

MOCHa: Multi-Objective Reinforcement Mitigating Caption Hallucinations

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<https://assafbk.github.io/mocha>

Abstract

While recent years have seen rapid progress in image-conditioned text generation, image captioning still suffers from the fundamental issue of hallucinations, the generation of spurious details that cannot be inferred from the given image. Dedicated methods for reducing hallucinations in image captioning largely focus on closed-vocabulary object tokens, ignoring most types of hallucinations that occur in practice. In this work, we propose MOCHa, an approach that harnesses advancements in reinforcement learning (RL) to address the sequence-level nature of hallucinations in an open-world setup. To optimize for caption fidelity to the input image, we leverage ground-truth reference captions as proxies to measure the logical consistency of generated captions. However, optimizing for caption fidelity alone fails to preserve the semantic adequacy of generations; therefore, we propose a multi-objective reward function that jointly targets these qualities, without requiring any strong supervision. We demonstrate that these goals can be simultaneously optimized with our framework, enhancing performance for various captioning models of different scales. Our qualitative and quantitative results demonstrate MOCHa’s superior performance across various established metrics. We also demonstrate the benefit of our method in the open-vocabulary setting. To this end, we contribute OpenCHAIR, a new benchmark for quantifying open-vocabulary hallucinations in image captioning models, constructed using generative foundation models. We will release our code, benchmark, and trained models.

1. Introduction

Image captioning, the task of generating text that describes an image, is one of the most fundamental machine learning tasks combining vision and language. Unfortunately, *hallucinations* plague the current state-of-the-art (SOTA), making it less usable for practical tasks that require confidence in the factual correctness of generated captions. Con-

BLIP	+MOCHa
A pregnant mother fills coffee into her new white cup	Coffee being poured into a white cup on a wooden table
Dimly shining coffee drink on top of wooden table with brown donut	A glass mug of coffee on a wooden table

Figure 1. Hallucinated details (shown as *highlighted text*) are prevalent in the outputs of modern image captioning models, as exemplified by generations sampled from BLIP [20] above. Our reinforcement learning-based approach adjusts captioning models to output detailed, valid captions while avoiding such hallucinations, as illustrated in the right-hand column (+MOCHa).

sider, for instance, the images in Figure 1. SOTA image captioning models can generate text that is highly semantically related to its associated imagery, but also contains spurious details (“dimly shining”, “brown donut”). Such hallucinated spurious details either damage user confidence or lead to uncritical acceptance of fallacious (and even potentially dangerous) generated content [4, 5, 25].

Conceptually, hallucinations in image captioning (and text generation in general) models stem from deficiencies in the standard language modeling (LM) objective. The *token-level* likelihood maximization LM objective does not directly optimize the *sequence-level* quality of generated text, and *factual groundedness* is inherently a sequence-level property of text. However, prior works mitigating hallucinations in image captioning mostly avoid the global sequence-level nature of hallucination by limiting their scope to a fixed set of possible object tokens (e.g. objects in MS-COCO) [2, 24, 28].

In general, the inability of LM to optimize sequence-level properties has inspired the use of reinforcement learning (RL) as an additional fine-tuning step to align text generation models to desired behaviors. This has been applied

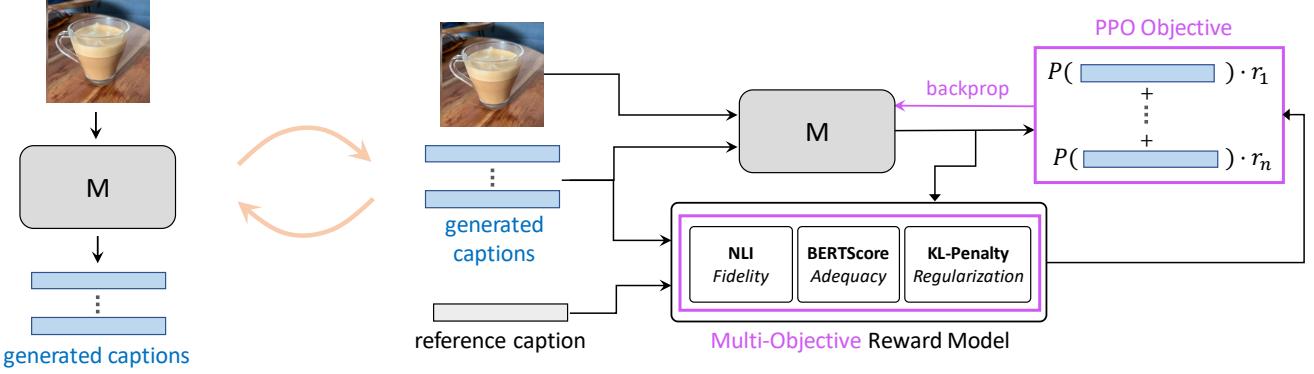


Figure 2. **The MOCHa framework.** The algorithm iteratively collects a batch of data from an image captioning model M (left side) and then applies an optimization step to this model (right side). The multi-objective reward reinforces M to produce captions closer to the high-scoring captions and further from the low-scoring captions.

to image captioning to optimize textual similarity to ground truth semantics [30, 35], and more recently, to align large language models (LLMs) and large vision-and-language models (VLMs) to human preferences [26, 36, 49]. However, existing applications of RL to NLP and multimodal learning focus on optimizing general text quality or estimated human preferences, which do not directly address *fidelity* to an input condition (e.g. consistency with an input image, in the case of image captioning) and hence, may lead to increased hallucinations in generated text [26].

In this work, we introduce *MOCHa* (Multi-Objective reinforcement mitigating Caption Hallucinations) – a RL-based approach for mitigating image captioning hallucinations in an open-world setup. We observe that RL applied to caption fidelity alone fails to preserve the semantic adequacy (i.e. descriptiveness) of output text, while optimizing for the latter does not enforce factually grounded text. Our key insight is that these two goals can be jointly optimized at the sequence-level by applying RL with a multi-objective reward function. Furthermore, we perform this optimization fully automatically by leveraging SOTA text-based learned metrics, without requiring direct supervision.

Finally, while established benchmarks and metrics for quantifying hallucinations in captioning models exist for closed-vocabulary object sets, such benchmarks (to the best of our knowledge) do not exist in an open-vocabulary setup. Therefore, we introduce *OpenCHAIR*, a new benchmark for quantifying hallucinations over an open-vocabulary set of objects, constructed automatically using LLMs and powerful text-to-image generation models. We show that our approach can be flexibly applied to a variety of captioning architectures and sizes, and it improves performance over a wide set of existing metrics used by prior works and also over our new benchmark.

Explicitly stated, our key contributions are:

- The *MOCHa* framework for optimizing a wide array of VLMs to produce high-quality factually-grounded output.

- The *OpenCHAIR* benchmark for evaluating open-vocabulary hallucinations in image captioning models.
- Results showing that *MOCHa* outperforms existing methods for hallucination mitigation on open- and closed-vocabulary measures while preserving caption quality.

2. Related Work

Deep RL for Image-Conditioned Text Generation. Deep RL has been widely applied to text generation tasks, as it allows for optimizing non-differentiable sequence-level metrics. One successful line of work optimizes such metrics for image captioning using an approach called Self-Critical Sequence Training (SCST) [30, 35]. Another more recent development is the rise of deep RL for large language model (LLM) *alignment* – adjusting models pre-trained with standard Language Modeling (LM) to user preferences and desired properties of output text. These works commonly use the Reinforcement Learning from Human Feedback (RLHF) framework, involving manual annotation for training a model to predict human preferences, and then optimizing text generation using the reward model as a signal via the Proximal Policy Optimization (PPO) algorithm [26, 36, 49]. Beyond LLMs, RLHF has been recently applied to aligning multimodal models with human preferences [1]. While such methods succeed in optimizing desired sequence-level properties, they often suffer from increased hallucinations as a side-effect of optimizing for text aligned with human preferences or standard NLG sequence-level metrics (see an illustration of this in the sup. mat.).

Reducing VLM Hallucinations. Research on mitigating hallucinations in image captioning has largely considered object (noun) hallucinations, typically confined to a closed vocabulary (e.g. the set of objects defined in MS-COCO). Biten et al. [2] identify object hallucinations with bias towards the prior distribution of objects in context found in the training data, and propose to train captioning models

on synthetically debiased captions. Liu et al. [24] focus on captioning models with a closed-vocabulary object detection backbone, inserting components into the object detector and text decoder to reduce spurious correlations. Petryk et al. [28] propose a text decoding method that may be applied to captioning models as-is, avoiding the generation of tokens corresponding to objects from COCO if they have insufficient confidence. Yin et al. [46] use a combination of closed-vocabulary object detection with LLM-guided decoding to avoid hallucinations in generated text. By contrast to these works, we are interested in mitigating hallucinations in the more challenging open-vocabulary setting.

In wake of the rapid development of instruction-following VLMs, multiple concurrent works have considered hallucinations in related tasks such as visual question-answering (VQA), applying RL-based methods adopted from research on LLMs. These approaches train a reward model using a manually labelled dataset of hallucinations, then use this model for RL fine-tuning to reduce hallucinations in large VLMs [7, 37, 39]. These methods, which do not directly target our task, also require laborious human annotation to train a supervised reward model (contrasting with our approach which does not require any explicit supervision). Detecting hallucinations has also attracted interest in other NLG tasks requiring factually grounded text generation, such as abstractive text summarization [6, 17, 32], which are not linked to a multimodal setting involving images.

Measuring Hallucinations in NLG. A number of methods for measuring hallucinations in generated text have been proposed [15]. In the context of image-conditioned text generation, the proposed metrics have mainly focused on the identification of hallucinated objects, as these are most easily compared to visually-grounded object annotations. Rohrbach et al. [31] propose the CHAIR metric for quantifying object hallucinations, by comparing tokens occurring in predicted captions to ground-truth object annotations. This requires a dataset such as COCO that contains object annotations along with images, and assumes a fixed vocabulary of object identities. Note that the CHAIR approach does not straightforwardly generalize to an open-vocabulary setting. In our work, we demonstrate that this metric can be extended by leveraging advancements in LLMs and text-to-image generation models, thereby providing diverse ground-truth object annotations paired with images for estimating open-vocabulary hallucinations.

A handful of works have proposed more holistic measures of the fidelity of generated text with respect to an input image. Hessel et al. [8] propose the use of CLIP cross-modal similarity for detecting mismatches between text and images, including hallucinations, and Shi et al. [34] propose a similar embedding-based metric for video captioning. However, Xu et al. [45] find that CLIP tends to assign

high similarity to texts with minor modifications (“hard negatives”) that contradict the corresponding image. Wang et al. [43] propose a learned fidelity metric, which must be trained on automatically-generated scene graphs. For VQA models, Li et al. [21] propose the POPE metric, comparing a list of known objects in a scene to the model’s answers when asked if each of these objects is present.

3. The MOCHA Framework

To jointly optimize for caption fidelity and semantic adequacy, we propose an RL-based pipeline using state-of-the-art methods for stable reinforcement along with a carefully designed reward function. See Figure 2 for an overview of our approach. We proceed to describe the learning procedure and objectives used by our framework. We first provide motivation and notation (Section 3.1), we then describe the reward function that our method optimizes (Section 3.2), and finally we describe the RL algorithm used to perform optimization (Section 3.3).

3.1. Preliminaries

In general, RL views a model as an *agent* that interacts with the external *environment* and receives a *reward*, learning to optimize for this reward via exploring the environment. In the case of image captioning, this model is a VLM which operates in an environment of input images and reference captions [30]. During training, the agent predicts a caption by sampling auto-regressively from its own token distribution (as illustrated on the left side of Figure 2), and receives a reward based on an estimate of the caption quality. After the agent has collected a full batch of rewards, we apply a RL optimization step (as illustrated on the right side of Figure 2) which improves the agent, and repeat this process iteratively until convergence. For a more thorough overview of the theory and applications of RL in general, we refer the reader to Sutton and Barto [40].

We use the following notation in our discussion: Let T and I be the sets of possible texts and images respectively, with joint distribution X . Given image $i \in I$, an image captioning model M with weights θ induces a conditional probability distribution $\pi_\theta(\cdot | \cdot)$ over generated captions $\hat{c} \in T$ conditioned on images $i \in I$. In the RL context, we refer to π_θ as the *policy*. A *reward function* $r : T \times T \times I \rightarrow \mathbb{R}$ assigns *reward* (or score) $r(\hat{c}; c, i)$ to generated caption \hat{c} relative to ground-truth caption c and image i .

3.2. Reward Function

We wish to optimize for the competing objectives of output fidelity (low hallucination rate) and adequacy (including sufficient details to describe the input image), while preserving other desired generation properties such as fluency and diversity. To achieve this, we design a reward function combining multiple objectives, composed as follows:

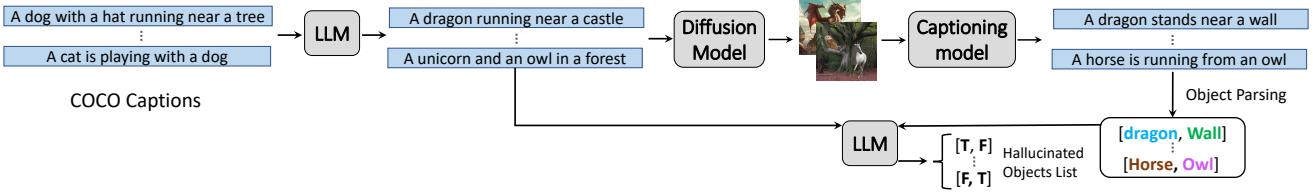


Figure 3. **The OpenCHAIR Benchmark.** The figure above illustrates the construction of the *OpenCHAIR* benchmark via an LLM and text-to-image generation model, and its usage for evaluating image captioning models. We first use captions from MS-COCO as seeds to generate diverse synthetic captions. Using syntactic parsing and filtering heuristics, we select for captions containing various open-vocabulary objects. We then generate images corresponding to these captions, producing our benchmark of images linked with object annotations. To evaluate a captioning model, we run it on this benchmark and compare predicted and GT object categories.



Figure 4. **OpenCHAIR Examples.** We show examples of images from the *OpenCHAIR* benchmark along with their accompanying ground-truth captions. We evaluate models on *OpenCHAIR* by generating predicted captions for these images, extracting objects from the generated text, and comparing to the ground-truth captions via LLM prompting. Long captions are truncated due to space considerations.

Fidelity Objective. (r_f). In order to measure output fidelity to the input image, we use the GT reference captions as a proxy for comparison, as we can directly check logical consistency between them and the generated caption via Natural Language Inference (NLI). We use a pretrained NLI model which outputs the probability $\bar{p}(\hat{c}, c)$ that the generated text \hat{c} logically contradicts c . This serves a strong signal for fidelity, as details which contradict ground-truth information about the image are guaranteed to be hallucinations¹. We use $r_f(\hat{c}; c) := 1 - 2\bar{p}(\hat{c}, c)$ as the fidelity reward. Note that this takes values in the range $[-1, 1]$. We implement this with BART [18] fine-tuned on the MNLI

¹Note that this does not directly penalize information that is neutral with respect to the image, as seen in the generations of Figure 8 that only optimize for this objective. As seen there, adding the r_a objective also helps to avoid generating generic text not directly grounded in the image.

dataset [44]. We average values over all reference captions.

Adequacy Objective. (r_a). To measure adequacy (whether the output caption contains sufficient and semantically relevant detail), we use BERTScore [48], a pretrained model measuring the general quality of text generation relative to ground-truth references. We use its F1 value, calculated against multiple references and scaled to be approximately in the range $[-1, 1]$ as described in the sup. material.

KL Regularization. Following prior work [13, 14, 26, 36, 49], we add a Kullback–Leibler (KL) divergence penalty to the reward model which constrains the agent to stay close to its initial policy π_0 . This serves to prevent mode collapse (i.e. preserving diversity of outputs) and adversarial policies which over-optimize the reward function. The KL penalty adds a term proportional to $K(\hat{c}; i) := -\log(\pi_\theta(\hat{c}|i)/\pi_0(\hat{c}|i))$ to the reward, which limits the agent

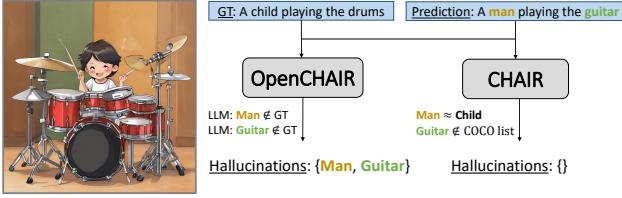


Figure 5. ***OpenCHAIR* vs. *CHAIR*.** The above illustrates the fundamentally different nature of quantifying open-vocabulary hallucinations with *OpenCHAIR*, compared to the closed-vocabulary evaluation of *CHAIR* [31]. Given the above image and ground-truth information, *OpenCHAIR* extracts concrete objects from a predicted caption and identifies hallucinated objects from this list by querying an LLM. By contrast, *CHAIR* checks if words or their synonyms (as given by fixed vocabulary lists) are found in ground-truth annotations. For example, in the above case the predicted object *guitar* would not be counted by *CHAIR* since it is not in its fixed vocabulary, while *man* would not be counted as a hallucination since it is given as a synonym of *child* in *CHAIR*'s vocabulary.

from excessively distancing itself from the initial policy.

Combined Objective. Our total reward function takes the form $r(\hat{c}; c, i) := \alpha \cdot r_f(\hat{c}; c) + (1 - \alpha) \cdot r_a(\hat{c}; c) + \beta K(\hat{c}; i)$, where α and β are positive scalars controlling the tradeoff between our multiple objectives.

3.3. Learning Procedure

To optimize for caption generations that satisfy the desired properties (described above in Section 3.2), we adopt the Proximal Policy Optimization (PPO) RL algorithm [33], which has been used by recent works on text generation as discussed in Section 2. This is a *policy gradient* algorithm, meaning that it optimizes the parameters θ in order to (approximately) maximize the expected reward $L(\theta) = E_{i, c \sim X, \hat{c} \sim \pi_\theta(\hat{c}|i)} [r(\hat{c}; c, i)]$. PPO extends the REINFORCE algorithm [40] (known as SCST in the context of image captioning [30]) by using a clipped surrogate objective to avoid instabilities; see Schulman et al. [33] for details.

4. The *OpenCHAIR* Benchmark

To measure object hallucination in the open-vocabulary settings, we propose the *OpenCHAIR* (OCH) benchmark. *OpenCHAIR* expands upon the previous object hallucination metric *CHAIR* [31], by relaxing the strong reliance of *CHAIR* on the closed list of 80 objects in the MS-COCO dataset. We provide an overview of *OpenCHAIR* below; further details on the construction and contents of the dataset, prompts used, and other implementation details are provided in the appendix.

In order to create a new benchmark that enables measuring the hallucination rate of arbitrary objects, while still maintaining high quality ground-truth captions, we use the pipeline illustrated in Figure 3. We first prompt the LLM Llama-2 [41] with few-shot examples of image captions

from MS-COCO, having it generate captions with a similar style but containing diverse details (and in particular, objects that are likely not contained in the closed set of MS-COCO object labels). We then parse these synthetic captions with a syntactic parsing model, identify nouns with high concreteness scores [3] (as these generally represent concrete objects), and balance the generated captions among object types to cover a wide array of objects. Subsequently, we utilize the text-to-image diffusion model Stable Diffusion XL [29] to generate an image from these newly formed caption. This process results in a dataset that consists of synthetic images with corresponding captions including diverse, open-vocabulary objects. We illustrate the difference between *OpenCHAIR* evaluation and the closed-vocabulary *CHAIR* metric in Figure 5.

To evaluate captioning models on *OpenCHAIR*, we proceed as follows. After generating captions for each image in the *OpenCHAIR* dataset, we parse these captions to identify objects as described above. For each extracted object o , we compare it to the ground-truth synthetic caption c by prompting an LLM, asking it whether an image with caption c contains the object o . We consider o to be a hallucination unless the LLM returns a positive answer for this question. We then follow the original procedure of *CHAIR* and calculate the hallucination rate as $OCH := n_h/n_{gen}$, where n_h is the number of hallucinated objects and n_{gen} is the total number of objects in the generated captions.

5. Experiments

5.1. Implementation Details

We test image captioning with *MOCHA* on various SOTA image captioning models of varying architectures and across various sizes. In particular, we test BLIP [20], BLIP-2 [19] and GIT [42]. Following standard practice in RL-based image captioning, we use models that have first been fine-tuned on with a standard language modeling loss on our captioning dataset (MS-COCO). We apply PPO reinforcement with clipping parameter $\epsilon = 0.2$. For our reward function, we use coefficients $\alpha = 0.5$ and $\beta \in [0.004, 0.06]$ (depending on the model optimized). During training, we sample 10 generations for each image using nucleus sampling [10] with $p = 0.9$ and temperature $t = 1.2$. See the appendix for model checkpoints, parameter counts, and further training settings and hyperparameters.

We test our method on the MS-COCO [23] captioning benchmark. Following Karpathy and Fei-Fei [16], we use their 113K-item train set for training and the 5K-item validation set for evaluation. For quantitative evaluation, standard captioning metrics along with *CHAIR* [31] using beam-search generated predictions (5 beams). We also pro-

²Reference ground truth captions: *A car with some surfboards in a field* (left) and *A boy holding umbrella while standing next to livestock* (right).

Model	B@4↑	C↑	S↑	CH _i ↓	CH _s ↓	OCH _b ↓	OCH _s ↓	\bar{p} ↓	BSc ↑
BLIP-B	24.8	87.5	165	2.6	2.8	0.227	0.289	0.206	0.557
BLIP-B+M (ours)	26.0	91.3	172	2.2	2.5	0.218	0.285	0.176	0.576
BLIP-L	41.5	138.4	244	2.3	3.5	0.270	0.316	0.244	0.679
BLIP-L + TLC-A	41.3	137.4	244	1.9	2.8	0.270	-*	0.241	0.676
BLIP-L+M (ours)	41.9	139.6	246	2.1	3.1	0.259	0.295	0.206	0.682
BLIP2	43.4	144.3	252	1.7	2.6	0.267	0.295	0.207	0.684
BLIP2+M (ours)	44.0	144.3	246	1.4	2.3	0.255	0.286	0.199	0.684
GIT-B	38.7	128.1	231	4.2	2.9	0.303	0.350	0.284	0.656
GIT-B+M (ours)	39.0	128.4	233	3.9	2.7	0.280	0.325	0.221	0.657

Table 1. **Quantitative results** for state-of-the-art VLM models on the COCO Caption Karpathy test set. +M refers to *MOCHA*. BSc and \bar{p} denote BERTScore and NLI contradiction probability rewards. B@4, C, S, CH, OCH, BSc and \bar{p} denote BLEU-4, CIDEr, SPICE, CHAIR (i for instance, s for sentence), OpenCHAIR (s for sampling, b for beam search), BERTScore, and NLI p (contr.) metrics respectively. All results are generated by using their officially provided checkpoints and hyperparameters. Best results are shown in **bold**. *Note that sampling is not well-defined for TLC-A, as it is only defined for deterministic decoding.

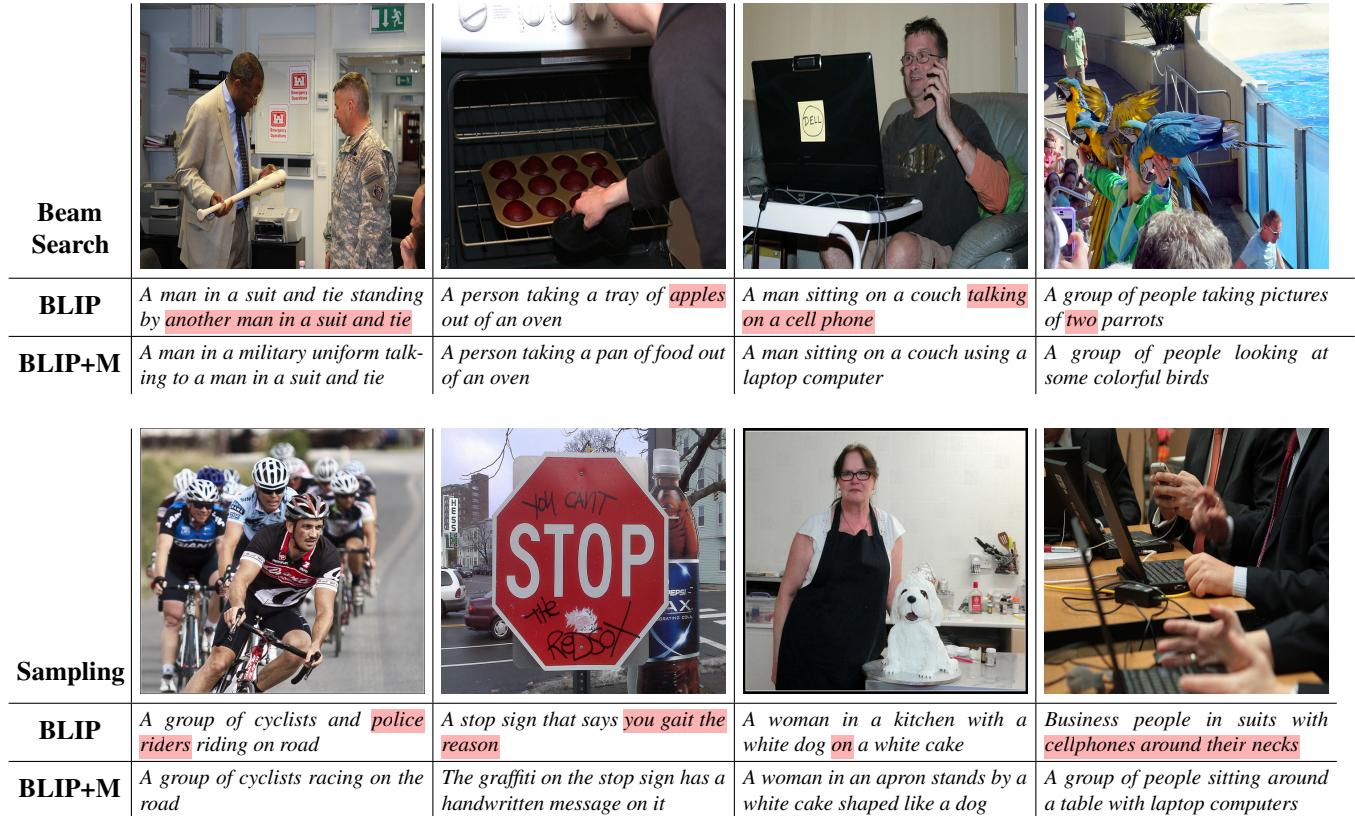


Figure 6. **Qualitative results** of *MOCHA* applied to an image captioning model (BLIP), along with baseline results without optimization. We show captions produced from each model using beam search decoding with 5 beams (upper row) and sampling (lower row). Hallucinated details are highlighted. These results illustrate that *MOCHA* encourages captions with high fidelity to the input image (i.e. avoiding hallucinations), while preserving a satisfying level of detail.

vide NLI (\bar{p}) and BERTScore values, directly optimized by *MOCHA*, as described in Section 3.2. We evaluate the *OpenCHAIR* open-vocabulary metric as described in Section 4. To provide a robust estimate of open-vocabulary hal-

lucinations, we calculate OCH by sampling a caption generation 10 times for each of the images in the benchmark and reporting the mean OCH value, also allowing us to test for statistical significance (demonstrated in the appendix).

Model	B@4↑	S↑	M↑	C↑	CH _s ↓	CH _i ↓
Dedicated						
UD-L+Occ _{XE}	33.9	20.3	27.0	110.7	5.9	3.8
UD-L+Occ _{SC}	37.7	22.2	28.7	125.2	5.8	3.7
CIIC _{XE}	37.3	21.5	28.5	119.0	5.3	3.6
CIIC _{SC}	40.2	23.2	29.5	133.1	7.7	4.5
COSNet _{XE}	39.1	22.7	29.7	127.4	4.7	3.2
COSNet _{SC}	42.0	24.6	30.6	141.1	6.8	4.2
End-to-end						
BLIP	41.5	24.4	31.1	138.4	3.5	2.3
BLIP-2	43.4	25.2	31.7	144.3	2.6	1.7

Table 2. **Older dedicated methods for reduced-hallucination captioning vs. end-to-end modern VLMs for image captioning.** Results are given on the Karpathy test split of MS-COCO dataset, including closed-vocabulary hallucination metrics as commonly reported by such dedicated methods. B@4, C, M, S, CH denote BLEU-4, CIDEr, METEOR, SPICE, and CHAIR metrics respectively. We see that older, dedicated methods with weaker backbones are outperformed by modern VLMs on all metrics, including the smaller BLIP(-Large) and the larger BLIP-2(-2.7B). XE and SC indicate cross-entropy and SCST (RL) optimization respectively. Best and second-best metric values are shown in **bold** and underlined text respectively.

Model	B@4↑	C↑	S↑	CH _i ↓	CH _s ↓	\bar{p} ↓	BSc ↑
BLIP	41.5	138.4	244	2.3	3.5	0.246	0.679
BLIP+M	41.9	139.6	246	2.1	3.1	0.206	0.682
$-r_f$	43.0	142.3	246	2.8	4.4	0.249	0.691
$-r_a$	41.1	132.9	244	1.5	2.3	0.174	0.66

Table 3. **Ablation results.** We ablate the effect of the fidelity r_f and adequacy r_a terms in our reward function. As seen above, removing r_f leads the model to only optimize for general textual quality metrics, while degrading performance with respect to hallucinations. Similarly, removing r_a leads to a significant drop in textual quality. By contrast, our method optimizing multiple rewards shows a synergistic effect between these rewards, leading to an overall improvement in both textual quality and a reduction in the degree of hallucination.

For qualitative results, we present results both using beam search decoding and using stochastic sampling. In the appendix, we provide results on additional image captioning datasets and metrics, further showing the generality of our approach.

5.2. Quantitative and Qualitative Results

See Table 1 for quantitative results of image captioning models on MS-COCO. We provide baseline captioning model results along with results on *MOCHA*-optimized models. As is seen their, *MOCHA* improves measures of

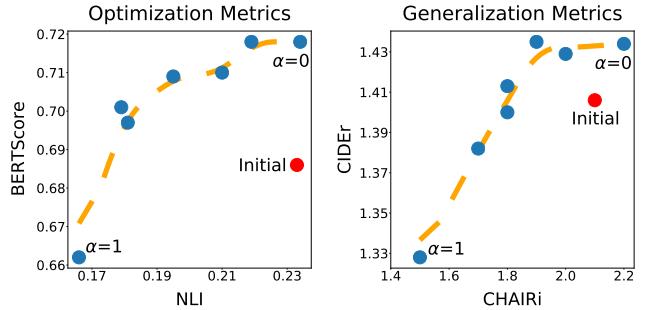


Figure 7. **Fidelity-adequacy graphs** for pretrained (“initial”) and *MOCHA*-optimized BLIP models. In each graph, the x-axis gives a fidelity metric and the y-axis a metric measuring caption adequacy (detailedness) relative to the GT. The left-hand graph shows metrics that are directly optimized by *MOCHA* (BERTScore and NLI \bar{p}), while the right-hand graph shows additional metrics that were not directly optimized; all results are calculated on the validation set. The blue points illustrate *MOCHA* results for different weightings of the adequacy and fidelity terms of the reward function, along with a smoothed isotonic regression curve (orange). The blue point in the top right corner is for a value of $\alpha = 0$, and α increases along the line until reaching the bottom left corner, where $\alpha = 1$. We see that intermediate α values yield stronger performance than the initial model by both metrics.

hallucinations in image captioning while generally preserving or even enhancing standard measures of caption quality. We also provide qualitative examples in Figure 6, illustrating the effect of *MOCHA* on both beam search decoding and sampling. We see that the *MOCHA*-optimized model generates captions consistent with the input images while preserving a satisfying level of detail, consistent with our numeric results. Note that the table also provides a comparison to TLC-A, a recent method for hallucination mitigation; see Section 5.3 for details.

5.3. Comparisons

A number of prior works have proposed dedicated methods for reduced-hallucination image captioning, often using data modification or build multi-component pipelines applied to older vision-language backbones. In Table 2, we provide a comparison between these methods and SOTA foundation VLMs applied as-is (the baseline for our main results); in particular, we reproduce results for the dedicated methods UD-L [2], CIIC [24], and COSNET [22]. We find SOTA VLMs outperform these methods across metrics, including both general textual quality and hallucination metrics. This motivates our focus on optimization applied on top of modern foundation models.

We also compare to the recent method TLC-A [28], a decoding (inference-time) method designed to mitigate hallucinated objects (from a closed list) which may be applied to any standard image captioning model. Results for TLC-A

		
\emptyset	<i>This is a picture of a large old fashioned car that was parked by a group of people</i>	<i>People at festival standing around in open field</i>
$-r_f$	<i>A car parked in the grass with a surfer standing near it</i>	<i>A woman standing next to a herd of animals with an umbrella</i>
$-r_a$	<i>Spectators could enjoy the old fashions of the fifties</i>	<i>That are some very nice people who are very fun to view them</i>
r	<i>A vintage car parked on a field next to people</i>	<i>A young man with a large umbrella next to a herd of animals</i>

Figure 8. Ablating our multi-objective reward function. Above we show captions sampled from models with different reward functions. Top row depicts the initial model (before optimization). As can be seen in the table, generations of the base model (\emptyset) and the model trained without the fidelity objective ($-r_f$) contain various hallucinations that contradict the image, like stating that the car was *parked by a group of people*, confusing between an ordinary person and a *surfer*, and stating that the boy is a *woman*. In contrast, those from the model without the adequacy objective ($-r_a$) are generic and neutral with respect to the image (without explicitly contradicting it), e.g. the abstract statement about the *spectators enjoying the old fashions of the fifties*. At last, optimizing for both (r) yields captions that are both descriptive and consistent with the input condition, similar to the reference captions² that were provided by human annotators.

are provided in Table 1 along with our method and baselines. As is seen there, TLC-A shows an expected advantage in the closed-vocabulary setting (CHAIR, measuring hallucination of COCO object types), but barely changes \bar{p} (which correlates with open-vocabulary hallucinations) and degrades other measures of caption quality. This contrasts with our method, which shows an improvement over all of these metrics. As an aside, we note that our OCH calculation is not well-defined for TLC-A, as we calculate it using multiple stochastic samples while TLC-A is only defined in the deterministic decoding setting.

5.4. Ablations

We ablate the effect of the components of our reward function in Table 3. As is seen there, optimizing for fidelity alone has a negative impact on general caption quality, while optimizing for adequacy alone fails to improve hallucinations; this is also seen in Figure 7 where extreme values of α (0 or 1) correspond to the edges of the curves. The effects of each reward function component are illus-

trated qualitatively in Figure 8; removing r_f from the reward function leads to increased hallucinations, and removing r_a leads to captions that do not contain sufficient details. In the appendix, we also illustrate the effect of removing the KL-Penalty from our reward, as well as ablating the effect of our chosen RL algorithm.

5.5. Discussion and Limitation

Our quantitative results show that *MOCHA* improves performance over base captioning models by most measures, across model architectures and sizes. Importantly, this effect is seen not only among metrics which we directly optimize (NLI, BERTScore) but also among non-optimized metrics, measuring general caption quality (e.g. CIDEr), closed-vocabulary hallucinations (CHAIR) and open-vocabulary hallucinations (*OpenCHAIR*). Along with our qualitative observations, this justifies our holistic approach to reducing hallucinations without restriction to a closed list of object types.

Crucially, this succeeds due to the weighting of multiple objectives (rather than optimizing for reduced hallucinations alone). As seen in Figure 7, adjusting the parameter α controlling the tradeoff between objectives traces a *Pareto frontier* which outperforms the base model, showing that joint optimization of these objectives has a synergistic effect. We conclude that sequence-level optimization is successful in reducing hallucinations with a well-designed reward function.

A potential limitation of our approach is that it relies only on text despite the fact that it addresses the problem of image captioning that is fundamentally grounded in visual data. While our strategy achieve a consistent improvement across different models, the fact that it does not directly consider the image information may limit its performance.

We emphasize that our work does not solve the hallucination problem completely, although it presents a significant step towards this goal. Note also that we have focused in this work on the image captioning domain, while modern VLMs are often applied to diverse tasks such as VQA and visual instruction-following for which hallucinations also pose a significant challenge. We hope that our proposed strategy will pave the way for future research on hallucination reduction in all of these domains, in which hallucination-aware RL also presents significant promise.

6. Conclusion

We have shown that using a multi-objective reward signal allows for optimizing image captioning models to reduce open-vocabulary hallucinations while preserving caption quality. In addition to superior results on standard captioning and hallucination metrics, our *OpenCHAIR* benchmark demonstrates the utility of our approach in an open-world setting, while providing a new metric for further work

on hallucination-aware image captioning. Moreover, our method and metrics may be applied flexibly to a variety of model sizes and architectures.

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MOCHa: Multi-Objective Reinforcement Mitigating Caption Hallucinations

Appendix

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A. Interactive Visualization

For additional qualitative results, we refer the reader to the interactive visualization tool provided at https://assafbk.github.io/mocha_vis_tool. We provide image captioning results using BLIP-Large with and without *MOCHa* for 500 randomly selected test images from MS-COCO [23] and Flickr30K [47]. To visually emphasize the hallucination rate in the predictions, for each model we calculate the NLI contradiction probability³ between the top beam and a ground-truth caption (which is depicted below the image), and report the difference in the contradiction probability between the two models. Samples are ordered via n-gram similarity between the predictions of both models, listing the most different predictions first, allowing for better emphasizing items with evident differences first. This is calculated by considering the top 5 beams of BLIP as reference texts and the top 5 beams of BLIP+*MOCHa* as candidate sentences; we then compute the average BLEU [27] score between each candidate and all references.

B. Additional Details

B.1. MOCHa Implementation Details

As discussed in Rennie et al. [30], we reduce variance in gradient estimates by shifting the reward function to have

³Using the same pretrained NLI model described in the main paper.

zero mean; we apply this to the reward function before adding the KL penalty. To perform this shifting, we subtract the sample mean of this reward (without KL penalty) among all predictions for a given image in a minibatch.

During each training iteration, we build minibatches by selecting 10 images and then generating 10 predictions per image (hence 100 image-prediction pairs total). Generation settings are detailed in the main paper; in addition, we cap generations to be at most 40 tokens. During *MOCHa* training, we freeze the image encoder of all models, training the text encoder components alone. For BLIP-Large and BLIP-Base we use gradient clipping of 5, learning rate of 1e-6 and 4 PPO steps in each iteration. BLIP-2 is trained with low rank adapters (LoRA) over the keys and values of the decoder attention layers [12] with a learning rate of 1e-6. GIT-base is trained with a learning rate of 1e-5 with 4 PPO steps and gradient clipping of 5.

All model checkpoints are taken from the Hugging Face Model Hub⁴):

- salesforce/blip-image-captioning-large
- salesforce/blip-image-captioning-base
- salesforce/blip2-opt-2.7b-coco
- microsoft/git-base-coco

We train these models for the following number of iterations: 350 for BLIP-B, 1200 for BLIP-L, 3400 for BLIP-2, and 600 for GIT-B.

B.2. OpenCHAIR Implementation details

Generating Diverse Captions We start by parsing all objects in MS-COCO’s human-annotated captions by first identifying nouns via syntactic parsing⁵. Then, we then filter these for highly concrete nouns, by using the values recorded by Hessel et al. [9] with threshold 4.5. We used these objects, coupled with their corresponding captions, to prompt an instruction-tuned LLM⁶ to rephrase the captions with different objects. We used stochastic sampling with top-p of 0.9 and temperature of 0.6 for this LLM generation. While this stage increases the object diversity, we notice that the output still includes many common objects that have a significant overlap with those in MS-COCO. To overcome this issue, we filter out all captions that do not include rare objects, defining an object as rare if its appearance frequency in the dataset is in the lowest 10th percentile. The remaining captions are used as few-shot examples for

⁴<https://www.huggingface.co/models>

⁵Using the *en_core_web_md* pipeline from the SpaCy [11] library.

⁶meta-llama/Llama-2-70b-chat-hf

a LLM⁷ (base, not instruction-tuned) to generate new captions, to further increase diversity. We used 10 few shot example for each generated caption, and text is generated using sampling with temperature 0.8. We generate 2,000 captions from the LLM and feed them as prompts to the text-to-image generation model Stable Diffusion XL [29], which generates a single image for each caption. For image generation, we use 40 sampling steps and guidance scale of 10. We also employ negative prompting using the prompt “*unclear, deformed, out of image, disfigured, body out of frame*” to encourage generation of clear objects in the output images.

Evaluation on the *OpenCHAIR* Benchmark Evaluating a captioning model on *OpenCHAIR* is performed as follows: First, all the objects in the caption generated by the captioning model are extracted using the parsing method described in the previous paragraph. For each detected object, an LLM⁸ is prompted to determine whether the object is in the GT caption or not using the prompt: “*An image has the following caption: <input caption>. Does the image contain the following object? <input object>*”. Answer yes/no/unsure. The answer is: ”. We use greedy decoding for this stage. Objects for which the LLM does not answer “yes” are counted as hallucinations. Finally, the *OpenCHAIR* hallucination rate is calculated as $OCH := n_h/n_{gen}$, where n_h is the number of hallucinated objects and n_{gen} is the total number of objects in the generated captions.

B.3. OpenCHAIR Analysis and Comparison to CHAIR

In Figure 9, we show the difference in object coverage for CHAIR (over MS-COCO) and *OpenCHAIR*. As can be seen in the figure, *OpenCHAIR* covers many more objects than CHAIR. This is also reflected qualitatively, as CHAIR is missing many common object types, including daily objects like *shoe* and *guitar*. More examples of objects from the OpenCHAIR dataset include: *pearl, tiger, sand, tricycle, corkscrew, toy, charcoal, text, pinecone, grandfather, chocolate, wheelchair, wand*. A list of all additional OpenCHAIR objects (those not found in CHAIR) can be found in https://github.com/assafbk/mocha_vis_tool/blob/main/openchair_objects.txt.

We also note an additional limitation of CHAIR related to object coverage, namely that CHAIR uses a fixed list of synonyms to coarsely aggregate different, semantically similar objects. For example, the word *person* is synonymous to *policeman, bride, thief, baby, girl, boy, hunter, etc.* A prediction that includes one of these words will be considered correct according to CHAIR. By contrast, *OpenCHAIR*

⁷meta-llama/Llama-2-13b

⁸meta-llama/Llama-2-13b-chat-hf

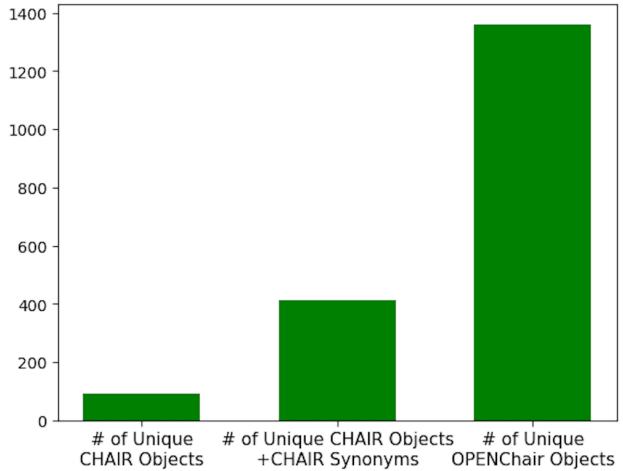


Figure 9. **Object Coverage, CHAIR vs. *OpenCHAIR*.** We display the object coverage of CHAIR (over MS-COCO) and *OpenCHAIR*, measured as the number of unique objects. In OPENChair, objects are found using the parsing method described in Section B.2. As can be observed, the proposed benchmark has significantly greater coverage of different objects.

relies on a LLM to determine whether two objects are identical, letting us for instance to consider the objects *tuna, salmon and goldfish* as distinct. Conversely, this LLM evaluation is robust to valid synonymous relations between different words, e.g. identifying the word *fish* as valid when it is predicted in place of one of the more fine-grained fish terms.

B.4. TLC-A Comparison Implementation Details

In order to compare our method to TLC-A [28], we received code from its authors and implemented it in our setup. TLC-A is a decoding-time method applied to auto-regressive captioning models, and in our setting we apply it to different models (e.g. BLIP-Large) than those tested by Petryk et al (e.g. OFA). Of particular note is that TLC-A requires selecting a threshold confidence value, which is used in the decoding phase to re-rank generated beams according to the confidence assigned to COCO object tokens. Petryk et al. recommend calibrating this threshold using the COCO validation set to achieve a precision level of at least 99%; however, in our experiments we find that this value cannot be achieved by the models we consider without sacrificing most of the recall, as illustrated in Figure 10. Therefore, we instead use the COCO validation set to select the best-performing threshold with respect to the CHAIR metric, as shown in Table 4. The selected confidence threshold is 0.33 and it achieves a precision of 98.3% and a recall of 84%.

⁸Reference ground truth captions: *Painting of oranges, a bowl, candle, and a pitcher* (left) and *A giraffe grazing on a tree in the wilderness with other wildlife* (right).

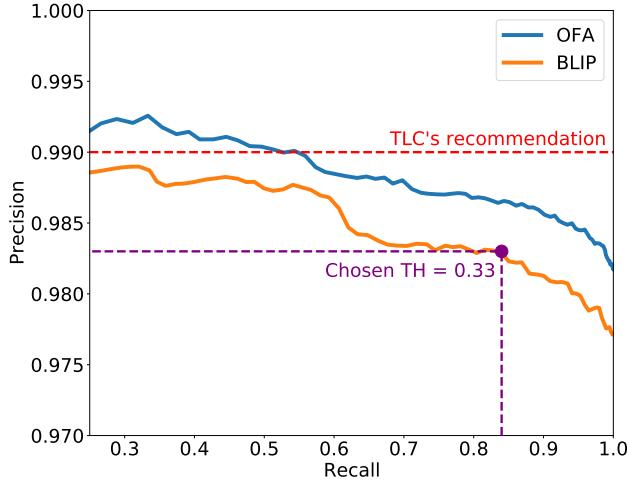


Figure 10. **Precision-recall curve for selecting TLC-A threshold.** As detailed in [28], we compute a precision-recall curve over the predicted object confidences. As illustrated above, the 99% precision threshold recommended by Petryk et al. [28] cannot be achieved by BLIP-Large on the COCO Karpathy validation set. Hence, in our setting we must adjust the threshold to find a reasonable balance between precision and recall.

TH	P	R	B@4↑	C↑	CH _i ↓	CH _s ↓	\bar{p} ↓	BSc ↑
-	-	-	41.5	138.4	2.3	3.5	0.246	0.679
0.10	0.978	0.99	41.4	138.0	2.2	3.38	0.246	0.677
0.21	0.980	0.94	41.4	137.7	2.1	3.14	0.243	0.677
0.33	0.983	0.84	41.2	137.5	1.91	2.82	0.243	0.676
0.52	0.986	0.61	41.1	136.7	1.97	2.9	0.242	0.675
0.56	0.988	0.55	41.2	136.8	1.94	2.86	0.243	0.675
0.94	1	0.01	41.4	137.7	2.21	3.32	0.247	0.677

Table 4. **Selecting a threshold for TLC-A.** We evaluate TLC-A with different thresholds (as described by Petryk et al. [28]) over the COCO caption Karpathy validation set. In the first row we have BLIP without TLC-A. We indicate the selected threshold which achieves the best CHAIR scores overall **in bold**. B@4, C, CH_i, CH_s, BSc, \bar{p} denote BLEU-4, CIDEr, CHAIR instance and CHAIR sentence, BERTScore, and NLI p (contr.) metrics respectively. P, R are the precision and recall that each threshold (for predicted object confidences) achieves over the validation set.

C. Additional Results

C.1. OpenCHAIR with Beam Search vs. Sampling

We note that *OpenCHAIR* can be calculated using either beam search (OCH_b) or sampling (OCH_s). While OCH_b matches the decoding method for deterministic image captioning, OCH_s has the advantage of allowing for statistical tests of significance, as its values across samples can be compared between models using a t-test. We reproduce

\emptyset	<i>a painting of oranges and a silver pitcher on a table</i>	<i>two giraffes eating leaves from a tree</i>
$-r_{kl}$	<i>a painting of some items</i>	<i>some giraffes in the field</i>
r	<i>a painting of a pitcher, oranges, and a candle on a table</i>	<i>a giraffe eating leaves from a tree in a field</i>

Figure 11. **Ablating the KL-penalty reward.** Above we show captions sampled from various models: the initial model (BLIP-Large) before optimization (\emptyset), the model with *MOCHA* optimization applied and KL penalty ablated ($-r_{kl}$), and an optimized model with our full reward function (r). As is seen above, while the base model outputs various hallucinations (e.g. *a silver pitcher*), the model optimized without KL penalty outputs generic texts without adequate detail, due to over-optimization of the fidelity objective. Optimizing with the full reward function yields captions that are both descriptive and consistent with the input condition.

LLaVa-RLHF	BLIP-L+MOCHA
	<i>A man sitting on a chair a man sitting on a chair with a large stuffed animal holding a large stuffed mal, specifically a teady bear, on his lap</i>

Figure 12. LLaVa-RLHF V.S MOCHA. We illustrate that RLHF training does not necessarily solve the hallucination problem of VLM models by showing a generation produced by LLaVa-RLHF [38] compared to BLIP+MOCHA. For both models, we use the prompt “*a photography of*” for generation. See Table 6 for a quantitative comparison.

our results with both OCH_b and OCH_s values reported in Tables 1 (core results) and 5 (ablation results). As is seen in both tables, these scores are highly correlated and are consistent with our general observations regarding hallucinations. Notably, in Table 1 we see that our model improves both open- and closed-vocabulary hallucination metrics, while TLC-A (a closed-vocabulary method) improves the closed-vocabulary CHAIR metric but fails to improve our open-vocabulary OCH_b .

We also note that the differences in OCH_s values before and after *MOCHA*-tuning in Table 1 are all statistically significant ($p < 0.05$), as measured by Welch’s two-sided t-tests applied to the OCH values for each sample between

Model	OCH _s ↓	OCH _b ↓	B@4↑	C↑	S↑	CH _i ↓	CH _s ↓	\bar{p} ↓	BSc ↑
BLIP-L	0.316	0.270	41.5	138.4	244	2.3	3.5	0.244	0.679
BLIP-L+M	0.295	0.259	41.9	139.6	246	2.1	3.1	0.206	0.682
$-r_f$	0.305	0.267	43.0	142.3	246	2.8	4.4	0.249	0.691
$-r_a$	0.303	0.257	41.1	132.9	244	1.5	2.3	0.174	0.66
$-r_{kl}$	0.241	0.225	27.6	98.9	179	1.4	1.9	0.135	0.62
$-ppo$	0.287	0.256	39.4	127.6	229	2.5	3.76	0.212	0.664

Table 5. **Additional ablation results.** We ablate the effect of the KL penalty reward r_{kl} and the selection of PPO algorithm. As seen above, removing r_{kl} causes the model to over-optimize the fidelity reward (\bar{p}), while replacing PPO with the simpler SCST algorithm (described in Section C.2) leads to instabilities that degrade performance across metrics.

models, and applying Bonferroni multiple testing correction to adjust significance levels for the four pairs of base and *MOCHA*-tuned models listed.

C.2. Additional Ablations

KL Penalty Ablation. We demonstrate the effect of our KL penalty in the reward function by performing *MOCHA* optimization without this term. As can be observed in the fifth row of Table 5, optimization without this penalty improves the NLI-based reward \bar{p} while degrading other measures of text quality (including non-optimized metrics like CIDEr and SPICE). We hypothesize that allowing the model to freely deviate from its initial distribution encourages it towards a degenerate solution with respect to \bar{p} , which may be the easiest reward term to over-optimize in an unconstrained setting. This is also reflected qualitatively as seen in Figure 11. As illustrated in the figure, captions generated by the model trained without the KL penalty ($-r_{kl}$) do not contradict the image, but rather contain generic text (e.g. *a painting with some items*), lacking adequate detail. By contrast, optimizing with the KL penalty reward yields captions that are both descriptive and consistent with the input condition, reflected in the improved scores across metrics in Table 5 and the quality of predictions of the full reward model (r) in Figure 11. This is attributed to the ability of the KL penalty to mitigate over-optimization, which benefits both optimized rewards.

PPO Ablation. We also ablated the selection of RL algorithm, by replacing PPO with the SCST algorithm upon which it is based (noting that SCST is the common name for the REINFORCE algorithm in the context of image captioning) [30, 33, 40]. As is seen in Table 5, PPO outperforms SCST across metrics, consistent with prior work on PPO finding that it avoids instabilities during optimization that may allow it to converge to a more optimal solution [26, 33, 49].

C.3. Additional Comparisons

Comparison to VLMs Finetuned with RLHF. LLaVa-RLHF [38] is a concurrent work, which aims to reduce

Model	OCH ↓
LLaVa-RLHF _S	0.396
LLaVa-RLHF _G	0.401
BLIP-L+M _G	0.360

Table 6. OPENChair comparison between LLaVa-RLHF and BLIP-L+*MOCHA* over 100 random samples. For LLaVa-RLHF, S stands for stochastic sampling with default parameters, and G stands for greedy decoding (as beam search is not implemented for LLaVa-RLHF). For fair comparison, we also apply greedy decoding to BLIP-L+*MOCHA*.

hallucinations in instruction tuned models using factually-grounded RLHF. In Table 6, we provide a quantitative comparison between LLaVa-RLHF and BLIP+*MOCHA* over 100 samples of the OPENChair dataset. For LLaVa-RLHF decoding we use both stochastic sampling with the default parameters recommended by the authors, as well as greedy sampling (as beam search is not implemented for LLaVa-RLHF). For a fair comparison, we use greedy decoding for BLIP+*MOCHA* as well. As LLaVa-RLHF tends to generate long paragraphs which follow an image description with subjective commentary, we terminate generation after a single sentence, which usually corresponds to an image caption. The instruction given to LLaVa-RLHF is “describe the image briefly”. As seen in the table, our method outperforms LLaVa-RLHF by this measure of open-vocabulary hallucinations. This is further seen in Figure 12, which shows example captioning predictions for these models, illustrating that LLaVa-RLHF may be more prone to hallucinations.

Evaluation over Flickr30K dataset. We perform a zero-shot generalization test by evaluating a *MOCHA*-tuned model on an additional dataset (different from COCO upon which the model was *MOCHA*-tuned). In Table 7 we can see that the model with *MOCHA* fine-tuning shows an improvement in metrics (NLI and BERTScore) that were optimized on the training data from COCO. Furthermore, we see that non-optimized text quality metrics have similar values be-

Model	B@4↑	C↑	S↑	\bar{p} ↓	BSc ↑
BLIP	29.0	73.2	168	0.335	0.603
BLIP+M	28.9	73.6	166	0.296	0.607

Table 7. **Evaluation over Flickr30K dataset.** We perform a zero-shot evaluation of BLIP-Large with and without *MOCHa* (performed on COCO) on an additional dataset. As seen above, improvements to the optimized metrics (\bar{p} and BERTScore) transfer to the new dataset, while other text quality metrics have similar values before and after *MOCHa*-tuning, suggesting that overall text quality is generally preserved.

tween both models, suggesting that *MOCHa* tuning generally preserves overall text quality. Supporting this quantitative evaluation, we provide detailed qualitative results on the Flickr30K dataset in the attached visualization tool.