dual-modal interactions such as vision-text, audio-text, and 3D-text, as well as omni-modal interactions like vision-audio-text and 3D-vision-text, showcasing the ability of Omni-MLLMs to handle arbitrary combinations of modalities.

2.4 Multi-modalities Generation

Omni-MLLMs can output text while also generating non-linguistic modalities by integrating different generation models. As shown in Figure 4, we categorize multi-modalities generation into three types: text-based generation, representation-based generation, and modality-token-based generation.

Text-based This approach directly utilizes the discrete text output from the LLM to invoke Text-to-X generation models (Liu et al., 2023b; Luo et al., 2023c; Brooks et al., 2023) based on the content of the text. For example, VITA (Fu et al., 2024b) employs TTS tools (RVC-Boss) to convert the output text into corresponding speech, while ModelVerse (Wang et al., 2024c) and UnifiedM-LLM (Li et al., 2024g) use the text to specify the generation model and utilize the corresponding descriptions to generate different modalities.

Modality-Token-based Works like MiniOmni-2 (Xie and Wu, 2024) and AnyGPT (Zhan et al., 2024) extend the corresponding LLM head with codebooks from different modality tokenizers to generate modality-specific discrete tokens. These tokens are then decoded using the corresponding de-tokenizers (Esser et al., 2021; Yu et al., 2024b; Zeghidour et al., 2022; Dhariwal et al., 2020) to produce various modalities.

Representation-based To alleviate the potential noise introduced by discrete tokens, works like X-VILA (Ye et al., 2024a) and NextGPT (Wu et al., 2024b) incorporate modality-specific signal tokens into the vocabulary. They then use transformers or MLPs to map the signal token representations into the ones that are understandable to the multimodal decoders, typically off-the-shelf latent-conditioned diffusion models (Rombach et al., 2022; Tang et al., 2023; Xue et al., 2024a; Blattmann et al., 2023), enabling effective generation capabilities.

3 Omni-MLLM Training

To achieve alignment across different vector spaces and improve instruction-following ability under arbitrary modality settings, Omni-MLLMs extend the standard two-stage training pipeline of Specific-MLLMs: *multi-modalities alignment pre-training* and *multi-modalities instruction fine-tuning*.

3.1 Multi-modalities Alignment Pre-training

Multi-modalities alignment pre-training involves *input alignment* training between the feature spaces of different modalities and the embedding space of LLMs on the encoding side, as well as *output alignment* training between the embedding space and the input spaces of various modality decoders on the decoding side. Input alignment and output alignment can be carried out separately (Wu et al., 2024b) or simultaneously (Ye et al., 2024a).

3.1.1 Input Alignment

Input alignment mainly uses X-Text paired datasets of different modalities and minimizes the text generation loss of the corresponding description text to optimize. In this phase, continuous encoding Omni-MLLMs normally update parameters of projectors, while discrete encoding Omni-MLLMs adjust the parameters of the embedding layer.

In terms of ***training order*** of different modalities alignment, multi-branch Omni-MLLM performs separate alignment training for each modality-specific projector, directly aligning each non-linguistic modality with text and using text as a bridge to align different non-linguistic modalities (Zhao et al., 2023b; Panagopoulou et al., 2024). The uni-branch Omni-MLLM, on the other hand, uses the unified projector for different modalities, which may lead to interference in the alignment performance between different modalities. Thus, Han et al. (2024a) employ a progressive alignment strategy to align multiple modalities in a specific order. In contrast, discrete encoding Omni-MLLMs, like AnyGPT (Zhan et al., 2024) and M3GPT (Luo et al., 2024), mix the alignment data from different modalities and perform alignment simultaneously.

Besides, in addition to directly leveraging X-Text paired datasets from different modalities for direct alignment, PandaGPT (Su et al., 2023), ImageBind-LLM (Han et al., 2023), and VideoLLaMA (Zhang et al., 2023b) utilize the pre-aligned modality feature space $\mathbb{V}_{uni}$ to achieve indirect alignment between other non-linguistic modalities and text by training solely on Image-Text data.

3.1.2 Output Alignment

The training of output alignment typically utilizes the same X-text paired dataset as input alignment and adheres to the identical training sequence. Meanwhile, the training objectives for output alignment vary depending on the multi-modality generation methods in Section 2.4. Token-based generative Omni-MLLMs optimize the extended LLM head by minimizing the text generation loss associated with modality-specific discrete tokens (Lu et al., 2024a; Wei et al., 2024). Representation-based generative Omni-MLLMs generally optimize their output projectors by minimizing the composite loss comprising three components (Xie and Wu, 2024; Yang et al., 2023b): 1) the text generation loss of signal tokens; 2) the L2 distance between the output representation and the condition vector of the corresponding decoder, i.e. MSE loss; and 3) the conditional latent denoising loss (Rombach et al., 2022). For text-based generative Omni-MLLMs, as there is no additional output structure, the output alignment training is generally not required (Wang et al., 2024c; Li et al., 2024g).

3.2 Multi-modalities Instruction Fine-tuning

The instruction fine-tuning phase aims to enhance generalization capability under arbitrary modalities of Omni-MLLMs (Panagopoulou et al., 2024; Wu et al., 2024b; Ye et al., 2024a). Instruction fine-tuning primarily utilizes instruction-following datasets and computes the text generation loss for the corresponding responses to optimize. For models with generation capabilities, the loss mentioned in section 3.1.2 may also be incorporated. During this phase, Omni-MLLMs further perform full-scale tuning of the LLM parameters (Han et al., 2024a; Cheng et al., 2024b) or use PEFT techniques (Han et al., 2024b), such as LoRA (Hu et al., 2022), for partial tuning (Wang et al., 2024e).

Compared to Specific-MLLMs, Omni-MLLMs not only leverage multiple uni-modal instruction data of different modalities for training but also use cross-modal instruction data to enhance their cross-modal ability (Ye et al., 2024a; Zhan et al., 2024; Li et al., 2024c). In addition to directly mixing different instruction data for training (Panagopoulou et al., 2024; Ye et al., 2024a), some works like Uni-Moe (Li et al., 2024f) and Lyra (Zhong et al., 2024) adopt a multi-step fine-tuning approach, introducing different uni-modal and cross-modal instruction data in a specific order for training to gradually enhance their uni-modal and cross-modal ability.

4 Data Construction and Evaluation

This section summarizes the construction of modality alignment data and instruction data used in the Omni-MLLM training process (§4.1), as well as the evaluation across four different capabilities (§4.2).

4.1 Training Data

Alignment Data Omni-MLLMs leverage caption datasets from various modalities to construct X-Text paired data for alignment pre-training, such as the WebVid (Bain et al., 2021) for visual modality and the AudioCaps (Kim et al., 2019) for auditory modality. However, for data-scarce modalities like depth maps and thermal maps, large-scale text-paired data is lacking (Zhu et al., 2024a; Girdhar et al., 2023). To address this, synthetic methods that use DPT models (Ranftl et al., 2021; Bhat et al., 2023; Xu et al., 2023) or image translation models (Lee et al., 2023) to convert image-text pairs into other modality text pairs are widely employed (Han et al., 2024a; Chen et al., 2024c; Zhu et al., 2024a). Moreover, interleaved datasets (Zhu et al., 2023a) are used for alignment pre-training in some works (Tang et al., 2024b) to enhance the contextual understanding capability.

Instruction Data Omni-MLLMs not only leverage uni-modal instruction datasets from Specific-MLLMs, but also construct cross-modal instruction data through diverse methods as follows.

(1) **Template-based Construction**: Most works (Sun et al., 2023a; Zhao et al., 2023b; Zhang et al., 2024b) utilize cross-modal downstream datasets (Sanabria et al., 2018; Chen et al., 2020b) combined with predefined templates to construct cross-modal instructions; (2) **GPT Generation**: Following the paradigm of LLaVA (Liu et al., 2023c), some Omni-MLLMs (Lyu et al., 2023; Zhao et al., 2023b) leverage the labels from the annotated dataset (Lin et al., 2014; Bain et al., 2021) or use pre-trained models like SAM (Chen et al., 2023c) and GRIT (Wu et al., 2024a) to extract meta-information (e.g., captions and object categories) of different modalities. Then they employ powerful LLMs (OpenAI, 2023b,a) to generate cross-modal instructions based on the obtained meta-information; (3) **T2X Generation**: Li et al. (2024f) use TTS tools to convert the Image-Text2Text uni-modal instructions from LLaVA-v1.5 (Liu et al., 2024a) into Image-Speech-Text2Text cross-modal instructions. AnyGPT (Zhan et al., 2024) and NextGPT (Wu et al., 2024b) leverage Text2X models such as DALL-E-3 (Shi et al., 2020) and MusicGen (Copet et al., 2023) to convert the GPT-generated pure text instructions into Xs2Xs cross-modal instructions. Details about training data are shown in Appendix C.1

4.2 Benchmark

We provide a brief overview of the benchmarks used to evaluate Omni-MLLMs. The statistics of the benchmarks are shown in Appendix C.2.

Uni-modal Understanding Uni-modal understanding assesses the ability of Omni-MLLMs to comprehend and reason on different non-linguistic modalities, including downstream X-Text2Text datasets such as X-Caption (Plummer et al., 2015; Xu et al., 2016), X-QA (Goyal et al., 2017; Xu et al., 2017), and X-Classification (Deitke et al., 2023), as well as comprehensive multi-task benchmarks (Liu et al., 2024d; Fu et al., 2024a, 2023).

Uni-modal Generation Uni-modal generation aims to evaluate the ability of Omni-MLLMs to generate a single non-linguistic modality, including the Text2X generation task (Kim et al., 2019; Ruiz et al., 2023) and the Text-X2Text editing task (Veaux et al., 2017; Perazzi et al., 2016).

Cross-modal Understanding Cross-modal understanding evaluates the ability of Omni-MLLMs to jointly comprehend and reason across multiple non-linguistic modalities like Image-Speech-Text2Text (Li et al., 2024f; OpenGV, 2024), Video-Audio-Text2Text (Li et al., 2022a,b), and Image-3D-Text2Text (Panagopoulou et al., 2024).

Cross-modal Generation Cross-modal generation further evaluates the ability of Omni-MLLMs to generate non-linguistic modalities in conjunction with other non-linguistic modality inputs. For example, the Xs-Text2X benchmark proposed by X-VILA (Ye et al., 2024a) includes tasks such as Image-Text2Audio and Image-Audio-Text2Video.

5 Challenges and Future Directions

Despite Omni-MLLMs having showcased remarkable performance on numerous tasks, there are still some challenges that necessitate further research.

5.1 Expansion of modalities

Most Omni-MLLMs can only process 2-3 types of non-linguistic modalities, and they still face several challenges when expanding more modalities.

Training efficiency The common method that introduces new modalities through additional alignment pre-training and instruction fine-tuning can lead to significant training cost. Leveraging prior knowledge from Specific-MLLMs (Panagopoulou

et al., 2024; Chen et al., 2024a) or using pre-aligned encoders for indirect alignment (Han et al., 2023; Su et al., 2023) can help reduce training overhead but may impact cross-modal performance.

Catastrophic forgetting Expanding new modalities may adjust the shared parameters, potentially causing catastrophic forgetting of previously trained modalities knowledge (Yu et al., 2024a). This issue can be partially mitigated by mixing trained modality data (Han et al., 2024a; Li et al., 2024f) or fine-tuning only the modality-specific parameters (Yu et al., 2024a,c), but both approaches make the training process more complex.

Low-resource modalities Although the data synthesis method in Section 4.1 can help alleviate the lack of text-paired data and instruction data for low-resource modalities (Han et al., 2024a; **?**), the absence of real modality may lead to biases in understanding of that modality.

5.2 Cross-modal capabilities

The Omni-MLLMs have achieved promising performance in cross-modal understanding and generation tasks, but there are still some challenges.

Long Context When the input contains multiple sequence modalities (video, speech...), the length of the multi-modalities token sequence may exceed the context window of LLMs and lead to memory overflow. While methods such as token compressing (Yu et al., 2024c; Li et al., 2024c) or token sampling (Zhan et al., 2024; Zhong et al., 2024) can reduce the number of input tokens, they also result in a decline in cross-modal performance.

Modality Bias Due to the imbalance in training data volume and the performance disparity among different modality encoders, Omni-MLLMs may tend to pay attention to the dominant modality while neglecting information from other modalities during cross-modal inference. Balancing the data volume across modalities or enhancing the corresponding modality-specific modules could potentially help mitigate this issue (Leng et al., 2024).

Temporal Alignment When dealing with different modalities that have temporal dependencies, retaining their temporal alignment information is crucial for subsequent cross-modal understanding. Some attempts have been made to preserve the temporal alignment information between audio and video, such as interleaved modality-specific tokens of video and audio (Tang et al., 2024a) and inserting the time-related special tokens into the multi-modalies tokens (Goel et al., 2024).

Data and Benchmark Although Omni-MLLMs employ various methods in Section 4.1 to generate cross-modal instruction data, there is still significant room for improvement and expansion, including enhancing the diversity of instructions, incorporating longer contextual dialogues, and exploring more diverse modality interaction paradigms. Similarly, cross-modal benchmarks such as OmniBench (Li et al., 2024e) and OmniR (Chen et al., 2024d) still fall short in terms of task richness and instruction diversity when compared to uni-modal benchmarks like MMMU (Yue et al., 2024) and MME (Fu et al., 2023). And the variety of modalities they cover is also relatively limited.

5.3 Application scenarios

The emergence of Omni-MLLM brings new opportunities and possibilities for various applications. **(1) Real-time Multi-modalities Interaction**: Fu et al. (2025) and Xie and Wu (2024) achieve robust capabilities in both vision and speech understanding, enabling efficient speech-to-speech interactions with vision in real-time. **(2) Comprehensive Planning**: Wang et al. (2023b) and Szot et al. (2024a) leverage the complementarity across multiple modalities to achieve better path planning and action planning capabilities than planning with vision information only. **(3) World Simulator**: Ge et al. (2024b) not only understands and generates different modalities but also predicts state transitions for any combination of modalities.

6 Conclusion

In this paper, we provide a comprehensive survey report on Omni-MLLM, offering a comprehensive review of the field. Specifically, we break down Omni-MLLM into four key components and categorize them based on modal encoding and alignment methods. Subsequently, we provide a detailed summary of the training process of Omni-MLLM and the related resources used. We also summarize the current challenges and the future development directions. This paper is the first systematic survey dedicated to Omni-MLLMs. We hope this survey will facilitate further research in this area.

Limitations

This study provides the first comprehensive survey of Omni-MLLMs. Related work, architecture statistics, more details of training and evaluation, as well as other training recipes, can be found in Appendix A,B,C.

We have made our best effort, but there may still be some limitations. On one hand, due to page limitations, we can only provide a concise overview of the core contributions of mainstream Omni-MLLMs, rather than exhaustive technical details. On the other hand, our review primarily covers research from *ACL, NeurIPS, ICLR, ICML, COLING, CVPR, IJCAI, ECCV, and arXiv, and there is a chance that we may have missed some important work published in other venues. We will stay updated with ongoing discussions in the research community and plan to revise our work in the future to include overlooked contributions.

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A Related Survey

With the advent of MLLMs, there are several surveys detailing the current progress of MLLMs. Yin et al. (2023a); Wu et al. (2023); Caffagni et al. (2024) focus on the early Vision-MLLMs, while Çoban et al. (2024) and Ma et al. (2024) respectively summarize the Audio-MLLMs and 3D-MLLMs. Zhang et al. (2024a); Wang et al. (2024a) conduct an investigation into various Specific-MLLMs of different modalities. He et al. (2024); Chen et al. (2024b) discuss the expansion of MLLM's generative capabilities. Some works discuss MLLMs in specific domains, such as medicine (Xiao et al., 2024), agriculture (Zhu et al., 2024b), and autonomous driving (Cui et al., 2024). Some works highlight some specific tasks such as safety (Fan et al., 2024), hallucination (Bai et al., 2024b), and acceleration (Zhu et al., 2024b). And Li and Lu (2024); Huang and Zhang (2024) focus on the evaluation of MLLM performance.

Distinct from the above-mentioned surveys, this paper focuses on MLLMs that align multiple non-linguistic modalities[2] with LLMs (Omni-MLLMs), enabling cross-modal understanding or cross-modal generation. As the first systematic survey on Omni-MLLMs, we hope our work will serve as an overview of this emerging direction, fostering future research in the field.

B Details about Omni-MLLMs architures

Table 1 presents the details of the structure of mainstream Omni-MLLMs. We will list some of the pre-trained models used.

B.1 Modality Encoder

Visual Specific-Encoder Vit (Dosovitskiy et al., 2021), SigCLIP Vit (Zhai et al., 2023), CLIP Vit (Radford et al., 2021), EVA CLIP Vit (Sun et al., 2023e), InternVit (Chen et al., 2023g), DINOv2 Vit (Oquab et al., 2024), DFNCLIP Vit (Fang et al., 2024a), and OpenCLIP ConvNext (Liu et al., 2022b) encode images to obtain continuous features. TimeSformer (Bertasius et al., 2021), VideoMAE (Tong et al., 2022), MAE-DFer (Sun et al., 2023c), Omni-VL (Sun et al., 2023d), Video-Swin (Liu et al., 2022a), and Vivit (Arnab et al., 2021) encode videos to obtain continuous features.

[2]Since MLLMs capable of comprehending both video and imagery generally process video as multiple frames and employ a single vision encoder, we categorize them as Specific-MLLMs, i.e. Vision-MLLMs.

Audio Specific-Encoder AST (Gong et al., 2021), Beats (Chen et al., 2023d), Whisper (Radford et al., 2023), HuBert (Hsu et al., 2021), CLAP (Elizalde et al., 2023), Conformer (Gulati et al., 2020), MERT (Li et al., 2024d), and PANN (Kong et al., 2020) encode the audio modality to obtain continuous features.

3D Specific-Encoder ULIP2 (Xue et al., 2024b), GD-MAE (Yang et al., 2023a), PointEncoder (Xu et al., 2024b), FrozenCLIP (Huang et al., 2022), and M3D-CLIP (Bai et al., 2024a) encode the 3D modality to obtain continuous features.

Pre-align Uni-Encoder LanguageBind (Zhu et al., 2024a), ImageBind (Girdhar et al., 2023), Meta-Transformers (Zhang et al., 2023d), TVL (Fu et al., 2024c), and SSVTP (Kerr et al., 2023) encode multiple non-linguistic modalities into a unified feature space and obtain continuous features. TVL, LanguageBind, ImageBind, and SSVTP construct modality-specific encoders for different modalities and achieve multi-modalities alignment through indirect alignment. Meta-Transformers design distinct modality-specific patch embeddings and use a shared encoder to encode multiple modalities.

Other Specific-Encoder IMU2CLIP (Moon et al., 2022) encodes the IMU modality to obtain continuous features. Individual modality-specific encoders from LanguageBind or ImageBind are often used independently as specific encoders.

B.2 Modality Tokenizer

Visual Tokenizer VQ-GAN (Esser et al., 2021), DALL-E (Ramesh et al., 2021), BEiT-V2 (Peng et al., 2022), MAGVIT-v2 (Yu et al., 2024b), and SEED (Ge et al., 2023) encode the visual modality into discrete visual tokens, which can be decoded back into the original image using the de-tokenizer.

Audio Tokenizer Jukebox (Dhariwal et al., 2020), SoundStream (Zeghidour et al., 2022), SpeechTokenizer (Zhang et al., 2023c), Encodec (Défossez et al., 2023), and S2U (Chen et al., 2024c) encode the audio modality into discrete audio tokens, which can be decoded back into the audio using the corresponding de-tokenizer.

Other Tokenizer Scene Tokenizer (Wei et al., 2024) encodes the 3D modality into discrete 3D tokens. LEO (Huang et al., 2024), Ground-Action (Szot et al., 2024a), OccLLaMA (Wei et al.,

2024), and GMA (Szot et al., 2024b) perform discrete encoding of the action modality to obtain corresponding action tokens, which can be decoded back into the original action using the corresponding de-tokenizer. M3GPT (Luo et al., 2024), Gesticulator (Pang et al., 2024), and SOLAMI (Jiang et al., 2024b) perform discrete encoding of the motion modality to obtain corresponding motion tokens, which can be decoded back into the original motion using the corresponding de-tokenizer.

B.3 Modality Generation Model

For image generation, Stable Diffusion (Rombach et al., 2022) and Instruct-Pix2Pix (Brooks et al., 2023) are used. Video generation models include Zeroscope (Cerspense, 2023), VideoFusion (Luo et al., 2023c), VideoCrafter (Chen et al., 2023b), and ModelScope (Wang et al., 2023a). For audio generation, models such as AudioLDM (Liu et al., 2023b), SNAC (Siuzdak et al., 2024), LLaMA-Omni's audio decoder (Fang et al., 2024b), MusicGen (Copet et al., 2023), and TiCodec (Ren et al., 2024) are utilized. Meanwhile, StyleTTS (Li et al., 2022d) and GPT-SoVITS (RVC-Boss) are employed for speech generation.

B.4 LLM Backbone

Commonly used LLMs include the T5 series (Raffel et al., 2020), LLaMA series (Touvron et al., 2023), Qwen series (Bai et al., 2023), Internlm series (Cai et al., 2024), Chatglm series (Zeng et al., 2024), OPT series (Zhang et al., 2022b), Mixtral series (Jiang et al., 2024a), Mistral series (Jiang et al., 2023), Phi series (Gunasekar et al., 2023), and Yi series (Young et al., 2024).

C Details of Training and evaluation

C.1 Details of Training Data

The statistical results of some commonly used alignment datasets and the instruction data of mainstream Omni-MLLMs are shown in Table 2 and Table 3. There is still a lack of alignment data for data-scarcity modalities and cross-modal instruction data.

C.2 Details of Benchmark

The statistical data of some commonly used benchmarks are shown in Table 4. Existing benchmarks still require improvements in terms of the number of modalities and the forms of modality interaction.

C.3 Other Train Recipes

In addition to the general training paradigms mentioned in Section 3, some other useful training recipes are also used. (1) **Prior knowledge from Specific-MLLMs**: Since Specific-MLLMs have already achieved effective alignment in single-modal scenarios, some Omni-MLLMs directly leverage their well-trained projectors to reduce the training overhead during the alignment phase. For example, InstructBLIP (Panagopoulou et al., 2024) and X-LLM (Chen et al., 2023a) use the Q-former trained by BLIP2 to align the visual modality, while NaviveMC and DAMC (Chen et al., 2024a) further leverage projectors from multiple models to handle alignment for visual, audio, and 3D modalities separately; (2) **Additional human preference training**: Szot et al. (2024b) and Ye et al. (2024b) adopt HF training methods like PPO and ADPO to better align with human preferences; (3) **Modalities Blending**: During progressive alignment pre-training or multi-step instruction fine-tuning, some works (Han et al., 2024a; Li et al., 2024c; Chen et al., 2024c) mix previously trained modality data with the current new modality data for training to prevent catastrophic forgetting.

C.4 Performance of Omni-MLLMs

We statistic the performance of various mainstream Omni-MLLMs in uni-modal understanding, cross-modal understanding, and cross-modal, as shown in Table 5. We also show the performance of several Specific-MLLMs (Lin et al., 2024; Li et al., 2024a; Chu et al., 2023; Xu et al., 2024b; Sun et al., 2024c; Jin et al., 2024) on selected tasks for comparison. The results are mainly from corresponding papers (some results are used as baselines in other papers). It is worth noting that due to differences in the size and performance of the pre-trained models, Omni-MLLMs with the same backbone LLM may still not be fairly comparable. Therefore, this table only provides a rough trend of performance.

It can be seen from the table that most Omni-MLLMs still exhibit a significant performance gap in uni-modal understanding tasks compared to Specific-MLLMs. Meanwhile, in uni-modal generation tasks, models like AnyGPT and CoDi-2 have achieved performance close to or even surpassing Specific-MLLMs. Additionally, Omni-MLLMs are capable of performing cross-modal tasks that Specific-MLLMs cannot handle.

Model	Capabilities	Multi-Modalities Encoding			Multi-Modalities Alignment			Multi-Modalities Interaction		Multi-Modalities Generation		
		Modalities	Method	Encoding Model	Method	Projector	Vocabulary	Method	LLM	Modalities	Method	Generation model
eP-ALM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	Vit/TimeSformer/AST	multi-branch	linear	–	injection	OPT	–	–	–
VALOR	Corss-modal Understanding	Visual/Audio	Continuous Encoding	Vit/VideoSwin/AST	multi-branch	MLP	–	injection	Bert	–	–	–
X-LLM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	Vit/Conformer	multi-branch	Q-former+Linear	–	concatenate	ChatGLM	–	–	–
ChatBridge	Corss-modal Understanding	Visual/Audio	Continuous Encoding	EVAL CLIP Vit/Beats	multi-branch	Preceiver	–	concatenate	Vicuna	–	–	–
PandaGPT	Corss-modal Understanding	Visual/Audio/3D/ IMU/thermal	Continuous Encoding	ImageBind	uni-branch	linear	–	concatenate	Vicuna	–	–	–
VideoLLama	Corss-modal Understanding	Visual/Audio	Continuous Encoding	EVA CLIP Vit/ ImageBind-Audio	multi-branch	Q-former+Linear	–	concatenate	Vicuna	–	–	–
LAMM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/ FrozenCLIP	multi-branch	MLP	–	concatenate	Vicuna	–	–	–
Macaw-LLM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	Vit/Whisper	multi-branch	Cross-Attention	–	concatenate	LLaMA	–	–	–
BuboGPT	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/ImageBind-Audio	multi-branch	Q-former+Linear	–	concatenate	LLaMA	–	–	–
Teal	Corss-modal Understanding && Generation	Visual/Audio	Discrete Encoding	VQ-GAN/ Whisper+K-means	embedding	–	Added Vocabulary	concatenate	LLaMA	Image	Modality-Token-based	VQGAN detokenizer
ImageBind-LLM	Corss-modal Understanding	Visual/Audio/3D	Continuous Encoding	ImageBind	uni-branch	MLP	–	injection	LLaMA	–	–	–
Next-GPT	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	Linear	–	concatenate	Vicuna	Image/Video/Audio	Representation-based	StableDiffusion1.5/ Zeroscope/AudioLDM
Any-MAL	Corss-modal Understanding	Visual/Audio/IMU	Continuous Encoding	CLIP Vit/CLAP/ IMU2CLIP	multi-branch	Preceiver	–	injection	LLaMA-2	–	–	–
FAVOR	Corss-modal Understanding	Visual/Audio	Continuous Encoding	EVA CLIP Vit/Whisper	multi-branch	Q-former+Linear	–	concatenate	Vicuna	–	–	–
Octavius	Corss-modal Understanding	Visual/3D	Continuous Encoding	CLIP Vit/Object-As-Scene	multi-branch	MLP	–	concatenate	Vicuna	–	–	–
LEO	Corss-modal Understanding && Generation	Visual/3D/Action	Hybrid Encoding	OpenCLIP Convnext/PointNet++/ LEO's Action tokenizer	multi-branch	MLP/ Spatial Transformer	Overwrite Vocabulary	concatenate	Vicuna	Action	Modality-Token-based	LEO's Action detokenizer
CoDi-2	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	ImageBind	uni-branch	MLP	–	concatenate	LLaMA-2	Image/Video/Audio	Representation-based	StableDiffusion2.1/ Zeroscope/AudioLDM2
X-InstructBLIP	Corss-modal Understanding	Visual/Audio/3D	Continuous Encoding	EVA CLIP Vit/Beats/ ULIP2	multi-branch	Q-former+Linear	–	concatenate	Vicuna	–	–	–
One-LLM	Corss-modal Understanding	Visual/Audio/3D/IMU/fMRI/ Normal Map	Continuous Encoding	Meta-transformer	uni-branch	UPM(self-attention)	–	concatenate	LLaMA-2	–	–	–
AV-LLM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/CLAP	multi-branch	Linear	–	concatenate	Vicuna	–	–	–
DriveMLM	Corss-modal Understanding	Visual/3D	Continuous Encoding	EVA CLIP Vit/GD-MAE	multi-branch	Q-former+Linear	–	concatenate	LLaMA	–	–	–
Omni-3D	Corss-modal Understanding	Visual/3D	Continuous Encoding	CLIP Vit/PointNet++	multi-branch	MLP	–	concatenate	LLaMA-2	–	–	–
ModaVerse	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	Linear	–	concatenate	Vicuna	Image/Video/Audio	Text-based	StabelDiffusion /AudioLDM/VideoFusion
MultiPLY	Corss-modal Understanding	Visual/Audio/3D /thermal/touch	Continuous Encoding	CLIP Vit/CLAP /ConceptGraph	multi-branch	MLP/Linear	–	concatenate	Vicuna	–	–	–
CREMA	Corss-modal Understanding	Visual/Audio/3D /thermal/touch/optical	Continuous Encoding	EVA CLIP Vit+Linear/ Beats+Linear/ConceptFusion+Linear	uni-branch	Q-former+Linear	–	concatenate	Flan-T5	–	–	–
GroundingGPT	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/ImageBind-Audio	multi-branch	Q-former+Linear/MLP	–	concatenate	Vicuna	–	–	–
DAMC	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/Beats/PointBert(PointLLM)	multi-branch	Q-former+Linear/MLP	–	concatenate	Vicuna	–	–	–
AnyGPT	Corss-modal Understanding && Generation	Visual/Audio	Diserect Encoding	SEED tokenizer/ Speech tokenizer/Encodec	embedding	–	Extend Vocabulary	concatenate	LLaMA-2	Image/Speech/Music	–	SEED de-tokenizer/Speech de-tokenizer/Encodec de-tokenizer
TVL-LLaMA	Corss-modal Understanding	Visual/Touch	Continuous Encoding	TVL Encoders	uni-branch	MLP	–	injection	LLaMA	–	–	–
SSVTP-LLaMA	Corss-modal Understanding	Visual/Touch	Continuous Encoding	SSVTP Encoders	uni-branch	MLP	–	injection	LLaMA	–	–	–
CAT	Corss-modal Understanding	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	Linear	–	concatenate	LLaMA-2	–	–	–
AVicuna	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/CLAP	multi-branch	MLP	–	concatenate	Vicuna	–	–	–
WorldGPT	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	LanguageBind	uni-branch	Linear	–	concatenate	Vicuna	Image/Video/Audio	Representation-based	Stable Diffusion /AudioLDM/Zeroscope
QaP	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/CLAP	multi-branch	dot attention+Linear	–	injection	DeBERTa-V2-XLarge	–	–	–
Uni-Moe	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/Beats	multi-branch	Q-former+Linear/MLP	–	concatenate	LLaMA	–	–	–
M3GPT	Corss-modal Understanding	Audio/Motion	Diserect Encoding	Jukebox tokenizer /M3GPT's Motion tokenier	embedding	Extend Vocabulary	–	concatenate	T5	Music/Motion	Modality-Token-based	Jukebox de-tokenizer /M3GPT's Motion de-tokenizer
X-VILA	Corss-modal Understanding	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	MLP	–	concatenate	Vicuna	Image/Video/Audio	Representation-based	Stable Diffusion /AudioLDM/VideoCrafter
REAMO	Corss-modal Understanding	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	Linear	–	concatenate	Vicuna	–	–	–
VideoLLaMA2	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/Beats	multi-branch	MLP	–	concatenate	Mistral	–	–	–
Ground-Action	Corss-modal Understanding	Visual/Action	Hybrid Encoding	CLIP Vit /Ground-Action action tokenizer	multi-branch	Preceiver	Overwrite Vocabulary	concatenate	Vicuna	Action	Modality-Token-based	Ground-Action action de-tokenizer
Emotion-LLaMA	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	CLIP Vit /HuBert-Chinese	multi-branch	MLP	–	concatenate	LLaMA-2	–	–	–
EmpathyEar	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	ImageBind	uni-branch	Linear	–	concatenate	ChatGLM	Video/Audio	Text-based	StyleTTS2/EAT
video-SALMONN	Corss-modal Understanding	Visual/Audio	Continuous Encoding	Vit/Beats	multi-branch	Q-former+Linear	–	concatenate	Vicuna	–	–	–
Meerkat	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/CLAP	multi-branch	MLP	–	concatenate	LLaMA-2	–	–	–
InternOmni	Corss-modal Understanding	Visual/Audio	Continuous Encoding	Intern VW/Whisper	multi-branch	MLP	–	concatenate	InternLM-2.5	–	–	–
SynesLM	Corss-modal Understanding	Visual/Audio	Hybird Encoding	SigCLIP Vit /XLSR+K-means	multi-branch	MLP	Extend Vocabulary	concatenate	OPT	–	–	–
UnifiedMLLM	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	CLIP Vit /ImageBind-Audio	multi-branch	Q-former+Linear	–	concatenate	OPT	Image/Video/Audio	Text-based	Instruct-pix2pix/ Auffusion/ModelScope
VITA	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	CLIP Vit /VITA's Audio Encoder	multi-branch	MLP	–	concatenate	Mixtral	Speech	Text-based	GPT-SoVITS
OccLLaMA	Corss-modal Understanding && Generation	3D/Action	Discrete Encoding	OccLLaMA's 3D tokenizer /OccLLaMA's Action tokenizer	embedding	–	Extend Vocabulary	concatenate	LLaMA-3.1	Action/3D	Modality-Token-based	OccLLaMA's 3D de-tokenizer /OccLLaMA's Action de-tokenizer
Llama-AVSR	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	AV-HuBert /Whisper	multi-branch	MLP	–	concatenate	LLaMA-3.1	–	–	–
MIO	Corss-modal Understanding && Generation	Visual/Audio	Discrete Encoding	SEED tokenizer /Speech tokenizer	embedding	–	Extend Vocabulary	concatenate	Yi	Image/Speech	Modality-Token-based	SEED de-tokenizer /Speech de-tokenizer
EMOVA	Corss-modal Understanding && Generation	Visual/Audio	Hybird Encoding	Intern Vit /EMOVA's S2U tokenizer	multi-branch	C-Abstractor	Extend Vocabulary	concatenate	LLaMA-3.1	Speech	Modality-Token-based	EMOVA's S2U de-tokenizer
LLM Gesticulator	Corss-modal Understanding && Generation	Audio/Motion	Diserect Encoding	MotionRVQ tokenizer /Encodec tokenizer	embedding	–	Extend Vocabulary	concatenate	Qwen-1.5	Audio/Motion	Modality-Token-based	MotionRVQ de-tokenizer /Encodec de-tokenizer
Baichuan-Omni	Corss-modal Understanding	Audio/Motion	Continuous Encoding	SigCLIP /Whisper	multi-branch	CNN+MLP/Conv-GMLP	–	concatenate	–	–	–	–
EGMI	Corss-modal Understanding && Generation	Audio/Motion	Continuous Encoding	ImageBind	uni-branch	Linear	–	concatenate	Vicuna	Image/Audio	Representation-based	StableDiffusion /AudioLDM
Dolphin	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	CLIP Vit/ImageBind-Audio	multi-branch	MLP	–	concatenate	Vicuna	–	–	–
Mini-Omni2	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	CLIP Vit/Whisper	multi-branch	MLP	–	concatenate	Qwen2	Audio	Modality-Token-based	SNAC de-tokenizer
OMCAT	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/ImageBind-Audio	multi-branch	Q-former+transformer	–	concatenate	Vicuna	–	–	–
PathWeave	Corss-modal Understanding	Visual/Whisper	Continuous Encoding	EVA CLIP Vit/Beats /ULIP2	uni-branch	Q-former+Linear	–	concatenate	Vicuna	–	–	–
CAD-MLLM	Corss-modal Understanding	Visual/3D	Continuous Encoding	DINO v2 /Michelangelo	multi-branch	Preceiver+Linear/Linear	–	concatenate	Vicuna	–	–	–
EAGLE	Corss-modal Understanding	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	MLP	–	concatenate	LLaMA-2	Image/Video/Audio	Text-based	StableDiffusion /AudioLDM/Zeroscope
Spider	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	ImageBind	multi-branch	MLP	–	concatenate	LLaMA-2	Image/Video/Audio	Text-based	StableDiffusion /AudioLDM/Zeroscope
Med-2E3	Corss-modal Understanding	Visual/3D	Continuous Encoding	SigCLIP Vit/M3D-CLIP	multi-branch	Q-former+Linear/MLP	–	concatenate	Phi	–	–	–
LongVALE-LLM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/Beats/Whisper	multi-branch	MLP	–	concatenate	Vicuna	–	–	–
SOLAMI	Corss-modal Understanding	Audio/Motion	Diserect Encoding	SpeechTokenizer /SOLAMI's MotionTokenizer	embedding	–	Extend Vocabulary	concatenate	Vicuna	Speech/Motion	Modality-Token-based	Speech de-tokenizer /SOLAMI's Motion de-tokenizer
MuMu-LLaMA	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	Vit/ViViT/MERT	multi-branch	Conv+MLP/Conv+Rnn+MLP	–	injection	LLaMA-2	Music	Representation-based	MusicGen
GMA	Corss-modal Understanding && Generation	Visual/Action	Hybird Encoding	SigCLIP Vit /GMA's Action tokenizer	multi-branch	MLP	Overwrite Vocabulary	concatenate	Qwen-2	Action	Modality-Token-based	GMA's Action de-tokenizer
Lyra	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	DFNCLIP Vit/Whipser	multi-branch	MLP	–	concatenate	Qwen-2	Audio	Representation-based	LLaMA-Omni's audio decoder
VITA-1.5	Corss-modal Understanding && Generation	Visual/Audio	Continuous Encoding	InternVit/VITA's Audio Encoder	multi-branch	MLP/CNN+MLP	–	concatenate	Mixtral	Speech	Representation-based	TiCodec decoder
EmpatheticLLM	Corss-modal Understanding	Visual/Audio	Continuous Encoding	CLIP Vit/Whisper	multi-branch	Q-former+Linear	–	concatenate	Qwen2.5	–	–	–

Table 1: **The architectures of mainstream OmniMLLMs.** The architectures of 70 Omni-MLLMs are displayed by encoding, alignment, interaction, and generation.

Name	Type	Modality	#Sample
MSCOCO (Lin et al., 2014)	X-Text	Image,Text	620K
Visual Genome (Krishna et al., 2017b)	X-Text	Image,Text	4.5M
Flickr30k (Plummer et al., 2015)	X-Text	Image,Text	158K
SBU (Ordonez et al., 2011)	X-Text	Image,Text	1M
DCI (Urbanek et al., 2024)	X-Text	Image,Text	7.8K
BLIP-Capfilt (Li et al., 2022c)	X-Text	Image,Text	129M
AI Challenger captions (Wu et al., 2017)	X-Text	Image,Text	1.5M
Wukong Captions (Gu et al., 2022)	X-Text	Image,Text	101M
CC12M (Changpinyo et al., 2021)	X-Text	Image,Text	12.4M
CC3M (Sharma et al., 2018)	X-Text	Image,Text	3.3M
LAION-5B (Schuhmann et al., 2022)	X-Text	Image,Text	5.9B
Redcaps (Desai et al., 2021)	X-Text	Image,Text	12M
LAION-COCO (Schuhmann et al., 2022b(b))	X-Text	Image,Text	600M
LAION-CAT (Radenovic et al., 2023)	X-Text	Image,Text	440M
LAION-AESTHETICS (Schuhmann et al., 2022b(a))	X-Text	Image,Text	120M
ShareGPT4V (Chen et al., 2024e)	X-Text	Image,Text	1.2M
LAION-115M (Schuhmann et al., 2021)	X-Text	Image,Text	115M
Journeydb (Sun et al., 2023b)	X-Text	Image,Text	4.4M
Multimodal c4 (Zhu et al., 2023b)	X-Text-X	Image,Text	43.3M
OBELICS (Laurençon et al., 2023)	X-Text-X	Image,Text	141M
Panda-70M (Chen et al., 2024f)	X-Text	Video,Text	70M
Webvid2M (Bain et al., 2021)	X-Text	Video,Text	2M
Valley-Pretrain-703k (Luo et al., 2023a)	X-Text	Video,Text	703K
Webvid10M (Bain et al., 2021)	X-Text	Video,Text	10M
YT-Temporal (Zellers et al., 2022)	X-Text	Video,Text	180M
ActivityNet Captions (Krishna et al., 2017a)	X-Text	Video,Text	100K
InterVid (Wang et al., 2024d)	X-Text	Video,Text	10M
MSRVTT (Xu et al., 2016)	X-Text	Video,Text	200K
ShareGemini (Share, 2024)	X-Text	Video,Text	530K
AudioSet (Gemmeke et al., 2017)	X-Text	Audio,Text	2.1M
Clotho (Drossos et al., 2020)	X-Text	Audio,Text	5k
Auto-ACD (Sun et al., 2024b)	X-Text	Audio,Text	1.5M
AudioCap (Kim et al., 2019)	X-Text	Audio,Text	46k
WavCaps (Mei et al., 2024)	X-Text	Audio,Text	403K
AISHELL-1 (Bu et al., 2017)	X-Text	Audio,Text	128K
AISHELL-2 (Du et al., 2018)	X-Text	Audio,Text	1M
Gigaspeech (Chen et al., 2021)	X-Text	Speech,Text	–
Common Voice (Ardila et al., 2020)	X-Text	Speech,Text	–
MLS (Pratap et al., 2020)	X-Text	Speech,Text	–
Music caption (Zhan et al., 2024)	X-Text	Music,Text	100M
Cap3D (Luo et al., 2023b)	X-Text	3D,Text	1M
Objaverse (Deitke et al., 2023)	X-Text	3D,Text	800K
ScanRefer (Chen et al., 2020a)	X-Text	3D,Text	51.5K
Normal Caption (Han et al., 2024a)	X-Text	Normal,Text	0.5M
Depth Caption (Han et al., 2024a)	X-Text	Depth,Text	0.5M
NSD (Allen et al., 2022)	X-Text	fMRI,Text	9K
Ego4d (Grauman et al., 2022)	X-Text	Video,IMU,Text	528k
PU-VALOR (Tang et al., 2024a)	X-Y-Text	Video,Audio,Text	114K
VALOR (Chen et al., 2023e)	X-Y-Text	Video,Audio,Text	16k
VAST (Chen et al., 2023f)	X-Y-Text	Video,Audio,Text	414k
VIDAL (Zhu et al., 2024a)	X-Y-Text	Video, Thermal, Depth, Audio	10M
TVL (Fu et al., 2024c)	X-Y-Text	Image,Touch,Text	44K
M3D-Cap (Bai et al., 2024a)	X-Y-Text	Image,3D,Text	115K

Table 2: **The statistics for alignment datasets in Omni-MLLMs**, including single non-linguistic modality text pairing data (X-Text), multiple non-linguistic modalities text pairing data (X-Text-Y), and single non-linguistic modality text interleaved data (X-Text-X).

Name	Source	Task	Modality	Construction Method	#Sample
XLLM's SFT (Chen et al., 2023a)	MiniGPT-4, AISHELL-2, VSDial-CN, ActivityNet Caps	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	Template Instructionalization, T2X generation	10k
ChatBridge's SFT (Zhao et al., 2023b)	MSRVTT, AudioCaps, VQAv2, VG-QA...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	Template Instructionalization, GPT generation	4.4M+209k
Macaw-LLM (Lyu et al., 2023)	MSCOCO, Charades, AVSD, VG-QA...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	GPT generation	69K+50K
BuboGPT's SFT	LLaVA, Clotho, VGGSS	Uni-Modal Understanding,Cross-Modal Understanding	Image,Audio,Text	Template Instructionalization, GPT generation	196K
NextGPT's SFT (Wu et al., 2024b)	WebVid, CC3M, AudioCap, Youtube...	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation,Cross-Modal Generation	Image,Video,Audio,Text	Template Instructionalization, GPT generation+retrieval, T2X generation	20K
AnyMal's SFT (Moon et al., 2024)	–	Uni-Modal Understanding	Image,Video,Audio,Text	Manual Annotation, GPT generation	210K
FAVOR's SFT (Sun et al., 2023a)	LLaVA, MSCOCO, Ego4D, LibriSpeech...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	Template Instructionalization, GPT generation	–
LEO's SFT (Huang et al., 2024)	ScanQA, SQA3D, 3RScan, CLIPort...	Uni-Modal Understanding,Cross-Modal Understanding	Image,3D,Text,Action	Template Instructionalization, GPT generation	220k
CoDi-2's SFT (Tang et al., 2024b)	MIMIC-IT, LAION-400M, AudioSet, Webvid...	Uni-Modal Understanding,Uni-Modal Generation	Image,Audio,Text	Template Instructionalization	–
X-InstructBLIP's SFT (Panagopoulou et al., 2024)	MSCOCO, Clotho, MSVD, Cap3D...	Uni-Modal Understanding	Image,Video,Audio,3D,Text	Template Instructionalization, GPT generation	1.6M
OneLLM's SFT (Han et al., 2024a)	LLaVA-150K, Clotho, Ego4D, NSD...	Uni-Modal Understanding	Image,Video,Audio,3D,ImU, Depth,fMRI,Normal,Text	Template Instructionalization, T2X generation	2M
AVLLM's SFT (Shu et al., 2023)	ACAV100M, VGGSound, WebVid2M, WavCaps...	Uni-Modal Understanding,Cross-Modal Understanding	Video,Audio,Text	GPT generation	1.4M
Uni-IO2's SFT (Lu et al., 2024a)	CC3M, AudioSet, Webvid3m, Omni3D...	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation,Cross-Modal Generation	Image,Video,Audio,Text	Template Instructionalization, GPT generation	775m
ModaVerse's SFT (Wang et al., 2024c)	–	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation	Image,Video,Audio,Text	GPT generation	2M
REAMO's SFT (Zhang et al., 2024b)	–	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	Template Instructionalization	10K
GroundingGPT's SFT (Li et al., 2024h)	Flickr30K, VCR, Activitynet Captions, Clotho...	Uni-Modal Understanding	Image,Video,Audio,Text	GPT Instructionalization	1M
AnyGPT's SFT (Du et al., 2018)	–	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation,Cross-Modal Generation	Image,Audio,Text	GPT Instructionalization, T2X generation	208K
CAT's SFT (Ye et al., 2024b)	VGGSound, AVQA, VideoInstruct100K...	Cross-Modal Understanding	Video,Audio,Text	GPT Instructionalization	100K
AVicuna's SFT (Tang et al., 2024a)	UnAV-100, VideoInstruct100K, ActivityNet Captions, DiDeMo	Uni-Modal Understanding,Cross-Modal Understanding	Video,Audio,Text	Template Instructionalization	49K
M3DBench'SFT (Li et al., 2024b)	Scannet, ScanRefer, ShapeNet...	Uni-Modal Understanding,Cross-Modal Understanding	Image,3D,Text	Template Instructionalization,//GPT Instructionalization	320k
Uni-Moe's SFT (Li et al., 2024f)	LLaVA-Instruct-150K, LibriSpeech, VideoInstruct100K...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	Template Instructionalization, T2X generation	874K
X-VILA's SFT (Ye et al., 2024a)	WebVid, ActivityNetCaption, LLaVA-Instruct-150K...	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation,Cross-Modal Generation	Image,Video,Audio,Text	Template Instructionalization	–
EMOVA's SFT (Chen et al., 2024c)	ShareGPT-4o, MSCOCO, LLaVA-Instruct-150K...	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation,Cross-Modal Generation	Image,Audio,Text	Template Instructionalization, GPT Instructionalization, T2X generation	4.4M
VideoLLaMA2's SFT (Cheng et al., 2024b)	AVQA, AVSD, MusicCaps...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Text	Template Instructionalization	1.5M
PathWeave's SFT (Yu et al., 2024a)	VQAV2, MSRVTT, Cap3D...	Uni-Modal Understanding	Image,Video,Audio,3D,Depth	Template Instructionalization, T2X generation	23.2M
Spider's SFT (Lai et al., 2024)	AudioCap, CC3M, Webvid...	Cross-Modal Understanding,Cross-Modal Generation	Image,Video,Audio,Text	Template Instructionalization, GPT Generation	–
GMA's SFT (Szot et al., 2024b)	Meta-World,CALVIN, Maniskill...	Uni-Modal Understanding,Cross-Modal Understanding, Cross-Modal Generation	Image,Text,Action	Template Instructionalization	2.2M
OCTAVIUS's SFT (Chen et al., 2024g)	MSCOCO,Bamboo, ScanNet...	Uni-Modal Understanding	Image,3D,Text	Template Instructionalization, GPT Generation	
Lyra's SFT (Zhong et al., 2024)	Mini-Gemini, Collected Youtube's Audio	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation	Image,Audio,Text	GPT Generation, T2X Generation	1.5M
video-SALMONN's SFT (Sun et al., 2024a)	LibriSpeech,AudioCaps, LLaVA-Instruct-150K...	Uni-Modal Understanding,Cross-Modal Understanding	Video,Audio,Text	Template Instructionalization, T2X Generation	–
Meerkat's SFT (Chowdhury et al., 2024)	VGG-SS,AVSBench, AVQA,MUSIC-AVQA...	Cross-Modal Understanding	Video,Audio,Text	Template Instructionalization, GPT Generation	3M
VITA's SFT (Fu et al., 2024b)	ShareGPT4V,LLaVA-Instruct-150K, ShareGTP4o,ShareGemini...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	T2X Generation	–
Baichuan-omni's SFT (Li et al., 2024c)	vFLAN,VideoInstruct100K...	Uni-Modal Understanding,Cross-Modal Understanding	Image,Video,Audio,Text	T2X Generation	–
LongVALE-LLM's SFT (Geng et al., 2024)	LongVALE	Uni-Modal Understanding,Cross-Modal Understanding	Video,Audio,Text	GPT Generation	25.4K
UnifiedMLLM's SFT (Li et al., 2024g)	LISA,SmartEdit...	Uni-Modal Understanding,Cross-Modal Understanding, Uni-Modal Generation,Cross-Modal Generation	Image,Video,Audio,Text	Template Instructionalization, GPT Generation	100K
Dolphin's SFT (Anonymous, 2024)	AVQA,Flickr-SoundNet, VGGSound,LLP...	Uni-Modal Understanding,Cross-Modal Understanding	Video,Audio,Text	Template Instructionalization, GPT Generation	–

Table 3: **The statistics for OmniMLLM's Instruction Data,** including the data sources, interaction forms, involved modalities, and construction methods.

Name	Capability Category	Modality	Specific-Task	Metrics
VQA v2 (Goyal et al., 2017)	Unimodal Understanding	Image,Text	QA	Acc
GQA (Hudson and Manning, 2019)	Unimodal Understanding	Image,Text	QA	Acc
DocVQA (Mathew et al., 2021)	Unimodal Understanding	Image,Text	QA	Acc
IconQA (Lu et al., 2021)	Unimodal Understanding	Image,Text	QA	Acc
OCR-VQA (Mishra et al., 2019)	Unimodal Understanding	Image,Text	QA	Acc
STVQA (Biten et al., 2019)	Unimodal Understanding	Image,Text	QA	Acc
VSR (Liu et al., 2023a)	Unimodal Understanding	Image,Text	QA	Acc
Hateful Meme (Kiela et al., 2020)	Unimodal Understanding	Image,Text	QA	AUC
OKVQA (Marino et al., 2019)	Unimodal Understanding	Image,Text	QA	Acc
VizWiz (Gurari et al., 2018)	Unimodal Understanding	Image,Text	QA	Acc
TextVQA (Singh et al., 2019)	Unimodal Understanding	Image,Text	QA	Acc
nocap (Agrawal et al., 2019)	Unimodal Understanding	Image,Text	Caption	CIDER
ScienceQA (Lu et al., 2022)	Unimodal Understanding	Image,Text	QA	Acc
MSCOCO Caption (Lin et al., 2014)	Unimodal Understanding	Image,Text	Caption	CIDER,BLEU
Flickr Caption (Plummer et al., 2015)	Unimodal Understanding	Image,Text	Caption	CIDER
Visual Dialog (Das et al., 2017)	Unimodal Understanding	Image,Text	Dialogue	MRR
RefCOCO (Yu et al., 2016)	Unimodal Understanding	Image,Text	Grounding	Acc
RefCOCO+ (Yu et al., 2016)	Unimodal Understanding	Image,Text	Grounding	Acc
RefCOCOg (Mao et al., 2016)	Unimodal Understanding	Image,Text	Grounding	Acc
A-okvqa (Schwenk et al., 2022)	Unimodal Understanding	Image,Text	QA	Acc
POPE (Li et al., 2023)	Unimodal Understanding	Image,Text	Hallucination	Acc
IIIT5K (Mishra et al., 2012)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
IC13 (Karatzas et al., 2013)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
IC15 (Karatzas et al., 2015)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
Total-Text (Chng and Chan, 2017)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
CUTE80 (Risnumawan et al., 2014)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
SVT (Wang et al., 2011)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
SVTP (Phan et al., 2013)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
COCO-Text (Veit et al., 2016)	Unimodal Understanding	Image,Text	OCR	WAC(word ACC)
MMB (Liu et al., 2024d)	Unimodal Understanding	Image,Text	Comprehensive Benchmark	GPT ACC
MME (Fu et al., 2023)	Unimodal Understanding	Image,Text	Comprehensive Benchmark	GPT ACC
LLaVA-Bench (Liu et al., 2023c)	Unimodal Understanding	Image,Text	Comprehensive Benchmark	GPT ACC
Mmmu (Yue et al., 2024)	Unimodal Understanding	Image,Text	Comprehensive Benchmark	GPT ACC
SEED (Ge et al., 2023)	Unimodal Understanding	Image,Text	Comprehensive Benchmark	GPT ACC
MM-Vet (Yu et al., 2024d)	Unimodal Understanding	Image,Text	Comprehensive Benchmark	GPT ACC
ActivityNet-QA (Yu et al., 2019)	Unimodal Understanding	Video,Text	QA	Acc
MSRVTT-QA (Xu et al., 2016)	Unimodal Understanding	Video,Text	QA	Acc
MSVD-QA (Xu et al., 2017)	Unimodal Understanding	Video,Text	QA	Acc
How2QA (Li et al., 2020)	Unimodal Understanding	Video,Text	QA	Acc
NExTQA (Xiao et al., 2021)	Unimodal Understanding	Video,Text	QA	ACC
STAR (Wu et al., 2021)	Unimodal Understanding	Video,Text	QA	Acc
MSVD-Caption (Xu et al., 2017)	Unimodal Understanding	Video,Text	QA	CIDER
VATEX (Wang et al., 2019)	Unimodal Understanding	Video,Text	Caption	CIDER
MSRVTT-Caption (Xu et al., 2016)	Unimodal Understanding	Video,Text	Caption	CIDER,BLEU
Video-ChatGPT Benchmark (Maaz et al., 2024)	Unimodal Understanding	Video,Text	Comprehensive Benchmark	GPT ACC,GPT Score
Kinetics-400	Unimodal Understanding	Video,Text	Classification	Acc
Perception test (Patraucean et al., 2023)	Unimodal Understanding	Video,Text	Comprehensive Benchmark	GPT ACC
EgoSchema (Mangalam et al., 2023)	Unimodal Understanding	Video,Text	Comprehensive Benchmark	GPT ACC
Mvbench (Li et al., 2024a)	Unimodal Understanding	Video,Text	Comprehensive Benchmark	GPT ACC
VideoMME (Fu et al., 2024a)	Unimodal Understanding	Video,Text	Comprehensive Benchmark	GPT ACC
Charades-STA (Sigurdsson et al., 2016)	Unimodal Understanding	Video,Text	Grounding	IoU
AudioCaps (Kim et al., 2019)	Unimodal Understanding	Audio,Text	Caption	CIDER,SPICE,METEOR,BLEU,SPIDER
ClothoAQA (Lipping et al., 2022)	Unimodal Understanding	Audio,Text	QA	Acc
Vocalsound (Gong et al., 2022)	Unimodal Understanding	Audio,Text	QA	Acc
Clotho v1 (Drossos et al., 2020)	Unimodal Understanding	Audio,Text	Caption	CIDER
Clotho v2 (Drossos et al., 2020)	Unimodal Understanding	Audio,Text	Caption	CIDER
ESC50 (Piczak, 2015)	Unimodal Understanding	Audio,Text	Classification	Acc
LibriSpeech (Panayotov et al., 2015)	Unimodal Understanding	Audio,Text	ASR	WER
AISHELL-2 (Du et al., 2018)	Unimodal Understanding	Audio,Text	ASR	WER
Wenetspeech (Zhang et al., 2022a)	Unimodal Understanding	Audio,Text	ASR	WER
MusicCap (Agostinelli et al., 2023)	Unimodal Understanding	Audio,Text	Caption	CLAP Score
TUT2017 (Mesaros et al., 2016)	Unimodal Understanding	Audio,Text	Classification	Acc
EHSL (Li et al., 2024f)	Unimodal Understanding	Audio,Text	QA	Acc
Cap3D Caption (Luo et al., 2023b)	Unimodal Understanding	3D,Text	Caption	CIDER
Objaverse Caption (Deitke et al., 2023)	Unimodal Understanding	3D,Text	Caption	METEOR,ROUGE,BLEU
Cap3D QA (Luo et al., 2023b)	Unimodal Understanding	3D,Text	QA	Acc
Objaverse Classification (Deitke et al., 2023)	Unimodal Understanding	3D,Text	Classification	GPT ACC
Modelnet40 (Wu et al., 2015)	Unimodal Understanding	3D,Text	Classification	Acc
ScanRefer (Chen et al., 2020a)	Unimodal Understanding	3D,Text	Grounding	mAP
Nr3D (Achlioptas et al., 2020)	Unimodal Understanding	3D,Text	Caption	BLEU,CIDER,METEOR,ROUGE-L
SQA3D (Ma et al., 2023)	Unimodal Understanding	3D,Text	QA	Acc
ScanQA (Azuma et al., 2022)	Unimodal Understanding	3D,Text	QA	Acc
SUN RGB-D (Song et al., 2015)	Unimodal Understanding	Depth,Text	Classification	Acc
NYUv2 (Silberman et al., 2012)	Unimodal Understanding	Depth,Text	Classification	Acc
SUN RGB-D_generated Nomral (Han et al., 2024a)	Unimodal Understanding	Normal,Text	Classification	Acc
NYUv2_generated Nomral (Han et al., 2024a)	Unimodal Understanding	Normal,Text	Classification	Acc
ThermalQA (Yu et al., 2024c)	Unimodal Understanding	Thermal, Text	QA	Acc
TochQA (Yu et al., 2024c)	Unimodal Understanding	Touch, Text	QA	Acc
Ego4D (Grauman et al., 2022)	Unimodal Understanding	IMU,Text	Caption	CIDER,ROUGE
NSD (Allen et al., 2022)	Unimodal Understanding	fMRI,Depth Map,Text	Caption	CIDER,ROUGE
MSCOCO (Lin et al., 2014)	Unimodal Generation	Image,Text	TX2X Edit	FID,CLIPSIM
MSRVTT (Xu et al., 2016)	Unimodal Generation	Video,Text	T2X Generate	CLIPSIM
AudioCaps (Kim et al., 2019)	Unimodal Generation	Audio,Text	T2X Generate,TX2X Edit	FAD
DAVIS (Perazzi et al., 2016)	Unimodal Generation	Video,Text	TX2X Edit	CLIPSIM
UCF-101 (Soomro et al., 2012)	Unimodal Generation	Video,Text	T2X Generate	FID,FVD,IS,CLIPSIM
Evalcrafter (Liu et al., 2024c)	Unimodal Generation	Video,Text	T2X Generate	FVD,CLIPSIM
VCTK (Veaux et al., 2017)	Unimodal Generation	Audio,Text	T2X Generate,TX2X Edit	WER,MCD
MusicCap (Agostinelli et al., 2023)	Unimodal Generation	Audio,Text	T2X Generate	FAD
Dreambench (Ruiz et al., 2023)	Unimodal Generation	Image,Text	T2X Generate	CLIP-I,CLIP-T,DINO
MUSIC-AVQA (Li et al., 2022b)	Crossmodal Understanding	Video,Audio,Text	QA	Acc
AVSD (AlAmri et al., 2018)	Crossmodal Understanding	Video,Audio,Text	Dialogue	CIDER,BLEU
RACE-Audio (Li et al., 2024f)	Crossmodal Understanding	Image,Audio,Text	Comprehensive Benchmark	Acc
VALOR Caption (Chen et al., 2023e)	Crossmodal Understanding	Video,Audio,Text	Caption	CIDER,BLEU
MMBench-Audio (Li et al., 2024f)	Crossmodal Understanding	Image,Audio,Text	Comprehensive Benchmark	Acc
AVQA (Li et al., 2022a)	Crossmodal Understanding	Video,Audio,Text	QA	Acc
MCUB (Chen et al., 2024a)	Crossmodal Understanding	Image,Video,Audio,3D,Text	Comprehensive Benchmark	Acc
DisCRn (Panagopoulou et al., 2024)	Crossmodal Understanding	Image,Video,Audio,3D	Comprehensive Benchmark	Acc
OmniXR (Chen et al., 2024d)	Crossmodal Understanding	Image,Video,Audio,Text	Comprehensive Benchmark	Acc
Curse (Leng et al., 2024)	Crossmodal Understanding	Image,Video,Audio,Text	Hallucination	Acc
ISQA (Sun et al., 2023a)	Crossmodal Understanding	Image,Audio,Text	QA	Acc
VGGSound (Chen et al., 2020b)	Crossmodal Understanding	Video,Audio,Text	QA	Acc
VATEX (Wang et al., 2019)	Crossmodal Understanding	Video,Audio,Text	Caption	CIDER
UnAV-100 (Geng et al., 2023)	Crossmodal Understanding	Video,Audio,Text	Ground	IoU
LLP (Tian et al., 2020)	Crossmodal Understanding	Video,Audio,Text	Ground	IoU
Presentation-QA (Sun et al., 2024a)	Crossmodal Understanding	Video,Audio,Text	QA	ACC
LongVALE Caption	Crossmodal Understanding	Video,Audio,Text	Caption	CIDER
TVL Benchmark (Fu et al., 2024c)	Cross-modal Understanding	Touch,Image,Text	QA	ACC
AVEB (Sun et al., 2023a)	Crossmodal Understanding,Unimodal Understanding	Image,Video,Audio,Text	Comprehensive Benchmark	ACC,METEOR,SPIDER,WER
XtoX Benchmark (Ye et al., 2024a)	Crossmodal Understanding,Crossmodal Generation	Image,Video,Audio,Text	Comprehensive Benchmark	X-to-X Alignment Score

Table 4: **An overview of benchmarks and tasks of Omni-MLLMs**, including the abilities being evaluated, the involved modalities, specific tasks, and evaluation metrics.

Model	LLM	Uni-Modal Understanding								Uni-Modal Generation			Cross-Modal Understanding			
		MSVD-QA	MSRVTT-QA	VQA$^{v2\ test}$	Flickr	MMB^{en}	AudioCaps$^{cap\ test}$	ClothoAQA	Objaverse	COCO^{gen}	AudioCaps^{gen}	MSRVTT^{gen}	VGGSS	AVSD	MUSIC-AVQA	AVQA
Omni-MLLMs																
ePALM	OPT-2.7B	38.4	38.51	54.47	–	–	61.86	–	–	–	–	–	–	–	–	–
ChatBridge 13B	Vicuna-13B	45.3	–	–	82.5	–	–	–	–	–	–	–	–		43	–
PandaGPT	Vicuna-13B	46.7	23.7	–	–	–	–	–	–	–	–	–	32.7	26.1	33.7	79.8
Video-LLaMA	Vicuna-7B	51.6	29.6	–	–	–	–	–	–	–	–	–	40.8	36.7	36.6	81
Macaw-LLM	LLAMA-7B	42.1	25.5	–	–	3.84	33.3	–	–	–	–	–	36.1	34.3	31.8	78.7
ImageBind-LLM	LLaMA-7B	–	–	–	23.49	–	–	10.3	31	–	–	–	–	–	39.72	54.26
NExT-GPT	Vicuna-7B	64.5	58.4	66.7	84.5	58	81.3	–	–	10.07	8.67	31.97	–	–	–	–
AnyMAL 13B	LLaMA2-13B	–	–	59.6	–	–	–	–	–	–	–	–	–	–	–	–
AnyMAL 70B	LLaMA2-70B	–	–	64.2	95.9	–	77.8	–	–	–	–	–	–	–	–	–
X-InstructBLIP 7B	Vicuna-7B	51.7	41.3	30.61	82.1	8.96	67.9	15.4	50	–	–	–	–	–	28.1	–
X-InstructBLIP 13B	Vicuna-13B	49.2	–	–	74.7	–	53.7	21.7	–	–	–	–	20.3	52.1	44.5	44.23
OneLLM 7B	LLaMA2-7B	56.5	–	71.6	78.6	60	–	57.9	44.5	–	–	–	–	–	47.6	–
AV-LLM	Vicuna-7B	67.3	53.7	–	–	–	35.5	–	–	–	–	–	47.6	52.6	45.2	–
UIO-2xxl 6.8B	–	52.2	41.5	79.4	–	71.5	48.9	–	–	13.39	5.89	–	–	–	–	–
ModaVerse	Vicuna-7b	–	56.5	–	–	–	79.2	–	–	11.24	8.22	30.14	–	–	–	–
CREMA 7B	Mistral-7B	–	–	–	–	–	–	–	–	–	–	–	–	–	52.6	–
GroundingGPT	Vicuna-7B	67.8	51.6	78.7	–	63.8	–	–	–	–	–	–	–	–	–	–
NaiveMC	Vicuna-7B	–	–	–	–	–	–	–	55	–	–	–	–	–	53.63	80.7
DAMC	Vicuna-7B	–	–	–	–	–	–	–	60.5	–	–	–	–	–	57.32	81.31
AnyGPT	LLaMA2-7B	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
CAT	LLaMA2-7B	–	62.7	–	–	–	–	–	–	–	–	–	–	48.6	92	
AVicuna	Vicuna-7B	70.2	59.7	–	–	–	–	–	–	–	–	–	–	53.1	49.6	–
Uni-MoE	LLaMA-7B	55.6	–	66.2	–	69.82	–	32.6	–	–	–	–	–	–	–	–
X-VILA 7B	Vicuna-7B	–	–	72.9	–	–	–	–	–	–	–	–	–	–	–	–
VideoLLaMA2-7B	Mistral-7B	71.7	–	–	–	–	–	–	–	–	–	–	71.4	57.2	80.9	–
Meerkat	Llama-2-7B-Chat	–	–	–	–	–	–	–	–	–	–	–	–	–	–	87.14
InternOmni	InternLM-2-Chat-7B	–	–	–	–	81.7	–	–	–	–	–	–	–	–	–	–
UnifiedMLLM	Vicuna-7B	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
VITA	Mixtral-8x7B	–	–	–	–	71.8	–	–	–	–	–	–	–	–	–	–
EMOVA	LLaMA-3.1-8B	–	–	–	–	82.8	–	–	–	–	–	–	–	–	–	–
BaiChuan-omni-7B	–	72.2	–	–	–	76.2	–	–	–	–	–	–	–	–	–	–
OMCAT	Vicuna-7B	–	–	–	–	–	–	–	–	–	–	–	–	49.4	73.8	90.2
PathWeave-7B	Vicuna-7B	47.8	37.4	–	–	–	64	33.5	–	–	–	–	–	–	–	–
Spider	Llama-2-7B	–	–	–	–	–	81.7	–	–	11.23	8.18	30.97	–	–	–	–
Specifc-MLLMs																
VILA-7B	LLaMA-2-7B	–	–	79.9	74.7	68.9	–	–	–	–	–	–	–	–	–	–
VideoChat2	Vicuna-7B	70	54.1	–	–	–	–	–	–	–	–	–	–	–	–	–
Qwen-Audio	Qwen-7B	–	–	–	–	–	–	57.9	–	–	–	–	–	–	–	–
PointLLM	Vicuna-7B	–	–	–	–	–	–	–	47.5	–	–	–	–	–	–	–
Emu-13B	–	–	–	52	–	–	–	–	–	11.66	–	–	–	–	–	–
Video-LaVIT	Llama2-7B	73.2	–	80.3	–	67.3	–	–	–	–	–	30.12	–	–	–	–

Table 5: **The performance of Omni-MLLMs on different benchmarks.** The selected uni-modal understanding benchmarks include Video-Text2Text (Xu et al., 2017, 2016), Image-Text2Text (Goyal et al., 2017; Plummer et al., 2015; Liu et al., 2024d), Audio-Text2Text (Kim et al., 2019; Lipping et al., 2022), and 3D-Text2Text (Deitke et al., 2023). The chosen uni-modal generation benchmarks include Text2Image (Lin et al., 2014), Text2Video (Xu et al., 2016), and Text2Audio (Kim et al., 2019). The selected cross-modal understanding benchmarks are Image-Audio-Text2Text (Chen et al., 2020b; AlAmri et al., 2018) and Video-Audio-Text2Text (Li et al., 2022b,a).