

Extract Free Dense Misalignment from CLIP

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Abstract

Recent vision-language foundation models still frequently produce outputs misaligned with their inputs, evidenced by object hallucination in captioning and prompt misalignment in the text-to-image generation model. Recent studies have explored methods for identifying misaligned elements, aiming not only to enhance interpretability but also to improve model performance. However, current approaches primarily rely on large foundation models in a zero-shot manner or fine-tuned models with human annotations, which limits scalability due to significant computational costs. This work proposes a novel approach, dubbed CLIP4DM, for detecting dense misalignments from pre-trained CLIP, specifically focusing on pinpointing misaligned words between image and text. We carefully revamp the gradient-based attribution computation method, enabling negative gradient of individual text tokens to indicate misalignment. We also propose F-CLIPScore, which aggregates misaligned attributions with a global alignment score. We evaluate our method on various dense misalignment detection benchmarks, covering various image and text domains and misalignment types. Our method demonstrates state-of-the-art performance among zero-shot models and competitive performance with fine-tuned models while maintaining superior efficiency. Our qualitative examples show that our method has a unique strength to detect entity-level objects, intangible objects, and attributes that can not be easily detected for existing works. We conduct ablation studies and analyses to highlight the strengths and limitations of our approach. Our code is publicly available at <https://github.com/naver-ai/CLIP4DM>.

Introduction

While recent advancements in generative models have garnered unprecedented progress, large-scale models still produce outputs misaligned with their inputs, exemplified by object hallucination (Li et al. 2023; Gunjal, Yin, and Bas 2024) in image-to-text (captioning) models and misalignment with text description (Rassin, Ravfogel, and Goldberg 2022; Chefer et al. 2023) in text-to-image generation models. It is crucial to effectively detect these misalignments in



Caption: A man riding snowboard down a snow covered slope.
CLIPScore: 61.3
Ours: A man **riding** **snowboard** down a snow covered **slope**.
Misaligned word: *snowboard*

Figure 1: **Overview of our work.** CLIPScore indicates the alignment between the image and text in a single scalar score, limiting the interpretation of the score. Our approach extracts both positive and negative attributions to identify misaligned tokens between the image and text caption.

order to develop a more reliable system.

To measure the alignment between an image and text, the similarity score from CLIP (Radford et al. 2021; Hessel et al. 2021) has become a de facto approach. However, as shown in Figure 1, this simple score lacks the granularity needed to identify specific misaligned words, limiting interpretability (Hu et al. 2023; Cho et al. 2024). To address this limitation, recent studies (Petryk et al. 2024; Gordon et al. 2024) have focused on detecting misalignments at a dense level (e.g., word, phrase) and provide feedback to the models (Yu et al. 2022; Yan et al. 2024) for further enhancement. These approaches either employ a pipeline comprising multiple foundation models in zero-shot or fine-tuned configurations, leveraging costly human-annotated data. While these methods show promising results, their computational expense limits their applicability in practical scenarios.

In this paper, we introduce a novel approach that leverages pre-trained CLIP for detecting dense misalignments efficiently. Specifically, our work aims at pinpointing words inconsistent with the image, offering richer explanations for text-image misalignments. While CLIP’s final output is a single similarity score, we hypothesize that rich token-specific information is embedded within the model’s intermediate representations, such as attention maps and gradients with respect to them. We propose a new method, dubbed as CLIP4DM(**CLIP** for **dense misalignment**), which carefully modifies existing gradient-based attribution assignment techniques (Selvaraju et al. 2017; Chefer, Gur, and Wolf 2021a,b). We compute attribution scores for each text token primarily based on relevance propagation methods, where our method is modified so that each relevance score

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can also be a negative attribution value. Then, we predict misaligned tokens by identifying text tokens with negative attribution lower than the threshold as shown in Figure 1. We also introduce F-CLIPScore, which combines the overall score with calculated attributions of misaligned tokens.

We thoroughly evaluate our method on diverse dense misalignment detection benchmarks (FOIL (Shekhar et al. 2017), nocaps-FOIL (Petryk et al. 2024), HAT (Petryk et al. 2024), SeeTRUE-Feedback (Gordon et al. 2024), and Rich-HF (Liang et al. 2024)), encompassing various text, image, and misalignment types. The results consistently demonstrate that our method achieves state-of-the-art performance among zero-shot models and competitive performance with fine-tuned models. Qualitative assessments reveal that our method robustly handles various misalignments, such as entity-level object class, intangible objects, and attributes. Moreover, our method demonstrates significantly higher efficiency compared to baselines, which utilize large foundation models, suggesting its potential for practical applications.

Related Work

Dense Misalignment Detection

There has been a growing emphasis on detecting dense misalignments between image and text, which focuses on identifying specific misaligned regions or tokens within the text. This approach provides detailed feedback that improves the evaluation of image-text alignment. Shekhar et al. (2017) introduce FOIL benchmark for detecting and correcting misaligned words, where replacing one noun of COCO caption with a semantically similar one. ALOHa (Petryk et al. 2024) extends its coverage to various objects while leveraging multiple foundation models. ALOHa makes a candidate object pool with an extracted noun phrase from reference captions and the results of object detectors (Carion et al. 2020), then perform bipartite matching based on scores derived from a language semantic similarity model (Reimers and Gurevych 2019). SeeTRUE-Feedback (Gordon et al. 2024) utilizes LLMs and a visual grounding model to create a dataset of textual and visual misalignment descriptions, which are then used to train a vision-language model for automatic feedback generation. Rich-HF (Liang et al. 2024) focuses on misalignments in a text-to-image generation model while collecting human annotations on misaligned keywords and implausible image regions and trains a multimodal language model to show the dense image-text alignment automatically.

Beyond simply detecting dense misalignments, there have been studies leveraging dense misalignment labels to enhance model performance or reduce object hallucinations, particularly in the context of reinforcement learning-based approaches. As the length of sequences generated by LLMs increases, the problem of hallucination becomes pronounced, making dense feedback that reduces ambiguity inherent in single scalar reward more critical. Yu et al. (2024) and Xiao et al. (2024) tackle object hallucination in large vision-language models by incorporating dense-level (e.g., sub-sentence, sentence) human feedbacks. ViGoR (Yan et al.

2024) additionally employs a pipeline combining named entity recognition models with open vocab object detector (Liu et al. 2024) to detect hallucinations automatically. However, its scope is limited to object hallucinations, and human annotations are still needed to detect comprehensive misalignments.

In summary, the increasing emphasis on dense misalignment detection underscores its crucial role in developing more interpretable and reliable vision-language models. While current work demonstrates promising results in providing dense misalignment detection, they predominantly rely on costly human annotations or incorporation of foundation models, resulting in substantial cost overhead. In this work, we propose a cost-efficient dense misalignment detection method, leveraging the pre-trained CLIP in a zero-shot manner. The result demonstrates its efficiency and competitive performance over other cost-expensive zero-shot baselines.

Explainable AI Methods

Understanding the decision-making process of complex machine learning models is crucial for building trust and ensuring reliable performance. Explainable AI (XAI) methodologies address this need by providing insights into how models arrive at their predictions. XAI methods can be broadly categorized into two groups: input manipulation methods and mechanistic approaches. Input manipulation methods, such as SHAP (Lundberg and Lee 2017), occlusion analysis (Zeiler and Fergus 2014), and LIME (Ribeiro, Singh, and Guestrin 2016), perturb or mask input features to observe their impact on model output. While intuitive, these methods are often computationally expensive, especially for large models and datasets.

Mechanistic approaches, on the other hand, delve into the internal workings of the model to directly analyze feature contributions. Grad-CAM (Selvaraju et al. 2017) uses class-specific gradients to highlight relevant input regions but can produce coarse visualizations. LRP (Bach et al. 2015), grounded in the Deep Taylor Decomposition framework (Montavon et al. 2017), propagates relevance scores backward through the network layers, ensuring conservation of relevance. LRP has been successfully applied to various tasks, including image classification (Bach et al. 2015), NLP (Arras et al. 2017), and vision-and-language tasks (Chefer, Gur, and Wolf 2021b), showcasing its versatility and effectiveness.

The widespread adoption of Transformer networks (Vaswani et al. 2017) in NLP and vision-and-language tasks brought new challenges for XAI. Roll-out (Abnar and Zuidema 2020) and Attention Flow (Abnar and Zuidema 2020) attempt to address complexities arising from self-attention, but limitations persist. Chefer, Gur, and Wolf (2021b) adapted LRP for single-modality Transformers, later extending it to multi-modal settings using a combination of attention scores and gradients for head averaging (Chefer, Gur, and Wolf 2021a). Unlike these approaches, which rely on positive-only relevance propagation, our work introduces the interpretation of negative attributions as indicators of misalignment in CLIP.

Recent studies (Zhou, Loy, and Dai 2022; Wang, Rudner, and Wilson 2023; Zhao et al. 2024) apply XAI techniques to CLIP; however, they also focus on identifying only relevant image regions corresponding to the text.

Method

Preliminary: CLIP

We provide a brief overview of the key elements of the CLIP architecture. We also define the relevant terminology to consistently notate our method.

CLIP employs a dual-encoder structure, processing image and text modalities through separate encoders. The text encoder takes a sequence of tokens padded or truncated to a fixed length n ,

$$t = [t_0, t_1, \dots, t_z, \dots, t_{n-1}], \quad (1)$$

where z is the index of the [EOS] token in the sequence. The image encoder processes the input image as a sequence of patches, including a special [CLS] token.

$$v = [v_0, v_1, \dots, v_m], \quad (2)$$

where v_0 is the [CLS] token and v_1, \dots, v_m are image patches. The input image patches v and text tokens t are first forwarded through the image encoder (V) and text encoder (T), respectively, after which the representations are pooled and projected from the [CLS] and [EOS] tokens:

$$e_v = W_v(V(v)[0, :]), \quad e_t = W_t(T(t)[z, :]), \quad (3)$$

where W_v and W_t are projection matrices. The final score is computed by the cosine similarity (dot product with L2 normalization):

$$\text{score}_{v,t} = \frac{e_v}{\|e_v\|_2} \cdot \frac{e_t}{\|e_t\|_2}. \quad (4)$$

This score indicates the degree of semantic alignment between the image and text inputs.

Our Method

In this section, we introduce our attribution calculation method, which is inspired by Generic Attention-model Explainability (GAE) (Chefer, Gur, and Wolf 2021a). We first introduce GAE briefly and how our method is different from GAE. We then introduce fine-grained CLIPScore (F-CLIPScore), a drop-in replacement of CLIPScore by aggregating word attributions.

Generic Attention-model Explainability To determine the direction and magnitude of each token’s attribution to the final output, GAE computes the gradients of the final score with respect to the attention map:

$$\nabla A_l^h = \frac{\partial \text{score}_{v,t}}{\partial A_l^h}, \quad (5)$$

where $A_l^h \in \mathbb{R}^{n \times n}$ denotes the attention map at l -th layer and h -th head. To aggregate its gradient, GAE calculates the element-wise product of this gradient with the corresponding attention map:

$$R_l^h = \text{ReLU}(\nabla A_l^h \odot A_l^h). \quad (6)$$

Note that relevance propagation methods (Selvaraju et al. 2017; Chefer, Gur, and Wolf 2021a,b; Montavon et al. 2017) typically employ ReLU operation in ∇A_l^h to remove negative attribution.

The relevancy for layer l is obtained by averaging across attention heads:

$$R_l = \frac{1}{H} \sum_{h=1}^H R_l^h. \quad (7)$$

The relevancy in the final layer is initialized as an identity matrix and updated layer by layer. At each layer l , R is updated by adding the product of the current layer’s relevancy R_l and the carried R as in the relevance propagation methods. This process propagates the attribution information through the network, accumulating each layer’s attribution. Finally, the relevancy is aggregated along the [EOS] token row, $R[z, :]$.

Allowing Negative Gradient Flow. Unlike GAE (Chefer, Gur, and Wolf 2021a), which focuses on only the positive value of gradient, our work aims to identify misaligned words by incorporating negative gradients. We simply remove the ReLU operation on Equation (6), allowing negative gradients to explain the model’s behavior.

$$R_l^h = \nabla A_l^h \odot A_l^h. \quad (8)$$

By adopting this formulation, our approach leverages both positive and negative gradients to capture a comprehensive spectrum of attributions.

Layer Aggregation. Since our method incorporates gradients of both signs, matrix multiplication could lead to ambiguous interpretations. To address this, we average the attribution map R_l across layers, preserving the interpretability of both positive and negative attributions.

$$R = \frac{1}{(L - \tilde{l} + 1)} \sum_{l=\tilde{l}}^L R_l, \quad (9)$$

where L is the total number of layers in the transformer model, \tilde{l} is the index of the starting layer for accumulation, which is a hyperparameter.

Token Aggregation and F-CLIPScore. To identify misaligned words, we calculate the word-level attribution w_j by averaging the attribution of its constituent tokens. We then predict a word as misaligned if its attribution falls below a threshold ϵ .

$$\text{mis}(w_j) = \begin{cases} 1, & \text{if } w_j < \epsilon \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

To get a global fine-grained misalignment score between images and text, similar to CLIPScore (Hessel et al. 2021), we devise a simple aggregation method to derive a single score, which is dubbed as F-CLIPScore, as follows:

$$\text{F-CLIPScore}(v, t) = (1 - \text{score}_{v,t}) \cdot \sum_j \text{mis}(w_j) \cdot w_j. \quad (11)$$

This aggregation integrates both overall semantic alignment and fine-grained misalignments for each token.

Benchmark	Source	Text / Image domain	Misalign Type	Num of Misaligns	Annotation Type	Dense Misalign	Global Misalign
FOIL	COCO caption	natural / natural	object	single	rule-based	Accuracy	Average Precision
nocaps-FOIL	nocaps	natural / natural	object	single	rule-based	Accuracy	Average Precision
HAT	COCO caption	generated / natural	various	multiple	human	Accuracy	Average Precision
SeeTRUE-Feedback	COCO-con	natural / natural	various	multiple	human	NLI Score	-
	COCO-T2I	natural / generated	various	multiple	human	NLI Score	-
	Drawbench	natural / generated	various	multiple	human	NLI Score	-
	Pick-a-pic-con	generated / generated	various	multiple	human	NLI Score	-
Rich-HF	Pick-a-pic	natural / generated	various	multiple	human	precision, recall, F1	corr. coeff.

Table 1: **Comprehensive overview of benchmarks for dense misalignment detection.** “Generated” in the Text / Image domain column indicates that the text or image was created by a captioning model or a text-to-image generation model, respectively. In contrast, “natural” signifies that the text or image originates from a human source.

Method	FPS	needs annotations	FOIL		nocaps-FOIL					
					Overall		In-Domain		Near-Domain	
			LA	AP	LA	AP	LA	AP	LA	AP
CHAIR	-	✓	0.790	0.925	0.144	0.583	0.135	0.578	0.176	0.591
CLIPScore (ViT-B/32)	13.4		-	0.707	-	0.692	-	0.651	-	0.675
CLIPScore (ViT-H/14)	8.72		-	0.763	-	0.722	-	0.690	-	0.707
RefCLIPScore (ViT-B/32)	8.75	✓	-	0.748	-	0.736	-	0.683	-	0.718
ALOHa	0.16	✓	0.400	0.614	0.452	0.695	0.474	0.718	0.473	0.667
Ours (ViT-B/32)	12.0		0.732	0.714	0.603	0.690	0.547	0.673	0.597	0.684
Ours (ViT-H/14)	7.06		0.836	0.806	0.716	0.794	0.661	0.789	0.708	0.793
										0.748
										0.802

Table 2: **Experiment results on FOIL and nocaps-FOIL.** LA: Localization Accuracy. AP: Average Precision. FPS is measured on the nocaps-FOIL dataset. *Italic* denotes that we remeasured the result with ViT-B/32.

Experiments

As summarized in Table 1, we comprehensively evaluate our method across a diverse range of dense misalignment detection benchmarks. Our evaluation spans text domains (natural and generated), image domains (natural and generated), misalignment types (object, attribute, relation, and action), and the number of misaligned words (single or multiple). This extensive testing demonstrates the robustness and versatility of our approach. For detailed information about the datasets and experiments on additional benchmarks, please refer to the supplementary materials.

We report two variants of CLIP: OpenAI CLIP ViT-B/32 (Radford et al. 2021), following Hessel et al. (2021), and ViT-H/14 trained on LAION-2B (Schuhmann et al. 2022) from OpenClip (Cherti et al. 2023), which yields our best score. Further analysis of other backbones is provided in the supplementary material. We use a template “A photo depicts” following Hessel et al. (2021). We set our hyperparameters by searching the development set of Rich-HF and a subset of the training set from the FOIL dataset. We use \tilde{l} to 10 and 22 for ViT-B/32 and ViT-H/14, respectively, utilizing the final three layers in both cases. Unless otherwise specified, ϵ is set to -0.00005. Frames-Per-Second (FPS) is measured with a single V100. Finally, we use F-CLIPScore for the global misalignment classification task.

Quantitative Results

FOIL and nocaps-FOIL. FOIL (Shekhar et al. 2017) and nocaps-FOIL (Petryk et al. 2024) are benchmarks for detecting misaligned captions where one object is replaced by a conceptually similar word (e.g., car, bicycle). We as-

sess performance on two protocols: (1) localization accuracy (LA) for dense misalignment detection and (2) average precision (AP) for global misalignment classification. Following existing works, our approach predicts a single word with the lowest attribution w_j . In nocaps-FOIL, we report results as in-domain, near-domain, or out-of-domain based on how similar the altered objects are to COCO object classes.

In Table 2, our ViT-B/32 variant demonstrates state-of-the-art performance on most dense misalignment detection (LA). It is worth noting that baselines such as CHAIR (Rohrbach et al. 2018) or ALOHa (Petryk et al. 2024) make use of ground truth segmentation labels or reference captions. The ViT-H/14 variant demonstrates significantly enhanced performance, showing improved results consistently across all domains. It shows the robustness of our approach, which utilizes CLIP model pre-trained on various alt-text. Furthermore, our F-CLIPScore boosts up global misalignment classification (AP) by a significant margin, even surpassing reference-based methods. Lastly, our proposed approach demonstrates significantly superior computational efficiency compared to ALOHa, achieving a 44-fold reduction in inference time.

HAT. The HAT dataset (Petryk et al. 2024) comprises 400 human-annotated samples featuring captions generated by VLM models (Li et al. 2022; Wang et al. 2022; Chan et al. 2023; Zhu et al. 2024). For evaluation, we measured with the same metric as FOILs: LA and AP. For LA, correctly identifying any hallucinated object in a sentence is considered accurate. To compare with ALOHa, which extracts a noun phrase, we concatenate neighboring misaligned words and average scores within a phrase. The phrase with the lowest

aggregate score was predicted as the erroneous segment.

In Table 3, our ViT-H/14 variant demonstrates superior performance in LA with significantly improved FPS. In terms of AP, our method shows a performance gap compared to models that utilize reference captions. Further analysis for AP is presented in the supplementary.

method	ref. captions	FPS	LA	AP
CHAIR	✓	-	0.067	0.369
CLIPScore (ViT-B/32)		18.8	-	0.385
RefCLIPScore (ViT-B/32)	✓	9.03	-	0.429
ALOHa	✓	0.24	0.203	0.486
Ours (ViT-B/32)		9.64	0.193	0.355
Ours (ViT-H/14)		6.56	0.348	0.360

Table 3: **Experiment results on HAT test set.** ref. captions denotes that the method utilizes reference captions. *Italic* denotes that we remeasured the result with ViT-B/32.

SeeTRUE-Feedback. SeeTRUE-Feedback (Gordon et al. 2024) comprises a test set of 2K samples covering various images, text domains, and misalignment types. We specifically focus on textual misalignment detection, which aims to extract mismatched spans from caption. Following established protocols, we report the natural language inference (NLI) (Bowman et al. 2015) score obtained from a BART-NLI model (Lewis et al. 2020). We calculate the entailment score where the premise is the ground truth label, and the hypothesis is the predicted word span. To form a single sequence, we take the same strategy as the one used in evaluating the HAT dataset.

As shown in Table 4, our method surpasses the zero-shot models, showing its efficiency and robustness in various domains. It is also worth noting that, as a non-generative model, ours offers faster inference times compared to larger vision language models.

Rich-HF. Rich-HF (Liang et al. 2024) comprises 955 prompt and image pairs with word-level misalignment annotations and overall alignment score. Since prompts are collected by real users (Kirstain et al. 2023), its captions cover various lengths, styles, and contents. We evaluate the performance of misalignment labels using precision, recall, and F1 scores at the word level. We also measure Pearson and Spearman’s correlation between our aggregated score and the Likert score for alignment. We further report the performance of ALOHa for comparison.

In Table 5, our method demonstrates promising performance as a zero-shot method. While precision is limited, it shows higher recall, resulting in a substantial F1 score. In Table 6, our aggregated score shows a significantly enhanced score in two correlation coefficients. Our ViT-H/14 variant even shows comparative performance with PickScore (Kirstain et al. 2023), which is finetuned with 583K human preference scores. These results suggest that the selected negative attributions effectively capture misalignment, leading to superior performance in measuring text-image discrepancies.

Model	ft.	FPS	NLI score
LLaVa-1.5 (Vicuna-7B)		0.24	0.173
PaLI 5B		-	0.226
mPLUG-Owl (LLaMa-7B)		0.24	0.297
InstructBLIP (FlanT5 _{XL})		0.51	0.555
MiniGPT-v2 (LLaMa2-7B)		0.28	0.560
Ours (ViT-B/32)		7.90	0.605
Ours (ViT-H/14)		5.81	0.660
PaLI 5B	✓	-	0.765
PaLI 17B	✓	-	0.785

Table 4: **Textual misalignment performance on SeeTRUE-Feedback test set.** ft. denotes that the model is fine-tuned.

Model	ft.	F1	precision	recall
ALOHa		0.344	0.311	0.385
Ours (ViT-B/32) _{$\epsilon = -0.00001$}		0.398	0.328	0.504
Ours (ViT-H/14) _{$\epsilon = -0.00001$}		0.427	0.365	0.516
Ours (ViT-H/14) _{$\epsilon = -0.00005$}		0.314	0.487	0.231
Rich-HF (multi-head)	✓	<u>0.433</u>	0.629	0.330
Rich-HF (augmented prompt)	✓	0.439	<u>0.613</u>	0.341

Table 5: **Experiment results on Rich-HF test set.** ft. denotes that the model is fine-tuned with the Rich-HF training set.

Model	ft.	pearson	spearman
CLIPScore (ViT-B/32)		0.185	0.130
PickScore (ViT-H/14)		0.346	0.340
Ours (ViT-B/32) _{$\epsilon = -0.00001$}		0.279	0.332
Ours (ViT-H/14) _{$\epsilon = -0.00001$}		0.368	0.433
CLIPScore (ViT-B/32)	✓	0.398	0.390
Rich-HF (multi-head)	✓	0.487	0.500
Rich-HF (augmented prompt)	✓	0.474	<u>0.496</u>

Table 6: **Experiment results on Rich-HF misalignment score correlation.**

Qualitative Results

We present qualitative examples on three representative datasets in Figure 2. Further examples of all datasets are shown in the supplementary materials. For the FOIL and nocaps-FOIL datasets, models need to predict a single word regardless of the presence or absence of misaligned words. When misaligned words exist, our model detects them well for images from various domains. In cases where misaligned words do not exist, our model predicts unimportant word ‘.’ and ‘medium’, a word that is difficult for the model to distinguish, as misaligned words as shown in the second and fourth images for the FOIL dataset. For the Rich-HF dataset, our model demonstrates decent misaligned word detection performance for generated images. In addition, ours shows the ability to detect multiple misaligned words or not detect misaligned words when misaligned words do not exist.

Ablation Studies

To demonstrate the efficiency of the proposed method, we conduct ablation studies using the ViT-H/14 variant.

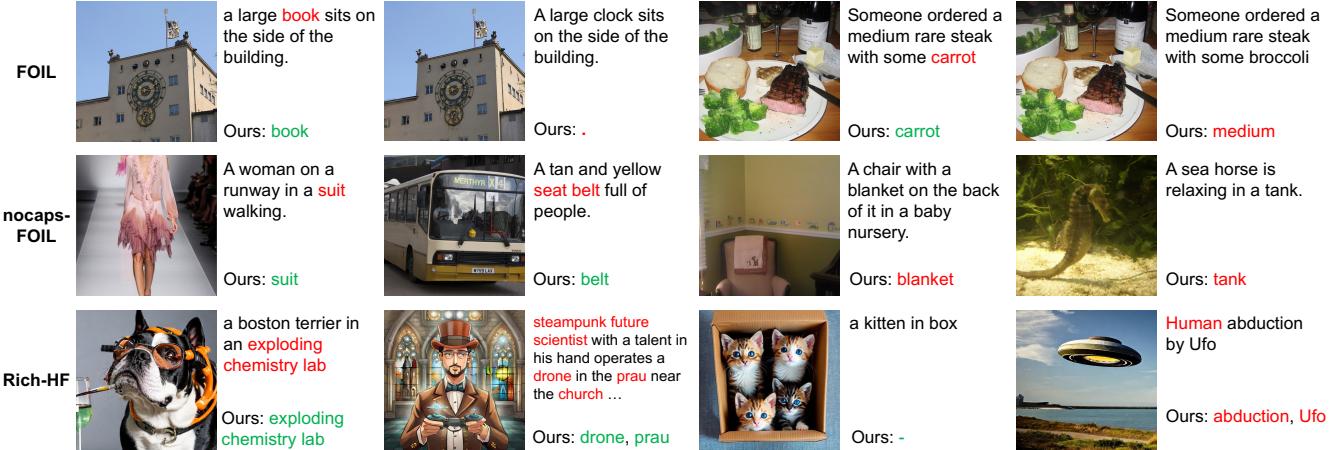


Figure 2: **Qualitative examples on FOIL, nocaps-FOIL, and Rich-HF datasets.** Misaligned words are highlighted in red in captions paired with images. Note that misaligned words may not exist. For predicted misaligned words, correct words are shown in green and incorrect words in red. If our model predicts that there are no misaligned words, it is indicated as ‘-’.

Method	FPS	LA	AP
occlusion-based	0.6	0.566	0.748
gradient-based			
∇A_l^h	5.8	0.423	0.741
$A_l^h \odot \nabla A_l^h$	5.8	0.716	0.794

Table 7: **Ablation study of attribution calculation methods on the nocaps-FOIL test set.**

$ReLU(-\nabla A_l^h)$	$ReLU(-\nabla A_l)$	LA	AP
✓		0.698	0.779
	✓	0.700	0.776
		0.716	0.794

Table 8: **Ablation study of the disabling positive gradients on nocaps-FOIL test set.** $ReLU(-\nabla A_l^h)$ and $ReLU(-\nabla A_l)$ indicate retaining only negative gradients before averaging across heads and layers, respectively.

Attribution Calculation Method. We conduct an ablation study on the attribution calculation method. The occlusion (Goyal et al. 2016) method iteratively omits individual words from the input text and identifies the word whose removal leads to the highest increase in the score as the most likely erroneous element. Among gradient-based methods, we ablate components used in extracting attribution maps. Table 7 shows that the occlusion-based method demonstrated superior performance, but its efficiency was limited due to the requirement of multiple forward passes. In contrast, gradient-based methods, particularly when combined with attention maps, achieved a balance of high efficiency and performance.

Disabling Positive Gradient. We examine the effectiveness of using both positive and negative gradients in attribution calculation. We compare removing positive gradients before averaging across heads or layers, similar to conventional relevance map approaches (Selvaraju et al. 2017; Chefer, Gur, and Wolf 2021a). Table 8 demonstrates that

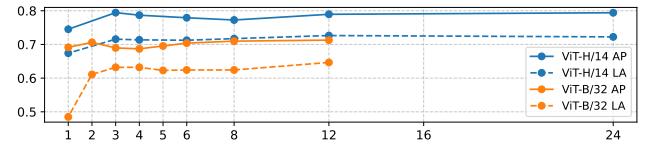


Figure 3: **Ablation on the number of text encoder layers used for attribution calculation on nocaps-FOIL dataset.**

Dataset	Method	AP	Pearson	Spearman
nocaps-FOIL	$score_{v,t}$	0.722	-	-
	$\sum_j \text{mis}(w_j) \cdot w_j$	0.776	-	-
	F-CLIPScore	0.794	-	-
Rich-HF	$score_{v,t}$	-	0.171	0.085
	$\sum_j \text{mis}(w_j) \cdot w_j$	-	0.352	0.419
	F-CLIPScore	-	0.368	0.433

Table 9: **Ablation on components of F-CLIPScore.** Result shows that simple aggregating negative attributions can enhance the capture of alignments, which is further improved with a combination of the overall score.

utilizing full gradients yields the best performance, outperforming methods that isolate negative gradients. This finding underscores the importance of considering both positive and negative contributions in gradient-based attribution calculation.

Number of Layers. We perform an ablation study on \tilde{l} , the number of text encoder layers used for attribution map calculation. Figure 3 demonstrates that utilizing multiple layers, rather than solely the final layer, significantly enhances performance across both metrics. It demonstrates that utilizing intermediate features across layers enhances the detection of misalignments.

Components of F-CLIPScore. We conduct an ablation study on the components of F-CLIPScore using the nocaps-FOIL and Rich-HF datasets. As shown in Table 9, the mere summation of negative attribution w_j yields significantly

improved AP and correlation coefficients. Moreover, integrating this with the overall similarity score further enhances performance, demonstrating our method’s efficacy in capturing fine-grained misalignments. Additional analyses are presented in the supplementary material.

Analysis

Comparsion with Baselines. In Figure 4, we present qualitative examples comparing our method to the baseline ALOHa (Petryk et al. 2024) on the HAT dataset. Our approach demonstrates robust and diverse detection capabilities, such as colors (e.g., white), numbers (e.g., two), entity-level objects (e.g., calf), and intangible objects (e.g., sunset), which can not be easily captured with combinations of foundation models. Different from ALOHa, which uses a language similarity module, CLIP, which is trained on diverse alt-text data, is sensitive to conceptually similar but visually distinct words (e.g., “blue” and “grey”). This underscores the effectiveness of our CLIP-based approach, which operates independently of additional foundation models. While showing promising results, our method also reveals some inherent limitations of CLIP, particularly in identifying discrepancies related to backgrounds (e.g., “wooden floor”) or small objects (e.g., “birds”). Further examples and analyses are presented in the supplementary materials.

We provide qualitative examples comparing our method to the baseline MiniGPT-v2 (Chen et al. 2023) on SeeTRUE-Feedback dataset, as shown in Figure 5. As a large vision-language model, MiniGPT-v2 has the advantage of providing natural and rich responses. However, despite a prompt that requests the model to answer in short words, it provides lengthy and unformatted responses to almost all examples. Since it is quite difficult to accurately extract misaligned words from unstructured responses, its usability as a dense misalignment detector is low. Furthermore, MiniGPT-v2 sometimes generates inconsistent responses. As shown in the third example in Figure 5, it shows a contradictory response, saying that the floor is grass while also saying that it is not grass. On the contrary, our method can detect misaligned words efficiently. It is also noteworthy that the FPS of ours is far higher than that of MiniGPT-v2.

Part-of-Speech. We report Rich-HF word level metrics per part-of-speech (POS) for further analysis. In Table 10, our method predicts all overall POS, which shows that our method has the capability to predict misaligned words of various types, not limited to nouns. Still, we observe a trend that shows decent performance with nouns but limited performance with adverbs, adjectives, numbers, and adpositions. The result shows that our result corresponds with studies that reveal CLIP’s weaknesses (Paiss et al. 2023; Nikolaus et al. 2022; Yuksekgonul et al. 2023). We leave it as future work to test with CLIP variants, which are further fine-tuned to tackle such shortcomings.

Conclusion and Future Work

In this paper, we present a novel approach for detecting dense misalignments between text and image using a pre-trained CLIP model. By extracting attributions from CLIP’s

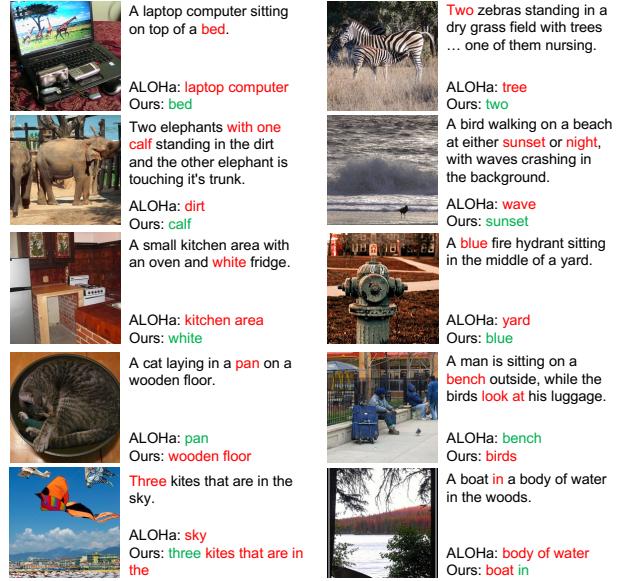


Figure 4: **Qualitative examples compared to ALOHa on HAT dataset.** Our method demonstrates improved robustness in various misalignment types.



Figure 5: **Qualitative examples compared to MiniGPT-v2 on SeeTRUE-Feedback dataset.** MiniGPT-v2 generates lengthy and unformalized responses that are hard to parse into misaligned words for most examples.

Metric	NOUN	PROPN	VERB	ADV	ADJ	NUM	ADP
F1	0.393	0.312	0.301	0.258	0.258	0.132	0.177
Precision	0.470	0.602	0.567	0.444	0.417	0.500	0.278
Recall	0.337	0.211	0.205	0.182	0.187	0.076	0.130

Table 10: **Comparison of metrics per part-of-speech on Rich-HF test set.**

intermediate gradients, our method provides a scalable and efficient solution that achieves state-of-the-art performance in zero-shot settings and competitive results with fine-tuned models across multiple benchmarks. Also, our proposed F-CLIPScore shows enhanced performance to capture global misalignments. While showing effectiveness in capturing various misalignment types, our analysis reveals that our method inherits weaknesses observed in CLIP. Further examination is needed to improve the detection of misalignments using CLIP variants specifically trained to address these shortcomings.

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References

- Abnar, S.; and Zuidema, W. 2020. Quantifying Attention Flow in Transformers. In *ACL*, 4190–4197. Online: Association for Computational Linguistics.
- Arras, L.; Montavon, G.; Müller, K.-R.; and Samek, W. 2017. Explaining Recurrent Neural Network Predictions in Sentiment Analysis. In *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, 159–168. Copenhagen, Denmark: ACL.
- Bach, S.; Binder, A.; Montavon, G.; Klauschen, F.; Müller, K.-R.; and Samek, W. 2015. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PLoS ONE*, 10(7): e0130140.
- Bowman, S. R.; Angeli, G.; Potts, C.; and Manning, C. D. 2015. A large annotated corpus for learning natural language inference. In *EMNLP*. Association for Computational Linguistics.
- Carion, N.; Massa, F.; Synnaeve, G.; Usunier, N.; Kirillov, A.; and Zagoruyko, S. 2020. End-to-end object detection with transformers. In *ECCV*, 213–229. Springer.
- Castro, S.; Ignat, O.; and Mihalcea, R. 2023. Scalable Performance Analysis for Vision-Language Models. In *Proceedings of the 12th Joint Conference on Lexical and Computational Semantics (* SEM 2023)*, 284–294.
- Chan, D.; Myers, A.; Vijayanarasimhan, S.; Ross, D.; and Canny, J. 2023. IC3: Image Captioning by Committee Consensus. In *EMNLP*, 8975–9003. Singapore: Association for Computational Linguistics.
- Chefer, H.; Alaluf, Y.; Vinker, Y.; Wolf, L.; and Cohen-Or, D. 2023. Attend-and-Excite: Attention-Based Semantic Guidance for Text-to-Image Diffusion Models. *ACM Trans. Graph.*, 42(4).
- Chefer, H.; Gur, S.; and Wolf, L. 2021a. Generic Attention-model Explainability for Interpreting Bi-Modal and Encoder-Decoder Transformers. In *ICCV*, 387–396. IEEE.
- Chefer, H.; Gur, S.; and Wolf, L. 2021b. Transformer Interpretability Beyond Attention Visualization. In *CVPR*, 782–791. Computer Vision Foundation / IEEE.
- Chen, J.; Zhu, D.; Shen, X.; Li, X.; Liu, Z.; Zhang, P.; Krishnamoorthi, R.; Chandra, V.; Xiong, Y.; and Elhoseiny, M. 2023. Minigpt-v2: large language model as a unified interface for vision-language multi-task learning. *arXiv preprint arXiv:2310.09478*.
- Cherti, M.; Beaumont, R.; Wightman, R.; Wortsman, M.; Ilharco, G.; Gordon, C.; Schuhmann, C.; Schmidt, L.; and Jitsev, J. 2023. Reproducible scaling laws for contrastive language-image learning. In *CVPR*, 2818–2829.
- Cho, J.; Hu, Y.; Baldridge, J. M.; Garg, R.; Anderson, P.; Krishna, R.; Bansal, M.; Pont-Tuset, J.; and Wang, S. 2024. Davidsonian Scene Graph: Improving Reliability in Fine-grained Evaluation for Text-to-Image Generation. In *ICLR*.
- Deng, J.; Dong, W.; Socher, R.; Li, L.-J.; Li, K.; and Fei-Fei, L. 2009. Imagenet: A large-scale hierarchical image database. In *CVPR*, 248–255. Ieee.
- Gordon, B.; Bitton, Y.; Shafir, Y.; Garg, R.; Chen, X.; Lischinski, D.; Cohen-Or, D.; and Szepk, I. 2024. Mis-match quest: Visual and textual feedback for image-text mis-alignment. In *ECCV*, 310–328. Springer.
- Goyal, Y.; Mohapatra, A.; Parikh, D.; and Batra, D. 2016. Towards transparent ai systems: Interpreting visual question answering models. In *ICML 2016 Workshop on Visualization for Deep Learning*.
- Gunjal, A.; Yin, J.; and Bas, E. 2024. Detecting and preventing hallucinations in large vision language models. In *AAAI*, volume 38, 18135–18143.
- Hessel, J.; Holtzman, A.; Forbes, M.; Le Bras, R.; and Choi, Y. 2021. CLIPScore: A Reference-free Evaluation Metric for Image Captioning. In *EMNLP*, 7514–7528. Online and Punta Cana, Dominican Republic: Association for Computational Linguistics.
- Hsieh, C.-Y.; Zhang, J.; Ma, Z.; Kembhavi, A.; and Krishna, R. 2023. SUGARCREPE: fixing hackable benchmarks for vision-language compositionality. In *NeurIPS*, 31096–31116.
- Hu, Y.; Liu, B.; Kasai, J.; Wang, Y.; Ostendorf, M.; Krishna, R.; and Smith, N. A. 2023. Tifa: Accurate and interpretable text-to-image faithfulness evaluation with question answering. In *ICCV*, 20406–20417.
- Kirstain, Y.; Polyak, A.; Singer, U.; Matiana, S.; Penna, J.; and Levy, O. 2023. Pick-a-Pic: an open dataset of user preferences for text-to-image generation. In *NeurIPS*, 36652–36663.
- Lewis, M.; Liu, Y.; Goyal, N.; Ghazvininejad, M.; Mohamed, A.; Levy, O.; Stoyanov, V.; and Zettlemoyer, L. 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In *ACL*, 7871–7880. Online: Association for Computational Linguistics.
- Li, J.; Li, D.; Xiong, C.; and Hoi, S. C. H. 2022. BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation. In *ICML*, volume 162 of *Proceedings of Machine Learning Research*, 12888–12900. PMLR.
- Li, Y.; Du, Y.; Zhou, K.; Wang, J.; Zhao, W. X.; and Wen, J.-R. 2023. Evaluating Object Hallucination in Large Vision-Language Models. In *EMNLP*, 292–305.
- Liang, Y.; He, J.; Li, G.; Li, P.; Klimovskiy, A.; Carolan, N.; Sun, J.; Pont-Tuset, J.; Young, S.; Yang, F.; et al. 2024. Rich human feedback for text-to-image generation. In *CVPR*, 19401–19411.
- Lin, Y.; He, C.; Wang, A. J.; Wang, B.; Li, W.; and Shou, M. Z. 2024. Parrot captions teach clip to spot text. In *ECCV*, 368–385. Springer.

- Liu, S.; Zeng, Z.; Ren, T.; Li, F.; Zhang, H.; Yang, J.; Jiang, Q.; Li, C.; Yang, J.; Su, H.; Zhu, J.; and Zhang, L. 2024. Grounding DINO: Marrying DINO with Grounded Pre-training for Open-Set Object Detection. In *ECCV*, 38–55. Cham: Springer Nature Switzerland. ISBN 978-3-031-72970-6.
- Lundberg, S. M.; and Lee, S. 2017. A Unified Approach to Interpreting Model Predictions. In *NeurIPS*, 4765–4774.
- Ma, Z.; Hong, J.; Gul, M. O.; Gandhi, M.; Gao, I.; and Krishna, R. 2023. CREPE: Can Vision-Language Foundation Models Reason Compositionally? In *CVPR*, 10910–10921.
- Montavon, G.; Lapuschkin, S.; Binder, A.; Samek, W.; and Müller, K.-R. 2017. Explaining nonlinear classification decisions with deep taylor decomposition. *Pattern recognition*, 65: 211–222.
- Mukhoti, J.; Lin, T.-Y.; Poursaeed, O.; Wang, R.; Shah, A.; Torr, P. H.; and Lim, S.-N. 2023. Open Vocabulary Semantic Segmentation with Patch Aligned Contrastive Learning. In *CVPR*, 19413–19423. IEEE Computer Society.
- Nikolaus, M.; Salin, E.; Ayache, S.; Fourtassi, A.; and Favre, B. 2022. Do Vision-and-Language Transformers Learn Grounded Predicate-Noun Dependencies? In *EMNLP*, 1538–1555.
- Paiss, R.; Ephrat, A.; Tov, O.; Zada, S.; Mosseri, I.; Irani, M.; and Dekel, T. 2023. Teaching CLIP to Count to Ten. In *ICCV*, 3147–3157. IEEE.
- Petryk, S.; Chan, D.; Kachinthaya, A.; Zou, H.; Canny, J.; Gonzalez, J.; and Darrell, T. 2024. ALOHa: A New Measure for Hallucination in Captioning Models. In *NAACL*, 342–357.
- Pezzelle, S. 2023. Dealing with Semantic Underspecification in Multimodal NLP. In *ACL*, 12098–12112.
- Radford, A.; Kim, J. W.; Hallacy, C.; Ramesh, A.; Goh, G.; Agarwal, S.; Sastry, G.; Askell, A.; Mishkin, P.; Clark, J.; Krueger, G.; and Sutskever, I. 2021. Learning Transferable Visual Models From Natural Language Supervision. In *ICML*, volume 139, 8748–8763.
- Rasskin, R.; Ravfogel, S.; and Goldberg, Y. 2022. DALLE-2 is Seeing Double: Flaws in Word-to-Concept Mapping in Text2Image Models. In *Proceedings of the Fifth BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, 335–345.
- Reimers, N.; and Gurevych, I. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In *EMNLP*, 3982–3992. Hong Kong, China: Association for Computational Linguistics.
- Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. “Why Should I Trust You?”: Explaining the Predictions of Any Classifier. In *SIGKDD*, 1135–1144. ACM.
- Rohrbach, A.; Hendricks, L. A.; Burns, K.; Darrell, T.; and Saenko, K. 2018. Object Hallucination in Image Captioning. In *EMNLP*, 4035–4045. Brussels, Belgium: Association for Computational Linguistics.
- Schuhmann, C.; Beaumont, R.; Vencu, R.; Gordon, C. W.; Wightman, R.; Cherti, M.; Coombes, T.; Katta, A.; Mullis, C.; Wortsman, M.; et al. 2022. LAION-5B: An open large-scale dataset for training next generation image-text models. In *NeurIPS*.
- Selvaraju, R. R.; Cogswell, M.; Das, A.; Vedantam, R.; Parikh, D.; and Batra, D. 2017. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. In *ICCV*, 618–626. IEEE Computer Society.
- Shekhar, R.; Pezzelle, S.; Klimovich, Y.; Herbelot, A.; Nabi, M.; Sangineto, E.; and Bernardi, R. 2017. FOIL it! Find One mismatch between Image and Language caption. In *ACL*, 255–265. Vancouver, Canada: Association for Computational Linguistics.
- Tong, S.; Liu, Z.; Zhai, Y.; Ma, Y.; LeCun, Y.; and Xie, S. 2024. Eyes Wide Shut? Exploring the Visual Shortcomings of Multimodal LLMs. In *CVPR*, 9568–9578.
- Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is All you Need. In *NeurIPS*, 5998–6008.
- Wang, P.; Yang, A.; Men, R.; Lin, J.; Bai, S.; Li, Z.; Ma, J.; Zhou, C.; Zhou, J.; and Yang, H. 2022. OFA: Unifying Architectures, Tasks, and Modalities Through a Simple Sequence-to-Sequence Learning Framework. In *ICML*, volume 162 of *Proceedings of Machine Learning Research*, 23318–23340. PMLR.
- Wang, Y.; Rudner, T. G.; and Wilson, A. G. 2023. Visual explanations of image-text representations via multi-modal information bottleneck attribution. In *NeurIPS*, volume 36, 16009–16027.
- Xiao, W.; Huang, Z.; Gan, L.; He, W.; Li, H.; Yu, Z.; Jiang, H.; Wu, F.; and Zhu, L. 2024. Detecting and mitigating hallucination in large vision language models via fine-grained ai feedback. *arXiv preprint*, arXiv:2404.14233.
- Yan, S.; Bai, M.; Chen, W.; Zhou, X.; Huang, Q.; and Li, L. E. 2024. ViGoR: Improving Visual Grounding of Large Vision Language Models with Fine-Grained Reward Modeling. In *ECCV*, 37–53. Cham: Springer Nature Switzerland. ISBN 978-3-031-73030-6.
- Yao, L.; Huang, R.; Hou, L.; Lu, G.; Niu, M.; Xu, H.; Liang, X.; Li, Z.; Jiang, X.; and Xu, C. 2022. FILIP: Fine-grained Interactive Language-Image Pre-Training. In *ICLR*.
- Yu, J.; Xu, Y.; Koh, J. Y.; Luong, T.; Baid, G.; Wang, Z.; Vasudevan, V.; Ku, A.; Yang, Y.; Ayan, B. K.; Hutchinson, B.; Han, W.; Parekh, Z.; Li, X.; Zhang, H.; Baldridge, J.; and Wu, Y. 2022. Scaling Autoregressive Models for Content-Rich Text-to-Image Generation. *TMLR*.
- Yu, T.; Yao, Y.; Zhang, H.; He, T.; Han, Y.; Cui, G.; Hu, J.; Liu, Z.; Zheng, H.-T.; Sun, M.; et al. 2024. Rlfh-v: Towards trustworthy mllms via behavior alignment from fine-grained correctional human feedback. In *CVPR*, 13807–13816.
- Yuksekgonul, M.; Bianchi, F.; Kalluri, P.; Jurafsky, D.; and Zou, J. 2023. When and why vision-language models behave like bags-of-words, and what to do about it? In *ICLR*.
- Zeiler, M. D.; and Fergus, R. 2014. Visualizing and understanding convolutional networks. In *ECCV*, 818–833. Springer.

- Zhang, B.; Zhang, P.; Dong, X.; Zang, Y.; and Wang, J. 2025. Long-clip: Unlocking the long-text capability of clip. In *European Conference on Computer Vision*, 310–325. Springer.
- Zhao, C.; Wang, K.; Zeng, X.; Zhao, R.; and Chan, A. B. 2024. Gradient-based visual explanation for transformer-based clip. In *ICML*, 61072–61091. PMLR.
- Zhou, C.; Loy, C. C.; and Dai, B. 2022. Extract free dense labels from clip. In *ECCV*, 696–712. Springer.
- Zhu, D.; Chen, J.; Haydarov, K.; Shen, X.; Zhang, W.; and Elhoseiny, M. 2024. ChatGPT Asks, BLIP-2 Answers: Automatic Questioning Towards Enriched Visual Descriptions. *TMLR*.

A. Further Details of Dense Misalignment Detection Benchmarks

We provide detailed information about the datasets, as shown in Table 11. The FOIL (Shekhar et al. 2017) and nocaps-FOIL (Petryk et al. 2024) dataset consist of misaligned sentences and aligned sentences in a 1:1 ratio. FOIL is characterized by each misaligned sentence containing a single incorrect word, whereas the nocaps-FOIL dataset primarily features sentences with one misaligned word but occasionally includes sentences with multiple misaligned words. The HAT dataset (Petryk et al. 2024) contains a lower proportion of misaligned sentences. In contrast, the SeeTRUE-Feedback dataset (Gordon et al. 2024) exclusively features misaligned sentences, often involving a large number of incorrect words. The Rich-HF dataset displays a wide variety of words, from 1 to 182.

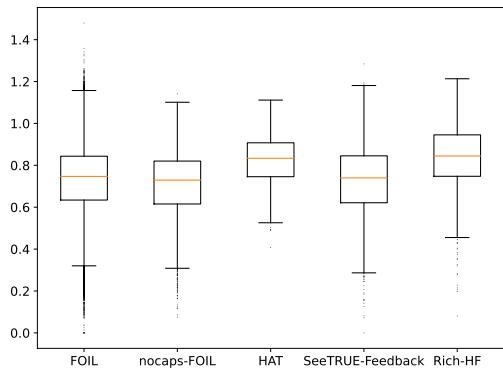


Figure 6: Box plots of CLIPScore for the dense misalignment detection benchmark datasets. We measure scores using ViT-H/14 trained on LAION-2B (Schuhmann et al. 2022).

As shown in Figure 6, we demonstrate the distribution of CLIPScore for five benchmarks through box plots. In general, we observe the CLIPScore distributions over 0.3. The median values of CLIPScore are generally similar across all benchmarks, around 0.8. Among the benchmarks, the HAT and Rich-HF show higher median and min values of CLIPScore, which can be attributed to their primary composition of generated image-text pairs. In contrast, synthetically generated misalignment benchmarks have a relatively wide range of CLIPScore.

B. Additional Qualitative examples

FOIL and nocaps-FOIL. As shown in Figure 7 and Figure 8, qualitative analysis reveals that our method effectively discriminates between conceptually similar but visually distinct objects, such as “motorcycles” and “bicycles”, as well as “waffles” and “bread”. However, it demonstrates reduced accuracy for small objects (e.g., “glasses”, “hat”) and background elements (e.g., “table”, “room”).

HAT. Additional examples from the HAT dataset are presented in Figure 9. Our method demonstrates proficiency in identifying a wide spectrum of misalignments, including numbers (e.g., “two ducks”) and abstract (e.g., “smiley

face”). However, the method’s performance is limited when detecting misalignments in adjectives (e.g., “busy”) and action verbs (e.g., “pulling in”, “holding”).

We further investigate the factors contributing to the decreased Average Precision (AP) on the HAT dataset in Figure 10. Our analysis reveals that false positives predominantly occur in scenarios involving background elements (e.g., “stairs”, “sky”), small or indistinct objects (e.g., “house”, “television”), and descriptive phrases (e.g., “in the corner”, “image of”). This pattern of errors aligns with the previously noted tendency of CLIP to prioritize foreground elements, suggesting that our method inherits CLIP’s bias towards salient visual features at the expense of more subtle or contextual information.

SeeTRUE-Feedback. Qualitative evaluations of our method on the SeeTRUE-Feedback dataset are presented in Figure 11. The results demonstrate enhanced capability in identifying diverse forms of misalignment, including objects, colors, attributes (e.g., “shiny”), and some actions (e.g., “sits”, “sleeping”). Notably, the method exhibits proficiency in recognizing entity-level objects (e.g., “batman”, “madonna”), which can not be easily captured by existing approaches. In line with known CLIP capabilities, our approach also demonstrates some optical character recognition (OCR) ability (Radford et al. 2021; Lin et al. 2024), as evidenced by samples such as “in the day of life”. However, persistent limitations in detecting background elements and small objects underscore areas for future improvement.

Rich-HF. Qualitative examples in Rich-HF are represented on Figure 12. Rich-HF dataset, which consists of real user prompts, reveals our method’s particular strength in identifying misalignments related to well-known entities, such as “GTA V”, “Sherlock”, “Chimera”), while missing some entities (e.g., “ONI”, “Santa Monica”). The Rich-HF dataset is characterized by a high proportion of highly descriptive and style-related terms (e.g., “advertising design”), which often present challenges for CLIP-based models to accurately capture and evaluate. Also, our model’s architecture constrains input to the first 77 tokens, resulting in limited performance on prompts with a significantly large number of words.

C. Further Results on Challenging Benchmarks

As research on CLIP progresses, challenging benchmarks (Tong et al. 2024; Hsieh et al. 2023; Yuksekgonul et al. 2023; Ma et al. 2023) addressing its weaknesses have been proposed. They are characterized by hard negatives with various visual and textual patterns, including attribution, relation, and order. Therefore, we compare CLIPScore and F-CLIPScore using the latest MMVP (Tong et al. 2024) and SugarCrepe (Hsieh et al. 2023) benchmarks. MMVP is composed of image and text pairs that include nine visual patterns that CLIP particularly struggles with, and SugarCrepe consists of hard negatives constructed using add, replace, and swap methods for attributes, relations, and ob-

Benchmark	Source	Misalign domain	# samples	Misaligned sentence ratio	# all words				# misaligned words			
					min	mean	med.	max	min	mean	med.	max
FOIL	COCO caption	synthetic	198960	0.5	6	10.67	10	50	1	1.0	1	1
nocaps-FOIL	Open Images / nocaps	synthetic	5000	0.5	7	11.53	11	40	1	1.12	1	5
HAT	COCO caption	generated	400	0.34	6	13.58	11	35	1	1.99	1	12
SeeTRUE-Feedback	COCO-con	synthetic	713	1.0	6	10.31	10	29	1	2.49	2	11
	COCO-T2I	generated	256	1.0	8	10.47	10	18	1	4.72	4	18
	Drawbench	generated	404	1.0	1	9.11	8	36	1	4.19	4	17
	Pick-a-pic-con	synthetic	623	1.0	4	12.10	12	83	1	3.15	2	14
Rich-HF	Pick-a-pic	generated	955	0.74	1	12.78	8	182	1	3.50	2	100

Table 11: **Detailed statistics of dense misalignment detection benchmark datasets.** The number of words is measured based on white spaces. Misalign domain refers to how misaligned words occur; synthetic refers to that misalignment is synthetically generated(e.g., altering noun by rule), and generated refers to that misalignment is generated by the model (e.g., hallucinated objects in the captioning model).

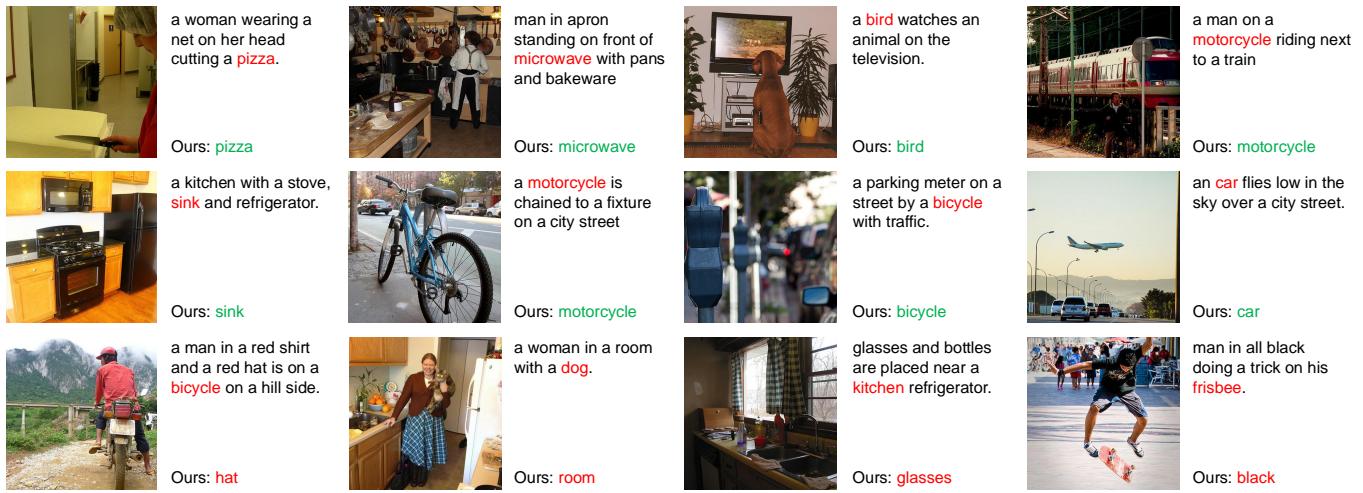


Figure 7: Qualitative examples on FOIL.

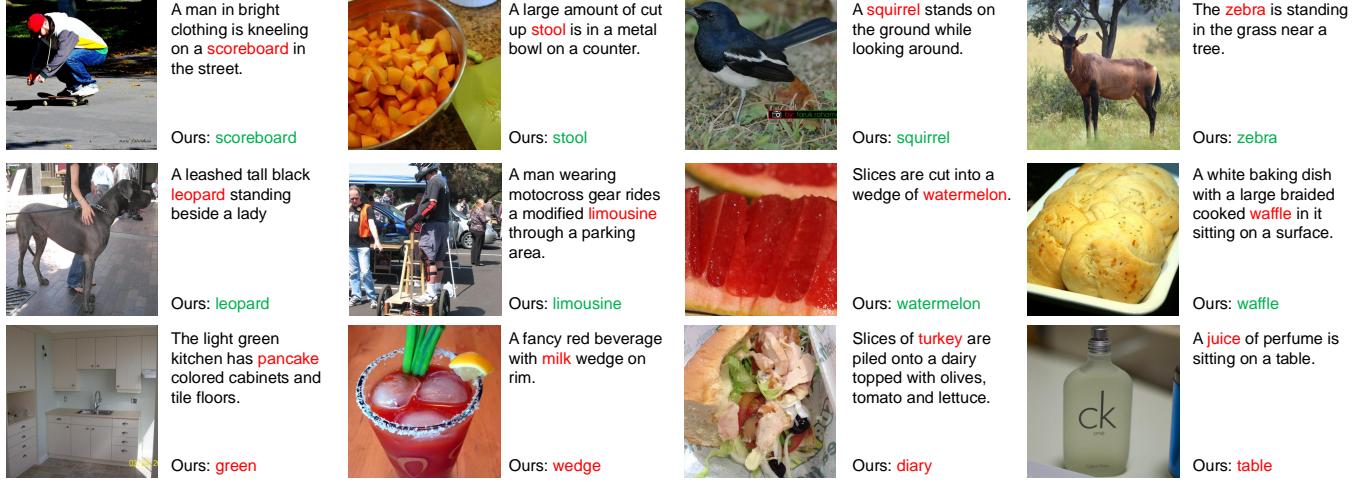


Figure 8: Qualitative examples on nocaps-FOIL.

jects. For experiments, we utilize the OpenAI ViT-L/14 variant, following the configuration used in MMVP.

F-CLIPScore demonstrates substantial improvements on the MMVP dataset, with an overall gain of over 6.6%

as shown in Table 12. Notably, we observe significant enhancements in detecting misalignments related to orientation & direction, viewpoint & perspective, and state & condition. These results underscore our method’s effectiveness

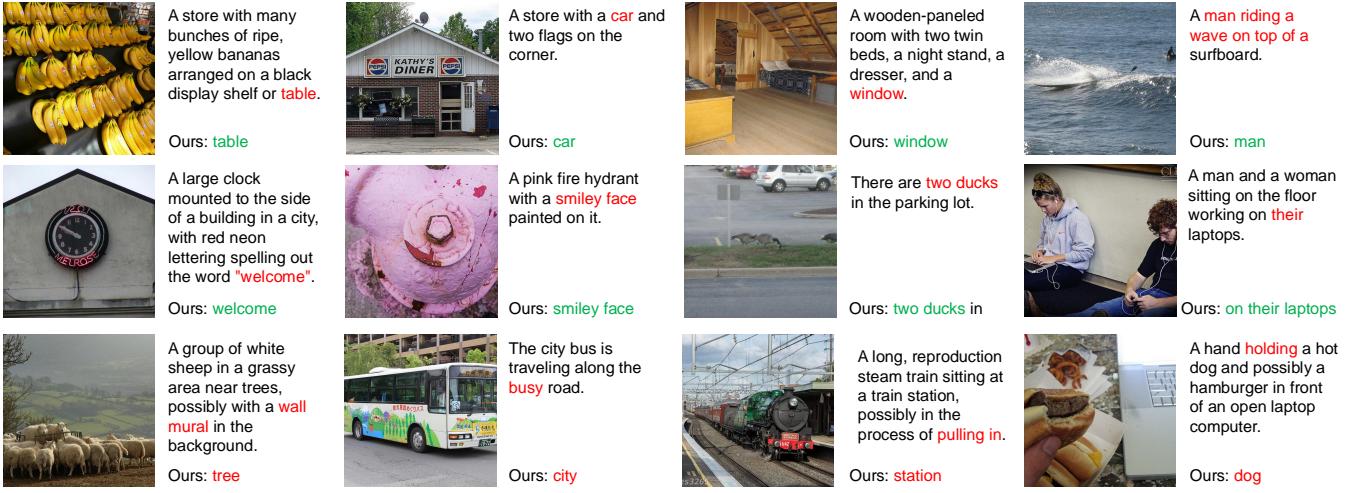


Figure 9: Qualitative examples on HAT.

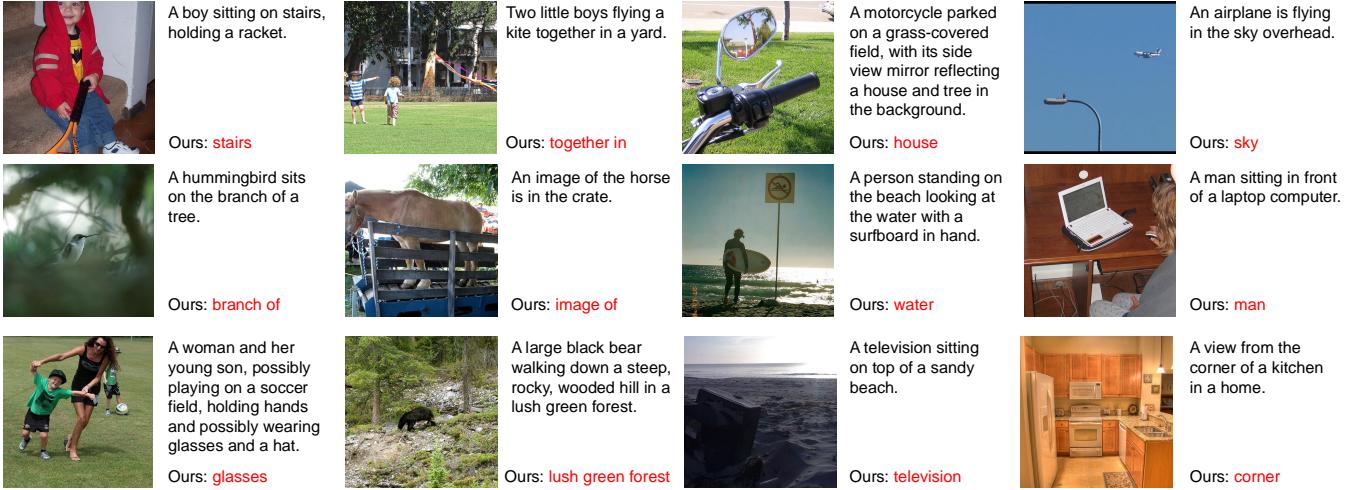


Figure 10: False positive cases on HAT.

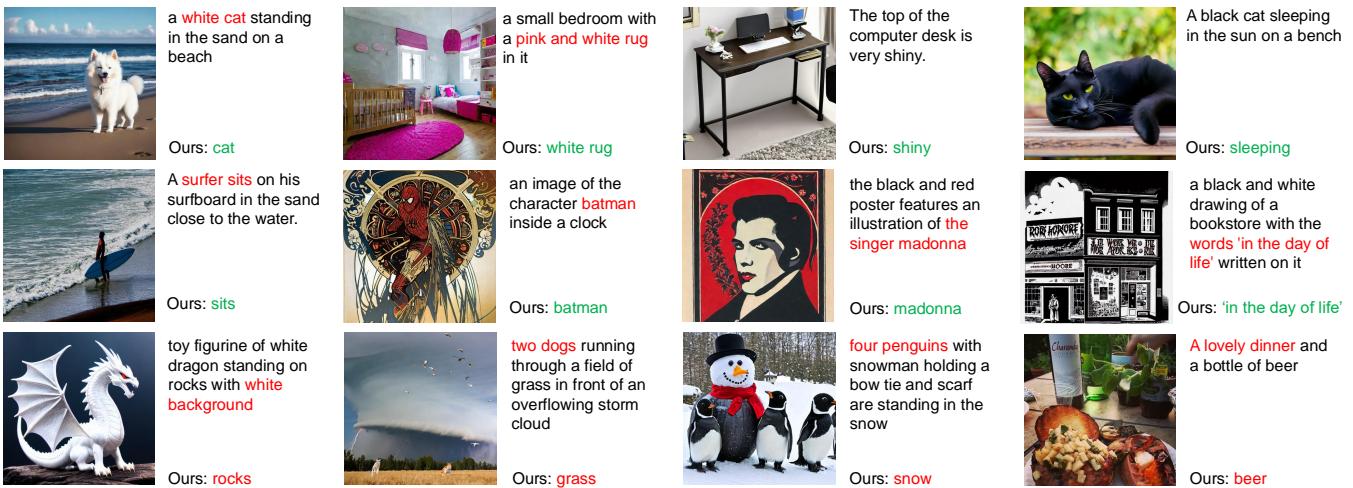


Figure 11: Qualitative examples on SeeTRUE-Feedback.

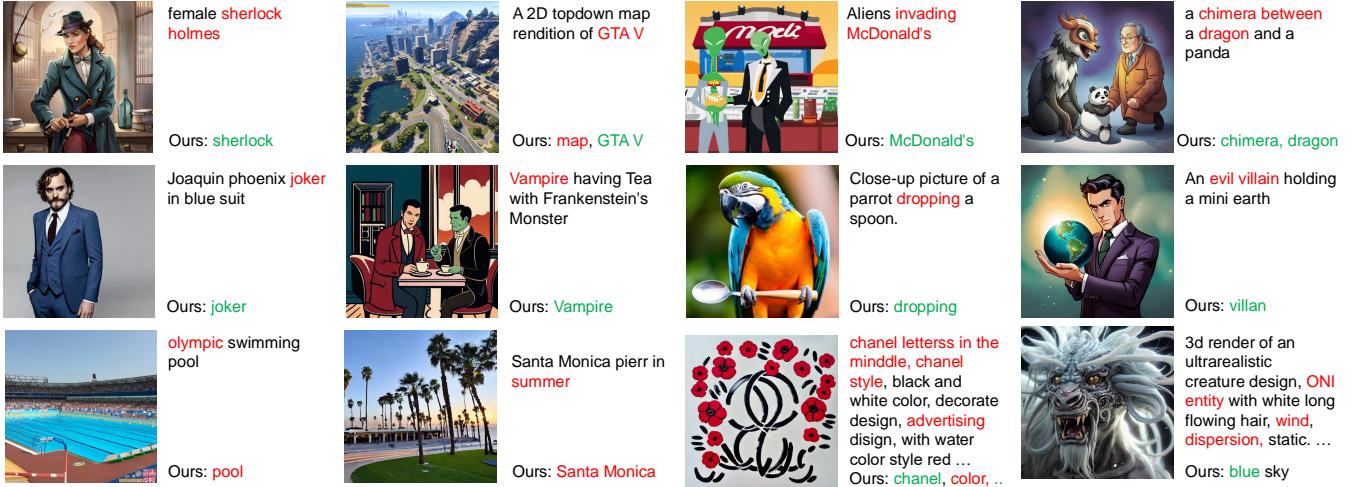


Figure 12: Qualitative examples on Rich-HF.

Model	Orientation Direction	Presence	State Condition	Quantity Count	Positional Relational	Color Appearance	Structural Physical	Texts	Viewpoint Perspective	MMVP Average
CLIPScore	6.7	13.3	20.0	13.3	6.7	53.3	26.7	6.7	13.3	17.8
F-CLIPScore	33.3	26.7	40.0	13.3	0.0	40.0	26.7	6.7	33.3	24.4

Table 12: Experiment results on MMVP benchmark. The scores of CLIPScore are reproduced using the publicly available repository. MMVP Average represents the macro average of the scores across nine visual patterns.

Model	REPLACE			SWAP		ADD		Overall
	Object	Attribute	Relation	Object	Attribute	Object	Attribute	
CLIPScore	94.07	79.19	65.15	60.41	62.31	78.32	71.53	76.78
F-CLIPScore	92.07	75.38	59.89	57.96	58.26	88.94	84.25	78.60

Table 13: Experiment results on SugarCrepe benchmark. The scores of CLIPScore are reproduced using the publicly available repository. Overall denotes the micro average score across the entire dataset.

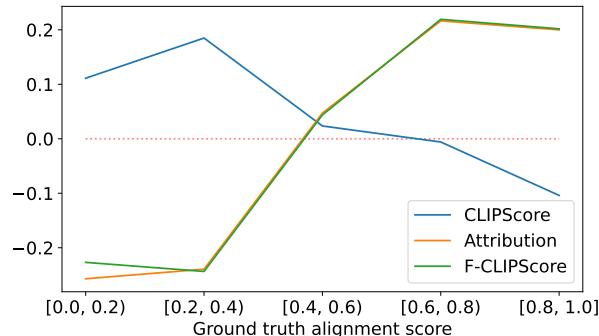
in distinguishing subtle misalignments. On the SugarCrepe benchmark, our approach achieves an overall improvement of 1.8%p gain as shown in Table 13. The main performance gain comes from the “add” form of hard negatives with a 10.6%p improvement in adding object concept and 12.7%p improvement in adding attribute concept. We hypothesize that adding words to a sentence can introduce a bias in CLIPScore due to its sensitivity to length (i.e., a longer sentence tends to yield higher CLIPScore regardless of correctness). In contrast, F-CLIPScore is more sensitive to detailed misalignments, improving performance. However, F-CLIPScore shows decreased performance compared to CLIPScore for “replace” and “swap” forms of hard negatives. We provide further analysis of the different tendencies of CLIPScore and F-CLIPScore in the following section.

D. Further Analyses on F-CLIPScore

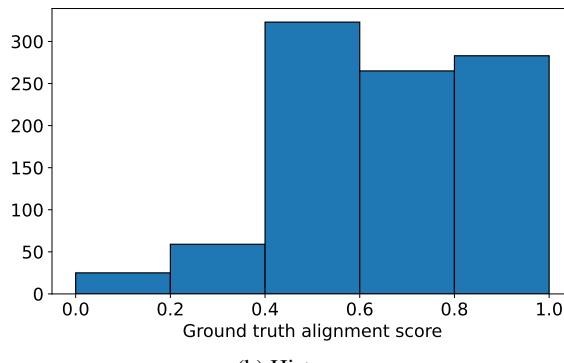
To evaluate the efficacy of F-CLIPScore, we present qualitative results on the nocaps-FOIL dataset. To elucidate the divergent tendencies between CLIPScore and F-CLIPScore, we sort the scores both in ascending and descending order. We then identify examples where the rank differential between the two metrics falls within the top 15% in opposite directions (e.g., instances where CLIPScore ranks in the top 1% while F-CLIPScore ranks in the bottom 13%).

Figure 14 and Figure 16 illustrate examples where CLIP-Score is high and F-CLIPScore is low. The results show that CLIPScore tends to assign significantly high values when salient and specific terms are correctly matched (e.g., “fishnet tights”, “zebra”, “superman”), even in the presence of obvious misalignments (e.g., “cookie” instead of “child”) in the caption. In contrast, F-CLIPScore exhibits greater sensitivity to these misaligned elements. This suggests that CLIP-Score may be disproportionately influenced by the presence of correctly identified prominent features, while F-CLIPScore is sensitive to misaligned words.

Figure 15 and Figure 17 show examples where F-CLIPScore is high, but CLIPScore is low. The observed pattern in these examples is subtle, revealing a complex relationship between the two metrics. In general, when captions are perfectly aligned but composed words are mainly common (e.g., “man”, “car”, “woman”), CLIPScore reports low value. It corresponds with a study that reveals CLIP has a bias for specified words (Pezzelle 2023). In contrast, F-CLIPScore reports high values for those captions. However, when apparent misalignments (e.g., “duck”) occur, F-CLIPScore unexpectedly yields high values in these cases. We observe that when CLIPScore is extremely low, the gradients are distributed across multiple tokens, resulting in few tokens having gradients lower than epsilon.



(a) Pearson correlation coefficients



(b) Histogram

Figure 13: Analysis of group-wise Pearson correlation coefficients and histogram distributions of ground truth alignment scores in Rich-HF dataset. We conduct analysis by dividing the ground truth alignment scores into five groups.

This phenomenon highlights a limitation of the proposed F-CLIPScore metric, necessitating careful interpretation, especially when CLIPScore is low. However, as discussed in Figure 6, the median CLIPScore typically ranges between 0.6 and 0.8, indicating that such extremely low scores are not common in the generated output. It may be advisable to exclude outlier samples whose CLIPScore is extremely low and apply F-CLIPScore selectively to capture factual alignments.

From the results, we conduct further analysis of the relationship between CLIPScore and F-CLIPScore. Since the Rich-HF dataset contains human-labeled alignment scores for images and text, we divide them into five groups and obtain Pearson correlation coefficients with CLIPScore, attribution scores, and F-CLIPScore for each group, as shown in Figure 13. Note that attribution scores indicate $\sum_j \text{mis}(w_j) \cdot w_j$ on the Equation (11) from the main manuscript. As shown in Figure 13a, CLIPScore and F-CLIPScore demonstrate opposite patterns: CLIPScore and F-CLIPScore show low performance in groups with high and low ground truth alignment scores, respectively.

As mentioned in the previous paragraph, because of this tendency, CLIPScore and F-CLIPScore should be inter-

backbone	source	pretrained	IN acc.	LA	AP
ViT-B/32	openai	WIT-400M	0.632	0.602	0.723
ViT-B/32	openclip	LAION-2B	0.656	0.667	0.760
ViT-B/16	openai	WIT-400M	0.687	0.679	0.747
ViT-L/14	openai	WIT-400M	0.753	0.653	0.781
ViT-L/14	openclip	LAION-2B	0.753	0.728	0.796
ViT-H/14	openclip	LAION-2B	0.780	0.716	0.806
ViT-g/14	openclip	LAION-2B	0.766	0.706	0.806

Table 14: Various backbone comparisons on nocaps-FOIL dataset. IN acc. refers to ImageNet accuracy.

preted carefully. However, since samples with low alignment scores are generally not generated in recent generative models as shown in Figure 13b, F-CLIPScore shows better performance than CLIPScore and will have higher usability for detecting misalignments.

E. Ablation on Backbones

We conduct an ablation study examining the impact of varying model backbone and pretraining corpora on performances (Radford et al. 2021; Cherti et al. 2023). Experiments were performed on the nocaps-FOIL dataset, with \tilde{l} set to the last three layers of each text encoder. Results in Table 14 demonstrate a scaling law in general. Performance in Localization Accuracy (LA) and Average Precision (AP) improve with increased backbone size. Notably, ImageNet accuracy shows a positive correlation with both LA and AP, indicating a strong dependence on CLIP backbone performance. Models pre-trained on LAION-2B (Castro, Ignat, and Mihalcea 2023) consistently outperform those trained on 400M WebImageText (WIT) (Radford et al. 2021) in both metrics. For instance, two ViT-L/14 variants, both achieving identical ImageNet accuracy (Deng et al. 2009) but pre-trained on different datasets (WIT-400M vs. LAION-2B), show varied performances. The variant trained on LAION-2B shows significantly improved performance, showing superior capabilities in detecting a wider range of misaligned words.

F. Discussions

Despite the efficacy of our method, several limitations merit further examination. Firstly, as discussed in our analysis, our approach inherits known weaknesses from CLIP. However, various studies have addressed these shortcomings of CLIP, focusing on issues such as numbers (Paiss et al. 2023), compositionality (Yuksekgonul et al. 2023), or small or insalient objects (Yao et al. 2022; Mukhoti et al. 2023). We leave evaluating CLIP variants specifically trained to address these shortcomings as future work.

Secondly, the token length constraint poses challenges for long-context understanding. Although CLIP models trained on extended sequences (Zhang et al. 2025) may partially alleviate this issue, it remains a potential drawback for tasks requiring broader contextual comprehension.

Thirdly, our analysis reveals that F-CLIPScore performs poorly when CLIPScore is extremely low due to the distribution of gradients. While our research primarily focuses on detecting dense misalignments from generated models, which typically have relatively well-aligned image-caption

pairs, applying F-CLIPScore to noisy alt-text could be sub-optimal. A sophisticatedly designed F-CLIPScore that can adapt to significantly low CLIPScores would be beneficial.

Lastly, our method generally shows higher recall but lower precision. It would be an interesting area of research to further sophisticate the design of the attribution calculation or refinement method to achieve more precise results. Despite its low precision, it is worth noting that its superior computational efficiency facilitates large-scale applications. We leave it as future work to explore whether leveraging this scalability for extensive data correction (e.g., removing mis-aligned words in captions) or for large-scale reinforcement learning from AI feedback could potentially enhance overall performance.

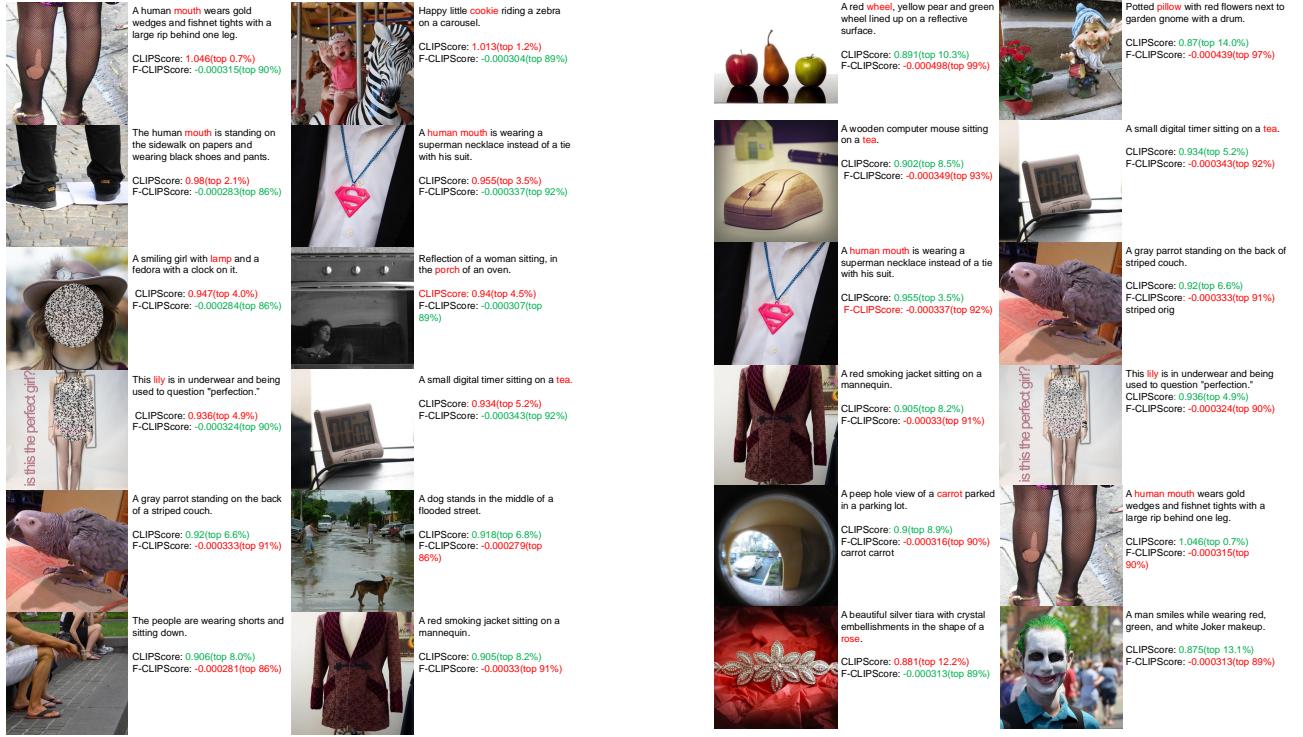


Figure 14: Qualitative examples on nocaps-FOIL sorted by CLIPScore in descending order.

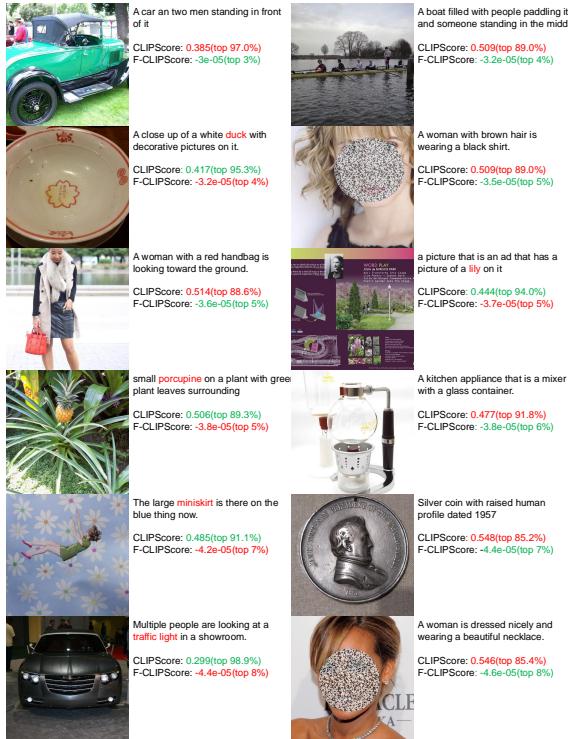


Figure 15: Qualitative examples on nocaps-FOIL sorted by F-CLIPScore in descending order.

Figure 16: Qualitative examples on nocaps-FOIL sorted by F-CLIPScore in ascending order.

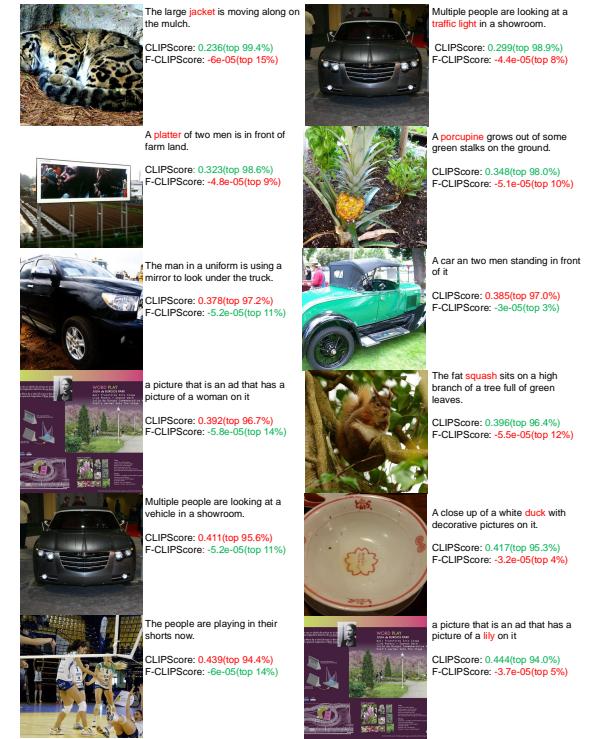


Figure 17: Qualitative examples on nocaps-FOIL sorted by CLIPScore in ascending order.