When Tokens Talk Too Much:
A Survey of Multimodal Long-Context Token Compression

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Abstract

Multimodal large language models (MLLMs) have made remarkable strides, largely driven by their ability to process increasingly **long and complex** contexts, such as high-resolution images, extended video sequences, and lengthy audio input. While this ability significantly enhances MLLM capabilities, it introduces substantial computational challenges, primarily due to the quadratic complexity of self-attention mechanisms with numerous input tokens. To mitigate these bottlenecks, token compression has emerged as an auspicious and critical approach, efficiently reducing the number of tokens during both training and inference. In this paper, we present the first systematic survey and synthesis of the burgeoning field of multimodal long context token compression. Recognizing that effective compression strategies are deeply tied to the unique characteristics and redundancies of each modality, we categorize existing approaches by their primary data focus, enabling researchers to quickly access and learn methods tailored to their specific area of interest: *(1) image-centric compression*, which addresses spatial redundancy in visual data; *(2) video-centric compression*, which tackles spatio-temporal redundancy in dynamic sequences; and *(3) audio-centric compression*, which handles temporal and spectral redundancy in acoustic signals. Beyond this modality-driven categorization, we further dissect methods based on their underlying mechanisms, including **transformation-based, similarity-based, attention-based,** and **query-based** approaches. By providing a comprehensive and structured overview, this survey aims to consolidate current progress, identify key challenges, and inspire future research directions in this rapidly evolving domain.

1 Introduction

Multimodal large language models (MLLMs) (Liu et al., 2023; Li et al., 2025a; Xu et al., 2024a; Bai et al., 2023; Xu et al., 2025b; Lin et al., 2024a; Zhang et al., 2023; Li et al., 2024a; 2023d; Cheng et al., 2024c; Zhang et al., 2025a) have demonstrated exceptional performance on complex tasks, including visual question answering (VQA), automatic speech recognition (ASR) and multimodal content generation, by extending the architectural of large language models (LLMs) (Chiang et al., 2023; Team, 2024; AI@Meta, 2024; Abdin et al., 2024). These powerful models derive their strength from processing long and diverse contexts, such as high-resolution images, extended video sequences, and long audio input, using transformer architectures.

Achieving this capability, however, faces a significant challenge: the quadratic complexity of the self-attention mechanism. As the number of tokens increases, this complexity leads to substantial computational and memory demands. This problem is particularly pronounced in MLLMs, where the tokenization of visual and audio data can generate sequences of orders of magnitude longer than text (Shao et al., 2025; Tao et al., 2025a; Yang et al., 2025b).

For instance, as illustrated in Figure 1, the number of image tokens is directly proportional to resolution, while the number of audio tokens is proportional to duration, and video tokens scale with both resolution and duration. A single content-rich video can produce tens of millions of tokens, dramatically exacerbating computational inefficiencies and leading to severe inference latency (90 minutes video will be converted
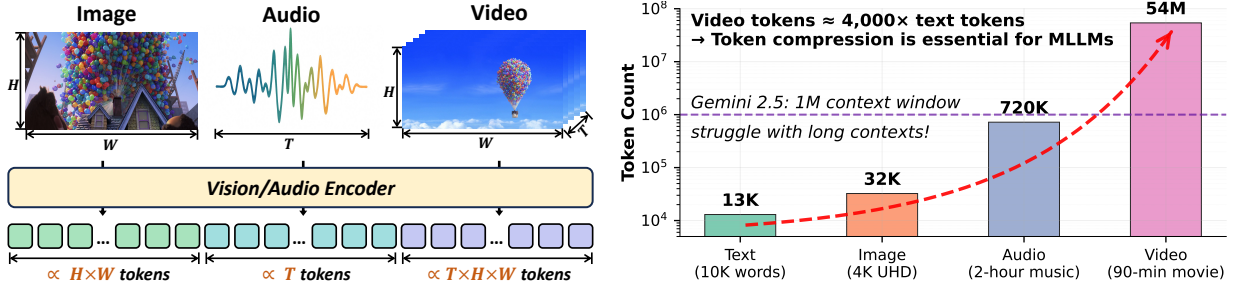
Figure 1: **Left:** Image, video, and audio data types can scale in their representation dimensions, leading to a corresponding increase in the number of tokens. **Right:** Top-performing MLLMs cannot address real-world demands, as the number of tokens for multimodal input, especially video, vastly exceeds that of text, and most visual tokens are redundant. Therefore, token compression is crucial to address this limitation.

into 54M tokens)[1]. Consequently, addressing this computational bottleneck is critical for unlocking the full potential of MLLMs in real-world applications.

To address the challenges posed by the long context, *token compression* has emerged as a critical research focus for enhancing the inference efficiency and practical deployment of MLLMs. This approach is highly effective because multimodal inputs, like those processed by vision transformers (ViT), contain significant redundancy (Rao et al., 2021; Liang et al., 2022; Bolya et al., 2022; Ryoo et al., 2021; Touvron et al., 2021; Vaswani et al., 2017; Yang et al., 2025c). Extensive research, for example, demonstrates that more than 50% of tokens in a typical MLLM sequence receive minimal attention during inference (Chen et al., 2024a; Huang et al., 2025c; Tao et al., 2025a; Shao et al., 2025; Alvar et al., 2025; Shang et al., 2025). While some advanced techniques integrate compression directly into a model's architecture or training framework (Chen et al., 2024c; Dai et al., 2024; Wang et al., 2024c; Bai et al., 2025; Li et al., 2025a; Zhang et al., 2024d; Cai et al., 2024; Yao et al., 2024; Cha et al., 2024; Chu et al., 2023; 2024a; Li et al., 2024c), a major advantage of token compression is its ability to be applied as a post-optimization technique without requiring expensive retraining. These methods typically operate by first establishing a specialized metric to evaluate token importance, then performing a corresponding pruning or compression. By significantly accelerating inference and reducing memory consumption, these techniques enable the practical deployment of MLLMs in real-world applications (Lin et al., 2025a; Chu et al., 2023; 2024a; Wei et al., 2025; Ma et al., 2024b).

Recent extensive research demonstrates that token compression substantially enhances inference efficiency, driving the continuous development of diverse compression strategies and sophisticated methodologies (Shen et al., 2025a; Chai et al., 2025; Alvar et al., 2025; Huang et al., 2025c; He et al., 2025; Yang et al., 2025b; Shang et al., 2025; Zhang et al., 2025b; Cao et al., 2023; Yang et al., 2025a; Chen et al., 2024a; Tao et al., 2025b; Zhang et al., 2024c; Liu et al., 2024c; Yang et al., 2025c). However, the inherent heterogeneity of multimodal data means that redundancy differs across modalities. Unlike textual prompts, where redundancy is primarily in syntactic or semantic, visual and auditory data exhibit unique structural properties. For instance, high-resolution images contain strong local correlations, while video streams feature extensive spatiotemporal redundancy across frames, and audio signals often contain extended segments of silence or stationary noise. Consequently, most existing methods focus on compressing one or two specific modalities.

Significant strides have been made in compressing tokens in text LLMs. For instance, (Li et al., 2025e) has thoroughly explored prompt compression for text LLMs, highlighting advancements in this domain. In MLLMs, position paper (Kong et al., 2025) has begun to broaden our understanding, emphasizing that token compression offers benefits beyond mere efficiency. Furthermore, some researchers argue that the focus of research for efficient AI is shifting from model-centric compression to data-centric compression (Liu et al., 2025d). However, there has not yet been a systematic classification of token compression methods specifically for MLLMs, leaving an opportunity for a comprehensive survey in this area.

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[1] $90\,\text{min} \times 60\,\text{s/min} \times 10\,\text{frames/s} \times 1000\,\text{tokens/frame}$.
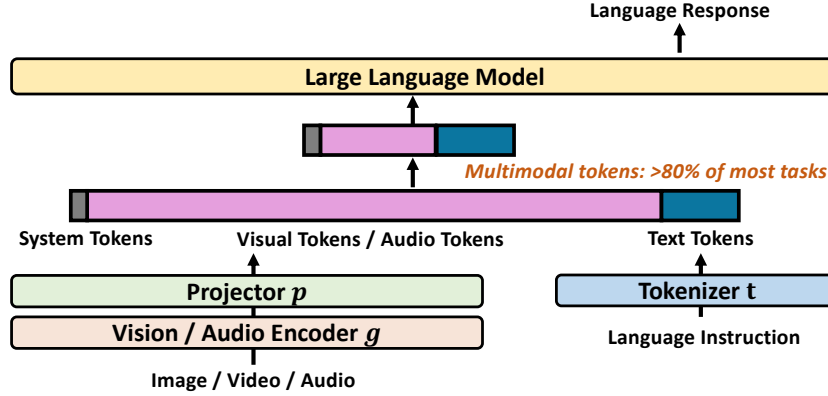
Figure 2: **Representative Architecture of MLLMs.** Within MLLM reasoning processes, token sequences comprise concatenated system tokens, multimodal tokens, and text tokens. Multimodal tokens usually constitute the majority of the sequence tokens.

Motivated by the critical need for efficiency in MLLMs and a desire to address this current research fragmentation, this work presents the first comprehensive, structured survey of long-context token compression techniques. We systematically categorize existing approaches according to their primary modality focus:

- **Image-centric** token compression addresses inherent spatial redundancy, leveraging the fact that neighboring patches usually represent similar textures or colors;

- **Video-centric** token compression targets spatiotemporal redundancy, mitigating the significant inter-frame correlation where consecutive frames typically share extensive background elements and limited motion;

- **Audio-centric** token compression mitigates temporal and spectral redundancy, as salient information often concentrates within sparse, brief segments and specific frequency bands amidst silent pauses or background noise.

Importantly, while acknowledging modality-specific influences on redundancy patterns and optimal compression strategies, we observe that fundamental algorithmic principles frequently transcend individual modalities. Effective compression fundamentally centers on *three* core computational objectives: *importance identification, redundancy quantification*, and *token merging or pruning*. These objectives manifest similarly across visual, temporal, and auditory domains despite distinct structural constraints. Consequently, we further categorize methodologies according to their underlying mechanisms: transform-based, similarity-based, attention-based, and query-based approaches.

This work presents the first structured survey of token compression techniques for MLLMs, a critical step in navigating their inherent computational complexities. By consolidating current progress, this survey identifies key challenges and illuminates promising future research directions, providing a foundational resource for both researchers and developers.

The remaining sections of the article are organized as follows: we will first discuss the architecture of MLLMs in the background section (Section 2.1), followed by an examination of how token compression has been utilized in prior methods for large language models (LLMs, Section 2.2) and vision transformers (ViTs, Section 2.3). Subsequent sections will be dedicated to token compression methods for specific modalities: Section 3 for image LLMs, Section 4 for video LLMs, and Section 5 for audio LLMs. Following this, Section 6 will provide insights into token compression research. Finally, Section 7 will introduce the broad application space of token compression, followed by the concluding Section 8.

Multimodal Token Compression

Image (§3)

Transformation-based (§3.1)
InternVL1.5 (Chen et al., 2024c), NVLM (Dai et al., 2024), Qwen2-VL (Wang et al., 2024c), Qwen2.5-VL (Bai et al., 2025), LaCo (Liu et al., 2025a), LLaVA-OneVision (Li et al., 2025a), LLaVA-Video (Zhang et al., 2024d), Seed1.5-VL (Guo et al., 2025b), M³ (Cai et al., 2024), DeCo (Yao et al., 2024), SlowFast-LLaVA (Xu et al., 2024b), PruMerge+ (Shang et al., 2025), C-Abstractor (Cha et al., 2024), MobileVLM (Chu et al., 2023), MobileVLM V2 (Chu et al., 2024a), LLaMA-VID (Li et al., 2024c), Dynamic-VLM (Wang et al., 2024b)

Similarity-based (§3.2)
ToMe (Bolya et al., 2023), FOLDER (Wang et al., 2025a), DivPrune (Alvar et al., 2025), AuroraCap (Chai et al., 2025), TopV (Yang et al., 2025a), Skip-Vision (Zeng et al., 2025), DyMU (Wang et al., 2025d), Dynamic-VLM (Wang et al., 2024b), STTM (Hyun et al., 2025), VisionZip (Yang et al., 2025b), VisPruner (Zhang et al., 2025e), PuMer (Cao et al., 2023), iLLaVA (Hu et al., 2024), G-Prune (Jiang et al., 2025b), BTP (Li et al., 2025b)

Attention-based (§3.3)
Attention in Encoder: PruMerge+ (Shang et al., 2025), VisionZip (Yang et al., 2025b), VisPruner (Zhang et al., 2025e), GlobalCom² (Liu et al., 2025c), MustDrop (Liu et al., 2024c), VScan (Zhang et al., 2025b), HiRED (Arif et al., 2025), FiCoCo (Han et al., 2024)
Attention in Decoder: FastV (Chen et al., 2024a), PyramidDrop (Xing et al., 2025), VTW (Lin et al., 2025c), FitPrune (Ye et al., 2025a), ST³ (Zhuang et al., 2025), ATP-LLaVA (Ye et al., 2025b), CoreMatching (Wang et al., 2025b), ZipVL (He et al., 2025), HoliTom (Shao et al., 2025), TokenCarve (Tan et al., 2025), SparseVLM (Zhang et al., 2024c), MustDrop (Liu et al., 2024c), VScan (Zhang et al., 2025b), FrameFusion (Fu et al., 2025b), iLLaVA (Hu et al., 2024), G-Search (Zhao et al., 2025), FiCoCo (Han et al., 2024), BTP (Li et al., 2025b)

Query-based (§3.4)
Token Distillation: InstructBLIP (Liu et al., 2023), BLIP-2 (Li et al., 2023c), mPLUG-Owl (Ye et al., 2023), Minigpt-4 (Zhu et al., 2024), Flamingo (Alayrac et al., 2022), Qwen-VL (Bai et al., 2023), LLaMA-VID (Li et al., 2024c), LLaVA-Mini (Zhang et al., 2025f), VoCo-LLaMA (Ye et al., 2025c), Victor (Wen et al., 2024)
Cross-Modal Selection: SparseVLM (Zhang et al., 2024c), AdaFV (Han et al., 2025), TRIM (Song et al., 2025a)

Video (§4)

Transformation-based (§4.1)
PLLaVA (Xu et al., 2024a), Video-ChatGPT (Maaz et al., 2024), LongVLM (Weng et al., 2024), VideoLLaMA 2 (Cheng et al., 2024c), SlowFast-LLaVA-1.5 (Xu et al., 2025c), QuoTA (Luo et al., 2025b), VideoChat-Flash (Li et al., 2024b), MobileVLM (Chu et al., 2023)

Similarity-based (§4.2)
Chat-UniVi (Jin et al., 2024), PruneVid (Huang et al., 2025c), FastVID (Shen et al., 2025a), HoliTom (Shao et al., 2025), DyCoke (Tao et al., 2025a), FrameFusion (Fu et al., 2025b), LongVU (Shen et al., 2025b), VidCom² (Liu et al., 2025b), DynTok (Zhang et al., 2025c), MovieChat (Song et al., 2024), VideoChat-Flash (Li et al., 2024b), Video-XL (Shu et al., 2025), TimeChat-Online (Yao et al., 2025), DTC (Huang et al., 2025b), LLaVA-Scissor (Sun et al., 2025), Aim (Zhong et al., 2025)

Attention-based (§4.3)
Attention in Encoder: PruMerge+ (Shang et al., 2025), VisionZip (Yang et al., 2025b), VisPruner (Zhang et al., 2025e), MustDrop (Liu et al., 2024c), FiCoCo (Han et al., 2024)
Attention in Decoder: FastV (Chen et al., 2024a), PyramidDrop (Xing et al., 2025), VTW (Lin et al., 2025c), CoreMatching (Wang et al., 2025b), ZipVL (He et al., 2025), SparseVLM (Zhang et al., 2024c), FastVID (Shen et al., 2025a), MustDrop (Liu et al., 2024c), HoliTom (Shao et al., 2025), VScan (Zhang et al., 2025b), FrameFusion (Fu et al., 2025b), iLLaVA (Hu et al., 2024), G-Search (Zhao et al., 2025), FiCoCo (Han et al., 2024), Aim (Zhong et al., 2025)

Query-based (§4.4)
Token Distillation: Token Turing Machines (Ryoo et al., 2023), BLIP-3-Video (Ryoo et al., 2024), Long-VMNet (Gurukar & Kadav, 2025), STORM (Jiang et al., 2025a), LinVT (Gao et al., 2024a), LLaMA-VID (Li et al., 2024c), LLaVA-Mini (Zhang et al., 2025f), VideoChat-Flash (Li et al., 2024b)
Cross-Modal Selection: LongVU (Shen et al., 2025b)

Audio (§5)

Transformation-based (§5.1)
HTS-AT (Chen et al., 2022), SLAM-ASR (Ma et al., 2024c), LLaMA-Omni (Fang et al., 2024), SpeechVerse (Das et al., 2024), Qwen2-audio (Chu et al., 2024b), Qwen2.5-Omni (Xu et al., 2025b), Baichuan-Audio (Li et al., 2025c), Llama-AVSR (Cappellazzo et al., 2025a), Llama-MTSK (Cappellazzo et al., 2025b), OSUM (Geng et al., 2025), LUCY (Gao et al., 2025)

Similarity-based (§5.2)
A-ToMe (Li et al., 2023f)

Attention-based (§5.3)
Attention in Encoder: Top-K (Lee & Lee, 2025)
Attention in Decoder: SpeechPrune (Lin et al., 2025b)

Query-based (§5.4)
Token Distillation: Video-LLaMA (Zhang et al., 2023), SALMONN (Tang et al., 2024), video-SALMONN (Sun et al., 2024a), Typhoon 2 (Pipatanakul et al., 2024), MMCE-Qformer (Xue et al., 2024), MMS-LLaMA (Yeo et al., 2025)
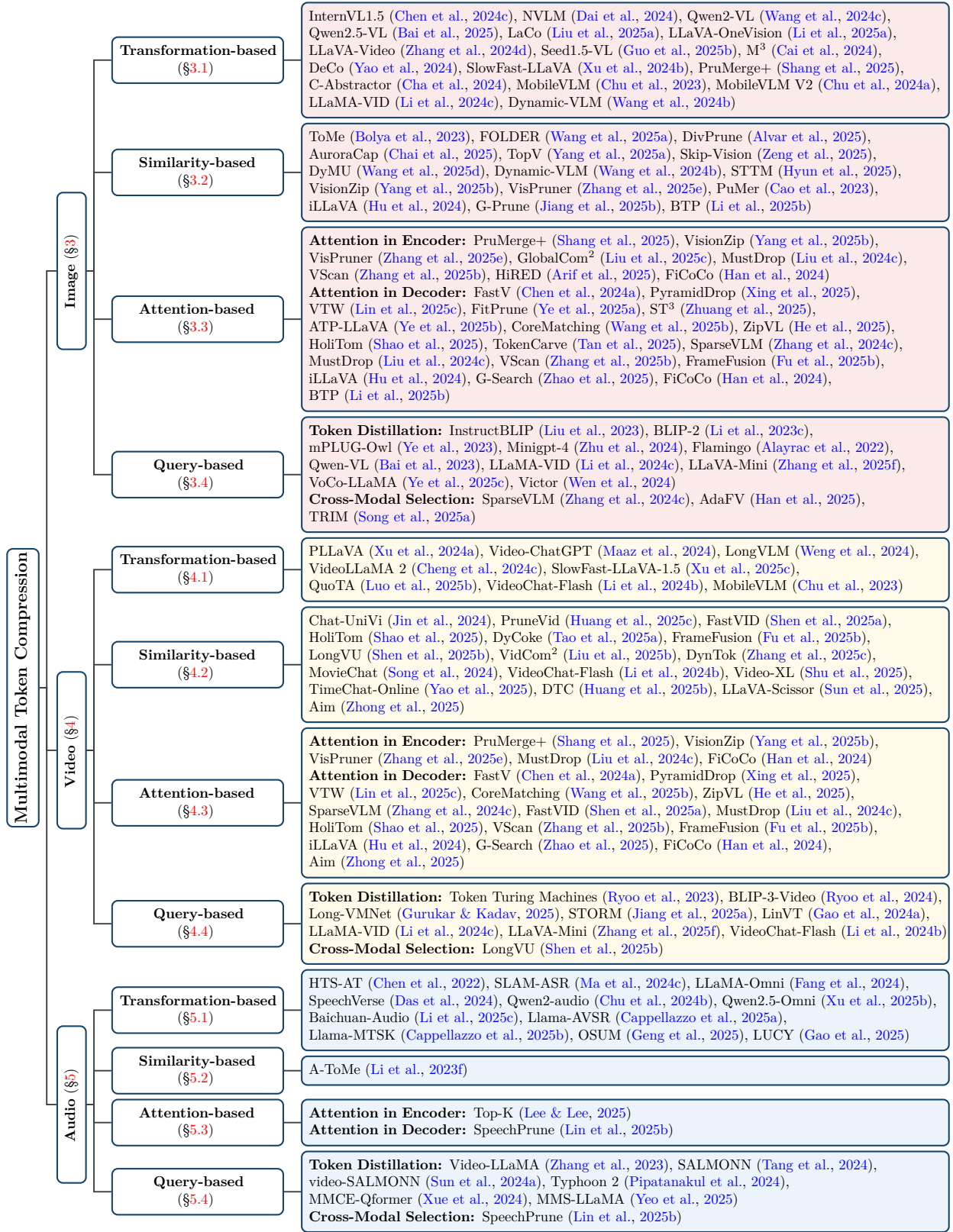**Cross-Modal Selection:** SpeechPrune (Lin et al., 2025b)

Figure 3: **Taxonomy of Multimodal Token Compression.** Our classification organizes existing methods by their dominant data modality, accounting for inherent differences in redundancy across modalities. This is further refined by a dissection of their underlying mechanisms, enabling researchers to quickly pinpoint methods tailored to specific research domains.

2 Background

2.1 Multimodal Architecture

The general multimodal large language model (MLLM) framework (see Figure 2), consists of three core components: (1) a modality-specific encoder (g), (2) a projector module (P), and (3) a pre-trained large language model (LLM).

The process begins with the modality encoder, g, which is responsible for processing a given input, such as a visual or audio signal. This encoder compresses the high-dimensional raw data into a sequence of compact and semantically meaningful patch embeddings. For an input image X_v and an audio X_a, this can be expressed as:

$$Z_v = g(X_v), \quad Z_a = g(X_a). \tag{1}$$

The encoding function g is a flexible component that can be specialized for various modalities, including vision, audio, sensor data, etc. Widely adopted encoders implementing this function include:

- **Vision encoders:** CLIP (Radford et al., 2021), SigLIP (Zhai et al., 2023), DINO (Caron et al., 2021; Oquab et al., 2023), and ViT (Bai et al., 2025);

- **Audio encoders:** Whisper (Radford et al., 2023) and Audio-CLIP (Guzhov et al., 2022).

Subsequently, the encoded embeddings (Z_v or Z_a) are transformed by the projector module, P. The primary role of this module is to bridge the modality gap by mapping the embeddings into the same latent space as the text embeddings of LLM.

$$H_v = P(Z_v), \quad H_a = P(Z_a). \tag{2}$$

The output of the projector, a sequence of projected embeddings, can then be seamlessly concatenated with the text prompts and fed into the LLM.

The pre-trained LLM (Chiang et al., 2023; Team, 2024; AI@Meta, 2024) forms the core of the framework, with its large-scale parameters providing emergent capabilities such as zero-shot generalization and in-context learning. The LLM receives a composite input sequence formed by concatenating the projected multimodal embeddings H_v and H_a, as well as the textual prompt embeddings H_q. The textual prompt X_q is first converted into embeddings H_q by an integrated tokenizer.

The LLM then generates a response sequence Y_a through autoregressive decoding:

$$p(Y_a|H_v, H_a, H_q) = \prod_{i=1}^{L} p(y_i|H_v, H_a, H_q, y_{<i}), \tag{3}$$

where L signifies the output sequence length.

The high dimensionality of multimodal data poses a computational challenge. As shown in Figure 2, the token sequence processed comprises a mix of system prompt, multimodal context, and textual instruction. In most reasoning tasks, multimodal tokens constitute over 80% of the total sequence length (Chen et al., 2024a), thereby forming the primary computational bottleneck. This bottleneck obstacle to scaling MLLMs and achieving efficient inference. Consequently, a key strategy to optimize computational efficiency involves employing specialized projector architectures. These projectors are designed to reduce the number of multi-modal tokens while preserving their semantic fidelity, thus mitigating the computational burden.

While MLLM architecture presents unique challenges, token compression has been explored for both encoders and LLMs independently. Therefore, the subsequent sections will first dive into techniques relevant to these individual components, paving the way for more efficient multimodal models. Specifically, Section 2.2 will focus on token compression methods for large language models (LLMs), and Section 2.3 will explore techniques for vision transformers (ViTs).

2.2 Large Language Model Token Compression

The backbone of modern MLLMs is often built upon and fine-tuned from powerful text-based LLMs. As a foundational component, a solid understanding of token compression techniques developed for text LLMs is crucial, as they offer an accurate and lightweight solution for handling real-world long-context scenarios, such as understanding an entire book or a code repository. Within the domain of large language models, these methods are frequently termed prompt compression (Li et al., 2025e).

AutoCompressor (Chevalier et al., 2023) condenses context into summary vectors as soft prompts. Extensible Tokenization (Shao et al., 2024) employs intermediate modules to compress embeddings, while SentenceVAE (An et al., 2024) represents sentences with single tokens. Selective Context (Li et al., 2023g) employs self-information metrics to eliminate low-information tokens. LLMLingua (Jiang et al., 2023a;b; Pan et al., 2024) series utilizes hierarchical token pruning with instruction tuning and further introduces LongLLMLingua (Jiang et al., 2023b) to mitigate position decay through semantic density ranking. In parallel, query-guided methods like QUITO (Wang et al., 2024e) and QUITO-X (Wang et al., 2024f) leverage attention scores or information bottleneck theory for relevance-based filtering. AdaComp (Zhang et al., 2024a) implements adaptive extraction governed by query complexity predictors. Concept Distillation (Shi et al., 2024) employs Abstract Meaning Representation (AMR) graphs to distill key concepts, whereas xRAG (Cheng et al., 2024b) collapses documents into single-token representations. ICAE (Ge et al., 2023) encodes context into discrete memory slots. Recursive frameworks including RCC (Huang et al., 2024) and XL3M (Wang et al., 2024d) generate piecewise summaries through relevant fusion. SoftPromptComp (Wang et al., 2024a) fuses natural language prompts with dynamic embeddings, while PromptIntern (Zou et al., 2024) internalizes task instructions into model parameters via phased training.

While these text-centric token compression techniques have demonstrated notable efficacy, their direct application to MLLMs faces fundamental challenges. The inherent heterogeneity of multimodal data introduces distinct redundancy patterns absent in unimodal text. These include, but are not limited to, spatial correlations in high-resolution images, spatiotemporal continuity in video sequences, and spectral-temporal locality in audio streams. Such specialized redundancies necessitate the development of dedicated compression strategies. Consequently, this survey systematically reviews emerging token compression methodologies for MLLMs that effectively reduce token redundancy while preserving task performance.

2.3 Vision Transformer Token Compression
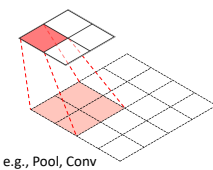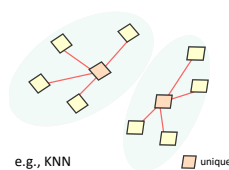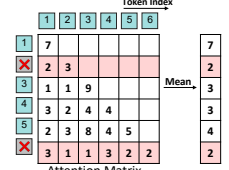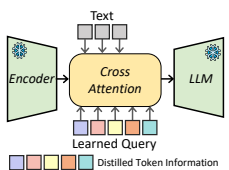
Visual token compression, originally pioneered in vision transformers (ViTs) (Vaswani et al., 2017; Dosovitskiy et al., 2020; Dong et al., 2022; Liu et al., 2021; Fan et al., 2021; Li et al., 2022; Graham et al., 2021; Huang et al., 2025a), offers insights for addressing analogous challenges in MLLMs.

Spatial redundancy manifests in ViTs through adjacent image patches, where not all tokens contribute equally to classification outcomes, compounded by semantic imbalance: foreground objects demand disproportionate computational resources compared to homogeneous backgrounds. To mitigate these issues, visual token compression techniques are employed to reduce computational overhead while maintaining model accuracy.

Foundational approaches, including DynamicViT (Rao et al., 2021) and EViT (Liang et al., 2022), quantify token relevance through attention scores, dynamically pruning low-saliency tokens. Complementary techniques like ToMe (Bolya et al., 2022) and TokenLearner (Ryoo et al., 2021) either merge semantically similar tokens using similarity metrics or generate compact token sets via learned spatial attention mechanisms. DeiT (Touvron et al., 2021) employs lightweight 'student' heads to predict categorical labels from compressed token subsets. Furthermore, methods such as MADTP (Cao et al., 2024) leverage cross-modal alignment to filter tokens.

The preceding analysis demonstrates that ViT token compression methodologies offer substantive inspiration for token reduction in MLLMs. However, MLLMs possess not only multimodal tokens encoding low-level features but also text tokens conveying high-level abstractions, coupled with significantly longer token sequences. Consequently, token compression in MLLMs presents greater challenges than in ViT while being increasingly critical for computational efficiency. Therefore, this survey analyzes the evolution and future directions of token compression techniques for MLLMs operating in long-context multimodal environments.

Table 1: Four Categories of Methods Based on Intrinsic Mechanisms: Diagram, Summary, and Pros & Cons.

Method	Transformation-based	Similarity-based	Attention-based	Query-based
Diagram	e.g., Pool, Conv	e.g., KNN / unique	Attention Matrix	Text / Encoder → Cross Attention → LLM / Learned Query / Distilled Token Information
Summary	Transform tokens into a more compact form	Compress by merging or grouping similar tokens	Remove less attentive tokens via attention sparsity	Use external queries to guide token compression
Pros	Preserve the structural representation of information well	Simplify processing, flexibility in choosing where to compress	Dynamically prune tokens by relevance; tie to original computation, boosting interpretability	Suitable for specific and video tasks, as compressed information is more relevant and concise
Cons	Limited by the transformation method, compression rate isn't flexible enough	May lose fine-grained info if tokens over-generalized; poor structural feature retention	Explicit attention score calculation might be incompatible with mainstream acceleration libraries	Not user-friendly for multi-turn conversations; requires re-condensing information

3 Image-centric Token Compression

Multimodal long context token compression methods generally fall into *four* categories based on their underlying mechanisms: **transformation-based** approaches directly transform the cross-modality information to compress tokens by altering their scale or representation; **similarity-based** techniques reduce tokens by leveraging the inherent resemblances between them; **attention-based** strategies exploit the sparsity of attention within the multimodal data to guide compression; and **query-based** methods selectively refine multimodal information, guided by prompts, to distill the most relevant tokens. Each of these methods has its own set of advantages and disadvantages, which are summarized in Table 1. Representative image-centric token compression methods are further compared in Table 2.

3.1 Transformation-based Image-centric Compression

Transformation-based image-centric compression methods leverage the spatial redundancy inherent in 2D image representations. Some image token compression techniques are derived from image downsampling operations (*e.g.*, pooling, bilinear interpolation). Based on the specific transformation method, these can be broadly categorized as follows:

3.1.1 Pixel Unshuffle

Pixel unshuffle is the inverse operation of pixel shuffle. It transforms a feature map from a high spatial resolution with a small number of channels into a lower-resolution feature map with a larger number of channels. This reduces the number of tokens. The transformation can be mathematically expressed as:

$$\text{Pixel Unshuffle: } H \times W \times D \to \frac{H}{r} \times \frac{W}{r} \times (D \cdot r^2), \tag{4}$$

where H, W denote the height and width of the token grid, D is the hidden dimension of each token, and r is the downsampling ratio.

Recent works like InternVL series (Chen et al., 2024c;b; Gao et al., 2024b; Zhu et al., 2025), Qwen2 series (Wang et al., 2024c; Bai et al., 2025), and NVLM (Dai et al., 2024) utilize pixel unshuffle to reduce the tokens generated by the vision tower by a factor of one-quarter. Subsequently, an MLP is employed to align the visual dimension with the text dimension, addressing the mismatch in the hidden dimension.

3.1.2 Spatial Pooling / Interpolation

Unlike pixel unshuffle, pooling and interpolation directly perform 2D downsampling on tokens, without altering the hidden dimension. This process can be defined as:

$$\text{Pooling / Interpolation: } H \times W \times D \to \frac{H}{S} \times \frac{W}{S} \times D, \tag{5}$$

where S is the downsampling factor.

LLaVA-OneVision (Li et al., 2025a) employs bilinear interpolation for 2D downsampling of aligned tokens, while LLaVA-Video (Zhang et al., 2024d) uses average pooling for downsampling. M³ (Cai et al., 2024) utilizes a simple pooling operation to learn an inherently multi-granular representation during training. This allows the model to achieve comparable performance with fewer tokens during inference, effectively addressing efficiency concerns. DeCo (Yao et al., 2024) argues that the Q-former (Liu et al., 2023; Li et al., 2023c) is an inefficient visual compressor and similarly achieves token compression through a straightforward average pooling approach, leading to improved convergence efficiency and performance.

3.1.3 Spatial Convolution

Convolutional operations offer a more sophisticated approach to token compression compared to simple pooling or interpolation, by learning to abstract local information while reducing spatial dimensions. The transformation can be expressed as:

$$\text{Convolution: } H \times W \times D_{in} \to \frac{H}{S} \times \frac{W}{S} \times D_{out}, \tag{6}$$

where S is the stride, which determines the downsampling factor, and D_{in}, D_{out} represent the input and output channel dimensions, respectively.

Honeybee (Cha et al., 2024) proposes the C-Abstractor, which uses convolution to extract and compress token information while preserving locality. MobileVLM (Chu et al., 2023), on the other hand, employs an LDP module that utilizes depth-wise convolution to reduce the number of tokens by 75%.

3.1.4 Comparative Analysis of Transformation Methods

These transformation-based image-centric compression methods effectively utilize all image tokens while consciously preserving the spatial local information of 2D features. Pixel unshuffle, pooling, and interpolation are inherently parameter-free, thus introducing no additional weight overhead, a key advantage. In contrast, convolution learn a more sophisticated local abstraction by introducing trainable weights.

Another notable difference lies in how these methods handle feature dimensions: pixel unshuffle typically alters the hidden dimension, necessitating a subsequent trained MLP to align with the text dimension. Conversely, pooling and interpolation can be implemented in a training-free manner as they operate directly on the aligned token dimension.

By extracting more condensed information, they achieve a superior balance between performance and efficiency. However, due to the inherent characteristics of 2D downsampling, their token compression ratios are typically limited to a few specific magnitudes, with a 25% compression rate being the most common.

3.2 Similarity-based Image-centric Compression

Similarity-based image-centric compression methods reduce the number of visual tokens by identifying and merging similar tokens based on their distance or similarity in an implicit space. This typically involves selecting representative cluster-center tokens to encapsulate visual information.

Early works in this area include ToMe (Bolya et al., 2023), an acceleration method for ViTs. ToMe introduces a token merge module between the attention and MLP blocks, calculating token similarity and merging similar tokens via bipartite soft matching. This process creates a new set of tokens, $\mathcal{T}$, by replacing the most

Table 2: Comparison of Training-Free Token Compression Methods for Image LLMs in Understanding Tasks

Method	#Vision Tokens	Res.	VQA^2	GQA	VisWiz	SciQA	VQA^T	POPE	MME	MMB	SEED	LLaVA^W	MM–Vet
BLIP-2 (Li et al., 2023c)	32	224	65.0	41.0	19.6	61.0	42.5	85.3	1293.8	–	46.4	38.1	22.4
IDEFICS-9B (Laurençon et al., 2023)	64	224	50.9	38.4	35.5	–	25.9	–	–	48.2	–	–	–
MobileVLM-3B (Chu et al., 2024a)	144	336	–	59.0	–	61.0	47.5	84.9	1288.9	59.6	–	–	–
mPLUG-Owl2 (Ye et al., 2023)	1024	448	79.4	56.1	54.5	68.7	54.3	–	1450.2	64.5	57.8	–	36.2
Video-LLaVA (Lin et al., 2024a)	256	224	74.7	60.3	48.1	66.4	51.8	84.4	–	60.9	–	73.1	32.0
Qwen-VL (Wang et al., 2024c)	256	448	78.8	59.3	35.2	67.1	63.8	–	–	38.2	56.3	–	–
LLaVA-v1.5 (Liu et al., 2023)	576	336	78.5	62.0	50.0	66.8	58.2	85.9	1510.7	64.3	58.6	63.4	30.5
LLaVA-v1.5-7B w/ Token Compression Methods (Training Free)													
ToMe (Bolya et al., 2023)	192	336	68.0	54.3	–	–	52.1	–	1563.0	60.5	–	–	–
FastV (Chen et al., 2024a)	192	336	67.1	52.7	–	–	52.5	64.8	1612.0	61.2	57.1	–	27.7
SparseVLM (Zhang et al., 2024c)	192	336	75.6	57.6	–	–	56.1	83.6	1721.0	62.5	55.8	–	31.5
MustDrop (Liu et al., 2024c)	192	336	76.0	58.2	51.4	–	56.5	–	1787.0	62.3	–	–	–
PruMerge+ (Shang et al., 2025)	144	336	76.8	–	–	68.3	57.1	84.0	1462.4	64.9	–	–	–
ATP-LLaVA (Ye et al., 2025b)	144	336	76.4	59.5	–	–	–	84.2	1473.9	66.0	57.3	–	31.5
VisionZip++ (Yang et al., 2025b)	128	336	76.6	58.9	–	–	57.0	83.7	1823.0	–	55.8	–	32.9
VisPruner (Zhang et al., 2025e)	128	336	75.8	58.2	52.7	–	57.0	84.6	1461.4	62.7	–	–	33.7
VisionZip++ (Yang et al., 2025b)	64	336	74.2	57.0	–	–	56.0	80.9	1756.0	–	53.4	–	30.2
TokenCarve (Tan et al., 2025)	64	336	74.8	–	–	–	57.0	79.9	1754.0	62.0	–	–	29.3
VisPruner (Zhang et al., 2025e)	32	336	67.7	52.2	53.0	–	53.9	72.7	1271.0	58.4	–	–	28.8
MLLMs w/ Token Compression													
LLaMA-VID (Li et al., 2024c)	2	336	–	55.5	–	68.8	49.0	83.1	–	–	–	–	–
LLaVA-Mini (Zhang et al., 2025f)	1	336	77.6	60.9	56.2	70.4	57.0	84.7	1466.0	65.6	58.5	68.9	36.6
VoCo-LLAMA (Ye et al., 2025c)	1	336	72.3	57.0	–	65.4	–	81.4	1323.3	58.8	53.7	–	–

similar tokens with their merged representations.

$$\mathcal{T} = (\mathcal{T}_{original} \setminus \bigcup_{i=1}^{k} C_i) \cup \{\mathrm{Merge}(C_i)\}_{i=1}^{k}, \tag{7}$$

where each C_i is a set of tokens identified as highly similar by ToMe's matching algorithm.

In the context of MLLMs, FOLDER (Wang et al., 2025a) employs a similar approach, inserting a token merge module within the last attention block of the vision encoder. This reduces the number of tokens that were subsequently passed to the LLM decoder. DivPrune (Alvar et al., 2025) reframes the token compression problem as a Max-Min diversity problem (Porumbel et al., 2011), aiming to select a subset of tokens with maximal internal differences. AuroraCap (Chai et al., 2025) adopts a strategy consistent with ToMe, performing token merging within each attention and MLP block of the vision tower. This progressively reduces the number of tokens throughout the ViT model. While the aforementioned methods primarily leverage similarity-based clustering of tokens within the ViT, TopV (Yang et al., 2025a) extends this principle to compress tokens within the LLM layers. TopV comprehensively considers both the similarity and distance functions between features to guide the token compression process, operating directly within the multimodal representation space of the LLM.

3.3 Attention-based Image-centric Compression

Attention-based token compression methods leverage the inherent sparsity of visual feature attention to guide token pruning. Tokens with low attention scores can often be considered removable without significantly impacting the original computation. In vision language models, both the vision encoder and the LLM decoder incorporate transformers. Consequently, attention-based compression strategies can be broadly categorized into those applied within the encoder and those within the decoder.

3.3.1 Attention in Encoder

Methods focusing on the vision encoder primarily select visual tokens based on attention scores within a single image or crops, relying on the capabilities of the vision transformer (ViT). This reduces the number of visual tokens before they're passed to the LLM. To achieve this, the set of retained tokens, $\mathcal{T}_{\mathrm{encoder}}$, is determined by selecting the top k tokens based on their attention scores relative to the [CLS] token:

$$\mathcal{T}_{\mathrm{encoder}} = \mathrm{TopK}_k \left(\{ \mathrm{Attention} \left(\mathbf{v}_i, \mathbf{v}_{\mathrm{cls}} \right) \mid \mathbf{v}_i \in \mathcal{V} \} \right), \tag{8}$$

where $\mathcal{V}$ is the original set of visual tokens, $\mathbf{v}_i$ is the i-th visual token, and $\mathbf{v}_{\text{cls}}$ is the [CLS] token. This strategy ensures that only the most salient visual information, as highlighted by the [CLS] attention, is carried forward for further processing.

Prumerge (Shang et al., 2025) selects cluster centers for visual tokens based on [CLS] attention in the encoder. It then merges the remaining less attentive tokens using K-nearest neighbors (KNN) clustering and a weighted cluster center update mechanism. VisionZip (Yang et al., 2025b) retains visual tokens with high attention scores and subsequently merges the remaining tokens through clustering. VisPruner (Zhang et al., 2025e) similarly preserves a subset of high-attention visual tokens. Then it progressively removes duplicates based on similarity in multiple rounds, ultimately retaining an additional set of diverse tokens. GlobalCom^2 (Liu et al., 2025c) employs a hierarchical strategy. It coordinates the attention scores of thumbnail tokens to guide the pruning of high-resolution crops, thereby achieving effective global context reduction.

3.3.2 Attention in Decoder

Unlike attention-based compression within the encoder, methods focusing on attention in the decoder leverage the capabilities of the LLMs to guide token compression. Here, attention is computed across all tokens within the LLM's attention window, which includes not only visual tokens but also textual tokens. This allows the LLM to determine the importance of visual and textual information in a joint space, leading to more context-aware token pruning.

A common approach for compression in the decoder involves selecting the most salient visual tokens. The set of retained tokens, $\mathcal{T}_{\text{decoder}}$, is typically determined by choosing the top k visual tokens based on the average attention they receive from all other tokens in that layer's attention window:

$$\bar{A}(\mathbf{v}_i) = \frac{1}{|\mathcal{S}|} \sum_{\mathbf{s}_j \in \mathcal{S}} \text{Attention}\,(\mathbf{v}_i, \mathbf{s}_j), \tag{9}$$

$$\mathcal{T}_{\text{decoder}} = \text{TopK}_k\left(\{\bar{A}(\mathbf{v}_i) \mid \mathbf{v}_i \in \mathcal{V}\}\right), \tag{10}$$

where $\mathcal{V}$ denotes the set of visual tokens, and $\mathcal{S}$ represents the entire set of tokens present in the current layer's attention window (which may include visual, textual, or special tokens). This method allows the model to prioritize the visual information that is most relevant in the ongoing context.

FastV (Chen et al., 2024a) is among the first to identify a significant inefficiency in large vision language models (LVLMs), namely the extremely low attention efficiency of visual tokens. For instance, in LLaVA-v1.5, visual tokens received only 0.21% of the attention obtained by system prompts after the second layer. FastV posits that this is due to an overabundance of visual signals, leading to specific features aggregating onto "anchor" tokens via shallow self-attention mechanisms. Consequently, pruning 50% of visual tokens based on attention scores after the second layer maintains maximal performance. PyramidDrop (Xing et al., 2025) structures the token compression process within the LLM into multiple stages. It employs progressive token compression to avoid excessive loss of visual information in shallower layers. VTW (Lin et al., 2025c) takes a more aggressive pruning approach, arguing that visual tokens can be entirely removed after a certain layer within the LLM. The specific layer for visual token removal is determined using a calibration dataset. FitPrune (Ye et al., 2025a) focuses on reducing the length of visual tokens per layer. It considers both the self-attention of visual tokens and their cross-attention with text tokens to guide compression. The goal is to find an optimal pruning "recipe" that minimizes the distributional gap before and after pruning. ST^3 (Zhuang et al., 2025) dynamically reduces tokens during the generation process. It also progressively prunes inattentive visual tokens as the layer goes deeper. ATP-LLaVA (Ye et al., 2025b) introduces an adaptive token pruning (ATP) module within the decoder layers. This module trains threshold heads to adaptively predict pruning thresholds for the current layer and instance, thereby removing redundant or text-irrelevant visual tokens. ZipVL (He et al., 2025) achieves progressive compression by determining the compression ratio for each layer based on its attention score distribution. This allows for a granular and adaptive reduction of visual tokens throughout the model.

3.3.3 Critical Challenge for Pruning in Decoder

While these methods leverage attention scores within the LLM decoder to offer sophisticated ways to compress visual tokens, they face a significant practical challenge: the explicit need to access attention scores. This direct access is often incompatible with highly optimized acceleration libraries like FlashAttention (Dao et al., 2022; Dao, 2024), which compute attention implicitly or in a fused manner for speed. This incompatibility can be mitigated by performing an additional, separate attention calculation solely for pruning purposes. However, for progressive pruning strategies such as FitPrune, ST3, and ZipVL, this additional computational overhead becomes significantly more pronounced, potentially negating the efficiency gains.

3.4 Query-based Image-centric Compression

Visual information often contains a substantial amount of features irrelevant to the given query. Query-based image-centric compression leverages the query prompt to guide the compression of visual tokens. These methods can be broadly categorized into two types: (1) **Token Distillation:** These methods compress visual tokens by distilling visual tokens into a specific, reduced number of tokens. (2) **Cross-Modal Selection:** These approaches compress tokens by matching between modality-aligned visual and text tokens.

3.4.1 Token Distillation

Token distillation originates from the early projector designs of MLLM. The goal is to distill visual tokens to learn the most text-relevant visual representations, reduce visual tokens while also aligning modalities.

The Q-Former series (Liu et al., 2023; Li et al., 2023c), a pioneering approach, uses learnable queries and cross-attention to extract pertinent visual cues from visual features. Similarly, mPLUG-Owl (Ye et al., 2023), MiniGPT-4 (Zhu et al., 2024), Flamingo (Alayrac et al., 2022), and Qwen-VL (Bai et al., 2023) all employ variations of learnable query-based architectures to condense visual information into a smaller fixed set of tokens that are then aligned with the language model. LLaMA-VID (Li et al., 2024c) employs a highly aggressive approach to visual token compression. For a single image or video frame, it utilizes context attention where the text query aggregates text-related visual cues from the visual embedding. Ultimately, it represents an entire image's information using only two tokens. LLaVA-Mini (Zhang et al., 2025f) achieves comparable performance by pre-fusing visual information directly into text tokens, requiring just one visual token. While previous methods relied on external modules for visual token compression, VoCo-LLaMA (Ye et al., 2025c) is notable as the first approach to use LLMs themselves for visual token compression. It distills the LLM's understanding of visual tokens into the processing of VoCo tokens via attention distillation. Victor (Wen et al., 2024) introduces a small number of learnable "register tokens" after the visual tokens. It then uses the shallow layers of a large model to distill visual information into these registers, discarding all original visual tokens to significantly improve inference and training efficiency.

3.4.2 Cross-Modal Selection

Cross-modal selection aims to reduce the number of tokens in one modality by leveraging aligned tokens from another. This compression is achieved by identifying and retaining only the most relevant information across modalities, leading to more efficient and effective processing. Several notable approaches have been proposed to address this challenge:

SparseVLM (Zhang et al., 2024c) employs visual tokens to pre-select relevant text tokens. By leveraging the visual modality as an initial filter, SparseVLM efficiently narrows down the textual search space, focusing on information pertinent to the visual content. AdaFV (Han et al., 2025) employs a dual-metric approach for selecting the most informative visual tokens. It calculates both text-to-image similarity and visual saliency extracted from the vision encoder. By combining these two indicators, AdaFV identifies visual tokens that are not only semantically aligned with the text but also visually prominent or significant. TRIM (Song et al., 2025a) introduces a unique method that begins by identifying outlier tokens based on the similarity between text and visual tokens; these outliers are deemed important. Subsequently, a clustering algorithm is utilized to merge the remaining, less critical tokens. This approach prioritizes distinct, highly relevant tokens before consolidating the rest.

Table 3: Comparison of Training-Free Token Compression Methods for Video LLMs in Understanding Tasks

Method	#Token Ratio	ActivityNet		Video-ChatGPT					Next-QA	EgoSchema	LongVideoBench	VideoMME	MVBench
		Acc.	Score	CI	DO	CU	TU	CO	mc	↑	↑	↑	↑
LLaVA-OneVision (Li et al., 2025a)	100%	48.09	3.47	3.37	3.78	3.52	3.02	2.63	81.33	60.4	56.4	58.6	58.3
50% Visual Token Retained Ratio													
FastV (Chen et al., 2024a)	50%	47.95	3.47	3.36	3.77	3.50	2.99	2.57	81.1	58.0	–	57.5	–
DyCoke (Tao et al., 2025a)	50%	47.88	3.47	3.33	3.76	3.51	3.01	2.58	81.1	57.7	–	57.4	57.5
PLLaVA (Xu et al., 2024a)	50%	47.59	3.45	3.36	3.73	3.52	3.00	2.66	81.0	57.7	–	56.9	–
LLaVA-Scissor (Sun et al., 2025)	50%	47.89	3.47	3.37	3.76	3.47	3.00	2.65	81.12	57.6	–	57.4	–
25% – 35% Visual Token Retained Ratio													
FastV (Chen et al., 2024a)	35%	47.83	3.46	3.32	3.74	3.47	2.97	2.61	80.5	57.8	–	56.0	61.3
DyCoke (Tao et al., 2025a)	35%	47.81	3.45	3.31	3.74	3.46	2.98	2.54	80.9	57.7	–	56.2	61.8
PLLaVA (Xu et al., 2024a)	35%	47.23	3.42	3.26	3.70	3.39	2.92	2.59	79.66	56.07	–	54.26	59.5
VisionZip (Yang et al., 2025b)	25%	–	–	–	–	–	–	–	–	60.3	56.5	58.2	57.9
PruneVid (Huang et al., 2025c)	25%	–	–	–	–	–	–	–	–	59.9	55.7	57.4	57.4
FastVID (Shen et al., 2025a)	25%	–	–	–	–	–	–	–	–	–	56.3	58.0	56.5
LLaVA-Scissor (Sun et al., 2025)	25%	47.79	3.47	3.33	3.76	3.47	2.98	2.62	80.66	57.64	–	56.44	–
HoliTom (Shao et al., 2025)	25%	–	–	–	–	–	–	–	–	61.2	56.7	58.9	58.4
5% – 15% Visual Token Retained Ratio													
VisionZip (Yang et al., 2025b)	15%	–	–	–	–	–	–	–	–	59.8	54.4	56.1	56.5
PruneVid (Huang et al., 2025c)	10%	–	–	–	–	–	–	–	–	59.8	54.5	56.0	56.2
FastVID (Shen et al., 2025a)	10%	–	–	–	–	–	–	–	–	–	56.3	57.3	55.9
LLaVA-Scissor (Sun et al., 2025)	10%	47.75	3.46	3.26	3.68	3.41	2.90	2.52	80.0	57.5	–	55.2	57.9
HoliTom (Shao et al., 2025)	10%	–	–	–	–	–	–	–	–	61.2	56.3	56.8	57.3

4 Video-centric Token Compression

Processing long high-definition (HD) videos poses significant challenges for VLMs due to the immense number of tokens generated, far exceeding those from high-resolution images. Unlike image-centric compression, video inherently possesses an additional temporal redundancy. While capturing complete temporal information typically requires a frame rate of at least 24 frames per second (FPS), processing a 10-minute HD video at even 1 FPS still yields token sequences orders of magnitude larger than those from high-resolution images, rendering conventional transformer-based MLLMs impractical for real-world deployment over the videos.

To address this, current video LLMs commonly employ a 1 FPS sampling rate to reduce token counts. Furthermore, unlike methods for single images, which often encode both the global image and a series of local patches for detailed feature extraction, video processing often foregoes this detailed frame-level segmentation to keep token numbers manageable. Even with these strategies, the quantity of video tokens remains substantial. During model training and understanding, **transformation-based** methods, such as the pooling technique used in LLaVA-Video (Zhang et al., 2024d), are usually employed to reduce tokens and aid the model's comprehension of video content.

Beyond training-time optimizations, alternative approaches primarily focus on post-training optimization. Specifically, **similarity-based** and **attention-based** methods offer generic compression techniques for pre-trained video MLLMs. These methods process encoded token sequences without modifying model weights, enabling plug-and-play acceleration across diverse architectures. By dynamically identifying critical spatio-temporal regions and pruning redundant tokens, these techniques significantly enhance the practicality of video MLLMs for real-world applications.

To fully grasp token compression for video LLMs, it is recommended to first review Section 3, which details spatial compression methods. Next, we will primarily discuss techniques addressing the temporal domain. Similar to image-centric methods, selected video-centric token compression methods are compared in Table 3.

4.1 Transformation-based Video-centric Compression

Like image LLMs, video LLMs use encoders for visual tokens. Consequently, transformation-based video-centric compression methods fundamentally operate on the principles established in Section 3.1, with the added capability of performing 3D transformations. A multitude of models showcase cross-modal applicability, performing effectively in both image and video inference tasks. Following the structure of Section 3.1, we will now detail transformation-based video-centric compression methods.

4.1.1 2D/3D Pooling

In video LLMs, token pooling is a crucial strategy for managing the high dimensionality of video data. While 2D spatial pooling, as seen in LLaVA-Video (Zhang et al., 2024d), can effectively reduce the token count within individual frames, its efficacy alone may be limited for long-duration videos. A growing number of video LLMs, including PLLaVA (Xu et al., 2024a), Video-ChatGPT (Maaz et al., 2024), SlowFast-LLaVA (Xu et al., 2025c), and LongVLM (Weng et al., 2024), consequently emphasize temporal pooling, which involves downsampling at the frame level.

Notably, PLLaVA demonstrates that model performance exhibits greater sensitivity to temporal pooling than to spatial pooling, highlighting its critical role. For extremely long video sequences, LLaMA-VID (Li et al., 2024c) employs a more aggressive adaptive pooling approach. This method intelligently maintains original resolution for single-image inputs but compresses each video frame to a single token during extended sequence processing, achieving substantial data reduction while aiming to preserve essential information.

This dual focus on spatial and increasingly on temporal pooling underscores their combined importance in enabling efficient processing and comprehensive understanding of video content, particularly as video durations extend. SlowFast-LLaVA (Xu et al., 2025c) incorporates a two-stream SlowFast projector into a LLaVA-style architecture, using a slow pathway to sample fewer, spatially rich frames and a fast pathway to sample more, spatially compressed frames, then concatenates both for the LLM—achieving efficient long-form video understanding with reduced token count while preserving spatiotemporal details.

4.1.2 2D/3D Convolution

Similar to pooling, convolution can also be employed for downsampling video tokens, but it does so in a parameterized manner. Instead of simply aggregating information like pooling, convolution layers learn filters to process and condense spatial and temporal features. VideoLLaMA 2 (Cheng et al., 2024c), for instance, thoroughly investigated both 2D and 3D pooling and convolution approaches. Their experiments showed that 3D convolution yielded the best balance of performance and efficiency for video token downsampling. This suggests that learning intricate spatiotemporal relationships through convolutions is more effective for comprehensive video understanding compared to pooling alone.

4.2 Similarity-based Video-centric Compression

Given the temporal redundancy inherent in video, where adjacent frames often exhibit high visual similarity, temporal compression is frequently prioritized over or integrated with spatial compression. To effectively handle this temporal redundancy, video frames are typically first clustered.

Chat-UniVi (Jin et al., 2024) initially pools each video frame into a single frame-level representation token. It then utilizes DPC-KNN (Du et al., 2016; Rodriguez & Laio, 2014) (density peak clustering based on K-nearest neighbors) to amalgamate non-essential frames based on these frame representation tokens. Within each resulting cluster, tokens from multiple frames are further clustered to obtain concise spatiotemporal visual representations. Similarly, FastVID (Shen et al., 2025a) divides video frames solely based on the similarity of their adjacent frame representation tokens. It then employs DPC-KNN within these clustered frames to merge tokens, thereby reducing spatiotemporal redundancy. PruneVid (Huang et al., 2025c) adopts the same frame clustering methodology as Chat-UniVi. The key distinction is that it performs an initial merging of temporally static tokens before executing the spatiotemporal token consolidation. HoliTom (Shao et al., 2025) argues that relying on a single frame-level representation token for video frame clustering can lead to suboptimal detail capture, and that the preliminary merging of static temporal tokens is disconnected from the original frame clustering method. HoliTom re-conceptualizes temporal redundancy compression as an optimization problem aimed at maximizing the compressible temporal redundant features within all clustered frames, thus addressing temporal compression more holistically. DyCoke (Tao et al., 2025a) groups frames into sets of four, directly performing temporal pruning within each group.

While some methods do not explicitly cluster video frames, FrameFusion (Fu et al., 2025b), for example, acts as a token compression technique for video LLMs. It directly merges temporally redundant tokens exceeding a specific threshold in the shallow layers of the model.

4.3 Attention-based Video-centric Compression

Current attention-based token compression methods in video LLMs and image LLMs share significant similarities. When attention is applied within the encoder to guide token compression, videos are typically treated as a sequence of images fed into an image encoder, making these approaches similar to image-centric token compression. For a more concise discussion of such attention-based methods, please refer to Section 3.3.

In contrast, methods employing attention within the decoder process video frames sequentially, concatenating their tokens over time. For longer videos, particularly in the context of streaming video LLMs, windowed attention is commonly used to mitigate computational overhead by focusing on local temporal visual information. However, it's notable that even these windowed attention-based methods within the decoder often share the same foundational principles as those discussed in Section 3.3.

4.4 Query-based Video-centric Compression

4.4.1 Token Distillation

Token distillation in video LLMs commonly relies on specialized adaptor modules, such as the Q-former (Liu et al., 2023; Li et al., 2023c) or Token Turing Machines (Ryoo et al., 2023). These modules typically process video tokens with the learnable query tokens to be attended.

Token Turing Machines (TTMs) (Ryoo et al., 2023) maintain a compact external memory of summary tokens, sequentially compressing both new input tokens and memory at each timestep via a Transformer-based read/write mechanism, allowing scalable and efficient processing of long video sequences. BLIP-3-Video (Ryoo et al., 2024) introduces an explicit temporal encoder that abstracts hundreds of frame-level visual tokens into as few as 16–32 spatiotemporal tokens using learnable pooling and sequential models, enabling efficient video understanding with limited token usage. LinVT (Gao et al., 2024a) proposes a plug-and-play Linear Video Tokenizer, which linearly aggregates frame-level visual tokens into a compact set of video tokens through spatio-temporal scoring, multi-scale pooling, and text-conditioned aggregation, enabling existing image-LLMs to efficiently process videos and dynamically extract question-relevant information. Long-VMNet (Gurukar & Kadav, 2025) accelerates long-form video understanding by using a neural sampler to select discriminative visual tokens from clips and storing them in a fixed-size memory bank for each video; downstream queries are answered by processing only these memory tokens, greatly reducing computational cost while preserving key spatiotemporal information. STORM (Jiang et al., 2025a) inserts a Mamba-based (Gu & Dao, 2024) temporal encoder between the image encoder and LLM, using spatiotemporal scanning and pooling to inject temporal context into frame tokens and then aggressively compresses tokens by temporal and spatial pooling, enabling efficient long video understanding with minimal token loss. To understand more methods and applications of token distillation in video LLMs, please also refer to Section 3.4 for a detailed explanation.

4.4.2 Cross-Modal Selection

In video large language models (video LLMs), a query is commonly used to guide the selection of salient frames. In extreme cases, only a handful of frames are relevant to the posed question, allowing the tokens from the vast majority of remaining frames to be discarded. When dealing with an immense number of frames, finding query-relevant information can be akin to searching for a "needle in a haystack" for the LLM. Query-based token compression methods can pre-filter query-relevant tokens, significantly alleviating the computational burden on the LLM.

LongVU (Shen et al., 2025b) exemplifies this approach. It calculates the relevance of each video frame to the query via cross-modal interaction. This relevance score then dictates a lower compression ratio for key frames, better preserving critical information, all while ensuring the total number of tokens remains within the maximum context length of the LLM.

5 Audio-centric Token Compression

For audio LLMs, the demand for longer context arises from the need to process higher sampling rates and extended durations of audio.

The extraction of information from the audio modality can be categorized according to the format of audio representation: (1) **continuous sequence modeling:** this approach utilizes a pre-trained audio encoder, typically models like Whisper (Radford et al., 2023) or Conformer (Gulati et al., 2020), to produce continuous audio embeddings; (2) **discrete sequence modeling:** this method transforms the input audio signal into discrete audio tokens, usually via vector quantization, where continuous audio features are encoded into a learnable codebook. Mainstream methods include HuBERT (Hsu et al., 2021) and EnCodec (Défossez et al., 2022; Zeghidour et al., 2021).

The second category inherently reduces the number of tokens by the design of the tokenizer structure and the codebook. Nevertheless, detailed exploration of these specific design considerations falls outside the purview of this survey.

Audio, a 1D signal representing amplitude over time, must be transformed into a suitable format for deep learning models, especially when integrating with MLLMs. MLLMs often leverage architectures designed for 2D data (like images) or general sequences. While the raw waveform is the source, spectrograms (especially Mel-spectrograms) are frequently the preferred representation for audio in MLLMs. This preference arises because spectrograms allow the application of processing techniques similar to those used for images, thereby facilitating multimodal learning.

Consequently, much like the visual modality, we categorize audio token compression methods as follows:

5.1 Transformation-based audio-centric Compression

Following the visual modality's categories, we can classify methods based on their downsampling operations:

5.1.1 Token Stacking

Similar to the pixel unshuffle operation in 2D image processing, this approach for audio LLMs token compression involves stacking multiple consecutive tokens along the hidden dimension of the token. This effectively reduces the total number of tokens. Notably, HTS-AT (Chen et al., 2022), an early example of audio token stacking for classification tasks within audio transformers, utilized 2D pixel-unshuffling on the 2D features extracted from Mel spectrograms to reduce audio tokens. More recent methods such as SLAM-ASR (Ma et al., 2024c), LLaMA-Omni (Fang et al., 2024), Llama-AVSR (Cappellazzo et al., 2025a) and others (Fathullah et al., 2024) stack the audio token. Since these token stacking operations alter the hidden dimension, an MLP is typically used to realign the dimension for compatibility with other modalities.

5.1.2 Pooling

Another common technique for reducing the number of audio tokens is pooling. Models like Qwen2-audio (Chu et al., 2024b) and Qwen2.5-Omni (Xu et al., 2025b) leverage pooling layers with a stride of 2 to directly decrease the length of the audio representation in a parameter-free manner. This effectively downsamples the audio features, leading to a more compact token sequence. Extending this concept, Llama-MTSK (Cappellazzo et al., 2025b) employs a matryoshka-based training approach for flexible token compression. It trains the model with multi-scale audio and video information by applying average pooling or token stacking at different rates to the initial tokens. This enables Llama-MTSK to dynamically adjust the number of tokens processed during inference, balancing compression and performance within a single model.

5.1.3 Temporal Convolution

For audio tokens, 1D convolutions applied across the temporal dimension can reduce the number of tokens. This method simultaneously allows for the alignment of the hidden dimension for subsequent LLM. Approaches like SpeechVerse (Das et al., 2024), Baichuan-Audio (Li et al., 2025c), OSUM (Geng et al.,

2025), and LUCY (Gao et al., 2025) have employed this technique, often resulting in a downsampled audio representation with an effective sampling rate of 12.5 Hz.

These methods demonstrate how insights from image compression, particularly involving transformations, can be effectively applied to the audio domain to achieve more efficient token representation for large models.

5.2 Similarity-based audio-centric Compression

Similarity-based compression methods aim for each audio token to carry unique information rather than being overly redundant. Similar to the ToMe (Bolya et al., 2022) method used in vision transformers (ViT), A-ToMe (Li et al., 2023f) inserts a token merge module between the multihead self-attention (MHSA) and feed-forward network (FFN). This module merges adjacent audio tokens that have high cosine similarity.

5.3 Attention-based audio-centric Compression

For audio tasks, attention-based methods are also effectively utilized to compress tokens.

5.3.1 Attention in Encoder

Top-K (Lee & Lee, 2025) is a token selection method operating within the audio spectrogram transformer block. It retains only the top K audio tokens ranked by the magnitude of their attention scores. This prunes less attentive tokens, focusing on those with higher relevance as determined by the self-attention mechanism.

5.3.2 Attention in Decoder

SpeechPrune (Lin et al., 2025b), works in the LLM backbone. It prunes audio tokens based on attention scores provided by the first transformer layer. By utilizing the initial layer's attention, SpeechPrune efficiently identifies and discards less crucial tokens early in the processing pipeline, aiming to reduce computational load and improve efficiency for subsequent layers without significant loss of information.

5.4 Query-based audio-centric Compression

Audio feature representations can also be compressed using other modalities or learned query mechanisms. Analogous to image LLMs, these methods can be broadly categorized into token distillation and cross-modal selection, based on whether learned queries are explicitly employed.

5.4.1 Token Distillation

This category leverages learnable query tokens to distill comprehensive audio information into a compact, fixed-length representation.

Video-LLaMA (Zhang et al., 2023) and SALMONN series (Tang et al., 2024; Sun et al., 2024a) employ an audio Q-former to transform variable-length audio inputs into a fixed-length sequence of learnable queries, thereby condensing audio information for the LLM. MMCE-Qformer (Xue et al., 2024) compresses acoustic information by utilizing learnable queries to extract global acoustic context from contextual audio embeddings. Concurrently, a cross-attention mechanism, guided by input text embeddings, captures local acoustic context relevant to each text token. This dual approach distills both broad and specific audio features into compact, text-relevant representations. MMS-LLaVA (Yeo et al., 2025) reduces multimodal token length for efficient speech LLMs. It first halves the sequence length with an Early AV-Fusion Module, which combines visual and audio features. Subsequently, an AV Q-Former further compresses these fused features into a fixed number of queries, effectively capturing full speech context to bridge the token gap with text.

5.4.2 Cross-Modal Selection

Similar to the visual modality, audio token compression can also be guided by information from other modalities. Speechprune (Lin et al., 2025b), for example, leverages audio-text correlation to identify semantically

important audio segments. This is achieved by calculating a cross-modal similarity matrix based on cosine similarity, which then guides the compression of audio tokens. This approach ensures that the most relevant audio information is retained.

6 Discussions

6.1 Synergies and Distinctions with Other Compression Methods

Beyond token compression, the research community has seen the emergence of several other compression methods, including model quantization (Lin et al., 2024b; Xiao et al., 2023a; Frantar et al., 2023; Shang et al., 2023; Sui et al., 2024a; Gholami et al., 2022), network pruning (Han et al., 2016; Ma et al., 2023; Sui et al., 2021; Cheng et al., 2024a), knowledge distillation (Hinton et al., 2015; Gou et al., 2021), and low-rank factorization (Yu et al., 2017; Yin et al., 2021; Xiao et al., 2023b; Sui et al., 2024b; Yang et al., 2024). These methods typically focus on directly compressing model weights to achieve efficiency.

For Transformer-based models, the computational cost (FLOPs) is mainly dominated by matrix multiplications, particularly in the self-attention and feed-forward layers. A simplified formulation is given as:

$$\text{FLOPs} \propto O(N \cdot D^2 + N^2 \cdot D), \tag{11}$$

where N is the number of tokens, D is the model dimension.

6.1.1 Weight-Focused Compression Methods

These methods mainly target the model dimension (D) by reducing the effective size or complexity of the model weights. **Model Quantization** reduces weight precision, directly impacting the memory associated with D. A key limitation is that highly aggressive quantization (e.g., 4-bit) often compromises accuracy, meaning there's no "free lunch" when it comes to achieving lossless performance. Furthermore, effectively accelerating these lower bit-rates often necessitates specialized hardware. **Network Pruning** removes redundant connections, effectively reducing the active parameters contributing to D. For LLMs, aggressive structured pruning (e.g., beyond 20% for downstream tasks) often leads to significant performance degradation or near-collapse due to the difficulty in preserving architectural integrity. **Knowledge Distillation** trains a smaller student model (with a smaller D) to mimic a larger teacher (Hinton et al., 2015). Its main limitation is the "knowledge gap", as the student may struggle to fully capture the teacher's comprehensive knowledge, leading to performance disparities, especially on complex or out-of-distribution data. **Low-Rank Factorization** decomposes weight matrices into lower-rank approximations, thus reducing parameters related to D. The challenge lies in finding an optimal low-rank approximation for diverse tasks without performance loss, as this is often task-dependent and complex to apply consistently across deep networks.

6.1.2 Token Compression

In contrast, token compression directly targets the sequence length (N) by reducing the number of tokens processed for long contexts. By reducing N, token compression significantly impacts FLOPs:

$$\text{FLOPs} \propto O(M \cdot D^2 + M^2 \cdot D), \tag{12}$$

where $M \ll N$ represents the reduced sequence length after token compression.

This approach offers benefits like greater efficiency for long context processing, overcoming context window limitations, and closer alignment with API cost reduction, as many LLM APIs charge by token count.

6.1.3 Complementary Nature and Synergistic Gains

The methods for compressing model weights and token compression are structurally orthogonal and can be effectively combined for superior results. For example: NVILA (Liu et al., 2025e) pushes inference latency reduction and throughput maximization to the extreme by simultaneously applying quantization

and token compression. CoreMatching (Wang et al., 2025b) achieves synergistic acceleration by concurrently compressing both neurons (a form of pruning/weight reduction) and tokens.

This orthogonality means that combining these approaches holds the potential for compounded efficiency gains that are greater than applying either method in isolation.

6.2 Token Compression: Efficiency and Beyond

Token compression is often perceived solely as a training-free method to boost efficiency. However, its significance extends far beyond this, having been intrinsically incorporated into the design of MLLM, particularly within the modality transition modules (*e.g.*, adapter). This integration not only facilitates superior modality alignment but also enhances the quality of information, leading to more efficient and stable training.

6.2.1 Enhanced Modality Alignment

Effectively aligning and comprehending information from disparate modalities remains a significant challenge. Traditional encoders segment and tokenize all multimodal information to align with linguistic representations. However, low-quality and low-density multimodal representations expand the alignment space, complicating the task of modality matching. Token compression addresses this by enabling a more precise correspondence between language representations and multimodal information.

A prime example is the Q-Former (Liu et al., 2023; Li et al., 2023c), which employs a trainable vector to distill visual tokens, achieving direct alignment of the modality simultaneously. Similarly, M^3 (Cai et al., 2024) adopts a coarse-to-fine semantic granularity training approach, empowering MLLMs to align with and interpret visual representations at various levels.

6.2.2 Improved Information Representation

The sheer volume of multimodal information often leads to inefficient training and inference, with an over-abundance of multimodal tokens that potentially degrade the capabilities of the text modality (Bellver-Soler et al., 2025). This issue is compounded by inherent redundancies within multimodal data itself: **(1) Feature Redundancy** arises from similar backgrounds in visual data or silent segments in audio. **(2) Task-Irrelevant Redundancy** is evident in tasks like visual question answering (VQA), where a significant portion of multimodal representations may be irrelevant to deriving the correct answer. **(3) Attention Computation Redundancy** emerges from two aspects: first, due to the nature of attention mechanisms, tokens positioned later in a sequence often receive disproportionately higher attention (Wen et al., 2025), suggesting potential computational redundancy for tokens not at the sequence's end; and second, because multimodal information receives inherently less attention than textual data (Chen et al., 2024a; Song et al., 2025a), an abundance of multimodal tokens can still introduce substantial computational redundancy.

Addressing these issues, the method classifications discussed earlier directly correspond to these types of data redundancy. Specifically, the transformation-based methods along with similarity-based approaches, are effective in mitigating the feature redundancy. Furthermore, attention-based methods play a crucial role in minimizing attention computation redundancy. Lastly, query-based methods are designed to reduce task-irrelevant redundancy.

6.2.3 Enable One-Shot Long-Context Understanding

Limited by the inherent length of the context, MLLMs are unable to comprehend real-world scenarios involving extremely long contexts, such as understanding entire code repositories or extended video and audio sequences (Qu et al., 2025). However, token compression significantly condenses and abstracts original information representations, making it possible for MLLMs to understand these long contexts in a single pass.

Traditional methods for handling long contexts in MLLMs, like FlashAttention (Dao et al., 2022; Dao, 2024) or RingAttention (Liu et al., 2024a), involve architectural changes to the model's attention mechanism to directly accommodate longer sequences. While effective, these require fundamental model modifications.

Token compression offers a different, often simpler, route. Instead of redesigning the model to fit more tokens, it focuses on making each token more powerful. By creating information-dense tokens, we pack more meaning into fewer pieces of data. This lets existing MLLM architectures process significantly longer conceptual contexts without major overhauls. It's a more efficient and accessible way to achieve that crucial one-shot understanding of vast, complex real-world information (Song et al., 2025b).

6.3 Combining Different Token Compression Methods

In Section 6.2.2, we explored three distinct types of redundancy and the corresponding methods to reduce them. Since prune different forms of redundancy and can be applied at various stages, they seem orthogonal in their function. This raises a natural question: can we combine multiple token compression methods to achieve a synergistic effect?

Surprisingly, the answer is often no. Research has shown that a simple combination can lead to a phenomenon where the total effect is less than the sum of its parts. For example, the MoB (Li et al., 2025d) found that the combining methods do not exhibit superiority. This is probably attributed to the difference in each compression technique. When methods target different redundancies, their compression metrics can be inconsistent, leading to conflicting pruning decisions and a suboptimal outcome. From an information theory perspective, the amount of redundant information itself is finite, and different compression methods cannot repeatedly take effect on it. Therefore, while each method excels separately, their combined use does not guarantee a better result and may even degrade performance.

6.4 Current Challenges

6.4.1 Performance Degradation

While token compression can effectively condense multimodal features, it also introduces a risk of performance degradation. Current research on visual MLLMs, for example, shows that for models like LLaVA-OV-7B (Li et al., 2025a), near-lossless performance can be achieved by retaining as few as 10% of the original tokens. However, performance declines sharply when the compression rate is pushed further. This challenge is more pronounced for larger and more recent models such as Qwen2.5-VL (Bai et al., 2025), LLaVA-Video-7B (Zhang et al., 2024d), and LLaVA-OV-72B (Li et al., 2025a), where achieving lossless compression seems to be more difficult.

This increased difficulty may stem from the models' enhanced representational capabilities. It has been suggested that less capable models are inherently less sensitive to information loss from aggressive compression, as their weaker understanding already struggles to process the complex, uncompressed data fully. In contrast, more sophisticated models, which possess a more nuanced and holistic comprehension of multimodal tokens, are more susceptible to the subtle degradation caused by compression. For these models, achieving high performance requires a far more delicate and precise approach to preserve the token.

6.4.2 Task-Specific Challenges

Token compression, while beneficial for efficiency, can be destructive to performance on tasks that demand high representational fidelity. For **optical character recognition (OCR)**, which requires a high information density within local regions, compression often leads to the loss of critical details and a subsequent drop in performance. This is particularly evident on benchmarks like RefCOCO (Yu et al., 2016), where the model's ability to ground objects based on fine-grained textual cues is compromised.

A similar challenge arises in preserving **temporal perception**. Video and audio are fundamentally structured by fixed sampling rates (Liu et al., 2025d). By merging adjacent frames or sequential tokens, compression methods disrupt this inherent temporal consistency, hindering the model's ability to reason about motion, pace, and other crucial temporal dynamics essential for a complete understanding of the content.

Table 4: Common Benchmarks for Performance Evaluation of Image-Language and Video-Language Tasks.

Benchmark	Task	Metric	System Prompt
Image Task			
GQA (Hudson & Manning, 2019)	CE-VQA	Exact Match	Answer the question using a single word or phrase.
MMB (Liu et al., 2024d)	MC-VQA	Accuracy	Answer with the option's letter from the given choices directly.
MME (Yin et al., 2024)	CE-VQA	Perception Score	Answer the question using a single word or phrase.
POPE (Li et al., 2023e)	CE-VQA	F1 Score	Answer the question using a single word or phrase.
ScienceQA-Image (Lu et al., 2022)	Visual reasoning	Exact Match	Answer with the option's letter from the given choices directly.
SeedBench-Image (Li et al., 2023a)	MC-VQA	Accuracy	Answer with the option's letter from the given choices directly.
VizWiz (Gurari et al., 2018)	CE-VQA	Exact Match	When the provided information is insufficient, respond with "Unanswerable". Answer the question using a single word or phrase.
VQA^2 (Goyal et al., 2017)	CE-VQA	Exact Match	Answer the question using a single word or phrase.
MM-Vet (Yu et al., 2023)	Visual reasoning	GPT-score	First please perform reasoning, and think step by step to provide the best answer to the following question:
LLaVA^W (Liu et al., 2023)	Visual reasoning	GPT-score	A chat between a curious human and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the human's questions.
Video Task			
ActivityNet (Yu et al., 2019)	CE-VQA	Accuracy / GPT-score	Answer the question using a single word or phrase.
VideoChatGPT (Maaz et al., 2023)	OE-VQA	GPT-score	Evaluate the temporal accuracy of the prediction compared to the answer.*
NextQA (Xiao et al., 2021)	CE-VQA	WUPS	Answer a question using a short phrase or sentence.
EgoSchema (Mangalam et al., 2023)	MC-VQA	Accuracy	Answer with the option's letter from the given choices directly.
MVBench (Li et al., 2024a)	MC-VQA	Accuracy	Carefully watch the video and pay attention to the cause and sequence of events, the detail and movement of objects, and the action and pose of persons. Based on your observations, select the best option that accurately addresses the question.
LongVideo Bench (Wu et al., 2024)	MC-VQA	Accuracy	Answer with the option's letter from the given choices directly.
VideoMME (Fu et al., 2025a)	MC-VQA	Accuracy	Select the best answer to the following multiple-choice question based on the video and the subtitles. Respond with only the letter (A, B, C, or D) of the correct option.
PerceptionTest (Patraucean et al., 2024)	MC-VQA	Accuracy	Answer with the option's letter from the given choices directly.
VideoDC (LMMs-Lab, 2024)	Video Caption	GPT-score	Please provide a detailed description of the video, focusing on the main subjects, their actions, and the background scenes
AuroraCap (Chai et al., 2025)	Video Caption	VDCscore	Describe the video in detail.
Chardes-STA (Gao et al., 2017)	Temporal Grounding	IoU	Please find the visual event described by a sentence in the video, determining its starting and ending times.

6.4.3 Deployment Hurdles

Despite their potential, many token compression methods face barriers to real-world deployment, stemming from a fundamental incompatibility with current large-scale model architectures and applications.

A major challenge lies in their integration with modern acceleration libraries (Dao et al., 2022; Dao, 2024). Methods that rely on explicit attention scores to prune tokens cannot be seamlessly integrated into *current optimized frameworks*, as these libraries fuse matrix multiplication and softmax operations to maximize throughput and minimize memory usage, thus making those scores inaccessible. This creates a critical gap, as these compression methods cannot leverage the performance gains of state-of-the-art deployment pipelines.

Furthermore, task-aware token compression methods are not suit for *multi-turn conversational tasks*. Methods that perform token compression internally within the model's backbone or rely on cross-modal fusion are not natively compatible with this type of application. They lack an efficient mechanism to carry over and update a compressed representation across turns, instead requiring a costly re-computation of the entire conversation history for each new query.

6.4.4 Evaluation Challenges

Rethinking Evaluation Metrics. Current evaluation methods for token compression techniques face limitations, hindering accurate and comprehensive comparisons.

For methods requiring training, various factors like training data and methodologies make it challenging to isolate and directly compare the effectiveness of different methods.

For training-free token compression methods, current evaluations often rely on metrics such as the number of compressed tokens and FLOPs. However, these metrics offer an incomplete picture. While the number of compressed tokens provides a preliminary classification, the compression location significantly impacts the downstream computational load; earlier pruning generally leads to greater reductions. Similarly, FLOPs, while useful for theoretical computational estimates, frequently do not accurately reflect actual inference speed. Therefore, for training-free methods, more practical metrics like Time To First Token (TTFT) and decoding latency per token are crucial for a more accurate assessment of real-world inference acceleration.

Evaluation Benchmarks Gap. Current evaluation datasets for MLLM token compression often rely on general multimodal benchmarks (Table 4) , provide insufficient granularity. For example, in challenging long video understanding tasks, performance hinges more on sparse frame sampling, capturing key frames, than on the specific token compression method. This can obscure the true impact of token compression, making its efficacy appear negligible.

This reveals a critical gap: current datasets often fail to isolate and precisely measure the effect of token compression. Therefore, adopting evaluation methodologies like EffiVLM-Bench (Wang et al., 2025c), which focuses on training-free acceleration evaluation, is crucial for accurately assessing the true efficacy and nuanced benefits of token compression methods.

6.5 Pruning Location and Trade-offs

Given the cascaded architecture of current MLLMs, the placement of the pruning operation directly influences the trade-off between computational efficiency and performance.

Pruning tokens at an early stage, such as within the encoder or projector, can dramatically shorten the sequence length. This significantly reduces the computational burden on the downstream LLM, leading to faster inference. However, this early compression carries a higher risk of discarding critical information, which can negatively impact model performance.

Conversely, token compression at a later stage, within the LLM's internal modules, is more computationally demanding. However, it reduces the risk of erroneous judgment because the tokens have already undergone initial processing and feature extraction, thereby retaining more refined information. The optimal location for token compression within these architectures remains an open question, warranting further investigation.

6.6 Future Directions

6.6.1 Unified Multimodal Token Compression

Although different modalities exhibit unique redundancy patterns requiring specialized compression strategies, contemporary MLLMs predominantly focus on joint multimodal inference (Cheng et al., 2024c), whereas unimodal scenarios remain constrained by single-modality inputs. As established in Sections 3, 4, and 5, fundamental algorithmic principles (including transformation-based, similarity-based, attention-based, and query-based approaches) demonstrate transmodal applicability, indicating the viability of developing a unified multimodal token compression framework. Furthermore, leveraging cross-modal correlations represents a promising research direction for the future.

6.6.2 Improved Architecture

Current token compression methods are often employed as a remedial measure to efficiently process long contexts. However, a more valuable approach might involve designing model architectures that intrinsically

account for data redundancy during their initial conception. By doing so, the number of tokens could be reduced during the abstraction of data features. This is particularly relevant for current architectures, especially those of video LLMs, where generated tokens still exhibit significant redundancy. Therefore, exploring architectural designs that inherently foster more condensed information abstraction from the outset represents a promising research direction.

7 Applications

The potential of multimodal token compression extends beyond technical enhancements, emerging as a universal efficiency engine for data-intensive AI systems. Multimodal models frequently process extreme-length token sequences exhibiting high task-agnostic redundancy according to empirical analyses. Capitalizing on recent breakthroughs, we delineate four high-impact application domains:

7.1 GUI Agents and Human-Computer Interaction

Graphical user interface (GUI) agents perceive and interact with visual interfaces, interpret natural language instructions, analyze GUI states, and execute corresponding actions. These agents have to parse screen streams in real-time, producing extensive token sequences that often exceed computational limits (Zhang et al., 2024b; Wang et al., 2024a). Multimodal token compression enhances the efficiency of GUI agents. This approach mitigates context overflow in extended operation sequences by dynamically compressing redundant visual elements (e.g., extra white space or simple backgrounds). For some small but important control elements, it should also eliminate other irrelevant visual elements and highlight their importance. For instance, ShowUI (Lin et al., 2025a) is the first model to apply token selection strategy to GUI agents. ShowUI segments GUI screenshots into connected components by clustering pixels with similar RGB values, significantly reducing the total number of discrete elements. During both training and inference phases, the system employs an adaptive token selection strategy that probabilistically prunes redundant tokens within these components, thereby optimizing computational efficiency while preserving functional semantics However, excessive compression risks inducing operational ambiguity, necessitating careful calibration.

7.2 Healthcare and Medical Imaging

The effective synthesis of multimodal medical data is pivotal to advancing contemporary medical diagnosis and research. MLLMs can integrate radiographic findings, medical histories, and ancillary diagnostic tests to generate differential diagnoses, which clinicians can correlate with patient records and physician notes to enhance diagnostic accuracy (Liang et al., 2024). Furthermore, MLLMs can automatically draft preliminary radiology reports, potentially reducing the workload of radiologists (Beddiar & Oussalah, 2023; Bazi et al., 2023; He et al., 2020). A major challenge for MLLMs in medical imaging is the processing of high-resolution images, such as Whole-slide Images (WSIs) in pathology, which can contain billions of pixels. To overcome this, TCP-LLaVA (Lyu et al., 2025) uses a set of trainable compression tokens to aggregate and condense crucial information from thousands of visual and textual inputs. Instead of feeding every single image patch token into the language model, only these compressed tokens are forwarded for answer generation. Token compression holds vast potential for widespread application in the field of healthcare and medical imaging, enabling the efficient analysis of complex, high-resolution images.

7.3 Robotics and Autonomous Systems

Leveraging the significant capabilities of video LLMs in long-form video comprehension enables their deployment in robotics (Wei et al., 2025) and autonomous driving systems (Ma et al., 2024b; Zhou et al., 2024). However, the inherent computational complexity of long-duration video processing creates fundamental latency-efficiency tradeoffs that challenge real-time implementation. Token compression addresses this by prioritizing salient spatio-temporal dynamics (e.g., agent movements, action trajectories) and fine-grained per-frame details, enabling computationally efficient video understanding for these domains. VTS (Ma et al., 2024b) proposes a token pruning strategy for autonomous driving scenarios. VTS employs a proposal model based on a lightweight convolutional neural network that is able to adaptively identify keyframes and pry

less informative tokens (e.g., invariant backgrounds and stationary objects). StreamVLN (Wei et al., 2025) further enhances inference efficiency for real-time navigation by employing a voxel-based spatial pruning strategy at test time to reduce memory tokens. This approach makes real-time navigation feasible.

7.4 Efficient Reasoning

Token compression improves efficiency by removing redundant input tokens. However, in many cases, the main source of computational cost shifts from input to output, most notably in reasoning models (Team et al., 2025; Guo et al., 2025a; Jaech et al., 2024), where lengthy generation chains are common. The "slow-thinking" paradigm improves reasoning ability but results in lengthy reasoning chains (Feng et al., 2025a; Sui et al., 2025; Chen et al., 2025; Feng et al., 2025b). Some efficient reasoning methods compress these chains using similar techniques (e.g., attention mechanisms, semantic importance) (Ma et al., 2025; Xia et al., 2025; Liu et al., 2024b; Fang et al., 2025), typically requiring fine-tuning via Supervised Fine-Tuning (SFT) or Reinforcement Learning (RL). Beyond token compression, other approaches improve reasoning efficiency by compressing model (Magister et al., 2022; Li et al., 2023b; Feng et al., 2024; Zhang et al., 2025d) or accelerating decoding (Sun et al., 2024b; Ma et al., 2024a; Luo et al., 2025a; Xu et al., 2025a; Ding et al., 2025).

8 Conclusion

This paper presents the first structured survey of token compression techniques for MLLMs. This is a critical area, driven by the growing need to process extensive and intricate data across various modalities. We systematically categorized existing methods based on their primary data focus: image-centric, video-centric, and audio-centric compression, acknowledging that effective strategies are intrinsically linked to the unique characteristics and redundancies of each modality. Furthermore, we delved into the underlying mechanisms of these methods, including transformation-based, similarity-based, attention-based, and query-based approaches. By consolidating current progress and identifying key challenges, this survey aims to inspire future research and accelerate advancements in this rapidly evolving field. The insights presented are designed to guide researchers in developing more efficient and scalable MLLMs, ultimately pushing the boundaries of what these powerful models can achieve with increasingly longer and more complex inputs.

References

Marah Abdin, Jyoti Aneja, Harkirat Behl, Sébastien Bubeck, Ronen Eldan, Suriya Gunasekar, Michael Harrison, Russell J Hewett, Mojan Javaheripi, Piero Kauffmann, et al. Phi-4 technical report. *arXiv preprint arXiv:2412.08905*, 2024.

AI@Meta. Llama 3 model card. https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md, 2024.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: A visual language model for few-shot learning. *NeurIPS*, 2022.

Saeed Ranjbar Alvar, Gursimran Singh, Mohammad Akbari, and Yong Zhang. Divprune: Diversity-based visual token pruning for large multimodal models. In *CVPR*, 2025.

Hongjun An, Yifan Chen, Zhe Sun, and Xuelong Li. Sentencevae: Enable next-sentence prediction for large language models with faster speed, higher accuracy and longer context. *arXiv preprint arXiv:2408.00655*, 2024.

Kazi Hasan Ibn Arif, JinYi Yoon, Dimitrios S Nikolopoulos, Hans Vandierendonck, Deepu John, and Bo Ji. Hired: Attention-guided token dropping for efficient inference of high-resolution vision-language models in resource-constrained environments. In *AAAI*, 2025.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025.

Yakoub Bazi, Mohamad Mahmoud Al Rahhal, Laila Bashmal, and Mansour Zuair. Vision-language model for visual question answering in medical imagery. *Bioengineering*, 10(3):380, 2023.

Romaissa Beddiar and Mourad Oussalah. Explainability in medical image captioning. *Explainable Deep Learning and Artificial Intelligence*, pp. 239–261, 2023.

Jaime Bellver-Soler, Mario Rodriguez-Cantelar, Ricardo Córdoba, and Luis Fernando D'Haro. Cutting through overload: Efficient token dropping for speech emotion recognition in multimodal large language models. In *ACL*, 2025.

Daniel Bolya, Cheng-Yang Fu, Xiaoliang Dai, Peizhao Zhang, Christoph Feichtenhofer, and Judy Hoffman. Token merging: Your vit but faster. In *ICLR*, 2022.

Daniel Bolya, Cheng-Yang Fu, Xiaoliang Dai, Peizhao Zhang, Christoph Feichtenhofer, and Judy Hoffman. Token merging: Your vit but faster. In *ICLR*, 2023.

Mu Cai, Jianwei Yang, Jianfeng Gao, and Yong Jae Lee. Matryoshka multimodal models. In *NeurIPS Workshop*, 2024.

Jianjian Cao, Peng Ye, Shengze Li, Chong Yu, Yansong Tang, Jiwen Lu, and Tao Chen. Madtp: Multimodal alignment-guided dynamic token pruning for accelerating vision-language transformer. In *CVPR*, 2024.

Qingqing Cao, Bhargavi Paranjape, and Hannaneh Hajishirzi. Pumer: Pruning and merging tokens for efficient vision language models. *arXiv preprint arXiv:2305.17530*, 2023.

Umberto Cappellazzo, Minsu Kim, Honglie Chen, Pingchuan Ma, Stavros Petridis, Daniele Falavigna, Alessio Brutti, and Maja Pantic. Large language models are strong audio-visual speech recognition learners. In *ICASSP*, 2025a.

Umberto Cappellazzo, Minsu Kim, and Stavros Petridis. Adaptive audio-visual speech recognition via matryoshka-based multimodal llms. *arXiv preprint arXiv:2503.06362*, 2025b.

Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *CVPR*, 2021.

Junbum Cha, Wooyoung Kang, Jonghwan Mun, and Byungseok Roh. Honeybee: Locality-enhanced projector for multimodal llm. In *CVPR*, 2024.

Wenhao Chai, Enxin Song, Yilun Du, Chenlin Meng, Vashisht Madhavan, Omer Bar-Tal, Jenq-Neng Hwang, Saining Xie, and Christopher D Manning. Auroracap: Efficient, performant video detailed captioning and a new benchmark. In *ICLR*, 2025.

Ke Chen, Xingjian Du, Bilei Zhu, Zejun Ma, Taylor Berg-Kirkpatrick, and Shlomo Dubnov. Hts-at: A hierarchical token-semantic audio transformer for sound classification and detection. In *ICASSP*, 2022.

Liang Chen, Haozhe Zhao, Tianyu Liu, Shuai Bai, Junyang Lin, Chang Zhou, and Baobao Chang. An image is worth 1/2 tokens after layer 2: Plug-and-play inference acceleration for large vision-language models. In *ECCV*, 2024a.

Xinghao Chen, Anhao Zhao, Heming Xia, Xuan Lu, Hanlin Wang, Yanjun Chen, Wei Zhang, Jian Wang, Wenjie Li, and Xiaoyu Shen. Reasoning beyond language: A comprehensive survey on latent chain-of-thought reasoning. *arXiv preprint arXiv:2505.16782*, 2025.

Zhe Chen, Weiyun Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Erfei Cui, Jinguo Zhu, Shenglong Ye, Hao Tian, Zhaoyang Liu, et al. Expanding performance boundaries of open-source multimodal models with model, data, and test-time scaling. *arXiv preprint arXiv:2412.05271*, 2024b.

Zhe Chen, Weiyun Wang, Hao Tian, Shenglong Ye, Zhangwei Gao, Erfei Cui, Wenwen Tong, Kongzhi Hu, Jiapeng Luo, Zheng Ma, et al. How far are we to gpt-4v? closing the gap to commercial multimodal models with open-source suites. *Science China Information Sciences*, 67(12):220101, 2024c.

Hongrong Cheng, Miao Zhang, and Javen Qinfeng Shi. A survey on deep neural network pruning: Taxonomy, comparison, analysis, and recommendations. *TPAMI*, 2024a.

Xin Cheng, Xun Wang, Xingxing Zhang, Tao Ge, Si-Qing Chen, Furu Wei, Huishuai Zhang, and Dongyan Zhao. Xrag: Extreme context compression for retrieval-augmented generation with one token. In *NeurIPS*, 2024b.

Zesen Cheng, Sicong Leng, Hang Zhang, Yifei Xin, Xin Li, Guanzheng Chen, Yongxin Zhu, Wenqi Zhang, Ziyang Luo, Deli Zhao, et al. Videollama 2: Advancing spatial-temporal modeling and audio understanding in video-llm. *arXiv preprint arXiv:2406.07476*, 2024c.

Alexis Chevalier, Alexander Wettig, Anirudh Ajith, and Danqi Chen. Adapting language models to compress contexts. *arXiv preprint arXiv:2305.14788*, 2023.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality. https://lmsys.org/blog/2023-03-30-vicuna, March 2023.

Xiangxiang Chu, Limeng Qiao, Xinyang Lin, Shuang Xu, Yang Yang, Yiming Hu, Fei Wei, Xinyu Zhang, Bo Zhang, Xiaolin Wei, et al. Mobilevlm: A fast, strong and open vision language assistant for mobile devices. *arXiv preprint arXiv:2312.16886*, 2023.

Xiangxiang Chu, Limeng Qiao, Xinyu Zhang, Shuang Xu, Fei Wei, Yang Yang, Xiaofei Sun, Yiming Hu, Xinyang Lin, Bo Zhang, et al. Mobilevlm v2: Faster and stronger baseline for vision language model. *arXiv preprint arXiv:2402.03766*, 2024a.

Yunfei Chu, Jin Xu, Qian Yang, Haojie Wei, Xipin Wei, Zhifang Guo, Yichong Leng, Yuanjun Lv, Jinzheng He, Junyang Lin, et al. Qwen2-audio technical report. *arXiv preprint arXiv:2407.10759*, 2024b.

Wenliang Dai, Nayeon Lee, Boxin Wang, Zhuolin Yang, Zihan Liu, Jon Barker, Tuomas Rintamaki, Mohammad Shoeybi, Bryan Catanzaro, and Wei Ping. Nvlm: Open frontier-class multimodal llms. *arXiv preprint arXiv:2409.11402*, 2024.

Tri Dao. Flashattention-2: Faster attention with better parallelism and work partitioning. In *ICLR*, 2024.

Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness. In *NeurIPS*, 2022.

Nilaksh Das, Saket Dingliwal, Srikanth Ronanki, Rohit Paturi, Zhaocheng Huang, Prashant Mathur, Jie Yuan, Dhanush Bekal, Xing Niu, Sai Muralidhar Jayanthi, et al. Speechverse: A large-scale generalizable audio language model. *arXiv preprint arXiv:2405.08295*, 2024.

Alexandre Défossez, Jade Copet, Gabriel Synnaeve, and Yossi Adi. High fidelity neural audio compression. *TMLR*, 2022. ISSN 2835-8856.

Yifu Ding, Wentao Jiang, Shunyu Liu, Yongcheng Jing, Jinyang Guo, Yingjie Wang, Jing Zhang, Zengmao Wang, Ziwei Liu, Bo Du, et al. Dynamic parallel tree search for efficient llm reasoning. *arXiv preprint arXiv:2502.16235*, 2025.

Xiaoyi Dong, Jianmin Bao, Dongdong Chen, Weiming Zhang, Nenghai Yu, Lu Yuan, Dong Chen, and Baining Guo. Cswin transformer: A general vision transformer backbone with cross-shaped windows. In *CVPR*, 2022.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *ICLR*, 2020.

Mingjing Du, Shifei Ding, and Hongjie Jia. Study on density peaks clustering based on k-nearest neighbors and principal component analysis. *Knowlege Based System*, 99:135–145, 2016.

Haoqi Fan, Bo Xiong, Karttikeya Mangalam, Yanghao Li, Zhicheng Yan, Jitendra Malik, and Christoph Feichtenhofer. Multiscale vision transformers. In *ICCV*, 2021.

Gongfan Fang, Xinyin Ma, and Xinchao Wang. Thinkless: Llm learns when to think. *arXiv preprint arXiv:2505.13379*, 2025.

Qingkai Fang, Shoutao Guo, Yan Zhou, Zhengrui Ma, Shaolei Zhang, and Yang Feng. Llama-omni: Seamless speech interaction with large language models. *arXiv preprint arXiv:2409.06666*, 2024.

Yassir Fathullah, Chunyang Wu, Egor Lakomkin, Junteng Jia, Yuan Shangguan, Ke Li, Jinxi Guo, Wenhan Xiong, Jay Mahadeokar, Ozlem Kalinli, et al. Prompting large language models with speech recognition abilities. In *ICASSP*, 2024.

Sicheng Feng, Gongfan Fang, Xinyin Ma, and Xinchao Wang. Efficient reasoning models: A survey. *arXiv preprint arXiv:2504.10903*, 2025a.

Sicheng Feng, Song Wang, Shuyi Ouyang, Lingdong Kong, Zikai Song, Jianke Zhu, Huan Wang, and Xinchao Wang. Can mllms guide me home? a benchmark study on fine-grained visual reasoning from transit maps. *arXiv preprint arXiv:2505.18675*, 2025b.

Tao Feng, Yicheng Li, Li Chenglin, Hao Chen, Fei Yu, and Yin Zhang. Teaching small language models reasoning through counterfactual distillation. In *EMNLP*, 2024.

Elias Frantar, Saleh Ashkboos, Torsten Hoefler, and Dan Alistarh. gptq: Accurate post-training compression for generative pretrained transformers. In *ICLR*, 2023.

Chaoyou Fu, Yuhan Dai, Yongdong Luo, Lei Li, Shuhuai Ren, Renrui Zhang, Zihan Wang, Chenyu Zhou, Yunhang Shen, Mengdan Zhang, et al. Video-mme: The first-ever comprehensive evaluation benchmark of multi-modal llms in video analysis. In *CVPR*, 2025a.

Tianyu Fu, Tengxuan Liu, Qinghao Han, Guohao Dai, Shengen Yan, Huazhong Yang, Xuefei Ning, and Yu Wang. Framefusion: Combining similarity and importance for video token reduction on large visual language models. In *ICCV*, 2025b.

Heting Gao, Hang Shao, Xiong Wang, Chaofan Qiu, Yunhang Shen, Siqi Cai, Yuchen Shi, Zihan Xu, Zuwei Long, Yike Zhang, et al. Lucy: Linguistic understanding and control yielding early stage of her. *arXiv preprint arXiv:2501.16327*, 2025.

Jiyang Gao, Chen Sun, Zhenheng Yang, and Ram Nevatia. Tall: Temporal activity localization via language query. In *ICCV*, 2017.

Lishuai Gao, Yujie Zhong, Yingsen Zeng, Haoxian Tan, Dengjie Li, and Zheng Zhao. Linvt: Empower your image-level large language model to understand videos. *arXiv preprint arXiv:2412.05185*, 2024a.

Zhangwei Gao, Zhe Chen, Erfei Cui, Yiming Ren, Weiyun Wang, Jinguo Zhu, Hao Tian, Shenglong Ye, Junjun He, Xizhou Zhu, et al. Mini-internvl: A flexible-transfer pocket multi-modal model with 5% parameters and 90% performance. *Visual Intelligence*, 2(1):1–17, 2024b.

Tao Ge, Jing Hu, Lei Wang, Xun Wang, Si-Qing Chen, and Furu Wei. In-context autoencoder for context compression in a large language model. *arXiv preprint arXiv:2307.06945*, 2023.

Xuelong Geng, Kun Wei, Qijie Shao, Shuiyun Liu, Zhennan Lin, Zhixian Zhao, Guojian Li, Wenjie Tian, Peikun Chen, Yangze Li, et al. Osum: Advancing open speech understanding models with limited resources in academia. *arXiv preprint arXiv:2501.13306*, 2025.

Amir Gholami, Sehoon Kim, Zhen Dong, Zhewei Yao, Michael W Mahoney, and Kurt Keutzer. A survey of quantization methods for efficient neural network inference. In *Proceedings of the Book: Low-Power Computer Vision*, pp. 291–326. 2022.

Jianping Gou, Baosheng Yu, Stephen J Maybank, and Dacheng Tao. Knowledge distillation: A survey. *IJCV*, 129(6):1789–1819, 2021.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In *CVPR*, 2017.

Benjamin Graham, Alaaeldin El-Nouby, Hugo Touvron, Pierre Stock, Armand Joulin, Hervé Jégou, and Matthijs Douze. Levit: A vision transformer in convnet's clothing for faster inference. In *ICCV*, 2021.

Albert Gu and Tri Dao. Mamba: Linear-time sequence modeling with selective state spaces. In *Proceedings of the Conference on Language Modeling*, 2024.

Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, et al. Conformer: Convolution-augmented transformer for speech recognition. In *Interspeech*, 2020.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025a.

Dong Guo, Faming Wu, Feida Zhu, Fuxing Leng, Guang Shi, Haobin Chen, Haoqi Fan, Jian Wang, Jianyu Jiang, Jiawei Wang, et al. Seed1. 5-vl technical report. *arXiv preprint arXiv:2505.07062*, 2025b.

Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. Vizwiz grand challenge: Answering visual questions from blind people. In *CVPR*, 2018.

Saket Gurukar and Asim Kadav. Long-vmnet: Accelerating long-form video understanding via fixed memory. *arXiv preprint arXiv:2503.13707*, 2025.

Andrey Guzhov, Federico Raue, Jörn Hees, and Andreas Dengel. Audioclip: Extending clip to image, text and audio. In *ICASSP*, 2022.

Jiayi Han, Liang Du, Yiwen Wu, Xiangguo Zhou, Hongwei Du, and Weibo Zheng. Adafv: Accelerating vlms with self-adaptive cross-modality attention mixture. *arXiv preprint arXiv:2501.09532*, 2025.

Song Han, Huizi Mao, and William J Dally. Deep compression: Compressing deep neural network with pruning, trained quantization and huffman coding. In *ICLR*, 2016.

Yuhang Han, Xuyang Liu, Zihan Zhang, Pengxiang Ding, Donglin Wang, Honggang Chen, Qingsen Yan, and Siteng Huang. Filter, correlate, compress: Training-free token reduction for mllm acceleration. *arXiv preprint arXiv:2411.17686*, 2024.

Xuehai He, Yichen Zhang, Luntian Mou, Eric Xing, and Pengtao Xie. Pathvqa: 30000+ questions for medical visual question answering. *arXiv preprint arXiv:2003.10286*, 2020.

Yefei He, Feng Chen, Jing Liu, Wenqi Shao, Hong Zhou, Kaipeng Zhang, and Bohan Zhuang. Zipvl: Efficient large vision-language models with dynamic token sparsification and kv cache compression. In *ICCV*, 2025.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM Transactions on Audio, Speech, and Language Processing.*, 29:3451–3460, 2021.

Lianyu Hu, Fanhua Shang, Liang Wan, and Wei Feng. Illava: An image is worth fewer than 1/3 input tokens in large multimodal models. *arXiv preprint arXiv:2412.06263*, 2024.

Chensen Huang, Guibo Zhu, Xuepeng Wang, Yifei Luo, Guojing Ge, Haoran Chen, Dong Yi, and Jinqiao Wang. Recurrent context compression: Efficiently expanding the context window of llm. *arXiv preprint arXiv:2406.06110*, 2024.

Hsiang-Wei Huang, Wenhao Chai, Kuang-Ming Chen, Cheng-Yen Yang, and Jenq-Neng Hwang. Tosa: Token merging with spatial awareness. In *IROS*, 2025a.

Hsiang-Wei Huang, Fu-Chen Chen, Wenhao Chai, Che-Chun Su, Lu Xia, Sanghun Jung, Cheng-Yen Yang, Jenq-Neng Hwang, Min Sun, and Cheng-Hao Kuo. Zero-shot 3d question answering via voxel-based dynamic token compression. In *CVPR*, 2025b.

Xiaohu Huang, Hao Zhou, and Kai Han. Prunevid: Visual token pruning for efficient video large language models. In *ACL*, 2025c.

Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *CVPR*, 2019.

Jeongseok Hyun, Sukjun Hwang, Su Ho Han, Taeoh Kim, Inwoong Lee, Dongyoon Wee, Joon-Young Lee, Seon Joo Kim, and Minho Shim. Multi-granular spatio-temporal token merging for training-free acceleration of video llms. *arXiv preprint arXiv:2507.07990*, 2025.

Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richardson, Ahmed El-Kishky, Aiden Low, Alec Helyar, Aleksander Madry, Alex Beutel, Alex Carney, et al. Openai o1 system card. *arXiv preprint arXiv:2412.16720*, 2024.

Huiqiang Jiang, Qianhui Wu, Chin-Yew Lin, Yuqing Yang, and Lili Qiu. Llmlingua: Compressing prompts for accelerated inference of large language models. In *EMNLP*, 2023a.

Huiqiang Jiang, Qianhui Wu, Xufang Luo, Dongsheng Li, Chin-Yew Lin, Yuqing Yang, and Lili Qiu. Longllm-lingua: Accelerating and enhancing llms in long context scenarios via prompt compression. In *ACL*, 2023b.

Jindong Jiang, Xiuyu Li, Zhijian Liu, Muyang Li, Guo Chen, Zhiqi Li, De-An Huang, Guilin Liu, Zhiding Yu, Kurt Keutzer, et al. Token-efficient long video understanding for multimodal llms. *arXiv preprint arXiv:2503.04130*, 2025a.

Yutao Jiang, Qiong Wu, Wenhao Lin, Wei Yu, and Yiyi Zhou. What kind of visual tokens do we need? training-free visual token pruning for multi-modal large language models from the perspective of graph. In *AAAI*, 2025b.

Peng Jin, Ryuichi Takanobu, Wancai Zhang, Xiaochun Cao, and Li Yuan. Chat-univi: Unified visual representation empowers large language models with image and video understanding. In *CVPR*, 2024.

Zhenglun Kong, Yize Li, Fanhu Zeng, Lei Xin, Shvat Messica, Xue Lin, Pu Zhao, Manolis Kellis, Hao Tang, and Marinka Zitnik. Token reduction should go beyond efficiency in generative models–from vision, language to multimodality. *arXiv preprint arXiv:2505.18227*, 2025.

Hugo Laurençon, Lucile Saulnier, Léo Tronchon, Stas Bekman, Amanpreet Singh, Anton Lozhkov, Thomas Wang, Siddharth Karamcheti, Alexander Rush, Douwe Kiela, et al. Obelics: An open web-scale filtered dataset of interleaved image-text documents. In *NeurIPS*, 2023.

Taehan Lee and Hyukjun Lee. Token pruning in audio transformers: Optimizing performance and decoding patch importance. *arXiv preprint arXiv:2504.01690*, 2025.

Bo Li, Yuanhan Zhang, Dong Guo, Renrui Zhang, Feng Li, Hao Zhang, Kaichen Zhang, Peiyuan Zhang, Yanwei Li, Ziwei Liu, and Chunyuan Li. Llava-onevision: Easy visual task transfer. *TMLR*, 2025a.

Bohao Li, Rui Wang, Guangzhi Wang, Yuying Ge, Yixiao Ge, and Ying Shan. Seed-bench: Benchmarking multimodal llms with generative comprehension. *arXiv preprint arXiv:2307.16125*, 2023a.

Chenglin Li, Qianglong Chen, Liangyue Li, Caiyu Wang, Yicheng Li, Zulong Chen, and Yin Zhang. Mixed distillation helps smaller language model better reasoning. *arXiv preprint arXiv:2312.10730*, 2023b.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In *ICML*, 2023c.

Kaiyuan Li, Xiaoyue Chen, Chen Gao, Yong Li, and Xinlei Chen. Balanced token pruning: Accelerating vision language models beyond local optimization. *arXiv preprint arXiv:2505.22038*, 2025b.

KunChang Li, Yinan He, Yi Wang, Yizhuo Li, Wenhai Wang, Ping Luo, Yali Wang, Limin Wang, and Yu Qiao. Videochat: Chat-centric video understanding. *arXiv preprint arXiv:2305.06355*, 2023d.

Kunchang Li, Yali Wang, Yinan He, Yizhuo Li, Yi Wang, Yi Liu, Zun Wang, Jilan Xu, Guo Chen, Ping Luo, et al. Mvbench: A comprehensive multi-modal video understanding benchmark. In *CVPR*, 2024a.

Tianpeng Li, Jun Liu, Tao Zhang, Yuanbo Fang, Da Pan, Mingrui Wang, Zheng Liang, Zehuan Li, Mingan Lin, Guosheng Dong, et al. Baichuan-audio: A unified framework for end-to-end speech interaction. *arXiv preprint arXiv:2502.17239*, 2025c.

Xinhao Li, Yi Wang, Jiashuo Yu, Xiangyu Zeng, Yuhan Zhu, Haian Huang, Jianfei Gao, Kunchang Li, Yinan He, Chenting Wang, et al. Videochat-flash: Hierarchical compression for long-context video modeling. *arXiv preprint arXiv:2501.00574*, 2024b.

Yangfu Li, Hongjian Zhan, Tianyi Chen, Qi Liu, and Yue Lu. Why 1+1< 1 in visual token pruning: Beyond naive integration via multi-objective balanced covering. *arXiv preprint arXiv:2505.10118*, 2025d.

Yanghao Li, Chao-Yuan Wu, Haoqi Fan, Karttikeya Mangalam, Bo Xiong, Jitendra Malik, and Christoph Feichtenhofer. Mvitv2: Improved multiscale vision transformers for classification and detection. In *CVPR*, 2022.

Yanwei Li, Chengyao Wang, and Jiaya Jia. Llama-vid: An image is worth 2 tokens in large language models. In *ECCV*, 2024c.

Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. Evaluating object hallucination in large vision-language models. In *EMNLP*, 2023e.

Yuang Li, Yu Wu, Jinyu Li, and Shujie Liu. Accelerating transducers through adjacent token merging. In *Interspeech*, 2023f.

Yucheng Li, Bo Dong, Chenghua Lin, and Frank Guerin. Compressing context to enhance inference efficiency of large language models. In *EMNLP*, 2023g.

Zongqian Li, Yinhong Liu, Yixuan Su, and Nigel Collier. Prompt compression for large language models: A survey. In *NAACL*, 2025e.

Chia Xin Liang, Pu Tian, Caitlyn Heqi Yin, Yao Yua, Wei An-Hou, Li Ming, Tianyang Wang, Ziqian Bi, and Ming Liu. A comprehensive survey and guide to multimodal large language models in vision-language tasks. *arXiv preprint arXiv:2411.06284*, 2024.

Youwei Liang, Chongjian Ge, Zhan Tong, Yibing Song, Jue Wang, and Pengtao Xie. Not all patches are what you need: Expediting vision transformers via token reorganizations. In *ICLR*, 2022.

Bin Lin, Yang Ye, Bin Zhu, Jiaxi Cui, Munan Ning, Peng Jin, and Li Yuan. Video-llava: Learning united visual representation by alignment before projection. In *EMNLP*, 2024a.

Ji Lin, Jiaming Tang, Haotian Tang, Shang Yang, Wei-Ming Chen, Wei-Chen Wang, Guangxuan Xiao, Xingyu Dang, Chuang Gan, and Song Han. Awq: Activation-aware weight quantization for on-device llm compression and acceleration. In *MLSys*, 2024b.

Kevin Qinghong Lin, Linjie Li, Difei Gao, Zhengyuan Yang, Shiwei Wu, Zechen Bai, Stan Weixian Lei, Lijuan Wang, and Mike Zheng Shou. Showui: One vision-language-action model for gui visual agent. In *CVPR*, pp. 19498–19508, 2025a.

Yueqian Lin, Yuzhe Fu, Jingyang Zhang, Yudong Liu, Jianyi Zhang, Jingwei Sun, Hai Li, Yiran Chen, et al. Speechprune: Context-aware token pruning for speech information retrieval. In *ICME*, 2025b.

Zhihang Lin, Mingbao Lin, Luxi Lin, and Rongrong Ji. Boosting multimodal large language models with visual tokens withdrawal for rapid inference. In *AAAI*, 2025c.

Hao Liu, Matei Zaharia, and Pieter Abbeel. Ringattention with blockwise transformers for near-infinite context. In *ICLR*, 2024a.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. In *NeurIPS*, 2023.

Juntao Liu, Liqiang Niu, Wenchao Chen, Jie Zhou, and Fandong Meng. Laco: Efficient layer-wise compression of visual tokens for multimodal large language models. *arXiv preprint arXiv:2507.02279*, 2025a.

Tengxiao Liu, Qipeng Guo, Xiangkun Hu, Cheng Jiayang, Yue Zhang, Xipeng Qiu, and Zheng Zhang. Can language models learn to skip steps? *arXiv preprint arXiv:2411.01855*, 2024b.

Ting Liu, Liangtao Shi, Richang Hong, Yue Hu, Quanjun Yin, and Linfeng Zhang. Multi-stage vision yoken dropping: Towards efficient multimodal large language model. *arXiv preprint arXiv:2411.10803*, 2024c.

Xuyang Liu, Yiyu Wang, Junpeng Ma, and Linfeng Zhang. Video compression commander: Plug-and-play inference acceleration for video large language models. *arXiv preprint arXiv:2505.14454*, 2025b.

Xuyang Liu, Ziming Wang, Yuhang Han, Yingyao Wang, Jiale Yuan, Jun Song, Bo Zheng, Linfeng Zhang, Siteng Huang, and Honggang Chen. Compression with global guidance: Towards training-free high-resolution mllms acceleration. *arXiv preprint arXiv:2501.05179*, 2025c.

Xuyang Liu, Zichen Wen, Shaobo Wang, Junjie Chen, Zhishan Tao, Yubo Wang, Xiangqi Jin, Chang Zou, Yiyu Wang, Chenfei Liao, et al. Shifting ai efficiency from model-centric to data-centric compression. *arXiv preprint arXiv:2505.19147*, 2025d.

Yuan Liu, Haodong Duan, Yuanhan Zhang, Bo Li, Songyang Zhang, Wangbo Zhao, Yike Yuan, Jiaqi Wang, Conghui He, Ziwei Liu, et al. Mmbench: Is your multi-modal model an all-around player? In *ECCV*, 2024d.

Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *ICCV*, 2021.

Zhijian Liu, Ligeng Zhu, Baifeng Shi, Zhuoyang Zhang, Yuming Lou, Shang Yang, Haocheng Xi, Shiyi Cao, Yuxian Gu, Dacheng Li, et al. Nvila: Efficient frontier visual language models. In *CVPR*, 2025e.

LMMs-Lab. Video detail caption, November 2024. Accessed: 2024-11.

Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. In *NeurIPS*, 2022.

Feng Luo, Yu-Neng Chuang, Guanchu Wang, Hoang Anh Duy Le, Shaochen Zhong, Hongyi Liu, Jiayi Yuan, Yang Sui, Vladimir Braverman, Vipin Chaudhary, et al. Autol2s: Auto long-short reasoning for efficient large language models. *arXiv preprint arXiv:2505.22662*, 2025a.

Yongdong Luo, Wang Chen, Xiawu Zheng, Weizhong Huang, Shukang Yin, Haojia Lin, Chaoyou Fu, Jinfa Huang, Jiayi Ji, Jiebo Luo, et al. Quota: Query-oriented token assignment via cot query decouple for long video comprehension. *arXiv preprint arXiv:2503.08689*, 2025b.

Weimin Lyu, Qingqiao Hu, Kehan Qi, Zhan Shi, Wentao Huang, Saumya Gupta, and Chao Chen. Efficient whole slide pathology vqa via token compression. *arXiv preprint arXiv:2507.14497*, 2025.

Chang Ma, Haiteng Zhao, Junlei Zhang, Junxian He, and Lingpeng Kong. Non-myopic generation of language models for reasoning and planning. In *ICLR*, 2024a.

Xinyin Ma, Gongfan Fang, and Xinchao Wang. Llm-pruner: On the structural pruning of large language models. In *NeurIPS*, 2023.

Xinyin Ma, Guangnian Wan, Runpeng Yu, Gongfan Fang, and Xinchao Wang. Cot-valve: Length-compressible chain-of-thought tuning. In *ACL*, 2025.

Yunsheng Ma, Amr Abdelraouf, Rohit Gupta, Ziran Wang, and Kyungtae Han. Video token sparsification for efficient multimodal llms in autonomous driving. *arXiv preprint arXiv:2409.11182*, 2024b.

Ziyang Ma, Guanrou Yang, Yifan Yang, Zhifu Gao, Jiaming Wang, Zhihao Du, Fan Yu, Qian Chen, Siqi Zheng, Shiliang Zhang, et al. An embarrassingly simple approach for llm with strong asr capacity. *arXiv preprint arXiv:2402.08846*, 2024c.

Muhammad Maaz, Hanoona Rasheed, Salman Khan, and Fahad Shahbaz Khan. Video-chatgpt: Towards detailed video understanding via large vision and language models. In *ACL*, 2023.

Muhammad Maaz, Hanoona Rasheed, Salman Khan, and Fahad Khan. Video-chatgpt: Towards detailed video understanding via large vision and language models. In *ACL*, 2024.

Lucie Charlotte Magister, Jonathan Mallinson, Jakub Adamek, Eric Malmi, and Aliaksei Severyn. Teaching small language models to reason. In *ACL*, 2022.

Karttikeya Mangalam, Raiymbek Akshulakov, and Jitendra Malik. Egoschema: A diagnostic benchmark for very long-form video language understanding. In *NeurIPS*, 2023.

Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv:2304.07193*, 2023.

Zhuoshi Pan, Qianhui Wu, Huiqiang Jiang, Menglin Xia, Xufang Luo, Jue Zhang, Qingwei Lin, Victor Rühle, Yuqing Yang, Chin-Yew Lin, et al. Llmlingua-2: Data distillation for efficient and faithful task-agnostic prompt compression. In *Findings of ACL*, 2024.

Viorica Patraucean, Lucas Smaira, Ankush Gupta, Adria Recasens, Larisa Markeeva, Dylan Banarse, Skanda Koppula, Mateusz Malinowski, Yi Yang, Carl Doersch, et al. Perception test: A diagnostic benchmark for multimodal video models. In *NeurIPS*, 2024.

Kunat Pipatanakul, Potsawee Manakul, Natapong Nitarach, Warit Sirichotedumrong, Surapon Nonesung, Teetouch Jaknamon, Parinthapat Pengpun, Pittawat Taveekitworachai, Adisai Na-Thalang, Sittipong Sripaisarnmongkol, et al. Typhoon 2: A family of open text and multimodal thai large language models. *arXiv preprint arXiv:2412.13702*, 2024.

Daniel Cosmin Porumbel, Jin-Kao Hao, and Fred Glover. A simple and effective algorithm for the maxmin diversity problem. *Ann. Oper. Res.*, 186:275–293, 2011.

Tianyuan Qu, Longxiang Tang, Bohao Peng, Senqiao Yang, Bei Yu, and Jiaya Jia. Does your vision-language model get lost in the long video sampling dilemma? *arXiv preprint arXiv:2503.12496*, 2025.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *ICML*, 2021.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. Robust speech recognition via large-scale weak supervision. In *ICML*, 2023.

Yongming Rao, Wenliang Zhao, Benlin Liu, Jiwen Lu, Jie Zhou, and Cho-Jui Hsieh. Dynamicvit: Efficient vision transformers with dynamic token sparsification. In *NeurIPS*, 2021.

Alex Rodriguez and Alessandro Laio. Clustering by fast search and find of density peaks. *science*, 344(6191): 1492–1496, 2014.

Michael S Ryoo, AJ Piergiovanni, Anurag Arnab, Mostafa Dehghani, and Anelia Angelova. Tokenlearner: What can 8 learned tokens do for images and videos? *arXiv preprint arXiv:2106.11297*, 2021.

Michael S Ryoo, Keerthana Gopalakrishnan, Kumara Kahatapitiya, Ted Xiao, Kanishka Rao, Austin Stone, Yao Lu, Julian Ibarz, and Anurag Arnab. Token turing machines. In *CVPR*, 2023.

Michael S Ryoo, Honglu Zhou, Shrikant Kendre, Can Qin, Le Xue, Manli Shu, Jongwoo Park, Kanchana Ranasinghe, Silvio Savarese, Ran Xu, et al. Xgen-mm-vid (blip-3-video): You only need 32 tokens to represent a video even in vlms. *arXiv preprint arXiv:2410.16267*, 2024.

Yuzhang Shang, Zhihang Yuan, Bin Xie, Bingzhe Wu, and Yan Yan. Post-training quantization on diffusion models. In *CVPR*, 2023.

Yuzhang Shang, Mu Cai, Bingxin Xu, Yong Jae Lee, and Yan Yan. Llava-prumerge: Adaptive token reduction for efficient large multimodal models. In *ICCV*, 2025.

Kele Shao, Keda Tao, Can Qin, Haoxuan You, Yang Sui, and Huan Wang. Holitom: Holistic token merging for fast video large language models. In *NeurIPS*, 2025.

Ninglu Shao, Shitao Xiao, Zheng Liu, and Peitian Zhang. Flexibly scaling large language models contexts through extensible tokenization. *arXiv preprint arXiv:2401.07793*, 2024.

Leqi Shen, Guoqiang Gong, Tao He, Yifeng Zhang, Pengzhang Liu, Sicheng Zhao, and Guiguang Ding. Fastvid: Dynamic density pruning for fast video large language models. *NeurIPS*, 2025a.

Xiaoqian Shen, Yunyang Xiong, Changsheng Zhao, Lemeng Wu, Jun Chen, Chenchen Zhu, Zechun Liu, Fanyi Xiao, Balakrishnan Varadarajan, Florian Bordes, et al. Longvu: Spatiotemporal adaptive compression for long video-language understanding. In *ICML*, 2025b.

Kaize Shi, Xueyao Sun, Qing Li, and Guandong Xu. Compressing long context for enhancing rag with amr-based concept distillation. *arXiv preprint arXiv:2405.03085*, 2024.

Yan Shu, Zheng Liu, Peitian Zhang, Minghao Qin, Junjie Zhou, Zhengyang Liang, Tiejun Huang, and Bo Zhao. Video-xl: Extra-long vision language model for hour-scale video understanding. In *CVPR*, 2025.

Dingjie Song, Wenjun Wang, Shunian Chen, Xidong Wang, Michael Guan, and Benyou Wang. Less is more: A simple yet effective token reduction method for efficient multi-modal llms. In *COLING*, 2025a.

Enxin Song, Wenhao Chai, Guanhong Wang, Yucheng Zhang, Haoyang Zhou, Feiyang Wu, Haozhe Chi, Xun Guo, Tian Ye, Yanting Zhang, et al. Moviechat: From dense token to sparse memory for long video understanding. In *CVPR*, 2024.

Enxin Song, Wenhao Chai, Weili Xu, Jianwen Xie, Yuxuan Liu, and Gaoang Wang. Video-mmlu: A massive multi-discipline lecture understanding benchmark. *arXiv preprint arXiv:2504.14693*, 2025b.

Yang Sui, Miao Yin, Yi Xie, Huy Phan, Saman Aliari Zonouz, and Bo Yuan. Chip: Channel independence-based pruning for compact neural networks. In *NeurIPS*, 2021.

Yang Sui, Yanyu Li, Anil Kag, Yerlan Idelbayev, Junli Cao, Ju Hu, Dhritiman Sagar, Bo Yuan, Sergey Tulyakov, and Jian Ren. Bitsfusion: 1.99 bits weight quantization of diffusion model. *Advances in Neural Information Processing Systems*, 37:76775–76818, 2024a.

Yang Sui, Miao Yin, Yu Gong, and Bo Yuan. Co-exploring structured sparsification and low-rank tensor decomposition for compact dnns. *IEEE Trans. Neural Netw. Learn. Syst.*, 36(4):6642–6654, 2024b.

Yang Sui, Yu-Neng Chuang, Guanchu Wang, Jiamu Zhang, Tianyi Zhang, Jiayi Yuan, Hongyi Liu, Andrew Wen, Hanjie Chen, Xia Hu, et al. Stop overthinking: A survey on efficient reasoning for large language models. *arXiv preprint arXiv:2503.16419*, 2025.

Boyuan Sun, Jiaxing Zhao, Xihan Wei, and Qibin Hou. Llava-scissor: Token compression with semantic connected components for video llms. *arXiv preprint arXiv:2506.21862*, 2025.

Guangzhi Sun, Wenyi Yu, Changli Tang, Xianzhao Chen, Tian Tan, Wei Li, Lu Lu, Zejun MA, Yuxuan Wang, and Chao Zhang. Video-salmonn: Speech-enhanced audio-visual large language models. In *ICML*, 2024a.

Hanshi Sun, Momin Haider, Ruiqi Zhang, Huitao Yang, Jiahao Qiu, Ming Yin, Mengdi Wang, Peter Bartlett, and Andrea Zanette. Fast best-of-n decoding via speculative rejection. In *NeurIPS*, 2024b.

Xudong Tan, Peng Ye, Chongjun Tu, Jianjian Cao, Yaoxin Yang, Lin Zhang, Dongzhan Zhou, and Tao Chen. Tokencarve: Information-preserving visual token compression in multimodal large language models. *arXiv preprint arXiv:2503.10501*, 2025.

Changli Tang, Wenyi Yu, Guangzhi Sun, Xianzhao Chen, Tian Tan, Wei Li, Lu Lu, Zejun MA, and Chao Zhang. Salmonn: Towards generic hearing abilities for large language models. In *ICLR*, 2024.

Keda Tao, Can Qin, Haoxuan You, Yang Sui, and Huan Wang. Dycoke: Dynamic compression of tokens for fast video large language models. In *CVPR*, 2025a.

Keda Tao, Haoxuan You, Yang Sui, Can Qin, and Huan Wang. Plug-and-play 1. x-bit kv cache quantization for video large language models. *arXiv preprint arXiv:2503.16257*, 2025b.

Kimi Team, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, Chenjun Xiao, Chenzhuang Du, Chonghua Liao, et al. Kimi k1. 5: Scaling reinforcement learning with llms. *arXiv preprint arXiv:2501.12599*, 2025.

Qwen Team. Qwen2 technical report. *arXiv preprint arXiv:2407.10671*, 2024.

Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. In *ICML*, 2021.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017.

Cangqing Wang, Yutian Yang, Ruisi Li, Dan Sun, Ruicong Cai, Yuzhu Zhang, and Chengqian Fu. Adapting llms for efficient context processing through soft prompt compression. In *Proceedings of the International Conference on Modeling, Natural Language Processing and Machine Learning*, 2024a.

Haicheng Wang, Zhemeng Yu, Gabriele Spadaro, Chen Ju, Victor Quétu, Shuai Xiao, and Enzo Tartaglione. Folder: Accelerating multi-modal large language models with enhanced performance. In *ICCV*, 2025a.

Han Wang, Yuxiang Nie, Yongjie Ye, Deng GuanYu, Yanjie Wang, Shuai Li, Haiyang Yu, Jinghui Lu, and Can Huang. Dynamic-vlm: Simple dynamic visual token compression for videollm. *arXiv preprint arXiv:2412.09530*, 2024b.

Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, et al. Qwen2-vl: Enhancing vision-language model's perception of the world at any resolution. *arXiv preprint arXiv:2409.12191*, 2024c.

Qinsi Wang, Hancheng Ye, Ming-Yu Chung, Yudong Liu, Yueqian Lin, Martin Kuo, Mingyuan Ma, Jianyi Zhang, and Yiran Chen. Corematching: A co-adaptive sparse inference framework with token and neuron pruning for comprehensive acceleration of vision-language models. In *ICML*, 2025b.

Shengnan Wang, Youhui Bai, Lin Zhang, Pingyi Zhou, Shixiong Zhao, Gong Zhang, Sen Wang, Renhai Chen, Hua Xu, and Hongwei Sun. Xl3m: A training-free framework for llm length extension based on segment-wise inference. *arXiv preprint arXiv:2405.17755*, 2024d.

Wenshan Wang, Yihang Wang, Yixing Fan, Huaming Liao, and Jiafeng Guo. Quito: Accelerating long-context reasoning through query-guided context compression. In *CCIR*, 2024e.

Yihang Wang, Xu Huang, Bowen Tian, Yueyang Su, Lei Yu, Huaming Liao, Yixing Fan, Jiafeng Guo, and Xueqi Cheng. Quito-x: A new perspective on context compression from the information bottleneck theory. *arXiv preprint arXiv:2408.10497*, 2024f.

Zekun Wang, Minghua Ma, Zexin Wang, Rongchuan Mu, Liping Shan, Ming Liu, and Bing Qin. Effivlm-bench: A comprehensive benchmark for evaluating training-free acceleration in large vision-language models. *ACL*, 2025c.

Zhenhailong Wang, Senthil Purushwalkam, Caiming Xiong, Silvio Savarese, Heng Ji, and Ran Xu. Dymu: Dynamic merging and virtual unmerging for efficient vlms. *arXiv preprint arXiv:2504.17040*, 2025d.

Meng Wei, Chenyang Wan, Xiqian Yu, Tai Wang, Yuqiang Yang, Xiaohan Mao, Chenming Zhu, Wenzhe Cai, Hanqing Wang, Yilun Chen, et al. Streamvln: Streaming vision-and-language navigation via slowfast context modeling. *arXiv preprint arXiv:2507.05240*, 2025.

Yuxin Wen, Qingqing Cao, Qichen Fu, Sachin Mehta, and Mahyar Najibi. Efficient vision-language models by summarizing visual tokens into compact registers. *arXiv preprint arXiv:2410.14072*, 2024.

Zichen Wen, Yifeng Gao, Weijia Li, Conghui He, and Linfeng Zhang. Token pruning in multimodal large language models: Are we solving the right problem? *arXiv preprint arXiv:2502.11501*, 2025.

Yuetian Weng, Mingfei Han, Haoyu He, Xiaojun Chang, and Bohan Zhuang. Longvlm: Efficient long video understanding via large language models. In *ECCV*, 2024.

Haoning Wu, Dongxu Li, Bei Chen, and Junnan Li. Longvideobench: A benchmark for long-context interleaved video-language understanding. In *NeurIPS*, 2024.

Heming Xia, Yongqi Li, Chak Tou Leong, Wenjie Wang, and Wenjie Li. Tokenskip: Controllable chain-of-thought compression in llms. *arXiv preprint arXiv:2502.12067*, 2025.

Guangxuan Xiao, Ji Lin, Mickael Seznec, Hao Wu, Julien Demouth, and Song Han. Smoothquant: Accurate and efficient post-training quantization for large language models. In *ICML*, 2023a.

Jinqi Xiao, Chengming Zhang, Yu Gong, Miao Yin, Yang Sui, Lizhi Xiang, Dingwen Tao, and Bo Yuan. Haloc: Hardware-aware automatic low-rank compression for compact neural networks. In *AAAI*, 2023b.

Junbin Xiao, Xindi Shang, Angela Yao, and Tat-Seng Chua. Next-qa: Next phase of question-answering to explaining temporal actions. In *CVPR*, 2021.

Long Xing, Qidong Huang, Xiaoyi Dong, Jiajie Lu, Pan Zhang, Yuhang Zang, Yuhang Cao, Conghui He, Jiaqi Wang, Feng Wu, et al. Pyramiddrop: Accelerating your large vision-language models via pyramid visual redundancy reduction. In *CVPR*, 2025.

Fangzhi Xu, Hang Yan, Chang Ma, Haiteng Zhao, Jun Liu, Qika Lin, and Zhiyong Wu. ϕ-decoding: Adaptive foresight sampling for balanced inference-time exploration and exploitation. *arXiv preprint arXiv:2503.13288*, 2025a.

Jin Xu, Zhifang Guo, Jinzheng He, Hangrui Hu, Ting He, Shuai Bai, Keqin Chen, Jialin Wang, Yang Fan, Kai Dang, et al. Qwen2. 5-omni technical report. *arXiv preprint arXiv:2503.20215*, 2025b.

Lin Xu, Yilin Zhao, Daquan Zhou, Zhijie Lin, See Kiong Ng, and Jiashi Feng. Pllava: Parameter-free llava extension from images to videos for video dense captioning. *arXiv preprint arXiv:2404.16994*, 2024a.

Mingze Xu, Mingfei Gao, Zhe Gan, Hong-You Chen, Zhengfeng Lai, Haiming Gang, Kai Kang, and Afshin Dehghan. Slowfast-llava: A strong training-free baseline for video large language models. *arXiv preprint arXiv:2407.15841*, 2024b.

Mingze Xu, Mingfei Gao, Shiyu Li, Jiasen Lu, Zhe Gan, Zhengfeng Lai, Meng Cao, Kai Kang, Yinfei Yang, and Afshin Dehghan. Slowfast-llava-1.5: A family of token-efficient video large language models for long-form video understanding. *arXiv preprint arXiv:2503.18943*, 2025c.

Jinlong Xue, Yayue Deng, Yicheng Han, Yingming Gao, and Ya Li. Improving audio codec-based zero-shot text-to-speech synthesis with multi-modal context and large language model. In *Interspeech*, 2024.

Cheng Yang, Yang Sui, Jinqi Xiao, Lingyi Huang, Yu Gong, Yuanlin Duan, Wenqi Jia, Miao Yin, Yu Cheng, and Bo Yuan. Moe-i^2: Compressing mixture of experts models through inter-expert pruning and intra-expert low-rank decomposition. *arXiv preprint arXiv:2411.01016*, 2024.

Cheng Yang, Yang Sui, Jinqi Xiao, Lingyi Huang, Yu Gong, Chendi Li, Jinghua Yan, Yu Bai, Ponnuswamy Sadayappan, Xia Hu, et al. Topv: Compatible token pruning with inference time optimization for fast and low-memory multimodal vision language model. In *CVPR*, 2025a.

Senqiao Yang, Yukang Chen, Zhuotao Tian, Chengyao Wang, Jingyao Li, Bei Yu, and Jiaya Jia. Visionzip: Longer is better but not necessary in vision language models. In *CVPR*, 2025b.

Senqiao Yang, Junyi Li, Xin Lai, Bei Yu, Hengshuang Zhao, and Jiaya Jia. Visionthink: Smart and efficient vision language model via reinforcement learning. *arXiv preprint arXiv:2507.13348*, 2025c.

Linli Yao, Lei Li, Shuhuai Ren, Lean Wang, Yuanxin Liu, Xu Sun, and Lu Hou. Deco: Decoupling token compression from semantic abstraction in multimodal large language models. *arXiv preprint arXiv:2405.20985*, 2024.

Linli Yao, Yicheng Li, Yuancheng Wei, Lei Li, Shuhuai Ren, Yuanxin Liu, Kun Ouyang, Lean Wang, Shicheng Li, Sida Li, Lingpeng Kong, Qi Liu, Yuanxing Zhang, and Xu Sun. Timechat-online: 80% visual tokens are naturally redundant in streaming videos. In *ACMMM*, 2025.

Qinghao Ye, Haiyang Xu, Guohai Xu, Jiabo Ye, Ming Yan, Yiyang Zhou, Junyang Wang, Anwen Hu, Pengcheng Shi, Yaya Shi, et al. Mplug-owl: Modularization empowers large language models with multi-modality. *arXiv preprint arXiv:2304.14178*, 2023.

Weihao Ye, Qiong Wu, Wenhao Lin, and Yiyi Zhou. Fit and prune: Fast and training-free visual token pruning for multi-modal large language models. In *AAAI*, 2025a.

Xubing Ye, Yukang Gan, Yixiao Ge, Xiao-Ping Zhang, and Yansong Tang. Atp-llava: Adaptive token pruning for large vision language models. In *CVPR*, 2025b.

Xubing Ye, Yukang Gan, Xiaoke Huang, Yixiao Ge, and Yansong Tang. Voco-llama: Towards vision compression with large language models. In *CVPR*, 2025c.

Jeong Hun Yeo, Hyeongseop Rha, Se Jin Park, and Yong Man Ro. Mms-llama: Efficient llm-based audio-visual speech recognition with minimal multimodal speech tokens. *arXiv preprint arXiv:2503.11315*, 2025.

Miao Yin, Yang Sui, Siyu Liao, and Bo Yuan. Towards efficient tensor decomposition-based dnn model compression with optimization framework. In *CVPR*, 2021.

Shukang Yin, Chaoyou Fu, Sirui Zhao, Ke Li, Xing Sun, Tong Xu, and Enhong Chen. A survey on multimodal large language models. *National Science Review*, 11(12):nwae403, 2024.

Licheng Yu, Patrick Poirson, Shan Yang, Alexander C Berg, and Tamara L Berg. Modeling context in referring expressions. In *ECCV*, 2016.

Weihao Yu, Zhengyuan Yang, Linjie Li, Jianfeng Wang, Kevin Lin, Zicheng Liu, Xinchao Wang, and Lijuan Wang. Mm-vet: Evaluating large multimodal models for integrated capabilities. In *ICML*, 2023.

Xiyu Yu, Tongliang Liu, Xinchao Wang, and Dacheng Tao. On compressing deep models by low rank and sparse decomposition. In *ICCV*, 2017.

Zhou Yu, Dejing Xu, Jun Yu, Ting Yu, Zhou Zhao, Yueting Zhuang, and Dacheng Tao. Activitynet-qa: A dataset for understanding complex web videos via question answering. In *AAAI*, 2019.

Neil Zeghidour, Alejandro Luebs, Ahmed Omran, Jan Skoglund, and Marco Tagliasacchi. Soundstream: An end-to-end neural audio codec. *IEEE/ACM Transactions on Audio, Speech, and Language Processing.*, 30:495–507, 2021.

Weili Zeng, Ziyuan Huang, Kaixiang Ji, and Yichao Yan. Skip-vision: Efficient and scalable acceleration of vision-language models via adaptive token skipping. In *ICCV*, 2025.

Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In *CVPR*, 2023.

Boqiang Zhang, Kehan Li, Zesen Cheng, Zhiqiang Hu, Yuqian Yuan, Guanzheng Chen, Sicong Leng, Yuming Jiang, Hang Zhang, Xin Li, et al. Videollama 3: Frontier multimodal foundation models for image and video understanding. *arXiv preprint arXiv:2501.13106*, 2025a.

Ce Zhang, Kaixin Ma, Tianqing Fang, Wenhao Yu, Hongming Zhang, Zhisong Zhang, Yaqi Xie, Katia Sycara, Haitao Mi, and Dong Yu. Vscan: Rethinking visual token reduction for efficient large vision-language models. *arXiv preprint arXiv:2505.22654*, 2025b.

Hang Zhang, Xin Li, and Lidong Bing. Video-llama: An instruction-tuned audio-visual language model for video understanding. In *EMNLP*, 2023.

Hongzhi Zhang, Jingyuan Zhang, Xingguang Ji, Qi Wang, and Fuzheng Zhang. Dyntok: Dynamic compression of visual tokens for efficient and effective video understanding. *arXiv preprint arXiv:2506.03990*, 2025c.

Nan Zhang, Yusen Zhang, Prasenjit Mitra, and Rui Zhang. When reasoning meets compression: Benchmarking compressed large reasoning models on complex reasoning tasks. *arXiv preprint arXiv:2504.02010*, 2025d.

Qianchi Zhang, Hainan Zhang, Liang Pang, Hongwei Zheng, and Zhiming Zheng. Adacomp: Extractive context compression with adaptive predictor for retrieval-augmented large language models. *arXiv preprint arXiv:2409.01579*, 2024a.

Qizhe Zhang, Aosong Cheng, Ming Lu, Renrui Zhang, Zhiyong Zhuo, Jiajun Cao, Shaobo Guo, Qi She, and Shanghang Zhang. Beyond text-visual attention: Exploiting visual cues for effective token pruning in vlms. In *ICCV*, 2025e.

Renshan Zhang, Yibo Lyu, Rui Shao, Gongwei Chen, Weili Guan, and Liqiang Nie. Token-level correlation-guided compression for efficient multimodal document understanding. *arXiv preprint arXiv:2407.14439*, 2024b.

Shaolei Zhang, Qingkai Fang, Zhe Yang, and Yang Feng. Llava-mini: Efficient image and video large multimodal models with one vision token. In *ICLR*, 2025f.

Yuan Zhang, Chun-Kai Fan, Junpeng Ma, Wenzhao Zheng, Tao Huang, Kuan Cheng, Denis Gudovskiy, Tomoyuki Okuno, Yohei Nakata, Kurt Keutzer, et al. Sparsevlm: Visual token sparsification for efficient vision-language model inference. *arXiv preprint arXiv:2410.04417*, 2024c.

Yuanhan Zhang, Jinming Wu, Wei Li, Bo Li, Zejun Ma, Ziwei Liu, and Chunyuan Li. Video instruction tuning with synthetic data. *arXiv preprint arXiv:2410.02713*, 2024d.

Shiyu Zhao, Zhenting Wang, Felix Juefei-Xu, Xide Xia, Miao Liu, Xiaofang Wang, Mingfu Liang, Ning Zhang, Dimitris N Metaxas, and Licheng Yu. Accelerating multimodal large language models by searching optimal vision token reduction. In *CVPR*, 2025.

Yiwu Zhong, Zhuoming Liu, Yin Li, and Liwei Wang. Aim: Adaptive inference of multi-modal llms via token merging and pruning. In *ICCV*, 2025.

Hao Zhou, Zhanning Gao, Maosheng Ye, Zhili Chen, Qifeng Chen, Tongyi Cao, and Honggang Qi. Hints of prompt: Enhancing visual representation for multimodal llms in autonomous driving. *arXiv preprint arXiv:2411.13076*, 2024.

Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. In *ICLR*, 2024.

Jinguo Zhu, Weiyun Wang, Zhe Chen, Zhaoyang Liu, Shenglong Ye, Lixin Gu, Hao Tian, Yuchen Duan, Weijie Su, Jie Shao, et al. Internvl3: Exploring advanced training and test-time recipes for open-source multimodal models. *arXiv preprint arXiv:2504.10479*, 2025.

Jiedong Zhuang, Lu Lu, Ming Dai, Rui Hu, Jian Chen, Qiang Liu, and Haoji Hu. St3: Accelerating multimodal large language model by spatial-temporal visual token trimming. In *AAAI*, 2025.

Jiaru Zou, Mengyu Zhou, Tao Li, Shi Han, and Dongmei Zhang. Promptintern: Saving inference costs by internalizing recurrent prompt during large language model fine-tuning. *arXiv preprint arXiv:2407.02211*, 2024.