

Multi-Modal Hallucination Control by Visual Information Grounding

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Abstract

Generative Vision-Language Models (VLMs) are prone to generate plausible-sounding textual answers that, however, are not always grounded in the input image. We investigate this phenomenon, usually referred to as *hallucination*, and show that it stems from an excessive reliance on the language prior. In particular, we show that as more tokens are generated, the reliance on the visual prompt decreases, and this behavior strongly correlates with the emergence of hallucinations. To reduce hallucinations, we introduce Multi-Modal Mutual-Information Decoding (M3ID), a new sampling method for prompt amplification. M3ID amplifies the influence of the reference image over the language prior, hence favoring the generation of tokens with higher mutual information with the visual prompt. M3ID can be applied to any pre-trained autoregressive VLM at inference time without necessitating further training and with minimal computational overhead. If training is an option, we show that M3ID can be paired with Direct Preference Optimization (DPO) to improve the model's reliance on the prompt image without requiring any labels. Our empirical findings show that our algorithms maintain the fluency and linguistic capabilities of pre-trained VLMs while reducing hallucinations by mitigating visually ungrounded answers. Specifically, for the LLaVA 13B model, M3ID and M3ID+DPO reduce the percentage of hallucinated objects in captioning tasks by 25% and 28%, respectively, and improve the accuracy on VQA benchmarks such as POPE by 21% and 24%.

1. Introduction

Recent autoregressive Vision-Language Models (VLMs) have shown remarkable multimodal capabilities [4, 13]. However, VLMs, similarly to large language models (LLMs), are prone to *hallucinations*—generating

Figure 1. **Multi-Modal Mutual Information Decoding (M3ID)**. Given a VLM p , an image c , and a text prompt, M3ID intervenes in the generative distribution by adding tokens that surprised the unconditioned VLM (i.e., the VLM without the image prompt). M3ID amplifies the conditioned directions that are not already predicted by the unconditioned model more as new tokens are generated by leveraging a progressively smaller ϵ . In the example, the VLM assigns a high likelihood to the hallucinated object *fridge*, over-relying on its unconditioned language prior. Instead, M3ID assigns a high likelihood to *toaster*, which is present in the image.

plausible-sounding answers without factual basis, leading to potentially *ungrounded* or fabricated information [7]. Consequently, the community has been developing ever so complex and expensive alignment algorithms involving direct human supervision [17] and often brittle prompt engineering methods (model begging) [28].

In this work, we propose to investigate hallucinations in VLMs through a quantifiable measure of visual *prompt dependency*. We assess whether a model output is ungrounded with respect to a visual prompt by comparing its likelihood with the likelihood of generating the same output

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without the visual information. In general, our measure of visual prompt dependency quantifies the extent to which a token is generic or specific to a visual signal. Importantly, low visual prompt dependency does not necessarily imply that a token is hallucinated, as it may occur in linguistically essential elements like conjunctions and prepositions. Yet, unlike the notion of hallucinations, which requires human judgment, our prompt dependency measure is always well-defined even without any ground truth annotations.

Our first contribution is to empirically demonstrate that the visual prompt dependency measure decreases as more tokens are generated. In Fig. 3, we show that, as more tokens are generated, the conditioning information gets diluted and “forgotten or ignored by the model, possibly leading to more hallucinations. We refer to this effect as *conditioning dilution* or *fading memory effect*.

To counteract this, we propose an intervention on the generative distribution of a VLM that maximizes visual prompt dependency at inference time. We show that our method for *prompt amplification* maximizes the mutual information between the text output tokens and the visual prompt, effectively rescaling the image-conditioned component against the unconditioned distribution. We name our inference-time intervention on the generative distribution *Multi-Modal Mutual Information Decoding* (M3ID). M3ID is applicable to any off-the-shelf model without additional training or access to model weights, offering a low computational overhead alternative to standard decoding algorithms [13, 24]. Our results show that M3ID enhances the dependence on the visual prompt and reduces the number of hallucinations across various benchmarks while preserving the linguistic fluency of the original model.

Additionally, for users with access to model weights, we propose a training objective to further ground the model outputs on visual prompts. This approach involves recasting our prompt amplification objective as a preference optimization problem, using Direct Preference Optimization (DPO) [19] to align the pre-trained VLM. This method aims to increase the likelihood of continuations with a higher visual prompt dependency measure and allows to learn a better generation policy, further reducing the conditioning dilution effect and hallucinations.

In summary, our main contributions are as follows:

1. We propose a visual prompt dependency measure (PDM) to assess whether a model output is ungrounded with respect to the visual input. Empirically, we demonstrate that PDM decreases as more tokens are generated making the generations more likely to be hallucinated.
2. We introduce M3ID, a training-free intervention on the generative distribution of autoregressive VLMs which improves visual grounding and reduces hallucinations by amplifying the importance of the visual prompt over the language prior. In addition, we extend M3ID with

DPO for multi-modal preference optimization to further improve visual grounding.

3. We show that applying M3ID or DPO reduces the percentage of hallucinated objects in *captioning tasks* [20] by 25% and by 28%, respectively and improves accuracy on the POPE [9] VQA hallucination benchmark by 21% and 24% over the base model.

2. Related work

Hallucinations in VLMs. A recent line of work introduced VLMs obtained by *grafting* visual encoders into pre-trained Large Language Models (LLMs) [4, 13, 32]. Forcing a pre-trained LLM to learn to “see” by reading vision tokens from a pre-trained vision backbone has proven successful and the resulting models show remarkable vision-language understanding capabilities on many multi-modal tasks [13, 23]. However, while inheriting strong linguistic capabilities and fluency from their base LLM, grafted VLMs also inherit the tendency to produce ungrounded or fabricated information [1, 6]. This is commonly referred to as *hallucination* in the recent machine learning literature [1, 6, 25]. In particular, several recent works empirically reported a sharp tendency of grafted VLMs to report objects not grounded on the visual information when probed with questions on the image content [1, 6, 9, 27]. The authors of [9] observed that this phenomenon is especially pronounced with objects that are either common or frequently appear together in the datasets used at training time. Furthermore, the authors of [11] suggest that VLMs often fail to correctly follow instructions involving absent objects and propose a new instruction-following training objective to enhance model alignment and robustness in the face of uncertainty. Parallel to our work, [31] delves into the factors contributing to object hallucinations in VLMs, exploring aspects like object co-occurrence, model uncertainty, and spatial position of hallucinations in the sentence. They propose a post-hoc algorithm to identify and correct hallucinations in VLM-generated content.

Context-dependent decodings. Decoding algorithms can be classified as either search or sampling algorithms [8]. Current search methods (e.g., greedy and beam search) can produce factually accurate generations but usually suffer from tedious and repetitive continuations. Sampling methods, on the other hand, (like nucleus [5], or typical decoding [15]) produce more diverse text, but suffer from topic drift. To solve these shortcomings, various decoding methods have been proposed to enhance reasoning and factual accuracy in generative autoregressive language models. Approaches such as context-aware decoding [21] and Pointwise Mutual Information (PMI) decoding [16, 25] focus on aligning the outputs of language models with the intended context or factual data. These strategies aim to reduce hal-

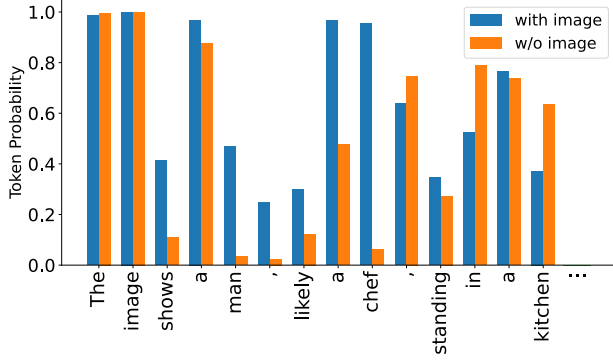


Figure 2. **How much does the conditioning prompt “surprise” the unconditioned predictor?** We report the likelihood that the conditioned and unconditioned models assign to each token in the string “The image ...”. The probability gap increases on tokens for which visual information is required (e.g. objects and attributes), while it decreases for punctuation and articles. Note that both models mostly agree when sufficient visual information has already been extracted and is present in the caption (e.g. “kitchen” is very likely for the unconditioned model as well). See Sec. D.1 for a plot with our prompt dependency measure.

lucinations in standard natural language processing tasks such as summarization. Mutual-information-based decoding techniques have proven to be helpful in steering the generation of LLMs to stay faithful to the given input text [25], or to promote diversity or relevance in neural dialogue models [7]. Our work is the first to use mutual information to improve multi-modal grounding and to vary the penalization of marginally likely outputs in a time-varying fashion to counteract the progressive forgetting of the visual prompt.

3. Analysis of hallucinations in VLMs

We start by investigating hallucinations in VLMs. We introduce a visual *prompt dependency measure* (PDM), which will later motivate our algorithms (Sec. 4). The main aim of this section is to assess whether a model output, such as a token, is hallucinated or not by comparing its likelihood with the likelihood of that same output being generated without the relevant conditioning factor, in this case, the image.

We consider decoding approaches for open-ended language generation of VLMs, where the model receives an input image and an input textual prompt and aims to generate a fluent and coherent continuation conditioned on both the image and the text. We denote probabilistic generative VLMs over a vocabulary of text tokens V with p and denote the probability of a token $y \in V$ given a textual prompt \mathbf{x} and an image context c as $p(y|\mathbf{x}, c)$. The goal of the VLM is to leverage the information contained in the input image c to provide a continuation $\mathbf{y} = [y_0, \dots, y_T]$ of the input prompt \mathbf{x} , e.g., “Describe this image in detail.”. The probability of a valid sequence \mathbf{y} can be computed as $p(\mathbf{y}|\mathbf{x}, c) = \prod_{t=1}^T p(y_t|\mathbf{y}_{<t}, \mathbf{x}, c)$, where $\mathbf{y}_{<t} = [y_0, \dots, y_{t-1}]$.

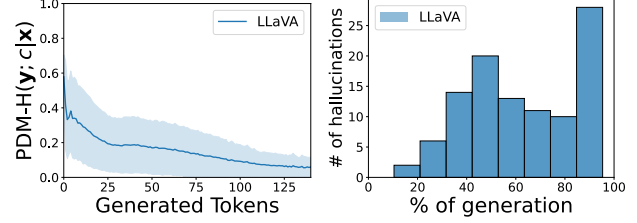


Figure 3. **The influence of the image conditioning decreases as we generate more tokens.** (Left) **Conditioning dilution.** We report the average of the prompt dependency measure (PDM-H) and its standard deviation for different synthetic captions generated by LLaVA on MS COCO validation split. We see that the influence of the image over the next token prediction decreases as we generate more. This suggests that the information within VLM’s visual prompt gets diluted and fades away as more tokens are generated. (Right) **Frequency of hallucinated objects as a function of the token position.** We report the number of non-existent objects present on the same synthetic captions as a function of the number of generated tokens. Note that very few objects are hallucinated for tokens near the visual prompt, while their number increases as more tokens are generated and with a smaller PDM.

We propose to study hallucinations on VLMs using PDMs defined as follows

$$\text{PDM}(\mathbf{y}_{<t}; c|\mathbf{x}) = \text{dist} \left(p(\cdot|\mathbf{y}_{<t}, \mathbf{x}, c), p(\cdot|\mathbf{y}_{<t}, \mathbf{x}) \right)$$

where dist is any distance measure between probability distributions, such as Hellinger, total variation, or KL. PDMs quantify how generic or context-specific a language model’s output is. In particular, a high PDM $(\mathbf{y}_{<t}; c|\mathbf{x})$ indicates that the token y_t is strongly associated with a specific input prompt, while a low PDM suggests that the token is more prompt-neutral or prompt-agnostic. Depending on the choice of the distance function, PDMs highlight different aspects of the generative distribution. We will mainly use PDM-H based on the Hellinger distance defined as $H(p, q) = 2^{-1/2} \sqrt{\sum_{i=1}^k (\bar{p}_i - \bar{q}_i)^2}$, where $p = (p_i)_{i \in [k]}$ and $q = (q_i)_{i \in [k]}$ are discrete probability distributions. We refer the reader to the Supplementary Material for an analysis of the impact of other distances.

Contextual pressure. Fig. 2 shows the conditional and unconditional prediction likelihoods on a single caption. First, we note that tokens that are required for linguistic fluency, like prepositions and conjunctions, are highly predictable by both the conditioned and the unconditioned models. This pattern also emerges when the model generates tokens to compose “fine-grained” objects. For example, when the model generates “Peanut butter” both the VLM and the LLM can correctly predict the last token even without looking at the image and only having access to a sufficiently long truncation (e.g. “Peanut bu”). Therefore, in these circumstances, $p(y_t|\mathbf{y}_{<t}, \mathbf{x}, c)$ and $p(y_t|\mathbf{y}_{<t}, \mathbf{x})$ can be very close

irrespective of the number of generated tokens and without implying a higher hallucination risk. We will refer to this phenomenon as *contextual pressure*.

Conditioning dilution and hallucinations. In Fig. 3 we show that PDM-H decreases as more tokens are generated, indicating that the visual information gets diluted and neglected by the model throughout the generation process. This phenomenon suggests that the conditioned model distribution gets closer to the unconditioned one, the language prior, as we generate more tokens. In other words, the VLM places high probability mass on marginally likely tokens that are mostly explained by their language priors, $p(y_t/y_{<t}, \mathbf{x}, c) \rightarrow p(y_t/y_{<t}, \mathbf{x})$ as t increases. We refer to this phenomenon as *conditioning dilution* or *fading memory effect*. While conditioning dilution is not necessarily an issue (for instance, if the generated text has already extracted all of the relevant information from the context), one ideally would want to prevent the model from only relying on language priors based on the generated caption which may lack important details and facilitate hallucinations. Notice that whereas PDMs are useful for measuring the importance of the visual prompt, their values do not fully characterize the likelihood of generating ungrounded tokens. Therefore, in Fig. 3 we empirically test how much our prompt dependency measure correlates with the number of hallucinated objects generated by a SOTA VLM (LLaVA [13]) on the MS COCO dataset [10]. In the figure, we report the number of non-existent objects on captions generated by LLaVA as a function of the number of generated tokens. Note that very few objects are hallucinated near the input context, while their number increases as the PDM gets smaller. This motivates us to intervene in the generative distribution to maximize the PDM in order to reduce hallucinations.

4. Methods

Building on insights from Sec. 3, we formalize how to model the generation of VLMs as a fading memory process and how to intervene in the generation to prevent the VLM from “forgetting” the visual prompt c . In this section, we denote the log probabilities as $l(y_t/y_{<t}, \mathbf{x}, c)$ $\log p(y_t/y_{<t}, \mathbf{x}, c)$.

4.1. M3ID: Improving grounding at inference time

As we have shown in Sec. 3, within their prediction horizon, VLMs can be modeled as fading memory autoregressive systems [14, 30]: the more they generate the smaller the impact of the visual information on the generated tokens. As such, the longer the generation, the higher the reliance on the language priors which favor continuations not specifically grounded on the conditioning signal.

Preventing conditioning dilution. Under the fading memory assumption, we model the conditioned log probabilities

$l(y_t/y_{<t}, \mathbf{x}, c)$ (for example, LLaVA [13]) as an interpolation between the unconditioned model and a model l that does not “forget” old context as more tokens are generated.

$$l(y_t/y_{<t}, \mathbf{x}, c) = \alpha_t l(y_t/y_{<t}, \mathbf{x}, c) + (1 - \alpha_t) l(y_t/y_{<t}, \mathbf{x}) \quad (1)$$

where $\alpha_t \in [0, 1]$ is a mixing coefficient which monotonically decreases over time. When α_t is small, the conditional distribution is mostly explained without providing the input image, and the conditioned distribution “forgets” c , while for higher α_t , the input image becomes more relevant. We take $\alpha_t = \exp(-\beta t)$, models the rate of change of α_t and defines the fading memory rate (forgetting rate [14, 30]).

Given observations from the conditioned distribution $l_c = l(y_t/y_{<t}, \mathbf{x}, c)$ and the unconditioned one $l_u = l(y_t/y_{<t}, \mathbf{x})$, our goal is to find an estimate \hat{l} of the latent generative distribution l which does not forget the past.

To do so, we assume that l is a perturbation of the conditioned distribution, $l = l_c + \delta$, where δ can be assumed to be a random variable with zero mean and bounded variance. Therefore we rewrite our model in Eq. (1) as:

$$(1 - \alpha_t)(l_c - l_u) = \alpha_t \delta. \quad (2)$$

Over the time index t , Eq. (2) is a stochastic process across tokens whose variance decreases over time. Hence, we can estimate the optimal intervention on l_c to counteract the fading memory effect and get closer to l as $\hat{l} = l_c + \hat{\delta}$. We use measurements from Eq. (2) to estimate the correction term $\hat{\delta}$. This brings us to the optimal intervention:

$$\hat{l} = l_c + \frac{1 - \alpha_t}{\alpha_t} (l_c - l_u). \quad (3)$$

Note that the optimal sampling distribution l is approximately proportional to l_c at the beginning of the generation (i.e., when α_t is close to 1), which translates to sampling from the conditioned distribution alone. On the other hand, far from the input prompt (i.e., $\alpha_t \rightarrow 0$) the optimal sampling distribution becomes proportional to $l_c - l_u$. This amplifies tokens proposed by l_c that surprise the unconditional policy l_u and can be thought of as a way to ameliorate the conditioning dilution phenomenon described in Sec. 3. From an information theory viewpoint, the second scenario corresponds to maximizing the pairwise mutual information between the visual input and the text tokens instead of maximizing the log-likelihood of the text tokens alone. In fact, $\max_{\mathbf{y}} \log \frac{p(c, \mathbf{y} | \mathbf{x})}{p(c)p(\mathbf{y} | \mathbf{x})} = \max_{\mathbf{y}} \log \frac{p(\mathbf{y} | \mathbf{x}, c)}{p(\mathbf{y} | \mathbf{x})} = \max_{\mathbf{y}} l_c - l_u$ [7, 25].

Accommodating for contextual pressure. Notice, however, that the contextual pressure forces l_c and l_u to be similar irrespective of the number of generated tokens. As such, penalizing the language prior l_u by amplifying $l_c - l_u$ indiscriminately would sometimes also penalize correct but

obvious tokens that do not require the input image to be inferred (like prepositions or conjunctions). To avoid such a scenario, we suppress our intervention in Eq. (3) when the contextual pressure is high. Specifically, if the conditioned model I_c is highly *confident* on the next token (i.e., it has the maximum probability above a threshold [8]) we do not apply the correction term $I_c - I_u$.

Multi-Modal Mutual Information Decoding (M3ID). Putting everything together, our Multi-Modal Mutual Information Decoding Algorithm 1 for generation is given by:

$$y_t = \arg \max_y \hat{I}(y/y_{<t}, \mathbf{x}, c) \quad (4)$$

where $\hat{I} = I_c + \max_k(I_c)_k < \log \frac{1-t}{t}(I_c - I_u)$. M3ID can be applied to different search algorithms like greedy search (as in Eq. (4)) or beam search.

4.2. M3ID+DPO to learn more grounded policies

With access to compute and model weights, we can optimize the model to output continuations that are more grounded to the image content. In this section, we reframe this goal into a *preference optimization problem*, where the objective is to prefer grounded continuations over ungrounded ones and fine-tune the VLM using this objective.

Multi-modal preference optimization. Consider two different continuations \mathbf{y}_w and \mathbf{y}_l of the same prompt \mathbf{x} for the image c , with \mathbf{y}_w being preferred over \mathbf{y}_l . Direct Preference Optimization (DPO) [19] is an alignment technique that aims at learning a generative policy that is more likely to generate continuations *similar* to \mathbf{y}_w rather than \mathbf{y}_l . In particular, given a dataset D containing preference data pairs $(\mathbf{y}_w, \mathbf{y}_l)$, DPO minimizes the following loss function,

$$\begin{aligned} L_{\text{DPO}} = -\mathbb{E}_{(c, \mathbf{x}, \mathbf{y}_w, \mathbf{y}_l) \in D} \log & \frac{p(\mathbf{y}_w/c, \mathbf{x})}{p_{\text{ref}}(\mathbf{y}_w/c, \mathbf{x})} \\ & - \log \frac{p(\mathbf{y}_l/c, \mathbf{x})}{p_{\text{ref}}(\mathbf{y}_l/c, \mathbf{x})}, \end{aligned}$$

where p_{ref} denotes the VLM before DPO training and p the model being trained. In short, the intuition behind this objective is to increase the likelihood of the completion \mathbf{y}_w with respect to the base model p_{ref} while decreasing the likelihood of generating \mathbf{y}_l relative to the base model.

Generating multi-modal preference data The success of DPO hinges on the quality of the pairs in the dataset D . Therefore, we propose to fine-tune a pre-trained VLM using the DPO objective while ensuring that the preferred continuations are more grounded to the visual information. To do so, we generate preferred continuations by sampling from the pre-trained conditioned distribution improved with M3ID $\mathbf{y}_w \sim p(\mathbf{y}/\mathbf{x}, c)$, while we generate negative continuations by sampling from the unconditioned distribution

Algorithm 1: M3ID

Input: VLM p , textual prompt \mathbf{x} , image c , threshold on confidence, forgetting rate

Output: Generated string \mathbf{y} conditioned on \mathbf{x} and c

$y_0 = \text{BOS}, t = 1$

while $y_t \neq \text{EOS}$ **do**

$t \leftarrow \exp(-t)$

$I_c \leftarrow \log p(y/y_{<t}, \mathbf{x}, c)$

$I_u \leftarrow \log p(y/y_{<t}, \mathbf{x})$

$\hat{I} = I_c + \max_k(I_c)_k < \log \frac{1-t}{t}(I_c - I_u)$

$y_t = \arg \max_y \hat{I}(y/y_{<t}, \mathbf{x}, c)$

end

$\mathbf{y}_l \sim p(\mathbf{y}/\mathbf{x})$. However, notice that generating text continuations from \mathbf{x} (e.g., "Describe the image.") with the unconditioned model leads to negative continuations \mathbf{y}_l that are often very different from the image caption and thus provide a little signal in the DPO objective. To overcome this limitation we append to \mathbf{x} the first sentence generated by the conditioned VLM to restrict the set of possible continuations.

5. Experiments

We evaluate our methods on standard captioning and VQA benchmarks on MS COCO [10], an object detection and captioning dataset with annotations for 80 object categories. We use ground-truth annotations to measure the number of ungrounded objects that are predicted by our models.

Architecture. Our method applies to any VLM, as long as it is possible to drop the visual conditioning to compute the language-only prior. In the following, we shall mainly use the LLaVA architecture [13]. LLaVA is an open-source VLM connecting a frozen pre-trained open-set visual encoder with a pre-trained large language model via a trainable linear mapping layer. As a vision encoder, we use CLIP ViT L-14 [18]. As a large language model, we use the 7B and 13B versions of Vicuna v1.3 [3], which are instruction-tuned from LLaMA [24]. All our base models have been trained on LCS-558K [12] and LLaVA-Instruct-80K [13]. We follow the default query format used in LLaVA-v1.3 for the input data [13]. Furthermore, in Sec. D.3 we extend our evaluations to InstructBLIP [4], which introduces a Q-Former to bridge the vision and language modalities.

Baselines. For our baseline methods, we consider generation using standard multinomial sampling [13, 24] where the next token is randomly sampled from the prediction distribution with a given temperature parameter (0.2 for LLaVA [13]). Furthermore, we compare M3ID with other training-free methods for autoregressive models like PMI [25] and Contrastive Decoding [8]. PMI is developed for text summarization and improves the grounding of text gen-

Table 1. Evaluation of vision-language grounding on the validation set of MS COCO [10]. Captioning results are obtained by prompting the model with the task “Describe the image”. *CHAIRi* and *CHAIRs* [20] denote the percentage of hallucinated objects and captions respectively, with lower values corresponding to fewer hallucinations. *Cover* indicates the percentage of annotated objects that are mentioned in the captions. We use LLaVA-v1.3.

	CHAIRi	Captioning CHAIRs	Cover
LLaVA _{7B}	8.1	17.5	53.3
LLaVA _{7B} PMI [25]	6.7	16.2	51.5
LLaVA _{7B} Contrastive [8]	6.3	14.8	55.2
LLaVA_{7B} M3ID	5.9	13.8	55.1
LLaVA _{13B}	7.4	18.5	55.2
LLaVA _{13B} PMI [25]	6.5	16.6	54.7
LLaVA _{13B} Contrastive [8]	6.5	14.5	54.7
LLaVA_{13B} M3ID	5.5	13.2	54.0
LLaVA _{13B} + LURE [31]	6.4	27.1	–
mPLUG-Owl + LURE [31]	5.4	18.8	–
LLaVA_{7B} M3ID + DPO	5.7	13.5	55.8
LLaVA_{13B} M3ID + DPO	5.3	12.6	54.2

eration by increasing the likelihood of generating tokens that are related to the text to be summarized. Differently from our method, the weight assigned to the realization of marginally likely continuations is time-independent. Similarly, Contrastive Decoding [7, 8] has been developed to foster generations of an *expert* LLM to contain plausible and *coherent* text with the textual input prompt by amplifying its prediction difference with respect to a weaker model. To ensure a fair comparison, we replace the text to be summarized with the input image for PMI and set the weaker model in Contrastive Decoding as the unconditioned model (see Sec. B for more details). We also compare with training-based methods that have been proposed to improve the grounding of VLMs on the visual prompt like LLaVA-RLHF [17], Robust mPLUG-Owl [11] and LURE [31]. However, all these methods require some form of annotations, like preference data [17] or positive/negative examples [11, 31], which M3ID+DPO does not require.

Evaluation. We evaluate our algorithm both on captioning and VQA benchmarks. On captioning, we measure object hallucinations by using the CHAIR (Captioning Hallucination Assessment with Image Relevance) metrics [20]. These metrics assess the quality of captions by comparing the mentioned objects to the annotated objects present in an image. In particular, CHAIR comprises two variants: one computes the fraction of hallucinated objects in the whole caption (CHAIRi) and the other evaluates the fraction of captions with at least one object hallucination (CHAIRs),

$$\text{CHAIRi} = \frac{\# \text{ hallucinated objects}}{\# \text{ generated objects}},$$

$$\text{CHAIRs} = \frac{\# \text{ hallucinated captions}}{\# \text{ generated captions}}.$$

Furthermore, we introduce the *Cover* metric to quantify the comprehensiveness of the captions by measuring the fraction of ground-truth annotated objects mentioned by the model,

$$\text{Cover} = \frac{|\{\text{correct mentioned objects}\}|}{|\{\text{annotated objects}\}|}.$$

To evaluate object perception, we use the POPE (Polling-based Object Probing Evaluation) VQA benchmark [9]. In particular, POPE recasts the evaluation of object hallucinations into a binary classification problem with yes/no questions of the type “Is a *object* present in the image?”

DPO training details. We use Hugging Face’s DPO implementation in the TRL library [26] and train LLaVA for 5 epochs on 10,000 self-generated preference pairs with LoRA and cosine decaying learning rate with 2×10^{-5} peak. Following [19], we set $\beta = 0.1$ in the DPO loss.

5.1. VLM grounding on captioning

In Tab. 1 we test how much our method can prevent the generation of hallucinated objects in image captions. In particular, we compare against training-free and training-based baselines. We prompt all baseline methods with the instruction “Describe the image.” and let the models generate until the EOS token is obtained.

First, we compare M3ID with other decoding strategies, PMI [25] and Contrastive Decoding [8]. The main difference between M3ID and these baselines is that M3ID increasingly counteracts the language prior as more tokens are generated. As such, M3ID reduces ungrounded generations compared to all other training-free baselines both on the large LLaVA13B and on the smaller LLaVA7B. Furthermore, it has uniformly good improvements for different model sizes over standard multinomial decoding, in particular, M3ID achieves 27%/21% relative improvement over LLaVA7B and 26%/29% over LLaVA13B on the CHAIRi and CHAIRs metrics. Importantly, this improvement does not come at the price of high reductions of the Cover metric, which actually improves on the 7B model and decreases by less than 2.2% for the larger 13B model¹. Lastly, we note that M3ID shows an improvement in absolute performance that correlates with model size, suggesting that further gains could be obtained as larger models are used. In Sec. D.2, we also show that M3ID still improves grounding when longer captions (twice as long on average) are generated and where other decodings do not perform as well.

In Tab. 1 we also report training-based results and show that pairing DPO with M3ID leads to a smaller number

¹Note that CHAIR metrics can be hacked by simply returning shorter captions that do not attempt to predict any object in the image.

Table 2. Evaluation on the POPE VQA hallucination benchmark [9]. ; \dagger indicate results taken from [11] and [23] respectively. *SUP.* Indicates that the method involves supervised training on annotated data, in contrast to our approaches. POPE is divided into three subsets, *Random*, *Popular*, and *Adversarial*. We report the VQA accuracy of the model using the following template: “Is a object present in the image? object where we sample object randomly (Random), among the most frequent objects in the dataset (Popular), or among the objects that frequently co-occur with object (Adversarial). *Acc.* is the binary classification accuracy and *Yes* is the percentage of “Yes” answers.

	POPE							
	Random		Popular		Adversarial		All	
	Acc.	Yes (%)	Acc.	Yes (%)	Acc.	Yes (%)	Acc.	Yes (%)
Robust mPLUG-Owl-7B [11] ^{SUP.}	86.0	–	73.0	–	65.0	–	74.7	–
LLaVA-RLHF $_{7B}^{\dagger}$ [23] ^{SUP.}	84.8	39.6	83.3	41.8	80.7	44.0	82.9	41.8
mPLUG-Owl-7B [29]	52.0	–	57.0	–	60.0	–	67.3	–
LLaVA $_{7B}$	74.8	75.1	61.8	86.7	58.1	90.1	64.9	84.0
LLaVA$_{7B}$ M3ID	76.0	67.7	69.3	73.3	65.8	77.6	70.3	72.9
LLaVA$_{7B}$ M3ID + DPO	81.2	65.6	73.9	67.3	68.2	75.4	74.4	69.4
LLaVA-RLHF $_{13B}^{\dagger}$ [23] ^{SUP.}	85.2	38.4	83.9	38.0	82.3	40.5	83.8	39.0
MiniGPT4-13B [32]	73.0	–	67.0	–	62.0	–	74.7	–
LLaVA $_{13B}$	67.9	80.6	63.8	83.2	59.8	87.3	63.8	83.7
LLaVA$_{13B}$ M3ID	84.3	55.6	77.0	61.6	71.3	68.2	77.5	61.8
LLaVA$_{13B}$ M3ID + DPO	85.2	53.4	79.1	57.5	73.2	67.5	79.2	51.1

of hallucinated objects and improved Cover numbers compared both to our training-free approach and LLaVA+LURE [31] a concurrent training based method to improve the grounding of VLMs that relies on GPT-3.5 annotations.

5.2. VLM grounding on VQA

Differently from the MS COCO captioning task, the POPE VQA benchmark only requires the generation of “Yes/No” tokens. As such, one does not expect the dilution effect to play a key role. However, we highlight that the image tokens and the output of the VLM are separated by the input template used to prime the model for the VQA task, which, as we show in Sec. D.4, introduces a non-negligible dilution effect.² To address this, we take an offset into account when using M3ID on POPE, and select $t = t_0$ where t_0 is the number of tokens in between the output and the image.

In Tab. 2, we report the results on the POPE VQA hallucination benchmark [9]. Hallucinations (wrong answers) tend to correlate with the tendency of the VLM to reply using the “Yes” token (see the disproportionately high percentage rate, 84%/83.7%, of “Yes” answers for the LLaVA $_{1.3}$ base model). This tendency can be counteracted at inference time and without any training by simply using M3ID. In our experiments, M3ID reduces the Yes ratio to 72.9%/61.8% for 7B and 13B models, respectively, which leads to relative accuracy improvements over standard LLaVA decoding by 8% and 21%, respectively.

To test whether our training-based approach increases the VLM’s grounding on the visual prompt we trained a

model with our DPO objective on the MS COCO captioning dataset and then tested it on the POPE benchmark. Note that improving caption generation does not directly imply improvements on the POPE VQA benchmark, in fact, even if the images are both from MS COCO, the output format is quite different: open-ended generation on the former and binary classification on the latter. However, intuitively, one expects that by improving the reliance on the visual prompt, the model could make better use of the visual information regardless of the output format required to solve the task at hand. Tab. 2 shows that M3ID+DPO further improves performance over M3ID inference time intervention. Specifically, M3ID+DPO achieves 15% and 24% accuracy improvements over the LLaVA 7B and 13B models respectively. For completeness, we also compare with other training-based baselines that are ϕ -tuned on labeled [11] and preference data [17]. While M3ID+DPO does not have access to any labeled information we show that it is close to these baselines without requiring any annotations.

5.3. Ablations

Conditioning dilution and “overcompensation” In Fig. 4 and Tab. 3 we show that when the forgetting factor ϕ is high, corresponding to the assumption that the input image gets forgotten quickly, M3ID effectively maintains a large PDM-H throughout the generation. However, while deviating from the unconditioned probability is often a desired behavior, an excessive deviation from it across the whole generation could result in “overcompensation” which, as we show in Tab. 3 can be counterproductive and can lead to

²We use [img] [Model Prompt] [Question], see Sec. D.4.

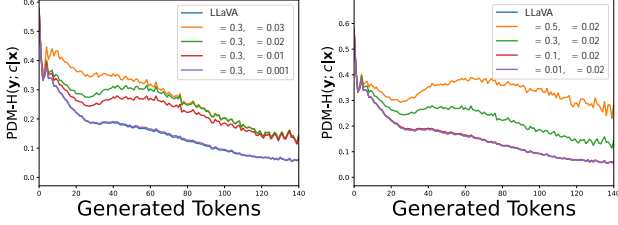


Figure 4. **Sensitivity analysis on hyper-parameters.** We vary both the forgetting factor β and the thresholding parameter α . Small β and α result in minor effects. Instead, either a high forgetting factor β or a high α results in a stronger intervention which leads to higher PDM-H.

higher hallucination rates. In particular, observe that higher corrections detrimentally impact the cover metric. This suggests that while M3ID tries to find tokens that diverge from the language prior the most, it is more likely to fail in captioning elements that are inherently predictable by the language prior alone. For instance, in describing *an image of a dog on a leash accompanied by a man*, M3ID might overlook mentioning the presence of the man, a token that the language prior could anticipate without necessitating any visual information only from context clues. We report examples of this behavior in the Sec. D.2.

Importance of the confidence threshold. When we set a high threshold β , the indicator function remains active more frequently along the generation, leading M3ID to consistently prioritize maximizing the distance of the generation from the language prior. Hence, similarly to the scenario with a high α , M3ID is likely to overcompensate and increase the rate of multi-modal hallucinations. However, too high β disrupts linguistic fluency. We report qualitative examples of this in Sec. D.2. In Tab. 4 we also show that adding the term to compensate for contextual pressure does not significantly change the results over LLaVA decoding in the POPE benchmark since it is essentially framed as a binary classification over the “Yes”/ “No” tokens and not open-ended generation like captioning.

6. Conclusions

We introduced M3ID, a new approach designed to combat multi-modal hallucinations by maximizing the mutual information between the text generated by VLMs and the corresponding visual context. M3ID operates at inference time and can be seamlessly integrated with any pre-trained autoregressive VLM. This makes M3ID a cost-effective and flexible solution to enhance vision-language grounding. Furthermore, for settings where model training is feasible and higher visual grounding is expected, we also paired M3ID with Direct Preference Optimization (DPO), showcasing reduced hallucinatory behaviors. Interestingly, our findings suggest that object hallucinations in VLMs result

Table 3. **Sensitivity to hyper-parameters.** β is the forgetting factor used to counteract conditioning dilution while α is the threshold used to mitigate overcompensation when the contextual pressure is high. We report results on LLaVA-7B.

	CHAIRi	Captioning CHAIRs	Cover
LLaVA _{7B}	8.0	17.8	53.5
M3ID $\beta = 0.3, \alpha = 0.02$	5.8	13.6	55.0
M3ID $\beta = 0.3, \alpha = 0.001$	7.3	17.4	53.7
M3ID $\beta = 0.3, \alpha = 0.03$	6.2	14.7	52.0
M3ID $\beta = 0.3, \alpha = 0.1$	7.2	16.3	45.5
M3ID $\beta = 0.5, \alpha = 0.02$	6.1	14.9	54.6
M3ID $\beta = 0.1, \alpha = 0.02$	6.9	15.4	53.1
M3ID $\beta = 0.01, \alpha = 0.02$	6.9	16.6	52.5

Table 4. **Ablation studies.** We ablate the components of M3ID on both model sizes. Removing the amplification term to counteract conditioning dilution leads to more hallucinations.

	POPE Accuracy	CHAIRi	Captioning CHAIRs	Cover
LLaVA _{7B}	64.9	8.0	17.8	53.5
w/ context pressure	65.5	6.9	16.7	54.5
w/ conditioning dilution	77.5	6.4	14.1	53.9
LLaVA_{7B} M3ID	77.5	5.8	13.6	55.0
LLaVA _{13B}	63.8	15.3	18.2	55.3
w/ context pressure	64.9	6.5	14.4	55.0
w/ conditioning dilution	70.3	5.9	14.8	53.7
LLaVA_{13B} M3ID	70.3	5.4	13.0	54.0

from excessive reliance on the language prior rather than a poor understanding of the visual modality. In fact, M3ID at inference time is sufficient to significantly reduce the amount of generated hallucinations without any training.

A limitation of M3ID is that it requires two forward passes at inference time, one for the conditioned and one for the unconditioned prediction. A possible solution to not increase inference time, but at the expense of higher memory consumption, is to use two batched queries with one having masked visual tokens. Furthermore, as we observed in Tab. 1, sometimes M3ID may prevent the generation of objects that are highly likely under the unprompted language prior (due to context clues). Interestingly, a similar observation has been reported in [22], where, people asked to provide a 10-word list of objects contained in a given image often failed to report the most obvious objects while mainly focusing on secondary ones. While we already showed that this can be mitigated with proper hyper-parameter selection Tab. 3 we believe that an interesting avenue for future research is to directly encode this preference within the model weights by favoring the generation of structured captions that get progressively more detailed while still being grounded to the image.

In general, integrating human- or AI-annotated preference pairs, assessed based on their level of grounding, constitutes a promising avenue for future investigation.

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