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Revisiting Image Captioning Training Paradigm via Direct CLIP-based Optimization

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Abstract

The conventional training approach for image captioning involves pre-training a network using teacher forcing and subsequent fine-tuning with Self-Critical Sequence Training to maximize hand-crafted captioning metrics. However, when attempting to optimize modern and higher-quality metrics like CLIP-Score and PAC-Score, this training method often encounters instability and fails to acquire the genuine descriptive capabilities needed to produce fluent and informative captions. In this paper, we propose a new training paradigm termed *Direct CLIP-Based Optimization* (DiCO). Our approach jointly learns and optimizes a reward model that is distilled from a learnable captioning evaluator with high human correlation. This is done by solving a weighted classification problem directly inside the captioner. At the same time, DiCO prevents divergence from the original model, ensuring that fluency is maintained. DiCO not only exhibits improved stability and enhanced quality in the generated captions but also aligns more closely with human preferences compared to existing methods, especially in modern metrics. Additionally, it maintains competitive performance in traditional metrics. Our source code and trained models are publicly available at <https://github.com/aimagelab/DiCO>.

1 Introduction

The task of image captioning [24, 56, 61, 67] requires an algorithm to describe a visual input in natural language. As a captioner should ideally match the level of detail and precision desired by the user, over time there has been an increasing interest in developing training strategies for aligning the behavior of a captioner to mimic a desired style and quality level.

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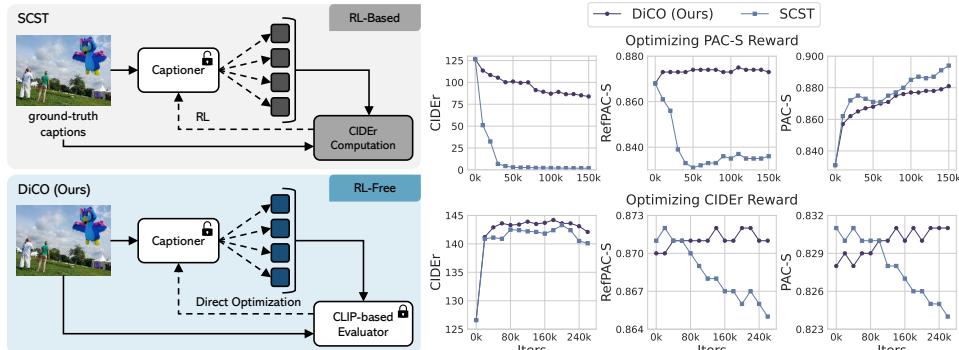


Figure 1: Comparison between SCST [48] and our *Direct CLIP-Based Optimization* (DiCO). DiCO distills a reward model from a learnable CLIP-based captioning evaluator, without requiring reinforcement learning and preventing reward hacking and divergence.

Traditionally, the quality of captions has been measured with textual similarity metrics, so captioners have been trained to maximize a non-differentiable metric like CIDEr [50] during a fine-tuning stage based on reinforcement learning, *i.e.* Self-Critical Sequence Training (SCST) [37, 47, 48]. As this strategy requires the availability of multiple reference captions and tends to produce less distinctive descriptions that ignore the fine detailed aspects of an image, recently there have been preliminary attempts to optimize higher-quality image captioning metrics based on embedding spaces that do not require human references [4, 7, 17], like CLIP-Score [19] and PAC-Score [51]. Besides, these metrics also consider the actual multi-modal alignment between the generated text and the visual content of the input image rather than just comparing texts. Most importantly, they also showcase a superior alignment with human judgment, making them ideal candidates for tuning the behavior of captioners towards a higher quality of generation.

Unfortunately, optimizing modern metrics with pre-existing strategies like SCST results in instability and model collapse [44]. We showcase this in Fig. 1, where we employ SCST for optimizing either PAC-S or CIDEr (light blue lines). When we try to optimize PAC-S, the fine-tuned captioner hacks the metric and deviates from a fluent and high-quality generation, resulting in a rapid decrease according to all other metrics and leading to repetitions and grammatical errors. To solve these issues, we propose DiCO, a novel training methodology that can align a captioner towards better quality captions by distilling from an external contrastive-based evaluator like CLIP-S or PAC-S, without incurring model collapse and without employing a reinforcement learning objective. Our approach achieves this goal by learning a reward model directly into the captioner and mimicking pairwise quality relations expressed by the external evaluator. This ensures a high degree of alignment with human preferences while avoiding reward hacking. This is visually represented in Fig. 1 (dark blue lines): DiCO can optimize both a modern metric like PAC-S and a traditional one like CIDEr by maintaining good scores across all metrics.

We assess the quality of the proposed training methodology by conducting extensive experiments on the COCO dataset [42]. Furthermore, in the supplementary materials, we prove the generalization capabilities of DiCO over other six image captioning benchmarks. Our experimental results demonstrate that DiCO features state-of-the-art quality in the generated captions and improved training stability. This also results in a better performance in terms of modern captioning metrics, while also balancing with competitive performances

on traditional handcrafted metrics. On the other hand, when adopted to maximize standard captioning metrics like CIDEr [60], DiCO achieves state-of-the-art results also in this setting. Going beyond automatic image captioning metrics, we confirm the effectiveness of our approach by also employing human-based evaluation.

To sum up, our proposal markedly differs from all fine-tuning strategies in the current image captioning literature. Presently, this field remains closely tied to traditional techniques, employing the classic SCST algorithm with rewards based on ground-truth captions, while overlooking a concerted emphasis on semantic and syntactic richness, as well as alignment with human cognition. Extensive experiments on standard image captioning datasets demonstrate the effectiveness of the proposal.

2 Related Work

Standard image captioning. Early attempts in the field of image captioning were based on an encoder-decoder architecture, wherein the visual input content is encoded through a CNN, while the textual output is aptly generated by an RNN conditioned on the visual encoding [7, 24, 48, 61]. Subsequently, this approach witnessed refinement through the integration of different attention-based strategies [62], eventually applied to image regions [63] and enhanced with spatial and semantic graphs [68, 69]. More recently, an alternative trend encompasses Transformer-based architectures, where numerous works have been developed exploring varied directions [8, 16, 27, 32]. While the aforementioned approaches exploited the same fine-tuning strategy usually composed of a pre-training with cross-entropy loss followed by reinforcement learning, we explore a different perspective. Along this line, Cho *et al.* [12] stands out as the method that is closely related to our proposal, as it defines a CLIP-based fine-tuning scheme that, however, relies on reinforcement learning. Concurrently, large-scale vision-and-language pre-training has been used to perform several tasks requiring multimodal capabilities, such as image captioning. These models [21, 31, 62, 63, 71] are pre-trained on millions or even billions of image-text pairs, usually collected from the web, and fine-tuned for a target task.

LLM-based image captioning. To leverage the power of LLMs demonstrated in different contexts, many attempts have emerged to bestow vision capabilities to a pre-trained LLM [17, 25, 26, 49, 73], resulting in impressive performance over various vision-and-language tasks like image captioning. In this context, ZeroCap [68] runs a few optimization steps for each new token, to align the text produced by GPT-2 [43] to the input image, using CLIP [42] as guidance. Other works [20, 46], instead, start from a pre-trained LLM and only learn cross-attention layers to mimic the interaction between textual and visual domains. Research efforts have also been dedicated to developing large-scale multimodal models [8], usually based on LLMs and trained on huge amounts of multimodal data [8, 10, 29, 30]. In this context, image captioning is employed as a pre-training task to help vision-and-language alignment, and eventually in the instruction-tuning stage [25, 26]. Thanks to the underlying LLM, all these solutions usually lead to image captioners with greater descriptive capabilities. In this work, we show how to increase the quality and descriptiveness of generated captions without relying on any pre-trained LLM.

Training strategies for LLMs. Aligning models with human judgment constitutes a well-known issue in both NLP and captioning literature. In this context, several strategies for fine-tuning LLMs have been explored. For example, a common research direction is to guide the model through a combination of input-output pairs and explicit instructions [13, 23, 34, 55].

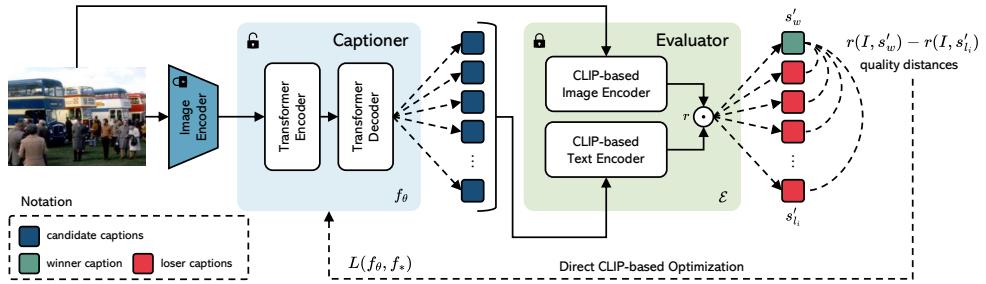


Figure 2: Overview of our approach. Given an image and candidate generations, the figure shows the process for captioner fine-tuning by distilling from a CLIP-based evaluator.

However, LLMs often exhibit a tendency to generate biased and potentially harmful text. To solve this issue, some works have attempted to align models with human judgment through reinforcement learning [42, 43, 44, 45], also designing methodologies for efficient fine-tuning to tackle the substantial memory requirements inherent in training LLMs [46, 47].

3 Proposed Method

Preliminaries. Self-critical sequence training (SCST [48]) is a traditional training paradigm for image captioning. It consists of a two-step training methodology which pre-trains a captioner using a time-wise cross-entropy loss with respect to ground-truth sequences, and fine-tunes the same network by maximizing the CIDEr score [49] using a reinforcement learning approach. Recently, it has been applied also with learnable metrics [50, 51, 52] such as CLIP-S [53], which employs a CLIP [54] embedding space trained to align the embeddings of 400M images and caption pairs. Consequently, a high similarity between a pair of visual-textual CLIP embeddings means that the image-caption pair is highly correlated as well. On the other hand, reinforcement learning from human feedback (RLHF [55]) has been shown to be effective in making LLMs behave more like humans. It starts with a self-supervised pre-trained LLM, then goes through a supervised training phase, and finally, a fine-tuning stage using reinforcement learning. This last step is focused on improving the quality of generated responses by maximizing the score given by a reward model trained to imitate human judgment when comparing two candidate answers. We refer to Appendix A for more details about SCST, RLHF, and image captioning metrics based on contrastive embedding spaces, *i.e.* CLIP-S [53] and PAC-S [56].

Motivation. While adopting significantly different technical choices, there are striking conceptual similarities between the modern RLHF paradigm employed in LLMs and the traditional SCST approach employed in image captioning. Both approaches, indeed, employ reinforcement learning to optimize a reward function, which nevertheless in SCST is a hand-crafted metric, while in RLHF is a learned function from human data. While using RLHF in captioning is impracticable due to the insufficient amount of human preference data to train the reward model (see the comparison with RLHF in Appendix C), contrastive-based learnable metrics offer a compelling alternative to it, as they show a significant alignment with human judgment [57]. Our proposal solves this issue by distilling a reward model from a pre-trained captioning evaluator, considering pairwise relationships from candidate captions. In addition, it also avoids model collapse which is frequent in SCST (cf. Fig. 1).

Deriving the fine-tuning objective. Following recent works on LLM alignment [11], we aim at fine-tuning a captioner f_θ with a Proximal Policy Optimization (PPO) objective [5], where given an image I and a caption s' sampled from the model, the environment produces a reward $r(s', I)$ through a reward model. In addition, we add a per-token KL penalty with the output of the pre-trained model to mitigate overoptimization of the fine-tuned captioner to the reward model. Our objective is therefore defined as

$$\max_{f_\theta} \mathbb{E}_{I \sim \mathcal{D}, s' \sim f_\theta(\cdot | I)} [r(s', I)] - \beta \mathbb{D}_{\text{KL}} [f_\theta(s' | I) || f_*(s' | I)], \quad (1)$$

where β controls the deviation from the pre-trained model, termed as f_* . As it can be seen, the second term has a crucial role, as it prevents the fine-tuned model f_θ from deviating from the distribution on which the reward model is accurate, and prevents the captioner from hacking it, *i.e.* collapsing to high-rewarded answers.

Under this objective, it can be shown [45] that the optimal solution to the fine-tuning problem is given by a model f_r defined as

$$f_r(s' | I) = \frac{1}{Z(I)} f_*(s' | I) \exp \left(\frac{1}{\beta} r(s', I) \right), \quad (2)$$

where $Z(I) = \sum_s f_*(s | I) \exp \left(\frac{1}{\beta} r(s, I) \right)$ is the partition function over possible captions. Although the partition function is difficult to estimate, we can still manipulate Eq. 2 to express the reward function in terms of the optimal captioner, the pre-trained captioner, and the partition function, as follows:

$$r(s', I) = \beta \log \frac{f_r(s' | I)}{f_*(s' | I)} + \beta \log Z(I). \quad (3)$$

Defining a distilled reward model. Since we do not have access to sufficiently large human preference data, defining the reward model in a purely data-driven way would be cumbersome. Instead, we learn our reward model by *distilling* it from a contrastive-based captioning evaluator \mathcal{E} . We assume that, given an image and a candidate sentence (I, s') , the evaluator returns a matching score $\mathcal{E}(s', I)$ proportional to the similarity between s' and I .

Given a dataset \mathcal{D} comprising images, we let the captioner generate $k+1$ candidate captions (*e.g.* through beam search). Then, for each image, we select the caption with the highest score according to \mathcal{E} and denote it as s'_w (*i.e.* “winner”). The others, instead, are denoted as $\{s'_{l_i}\}_{i=1}^k$ (*i.e.* “losers”). Based on the evaluator, we define a reward model which distinguishes between the winner caption s'_w and the loser captions $\{s'_{l_i}\}_i$. To make the reward model more robust and accurate, we also impose that it can predict the *relative quality distances* between the winner and the loser captions. Formally, we define our reward model through the following objective:

$$\mathcal{L}_R(r) = -\mathbb{E} \left[\log \sigma \left(\sum_{i=1}^k \gamma_i (r(I, s'_w) - r(I, s'_{l_i})) \right) \right], \quad (4)$$

where the expectation is taken over images in the dataset and winner and loser captions. Also, γ_i weights the relative distance between the winner caption s'_w and the i -th loser caption s'_{l_i} according to the evaluator \mathcal{E} . Specifically, it is computed as a normalized probability distribution between score distances, as follows:

$$\gamma_i = \text{softmax}_{s'_{l_1}, \dots, s'_{l_k}} \left(\frac{\mathcal{E}(I, s'_w) - \mathcal{E}(I, s'_{l_i})}{\tau} \right), \quad (5)$$

where τ is a temperature parameter. Clearly, considering that γ_i sum up to 1, the reward model objective can be rewritten as

$$\mathcal{L}_R(r) = -\mathbb{E} \left[\log \sigma \left(r(I, s'_w) - \sum_{i=1}^k \gamma_i r(I, s'_{l_i}) \right) \right]. \quad (6)$$

Overall loss function. Following [45], we learn the reward model directly into the captioner. Recalling that the Bradley-Terry model depends only on the difference in rewards between two completions and that γ_i are a valid probability distribution, we replace the definition of $r(s', I)$ as a function of the optimal fine-tuned and pre-trained captioner (Eq. 3) into the reward model objective (Eq. 6), and obtain the final fine-tuning loss of DiCO as

$$L(f_\theta, f_*) = -\mathbb{E} \left[\log \sigma \left(\beta \log \frac{f_\theta(s'_w | I)}{f_*(s'_w | I)} - \beta \sum_{i=1}^k \gamma_i \log \frac{f_\theta(s'_{l_i} | I)}{f_*(s'_{l_i} | I)} \right) \right], \quad (7)$$

where, noticeably, the unknown partition function $Z(I)$ has been cancelled out. Furthermore, the obtained fine-tuning loss, while being derived from the optimal solution to a PPO objective, can be directly optimized through gradient descent, without the need of employing reinforcement learning techniques.

Comparing DiCO with SCST and RLHF. DiCO fine-tunes a captioning model by aligning it to a contrastive-based evaluator while avoiding over-parametrization and model collapse. In comparison with SCST and RLHF, its unique feature is that of *distilling a reward model from an external evaluator by learning it directly inside of the captioner*. Further, this is done by avoiding the usage of reinforcement learning at fine-tuning time, which is common to both SCST and RLHF. Differently from RLHF, also, caption candidates are directly sampled from the model, so that a dataset of human-annotated preferences can be avoided. Finally, differently from SCST, DiCO embeds a regularizer to prevent the fine-tuned model from deviating too much from the pre-trained captioner.

4 Experiments

4.1 Experimental Setting

Datasets. All experiments are performed on the COCO dataset [34], using the standard splits defined in [24] with 5,000 images for both test and validation and the rest for training. We report our experimental results on the test set of COCO. Further, we refer the reader to Appendix C for results on six additional datasets, namely nocaps [2], VizWiz [38], TextCaps [35], Conceptual Captions 3M (CC3M) [33], FineCapEval [12], and Flickr30k [70].

Evaluation metrics. In addition to the standard image captioning metrics like BLEU [24], METEOR [8], and CIDEr [50], we employ two CLIP-based scores, namely CLIP-S [39] and PAC-S [50], in both their reference-free and reference-based versions, using the ViT-B/32 backbone for both metrics (also see Appendix A). Moreover, following recent works [10, 27], we measure the quality of generated captions in distinguishing images in a dataset and compute the percentage of the times the image corresponding to each generated caption is retrieved among the first K retrieved items. This is done by ranking the images in terms of CLIP similarity between visual and textual embeddings, using the CLIP ViT-B/32 model, and computing recall at K with $K = 1, 5, 10$. We also compute the mean reciprocal rank

Model	Reference-based Metrics						Reference-free Metrics							
	B-4	M	C	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S	R@1	R@5	R@10	MRR			
<i>Standard Captioners</i>		Backbone												
CLIP-VL [2]	RN50×4	40.2	29.7	134.2	0.820	0.862	0.770	0.826	24.0	48.9	61.5	34.8		
COS-Net [2]	RN101	42.0	30.6	141.1	0.814	0.870	0.758	0.832	25.8	52.3	64.9	37.1		
PMA-Net [8]	ViT-L/14	43.0	30.6	144.1	0.814	0.869	0.755	0.821	-	-	-	-		
<i>LLM-based Captioners</i>		Backbone												
ZeroCap [2]	ViT-B/32	2.3	10.1	15.1	0.771	0.800	0.810	0.816	-	-	-	-		
ClipCap [2]	ViT-B/32	32.3	28.1	108.5	0.809	0.862	0.766	0.833	27.1	53.3	65.5	38.3		
SmallCap [2]	ViT-B/32	37.0	27.9	119.7	0.804	0.863	0.748	0.826	23.1	48.2	60.0	33.7		
MiniGPT-v2 [2]	ViT-g/14	18.8	24.6	80.4	0.795	0.848	0.752	0.818	27.4	52.0	63.0	37.9		
BLIP-2 [2]	ViT-g/14	43.7	32.0	145.8	0.823	0.877	0.767	0.837	31.4	57.5	69.1	42.7		
<i>CLIP-based Optimization</i>		Reward	Backbone											
Cho et al. (SCST) [2]	CLIP-S	RN50	6.3	19.7	11.2	0.786	0.823	0.843	0.837	43.2	71.9	82.3	55.5	
Cho et al. (SCST) [2]	CLIP-S+Gr.	RN50	16.9	24.9	71.0	0.792	0.849	0.779	0.839	35.3	63.4	75.2	47.4	
SCST	CLIP-S	RN50	14.3	24.7	3.1	0.765	0.830	0.804	0.837	36.9	64.9	75.9	48.7	
SCST	PAC-S	RN50	18.5	26.5	32.2	0.785	0.849	0.799	0.860	44.3	73.2	83.4	56.5	
DiCO (Ours)	CLIP-S	RN50	20.7	25.7	78.9	0.811	0.852	0.815	0.842	37.5	66.6	78.1	49.8	
DiCO (Ours)	PAC-S	RN50	22.7	27.0	79.8	0.801	0.865	0.797	0.869	44.3	73.9	84.2	56.8	
SCST	CLIP-S	ViT-B/32	11.4	23.1	1.1	0.778	0.830	0.851	0.846	43.4	70.8	81.1	55.1	
SCST	PAC-S	ViT-B/32	20.3	27.1	40.7	0.796	0.858	0.810	0.870	50.0	77.6	87.0	61.8	
DiCO (Ours)	CLIP-S	ViT-B/32	22.6	27.0	81.7	0.817	0.861	0.825	0.858	46.3	74.0	83.7	58.0	
DiCO (Ours)	PAC-S	ViT-B/32	23.7	27.3	84.8	0.810	0.872	0.814	0.882	52.9	80.8	89.5	64.8	
SCST	CLIP-S	ViT-L/14	10.2	23.0	1.1	0.793	0.827	0.865	0.834	43.3	70.7	80.5	55.0	
SCST	PAC-S	ViT-L/14	22.3	28.4	51.1	0.801	0.861	0.805	0.862	46.7	74.7	84.8	58.8	
DiCO (Ours)	CLIP-S	ViT-L/14	21.4	27.1	82.6	0.824	0.863	0.837	0.856	46.5	74.7	84.7	58.4	
DiCO (Ours)	PAC-S	ViT-L/14	25.2	28.4	89.1	0.815	0.875	0.812	0.877	50.9	78.7	87.6	62.9	

Table 1: Comparison with state-of-the-art models on the COCO test set. Bold font indicates the best results among captioners optimized via CLIP-based rewards with comparable backbones, while underlined indicates the overall best results.

(MRR) for each generated caption: higher MRR scores indicate that captions are more discriminative and therefore usually more detailed.

Implementation and training details. Our baseline architecture is a standard Transformer model with 3 layers in both encoder and decoder, a hidden dimensionality equal to 512, and 8 attention heads. To extract visual features, we use either RN50, ViT-B/32, or ViT-L/14 pre-trained with a CLIP-based objective [2]. Our code is based on the popular Hugging Face Transformers¹ library. All experiments are performed using the Adam optimizer, initially pre-training all the models with cross-entropy. During fine-tuning, we use a batch size of 16, a fixed learning rate equal to $1 \cdot 10^{-6}$, and a beam size of 5 (*i.e.* the number k of looser captions is set to 4). For efficiency, we train with ZeRo memory offloading and mixed-precision [39]. Unless otherwise specified, the β parameter is set to 0.2 and the ViT-L/14 backbone is used to extract visual features. The temperature parameter τ defined in Eq. 5 is set to $1/(3 \cdot 10^2)$. Early stopping is performed according to the reference-based version of the CLIP metrics used as reward. Ablation studies and analyses with different hyperparameters are reported in Appendix B.

4.2 Comparison with the State of the Art

Results on COCO test set. We compare our model trained with the proposed DiCO strategy with other state-of-the-art solutions. We restrain the comparison by only considering captioning models that use CLIP-based visual features to encode images, which have proven

¹<https://huggingface.co/docs/transformers>



SCST: A rusted rusty rusty rusty rusty rusty rusty scissors in a garden with plants in the background.

DiCO (Ours): A rusted scissors sticking out of a metal fence with plants in the background.



SCST: Several cows grazing in a field on a mountain range with a mountain in distance under mountain range in background.

DiCO (Ours): A herd of cattle grazing on a lush green hill next to a large mountain range.



SCST: A little boy with headphones sitting in front of a computer with headphones on a desk in corner with headphones on background.

DiCO (Ours): A little boy with headphones sitting at a desk using a computer.



SCST: A person holding up a clear plastic plastic container filled with sugar covered donuts with people in background in background on background.

DiCO (Ours): A hand holding a plastic container filled with sugar covered donuts.

Figure 3: Qualitative results on COCO sample images, using PAC-S as reward.

to be the most widely employed choice in recent works. In particular, we include some recent standard image captioning models exclusively trained on the COCO dataset with a standard XE+SCST training paradigm like CLIP-VL [54], COS-Net [32], and PMA-Net [6]. Moreover, we compare with LLM-based captioning models focused on zero-shot generation capabilities such as ZeroCap [58], lightweight architectures like ClipCap [40] and Small-Cap [46], or large-scale training paradigms such as the recently proposed MiniGPT-v2 [20] and BLIP-2 [30] models. To directly compare our solution with other CLIP-based optimization strategies, we also report the results of our base model trained with SCST using CLIP-S or PAC-S as reward and those of the model proposed in [14] in which a standard Transformer is optimized via SCST with a CLIP-based reward, eventually regularizing the training with an additional score that considers the grammatical correctness of generated sentences.

Results are shown in Table 1, including our model trained with DiCO using RN50, ViT-B/32, and ViT-L/14 as visual backbones. Notably, all versions of our model achieve better results than other methods optimized with CLIP-based rewards on almost all evaluation metrics. For example, when comparing our solution optimized via PAC-S reward with SCST and the model proposed in [14], we can notice how not only DiCO improves the performance in terms of standard metrics (*e.g.* 79.8 CIDEr points using RN50 features vs. 32.2 and 71.0 respectively obtained by SCST and [14]), but also obtains increased retrieval-based scores indicating that captions generated by our model are more discriminative and detailed than those generated by competitors. Additionally, DiCO leads to the overall best results on reference-free metrics also surpassing huge models trained on millions or even billions of data like MiniGPT-v2 and BLIP-2, further confirming the effectiveness of our training strategy. To validate the quality of generated captions, we report in Fig. 3 some qualitative results on sample images from the COCO dataset. DiCO can generate more descriptive and detailed captions while reducing repetitions and grammatical errors typically generated using SCST. We refer to Appendix E for additional qualitative results.

Human-based and LLM-based evaluations. As a complement of standard metrics, we also perform a user study and an evaluation based on a widely used LLM (*i.e.* GPT-3.5). To perform the user study, we present the users with an image and a pair of captions, one generated by our model and the other generated by a competitor, and ask them to select the preferred caption judging in terms of (1) *helpfulness* (*i.e.* which caption is most helpful to someone who can not see the image), and (2) *correctness* (*i.e.* which caption is more correct both in terms of grammar and consistency with the image). Users could also state that captions are equivalent on one or both evaluation axes. In this case, 0.5 points are given to both captions. To perform LLM-based evaluation, instead, we leverage the Turbo

version of GPT-3.5 and directly ask it to evaluate a pair of captions taking into account the corresponding reference sentences. In particular, we ask the LLM to return a score between 0 and 100 for each caption between the two in the prompt, where one is generated by our model and the other by a competitor, and use this score to compute the number of times GPT-3.5 prefers our solution against a competitor and vice versa. If the score is the same for both captions, we give 0.5 points to both of them. To force the

model to produce a more accurate evaluation, we also ask it to produce a reason for each score, which has been shown to lead to ratings that correlate well with human judgment [10].

Table 2 shows one-to-one comparisons between our model and one of the considered competitors in terms of both human-based and LLM-based evaluations. Results are reported on a subset of 1,000 images randomly taken from the COCO test set. For each comparison, we report the percentage of times a caption generated by one of the competitors is preferred against the one generated by our solution with PAC-S reward. As it can be seen, DiCO is almost always preferred more than 50% of the time, having a comparable number of preferences only when compared with BLIP-2. When instead considering other CLIP-based optimized models, captions generated by our solution are selected in a considerable number of cases from both human evaluators and GPT-3.5 (*e.g.* more than 55-60% compared to [10] with CLIP-S+Grammar reward). Additional details are reported in Appendix D.

Additional results on grammar metrics. Besides the semantic coherence between images and their descriptions, we compare our method against SCST from the point of view of the fluency and grammatical correctness of the generated captions. To this end, in Table 3 we

	Humans		GPT-3.5
	Helpfulness	Correctness	
ZeroCap [10]	20.3	27.8	20.8
SmallCap [10]	27.8	36.1	50.0
MiniGPT-v2 [10]	33.3	42.9	44.8
BLIP-2 [10]	49.1	48.6	51.2
Cho <i>et al.</i> (CLIP-S Reward) [10]	11.2	17.9	21.5
Cho <i>et al.</i> (CLIP-S+Gr. Reward) [10]	41.3	36.7	43.0
SCST (PAC-S Reward)	44.6	40.6	48.5

Table 2: Percentage of times a caption from a competitor is preferred against that generated by our proposal, using either human-based evaluations or GPT-3.5. Our solution is preferred more than 50% of the time in almost all cases.

Table 3: Comparison on semantic and grammar metrics. n_i means i -gram repetitions. Results are reported on the COCO test set.

Model	Reward	Backbone	Semantic			Grammar					
			C	CLIP-S	PAC-S	n_1	n_2	n_3	n_4	RE	%Correct
SCST	CLIP-S	RN50	3.1	0.804	0.837	11.762	5.168	2.809	1.518	6.0	24.7
SCST	PAC-S	RN50	32.2	0.799	0.860	5.453	1.588	0.645	0.288	1.6	71.6
DiCO	CLIP-S	RN50	78.9	0.815	0.842	1.583	0.143	0.039	0.015	0.1	96.1
DiCO	PAC-S	RN50	79.8	0.797	0.869	2.051	0.219	0.055	0.017	0.1	94.4
SCST	CLIP-S	ViT-B/32	1.1	0.851	0.846	11.166	3.566	1.232	0.395	1.5	3.9
SCST	PAC-S	ViT-B/32	40.7	0.810	0.870	5.078	1.443	0.584	0.260	1.6	73.3
DiCO	CLIP-S	ViT-B/32	81.7	0.825	0.858	1.938	0.230	0.071	0.026	0.2	94.8
DiCO	PAC-S	ViT-B/32	84.8	0.814	0.882	1.939	0.190	0.048	0.014	0.1	96.4
SCST	CLIP-S	ViT-L/14	1.1	0.865	0.834	8.788	2.114	0.716	0.248	1.0	2.6
SCST	PAC-S	ViT-L/14	51.1	0.805	0.862	8.788	4.611	1.200	0.479	1.3	72.6
DiCO	CLIP-S	ViT-L/14	82.6	0.837	0.856	1.710	0.142	0.039	0.014	0.1	95.4
DiCO	PAC-S	ViT-L/14	89.1	0.812	0.877	2.107	0.218	0.056	0.017	0.1	94.3

Model	Reference-based						Reference-free		
	B-4	M	R	C	S	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S
Up-Down [1]	36.3	27.7	56.9	120.1	21.4	0.787	0.848	0.723	0.803
SGAE [2]	39.0	28.4	58.9	129.1	22.2	0.796	0.855	0.734	0.812
AoANet [3]	38.9	29.2	58.8	129.8	22.4	0.797	0.857	0.737	0.815
\mathcal{M}^2 Transformer [4]	39.1	29.8	58.3	131.3	22.6	0.793	0.852	0.734	0.813
COS-Net [5]	42.0	30.6	60.6	141.1	24.6	0.814	0.870	0.758	0.832
PMA-Net [6]	43.0	30.6	61.1	144.1	24.0	0.814	0.869	0.755	0.821
Transformer (SCST)	43.6	30.8	61.0	143.3	23.2	0.809	0.866	0.750	0.826
Transformer (DiCO w/ $\beta = 0.05$)	43.2	31.2	61.1	144.2	24.4	0.815	0.871	0.756	0.831
Transformer (DiCO w/ $\beta = 0.1$)	43.7	31.2	61.2	143.8	24.5	0.817	0.872	0.757	0.832
Transformer (DiCO w/ $\beta = 0.2$)	43.7	31.3	61.3	143.5	24.4	0.816	0.872	0.756	0.831

Table 4: Comparison with standard captioners using CIDEr-based optimization.

report the average number of n -gram repetitions per caption (*i.e.* n_i with $i = 1, 2, 3, 4$), computed using the `nltk` language toolkit². We also include the Repetition Evaluation (RE) proposed in [16], which measures the redundancy of n -grams inside a caption (where $n = 4$ as in the original paper). Additionally, we employ the text encoder from [14] and present the percentage of captions classified as grammatically correct (*i.e.* %Correct). Experiments across different backbones confirm that SCST reaches high scores on the optimized metrics, but collapses to predictions that exhibit many repetitions, undermining the fluency of the generated text. DiCO does not suffer from the same problem, keeping low values for repetitions while showcasing state-of-the-art performance over the reward metrics.

CIDEr-based optimization. Finally, we assess whether our training paradigm can also be applied using the CIDEr score as reward, as usually done in standard image captioning approaches. Results are reported in Table 4, showing the performance of a standard Transformer model fine-tuned with the classical SCST procedure and that of other captioners. For completeness, we also include the results in terms of ROUGE [33] and SPICE [8] which are typically used in standard image captioning evaluation. In this case, we apply DiCO with different β values on the same baseline architecture used in previous experiments (*i.e.* a vanilla Transformer with 3 layers in both encoder and decoder). Interestingly, our solution achieves better results than SCST also in this setting, with 144.2 CIDEr points vs. 143.3 obtained by SCST. As an additional result, DiCO reaches better or comparable performance to that obtained by recent captioning models based on more complex architectures and optimized via SCST, thus proving to be a valid alternative also in a standard CIDEr-based setting.

5 Conclusion

We presented DiCO, a novel fine-tuning strategy for image captioning which aligns a model to a learnable evaluator with high human correlation. Our approach optimizes a distilled reward model by solving a weighted classification problem directly inside the captioner, which allows it to capture fine-grained differences between multiple candidate captions. Experimental results on several datasets, conducted through automatic metrics and human evaluations, validate the effectiveness of our approach, which can generate more descriptive and detailed captions than competitors. At the same time, it achieves state-of-the-art results when trained to optimize traditional reference-based metrics.

²<https://www.nltk.org/>

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In the following, we present additional materials about DiCO. In particular, we provide additional analyses and ablation studies, comparing DiCO with the standard SCST training paradigm. Moreover, we report further implementation details and qualitative results on all considered datasets and settings.

A Preliminaries

In this section, we first recap the definition of the SCST and Reinforcement Learning from Human Feedback (RLHF) training protocols [41, 48]. Then, we introduce captioning metrics based on contrastive embedding spaces [42].

Self-critical sequence training. SCST [48] is a two-step training methodology which (1) pre-trains a captioner f_θ using a time-wise cross-entropy loss with respect to ground-truth sequences, and (2) fine-tunes the same network by maximizing the CIDEr score [60] using a reinforcement learning (RL) approach. We assume that the captioner takes as input an image I described with a sequence of visual features (v_1, v_2, \dots, v_R) , and a ground-truth sequence $s = (w_1, w_2, \dots, w_T)$, where w_i is a token belonging to a pre-defined vocabulary. Noticeably, depending on the dataset there might be multiple ground-truth sequences associated with each image. During the first training stage, the network is conditioned on visual features and all ground-truth tokens up to the current prediction step t , and f_θ is optimized using the cross-entropy loss (teacher forcing). In the second training stage, instead, the network is only conditioned on the input image and generates an entire caption $s' = (w'_1, w'_2, \dots, w'_{T'})$ by sampling input tokens from the output probability distribution generated at the previous time step. For instance, w'_t might be chosen as $w'_t = \text{argmax}_\theta f_\theta(w_t | w'_{t-1}, \dots, w'_1, v_1, \dots, v_R)$, or multiple sentences can be sampled via beam search. The generated sentences are then employed to compute the CIDEr metric, which is later used as a reward to guide a policy-gradient RL update step (see [48] for details).

Reinforcement learning from human feedback. Recent NLP literature has employed techniques based on RLHF [41] to align the behavior of a large language model to human preferences. This approach is usually based on the collection of large-scale datasets of human preferences: the language model f_θ ³ is prompted with a prompt x to produce pairs of answers $(s'_1, s'_2) \sim f_\theta$, which are then presented to human labelers who express preference for one answer, *i.e.* $s'_w \succ s'_l$, where s'_w and s'_l indicate, respectively, the preferred and dispreferred completion. The resulting dataset of human preferences $\mathcal{D} = \{x_i, s'_{w,i}, s'_{l,i}\}_{i=1}^N$ is

³With a slight abuse of notation, in this paragraph we use f_θ to refer to a single-modality language model.

then employed to train a reward model on top of it [13], for subsequent optimization with reinforcement learning. In image captioning, due to the lack in size of existing human preference datasets [11, 20, 60], *training a learnable reward model to follow the RLHF approach is impracticable* (see also Sec. C).

Learnable contrastive captioning metrics. As pointed out by recent literature on captioning evaluation, a model learned with language-image pre-training [24] can be straightforwardly employed as a captioning metric. Given a caption s' generated from I , indeed, its correctness score can be defined as a function of the similarity predicted by the image-text model, *i.e.* $\text{sim}(I, s')$. A popular choice [19] is to define the score to be proportional to the ReLU of the predicted similarity and to employ a scalar multiplier w to stretch the resulting score within the range of $[0, 1]$:

$$\text{CLIP-S}(I, s') = w \cdot \text{ReLU}(\text{sim}(I, s')). \quad (8)$$

In the original formulation of [19] (termed CLIP-S), the backbone employed for computing similarities was pre-trained on 400M noisy (image, text) pairs collected from the internet. While CLIP-S shows a significantly higher alignment with human judgments compared to traditional metrics (*e.g.* BLEU, METEOR, CIDEr), the noisy nature of the training data limits the CLIP-S capability to distinguish fluent human-generated captions. To overcome this issue, a recent choice [51] is that of fine-tuning the backbone on cleaned data, which further boosts the correlation with human judgments. Specifically, the PAC-S score [51] trains on the basis of a similarity matrix built with human-collected captions and machine-generated ones, where the latter are obtained from a captioner trained to mimic the same distribution of human captions. In case a set of reference captions $R = \{r_i\}_{i=1}^N$ is given, there exists a version of the CLIP-based metrics accounting for them [19], which is defined as follows:

$$\text{RefCLIP-S}(I, s', R) = \text{H-Mean}(\text{CLIP-S}(I, s'), \text{ReLU}(\max_{r \in R} \cos(s', r))). \quad (9)$$

Following [51], the same formula can be applied to compute the reference-based version of PAC-S (RefPAC-S).

B Ablation Studies

Early stopping condition. When comparing multiple training strategies, we always employ an early stopping condition based on the validation value of the reference-based version of the metric used as a reward. In practice, when optimizing for CLIP-S, we early stop the training according to the validation RefCLIP-S, while when optimizing for PAC-S we early stop based on the validation RefPAC-S. We then take the model state corresponding to the epoch with the highest validation score and report its evaluation metrics. While this provides a reasonable evaluation strategy that equally promotes all compared approaches, evaluating a single model state does not capture the full training behavior of different fine-tuning strategies.

To complement Fig. 1 of the main paper, in Fig. 4 we report the test curves of CIDEr, RefCLIP-S, and CLIP-S obtained when optimizing the CLIP-S score and again those of CIDEr, RefPAC-S, and PAC-S obtained when optimizing the PAC-S score. For both cases, we compare the results using DiCO and SCST. With a red marker, we indicate the model state

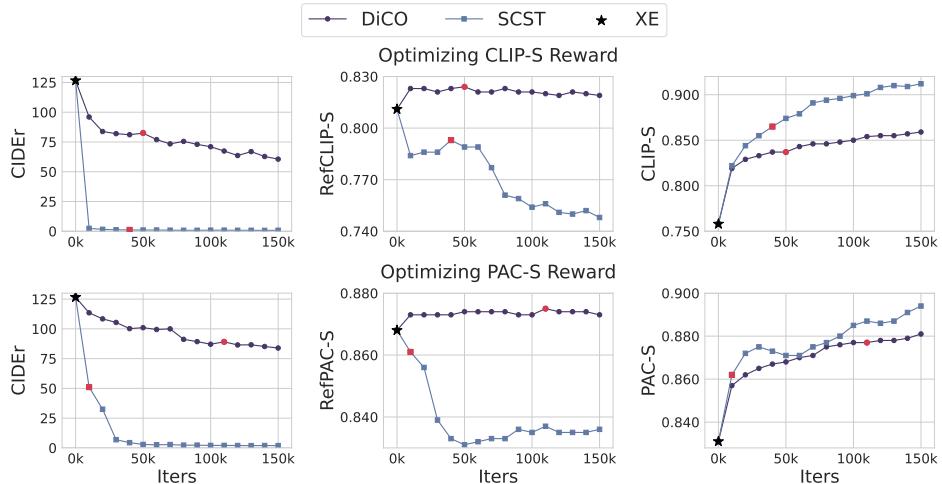


Figure 4: Metric curves when optimizing CLIP-S (top) and PAC-S (bottom) scores with DiCO and SCST. The red dot indicates the early stopping point we employ.

Training	Reward	Reference-based					Reference-free			
		B-4	M	C	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S	R@1	MRR
DiCO (w/o quality distances)	CLIP-S	19.3	25.6	79.5	0.820	0.858	0.836	0.851	45.7	57.2
DiCO	CLIP-S	21.4	27.1	82.6	0.824	0.863	0.837	0.856	46.5	58.4
DiCO (w/o quality distances)	PAC-S	24.9	27.6	91.7	0.812	0.873	0.809	0.875	50.6	62.4
DiCO	PAC-S	25.2	28.4	89.1	0.815	0.875	0.812	0.877	50.9	62.9

Table 5: Effectiveness analysis of using quality distances to weight rewards. Results are reported on the COCO test set using ViT-L/14 as backbone.

chosen by the early stopping condition, while a star marker indicates the model state after XE pre-training. As it can be seen, SCST hacks the reward metric immediately after the start of the fine-tuning phase, at the expense of CIDEr, RefCLIP-S, and RefPAC-S. Correspondingly, when optimizing using PAC-S as reward, the early stopping condition is forced to select the model state corresponding to the first fine-tuning epoch, which indeed showcases the highest RefPAC-S. Continuing the fine-tuning, though, would let SCST hack the reward metric even further and provide lower-quality captions.

On the contrary, DiCO showcases a more robust training behavior. While CLIP-S and PAC-S values increase during fine-tuning as a result of the optimization process, the decrease in CIDEr is well restrained, while RefCLIP-S and RefPAC-S even increase with respect to the XE state. This highlights that DiCO can optimize modern captioning metrics without incurring reward hacking and without deviating from a fluent and high-quality generation. Finally, in Fig. 6 we also report sample captions from the COCO Karpathy test split when optimizing the PAC-S score with SCST at different training stages, in comparison with DiCO. While SCST optimization tends to produce degraded and repetitive captions over time, DiCO maintains fluency and generation quality.

Effectiveness of using quality distances. We also evaluate the effectiveness of weighting rewards with quality distances (cf. Eq. 4) and train a different version of our DiCO approach setting $\gamma = \frac{1}{k}$. Table 5 reports the results of this analysis, using both CLIP-S and PAC-S as rewards. Notably, using quality distances to weight rewards improves the performance on

Training	Reward	k	Reference-based					Reference-free			
			B-4	M	C	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S	R@1	MRR
SCST	PAC-S	-	22.3	28.4	51.1	0.801	0.861	0.805	0.862	46.7	58.8
DiCO (Ours)	PAC-S	1	30.4	28.2	109.5	0.819	0.876	0.790	0.861	41.4	54.0
DiCO (Ours)	PAC-S	2	27.1	28.3	99.9	0.818	0.876	0.802	0.871	46.2	58.9
DiCO (Ours)	PAC-S	4	25.2	28.4	89.1	0.815	0.875	0.812	0.877	50.9	62.9
DiCO (Ours)	PAC-S	6	24.9	28.6	86.9	0.813	0.874	0.811	0.876	50.9	62.5
DiCO (Ours)	PAC-S	7	24.8	28.5	86.5	0.812	0.873	0.811	0.876	50.5	62.4

Table 6: Performance varying the number of “loser” captions k . Results are reported on the COCO test set using ViT-L/14 as backbone.

both reference-based and reference-free metrics, thus demonstrating the usefulness of our strategy.

Effect of varying the β parameter. Fig. 5 shows how evaluation metrics vary when changing the β parameter, which regularizes the deviation from the pre-trained model. In particular, we report CIDEr, CLIP-S, and PAC-S scores using six different β values (*i.e.* from 0.05 to 0.3). As it can be seen, a higher β value prevents the model from deviating from the original pre-trained captioner (trained with XE loss), with CIDEr scores greater than 100 and, as a consequence, lower CLIP-S and PAC-S. On the contrary, when using a lower β value, reference-based metrics like CIDEr are penalized as the model is more inclined to deviate from the original version, thus boosting CLIP-S and PAC-S metrics. Overall, we find that $\beta = 0.2$ represents a good compromise between reference-based and reference-free metrics, and therefore we employ this value for all experiments.

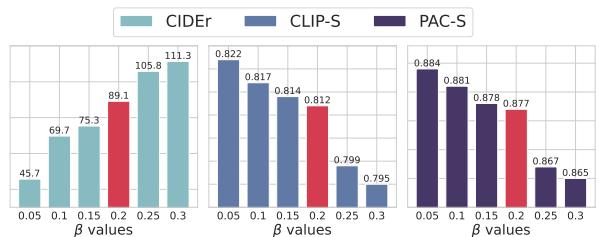


Figure 5: CIDEr, CLIP-S, and PAC-S scores when changing the β parameter using ViT-L/14 as backbone. Higher β values prevent the model from deviating from the pre-trained captioner, while penalizing reference-free metrics. The best trade-off is given by $\beta = 0.2$.

Number of loser captions. DiCO requires generating $k + 1$ captions at each training step, of which the k worst are selected as losers according to the metric employed as reward. Table 6 shows the results as we vary the parameter k . In our experiments, we select $k = 4$ as it achieves the highest scores on reference-free metrics while keeping competitive performance on reference-based metrics.

C Additional Experimental Results

Comparison with SCST and RLHF. To complement the analyses reported in the main paper, we compare our fine-tuning strategy with SCST [3] and RLHF [1]. As we focus on the optimization of modern captioning metrics, for SCST experiments we directly apply a CLIP-based reward using either CLIP-S or PAC-S. Further, we adapt the RLHF paradigm to a captioning setting by first training a reward model based on human feedback and then optimizing the captioning model via reinforcement learning based on the PPO objective [5], using the score from the reward model as a reward. To train the reward model, we employ

a combination of datasets typically used to evaluate the correlation of captioning metrics with human judgments, namely Flickr8k-Experts, Flickr8k-CF, and Composite [10, 20]. All datasets contain multiple candidate captions, either human-annotated or generated by a captioning model, associated with a given image and corresponding human ratings that evaluate whether each caption correctly describes the image. Overall, we obtain around 3.5k unique images and 50k captions each associated with a normalized rating between 0 and 1. At training time, we sample a pair of candidate captions for each image and use the associated human ratings to train the reward model, using maximum likelihood estimation. The reward model is built by modifying the captioner pre-trained with XE so to have a single final output and is trained with a negative log-likelihood loss following [40]. In addition to this adaptation of the RLHF training strategy, we also design a variant in which the human preferences-based reward model is replaced with a CLIP-based evaluator, directly employing CLIP-S or PAC-S as reward. For completeness, we also include the results of the model trained with XE loss only, which is the starting point for all other fine-tuning strategies.

Results are reported in Table 7 in terms of reference-based and reference-free evaluation metrics. As it can be seen, the proposed optimization strategy generally leads to better results across all metrics, surpassing both SCST and RLHF by a significant margin. Specifically, we can notice that optimizing the captioner with human feedback does not improve the final results. This is probably due to the limited size of available captioning datasets with human ratings, that prevent the effective application of standard RLHF fine-tuning to a captioning model. When instead using CLIP-S and PAC-S as rewards, both SCST and RLHF experience a significant drop in standard image captioning metrics. In terms of CLIP-based metrics, SCST obtains quite good results which however are not supported with robustness on all other metrics. Overall, our DiCO strategy exhibits good performance in all evaluation directions, obtaining the best results in terms of CLIP-based and retrieval-based scores while maintaining competitive performance on standard metrics.

Fine-grained image captioning evaluation. As an additional analysis, we report in Table 8 fine-grained image captioning results on the FineCapEval dataset [24], which contains 1,000 images from COCO and CC3M [53] annotated with 5 detailed and fine-grained captions, describing the background of the scene, the objects and their attributes, and the relations between them. Also in this setting, DiCO confirms its superior performance compared to other CLIP-based optimized captioners [24], thus further demonstrating the effectiveness of directly optimizing a captioning model with the proposed solution. Specifically, when considering the same backbone used in [24] (*i.e.* RN50), DiCO achieves the best results in terms of both standard captioning metrics and CLIP-based scores.

Training	Reward	Reference-based					Reference-free			
		B-4	M	C	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S	R@1	MRR
XE	-	37.3	30.4	126.6	0.811	0.868	0.758	0.831	27.7	38.5
RLHF	HF	21.4	27.8	57.9	0.776	0.843	0.745	0.819	24.7	34.9
RLHF	CLIP-S	12.9	24.2	2.3	0.714	0.800	0.732	0.794	19.5	29.0
SCST	CLIP-S	10.2	23.0	1.1	0.793	0.827	0.865	0.834	43.3	55.0
DiCO	CLIP-S	21.4	27.1	82.6	0.824	0.863	0.837	0.856	46.5	58.4
RLHF	PAC-S	12.4	23.7	2.0	0.712	0.798	0.726	0.790	18.1	27.5
SCST	PAC-S	22.3	28.4	51.1	0.801	0.861	0.805	0.862	46.7	58.8
DiCO	PAC-S	25.2	28.4	89.1	0.815	0.875	0.812	0.877	50.9	62.9

Table 7: Comparison with different fine-tuning strategies. Results are reported on the COCO test set using ViT-L/14 as backbone.

Model	Backbone	Reward	Reference-based					Reference-free	
			B-4	M	C	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S
Cho <i>et al.</i> (SCST) [2]	RN50	CLIP-S	5.9	14.2	13.9	0.689	0.769	0.721	0.803
Cho <i>et al.</i> (SCST) [2]	RN50	CLIP-S+Gr.	11.1	16.3	19.1	0.683	0.784	0.684	0.808
DiCO (Ours)	RN50	CLIP-S	14.2	16.1	17.2	0.688	0.782	0.696	0.805
DiCO (Ours)	RN50	PAC-S	13.6	16.4	19.2	0.695	0.800	0.704	0.835
DiCO (Ours)	ViT-B/32	PAC-S	13.8	16.7	19.3	0.708	0.811	0.726	0.855
DiCO (Ours)	ViT-L/14	PAC-S	15.0	17.4	23.2	0.722	0.822	0.731	0.855

Table 8: Fine-grained image captioning results on the FineCapEval dataset.

Model	Reward	Backbone	nocaps			VizWiz			TextCaps			CC3M		
			C	CLIP-S	PAC-S									
Cho <i>et al.</i> (SCST) [2]	CLIP-S	RN50	10.9	0.765	0.819	4.7	0.693	0.784	7.6	0.731	0.813	3.6	0.717	0.784
Cho <i>et al.</i> (SCST) [2]	CLIP-S+Gr.	RN50	54.0	0.712	0.822	20.4	0.648	0.774	26.8	0.680	0.814	18.0	0.671	0.790
SCST	PAC-S	RN50	20.9	0.741	0.850	13.0	0.668	0.795	22.0	0.683	0.822	5.8	0.699	0.797
DiCO (Ours)	PAC-S	RN50	44.6	0.733	0.851	29.3	0.680	0.813	30.8	0.696	0.838	21.4	0.690	0.815
SCST	PAC-S	ViT-B/32	35.7	0.750	0.854	20.1	0.715	0.837	21.9	0.699	0.835	9.8	0.698	0.809
DiCO (Ours)	PAC-S	ViT-B/32	66.5	0.754	0.869	32.7	0.710	0.842	31.8	0.712	0.853	23.4	0.697	0.821
SCST	PAC-S	ViT-L/14	44.8	0.746	0.850	26.8	0.701	0.820	23.6	0.705	0.836	13.2	0.701	0.811
DiCO (Ours)	PAC-S	ViT-L/14	74.3	0.755	0.865	40.6	0.706	0.832	33.7	0.717	0.852	26.7	0.704	0.824

Table 9: Image captioning results on out-of-domain datasets like nocaps, VizWiz, TextCaps, and CC3M.

Out-of-domain evaluation. To evaluate generalization capabilities to out-of-domain images, we extend our analysis by considering diverse image captioning datasets, including nocaps [2], which has been introduced for novel object captioning and contains object classes that are not present in the COCO dataset, VizWiz [18], composed of images taken by blind people, TextCaps [2], which is instead focused on text-rich images, and CC3M [23], composed of image-caption pairs collected from the web. In Table 9 we report the results of our approach using PAC-S as reward, compared to the CLIP-based training strategy proposed in [12] and the standard SCST with the same reward as in our approach. Even in this challenging context, DiCO achieves the best results across all datasets and backbones, demonstrating better descriptive capabilities than competitors.

Additional results on Flickr30k. Finally, we also benchmark our method on images from the Flickr30k dataset [24]. We report the results in Table 10, using both PAC-S and CLIP-S as reward and comparing with the approach proposed in [12]. As it can be noticed, DiCO demonstrates strong generalization capabilities, achieving the best results on almost all evaluation metrics further confirming the effectiveness of our training strategy.

D Additional Details

Additional implementation and training details. During cross-entropy pre-training, we accumulate gradients for 8 training steps over 2 GPUs, resulting in 1,024 samples per batch. For this training stage, the learning rate is linearly increased up to $2.5 \cdot 10^{-4}$. Each fine-tuning experiment starts from the XE checkpoint with the highest CIDEr, leveraging 2 GPUs and a global batch size of 16. Training the reward models for RLHF follows the same settings as the fine-tuning phase.

CIDEr-based optimization. In computing quality distances with CIDEr metric as reward

Model	Backbone	Reward	Reference-based				Reference-free		
			B-4	M	C	RefCLIP-S	RefPAC-S	CLIP-S	PAC-S
Cho <i>et al.</i> (SCST) [10]	RN50	CLIP-S	4.0	16.5	10.0	0.751	0.806	0.818	0.839
Cho <i>et al.</i> (SCST) [10]	RN50	CLIP-S+Gr.	11.0	20.9	36.8	0.750	0.826	0.755	0.839
DiCO (Ours)	RN50	CLIP-S	16.8	22.0	44.9	0.762	0.829	0.774	0.839
DiCO (Ours)	RN50	PAC-S	17.2	22.6	46.8	0.769	0.846	0.786	0.871
DiCO (Ours)	ViT-B/32	PAC-S	17.8	22.8	48.6	0.780	0.855	0.810	0.890
DiCO (Ours)	ViT-L/14	PAC-S	19.0	24.5	55.8	0.790	0.862	0.804	0.883

Table 10: Image captioning results on the Flickr30k dataset.

(see Table 4 of the main paper), we set the softmax temperature τ to 1, a higher value than the one used for CLIP-S and PAC-S optimization (equal to $1/(3 \cdot 10^2)$). We argue that the CIDEr score is discriminant enough to discern the goodness of similar captions sampled from a beam search. On the contrary, CLIP-based metrics are less sensible to small changes, thus needing a lower temperature to amplify the score differences.

Human-based evaluation. As shown in the main paper, we conducted a user study to evaluate the quality of generated captions. To this end, we developed a custom web interface that presents the users with an image and two captions, one generated by DiCO, and one drawn from a different model (cf. Table 2), and asks them to select the best caption based on correctness and helpfulness. We show a screenshot of the developed interface is shown in Fig. 7. Overall, the evaluation involved more than 50 different users, collecting approximately 3,000 evaluations for both criteria.

LLM-based evaluation. GPT-3.5 Turbo proves itself very compliant with our requests. However, we find about a hundred failure cases (*e.g.* wrong JSON format, more scores than the number of candidate captions, etc.) out of 7,000 requests. We opt for simply discarding them in the winner rate computations. For fair evaluation, we randomly swap the order in which we insert the two candidate captions in the prompt. This ensures that the descriptions generated by our competitors have on average the same probability as ours to be processed first by the LLM causal attention, which may influence the final score. Following [10], the prompt we used is:

You are trying to tell if each sentence in a candidate set of captions is describing the same image as a reference set of captions.

Candidate set: {candidate captions}

Reference set: {target captions}

You have to determine how likely is that each of the sentences in the candidate set is describing the same image as the reference set, on a scale from 0 to 100. Please output exclusively a JSON list, with an item for each candidate. Each item should be a dictionary with a key "score", containing a value between 0 and 100, and a key "reason" with a string value containing the justification of the rating. Start directly with the json.

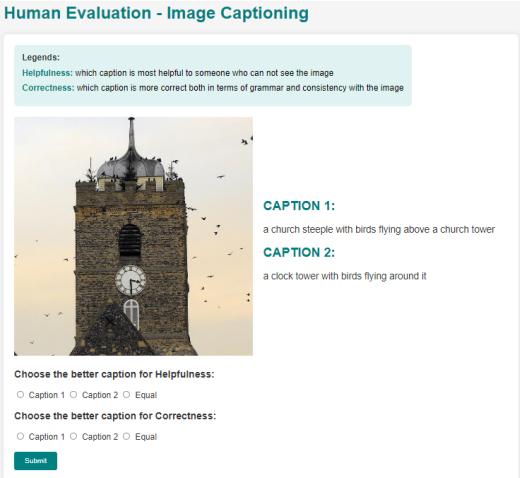


Figure 7: User study interface to evaluate helpfulness and correctness of given captions.

E Additional Qualitative Results

Finally, we report additional qualitative results to qualitatively validate the effectiveness of our training strategy. In particular, Fig. 8 and Fig. 9 show sample images from the COCO dataset and captions predicted by DiCO in comparison to those generated by SCST, the model proposed in [12], and the large-scale model BLIP-2 [30]. As it can be seen, DiCO generates significantly more detailed captions than BLIP-2, while reducing repetitions typically present in SCST-generated sentences. To qualitatively validate the generalization capabilities to out-of-domain images, we report sample captions predicted by DiCO and SCST using PAC-S as reward on nocaps [0] (Fig. 10), VizWiz [13] (Fig. 11), TextCaps [23] (Fig. 12), and CC3M [31] (Fig. 13).

In Fig. 14, we instead show some qualitative results when using CIDEr as reward. In this case, we compare DiCO with standard image captioning models, including a vanilla Transformers trained with the same visual features used in our approach, COS-Net [20], and \mathcal{M}^2 Transformer [16]. All competitors have been trained with a standard XE+SCST training protocol. Also in this setting, DiCO is able to generate high-quality captions compared to competitors, confirming that it can also be employed as a valid alternative to SCST for training standard image captioning models.

F Limitations

As with all image captioning models, we acknowledge that our method might fail to provide informative captions in some rare contexts. To qualitatively evaluate the limitations of our approach, we report some failure cases in Fig. 15. As it can be seen, DiCO may produce factual errors, *e.g.* mistaking balloons for *kites* (first sample, first row) or a *stuffed animal* for a seal (first sample, second row). Additionally, DiCO may fail to recognize known entities, thus providing only a broad description of the scene (*e.g.* a *white monument* rather than the Taj Mahal mausoleum, or a *black silver car* rather than an Aston Martin). This can be conducted to the image-caption pairs contained in the COCO dataset, which lack open-world knowledge. Finally, when the main subject of the image is uncertain (second sample, third row), DiCO may overlook the picture and generate captions based on its learned priors, resulting in hallucinations.



SCST (after 10k iters): A group of people with umbrellas walking down a street with people walking down a wet sidewalk holding pink umbrellas in rain.

SCST (after 50k iters): Many people crossing wet wet alley with people walking with colorful umbrellas outside a building with wet alley with people walking under umbrellas outside rainy surface.

SCST (after 100k iters): Pedestrians walking down wet wet road with pedestrians carrying pink umbrellas outside a building on wet sidewalk outside rainy wall with buildings outside surface poles surface poles.

DiCO (Ours): A group of people walking down a wet sidewalk with umbrellas in the rain.



SCST (after 10k iters): A group of young boys kicking around a soccer ball on a soccer field with other young boys running around with net in background.

SCST (after 50k iters): Young boys kicking soccer ball around soccer goal kicking grass underneath a goal on grass behind background behind surface surface with trees in background behind surface surface.

SCST (after 100k iters): Young boys soccer teams chasing after after soccer soccer goalie in background with green leaves on grass behind background surface court with young boy.

DiCO (Ours): A group of young children kicking a soccer ball in a field.



SCST (after 10k iters): A group of people playing frisbee with a man laying on ground with a person laying on ground with other people in background.

SCST (after 50k iters): Group of kids playing ultimate frisbee with man laying on ground with people on sand floor with frisbees while people gather around background behind surface surface.

SCST (after 100k iters): A group of kids playground with man laying on cement floor playing frisbee game with man laying outside a crowd in background surface outside surface poles leg.

DiCO (Ours): A group of people playing with a frisbee on a beach with other people in the background.



SCST (after 10k iters): A black motorecycle parked on a sidewalk next to a parked motorcycle on a sidewalk next to a rack with bicycles in background.

SCST (after 50k iters): An old motorcycle parked on sidewalk with parked bicycle outside a brick background with other bikes on sidewalk outside clear background behind surface background behind surface surface.

SCST (after 100k iters): Antique motorcycle parked outside a brick building with a silver seat outside a bike on a sidewalk with other bikes outside background surface outside surface poles top.

DiCO (Ours): A small black motorcycle parked on a sidewalk next to other bikes.



SCST (after 10k iters): A small pizza with vegetables on a wooden picnic table with a pizza on a picnic table with silverware and wine in background.

SCST (after 50k iters): Small vegetable pizza with vegetable vegetable on wooden picnic table with serving dish with other foods on grass outside clear surface behind background behind surface outside surface.

SCST (after 100k iters): Cooked vegetable vegetable vegetable vegetable pizza served outside outside table with fork on picnic table outside a wine holder on sun surface outside background surface poles hand.

DiCO (Ours): A small pizza on a wooden picnic table with silverware and a wine glass in the background.

Figure 6: Qualitative results on sample images from the COCO Karpathy test split [34] using SCST optimization with PAC-S reward at different fine-tuning states, in comparison with DiCO.



BLIP-2 [51]: A group of colorful umbrellas under a covered area.

Cho et al. [42]: A large blue vase sitting on the dirt ground with colorful decorations next to a market.

SCST: Several colorful colorful umbrellas hanging from a wooden structure under a tree tree with statues on display in outdoor market under palm trees on clear background.

DiCO (Ours): A display of colorful umbrellas in a shop with decorations.



BLIP-2 [51]: A green and yellow train pulling into a station.

Cho et al. [42]: A green commuter train parked near a platform area with a green trees area motion stance ear stance.

SCST: A green and yellow passenger train traveling down train tracks next to a loading platform with a green passenger on a platform with trees in background.

DiCO (Ours): A green and yellow passenger train traveling down train tracks next to a platform.



BLIP-2 [51]: A black and white photo of a train.

Cho et al. [42]: A large metal train driving next to a lot of tanks on the tracks.

SCST: Black and white photograph of freight freight freight freight cars on railroad tracks with tanker cars on track with wires in background on background.

DiCO (Ours): A black and white photo of a freight train traveling down railroad tracks next to wires.



BLIP-2 [51]: A woman in a boat selling food on the water.

Cho et al. [42]: A couple of women preparing a tray of food in the river with bananas.

SCST: Two women in canoes with baskets full of bananas and other asian asian workers carrying baskets on shelves with baskets on clear surface in background.

DiCO (Ours): Two asian women in a small boat filled with food and bananas.



BLIP-2 [51]: A birthday cake with dora the explorer on it.

Cho et al. [42]: A large blue birthday cake with toys and toys on the table.

SCST: A colorful birthday cake decorated with purple and green flowers on top of purple birthday cake with decorations on table in background on background.

DiCO (Ours): A birthday cake with purple and green decorations on it.



BLIP-2 [51]: A bunch of carrots next to a plate of food.

Cho et al. [42]: A bunch of carrots and other carrots on a white plate with a knife behind them.

SCST: A white plate topped with carrots and other vegetables on a clear surface with other vegetables on display in background on background in background.

DiCO (Ours): A bunch of carrots and other vegetables on a white plate.

Figure 8: Qualitative results on sample images from the COCO Karpathy test split using DiCO with PAC-S reward. We compare our approach with SCST using PAC-S as reward, the model proposed in [44] with CLIP+S+Grammar as reward, and the BLIP-2 model [51] which has been trained on large-scale vision-and-language datasets.



BLIP-2 [30]: A group of teddy bears on a boat.

Cho et al. [30]: A couple of teddy bears wearing hats sitting on a boat with a plant behind them.

SCST: Teddy bears dressed in green costumes riding a miniature boat decorated with green hats on a blue wall in military uniform on display in background.

DiCO (Ours): Stuffed animals dressed in green costumes riding in a boat.



BLIP-2 [30]: A herd of zebras walking through a grassy field.

Cho et al. [30]: A large herd of zebra and other animals grazing in the prairie.

SCST: A herd of zebras running through tall brown grass in savanna with distance in distance in background on clear surface in background on background.

DiCO (Ours): A large herd of zebras walking through tall brown grass in a large field.



BLIP-2 [30]: A table topped with food and a bottle of wine.

Cho et al. [30]: Two plates of food and a bottle of wine on the table with a bottle.

SCST: A white plate topped with meat cheese and vegetables next to a bottle of wine and bread with cheese and tomatoes on wooden surface in background.

DiCO (Ours): A table topped with two bowls of food next to a bottle of wine and cheese.



BLIP-2 [30]: A small train that is on display in a mall.

Cho et al. [30]: A large red train driving on a busy street with people near it.

SCST: A miniature miniature train with a miniature train on a sidewalk with people walking around a mall with a mall on a mall platform in background.

DiCO (Ours): People walking around a miniature train on a sidewalk in a shopping mall.



BLIP-2 [30]: A woman with a bunch of bananas on her head.

Cho et al. [30]: A smiling woman wearing a colorful costume holding a bunch of bananas on the background.

SCST: A woman dressed in colorful costume with yellow bananas on her head with a man's head dressed in colorful costume in background on background.

DiCO (Ours): A smiling woman wearing a large banana costume on her head with people in the background.



BLIP-2 [30]: Two horses walking in the desert with mountains in the background.

Cho et al. [30]: A group of three brown horses walking together in the desert.

SCST: Two brown horses walking through dry desert desert with sand on clear surface in distance with clear background on clear surface in background.

DiCO (Ours): Two brown horses walking through a desert plain with sand and bushes in background.

Figure 9: Qualitative results on sample images from the COCO Karpathy test split using DiCO with PAC-S reward. We compare our approach with SCST using PAC-S as reward, the model proposed in [12] with CLIP+S+Grammar as reward, and the BLIP-2 model [30] which has been trained on large-scale vision-and-language datasets.

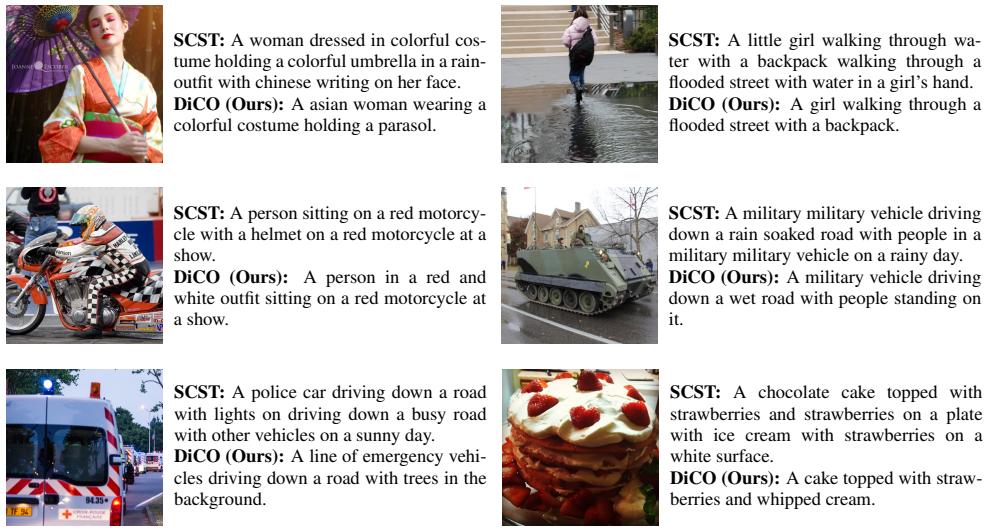


Figure 10: Qualitative results on sample images from nocaps.



Figure 11: Qualitative results on sample images from VizWiz.



Figure 12: Qualitative results on sample images from TextCaps.



Figure 13: Qualitative results on sample images from CC3M.



\mathcal{M}^2 Transf. [16]: A young boy sitting in the passenger seat of a car.
COS-Net [32]: A little girl sitting in the back seat of a car holding a cell phone.
Transf. (SCST): A child sitting in a car holding a cell phone.
Transf. (DiCO): A child sitting in the back seat of a car talking on a cell phone.



\mathcal{M}^2 Transf. [16]: A man sitting on the back of a truck with bananas.
COS-Net [32]: An old truck with a man standing on the back of it.
Transf. (SCST): A man standing next to a truck full of bananas.
Transf. (DiCO): A black and white photo of a man with a truck full of bananas.



\mathcal{M}^2 Transf. [16]: A woman laying on the beach under an umbrella on a.
COS-Net [32]: A woman laying on a beach under an umbrella.
Transf. (SCST): A woman laying on a blanket under an umbrella on a.
Transf. (DiCO): A woman laying on a blanket under an umbrella on the beach.



\mathcal{M}^2 Transf. [16]: A bunch of green suitcases stacked on top of a fireplace.
COS-Net [32]: A group of green luggage sitting on a couch in a living room.
Transf. (SCST): Three green suitcases stacked on top of each other.
Transf. (DiCO): Three green suitcases sitting on the floor in a living room.



\mathcal{M}^2 Transf. [16]: A tray of food with rice and vegetables in a.
COS-Net [32]: A group of plastic containers filled with food.
Transf. (SCST): Four containers of food with carrots and a.
Transf. (DiCO): Four plastic containers filled with different types of food.



\mathcal{M}^2 Transf. [16]: An empty street at sunset with a green traffic light.
COS-Net [32]: An intersection with traffic lights and a city street.
Transf. (SCST): A city street with traffic lights and a.
Transf. (DiCO): A street with traffic lights and a building in the background.

Figure 14: Qualitative results on sample images from the COCO Karpathy test split using DiCO with CIDEr reward. We compare our approach with a standard Transformer trained with SCST and CIDEr as reward, \mathcal{M}^2 Transformer [16] and COS-Net [32].



SCST: Two colorful colorful kites flying over a grassy field with a yellow yellow red yellow and yellow flags on clear day.
DiCO (Ours): Two colorful kites flying through a field on a clear day.



SCST: A hand holding up a piece of cake with a picture of a person's hand holding out a paper on a dark surface.
DiCO (Ours): A person's hand holding up a piece of cake with a picture of a sign on it.



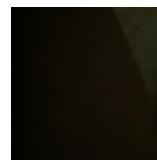
SCST: A close up picture of a penguin with its eyes open with its eyes open.
DiCO (Ours): A close up picture of a very small brown stuffed animal.



SCST: A black car with a black leather seat parked in a parking lot with people looking at something in the background.
DiCO (Ours): A black silver car parked in a parking lot.



SCST: Two people sitting in front of a white monument with a monument in front of a white monument.
DiCO (Ours): Two people sitting on a bench in front of a large white monument.



SCST: A close up view of a person's leg in a dark dark dark dark dark colored shadow against a white background.
DiCO (Ours): The shadow of a person's feet in a dark room.

Figure 15: Qualitative results showcasing samples where DiCO fails in comparison to the SCST training methodology.