
Analyzing Fine-Grained Alignment and Enhancing Vision Understanding in Multimodal Language Models

Jiachen Jiang[†], Jinxin Zhou[†], Bo Peng[†], Xia Ning^{†,◇,♡}, Zhihui Zhu^{† *}

[†]Department of Computer Science and Engineering, The Ohio State University

[◇]Translational Data Analytics Institute, The Ohio State University

[♡]Department of Biomedical Informatics, The Ohio State University

{jiang.2880, zhou.3820, peng.707, ning.104, zhu.3440}@osu.edu

Abstract

Achieving better alignment between vision embeddings and Large Language Models (LLMs) is crucial for enhancing the abilities of Multimodal LLMs (MLLMs), particularly for recent models that rely on powerful pretrained vision encoders and LLMs. A common approach to connect the pretrained vision encoder and LLM is through a projector applied after the vision encoder. However, the projector is often trained to enable the LLM to generate captions, and hence the mechanism by which LLMs understand each vision token remains unclear. In this work, we first investigate the role of the projector in compressing vision embeddings and aligning them with word embeddings. We show that the projector significantly compresses visual information, removing redundant details while preserving essential elements necessary for the LLM to understand visual content. We then examine patch-level alignment—the alignment between each vision patch and its corresponding semantic words—and propose a *multi-semantic alignment hypothesis*. Our analysis indicates that the projector trained by caption loss improves patch-level alignment but only to a limited extent, resulting in weak and coarse alignment. To address this issue, we propose *patch-aligned training* to efficiently enhance patch-level alignment. Our experiments show that patch-aligned training (1) achieves stronger compression capability and improved patch-level alignment, enabling the MLLM to generate higher-quality captions, (2) improves the MLLM’s performance by 16% on referring expression grounding tasks, 4% on question-answering tasks, and 3% on modern instruction-following benchmarks when using the same supervised fine-tuning (SFT) setting. The proposed method can be easily extended to other multimodal models.

1 Introduction

Multimodal Large Language Models (MLLMs) [1, 2, 3, 4, 5, 6, 7] have recently gained significant attention and made notable progress. These models possess the ability to process and understand both visual and textual information, enabling them to perform complex reasoning [8, 9], generate textual descriptions from images [10], and answer image-related questions [11].

Consider an MLLM $\mathcal{M} = (\mathcal{E}, \mathcal{L}, \mathcal{P})$ where $\mathcal{E}$ is the vision encoder, $\mathcal{L}$ is the LLM, and $\mathcal{P}$ is the lightweight projector that connects the two parts. The standardized training paradigm follows two key phases: pretraining and instruction-tuning [1, 2]. During the pretraining phase, only the lightweight projector $\mathcal{P}$ is trained leaving the vision encoder $\mathcal{E}$ and the LLM $\mathcal{L}$ frozen. In instruction-tuning stage, both projector $\mathcal{P}$ and the LLM $\mathcal{L}$ are trainable. Despite the remarkable progress achieved through

*The corresponding author.

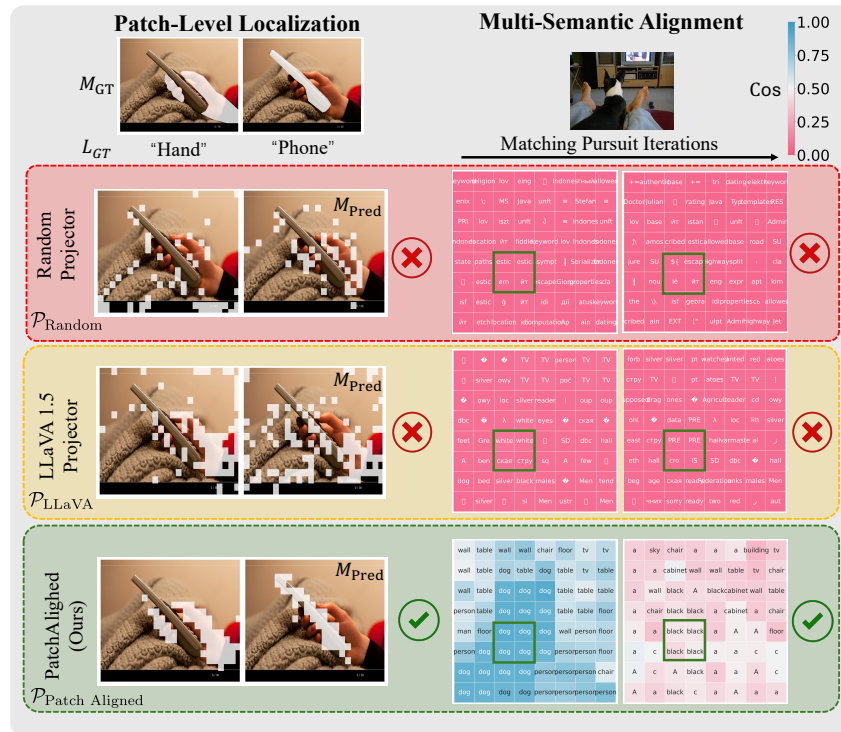


Figure 1: The patch-level alignment is measured in two aspects: Left) **patch-level localization**. Using LLM word embeddings of labels L_{GT} , we predict the most relevant image regions by calculating cosine similarity with the vision embedding. Right) **multi-semantic alignment**. Using matching pursuit, we decompose each vision embedding into several discrete words by treating LLM word embeddings as a basis. Since the vision embedding are obtained after the MLLM projector, we compare across three projectors: random projector $\mathcal{P}_{Random}$ (top), LLaVA1.5 projector $\mathcal{P}_{LLaVA}$ (middle), and our patch-aligned projector $\mathcal{P}_{Patch Aligned}$ (bottom). Results show that $\mathcal{P}_{LLaVA}$ exhibits weak patch-level alignment abilities, while our $\mathcal{P}_{Patch Aligned}$ significantly enhances these two aspects.

this training paradigm, recent works [12, 13, 14, 15, 16] reveal that these MLLMs still struggle with region-specific understanding and tend to hallucinate with irrelevant or incorrect information. The reason of these issues remains an active area. In addition to limitations in the vision encoder or the capabilities of the language model, a significant contributing factor lies in the projector [4, 17].

The platonic representation hypothesis [18] suggests that representations in deep networks are converging across data modalities², implying a shared structural alignment. However, for a vision encoder $\mathcal{E}$ and an LLM $\mathcal{L}$ that are pretrained separately, there is no guarantee that the embedding space induced by $\mathcal{E}$ will share the same basis as the embedding matrix $\mathbf{W}$ in $\mathcal{L}$, even if they have the same dimensionality. Thus, as the only connection between the two modalities, the projector $\mathcal{P}$ plays a crucial role. However, current work remains at a superficial understanding that the projector performs alignment, lacking a thorough and systematic analysis of its function. Thus, in this paper, we are motivated by the following questions:

*How does the projector align multimodal information in MLLMs?
How to quantify and improve alignment in current models?*

Contributions. In this work, we provide a detailed analysis of the alignment between each vision patch and its corresponding semantic words and develop methods to improve patch-level alignment, enabling the LLM to better understand visual content in the input space. Our contributions as follows,

Projector compresses visual information. Vision embeddings are naturally continuous and contain redundant information, whereas LLM input word embeddings are discrete. Thus, a natural question arises: *Is the information contained in the vision embeddings compressed through the projector?* To address this question, we propose quantifying the amount of information contained in the embeddings

²In the sense that vision and language models measure the distance between data points in a similar way.

using Von Neumann entropy [19]. Our experiments show that information is significantly compressed after projection, indicating that the projector plays a crucial role in eliminating redundant information while preserving the essential elements needed for the LLM to understand the visual content.

Analyzing patch-level alignment. We then examine each image patch in detail and study how its embedding aligns with the corresponding text embedding. However, challenges arise due to (1) a lack of text labels for each image patch and (2) the possibility that each image patch contains multiple semantic meanings. To address these challenges, we propose two complementary approaches to quantitatively and qualitatively study patch-level alignment.

We first focus on alignment with respect to the objects in the image. Specifically, for an input image $\mathbf{X}$ with embedding $\mathbf{V} = \mathcal{P} \circ \mathcal{E}(\mathbf{X})$, which serves as input to an LLM $\mathcal{L}$, we propose a patch-level alignment measure $\text{Align}(\mathbf{V}, \mathbf{W})$ to quantify the alignment between $\mathbf{V}$ and the word embedding $\mathbf{W}$. A higher $\text{Align}(\mathbf{V}, \mathbf{W})$ indicates a greater ability of the LLM to identify objects, even in the word embedding space. Inspired by previous work on decomposing word embedding vectors [20, 21], we then propose a *multi-semantic alignment* hypothesis, which states that the embedding for each vision patch can be decomposed as a linear combination of word embeddings corresponding to all semantic meanings within the patch. To verify this hypothesis, we apply the matching pursuit algorithm [22] to identify the most relevant tokens from the LLM dictionary for each vision patch.

As shown in Figure 1, our analysis indicates that the LLaVA projector improves patch-level alignment but only to a limited extent, resulting in weak and coarse alignment. This is due to (1) the caption loss only implicitly enforces token-level alignment, (2) captions tend to be short and primarily focus on a few prominent regions of interest, often neglecting many other regions. Consequently, numerous visual tokens (e.g., floor and TV cabinet) are often aligned with meaningless or garbled words.

Patch-Aligned Training for Improving Patch-Level Alignment. To address this issue, we propose a simple yet effective method called *Patch-Aligned Training* to enhance fine-grained alignment. In addition to the standard image caption loss in the pretraining state, we introduce additional patch loss, similar to $\text{Align}(\mathbf{V}, \mathbf{W})$, to capture the alignment between $\mathbf{V}$ and the word embedding $\mathbf{W}$. Notably, the patch loss relies only on the LLM embedding matrix $\mathbf{W}$ and is therefore computationally negligible compared to the caption loss, which requires inference and backpropagation through the LLM. As demonstrated in Figure 1, experiments show that Patch-Aligned training achieves stronger compression capability and improved patch-level alignment, enabling the LLM to generate higher-quality captions. Moreover, under the same SFT setting, the enhanced projector improves the MLLM’s performance by 16% on referring expression grounding tasks, 4% on question-answering tasks, and 3% on modern instruction-following benchmarks.

Patch-Aligned Dataset with Detailed Patch-Level Semantic Labels. To enable patch-aligned training, we address the lack of patch-level annotated data by introducing an automated data annotation pipeline that sequentially leverages RAM [23], Grounding DINO [24], and SAM [25]. Applying this pipeline to the 558K LLaVA pretraining dataset, we construct the Patch-Aligned Dataset (PAD), which provides extensive and diverse patch-level annotations. To support future research, we publicly release both the annotation pipeline and the resulting dataset.

2 Related Works

Multimodality Large Language Models. Many MLLMs, such as LLaVA-1.5/1.6 [2, 26], BLIP-2 [4], InstructBLIP [27], MiniGPT-4 [5], Otter [28], and mPLUG-Owl [29], can be viewed as stitched models, formed by connecting a pretrained (and often frozen) vision encoder (such as ViT) to a pretrained LLM through a projector or connector. The projector can be trained using either (i) a 1-stage approach, where it is directly trained alongside the fine-tuning LLM during instruction training [30], or (ii) a 2-stage approach, where the projector is first pretrained on adapter data before unfreezing the LLM and connector during instruction tuning [2]. The 2-stage approach has been widely adopted since LLaVA and has been shown to be beneficial [31]. However, during the pretraining stage, these models primarily rely on caption loss to achieve coarse alignment between modalities, which tends to lack region-level understanding abilities. Recent efforts, such as GPT4RoI [13], Kosmos-2 [14], and GLaMM [15], have attempted to improve region-specific, fine-grained understanding. However, these approaches often rely on grounding techniques or introduce additional tokens to enhance inference-time capabilities. They focus on improving inference rather than representation analysis of

fine-grained alignment. In contrast, our approach seeks to enhance fine-grained understanding by improving patch-level alignment without requiring additional training or tokens.

MultiModal Alignment Analysis. Existing works analyze cross-modal alignment from two perspectives: coarse alignment and fine-grained alignment. Coarse alignment is evaluated using metrics such as AC Score [32], which heavily depends on the CLIP [33] model, and Modality Integration Rate (MIR) [34], a statistic-based measure akin to FID. While these metrics provide insights into pretraining performance, they fail to address fine-grained token-level alignment. For fine-grained alignment, methods like Logit Lens Analysis [35] show that object-specific information is localized to token positions corresponding to image regions but lack proposals for improvement. Other works align coordinate, text, and image modalities through question-answer formats but overlook feature-level understanding [36]. Concurrently, SEA [37] enhances token-level alignment using predefined word lists and contrastive loss, but its reliance on the CLIP model and fixed vocabularies limits accuracy and flexibility. In contrast, as a fine-grained alignment model, our approach employs annotations from the RAM [23] model, which avoids predefined word lists for more accurate tagging, and introduces a cosine similarity loss, offering a simpler and more efficient alternative to contrastive loss.

3 Understanding Multimodal Projector by Compression and Alignment

In this section, we study the projector from both macro and micro perspectives: 1) information compression in Section 3.1 and 2) patch-level alignment in Section 3.2.

3.1 Macro-scale Analysis: Information Compression

Consider a MLLM $\mathcal{M} = (\mathcal{E}, \mathcal{L}, \mathcal{P})$. For each input images $\mathbf{X}$, the vision embedding of the n -th image before and after the projector is a sequence of embeddings as

$$\mathbf{V}_{\text{before}} = \mathcal{E}(\mathbf{X}) \in \mathcal{R}^{d \times S}, \quad \mathbf{V}_{\text{after}} = \mathcal{P} \circ \mathcal{E}(\mathbf{X}) \in \mathcal{R}^{d' \times S} \quad (1)$$

where S is the number of vision tokens and d, d' are the embedding dimensions of the vision encoder $\mathcal{E}$ and LLM $\mathcal{L}$. For N images, we compute the embeddings for each image and stack them together. We denote the resulting embeddings as $\mathbf{V}_{\text{before}} \in \mathcal{R}^{d \times NS}$ and $\mathbf{V}_{\text{after}} \in \mathcal{R}^{d' \times NS}$.

We hypothesize that the projector plays a crucial role in eliminating redundant information while preserving essential elements for the LLM to understand vision content. To quantify this, we measure the information using the basis-independent, transformation-invariant Von Neumann entropy [19].

Definition 3.1 (Von Neumann Entropy of Feature Embeddings). Let $\mathbf{V} \in \mathbb{R}^{d \times n}$ be a set of n feature vectors, each of dimension d , and let $\mathbf{v}_i \in \mathbb{R}^d$ denote the i -th column of $\mathbf{V}$. Define the normalized empirical covariance matrix by,

$$\rho_{\mathbf{V}} = \frac{\Sigma_{\mathbf{V}}}{\text{Tr}(\Sigma_{\mathbf{V}})}, \quad \Sigma_{\mathbf{V}} = \frac{1}{n} \sum_{i=1}^n \mathbf{v}_i \mathbf{v}_i^{\top} \in \mathbb{R}^{d \times d},$$

where $\Sigma_{\mathbf{V}}$ is normalized by its trace to obtain the density matrix of trace 1. Then, we compute the information contained in the embeddings $\mathbf{V}$ through the *Von Neumann entropy* [19] as follows,

$$\text{H}(\mathbf{V}) = -\text{Tr}(\rho_{\mathbf{V}} \log \rho_{\mathbf{V}}) = -\sum_j \lambda_j \log(\lambda_j),$$

where $\{\lambda_j\}$ are the eigenvalues of $\rho_{\mathbf{V}}$.

The Von Neumann Entropy measures how evenly information spreads across the feature space of learned embeddings, indicating their effective dimensionality. Higher values show a well-distributed, high-rank representation with diverse features, while lower values indicate compression—resulting in information loss and a reduced effective rank of the covariance matrix.

To measure the compression abilities of different projectors, we compare pretrained (stage 1) and randomly initialized variants. We evaluate several projector types commonly used in the MLLM field, including Linear, 2-layer MLP, and C-Abstractor [38]. We evaluated these across 100 selected images from the COCO2017 dataset [39]. The Von Neumann Entropy of vision embeddings before and after projection are shown in Table 1.

Table 1: Comparison of Von Neumann Entropy of vision embedding before and after projection.

Projector	$\mathcal{P}_{\text{LLaVA Linear}}$	$\mathcal{P}_{\text{Random Linear}}$	$\mathcal{P}_{\text{LLaVA MLP}}$	$\mathcal{P}_{\text{Random MLP}}$	$\mathcal{P}_{\text{LLaVA C-Abs}}$	$\mathcal{P}_{\text{Random C-Abs}}$
$H(\mathbf{V}_{\text{before}})$	4.8353	4.8353	4.8353	4.8353	4.8353	4.8353
$H(\mathbf{V}_{\text{after}})$	2.4829	4.8197	2.0362	4.8245	3.5850	7.4913

Based on Table 1, we make several key observations:

- **Pretrained v.s. Random.** The vision feature after the pretrained projectors ($\mathcal{P}_{\text{LLaVA Linear}}$, $\mathcal{P}_{\text{LLaVA MLP}}$ and $\mathcal{P}_{\text{LLaVA C-Abstractor}}$) exhibit lower entropy compared to random initialized ones ($\mathcal{P}_{\text{Random Linear}}$, $\mathcal{P}_{\text{Random MLP}}$ and $\mathcal{P}_{\text{Random C-Abstractor}}$), indicating that the pretrained project actively *compresses* the vision features. By contrast, the random projector barely changes the entropy, suggesting no meaningful compression occurs.
- **MLP v.s. Linear.** The vision feature after the MLP projector $\mathcal{P}_{\text{LLaVA MLP}}$ yields a larger drop in entropy than a linear projector $\mathcal{P}_{\text{LLaVA Linear}}$, suggesting that a deeper, non-linear transformation can better remove “redundant” information. A simple linear mapping merely rotates or shifts the embedding space; it has limited capacity that discards irrelevant information. This provides an explanation for the performance advantage of MLP over linear projector [2].

The compression appears essential for alignment since text embeddings, unlike visual inputs, are compact and discrete—structured around a finite vocabulary and token-based representation. The vision projector must therefore transform high-dimensional, continuous visual data into a format that aligns with text embeddings, naturally producing a more condensed output. However, entropy analysis alone cannot reveal how this alignment occurs at the patch level. Therefore, we examine patch-level alignment from a micro-scale perspective in the next section.

3.2 Micro-scale Analysis: Patch-Level Alignment

Unlike the CLIP model, where an image and its corresponding caption are encoded as an embedding vector, alignment can be simply measured using the cosine similarity between the two embedding vectors. Here, however, since the image patch embeddings are given as input to the LLM $\mathcal{L}$, we aim to measure their alignment with word embeddings $\mathbf{W}$. This presents several challenges: (1) There is a lack of text labels for each patch; (2) each word may be decomposed into multiple tokens or subwords in the LLM; (3) each image patch may contain multiple semantic meanings. To address these challenges, we propose two complementary approaches to study patch-level alignment.

3.2.1 Patch-Level Localization

Given an input image $\mathbf{X}$ with S patches, we use $\mathbf{V} = \mathcal{P} \circ \mathcal{E}(\mathbf{X}) \in \mathbb{R}^{d \times S}$ to denote the S vision embeddings. Due to the lack of labels for each patch, we adopt a simpler approach that relies only on labels for the objects within the image. In particular, suppose the image $\mathbf{X}$ contains P objects, each defined by its object tags and bounding box locations. We will develop a mask-label annotation pipeline in the next section. Let the ground-truth mask-label pairs be denoted as $\{(M^{(p)}, L^{(p)})\}_{p=1}^P$.

For each label $L^{(p)}$ which may contain multiple words or a single word that is decomposed into multiple subtokens in the LLM, we compute its text embedding $\mathbf{t}^{(p)}$ by averaging the LLM word embeddings of all its subtokens:

$$\mathbf{t}^{(p)} = \frac{1}{K} \sum_{k=1}^K \mathbf{w}_k^{(p)}, \quad \{\mathbf{w}_k^{(p)}\}_{k=1}^K = \mathbf{W}(\phi(L^{(p)})), \quad (2)$$

where ϕ is the tokenizer that converts $L^{(p)}$ into K subtokens, and $\mathbf{w}_k^{(p)} \in \mathbf{W}$ represents the k -th subtoken embedding. As each object may occupy multiple patches, we identify the relevant patches by computing the cosine similarity $\text{COS}(\mathbf{t}^{(p)}, \mathbf{v}_i)$ between vision patch $\mathbf{v}_i \in \mathbf{V}$ and the text embedding $\mathbf{t}^{(p)}$. We then select the patches whose similarity score exceeds an adaptive threshold $c > 0$, i.e.,

$$\text{Idx}^{(p)} = \{i \mid \text{COS}(\mathbf{t}^{(p)}, \mathbf{v}_i) > c, \forall \mathbf{v}_i \in \mathbf{V}\}, \quad (3)$$

which further gives the predicted bounding box locations M_{pred} . A visualization of the ground truth mask M and predicted mask M_{pred} is shown in Figure 1 (left).

We now quantify the patch alignment $\text{Align}(\mathbf{V}, \mathbf{W})$ between the image embeddings $\mathbf{V}$ and the word embeddings $\mathbf{W}$ through the Intersection over Union (IoU) against the ground-truth mask M :

$$\text{Align}(\mathbf{V}, \mathbf{W}) = \frac{1}{P} \sum_{p=1}^P \frac{\text{Intersection}(M_{\text{pred}}^{(p)}, M^{(p)})}{\text{Union}(M_{\text{pred}}^{(p)}, M^{(p)})}. \quad (4)$$

To measure the patch-level alignment of projector, we compare the above measure over three variants: the projector after pretraining ($\mathcal{P}_{\text{LLaVA Stage1}}$), the projector after SFT ($\mathcal{P}_{\text{LLaVA Stage2}}$), and a random MLP projector ($\mathcal{P}_{\text{Random MLP}}$). The results on GrandF dataset [15] are shown in Table 2.

Table 2: Patch alignment of projectors.

Projector	Align($\mathbf{V}, \mathbf{W}$)
$\mathcal{P}_{\text{Random MLP}}$	0.065
$\mathcal{P}_{\text{LLaVA Stage1}}$	0.142
$\mathcal{P}_{\text{LLaVA Stage2}}$	0.152

Projector improves patch-level alignment. As shown in Table 2, the pretrained projector achieves a higher $\text{Align}(\mathbf{V}, \mathbf{W})$ than a random one, with the measure further improving after SFT, indicating better alignment between the vision and word embedding spaces. However, we also observe that the LLaVA projector exhibits low mIoU values in both Stage 1 and Stage 2, suggesting that text labels derived from LLM embeddings cannot accurately identify their corresponding image patch positions. *This underscores the limitation of the original LLaVA projector in patch-level alignment.*

3.2.2 Multi-Semantic Alignment

While the above approach provides a quantitative method to measure patch-level alignment, the label for each object is often very short. For example, a TV may be labeled simply as “TV,” without additional attributes such as color. On the other hand, the continuous vision embedding $\mathbf{v}$ is expected to carry multiple semantic meanings that are understandable by the LLM. We express this as the following hypothesis.

Hypothesis 3.1. *In an MLLM, the embedding $\mathbf{v}$ for each vision patch can be decomposed as a sparse linear combination of word embeddings: $\mathbf{v} \approx \sum_{k \in \Omega} \alpha_k \mathbf{w}_k$, where Ω is the set of subtokens representing all semantic meanings within the patch, and α_k is the coefficient for each subtoken.*

This hypothesis is similar to previous ones on (contextualized) word embedding vectors as a sparse linear combination of word/transformer factors [20, 21], but extended to multimodal embeddings. To support this hypothesis, we utilize the matching pursuit algorithm [22] to identify the top- K most relevant subtokens. Specifically, at the i -th iteration, the algorithm selects the discrete word embedding $\mathbf{w}^{(i)}$ from the LLM embedding space $\mathbf{W}$ that has the highest similarity with the current vision embedding $\mathbf{v}^{(i)}$, ensuring it is the most semantically aligned token. Once selected, its contribution is removed from the vision embedding. Through this iterative process, we identify the key semantic components within the vision embedding. We present the details in Algorithm 1.

As in [20, 21], we provide qualitative results due to the lack of ground-truth multi-semantic labels. As shown in Figure 1, while LLaVA vision embeddings can encode basic object information (e.g., “TV”) and color attributes (e.g., “white”), many patches remain uninterpretable. This analysis reveals that the projector has limited multi-semantic alignment capabilities. More results in Appendix D.

4 Patch-Aligned Training and Analysis

The previous section demonstrates that training with image caption task leads to weak patch-level alignment. In this section, we propose *patch-aligned training* to enhance fine-grained alignment.

Algorithm 1 Matching Pursuit for Vision Embedding

Input: Vision embedding $\mathbf{v} \in \mathbb{R}^d$; LLM word embedding matrix $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_M] \in \mathbb{R}^{d \times M}$; Number of selected word embeddings K .

Output: Top- K matched word embeddings $\{\mathbf{w}^{(i)}\}_{i=1}^K$.

```

Initialize  $\mathbf{v}^{(1)} \leftarrow \mathbf{v}$ 
Initialize an empty set  $\mathcal{S} \leftarrow \emptyset$ 
for  $i = 1$  to  $K$  do
    // Find the most relevant word embedding
     $\mathbf{w}^{(i)} \leftarrow \arg \max_{\mathbf{w} \in \mathbf{W}} \langle \mathbf{w}, \mathbf{v}^{(i)} \rangle$ 
    // Store selected embedding
     $\mathcal{S} \leftarrow \mathcal{S} \cup \{\mathbf{w}^{(i)}\}$ 
    // Remove projection
     $\mathbf{v}^{(i+1)} \leftarrow \mathbf{v}^{(i)} - \langle \mathbf{w}^{(i)}, \mathbf{v}^{(i)} \rangle \mathbf{w}^{(i)}$ 
end for
Return  $\mathcal{S}$ 

```

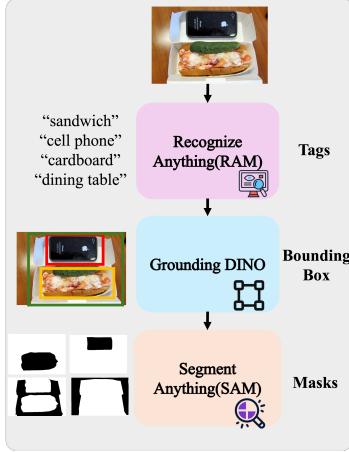


Figure 2: Annotation pipeline.

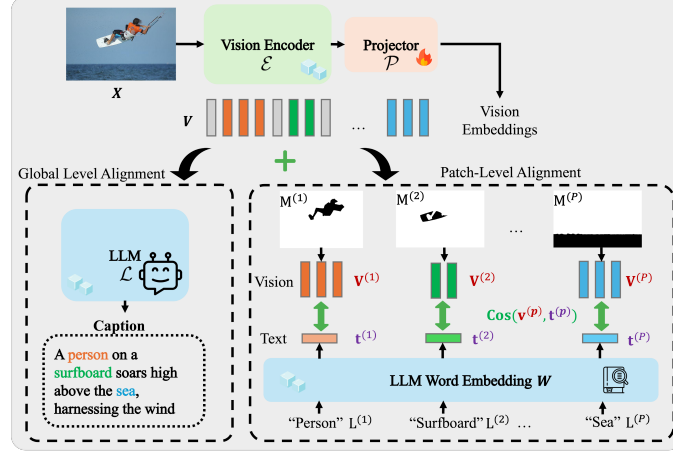


Figure 3: Overview of patch-level alignment method.

4.1 Patch-Aligned Training

Mask-Label Annotation Pipeline. We develop an automated pipeline to create the Patch-Aligned Dataset (PAD), which enriches the LLaVA-pretrained dataset with fine-grained annotations including object tags, bounding boxes, and segmentation masks. Our pipeline combines state-of-the-art models (RAM[23], Grounding DINO[24], and SAM[25]) for object recognition and segmentation. As shown in Figure 2, RAM first generates object tags, which Grounding DINO uses to create bounding boxes. After filtering with non-maximum suppression, SAM generates segmentation masks for each object. More details about the format of PAD can be found in Appendix A.

Patch-Aligned Training. Given an input image X with P associated mask-label pairs $\{(M^{(p)}, L^{(p)})\}_{p=1}^P$, the vision embedding after projection is represented as $V = \mathcal{P} \circ \mathcal{E}(X) \in \mathbb{R}^{d \times S}$. For each mask $M^{(p)}$, let $\text{Idx}^{(p)}$ represent the set of vision tokens that are covered by the mask for at least half of the patch area. We use $V^{(p)}$ to denote the embeddings of the selected vision tokens in Figure 3. Using the same approach as in eq. (2) to compute the text embedding $t^{(p)}$ for the label $L^{(p)}$, we similarly represent the vision embedding of the object by taking the mean of the selected vision embeddings $v^{(p)} = \frac{1}{L^{(p)}} \sum_{i \in \text{Idx}^{(p)}} v_i \in \mathbb{R}^d$. We then introduce the *patch-alignment loss* to maximize the cosine similarity between the mask-selected vision embedding $v^{(p)}$ and the corresponding text embedding $t^{(p)}$:

$$L_{\text{patch}} = 1 - \frac{1}{P} \sum_{n=1}^P \text{COS}(v^{(p)}, t^{(p)}). \quad (5)$$

To achieve global-level alignment, we retain the commonly used *caption loss*. Specifically, given tokenized caption tokens $(x_1, x_2, \dots, x_T)$ for the input image, the caption loss computes the ability to predict each subsequent word in the caption sequence

$$L_{\text{caption}} = - \sum_{t=1}^T \log p_{\mathcal{L}}(x_t | V, x_{<t}), \quad (6)$$

where $p_{\mathcal{L}}(x_t | V, x_{<t})$ denotes the predicted probability for the t -th token x_t based on the previous tokens $x_{<t}$ and the vision embedding V .

Our patch-aligned training combines both the caption loss and the patch-alignment loss

$$L = L_{\text{caption}} + \beta L_{\text{patch}}, \quad (7)$$

where $\beta > 0$ is used to balance the global-level alignment and patch-level alignment.

Efficiency of the patch-alignment loss. The patch-alignment loss L_{patch} is computationally more efficient than the caption loss, as it does not rely on the LLM. It only requires calculating cosine similarity with the LLM word embedding matrix W , making it lightweight to compute and optimize.

4.2 Ablation Study on β

In this section, we present our ablation studies on hyperparameter β in Equation (7) in two aspects:

Linear increasing vs. fixed schedule. The linear schedule gradually increases β to impose patch-level alignment progressively. This design choice stabilizes early training and prevents premature over-compression. As shown in Table 3, when comparing fixed $\beta = 5$ versus linearly increasing β from 0 to 5, the linear schedule showed better performance. Therefore, we adopted the linear increasing schedule for all subsequent experiments.

Optimal final β value: Since β in the objective function balances global-level and patch-level alignment, a larger β emphasizes patch-alignment loss over caption loss. We examined the impact of $\beta \in \{0, 2, 5, 10\}$, where the baseline LLaVA-1.5 corresponds to $\beta = 0$. As shown in Table 3, when β is too small ($\beta = 0$ or 2), patch-level alignment remains insufficient, leading to suboptimal performance. Conversely, when β is too large ($\beta = 10$), the model overly focuses on local regions, compromising its ability to establish comprehensive correspondence between the entire image and sentences. This imbalance degrades global-level alignment and ultimately harms overall performance.

Table 3: Comparison of different β schedules on various benchmarks.

Setting	GQA	Science QA	VizWiz VQA	OKVQA	Avg
fixed ($\beta = 0$)	61.93	66.80	50.00	53.42	58.04
fixed ($\beta = 5$)	62.16	68.07	54.86	56.51	60.40
linear increasing ($\beta \in [0, 2]$)	62.64	68.12	50.84	57.52	59.78
linear increasing ($\beta \in [0, 10]$)	62.64	68.57	50.82	56.85	59.72
linear increasing ($\beta \in [0, 5]$)	62.99	68.67	52.29	58.29	60.56

4.3 Compression–Information Loss Tradeoff

There exists a tradeoff between redundancy removal and semantic information loss when the compression level continues to increase. Within a proper compression range, more compression improves performance by removing redundant information and enhancing alignment. However, over-compression may potentially cause useful semantic information loss and performance degradation. To empirically validate this tradeoff, we conducted a controlled ablation where we varied the patch loss weight β in Equation (7). Larger β encourages stronger patch-level alignment and induces more compression. As shown in Figure 4, as ΔH increases, the overall performance first improves then declines. Before the tipping point, redundant information is removed, which improves performance compared to the original LLaVA with $\beta = 0$. However, after the tipping point, performance drops rapidly as over-compression causes semantic information loss.

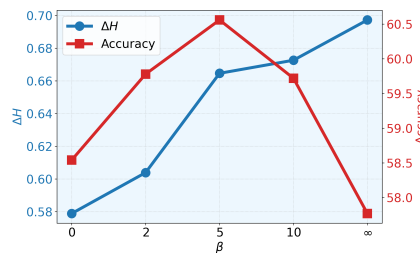


Figure 4: Tradeoff between compression and information loss.

Here, the change of entropy is measured as a normalized one $\Delta H(\mathbf{V}) = (H_{\text{before}}(\mathbf{V}) - H_{\text{after}}(\mathbf{V})) / H_{\text{before}}(\mathbf{V}) \in [0, 1]$. Task performance is measured by taking the average of the performance over the QA datasets (GQA, Science QA, VizWiz VQA, and OKVQA).

5 Experiments

In this section, we first introduce the experiment setup and training details for Patch-Aligned Training, which is used only in the pretraining stage for training the projector $\mathcal{P}$. We evaluate the effectiveness of our methods in two stages: pretraining stage and SFT stage. In the pretraining stage, we verify that the patch-aligned training achieves better compression and patch-level alignment abilities, enabling

Table 4: Compression and alignment.

Projector	$\Delta H(V)$	Align(V, W)	Cos Sim
$\mathcal{P}_{\text{Random}}$	0.0108	0.065	0.06
$\mathcal{P}_{\text{LLaVA}}$	2.7991	0.142	0.07
$\mathcal{P}_{\text{Patch Aligned}}$	3.8352	0.279	0.56

Table 5: LLaVA v.s. Patch aligned method for caption generation qualities.

Model	METEOR	ROUGE_L	SPICE
$\mathcal{M}_{\text{LLaVA}}$	0.1220	0.1661	0.1571
$\mathcal{M}_{\text{Patch Aligned}}$	0.1256	0.1759	0.1710

Table 6: Comparison on refer expression comprehension benchmarks.

Models	RefCOCO			RefCOCO+			RefCOCOg	
	val	test-A	test-B	val	test-A	test-B	val	test
LLaVA 1.5-7B	56.22	64.43	47.38	50.00	59.2	39.0	48.8	48.4
Patch Aligned (Ours)	65.97	72.26	55.82	58.49	66.87	48.09	55.78	56.24

the LLM to generate higher-quality captions. In the SFT stage, we verify that fine-tuning with the new projector yields better performance across three aspects: (1) refer expression comprehension, (2) visual question answering and (3) instruction following benchmarks.

5.1 Experiment Setup

For a fair comparison, we follow LLaVA-1.5 [1]’s architecture, training setup, and datasets. Our approach differs in two key aspects: (1) we introduce a patch-aligned loss where β increases linearly from 0 to 5 during stage 1, and (2) we use the PAD dataset with detailed annotations to pretrain the projector. See Appendix B for details.

5.2 Stage1: Pretrained Model Evaluation

5.2.1 Compression and Patch-Level Alignment

We evaluate the patch-aligned projector $\mathcal{P}_{\text{Patch Aligned}}$ using: Von Neumann entropy reduction $\Delta H(V) = H(V_{\text{before}}) - H(V_{\text{after}})$, patch alignment $\text{Align}(V, W)$ (Section 3.2.1), and vision-text embedding cosine similarity (Section 3.2.2). As shown in Table 4, compared to baselines $\mathcal{P}_{\text{Random}}$ and $\mathcal{P}_{\text{LLaVA}}$ on 100 COCO 2017 images [39], our projector achieves higher entropy reduction and better performance on both mIoU and cosine similarity, demonstrating superior patch-level alignment.

5.2.2 Measuring Caption Quality

To examine the advantages of improved patch-level alignment, we first evaluate the stage1 MLLM $\mathcal{M}_{\text{Patch Aligned}} = (\mathcal{E}, \mathcal{L}, \mathcal{P}_{\text{Patch Aligned}})$ directly on caption generation while keeping both the vision encoder and LLM frozen. To measure the caption quality, we utilize three metrics: METEOR, ROUGE-L, and SPICE. As shown in Table 5, $\mathcal{M}_{\text{Patch Aligned}}$ generate higher quality of captions that benefits from the explicit patch-level alignment process in the pretraining stage.

5.3 Stage2: SFT Model Evaluation

5.3.1 Refer Expression Comprehension

To better demonstrate the method’s enhanced fine-grained image understanding and localization capabilities, we further evaluate our approach on the refer expression comprehension(REC) tasks, including the RefCOCO[40], RefCOCO+[41], and RefCOCOg[41]. Specifically, the REC task requires the model to localize the target object under the guidance of a description. Here we report Acc@0.5(higher is better). As shown in Table 6, our method achieves **significant** improvements across all test splits, with approximately a 16% improvement on average. Notably, our approach uses the same architecture and training data as LLaVA-1.5, only adding patch alignment during pretraining. This minimal change yields substantial improvements in grounding and localization abilities.

5.3.2 Visual Question Answering

Visual understanding plays an important role in many real-world applications. We test how well our models perform on text-based visual question answering tasks using multiple benchmark datasets. As shown in Table 7, our method outperforms the LLaVA-1.5 baseline under identical conditions, demonstrating that initializing the MLLM with improved patch-level aligned vision embeddings leads to better fine-grained understanding and enhanced overall performance.

Table 7: Comparison on visual question answering benchmarks.

Models	LM	Img Sz	GQA	SciQA	VizWiz	OKVQA
BLIP-2 [4]	Vicuna-13B	224	41.0	61.0	19.6	-
InstructBLIP [27]	Vicuna-7B	224	49.2	60.5	34.5	-
InstructBLIP [27]	Vicuna-13B	224	49.5	63.1	33.4	-
Shikra [42]	Vicuna-13B	224	-	-	-	-
IDEFICS-9B [43]	LLaMA-7B	224	38.4	-	35.5	-
IDEFICS-80B [43]	LLaMA-65B	224	45.2	-	36.0	-
Qwen-VL [44]	Qwen-7B	448	59.3	67.1	35.2	-
Qwen-VL-Chat [44]	Qwen-7B	448	57.5	68.2	38.9	-
LLaVA [1]	Vicuna-7B	224	-	-	-	-
LLaVA-1.5 [2]	Vicuna-7B	336	62.0	66.8	50.0	53.4
PatchAligned (Ours)	Vicuna-7B	336	63.0	68.7	52.3	58.3

Table 8: Comparison on instruction following benchmarks.

Models	MMMU	MMVet	CMMMU	MMB ^{EN}	MME ^C	MME ^P
LLaVA 1.5	35.30	30.70	21.80	64.00	316.10	1510.75
Patch Aligned (Ours)	36.56	31.61	22.70	63.14	339.64	1531.33

Table 9: Analysis of compatibility when switching between base LLMs and projector types.

Models	RefCOCO			RefCOCO+			RefCOCOG	
	val	test-A	test-B	val	test-A	test-B	val	test
<i>Applying to different LLMs (Vicuna 7B [45] → Llama 3.1 8B[46])</i>								
LLaVA (LLaMA3.1 8B)	66.32	74.30	56.09	58.92	68.62	48.21	56.90	55.87
Patch Aligned (LLaMA3.1 8B)	68.27	74.99	58.49	61.25	68.88	50.93	58.41	57.58
<i>Applying to different projectors (MLP → C-Abstractor [38])</i>								
LLaVA (C-Abstractor)	58.08	65.83	49.44	50.28	59.10	41.01	49.38	49.81
Patch Aligned (C-Abstractor)	60.89	67.70	51.21	53.56	60.74	42.01	51.91	51.61

5.3.3 Instruction Following Benchmarks

In addition to conventional vision-language evaluations, we assess our method’s real-world capabilities by conducting evaluations on modern instruction-following benchmarks. As shown in Table 8, our model demonstrates superior performance in understanding when following user instructions.

5.3.4 Compatibility of Patch Aligned Training

We demonstrate our method’s general effectiveness by replacing both the MLLM (from Vicuna 7B[45] to Llama 3.1 8B[46]) and the projector (from MLP to C-Abstractor[38]). Using C-Abstractor, we set the number of output visual tokens to 256. All models follow the same training as LLaVA 1.5. We focus our evaluation on referring expression comprehension capabilities. As shown in Table 9, patch-aligned methods achieve consistent improvements compared to their variants.

6 Conclusion

In this paper, we examine the projector’s role at macro and micro scales, showing it compresses visual information while improving patch-level alignment. Though alignment remains coarse, our proposed patch-aligned training enhances both compression and alignment capabilities. This leads to better caption generation and grounding performance, providing insights into multimodal reasoning.

However, despite the improvements, certain limitations remain to be addressed. First, while we introduce the multi-semantic alignment hypothesis, finding an optimal representation for each visual token in the embedding space remains a significant challenge. Simply aligning with the same averaged word embedding may limit the interpretability and expressive power of LLMs. Moreover, due to the inherent compactness of language, manually guiding the projector for semantic alignment raises concerns about potential information loss in visual tokens. Addressing these challenges requires the development of more effective alignment strategies, which will be crucial for further enhancing the capabilities and robustness of multimodal LLMs.

Acknowledgements

We acknowledge support from NSF grants IIS-2312840 and IIS-2402952, as well as the ORAU Ralph E. Powe Junior Faculty Enhancement Award.

References

- [1] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *Advances in neural information processing systems*, 36, 2024.
- [2] Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 26296–26306, 2024.
- [3] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *International conference on machine learning*, pages 12888–12900. PMLR, 2022.
- [4] 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 *International conference on machine learning*, pages 19730–19742. PMLR, 2023.
- [5] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.
- [6] 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. *Advances in neural information processing systems*, 35: 23716–23736, 2022.
- [7] Shaohan Huang, Li Dong, Wenhui Wang, Yaru Hao, Saksham Singhal, Shuming Ma, Tengchao Lv, Lei Cui, Owais Khan Mohammed, Barun Patra, et al. Language is not all you need: Aligning perception with language models. *Advances in Neural Information Processing Systems*, 36: 72096–72109, 2023.
- [8] Zhuosheng Zhang, Aston Zhang, Mu Li, Hai Zhao, George Karypis, and Alex Smola. Multimodal chain-of-thought reasoning in language models. *arXiv preprint arXiv:2302.00923*, 2023.
- [9] Kimi Team, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, Chenjun Xiao, Chenzhuang Du, Chonghua Liao, Chuning Tang, Congcong Wang, Dehao Zhang, Enming Yuan, Enzhe Lu, Fengxiang Tang, Flood Sung, Guangda Wei, Guokun Lai, Haiqing Guo, Han Zhu, Hao Ding, Hao Hu, Hao Yang, Hao Zhang, Haotian Yao, Haotian Zhao, Haoyu Lu, Haoze Li, Haozhen Yu, Hongcheng Gao, Huabin Zheng, Huan Yuan, Jia Chen, Jianhang Guo, Jianlin Su, Jianzhou Wang, Jie Zhao, Jin Zhang, Jingyuan Liu, Junjie Yan, Junyan Wu, Lidong Shi, Ling Ye, Longhui Yu, Mengnan Dong, Neo Zhang, Ningchen Ma, Qiwei Pan, Qucheng Gong, Shaowei Liu, Shengling Ma, Shupeng Wei, Sihan Cao, Siying Huang, Tao Jiang, Weihao Gao, Weimin Xiong, Weiran He, Weixiao Huang, Wenhao Wu, Wenyang He, Xianghui Wei, Xianqing Jia, Xingzhe Wu, Xinran Xu, Xinxing Zu, Xinyu Zhou, Xuehai Pan, Y. Charles, Yang Li, Yangyang Hu, Yangyang Liu, Yanru Chen, Yejie Wang, Yibo Liu, Yidao Qin, Yifeng Liu, Ying Yang, Yiping Bao, Yulun Du, Yuxin Wu, Yuzhi Wang, Zaida Zhou, Zhaoji Wang, Zhaowei Li, Zhen Zhu, Zheng Zhang, Zhexu Wang, Zhilin Yang, Zhiqi Huang, Zihao Huang, Ziyao Xu, and Zonghan Yang. Kimi k1.5: Scaling reinforcement learning with llms, 2025. URL <https://arxiv.org/abs/2501.12599>.
- [10] Jun Yu, Jing Li, Zhou Yu, and Qingming Huang. Multimodal transformer with multi-view visual representation for image captioning. *IEEE transactions on circuits and systems for video technology*, 30(12):4467–4480, 2019.
- [11] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In *Proceedings of the IEEE international conference on computer vision*, pages 2425–2433, 2015.

- [12] Shengbang Tong, Zhuang Liu, Yuexiang Zhai, Yi Ma, Yann LeCun, and Saining Xie. Eyes wide shut? exploring the visual shortcomings of multimodal llms. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9568–9578, 2024.
- [13] Shilong Zhang, Peize Sun, Shoufa Chen, Min Xiao, Wenqi Shao, Wenwei Zhang, Yu Liu, Kai Chen, and Ping Luo. Gpt4roi: Instruction tuning large language model on region-of-interest. *arXiv preprint arXiv:2307.03601*, 2023.
- [14] Zhiliang Peng, Wenhui Wang, Li Dong, Yaru Hao, Shaohan Huang, Shuming Ma, and Furu Wei. Kosmos-2: Grounding multimodal large language models to the world. *arXiv preprint arXiv:2306.14824*, 2023.
- [15] Hanoona Rasheed, Muhammad Maaz, Sahal Shaji, Abdelrahman Shaker, Salman Khan, Hisham Cholakkal, Rao M Anwer, Eric Xing, Ming-Hsuan Yang, and Fahad S Khan. Glamm: Pixel grounding large multimodal model. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13009–13018, 2024.
- [16] Zechen Bai, Pichao Wang, Tianjun Xiao, Tong He, Zongbo Han, Zheng Zhang, and Mike Zheng Shou. Hallucination of multimodal large language models: A survey. *arXiv preprint arXiv:2404.18930*, 2024.
- [17] Junbum Cha, Wooyoung Kang, Jonghwan Mun, and Byungseok Roh. Honeybee: Locality-enhanced projector for multimodal llm. *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13817–13827, 2023. URL <https://api.semanticscholar.org/CorpusID:266174127>.
- [18] Minyoung Huh, Brian Cheung, Tongzhou Wang, and Phillip Isola. The platonic representation hypothesis. *arXiv preprint arXiv:2405.07987*, 2024.
- [19] John von Neumann. *Mathematische Grundlagen der Quantenmechanik*. Springer, Berlin, Germany, 1932. English translation: *Mathematical Foundations of Quantum Mechanics*, Princeton University Press, 1955.
- [20] Sanjeev Arora, Yuanzhi Li, Yingyu Liang, Tengyu Ma, and Andrej Risteski. Linear algebraic structure of word senses, with applications to polysemy. *Transactions of the Association for Computational Linguistics*, 6:483–495, 2018.
- [21] Zeyu Yun, Yubei Chen, Bruno A Olshausen, and Yann LeCun. Transformer visualization via dictionary learning: contextualized embedding as a linear superposition of transformer factors. *arXiv preprint arXiv:2103.15949*, 2021.
- [22] Joel A Tropp and Anna C Gilbert. Signal recovery from random measurements via orthogonal matching pursuit. *IEEE Transactions on information theory*, 53(12):4655–4666, 2007.
- [23] Youcai Zhang, Xinyu Huang, Jinyu Ma, Zhaoyang Li, Zhaochuan Luo, Yanchun Xie, Yuzhuo Qin, Tong Luo, Yaqian Li, Shilong Liu, et al. Recognize anything: A strong image tagging model. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1724–1732, 2024.
- [24] Shilong Liu, Zhaoyang Zeng, Tianhe Ren, Feng Li, Hao Zhang, Jie Yang, Qing Jiang, Chunyuan Li, Jianwei Yang, Hang Su, et al. Grounding dino: Marrying dino with grounded pre-training for open-set object detection. In *European Conference on Computer Vision*, pages 38–55. Springer, 2025.
- [25] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4015–4026, 2023.
- [26] Feng Li, Renrui Zhang, Hao Zhang, Yuanhan Zhang, Bo Li, Wei Li, Zejun Ma, and Chunyuan Li. Llava-next-interleave: Tackling multi-image, video, and 3d in large multimodal models. *arXiv preprint arXiv:2407.07895*, 2024.

- [27] Wenliang Dai, Junnan Li, D Li, AMH Tiong, J Zhao, W Wang, B Li, P Fung, and S Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning. *arXiv preprint arXiv:2305.06500*, 2, 2023.
- [28] Bo Li, Yuanhan Zhang, Liangyu Chen, Jinghao Wang, Fanyi Pu, Jingkang Yang, Chunyuan Li, and Ziwei Liu. Mimic-it: Multi-modal in-context instruction tuning. *arXiv preprint arXiv:2306.05425*, 2023.
- [29] 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 multimodality. *arXiv preprint arXiv:2304.14178*, 2023.
- [30] Siddharth Karamcheti, Suraj Nair, Ashwin Balakrishna, Percy Liang, Thomas Kollar, and Dorsa Sadigh. Prismatic vlms: Investigating the design space of visually-conditioned language models. *arXiv preprint arXiv:2402.07865*, 2024.
- [31] Shengbang Tong, Ellis Brown, Penghao Wu, Sanghyun Woo, Manoj Middepogu, Sai Charitha Akula, Jihan Yang, Shusheng Yang, Adithya Iyer, Xichen Pan, et al. Cambrian-1: A fully open, vision-centric exploration of multimodal llms. *arXiv preprint arXiv:2406.16860*, 2024.
- [32] Shijia Yang, Bohan Zhai, Quanzeng You, Jianbo Yuan, Hongxia Yang, and Chenfeng Xu. Law of vision representation in mllms. *arXiv preprint arXiv:2408.16357*, 2024.
- [33] 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 *International conference on machine learning*, pages 8748–8763. PMLR, 2021.
- [34] Qidong Huang, Xiaoyi Dong, Pan Zhang, Yuhang Zang, Yuhang Cao, Jiaqi Wang, Dahua Lin, Weiming Zhang, and Nenghai Yu. Deciphering cross-modal alignment in large vision-language models with modality integration rate. *arXiv preprint arXiv:2410.07167*, 2024.
- [35] Clement Neo, Luke Ong, Philip Torr, Mor Geva, David Krueger, and Fazl Barez. Towards interpreting visual information processing in vision-language models. *arXiv preprint arXiv:2410.07149*, 2024.
- [36] Wei Wang, Zhaowei Li, Qi Xu, Linfeng Li, YiQing Cai, Botian Jiang, Hang Song, Xingcan Hu, Pengyu Wang, and Li Xiao. Advancing fine-grained visual understanding with multi-scale alignment in multi-modal models. *arXiv preprint arXiv:2411.09691*, 2024.
- [37] Yuanyang Yin, Yaqi Zhao, Yajie Zhang, Ke Lin, Jiahao Wang, Xin Tao, Pengfei Wan, Di Zhang, Baoqun Yin, and Wentao Zhang. Sea: Supervised embedding alignment for token-level visual-textual integration in mllms. *arXiv preprint arXiv:2408.11813*, 2024.
- [38] Junbum Cha, Wooyoung Kang, Jonghwan Mun, and Byungseok Roh. Honeybee: Locality-enhanced projector for multimodal llm. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13817–13827, 2024.
- [39] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014.
- [40] Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara Berg. Referitgame: Referring to objects in photographs of natural scenes. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 787–798, 2014.
- [41] Junhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan L Yuille, and Kevin Murphy. Generation and comprehension of unambiguous object descriptions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 11–20, 2016.
- [42] Keqin Chen, Zhao Zhang, Weili Zeng, Richong Zhang, Feng Zhu, and Rui Zhao. Shikra: Unleashing multimodal llm’s referential dialogue magic. *arXiv preprint arXiv:2306.15195*, 2023.

- [43] Hugo Laurençon, Daniel van Strien, Stas Bekman, Léo Tronchon, Lucile Saulnier, Thomas Wang, Siddharth Karamcheti, Amanpreet Singh, Giada Pistilli, Yacine Jernite, and Victor Sanh. Introducing idefics: An open reproduction of state-of-the-art visual language model. 2023. URL <https://huggingface.co/blog/idefics>. Accessed: 2025-01-30.
- [44] Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. Qwen-vl: A frontier large vision-language model with versatile abilities. *arXiv preprint arXiv:2308.12966*, 2023.
- [45] Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. Instruction tuning with gpt-4. *arXiv preprint arXiv:2304.03277*, 2023.
- [46] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- [47] Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E Gonzalez, et al. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality. See <https://vicuna.lmsys.org> (accessed 14 April 2023), 2(3):6, 2023.
- [48] Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. Towards vqa models that can read. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8317–8326, 2019.
- [49] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6700–6709, 2019.
- [50] Anand Mishra, Shashank Shekhar, Ajeet Kumar Singh, and Anirban Chakraborty. Ocr-vqa: Visual question answering by reading text in images. In *2019 international conference on document analysis and recognition (ICDAR)*, pages 947–952. IEEE, 2019.
- [51] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International journal of computer vision*, 123:32–73, 2017.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: The abstract and introduction is accurate.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: We discuss the limitations of our work in the conclusion.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [\[Yes\]](#)

Justification: We provide the assumptions and proof.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: This paper provide all the information to reproduce the main experimental results.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We would release the dataset and code to reproduce the main experimental results.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We provide experimental setting in the appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: Error bars are not reported because it would be too computationally expensive.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We provide the computer resources in experimental setting in appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: This paper conducted in the paper conform.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification: There is no societal impact of the work performed.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: the paper poses no such risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: all datasets used in this paper are public available.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: the paper does not release new assets.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: the paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: the paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: This paper do research related to multimodal LLMs.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

Appendix

The appendix is organized as follows. First, we show the details of mask-label annotation pipeline and the the patch-aligned dataset format in Appendix A. Then, we introduce the details about experiment setting in Appendix B. Finally, we present visualizations related to token-level alignment—specifically patch-level localization in Appendix C and multi-semantic alignment in Appendix D.

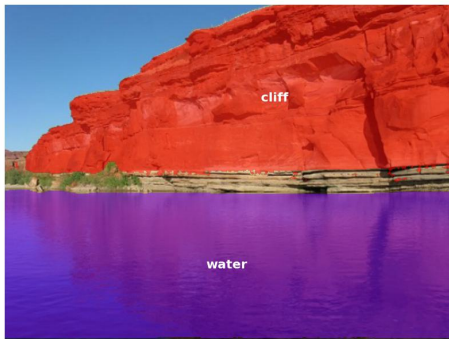
A Patch Aligned Dataset

In this section, we present the format of the Patch Aligned Dataset(PAD) in comparison to the LLaVA pretraining dataset following the mask-label annotation pipeline.

Mask-Label Annotation Pipeline. To address the lack of patch-level annotated data, we develop an automated annotation pipeline for generating the Patch-Aligned Dataset (PAD), designed to refine the LLaVA-pretrained dataset by incorporating fine-grained details. PAD enriches this dataset with detailed annotations, including object tags, bounding box locations, and segmentation masks for individual objects. By incorporating dense, pixel-level grounding information, PAD is designed to enhance fine-grained image-text alignment during the pretraining stage, thereby improving the model’s ability to understand localized regions within the image.

As illustrated in Figure 2, our automated annotation pipeline consists of diverse state-of-the-art models, including Recognize Anything Model (RAM) [23], Grounding DINO [24], and Segment Anything Model (SAM) [25]—to perform grounded image segmentation and object recognition. First, RAM generates object tags from the input image. These tags are then passed to Grounding DINO, which generates bounding boxes for each identified object. Afterward, a Non-Maximum Suppression (NMS) process is applied to filter overlapping bounding boxes based on Intersection over Union (IoU) thresholds. The remaining bounding boxes are passed to SAM, which generates segmentation masks for each object. The pipeline outputs the segmented image with bounding boxes, along with metadata in JSON format, including object tags, bounding box coordinates, and RLE-encoded masks for further analysis. As shown in Table 10, we annotate the images of the LLaVA pretraining dataset with additional object tags, bounding box coordinates, and RLE-encoded masks stored in JSON file. The RLE-encoded masks can be decoded back into binary masks that have the image size.

Table 10: Comparison of LLaVA Pretraining Dataset and Patch Aligned Dataset (Ours).

	
LLaVA Pretraining Dataset	<pre>"image_id" : "00000/00000030.jpg" "size": [448, 336] "caption": "a canyon wall reflects the water on a sunny day in utah."</pre>
Patch Aligned Dataset (ours)	<pre>"image_id" : "00000/00000030.jpg" "size": [448, 336] "caption": "a canyon wall reflects the water on a sunny day in utah." "labels": [{ "tag": "water", "bbox": [-0.0003204345703125, 182.57894897460938, 447.99951171875, 335.67926025390625], "rle_mask": "k5d4L50000001000000010001000000000000..." }, { "tag": "cliff", "bbox": [-0.064117431640625, 0.34404754638671875, 447.9346005859375, 182.572509765625], "rle_mask": "S32.:0eEOV:5004LXY2:[fM302M20200N2N3N10101N20101N20..." }]</pre>

To find the optimal hyperparameters in our mask-label annotation pipeline, we conducted a thorough ablation study using the coco-val 2017 [39] dataset, which provides ground truth bounding boxes. We focused on two key hyperparameters:

- **Score threshold:** Only boxes with confidence scores above this threshold are selected.
- **NMS threshold:** During non-maximum suppression (NMS), this determines the maximum allowed overlap between two boxes—if their IoU exceeds this threshold, the box with the lower confidence score is removed.

We evaluated performance using F1 score at IoU of 0.5, which classifies predictions as true or false positives based on an IoU threshold of 0.5. First, we tested various score threshold values:

Table 11: Effect of varying score thresholds.

Score threshold	0.1	0.2	0.3	0.4	0.5
F1 @ [IoU=0.5]	0.2762	0.4931	0.6326	0.6677	0.6207

Next, we fixed the score threshold at 0.4 and evaluated various NMS threshold values:

Table 12: Effect of varying NMS thresholds.

NMS threshold	0.3	0.5	0.7	0.8	0.9
F1 @ [IoU=0.5]	0.6530	0.6677	0.6702	0.6722	0.6717

Based on this analysis, we selected the optimal hyperparameters (Score threshold = 0.4 and NMS threshold = 0.8) for our final implementation.

To evaluate our pipeline with optimal hyper-parameters, we compare it with the original Grounding DINO[24] on coco-val 2017 [39]. The results are as follows:

Table 13: Comparison of between our pipeline and original Grounding DINO.

	AP@[IoU=0.50:0.95]	AP@[IoU=0.50]	AP@[IoU=0.75]
Original Grounding DINO	0.485	0.644	0.529
Our pipeline	0.531	0.676	0.572

where AP@[IoU=0.50:0.95] is the mean precision across IoU thresholds from 0.50 to 0.95 (stepped by 0.05). A prediction is considered correct if its overlap with ground-truth exceeds the IoU threshold. As the results demonstrate, our pipeline consistently outperforms the baseline.

B Experiment Setup

- **Architecture** To evaluate the effectiveness of our method, we ensure a fair comparison by following the same architecture as LLaVA 1.5. Specifically, we use CLIP-ViT-L@336px [33] as the vision encoder $\mathcal{E}$, Vicuna-1.5-7B[47] as the LLM $\mathcal{L}$, and a 2-layer MLP as the projector $\mathcal{P}$. The parameter β follows a linear schedule, increasing from 0 to 5.
- **Training Details** Following the standard training paradigm in LLaVA [1], our training pipeline consists of two stages. In stage 1, keeping the vision encoder $\mathcal{E}$ and LLM $\mathcal{L}$ frozen, we train only the projector $\mathcal{P}$ using our proposed *Patch Aligned Training* method to obtain the patch-aligned projector $\mathcal{P}_{\text{Patch Aligned}}$. In stage 2, we perform supervised fine-tuning on both the LLM $\mathcal{L}$ and the patch-aligned projector $\mathcal{P}_{\text{Patch Aligned}}$. Following LLaVA’s hyperparameters, we optimize all models for 1 epoch using the AdamW optimizer with a cosine learning schedule. The learning rates are set to 1e-3 for pretraining and 2e-5 for instruction tuning. Pretraining requires approximately 8 hours using 8xA5000 GPUs (24G), while visual instruction tuning takes about 10 hours for LLaVA-v1.5-7B on 8xH100 (80G).
- **Dataset** For pretraining dataset, utilizing our automated annotation pipeline, we annotate the 558K subset of the LAION-CC-SBU dataset, which is used as the pretraining dataset of LLaVA. The

resulting dataset comprises 2.3M regions, each associated with a segmentation mask, and includes 33.5K unique tags. For fair comparison, we use the same vision instruction tuning dataset as the one in the LLaVA-1.5, containing LLaVA-Instruct [1], TextVQA [48], GQA [49], OCR-VQA [50], and Visual Genome[51].

C Patch-Level Localization: More Visualizations

Following the micro-scale analysis on patch-level localization in Section 3.2.1, we provide more examples comparing the ground truth mask M_{GT} and predicted mask M_{pred} generated by three projectors: the random projector $\mathcal{P}_{Random}$, pretrained LLaVA 1.5 projector $\mathcal{P}_{LLaVA}$, and our PatchAligned Projector $\mathcal{P}_{Patch\ Aligned}$. As shown in Figure 5, the $\mathcal{P}_{Patch\ Aligned}$ predicts more accurate masks.



Figure 5: Additional visualization for patch-level localization.

D Multi-Semantic Alignment: More Visualizations

We begin by showing the first iteration of matching pursuit, which finds the token in the LLM embedding space that has the highest similarity with the vision embedding. We show the full tokenmap in Figure 6, displaying the found token for each vision patch. We use font size to represent similarity. Tokens recognizable by NLTK are shown in color, while unrecognized tokens remain black. For LLaVA, only partial areas or objects achieve alignment. In contrast, PatchAligned LLaVA achieves better alignment across most patches.



Figure 6: Additional visualization for tokenmap comparing LLaVA and PatchAligned LLaVA.

Next, following Section 3.2.2, we apply matching pursuit on PatchAligned LLaVA for 5 iterations. As shown in Figure 7, the semantic meanings are decoded for each iteration, with cosine similarity decreasing across iterations.

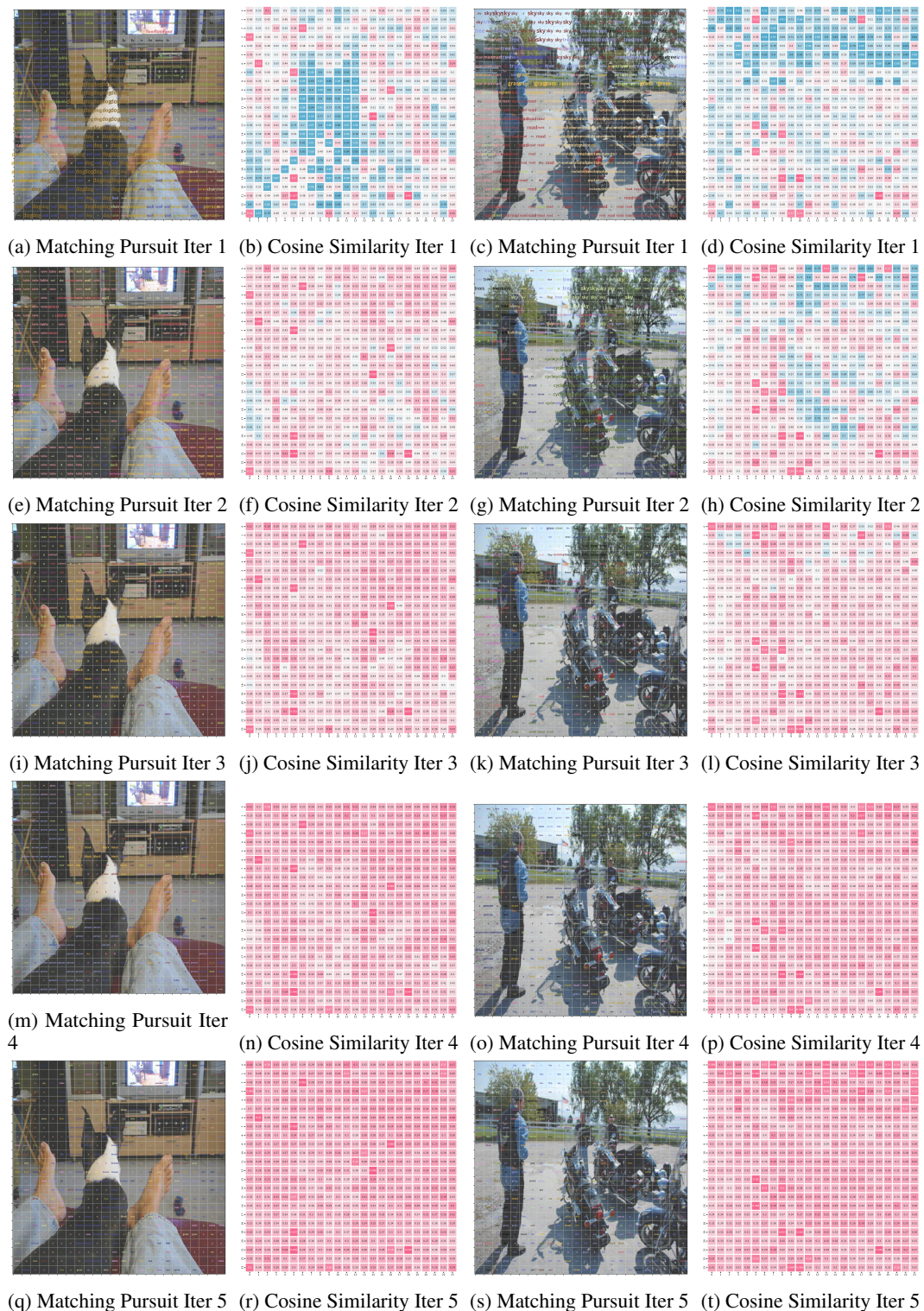


Figure 7: Perform Matching Pursuit using PatchAligned LLaVA. Each row represents an iteration, with selected tokenmap (Column 1,3) and cosine similarity maps (Column 2,4).